COVID-19 and labour market inequality in South Africa

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Declaration of own work

I, Timothy Köhler, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university.

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I, Timothy Köhler, confirm that I have been granted permission by the University of Cape Town's Doctoral Degrees Board to include the following publications in my PhD thesis, and where co-authorships are involved, my co-authors have agreed that I may include the publications:

1. **Köhler, T.** (2023). What we know about COVID-19 and the South African labour market. Research on Socio-Economic Policy (RESEP) Covid Generation Research Note. RESEP, Stellenbosch University.

2. **Köhler, T.**, & Bhorat, H. (2023). Wages and wage inequality during the COVID-19 pandemic in South Africa. Development Policy Research Unit Working Paper 202308. DPRU, University of Cape Town.

3. **Köhler, T.**, Bhorat, H., Hill, R., & Stanwix, B. (2023). Lockdown stringency and employment formality: Evidence from the COVID-19 pandemic in South Africa. *Journal for Labour Market Research, 57(3)*, 1-28.

I further declare that earlier versions of Chapters 4 and 5 have been presented at several conferences, workshops, and seminars. These papers and presentations may appear on the websites of the following events:

Year	Conference, workshop, or seminar title	Location
2024	Centre for the Study of African Economies Conference	Oxford, United Kingdom
2023	University of Pretoria – Stellenbosch University PhD Workshop	Stellenbosch, South Africa
2023	University of Cape Town School of Economics seminar	Cape Town, South Africa
2023	Research on Socio-Economic Policy Brown Bag Lunch seminar	Stellenbosch, South Africa
2023	Economic Society of South Africa's National PhD Conference	East London, South Africa
2022	International Conference in Development Economics	Clermont-Ferrond, France
2021	United Nations University World Institute for Development Economics Research Development Conference	Virtual
2021	Pan-African Scientific Research Council's COVID-19 Conference	Virtual
2021	London School of Economics and Political Science Society for the Study of Economic Inequality PhD Workshop	Virtual
2021	Economic Research Southern Africa webinar	Virtual
2021	University of Pretoria PhD Economics Workshop	Virtual
2021	University of Cape Town School of Economics seminar	Virtual

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Abstract

In 2020, the world was gripped by the COVID-19 pandemic. Beyond its health implications, the pandemic led to unprecedented economic contractions and one of the largest increases in poverty and income inequality to date. Effects on labour markets are of particular interest given their dominant role in determining wellbeing. Existing evidence reveals substantial, regressive effects globally. This holds particular relevance in South Africa, measurably the most unequal country in the world, primarily due to the nature of its labour market, which also experienced one of the most stringent lockdowns globally. This thesis provides a micro-econometric examination of the aggregate and heterogenous labour market effects of the pandemic in South Africa. To do so, it employs descriptive and quasi-experimental econometric techniques applied on nationally representative, individual-level household survey data.

After providing a synthesised review of the extensive international literature, the first substantive contribution concerns aggregate and between-group adjustments to employment and working hours. I estimate substantial aggregate job loss accompanied by a surge in inactivity, and document significant regressivity in both the short- and longer-terms, thus reinforcing pre-existing inequalities on both the extensive and intensive margins. I reveal the principal roles of two key features of the pandemic labour market - remote work ability and 'essential' worker status - in explaining these outcomes. Modelling the evolution of outcome determinants suggests some persistent changes to the structure of the labour market.

In my second substantive contribution, I analyse the evolving level and nature of wages and wage inequality. I first characterise the non-negligible, non-randomly distributed missing wage data. After obtaining reliable estimates through parametric techniques, I estimate extremely high and stable pre-pandemic inequality levels. At the pandemic's onset, I show that wages increased primarily due to an inequality-enhancing composition effect, driven by a regressive job loss distribution related to the two aforementioned features. Inequality-reducing within-worker wage gains are also evident, but the dominance of the composition effect resulted in a large but transient increase in inequality on net. Persistent changes to wage determinants drove wages and wage inequality back toward their pre-pandemic levels as the labour market recovered.

The third contribution concerns the role of a key policy globally - sector-specific restrictions. I exploit temporal and between-industry variation induced by these to estimate their causal effect on employment. The analysis isolates how much job loss was attributable to this policy relative to other pandemic-related factors. I find significant negative effects, and estimate that they accounted for two-thirds of the total employment decline. This reflects both the severity of South Africa's restrictions but additionally that job loss would have still occurred in their absence, consistent with the literature. I further take advantage of overlap in policy variation and data collection periods to examine heterogeneity by policy stringency and sectoral formality, highlighting disproportionate effects on informal workers.

The thesis concludes with a summary of key findings, limitations, and implications for future research.

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This thesis provided me with several opportunities to participate in a number of local and international conferences, workshops, and seminars. The benefits of doing so cannot be understated. These experiences would not have been possible without generous funding from the organisers, whom I sincerely appreciate.

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Chapter 1

Introduction

1.1 Background and motivation

During the first half of 2020, the world was gripped by a pandemic. A new coronavirus named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) which caused the disease named coronavirus disease 2019 (COVID-19) was first identified in December 2019 in Wuhan, one of the largest cities in China. Soon, the virus spread rapidly across the world. On 30 January 2020, the World Health Organisation (WHO) declared the outbreak as a Public Health Emergency of International Concern, and shortly thereafter a pandemic on 11 March 2020. Later in the year, trials began to develop vaccinations and at the end of the year the WHO issued its first emergency use validation for one. Since then, multiple vaccines have been approved for use and rolled out across the world. Despite this development, the pandemic resulted in substantial human tragedy during its course. By three years later in May 2023, when the WHO announced that it no longer considers COVID-19 to be a global health emergency, 765 million confirmed cases had been reported alongside nearly 7 million deaths attributed to the disease (World Health Organisation, 2023). However, excess mortality estimates suggest the actual number of the latter is about three times higher (Msemburi et al., 2023).[1]

In response to the pandemic, governments across the world introduced a range of non-pharmaceutical interventions aimed at restricting mobility and social interaction to curb the spread of COVID-19 and reduce pressure on health services. These measures effectively paused economic activity and varied in severity, ranging from nationwide lockdowns or mandatory 'stay-at-home' orders, sector-specific restrictions, school closures, domestic and international travel bans, curfews, and the prohibition of large events to work-from-home directives, public physical distancing, face mask rules, and voluntary self-compliance measures. While these policies varied in stringency both within and between countries over time, their adoption was almost universal. During the second quarter of 2020, it is estimated that nearly all (94 percent) of the world's workers were living in countries with some form of

[1]This is because reported statistics are considered to be problematic due to differences in testing access, diagnostic capacity, and inconsistent certification of COVID-19 as a cause of death (Msemburi et al., 2023).

workplace closure policy in place (International Labor Organisation, 2020). These responses severely disrupted economic and social life and incurred substantial costs. This led to a perceived trade-off between saving lives versus livelihoods, and a vigorous debate surrounding how much of these costs were due to government-mandated restrictions versus voluntary reductions in economic activity. As discussed later, the empirical literature provides strong evidence that while both were to blame, the primary culprit was the virus itself (Aum et al., 2021; Baek et al., 2021; Juranek et al., 2021; Morales et al., 2022). To mitigate these costs and provide support to firms and households, governments concurrently introduced several fiscal, monetary, and regulatory policies such as job retention schemes, wage subsidies, short-term work schemes, forgivable loans, cash and in-kind transfers, deferred tax obligations, and other forms of social protection. The speed and scale of the introduction of these measures were widely regarded to have been unprecedented. For instance, cash transfers - the single most-widely used intervention - alone reached an estimated 1.4 billion people, or one in every six people globally (Gentilini et al., 2022; Gentilini, 2022). While most of these measures were temporary, some have persisted beyond the pandemic, implying a shift in equilibrium.

Despite this extent of government support, the pandemic and associated restrictions resulted in economic recessions deep and often unparalleled in both magnitude and nature. Globally, the contraction was the largest since the Second World War. Global real Gross Domestic Product (GDP) shrunk by 2.8 percent in 2020, significantly more than the 0.1 contraction of the Great Recession, making it unprecedented in living memory (International Monetary Fund, 2023). Concurrently, the global employment-to-population ratio fell by 2.4 percentage points, equivalent to about 100 million people losing their jobs, more than three times the Great Recession's 0.7 percentage point contraction (International Labour Organization, 2022). These are, of course, observed losses. A large empirical literature suggests that these would have much more severe in the absence of the aforementioned large-scale policy support. In addition to magnitude, the nature of the pandemic recession was distinct. Unlike shocks of the past which were characterised as demand shocks, the COVID-19 crisis was unique in that economic activity was deliberately as opposed to organically halted, beginning with a supply shock - a suspension of production induced by government-mandated restrictions - which also affected aggregate demand - reflected by both the inability of households to participate in the economy alongside voluntary reductions in activity. While these simultaneous contractions were felt globally, extreme inequalities emerged across countries of varying levels of development. Together with developed countries, most developing countries also experienced (in many cases more severe) contractions, in contrast to their experience during the Great Recession. This had significant consequences for both poverty and inequality, not only due to the concentration of the poor in these countries, but also their more limited fiscal space to support firms and households as well as larger informal sectors which primarily comprise workers in contact-intensive occupations who additionally, by definition, face lower access to legal protections. Compared to a counterfactual, it is estimated that the pandemic increased global extreme poverty in 2020 by 90 million people and income inequality by 0.7 Gini points, representing the largest increases to both since 1990 (Mahler et al., 2022).[2]

While the pandemic disrupted almost all aspects of economic activity, its labour market implications are especially of interest due to the labour market's role in determining pecuniary and non-pecuniary aspects of wellbeing, from both a static and dynamic perspective. This is particularly relevant in high-unemployment developing country contexts where decent employment generation is widely regarded as key to achieving meaningful poverty alleviation. By simultaneously affecting the supply, demand, and nature of work, the pandemic's labour market effects were far-reaching, unequally distributed, and often persistent both across and within countries. On the extensive margin, unprecedented job losses characterised by both increased separations and reduced hiring were recorded. As an alternative to layoffs, adjustments on the intensive margin - such as to working hours and wages - varied in response to either reduced aggregate demand, new demands among a subset of workers, as well as school closures which altered time allocations to paid and unpaid labour. While aggregate effects were substantial, and the infectious nature of COVID-19 led some to posit the pandemic as a "great equaliser", empirical evidence revealed that effects were not distributed evenly. Across the world, unfavourable occupational distributions with respect to sector-specific restrictions, or the specification of 'essential' work, and remote work ability meant that workers who were already in precarious, disadvantaged positions tended to be disproportionately affected. Remote work was a defining characteristic of pandemic labour markets globally, but because it increases with income both within and between countries, the pandemic not only reinforced or exacerbated pre-existing inequalities but also created a new one. Because the increased prevalence of remote work has persisted beyond the pandemic, these consequences may result in notable structural changes in the long term.

These implications hold particular relevance in the South African context. The labour market is regarded as the primary institution for determining socio-economic wellbeing in the country. A large literature documents South Africa as the most unequal country in the world among those which have adequate data. In 2021, the richest decile accounted for 65 percent of aggregate income while just 6 percent accrued to the poorest 50 percent (Shifa et al., 2023). Inequality within the labour market drives this extreme level of aggregate income inequality, due to both a large share of the population lacking access to labour market incomes - unemployment - as well as a very unequal income distribution among the employed (Finn et al., 2016; Wittenberg, 2017; Bhorat et al., 2020c; Díaz Pabon et al., 2021; Kerr & Wittenberg, 2021; Leibbrandt et al., 2012, 2020; Ranchhod & Daniels, 2021; Bhorat et al., 2022; Leibbrandt & Díaz Pabón, 2022). As such, a better understanding of the pandemic's effects on South Africa's labour market is essential in gaining an understanding of its effects on overall wellbeing in the country.

Following the first confirmed COVID-19 case in the country on 5 March 2020, the govern-

[2]Using a money-metric poverty line of $2.15 per person per day in Purchasing Power Parity (PPP) United States (US) dollars.

ment declared a National State of Disaster on 15 March 2020 followed by the implementation of a nationwide lockdown or 'stay-at-home' order on 27 March 2020. This initial lockdown lasted until the end of April 2020 and was relatively stringent by international standards (Bhorat et al., 2020a; Gustaffson, 2020), making no allowances for any non-essential activity outside the home. All schools were closed, public gatherings were prohibited, domestic and international travel were banned, a curfew was enforced, and sector-specific restrictions meant that only workers in occupations deemed 'essential' for economic function and pandemic response - representing the minority as shown later - were permitted to work at their usual workplace. Additionally, the sale of alcohol and tobacco products was forbidden, with the latter regulation making the country one of only three in the world to do so (Filby et al., 2022).[3]

Concurrently and similar to the international context, the government introduced a broad economic policy package to provide largely cash-based relief to firms and households. Initially amounting to 10 percent of GDP, this package primarily comprised tax relief measures and a combination of existing and new social protection and labour market programmes, many of which were extended and revised as the pandemic progressed and lockdown regulations varied. Support to households largely leveraged off the country's large, non-contributory social assistance infrastructure and included an expansion on both the intensive and extensive margins: a temporary increase in the value of all existing unconditional cash transfers, benefitting over 18 million recipients as well as their co-residents in poor households; and the introduction of the new COVID-19 Social Relief of Distress (SRD) grant of R350 (US$50 in PPP terms) per person per month. This grant is distinct in the country's social assistance system in that it is the first to target unemployed adults, which highlights its relevance to the labour market. Additionally however, informal workers also benefited, which was not unexpected given the inability of the verification systems to distinguish these workers from the unemployed (Köhler & Bhorat, 2021).[4] The reader is referred to Gronbach et al. (2022) and Bhorat et al. (2023) for comprehensive descriptions of the policy. At its peak, the grant brought over 10 million previously unreached adults into the system (South African Social Security Agency, 2022), and remained in place at the time of writing. Existing evidence suggests that the SRD has been progressively distributed and has had positive effects on welfare and labour market outcomes (Barnes et al., 2021; Bassier et al., 2021, 2022; Bhorat et al., 2021b, 2023; Köhler & Bhorat, 2021; Turok & Visagie, 2022). Another core policy relevant to the labour market was the Temporary Employer-Employee Relief Scheme (TERS), a wage subsidy scheme which provided relief to workers who suffered income loss due to a full or partial closure of their employer's operations. The policy's primary aim was to mitigate job loss. Considering South Africa's extreme level of unemployment, the TERS was arguably the country's most important labour market intervention during the pandemic. Köhler & Hill

[3]Botswana and India were the only other countries to introduce tobacco sales bans in response to the pandemic. These were lifted after 12 weeks and 6 weeks, respectively, while South Africa's lasted for 5 months (Filby et al., 2022).

[4]In fact, the SRD was initially conceptualised to target the informally employed (Bassier et al., 2021).

(2022) and Köhler et al. (2023) provide detailed descriptions of the policy. Cumulatively, nearly 6 million workers had benefitted during the policy's two years, equivalent to one in every three workers in the country. Existing evidence suggests that the policy was largely successful in its aim of saving jobs, at least in the short term (Barnes et al., 2021; Köhler & Hill, 2022; Köhler et al., 2023). Together, the TERS and SRD grant provided important sources of relief to the unemployed as well as firms and workers in both the formal and informal sectors.

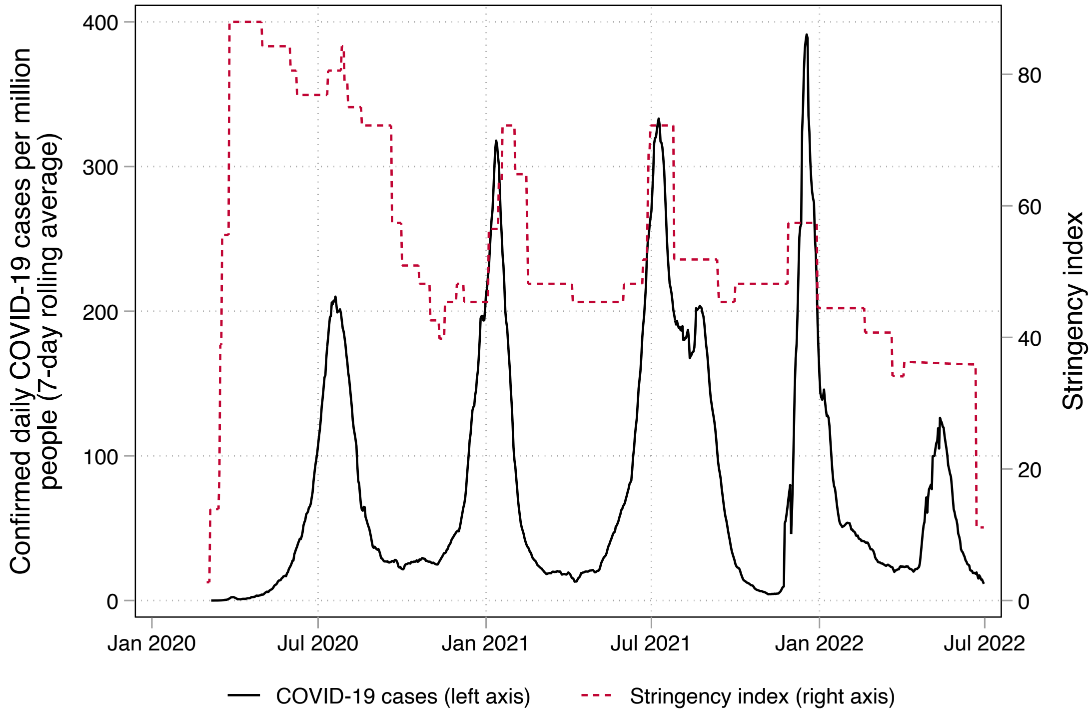
Following the initial lockdown, the government adopted a five-level risk-adjusted strategy which implemented national lockdown regulations according to the severity of contagion, with the first 'hard' lockdown period being categorised as level 5. In May 2020, the country moved to level 4 which permitted all agricultural activities and a limited number of manufacturing, construction, and mining activities to resume. Restaurant services were permitted, but only in the form of delivery services for off-site consumption during limited times. From June 2020, the introduction of level 3 regulations permitted almost all sectors to resume operations except for tourism, hospitality, and several entertainment industries whose activities remained highly restricted and, in some cases, prohibited. In the education sector, a phased re-opening of schools was adopted with learners in select grades being allowed to attend school, while attendance for all grades was only permitted from 31 August 2020. The gradual easing of regulations over this period can be observed in Figure 1.1 which presents trends in confirmed COVID-19 cases alongside a composite index of government policy stringency which measures the extent policies restrict people's behaviour from 2020 to 2022.[5] Government policy stringency was highest during the initial lockdown period given an index score of about 88 during April 2020. Thereafter, policy stringency closely tracked the five waves of the pandemic in the country but varied greatly in terms of composition over time as the epidemiological situation progressed. After approximately 750 days of being in place, the government repealed the National State of Disaster in April 2022 and all remaining pandemic-related restrictions in June 2022. By May 2023 when the WHO declared the end of the pandemic, South Africa had reported over 4 million confirmed cases and 100 000 deaths (World Health Organisation, 2023), although again, the estimated true number of the latter is 2.5 to 3 times larger (Bradshaw et al., 2022), consistent with global estimates (Msemburi et al., 2023).

Overall, this thesis provides an in-depth, micro-econometric examination of the heterogenous labour market effects of the COVID-19 pandemic in South Africa. While the existing empirical literature is substantial in size, it remains limited in scope and hence much remained unknown at the time of writing. The overarching objective here is to document and understand aggregate and between-group variation in labour market outcomes at the

[5]The stringency index is sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT) dataset and is calculated as the mean value of nine indicators, each of which vary between 0 and 100. These indicators include school and workplace closures, restrictions of public gatherings, stay-at-home requirements, and domestic and international travel controls. A higher index score is indicative of a stricter policy response. See Hale et al. (2021) for more information on the methodology.

pandemic's onset and as it progressed over time. Throughout, I pay particular attention to the pandemic-induced series of distinct complications and mechanisms in the interpretation of such variation. To do so, I employ a range of descriptive and quasi-experimental econometric techniques on nationally representative, individual-level, cross-sectional and panel household survey data, both available in the public domain and privately provided by South Africa's national statistics office. I consider the dynamics of several extensive and intensive margin outcomes over a relatively long time horizon spanning the pre-pandemic baseline period (2019) to the middle of 2022 when all remaining pandemic regulations were repealed. Four main chapters are included comprising a synthesised review of the international and South African literature, followed by three empirical chapters which together analyse data quality, short- and longer-term aggregate and between-group adjustments, their compositional and structural drivers, the isolated role of time-varying sector-specific restrictions, and consequences for pre-existing and new labour market inequalities.

Figure 1.1: Trajectories of COVID-19 cases and lockdown stringency in South Africa, 2020 - 2022



[a] Author's own arrangement. Source: Our World in Data (Mathieu et al., 2020); Oxford Covid-19 Government Response Tracker (OxCGRT) dataset (Hale et al., 2021).
[b] Notes: This figure presents the 7-day rolling average of confirmed daily COVID-19 cases and the government policy stringency index values over time. The stringency index measures the strictness of policies that restrict people's behaviour, calculated using data on nine indicators of government containment and closure policy and public information campaigns. The index ranges from 0 to 100 with higher scores indicative of stricter policy responses.

1.2 Thesis structure

The thesis is structured as follows. First, Chapter 2 provides a synthesised review of the literature and, in doing so, characterises the pandemic labour market. I consider effects and mechanisms in both the international and South African contexts. On the latter, I highlight its substantial size but limited scope, with existing studies focusing on immediate impacts, a narrow set of worker groups, and extensive margin adjustments alone. In Chapter 3, I provide a comprehensive, descriptive analysis of aggregate and between-group adjustments on both the extensive and intensive margins. Attention is given to a wide range of worker groups across demographic, labour market, institutional, and pandemic-specific characteristics over a relatively long time horizon spanning the pre-pandemic period through to when all remaining restrictions were repealed. Using several econometric techniques, I examine aggregate and between-group dynamics of three extensive margin outcomes - participation, employment, and unemployment - and one intensive margin outcome - working hours. To examine structural implications, I model outcome determinants over time, and further exploit the temporary panel nature of the data to model several types of labour market churn.

Wages take focus in Chapter 4. The pandemic introduced unusual complications in their interpretation over time, resulting in *ex ante* unclear wage inequality implications. Due to data availability, these implications were not understood at the time of writing. In this chapter, I analyse the evolution of the level and nature of wages and wage inequality and its drivers during the aforementioned period. To do so, I use micro-data privately provided by South Africa's national statistics office not available in the public domain. In doing so, I avoid significant concerns raised in the literature. I first review the literature on pre-pandemic wage inequality in South Africa, and thereafter interrogate the quality of the data and employ parametric techniques to obtain reliable wage estimates. I then analyse aggregate and within-worker temporal variation in wages across the distribution alongside several descriptive and normative wage inequality indices. After revealing the sensitivity of estimates to pandemic-induced worker composition changes, I conduct decomposition analyses to isolate the extent wage changes were explained by compositional changes versus changes in the returns to individual-level characteristics, both at the mean and across the distribution.

In South Africa and across the world, government-mandated mitigation or lockdown policy was not time-invariant but instead constantly and swiftly responded to the uncertain and evolving epidemiological situation. This variation in lockdown stringency partially shaped the extent and nature of job losses on aggregate and across worker groups. As a consequence of unfavourable occupational distributions, the literature highlights the disproportionate incidence of effects among those who were already in precarious labour market positions. Informal workers, who are less likely to be able to work remotely, work in 'essential' jobs, and access various legal protections, were particularly hard hit. In Chapter 5, I exploit temporal and between-industry variation induced by a core pandemic policy - sector-specific restrictions - and adopt a Difference-in-Differences (DiD) approach to estimate their causal effect on employment in South Africa. By isolating this effect, the analysis speaks to how much job loss was attributable to these restrictions as opposed to other pandemic-related factors such a voluntary reductions in economic activity. While such studies exist in the international context, there is a lack of evidence on how variation in the stringency of these restrictions differentially affects employment, both on average and across worker groups. I examine such heterogeneity by taking advantage of the coincidental timing of the country's policy changes and data collection periods, and analyse how these effects vary by employment formality. Finally, Chapter 6 provides a summary of the thesis' key findings, limitations, and recommendations for future research.

1.3 Contributions

The thesis makes several contributions to existing literatures. Broadly, it contributes to the literature on the impacts of large, transient shocks on labour market outcomes (Manning, 2000; Summers, 2000; McKenzie, 2004; Eichhorst et al., 2010; Rinne & Zimmermann, 2012; Cazes et al., 2013; Carneiro et al., 2014; Fabiani et al., 2015; Colombo et al., 2019; Bodnár et al., 2021), specifically with respect to health crises and disease outbreaks (Karlsson et al., 2014; Lee & Cho, 2016, 2017; Bodenhorn, 2020; Ceylan et al., 2020; Basco et al., 2021, 2022). Primarily though, it situates itself within the substantial and still evolving literature on the labour market effects of the COVID-19 pandemic (for instance, see Adams-Prassl et al., 2020; Balde et al., 2020; Betcherman et al., 2020; Dingel & Neiman, 2020; Lee & Yang, 2022; Lemieux et al., 2020; Casarico & Lattanzio, 2022; Koczan, 2022; Cortes & Forsythe, 2023b; Soares & Berg, 2022; Angelov & Waldenström, 2023; de Mahieu & Lastunen, 2023).

Within this latter literature, my findings are largely consistent with the documented substantial adjustments in both developed and developing countries on the extensive margin (Betcherman et al., 2020; Borjas & Cassidy, 2020; Lemieux et al., 2020; Djoumessi, 2021; Bundervoet et al., 2022; Cortes & Forsythe, 2023a) and intensive margin (Fairlie, 2020; Guven et al., 2020; Craig & Churchill, 2021; McDermott & Hansen, 2021; Zimpelmann et al., 2021; Blundell et al., 2022; Hanzl & Rehm, 2023) at the pandemic's onset. By considering outcome dynamics beyond its onset, it also contributes to the emerging understanding of the pandemic's longer-term effects (Khamis et al., 2021; Blundell et al., 2022; Lee & Yang, 2022; Angelov & Waldenström, 2023; Cortes & Forsythe, 2023b; de Mahieu & Lastunen, 2023).

Regarding effects on the intensive margin, my analysis in Chapter 3 fills the notable gap concerning aggregate and between-group working hour adjustments in the South African literature, discussed in Chapter 2. Chapter 4 provides evidence in favour of the use of parametric multiple imputation to adequately address non-random non-response in earnings survey data (Greenlees et al., 1982; David et al., 1986; Brownstone & Valletta, 1996; Hirsch & Schumacher, 2004). The analysis here is the first to use a relatively long uninterrupted series of the raw, unimputed data privately provided by South Africa's national statistics office. In doing so, it provides an indication of the stability of estimates when each quarterly dataset is appended to one another, thus contributing to the recent debate surrounding the quality of the public release wage data among labour economists in South Africa (Wittenberg, 2017; Kerr & Wittenberg, 2019b; Kerr, 2021; Kerr & Wittenberg, 2021; Köhler et al., 2023). This chapter also serves as the first to analyse wages and wage inequality during the pandemic for the entire employed population in South Africa, adding to the country's large literature on wage inequality (Finn et al., 2016; Wittenberg, 2017; Bhorat et al., 2020c; Díaz Pabon et al., 2021; Leibbrandt et al., 2012, 2020; Bhorat et al., 2022; Leibbrandt & Díaz Pabón, 2022). As discussed in Chapters 2 and 4, while few studies have made use of alternative wage data collected during the pandemic in the country, the samples used are substantially smaller, subject to representivity issues, and the studies themselves focus on either a limited worker group or short time period. It therefore contributes to the evidence base on pandemic-era wage dynamics in developing country labour markets, comprising a relatively scarce literature (Balde et al., 2020; Djoumessi, 2021; Khamis et al., 2021; Bundervoet et al., 2022; de Mahieu & Lastunen, 2023).

Throughout the thesis, the results consistently reveal a substantial amount of between-worker heterogeneity - specifically, an unequal and regressive effect distribution - which is strongly consistent with the international literature (Adams-Prassl et al., 2020; Béland et al., 2020; Khamis et al., 2021; Bundervoet et al., 2022; Immel et al., 2022; Lariau & Liu, 2022; Soares & Berg, 2022; Webster et al., 2022; Cortes & Forsythe, 2023b; Kugler et al., 2023; Oyenubi, 2023). The results in Chapters 3 and 5 also highlight the disproportionate incidence of effects on informal workers, again in line with the international experience (Balde et al., 2020; Fox & Signe, 2020; Delaporte et al., 2021; Krafft et al., 2021; Schotte et al., 2023; Soares & Berg, 2022). As discussed in Chapter 2, this regressive effect distribution has been largely attributed to the distribution of 'essential' work and remote work ability (Adams-Prassl et al., 2020; Béland et al., 2020; Borjas & Cassidy, 2020; Dingel & Neiman, 2020; Guven et al., 2020; Craig & Churchill, 2021; Zimpelmann et al., 2021; Bamieh & Ziegler, 2022; Casarico & Lattanzio, 2022), which I also document in the South African context.

By estimating the employment effects of sector-specific restrictions, Chapter 5 contributes to the empirical literature on the labour market effects on government-mandated mitigation measures, which remains scarce in developing countries (Morales et al., 2022; Schotte et al., 2023). More specifically, it adds to the debate on how much the observed adverse labour market effects of the pandemic can be explained by these policies as opposed to other pandemic-related factors, such as voluntary reductions in activity (Aum et al., 2021; Baek et al., 2021; Juranek et al., 2021; Morales et al., 2022; Schotte et al., 2023). Finally, the thesis of course contributes to the existing South African literature on the pandemic's labour market effects which, as discussed in Chapter 2, is large in magnitude but limited in scope, particularly with respect to intensive margin adjustments (for instance, see Bhorat et al., 2020d; Barnes et al., 2021; Casale & Posel, 2021; Hill & Köhler, 2021; Ranchhod & Daniels, 2021; Shifa et al., 2021, 2022; Bassier et al., 2022, 2023; Casale & Shepherd, 2022; Daniels et al., 2022; Daniels & Casale, 2022; Espi-Sanchis et al., 2022; Mosomi & Thornton, 2022;

Nwosu et al., 2022; Rogan & Skinner, 2022; Turok & Visagie, 2022; Yu et al., 2023).

Chapter 2

The pandemic labour market: An international review

2.1 Introduction

The COVID-19 pandemic was far-reaching, incurring significant labour market effects across the world both between and within countries of varying levels of economic development, and as this thesis will show, South African notwithstanding. The literature highlights significant cross-country variation in effects with respect to a given outcome on either the extensive or intensive margin, the distribution of effects across worker sub-groups, as well as the pace and trajectory of recovery. Alongside these differences, however, many similarities exist. Examining the literature, in most parts of the world the pandemic's labour market effects can be broadly attributed to one or a combination of factors within four categories. First, government-mandated lockdown policy, sector-specific restrictions, and other mitigation measures which sought to limit activity and contain the pandemic. Second, voluntary reductions in economic activity in response to the risk of infection. Third, the occupational and sectoral compositions of a given economy, in particularly the shares of jobs which were vulnerable to sector-specific restrictions and could effectively be done at home or remotely. And fourth, government support policy which provided relief to firms, workers, and households through, for instance, income support and job retention schemes.

Preceding this thesis' three empirical chapters, this chapter provides a synthesised review of the extensive international literature of the labour market effects of the pandemic. In doing so, it characterises and provides several stylised facts of the pandemic labour market. The review seeks to be comprehensive in scope; however, given the vast size and evolving nature of the empirical literature to date, it is not intended to necessarily be exhaustive. It pays particular attention to the three outcomes examined throughout this thesis - employment, and conditional on employment, working hours and wages. Concurrently, it sheds light on the aforementioned mechanisms. It begins with the international context, considering dynamics both within and between developed and developing countries at the pandemic's onset and as it progressed, and thereafter focuses on the South African context.

2.2 The international context

2.2.1 Employment

I first consider effects in the international context on the extensive margin; that is, with respect to transitions between mutually-exclusive labour market states. It is apparent that the majority of the literature focuses on these transitions, highlighting that job losses were substantial in magnitude. Examining outcomes in 14 advanced and emerging economies, Koczan (2022) shows that job losses during the beginning of the pandemic were already comparable to the cumulative effects of the 2007/8 Global Financial Crisis. Globally, the International Labour Organization (2022) estimates larger reductions in employment rates at the pandemic's onset for middle-income countries relative to low- and high-income countries. From 2019 to 2020, employment-to-population rates reduced by 2.1 percent for low-income countries, 4.2 percent for lower-middle income countries, 4.9 percent for upper-middle income countries, and 3.1 percent for high-income countries. This larger reduction experienced by middle-income countries is consistent with Khamis et al. (2021)'s analysis of high-frequency phone survey data in 39 developing countries. As the pandemic progressed, employment had recovered in most high-income countries while lower employment, up to five fewer percentage points relative to pre-pandemic levels, had persisted for most middle-income countries. Interestingly, Koczan (2022) finds that while disemployment effects were more severe in developing countries, they were more unequally distributed in developed economies.

The pandemic's larger effects in developing countries have been attributed to two underlying mechanisms: more limited fiscal space to support firms and workers (Koczan, 2022) and large informal sectors which comprise workers who, by definition, face lower access to legal protections such as paid leave and unemployment insurance, and whose occupations tend to be contact-intensive and cannot be effectively done from home (Fox & Signe, 2020; International Labor Organisation, 2020; Benhura & Magejo, 2020; Balde et al., 2020; Schotte et al., 2023). Dingel & Neiman (2020) show that developing countries tend to have lower shares of jobs that can be done at home compared to their developed counterparts, such as 25 percent for Mexico and Turkey as opposed to 40 percent for Sweden and the United Kingdom (UK). This suggests that developing countries, characterised by large informality, faced a greater challenge in continuing to work during the pandemic. Indeed, the International Labour Organization (2022) estimates that global informal employment contracted by double the rate of global formal employment (20 vs. 10 percent, respectively). Several studies document these disproportionate effects in a wide array of contexts, such as Brazil, Costa Rica, Mexico, Poland, Portugal, the UK, and the United States (US) (Soares & Berg, 2022), Senegal, Mali, and Burkina Faso (Balde et al., 2020), Egypt, Jordan, Morocco, and Tunisia (Krafft et al., 2021), Zambia (Oyenubi, 2023), and Ghana (Schotte et al., 2023). As I show in Chapter 5, the South African labour market experienced similar unequal effects by formality.

The empirical literature appears concentrated on developed country labour markets, presumably at least partially due to differences in data availability. This concentration may also be explained by developing country researcher deficiencies in research skills, English language proficiency, scientific networks, and access to funding (Amarante et al., 2022). In particular, a substantial number of studies give attention to the US labour market. Just prior to the pandemic in February 2020, the economy was experiencing historically low levels of unemployment (3.5 percent under the narrow definition) - considered as full employment (Holder et al., 2021). The pandemic's onset saw 20 percent of workers losing their jobs (Adams-Prassl et al., 2020) and the unemployment rate quadrupling to nearly 15 percent in April 2020, representing the sharpest drop in employment since the Great Depression (Betcherman et al., 2020; Borjas & Cassidy, 2020; Autor et al., 2023; Cortes & Forsythe, 2023a,b).[1] Concurrently, claims for unemployment insurance rose to unprecedented levels, from an average of about 220 000 new weekly claims in the beginning of 2020 to nearly 7 million at the end of March (Holder et al., 2021). Analysing impacts on hiring decisions, Campello et al. (2020) show that active job postings in the first week of May fell by 40 percent below the average level of the same week in several years prior. This was driven by both a contraction in hiring by firms which continued to operate, as well as a contraction in the number of working business owners which fell by 22 percent (Fairlie, 2020).

While the contraction in hiring in the US was significant, the vast majority of the employment drop in the country was attributable to an increase in separations; that is, among those who were already employed prior to the pandemic (Cortes & Forsythe, 2023b). This was not, however, a universal experience. In South Korea, Aum et al. (2021) shows that employment losses were primarily due to reduced hiring. Betcherman et al. (2020) arrives at a similar conclusion in the case of Greece. In Italy, the employment contraction was characterised by pronounced drops in both hirings and separations (Casarico & Lattanzio, 2022). In addition to other factors such as different economic structures, these differences may at least partially be explained by variation in policy response. For instance, while most US states implemented stay-at-home orders, South Korea refrained from introducing such restrictions and instead relied on testing and contact tracing. In Greece, mitigation measures such as income support conditional on the maintenance of employment relationships arguably played a role (Betcherman et al., 2020).

The labour market dynamics in the US were similar in sign but varied in magnitude across other developed countries. Lemieux et al. (2020) documents a 15 percent decline in employment in Canada at the pandemic's onset. Similarly, in the UK, 17 percent of workers employed prior to the pandemic fell into unemployment, but in Germany only 5 percent did (Adams-Prassl et al., 2020). The share of the working-age population not working in the UK surged by over 10 percentage points during the first lockdown, mostly due to temporary furlough (Blundell et al., 2022). In the Netherlands, Zimpelmann et al. (2021) show that unemployment rose by just 1.1 percentage points, representing a much smaller contraction

[1] Couch et al. (2020) estimate the unemployment rate to have risen even higher to 24.4 percent after correcting for potential data misclassification by the US Bureau of Labor Statistics.

than other countries. Unemployment rose by a similar magnitude in Australia coupled by a surge in inactivity (Guven et al., 2020), reflecting a transition of individuals leaving the labour force entirely. Guven et al. (2020) also highlight a drop in the probability of working on Fridays, reflecting an intensive margin adjustment discussed in more detail later. Adjustments in South Korea were of a similar magnitude. Using a synthetic control method to infer causality, Lee & Yang (2022) show that, while on aggregate employment reduced by just under 2 percent, the pandemic itself caused a 4.2 percent reduction which persisted until the end of 2020. On the other hand, Italy, which was the first country in Europe to be hit by the pandemic and implement a national lockdown, experienced a significant decline in both hirings and separations, as previously noted (Betcherman et al., 2020; Casarico & Lattanzio, 2022). Spain's employment decline was twice as large as the European Union average (Lariau & Liu, 2022). In Greece, Betcherman et al. (2020) show that new unemployment insurance benefit claims tripled in April 2020, and by the end of June, they estimate that formal employment was 12 percent less than what it would have been in the pandemic's absence. Both Juranek et al. (2021) and Angelov & Waldenström (2023) highlight significant increases in unemployment and furlough spells in all Nordic countries, to varying degrees.

The literature largely shows that the above disemployment effects were mirrored in developing countries, however as previously discussed, to a more severe degree. In West Africa, Balde et al. (2020) estimate that 22, 23, and 29 percent of workers in Burkina Faso, Mali, and Senegal lost their jobs at the pandemic's onset. In their sample of workers in Cameroon, Djoumessi (2021) shows that nearly a third (32 percent) of respondents experienced a temporary job suspension, while 7.5 percent suffered job loss. Using high-frequency phone survey data from 31 low- and middle-income countries across Africa, East Asia and the Pacific, Latin America, Europe, Central Asia, the Middle East, and Northern Africa, Bundervoet et al. (2022) find that an average of 36 percent of respondents stopped working at the pandemic's onset. They also document a significant relationship between job loss and country-level containment policy stringency. Using similar data in 39 developing countries including some in Sub-Saharan Africa, Khamis et al. (2021) estimate that 34 percent of respondents fell into unemployment. Moreover, these effects were largest for middle-income countries which, as previously noted, is consistent with the International Labour Organization (2022)'s estimates.[2] These effects documented in the Middle East and North Africa region were similarly found by Krafft et al. (2021) who consider the cases of Egypt, Jordan, Morocco, and Tunisia. A recent study on Viet Nam reveals that 14 percent of the working-age population had to stop working altogether or suspended production and business activities, resulting in 1.2 million workers falling into unemployment - the first significant labour market decline over the past few years (de Mahieu & Lastunen, 2023). Finally, in their firm-level study of El Salvador, Guatemala, Honduras, and Nicaragua in Central America, Webster et al. (2022) document large losses in firm sales which translated into significant employment reductions

[2]Specifically, Khamis et al. (2021) estimate job loss rates of 19 percent for low-income countries, 37 percent for lower-middle-income countries, 41 percent for upper-middle-income countries, and 26 percent for high-income countries in their sample.

of up to 22 percent. Overall, it is clear that the labour market adjustments to the pandemic were far-reaching, substantial, and in several cases, notably unequal across countries.

During the pandemic and at the time of writing, it was vigorously debated how much of these adverse labour market effects were attributable to government-mandated restrictions versus voluntary reductions in economic activity to avoid infection. Several studies, primarily by leveraging geographic variation through a DiD approach, exploit the nature of the outbreak and implementation of government policies to disentangle these two sources of the shock. For instance, unlike most countries, South Korea did not implement a lockdown but instead relied on testing and contact tracing, as noted previously. Moreover, during the beginning of the pandemic only one region experienced a significant number of infections. Aum et al. (2021) exploit this exogenous regional variation in infections to isolate the causal effect of the pandemic alone on local employment, finding that a one per thousand increase in infections caused a 2.7 percent decrease in local employment.[3] This effect is about half the size of non-causal estimates from several other settings, suggesting that a large share of job losses - around half but possibly the majority (Aum et al., 2021) - is due to voluntary reductions. On the policy front, Juranek et al. (2021) compare the outcomes of Sweden who imposed relatively light restrictions to that of their Nordic neighbours who imposed relatively strong restrictions. Their results show that, had Denmark imposed restrictions similar to Sweden, they would have accumulated up to 25 percent less unemployment and furlough spells, suggesting that a quarter of labour market effects are attributable to restrictions (Juranek et al., 2021). This implies that most effects in the Nordic context are due to the pandemic itself, in line with Aum et al. (2021)'s conclusion. In the US, Baek et al. (2021) exploit the decentralised implementation of stay-at-home orders, finding that each week of these restrictions caused an increase in state-level unemployment insurance claims by 2 percent. This implies that, at most, half of the total rise in claims can be attributed to these restrictions (Baek et al., 2021), again in line with prior findings. Comparing outcomes in lockdown versus non-lockdown districts in Ghana, Schotte et al. (2023) find that the country's lockdown restrictions caused employment to reduce by 34 percentage points.[4] The authors also show that, while this effect dissipated after the lifting of the restrictions, employment remained below pre-pandemic levels as the pandemic progressed. This again implies that both restrictions and the virus incur adversity in the labour market. Finally, Morales et al. (2022) exploit the introduction of sector-specific mobility restrictions which authorised some but not all sectors to continue operating (related to the definition of 'essential' workers) to isolate causal effects in Columbia. Chapter 5 of this thesis employs a similar identification strategy in the South African context. They estimate that these restrictions caused a 9.4 percent employment contraction, which suggests that the restrictions accounted for approximately one quarter of total employment loss with other epidemiological

[3]The authors show that these employment losses stem from reduced hiring, mirrored by a rise in labour market non-participation, as opposed to unemployment (Aum et al., 2021).

[4]Notably, the magnitude of this effect is substantially larger than those documented for restrictions in developed countries, consistent with the discussion prior.

and economic factors accounting for the remainder (Morales et al., 2022). Taken together, the results of these studies have several implications. Overall, both restrictions and the virus itself incur negative labour market effects. Expectedly, restrictions add an additional economic burden on top of the threat of the virus and hence may have caused more economic damage than necessary. Perhaps most importantly, however, significant and negative labour market effects are still evident in the absence of restrictions, suggesting that the primary culprit is the virus itself. If so, then as described by Aum et al. (2021), virus eradication serves as the best way to revive the labour market.

Working-from-home or 'remote' work served as a defining characteristic of the pandemic labour market in most countries globally. The number of people who worked-from-home surged, in some cases to comply with restrictions on economic activity, and in others in response to internal allowances or mandates issued by their employers. Stark inequalities, however, emerged both across and within countries. Making use of pre-pandemic survey data from the Occupational Information Network (O*NET),[5] Dingel & Neiman (2020) estimate that 37 percent of jobs in the US can plausibly be done at home, in contrast to 25 percent of jobs in Mexico and Turkey, as mentioned previously. The authors show that the share of jobs that can be done at home increases with country income, again highlighting a greater challenge for lower-income economies. The demand for remote work persisted as the pandemic progressed. Using data from Austrian vacancy postings, Bamieh & Ziegler (2022) show that one year after the pandemic's onset, employers were up to three times more likely to offer a remote work option relative to before the pandemic. This difference persisted even after economic activity restrictions were relaxed, and is neither explained by more tele-workable occupations nor tele-working-friendly firms but instead by a structural change to select occupations. Importantly, over and above what can be explained by other job characteristics, remote work was a particularly significant predictor of job loss in most labour markets, including the US, UK, and Germany (Adams-Prassl et al., 2020; Béland et al., 2020; Borjas & Cassidy, 2020), the Netherlands (Zimpelmann et al., 2021), Italy (Casarico & Lattanzio, 2022), and Australia (Craig & Churchill, 2021; Guven et al., 2020). Because these occupations tend to be concentrated towards the top of wage distributions (Dingel & Neiman, 2020), inequality in remote work ability has been shown to largely explain the regressivity of job loss. For instance, Zimpelmann et al. (2021) estimate that, in addition to 'essential' worker status, the share of work that be be done remotely explains most of the socioeconomic gradient in job loss in the Netherlands. Borjas & Cassidy (2020) estimate that, in the US, about one-third of in-work immigrants' higher job loss rate relative to natives' is attributable to a lower likelihood of being able to work remotely. Overall, these dynamics suggest that the pandemic not only exacerbated pre-existing labour market inequalities, but also created a new one. While most enterprises still have an in-person component to their operations (International Labour Organization, 2022), at the time of writing, this consequence of the pandemic on the organisation of work is expected to persist.

[5]The O*NET is an occupational survey conducted by the US Bureau of Labour Statistics.

Another defining feature of most labour markets during the pandemic was the disproportionate incidence of job loss among women. This outcome has been documented in an array of contexts, including the US (Adams-Prassl et al., 2020; Fairlie, 2020; Albanesi & Kim, 2021; Holder et al., 2021; Folbre et al., 2021; Couch et al., 2022; Soares & Berg, 2022), the UK (Adams-Prassl et al., 2020; Soares & Berg, 2022), Italy (Casarico & Lattanzio, 2022), Australia (Craig & Churchill, 2021), South Korea (Ham, 2021; Lee & Yang, 2022), Germany (Immel et al., 2022), Spain (Lariau & Liu, 2022), China (Yueping et al., 2021), Sweden (Angelov & Waldenström, 2023), Columbia (Morales et al., 2022), Zambia (Oyenubi, 2023), Ghana (Schotte et al., 2023), Guatemala, Honduras, and Nicaragua (Webster et al., 2022), Egypt, Jordan, Morocco, and Tunisia (Krafft et al., 2021), Brazil, Costa Rica, Mexico, Poland, and Portugal (Soares & Berg, 2022), and several other developed and developing countries (Bundervoet et al., 2022; Koczan, 2022; Kugler et al., 2023).[6] Examining 40 low and middle-income countries, Kugler et al. (2023) show that employment disparities by gender tended to be larger than those by age, education, and locality. This outcome is in contrast to previous recessions which exhibited more severe effects in male-dominated sectors (Albanesi & Kim, 2021; Koczan, 2022).

Broadly, two underlying mechanisms explain the pandemic's gendered effects: occupational and sectoral segregation on the demand-side and increased caregiving responsibilities on the supply-side. First, women were more likely to work in services sectors while men were primarily employed in production occupations. Consequently, the pandemic-induced drop in demand for services in response to economic restrictions and risk aversion disproportionally affected female-dominated sectors (Fairlie, 2020; Albanesi & Kim, 2021; Ham, 2021; International Labour Organization, 2022; Kugler et al., 2023). Moreover, Lewandowski et al. (2021) show that, because of such segregation, women were more likely to work in jobs which require contact with diseases, frequent interpersonal interactions, and high levels of physical proximity, and hence workplace-related exposure to the virus was gendered. Second, large-scale school closures - which in an extreme case like Uganda lasted for nearly two whole years (International Labour Organization, 2022) - resulted in increased home-based caregiving for those with school-aged children. Because of gender norms this mechanism, coined the "COVID motherhood penalty", disproportionately impacted women's ability to work, leading many to exit the labour force entirely. In the US, Couch et al. (2022) show that women with school-aged children were more affected than both their male counterparts as well as women without children. Similarly, in China, Yueping et al. (2021) find that having a preschool-age child had a strong negative effect on women's employment outcomes, but not that of men's. In Australia, while both men and women experienced a rise in unpaid care work, the additional workload was disproportionately borne by women (Craig & Churchill,

[6] Few studies in some contexts did not detect such disparities. For instance, Adams-Prassl et al. (2020) find that gender does not predict job loss in Germany. Blundell et al. (2022) show that, in the UK, initially job loss rates for women were lower than those for men. In Turkey, İlkkaracan & Memiş (2021) document a relatively higher contraction in men's work.

2021). In Turkey, women's unpaid work time almost doubled (İlkkaracan & Memiş, 2021). In the Middle East, Krafft et al. (2021) highlight the role that norms played in favouring employment opportunities for men. Finally, in South Korea, Ham (2021) find that over 60 percent of gender differences in leaves of absence is explained by this gendered caring role. Overall, these dynamics show that the pandemic reproduced, if not expanded, existing gender inequalities in labour markets around the world.

Most studies point to the disproportionate and more persistent incidence of job loss among worker groups who were already in precarious, disadvantaged positions prior to the pandemic, thus reinforcing or exacerbating pre-existing inequalities. In Brazil, Costa Rica, Mexico, Poland, Portugal, and the UK, Soares & Berg (2022) find larger rates of job loss among the youth, the less-educated, those from lower-income households, and workers with temporary and informal contracts. Again in the UK, Blundell et al. (2022) and Adams-Prassl et al. (2020) also document higher employment contractions among the youth, the less-educated, and those on temporary contracts, but additionally the self-employed and low-wage workers. In the US, this regressive distribution of job loss is also widely-documented, with job loss having disproportionately affected less-educated and lower-wage workers (Autor et al., 2023), the youth, Hispanics, and the self-employed (Béland et al., 2020), those in lower-paying occupations and industries (Cortes & Forsythe, 2023a,b), those working in smaller firms and non-tradable sectors (Campello et al., 2020), and African-American, Latinx, immigrant, and female business owners (Fairlie, 2020). In Canada, half of all job losses fell on the bottom earnings quartile (Lemieux et al., 2020). Similar regressive effects were also documented in Italy (Casarico & Lattanzio, 2022), Australia (Guven et al., 2020), Germany (Immel et al., 2022), Spain (Lariau & Liu, 2022), South Korea (Aum et al., 2021; Lee & Yang, 2022), Sweden (Angelov & Waldenström, 2023), Senegal, Mali, and Burkina Faso (Balde et al., 2020), Zambia (Oyenubi, 2023), Ghana (Schotte et al., 2023), Egypt, Jordan, Morocco, and Tunisia (Krafft et al., 2021), and a wide array of developing countries (Khamis et al., 2021; Bundervoet et al., 2022; Webster et al., 2022; Kugler et al., 2023). In the overwhelming majority of countries, this pattern of job loss has been attributed to unfavourable occupational distributions; specifically, the concentration of these workers in jobs that are neither in 'essential' industries nor are amenable to remote work. Interestingly, Aum et al. (2021) find that the job loss distribution in South Korea holds even after accounting for cross-industry effects, implying that the pandemic's unequal effects remain with or without lockdown restrictions. This is consistent with these effects being similarly observed across the variety of countries above despite their varying policy responses. Together, these studies show that the pandemic widened pre-existing labour market inequalities in most labour markets, both in the short-term and as it progressed and labour markets recovered.[7]

[7]While not documented here, many other studies document interesting pandemic-induced labour market dynamics. For instance, Campello et al. (2020) estimate significantly higher hiring cuts in highly concentrated industries in the US, attributable to the greater bargaining power of employers in such industries who face a greater ability to rehire when conditions improve. Cortes & Forsythe (2023b) document how the pandemic induced older workers in the US to retire at faster rates. Finally, to examine how the pandemic affects long-run worker productivity, Fischer et al. (2022) employ a staggered DiD design on a unique dataset of professional

2.2.2 Working hours

I now consider effects on the intensive margin, first with respect to paid working hours. Globally, the International Labour Organization (2022) estimates that working hours reduced by 19 percent at the pandemic's onset, which is considerably larger than the equivalent employment estimate. Examining the literature, at least three mechanisms explain this contraction.[8] The first relates to reduced demand due to government-mandated restrictions and voluntary contractions in economic activity, which led many firms to reduce their operations or incur financial difficulties, and consequently, reduce the working hours of their retained workers to manage costs as an alternative to layoffs (Guven et al., 2020; Blundell et al., 2022). Second, the working hours of some individuals who remained employed increased as a consequence of a shift to non-traditional hours in response to new demands. This includes 'essential' workers who faced increased workloads and overtime to meet the rising demand for their goods and services, as well as the increased prevalence of remote work which often allowed for greater flexibility in working hours or such workers selecting into working more because economic restrictions limited traditional leisure options (McDermott & Hansen, 2021; Zimpelmann et al., 2021). The third mechanism, connected to the second, relates to large-scale school closures and the gendered division of paid and unpaid labour for workers with children living at home. The feminist economics literature highlights the double-edged sword of remote work in that, in addition to increased flexibility for some, these school closures increased the caregiving responsibilities for working parents at home which, given traditional gender roles, disproportionately led women to reduce their paid working hours to meet these demands (Collins et al., 2021; McDermott & Hansen, 2021; Casale & Posel, 2021; Casale & Shepherd, 2022; Hanzl & Rehm, 2023). These mechanisms are thus important to keep in mind when considering temporal changes in the working hours distribution during the pandemic.

Empirical studies which give attention to working hours are notably more sparse relative to those which consider extensive margin outcomes. In the US, Béland et al. (2020) estimate that working hours among workers reduced only marginally at the pandemic's onset, by 0.25 hours at the mean, but highlight larger reductions among younger workers, Hispanics, less-educated workers, and the self-employed. The authors also estimate a significant, negative association between working hours and the number of confirmed cases, suggesting that local labour markets tend to be more affected when the pandemic is more severe. Fairlie (2020) estimate a much larger working hours reduction of 29 percent among all business owners. Faberman et al. (2022) considers desired work hours as a measure of willingness to work, documenting a decline of nearly 5 percent, and hence a lower willingness to participate in the labour market, that persists until the end of 2021.[9] Collins et al. (2021) consider gen-

soccer leagues in Germany and Italy, finding a significant negative effect of COVID-19 infection, but not other respiratory infections, on labour productivity which persists for at least eight months.

[8] In addition to the discussion of mechanisms to follow, these larger working hour reductions may be partially explained by, in many cases, working hours not being protected by government policies such as furlough or short-time work schemes, unlike employment or income (Blundell et al., 2022)

[9] This contraction in desired working hours is double the contraction of the labour force participation rate, implying that ignoring the former reduction overstates the degree of labour underutilisation (Faberman et al.,

dered impacts, hypothesising that the increased prevalence of remote work may facilitate greater gendered division of labour at home through men's greater contributions to childcare demands as a result of increased visibility. However, they estimate a four to five times larger reduction in paid working hours for mothers with young children relative to fathers, increasing the gender gap in paid hours by up to 50 percent. The authors' findings indicate that fathers then, on average, did not increase their household contributions at the cost of women's work commitments (Collins et al., 2021). Similarly, Couch et al. (2022) find especially large losses in paid working hours among women with school age children relative to men.

Similar downward adjustments are documented in several other countries. Craig & Churchill (2021) document a reduction in hours in Australia, with larger reductions among women. Guven et al. (2020) also consider Australia and estimate larger adjustments for those with up to a high-school education level. Hanzl & Rehm (2023) estimate significant reductions in Austria, especially in the first few months of the pandemic. The authors show that mothers increased time spent on childcare and reduced their paid working hours when school closures were in place, while fathers also reduced their paid working hours, but by a smaller rate, and additionally reduced their time spent on caregiving. Notably, they highlight how fathers reduced their paid working hours even less than individuals without children (Hanzl & Rehm, 2023). Providing evidence on remote work flexibility, McDermott & Hansen (2021) use real-time data from 15 million global users of GitHub - the world's largest platform for software development and scientific code at the time of writing - to document a sharp pattern of labour reallocation. They show that users during the beginning of the pandemic both worked more (as opposed to only reallocating a given amount of work) and also became more likely to work outside traditional working hours.[10] This pattern of reallocation was more prominent among men, suggesting that men benefitted more from remote work's increased flexibility, which is consistent with the findings of gender studies referenced above. In contrast to the US, Lemieux et al. (2020) estimate that the pandemic reduced paid working hours by 32 percent in Canada. Zimpelmann et al. (2021) estimate that working hours in the Netherlands reduced by 15 percent and persisted for the remainder of 2020. While the magnitude of these reductions differ, their patterns of heterogeneity are similar. Both Lemieux et al. (2020) and Zimpelmann et al. (2021) find that less educated or lower-income workers experience significantly larger reductions, a gradient which became smaller when infection rates were low and restrictions more relaxed. Zimpelmann et al. (2021) also show that both the ability to work-from-home and 'essential' worker status primarily explain this gradient in their setting. Working hours in the UK fell by a similar magnitude of 18 percent (Blundell et al., 2022), while in Spain they declined by twice as large as the EU27 average (Lariau & Liu, 2022). Lee & Yang (2022) estimate a large but transient reduction in South Korea.

2022).

[10] The greater level of working hours was however transient and reduced to pre-pandemic levels by the end of 2020, however the reallocation of working hours towards non-traditional times persisted, indicative of a 'new normal' for a subset of workers (McDermott & Hansen, 2021).

At the time of writing, much fewer studies consider working hour dynamics in developing countries. de Mahieu & Lastunen (2023) document a significant decline in Viet Nam, as does Krafft et al. (2021) in Egypt, Jordan, Morocco, and Tunisia, while additionally highlighting larger reductions for informal workers. Using firm-level data, Webster et al. (2022) show that nearly a third of firms in El Salvador, Guatemala, Honduras, and Nicaragua reduced their workers' working hours on average, highlighting significant variation across countries.[11] Finally, using a DiD design discussed in the preceding section, Morales et al. (2022) show that sector-specific mobility restrictions in Columbia also reduced working hours in addition to employment.

2.2.3 Wages

By simultaneously affecting the supply, demand, and nature of work, the pandemic introduced a series of unusual complications in the interpretation of the wage distribution over time, with respect to both compositional and structural dynamics. The first speaks to the 'composition effect'. In times of crisis, aggregate measures of wages - such as averages or another moment of the distribution - can be skewed by significant changes to the underlying workforce. Average wages may then mechanically rise, reflecting not an improvement to the labour market, but simply as a consequence of the concentration of job loss and working hour contractions on lower-wage workers. Second, considering within-worker changes among those who remain employed, as an alternative to layoffs firms may reduce their workers' wages in response to reduced demand due to government-mandated restrictions and voluntary contractions in economic activity, similar to working hours adjustments. Earnings is, however, a function of both hourly wages and working hours and hence is sensitive to variation in either. Third, government support measures such as job retention programmes, wage subsidies, and short-time work schemes may have mitigated such changes on both the extensive and intensive margins, resulting in little to no change in observed wages or earnings. Finally, it is plausible that through these and other mechanisms, the pandemic affected the returns associated with various individual-level characteristics among those who remained employed. Arguably then, both structural and compositional dynamics ought to be considered in any analysis of wages during the pandemic. I consider these in the review of the literature here.

Globally, at the pandemic's onset the level of average wages fell in two in every three countries for which data was available for, with a mean reduction of 3.5 percent relative to the end of 2019 (International Labour Organisation, 2020; International Labour Organization, 2022). Similar to employment, this contraction was unequally distributed across country income groups, with middle-income countries experiencing the largest contraction of about 7 percent, in contrast to the 3.9 percent and 2.5 percent contractions experienced by low- and high-income countries, respectively. The smaller reduction for the latter group has been attributed to the widespread combined use of job retention schemes, which sought to retain

[11] While all four countries experienced furloughs, 30 percent of firms in Guatemala reported furloughs in comparison to just 11 percent of firms in Nicaragua (Webster et al., 2022).

employment relationships, alongside temporary wage subsidies, which sought to partially or fully compensate wage losses conditional on employment (International Labour Organisation, 2020). The literature, however, highlights considerable cross-country variation. In the US, given that most job loss has been attributed to increased separations as opposed to reduced hiring, Cortes & Forsythe (2023a) use panel survey data to examine the outcomes of the previously employed, distinguishing between earnings impacts on the extensive (among job-losers) and intensive (among job-retainers) margins. They show that the earnings growth rate of the average worker reduced by 10 percentage points, but adjustments to the latter were not atypical, and hence this impact was entirely driven by job loss. In Sweden, average earnings fell by approximately 4 percent (Angelov & Waldenström, 2023), and in Spain, Aspachs et al. (2021) estimate that such reductions led to wage inequality increasing by 10 percent in just one month.[12] In contrast, in the Netherlands, Zimpelmann et al. (2021) show that the distribution of earnings remained relatively constant at the pandemic's onset, on aggregate and for varied worker sub-groups, in contrast to the UK where median earnings contracted by 15 percentage points.

Studies which consider developing countries are generally suggestive of more severe impacts. In Burkina Faso, Mali, and Senegal, Balde et al. (2020) estimate that large shares of workers - 45, 65, and 53 percent, respectively - experienced a decrease in earnings. de Mahieu & Lastunen (2023) find that nearly 70 percent of the working-age population experienced earnings reductions in Viet Nam. Similarly, 61 percent of workers suffered a wage cut in Cameroon (Djoumessi, 2021). To a smaller degree, in their sample of firms in El Salvador, Guatemala, Honduras, and Nicaragua, Webster et al. (2022) show that an average of 26 percent reduced the wages of their workers. Examining 31 low- and middle-income countries, Bundervoet et al. (2022) estimate that 65 percent of households experienced a decrease in labour income. Khamis et al. (2021) find that 20 percent of wage workers in Latin America and the Caribbean experienced partial or zero wage payments. Morales et al. (2022) document a relatively small negative effect of 3 percent on wages in Columbia, however given their study design, this adjustment is attributable to sector-specific restrictions alone as opposed to the sum of epidemiological and economic factors.

In addition to variation in wage adjustments between countries, the literature highlights significant variation within countries. Similar to changes in employment and working hours, wage adjustments tended to be greater among workers in more precarious labour market positions. In the US, earnings declines were concentrated among the youth, Hispanics, less-educated workers, the self-employed, and low-wage workers (Adams-Prassl et al., 2020; Béland et al., 2020; Cortes & Forsythe, 2023b). The average worker in the bottom decile of workers experienced a 85 percentage points contraction at the pandemic's onset (Cortes & Forsythe, 2023b). However, following its onset and despite the high inflationary environment, there was substantial wage growth at the bottom of the distribution. Autor et al. (2023)

[12] However, Aspachs et al. (2021) estimate that inequality would have increased by a much larger rate - almost 30 percent - in the absence of government income support programmes.

show that, between January 2020 and September 2022, real hourly wages at the 10$^{\text{th}}$ percentile grew by 6.4 percent, in contrast to wages at the median and 90$^{\text{th}}$ percentile where real wages were lower. The authors attribute the strong wage growth at the bottom to increased competition which led to a reallocation of jobs from low-wage to higher-wage employers, and subsequently show that it reversed one-quarter of the rise in wage inequality in the US since 1980 (Autor et al., 2023). In the UK, the youth were also more likely than other age groups to experience a fall in their earnings (Adams-Prassl et al., 2020), as well as those living in poorer households (Zimpelmann et al., 2021). In Spain, low-wage workers were also more likely to experience wage cuts (Aspachs et al., 2021), as well as in Sweden in addition to youth and part-time workers, which led to a 2.5 percent increase in wage inequality (Angelov & Waldenström, 2023). In Italy, Carta & De Philippis (2021) simulate that in the absence of government support, the pandemic would have affected workers in lower-income households the most, due to their concentration in non-'essential' sectors and jobs which cannot feasibly be done remotely.

This regressive distribution of wage losses is also documented in many, but not all, developing countries. In these contexts, again, these effects appear to be primarily explained by sectoral and occupational structures; in particular, the high extent of informality (Delaporte et al., 2021). In China, long-standing indicators of social status such as education, family economic status, Communist Party membership, and state-sector employment mitigate effects on individuals' earnings losses (Qian & Fan, 2020). In West Africa, Balde et al. (2020) show that informal workers, who are over-represented in high-risk, contact-intensive sectors, were significantly more likely to experience a decrease in earnings. In their sample of 31 low- and middle-income countries, Bundervoet et al. (2022) document larger earnings losses among the self-employed who are also concentrated in contact-intensive sectors. In their sample of 20 Latin American and Caribbean countries, Delaporte et al. (2021) find that labour income losses also disproportionately affected informal workers. This was similarly found in the Middle East and North Africa region (Krafft et al., 2021). In contrast, de Mahieu & Lastunen (2023) show that in Viet Nam, the most pronounced effects were experienced by higher-income households, which the authors attribute to well-targeted government assistance programmes.

As referred to above, meaningful selection effects can arise when interpreting aggregate measures of wages, such as averages, during times of crisis. Average wages may change due to changes to the underlying workforce as opposed to earnings changes among the employed.[13] As a consequence of the concentration of job loss and working hour contractions among lower-wage workers during the pandemic, average wages mechanically rose in many countries. This composition effect has been documented in several developed and developing countries, such as the US (Cajner et al., 2020; Grigsby, 2022; Autor et al., 2023), Canada, France, Italy, and Norway (International Labour Organisation, 2020; Béland et al., 2020; Gherghina, 2022),

[13] As described by Grigsby (2022), movements in aggregate measures of wages often reflect worker reallocation across and within labour market states, particularly in times of crisis.

Romania (Gherghina, 2022), Hungary (Gáspár & Reizer, 2020), and many Latin American countries including Brazil, Chile, and Mexico (Economic Commission for Latin America and the Caribbean, 2022). Notably, Gáspár & Reizer (2020) show that the wage increase in Hungary was due not only to a regressive incidence of job loss but also, among the employed, a movement of workers from full-time to part-time and unpaid leave states. As I show later in Chapter 4, such composition effects were also evident at the pandemic's onset in South Africa.

2.3 The South African context

2.3.1 Employment

I now consider the South African context, again first with respect to effects on the extensive margin. A large literature now exists which documents the substantial and often persistent extensive margin adjustments in response to the pandemic. Existing studies, however, tend to focus on either a limited subgroup or short time period, with most using representative survey data from either the country's official source of labour statistics - Statistics South Africa's (StatsSA) Quarterly Labour Force Survey (QLFS) - or the National Income Dynamics Study - Coronavirus Rapid Mobile Survey (NIDS-CRAM), a temporary, telephonic panel survey conducted between May 2020 and May 2021, described later. The QLFS data indicates a significant extent of net employment loss at the pandemic's onset, amounting to 13 percent year-on-year or 2.2 million fewer workers in the second quarter of 2020 (Statistics South Africa, 2020f). As I describe later in Chapter 3, this contraction is the largest on record, equivalent to the magnitude of jobs growth in the entire decade prior. Using the same data, Daniels et al. (2022) show that the employment-to-population rate fell by over 8 percentage points, and Yu et al. (2023) show that labour force participation concurrently dropped from 59.9 percent to 46.9 percent - the first time it fell below 50 percent since 1999. The contraction in the latter was also due to a significant drop in narrow unemployment. Coupled by a surge in inactivity, examined in detail in the proceeding chapter, this latter outcome does not, of course, reflect an improved labour market but instead how the nature of the pandemic and associated restrictions limited the abilities of both workers and jobseekers from participating in the labour market.

In response to the pandemic and associated government-mandated restrictions, many national statistics offices around the world had to temporarily suspend face-to-face data collection activities (Betcherman et al., 2020; Daniels et al., 2022; Kugler et al., 2023). South Africa was no exception. To continue providing labour market statistics, StatsSA changed the data collection mode of all of its surveys, including the QLFS, to computer-assisted telephone interviewing (CATI) for the first time (Statistics South Africa, 2020f). The very little time they had to adapt had important implications on the timeliness of data availability. Prior to the pandemic, the data for the second quarter of 2020 (henceforth 2020Q2) was scheduled for release on 11 August 2020, but was delayed to the end of September 2020

(Statistics South Africa, 2020e,g). This is equivalent to three months after the end of the data collection period, and six months after the beginning of the government's national lockdown. This significant delay led to the rapid development of a new survey - the NIDS-CRAM - whose purpose was to capture timely information on the impacts of the pandemic on a range of socio-economic outcomes, including but not limited to labour market outcomes, income support, hunger, schooling, and mental health. Developed by a team of over thirty researchers from institutions across the country, the NIDS-CRAM was a broadly representative, five-wave, panel survey of a sample of adults conducted approximately every three months between May 2020 and May 2021, and served as one of the largest data collection projects in Africa during the pandemic's first year (Daniels & Casale, 2022). While the survey is not strictly comparable to the QLFS primarily due to different sampling designs, reference periods, and measurements of job attachment (Daniels et al., 2022) and comprises a much smaller sample (equivalent to about 15 percent of the 2020Q2 QLFS sample), it became an indispensable resource to assist in the understanding of the consequences of the pandemic as it unfolded during its first year (Daniels & Casale, 2022).

A large local literature makes use of the NIDS-CRAM data to examine labour market dynamics in South Africa during the pandemic's first year. Using the Wave 1 data, Ranchhod & Daniels (2021) estimate that from February (the pre-pandemic baseline) to April 2020, the employment-to-population rate shrunk from 56.6 to 48.3 percent, and further to 38 percent if furloughed workers are regarded as unemployed. This suggests that one out of every three workers either fell out of employment or did not work and received no earnings at the pandemic's onset. This is consistent with Bassier et al. (2023) who also highlight both extensive and intensive margin adjustments, showing that about half of this reduction in what they term 'active' employment (which only includes workers who report positive workdays) was due to job terminations as opposed to furloughs. Data from follow-up waves reveal significant labour market churn which far exceeded historical rates, highlighting the sensitivity of the labour market to the progression of the pandemic and variation in economic activity restrictions (Daniels & Casale, 2022; Espi-Sanchis et al., 2022; Yu et al., 2023). Following a moderate easing of restrictions, by June 2020 active employment partially recovered but was still 20 percent lower than the pre-pandemic level, primarily due to persistent terminations but further additional terminations of 40 percent of those who were previously furloughed (Bassier et al., 2023). Further employment growth materialised by October 2020 as more restrictions were repealed, only for it to contract again in January 2021 when many restrictions were re-introduced in response to another pandemic wave (Daniels & Casale, 2022). Again, a significant amount of churn characterises this period. Yu et al. (2023) estimate that only half (51 percent) of those who were employed prior to the pandemic were still working in all five waves, just 0.5 percent were unemployed in all waves, and among those who fell out of employment at the pandemic's onset, by March 2021 most (60 percent) were working again while 22 percent remained unemployed. Overall, following a subsequent easing of restrictions, the final Wave 5 data suggests a full net employment recovery to the pre-pandemic level by March 2021. This however paints a markedly different picture of the labour market compared to the QLFS which, as I show in Chapter 3, suggests that net employment remained only partially recovered, implying that the smaller NIDS-CRAM sample may comprise individuals who were simply more likely to be employed relative to a fully representative sample (Daniels et al., 2022; Espi-Sanchis et al., 2022).

Consistent with the international context, job loss in South Africa was disproportionately borne by worker groups who were already in precarious labour market positions prior to the pandemic. Examining the QLFS and NIDS-CRAM data, Yu et al. (2023) and Ranchhod & Daniels (2021) show that those with lower levels of education, African/Black workers, the youth, and those in less-skilled occupations were most vulnerable to job loss at the pandemic's onset. Shifa et al. (2021) and Shifa et al. (2022) estimate a significant relationship between pre-existing socio-economic inequalities and inequalities in vulnerability to COVID-19 infection, implying that workers more vulnerable to job loss tended to also be more vulnerable to infection. Turok & Visagie (2022) highlight geographic disparities in employment outcomes, showing that urban informal settlement residents experienced an 18 percentage point reduction in their employment rate at the pandemic's onset, in contrast to the 7 percentage point contraction experienced by suburban residents. The authors additionally highlight these groups' varied trajectories as the pandemic progressed. By March 2021, urban informal settlement residents only partially recovered to 10 percentage points below the pre-pandemic rate, compared to the trajectory of suburban residents which had almost fully recovered. This latter group exhibits a considerably different occupational structure, including being more likely to work in higher-skilled occupations, have formal employment contracts, and being able to work-from-home (Turok & Visagie, 2022). Espi-Sanchis et al. (2022) focus on inequalities across age groups and, in line with Yu et al. (2023), Ranchhod & Daniels (2021), and the international literature referenced in the preceding section, highlight the disproportionate burden of job loss among youth during the beginning of the pandemic. As it progressed, however, the authors estimate that the youth experienced the largest recovery in employment during the year thereafter; however, the small NIDS-CRAM sample size prohibits them from making a conclusive statement. Additionally, informal workers were significantly more likely to experience job loss relative to their formal counterparts, again consistent with the international experience (Daniels & Casale, 2022; Rogan & Skinner, 2020, 2022; Bassier et al., 2023). Rogan & Skinner (2022) estimate that informal jobs accounted for 1.5 million of the 2.2 million net jobs lost at the pandemic's onset, and among informal workers, those working in the informal sector were particularly hard hit. This deeply regressive distribution of job loss has been estimated to have led to a substantial increase in both the incidence and depth of poverty. By using the QLFS data during the pandemic to simulate incomes in pre-pandemic household survey data, Bassier et al. (2022) estimate that job losses between 2020Q1 and 2021Q4 led to 3 and 2.5 percentage point increases in the upper-bound poverty headcount rate (equivalent to 1.8 million people) and gap, respectively.

Similar to many labour markets across the world, remote work ability in South Africa is strongly inversely correlated to labour market vulnerability, and hence has been argued to at least partially explain the above regressive distribution of job loss. Benhura & Magejo (2020) and Nwosu et al. (2022) use the NIDS-CRAM data to estimate the number and characteristics of remote workers in the country. Nwosu et al. (2022) show that this comprised the minority - between 22 and 27 percent - of workers during the pandemic's first year. This is similar to the equivalent share in other developing countries such as Mexico and Turkey, and significantly lower than, for instance, the US or UK (Dingel & Neiman, 2020). Using pre-pandemic QLFS data, Kerr & Thornton (2020) estimate a notably smaller share of 13.8 percent. This disparity may be due to their estimates not yet reflecting job loss and hence representing a larger employed population, not accounting for within-occupation changes in remote work arrangements during the pandemic, or simply the use of different samples. Kerr & Thornton (2020), Benhura & Magejo (2020), and Nwosu et al. (2022) highlight significant inequalities associated with remote work ability. Notably, those less likely to be able to work-from-home include workers of colour, informal settlement residents, those working in less-skilled occupations, and those residing in poorer households (Benhura & Magejo, 2020; Nwosu et al., 2022). Kerr & Thornton (2020) similarly find that those who could work at home were more likely to work in higher-skilled occupations and earn higher wages. Nwosu et al. (2022) quantify this latter gap, estimating that the mean wage of workers who were able to work remotely was two to three times that of those who could not during the period. Also using pre-pandemic survey data, Bhorat et al. (2020d) additionally document that lower work-from-home ability is positively related to higher physical interaction in the workplace, again highlighting the vulnerability of lower-wage workers to both job loss as well as infection. The authors also estimate that this group represents the majority (59 percent) of workers in the country (Bhorat et al., 2020d). Similarly, Kerr & Thornton (2020) estimate that 63 percent of workers prior to the pandemic could neither work-from-home nor were regarded as 'essential' and stressed that job losses were likely to be concentrated amongst this group, which is consistent with the empirical literature.

Several studies highlight the unequal, gendered labour market effects of the pandemic in South Africa, consistent with the experiences of other countries as documented in the previous section. Using the NIDS-CRAM data, Ranchhod & Daniels (2021), Casale & Posel (2021), Casale & Shepherd (2022), Mosomi & Thornton (2022), and Bassier et al. (2023) show that women faced significantly greater contractions in net employment relative to men.[14] Women accounted for two-thirds of net job losses at the pandemic's onset, despite representing less than half of the employed population prior to the pandemic (Casale & Posel, 2021; Casale & Shepherd, 2022). These employment effects persisted over the course of 2020 and into 2021. By March 2021, only 51 percent of women compared to 62 percent of men who were employed prior to the pandemic were still employed, while 5 percent of women but only 2.5 percent of men became chronically unemployed (Mosomi & Thornton,

[14] Mosomi & Thornton (2022) show that the QLFS suggests men and women lost approximately the same number of jobs, however women lost a greater share of jobs, which is consistent with global findings. Moreover, they show that more women than men dropped out of the labour force, increasing the gender labour force participation gap.

2022). Consequently, women's employment level was slower to recover to pre-pandemic levels (Casale & Shepherd, 2022). Within the informal economy, Rogan & Skinner (2022) estimate that employment of female informal workers was particularly affected. The two mechanisms which primarily explain these gendered effects globally - occupational and sectoral segregation on the demand-side and increased caregiving responsibilities on the supply-side - were also evident in the South African context. Women were not only more likely to work in service occupations which were particularly vulnerable to the pandemic and sector-specific restrictions, but were also overrepresented in less secure forms of employment (Casale & Posel, 2021; Casale & Shepherd, 2022). Further, evidence suggests that school closures in the country - which has been estimated to have led to a quadrupling of the number of learners not attending school, the largest number in two decades (Shepherd & Mohohlwane, 2022) - increased home-based caregiving for women with school-aged children, negatively affecting their ability to work. Casale & Shepherd (2022) show that changes in the time women spent on unpaid care work closely followed the closure and re-opening of schools in the country. Overall, these dynamics are largely consistent with the international literature, and suggest that the pandemic increased gender labour market inequality in South Africa and, as phrased by Casale & Posel (2021), reversed some of the hard-won gains over the past 25 years since democratisation.

As discussed in Chapter 1, the South African government introduced a range of economic support policies at the onset of the pandemic to provide relief to firms, workers, the unemployed, and individuals residing in poor households. These largely comprised tax relief measures, labour market programmes, and an expansion of social protection on both the extensive and intensive margins, many of which were extended and revised as the pandemic progressed. Despite some implementation delays, the government's bold fiscal response was consistent with international best practices and was regarded as being largely successful in providing considerable support to households and firms (Barnes et al., 2021; Bhorat et al., 2021b; Daniels & Casale, 2022). While a comprehensive assessment of all of these policies is beyond the scope of this chapter, here focus is placed on two which were relevant to the labour market - the TERS wage subsidy scheme and the SRD cash transfer or grant - which collectively targeted workers in both the formal and informal sectors as well as the unemployed.

Introduced at the end of March 2020, the TERS was a wage subsidy scheme which provided relief to employees who suffered income loss due to a full or partial closure of their employer's operations. By subsidising firm liquidity, wage subsidies were one of the primary tools used by governments across the world to help employers retain workers, avoid the costly process of hiring and training as economic activity recovered, as well as help workers avoid adverse scarring effects associated with periods of unemployment (Bennedsen et al., 2020; Giupponi & Landais, 2020; International Labor Organisation, 2020; Keenan & Lydon, 2020; Gentilini et al., 2022; Köhler & Hill, 2022). While a comprehensive description of the policy is provided in Köhler & Hill (2022), the primary aim of the TERS was to mitigate job loss. Considering South Africa's extreme level of unemployment, the policy was arguably the country's most important labour market intervention during this period. Cumulatively, over 5.7 million workers had benefitted during the policy's two years at a cost of R64 billion. Existing evidence suggests that the TERS policy was largely successful, at least during the beginning of the pandemic. Using a microsimulation model, Barnes et al. (2021)'s analysis suggests that the policy helped mitigate the pandemic's effects on earnings. Köhler & Hill (2022) estimate a positive and robust association between TERS receipt and job retention, however their analysis is correlational and not causal in nature. Köhler et al. (2023) overcome this limitation by exploiting a temporary eligibility criterion and adopting a DiD design. They show that the policy increased the probability of remaining employed by 16 percentage points in the short-term, implying that it saved at least 2 million jobs during the first few months of the pandemic.[15] Overall, these studies suggest that job loss in the South African labour market would have been notably more severe in the absence of the policy. These findings are consistent with the international literature on the effectiveness of wage subsidies during periods of large, transient shocks (McKenzie, 2017; Bruhn, 2020) and during the COVID-19 pandemic in particular (Bishop & Day, 2020; Chetty et al., 2020; Hubbard & Strain, 2020; Dalton, 2021; Autor et al., 2022; Granja et al., 2022; Smart et al., 2023).

Introduced in April 2020, the SRD grant is an unconditional cash transfer of R350 per person per month. The grant is distinct from other transfers in the country's relatively comprehensive social assistance system in that it is the first to target unemployed adults. Despite this criterion, informal workers also benefited, which was not unexpected given the ability of verification systems to distinguish them from the unemployed (Köhler & Bhorat, 2021). In fact, the SRD was initially conceptualised to target the informally employed (Bassier et al., 2021). While the reader is referred to Gronbach et al. (2022) and Bhorat et al. (2023) for comprehensive descriptions of the policy, at its peak the grant brought over 10 million previously unreached adults into the system (South African Social Security Agency, 2022). Existing evidence suggests that the SRD has been progressively distributed and had positive effects on welfare and labour market outcomes. Köhler & Bhorat (2020) show that application for and receipt of the grant was pro-poor, which is reflected by the observation that individuals in households in typically poorer areas were significantly more likely to receive the grant relative to their more affluent counterparts (Turok & Visagie, 2022). Expectedly then, several studies simulate that extreme income poverty would have been higher in the grant's absence (Barnes et al., 2021; Bassier et al., 2021; Bhorat et al., 2021b; Köhler & Bhorat, 2021; Bassier et al., 2022). Bhorat et al. (2023) adopt a staggered DiD design to estimate the labour market effects of SRD receipt during its first year.[16] Although its primary aim was to provide income relief and not necessarily influence labour market outcomes, the authors estimate a significant, positive average effect of about 3 percentage points on the probability of employment - an unsurprisingly small magnitude given the small

[15] Köhler et al. (2023) also estimate that the TERS cost R13 195 per month per job saved on average, which they argue is large relative to the wage costs of jobs supported by the policy, however it compares favourably to similar policies in more developed country contexts.

[16] Importantly, this period was prior to the revision of one of the grant's eligibility criteria which made unemployed Child Support Grant caregivers eligible from the second half of 2021 onwards.

size of the transfer. Importantly, this effect is largest in the short-term but reduces to zero with additional periods of receipt (Bhorat et al., 2023). This suggests that the grant, at least in its initial design, provided both income relief and enabled more favourable labour market outcomes in the short-term, however these latter benefits did not materialise in the longer-term. As of November 2023, the grant was scheduled to remain in place until March 2025 while its availability beyond then remained unclear.

2.3.2 Working hours

At the time of writing, the empirical literature on working hour adjustments in South Africa was sparse relative to that of extensive margin adjustments. While this is consistent with the international literature as discussed in Section 2.2.2, the literature in the South African case appears even more limited. Among the few which do consider hours, all document stronger downward adjustments relative to employment, which is again consistent with the international literature. Using the NIDS-CRAM data, Ranchhod & Daniels (2021) estimate that the share of workers reporting working zero hours per day (in other words, furloughed workers) surged from 3 percent prior to the pandemic, due to temporary absences such as paid holiday or parental leave, to 19 percent in April 2020. As I show in Chapter 3, this difference is consistent with the QLFS data. The authors' analysis suggests these workers largely comprise those who were previously working on a full-time basis, which shrunk from 86 to 67 percent of workers over the period (Ranchhod & Daniels, 2021).[17] This adjustment, however, appeared short-lived. Using the second round of data collected in June 2020, Yu et al. (2023) show that mean working hours immediately recovered to the pre-pandemic level just a few months following the pandemic's onset. Again, I show in the proceeding chapter that this trajectory is consistent with the QLFS data. While this implies a temporary contraction in mean working hours, to the authors' knowledge, neither of these studies nor any other documents the evolution of working hours throughout the course of the pandemic, either on average or across worker groups, with the exception of one group discussed below. The analysis of working hour adjustments on average and between a wide array of groups in Chapter 3 seeks to fill this notable gap in the literature.

Among studies which do consider between-group inequalities in working hour adjustments, to date only gender has received explicit attention in the South African literature. Similar to the case of employment, the focus on this covariate relates to the effects of large-scale school closures on the gendered division of paid and unpaid labour, as highlighted in the international literature (Collins et al., 2021; Craig & Churchill, 2021; McDermott & Hansen, 2021; Couch et al., 2022; Hanzl & Rehm, 2023) and discussed in Sections 2.2.2 and 2.3.1. As observed across the world, a similar pattern with respect to working hours has been documented. Among those who remained employed, women's working hours contracted significantly more than men's, while concurrently women took on more of additional childcare work (Casale & Posel, 2021; Casale & Shepherd, 2022; Daniels & Casale, 2022; Mosomi &

[17] Ranchhod & Daniels (2021) define full-time work as working between 6 and 12 hours per day.

Thornton, 2022). Using the NIDS-CRAM data, Casale & Posel (2021) and Casale & Shepherd (2022) show that while women worked fewer pre-pandemic hours than men on average - 35 versus 39 per week - after the pandemic's onset in April 2020 working hours among women and men shrunk by 35 and 26 percent, respectively. However, Mosomi & Thornton (2022) estimate that, when labour market production and childcare are considered together, women work more hours than men, a gap evident prior to the pandemic which only grew larger after its onset.

During this period, most men and women living with children reported spending more time than usual on childcare, but women were disproportionately affected. 73 percent of women reported such compared to 66 percent of men, and within this sub-group, more women (80 percent) than men (65 percent) reported spending at least four additional hours per day on childcare (Casale & Shepherd, 2022; Casale & Posel, 2021). Notably, Casale & Posel (2021) show that this additional time spent on childcare is relatively insensitive to employment status; that is, even employed women perform more childcare than employed men. Twice as many women as men reported that having to perform additional childcare affected their ability to work, search for work, or work the same number of hours as before (Casale & Shepherd, 2022; Daniels & Casale, 2022). As the economy and schools started to re-open, men and women continued to be differentially affected. While the gender gap in childcare hours narrowed, women's working hours exhibited greater volatility relative to men's, and one year into the pandemic men's mean working hours appeared to have fully recovered to the pre-pandemic level while that of women's remained two hours lower (Casale & Shepherd, 2022; Daniels & Casale, 2022). Overall, these studies provide evidence that women's time spent on paid and unpaid labour in South Africa was strongly responsive to the pandemic and its associated regulations, in line with gendered labour market dynamics observed in many economies across the world.

2.3.3 Wages

Similar to working hours, the empirical literature on the effects of the pandemic on earnings and wages in South Africa is also sparse. This is relative to both the literature on other labour market outcomes in the country as well as the international literature on wage adjustments. Despite this, existing studies document significant changes to South Africa's wage distribution in response to the pandemic, largely attributable to the previously-documented regressive distribution of job loss as well as heterogenous effects among those who remained employed. As discussed in Section 2.3.1, using the NIDS-CRAM data Ranchhod & Daniels (2021) show that lower-wage workers were significantly more likely to experience job loss. This is consistent with Barnes et al. (2021)'s microsimulation analysis which suggests that both jobs and unconditional earnings losses were greater at the bottom of the household income distribution. Using the cross-sectional samples, Ranchhod & Daniels (2021) additionally estimate that 12 percent of workers in April 2020 earned zero wages, up from 5 percent prior to the pandemic. While this share is non-negligible, it does suggest that the majority of workers who remained employed continued to earn some non-zero, positive wage. Using the same data, Bassier et al. (2023) estimate a 10 percent reduction in unconditional mean monthly earnings.[18] Notably, Barnes et al. (2021)'s simulation suggests that the observed decline in unconditional earnings would have been significantly greater in the absence of the government's policy interventions. Using the panel sample of individuals who remained actively employed, Bassier et al. (2023) observe no statistically significant change in average earnings, while among those who remained employed but became furloughed, they estimate a 5 percent decrease. Together with the discussion in the preceding sections, these results suggest that in response to the pandemic, the South African labour market was more sensitive to changes in employment and working hours relative to earnings among those who remained employed.

Very few studies consider heterogeneity in wage or earnings changes across worker groups in South Africa. Among those who remain employed, Bassier et al. (2023) do not find any statistically significant heterogeneity in earnings changes across workers of different genders, racial groups, levels of education, or occupations to name a few. However, they do find some evidence of variation among workers who remained employed but also became furloughed (what the authors refer to as 'paid leave'). They estimate a 5 percent reduction among both women and African/Black workers and approximately 7 percent among those with less than a tertiary-level education (Bassier et al., 2023). This is consistent with several studies in the international literature which, as discussed in Section 2.2.3, highlight greater wage cuts among workers already in precarious labour market positions (Adams-Prassl et al., 2020; Béland et al., 2020; Aspachs et al., 2021; Zimpelmann et al., 2021; Autor et al., 2023; Cortes & Forsythe, 2023b). The greater wage reduction experienced by women observed by Bassier et al. (2023) is consistent with Casale & Posel (2021) and Casale & Shepherd (2021). Casale & Posel (2021) show that a larger share of employed women than employed men reported earning zero wages in April 2020. Excluding zero-earners, Casale & Shepherd (2021) estimate that at the pandemic's onset, mean real monthly earnings increased among both men and women.[19] As previously discussed, this likely reflects a compositional effect relating to selection into job loss. Using the same data but accounting for inter-gender differences in several demographic and labour market characteristics, Hill & Köhler (2021) estimate a consequent widening of the average gender wage gap from 29 in February to 43 percent in June 2020. While the authors show that this gap existed across the wage distribution in both periods, they highlight they it grew the most among the poorest 40 percent of earners. Over time, Casale & Shepherd (2021) show that cross-sectional estimates of earnings changes fluctuated significantly, usually in the opposite direction of employment changes, which they attribute to composition effects. One year following the pandemic's onset, mean real monthly earnings among women and men remained 5 and 3 percent lower

[18] To arrive at this estimate, the authors code the earnings of the unemployed and temporarily laid off workers as zero.

[19] The authors find that mean real hourly wages for both men and women increased at larger rates relative to real monthly earnings, which is likely attributable to the concurrent reduction in working hours.

than their pre-pandemic levels, respectively (Casale & Shepherd, 2021). However, neither of these differences are statistically significant, which may be a consequence of the NIDS-CRAM's small sample size.

2.4 Conclusion

This chapter sought to provide a synthesised review of the international literature of the labour market effects of the COVID-19 pandemic, both in the international context and in South Africa in particular. Globally, these effects were far-reaching and substantial in magnitude, being largely attributable to one or a combination of four broad categories: government-mandated mitigation measures; voluntary reductions in economic activity; occupational and sectoral compositions, specifically the shares of jobs which are vulnerable to sector-specific restrictions and were amenable to remote work; and government support policy. Despite these similarities, the literature highlights significant inequalities in adjustments to extensive and intensive margin outcomes both across and within countries over time.

Both the international and South African literatures focus on extensive margin adjustments, particularly employment. In many contexts, job losses were unprecedented in magnitude and coupled with surges in economic inactivity, reflecting large-scale transitions of both job-losers and job-seekers out of the labour force entirely. Job losses were primarily due to increased separations, however in some countries lower hiring was dominant while in some cases both played a role. Many of these dynamics were mirrored in South Africa. The country experienced the largest net employment contraction on record, characterised by both terminations and temporary furloughs and again accompanied by a fall in labour force participation and surge in inactivity. As the pandemic progressed, the labour market experienced a substantial amount of churn which far exceeded historical rates. Globally, the literature on intensive margin adjustments remains relatively sparse. Existing studies show that fewer working hours were driven by both reductions in non-zero, positive hours as well as complete furloughs which were, in many cases, larger relative to employment but more transient in nature, South Africa notwithstanding. In addition to government-mandated restrictions, these adjustments were also due to shifts towards non-traditional hours in response to new demands among certain worker groups as well as large-scale school closures which affected time allocations to paid and unpaid labour.

The literature documents substantial and heterogenous changes to wage distributions at the pandemic's onset. In some cases, these changes were characterised by wage reductions among those who remain employed, while in others, average wages mechanically spiked due to significant changes to the composition of employed populations, reflecting the general concentration of job loss and working hour contractions among lower-wage workers. The literature in South Africa is especially limited in this regard. Existing studies suggest no detectable change in earnings on average for those who remained actively employed, but a small negative change among those who became furloughed. Most workers who remained employed continued to earn some non-zero, positive amount, and overall, the labour market appears to have been relatively more sensitive to employment and working hour reductions, which is largely consistent with the international experience. Across countries, adjustments to all outcomes were typically more severe in developing countries, which has been attributed to a combination of more limited fiscal space and large informal sectors which comprise workers who cannot access legal protections and whose occupations tend to be contact-intensive, vulnerable to sector-specific restrictions, and not amenable to remote work.

The overwhelming majority of studies highlight that, within countries, adjustments to employment, working hours, and wages disproportionately affected worker groups who were already in precarious, disadvantaged positions prior to the pandemic. This includes but is not limited to the youth, the less-educated, those in less-skilled occupations, and informal workers. Again, South Africa was not excluded in this regard, with some studies estimating significant poverty effects as a consequence. This regressive effect distribution suggests that the pandemic reinforced and possibly exacerbated both within and between-country labour market inequalities. This has been largely attributed to unfavourable occupational distributions; specifically, the concentration of these workers in jobs that are vulnerable to government-mandated restrictions or are not amenable to remote work. On the former, a subset of studies provide strong causal evidence that, while restrictions did incur significant and negative effects, these are still evident in the absence of restrictions, suggesting that restrictions may have caused more damage than necessary but that the primary culprit is the virus itself. On the latter, remote work was a defining characteristic of pandemic labour markets globally, including South Africa where about a quarter of all workers worked remotely during the pandemic. However, significant inequalities in remote work ability exist both within and across countries. Within countries, remote work tends to be concentrated among more privileged workers, and across countries, the share of jobs that can be done at home increases with country income. Hence, inequality in remote work ability has been shown to at least partially explain the observed regressivity of job loss. The pandemic thus not only exacerbated pre-existing labour market inequalities, but also created a new one. While remote work is expected to persist into the future, the task content of many occupations cannot yet be replicated online. As such, most work in both developed and developing countries, South Africa notwithstanding, will likely continue to have an in-person component to some extent.

In contrast to previous recessions, another defining feature of labour markets during the pandemic was the disproportionate incidence of effects on women's paid and unpaid labour. Across developed and developing countries, South Africa included, women lost a greater share of jobs and among those who remained employed suffered larger working hour and wage reductions relative to their male counterparts. Accompanying their reduced working hours, employed women with children at home concurrently took on more of additional childcare work. Two mechanisms explain these effects. On the demand-side, occupational and sectoral segregation meant that female-dominated sectors were especially vulnerable to sector-specific restrictions and reduced consumer demand. On the supply-side, large-scale school closures increased caregiving responsibilities for those with children at home, and due to gender norms, disproportionately reduced women's ability to work. Consequently, the pandemic widened gender labour market inequality and, in South Africa, reversed some of the hard-won gains since democratisation.

Overall, the vast and still evolving empirical literature makes is clear that the labour market impacts of the pandemic were exceptionally large and unequally distributed both across and within countries. Effects in South Africa were largely consistent with the international experience, especially regarding its regressive distribution. This is particularly relevant considering the country's status as one of the most unequal in the world. Given the labour market's dominant role in driven overall inequality dynamics, it can then be said that the pandemic's overarching outcome was a reinforcement of inequality in the country. However, at the time of writing much remained unknown. The existing South African literature is substantial in size, but limited in scope. While existing studies have undoubtedly provided important insights, they tend to focus on a limited time period or subgroup of workers, and pay much less attention to intensive margin adjustments. For instance, no study documents the evolution of working hours throughout the course of the pandemic, either on average or across worker groups, with gender serving as the single exception but only until one year following its onset. As such, the analysis of working hour adjustments on average and between a wide array of groups in Chapter 3 of this thesis seeks to fill this notable gap in the literature. Moreover, no study has analysed the evolution of wages as the pandemic progressed beyond its first year, either on average or among specific worker groups, and none examine changes in the magnitude and drivers of wage inequality. Among those that do consider wages, all use data from a relatively small sample characterised by relatively high amounts of imprecision and representivity issues. This latter point may be at least partially attributable to a lack of access to adequate wage data. The analysis in Chapter 4 seeks to contribute to the literature by using a representative and substantially larger sample of workers from the QLFS provided by StatsSA to conduct an in-depth examination of the magnitude and drivers of wages and wage inequality during the pandemic's full two years.

Chapter 3

Labour market adjustments to COVID-19 in South Africa

3.1 Introduction

A vast and still evolving empirical literature of the labour market effects of the COVID-19 pandemic has materialised globally. As documented in Chapter 2, labour supply and demand contracted significantly in response to government-mandated mitigation measures alongside voluntary reductions in economic activity, with the consequence being effects both substantial in magnitude and unequally distributed. Most studies highlight that those who were already in precarious labour market positions prior to the pandemic were disproportionately affected (for instance, see Adams-Prassl et al., 2020; Balde et al., 2020; Béland et al., 2020; Campello et al., 2020; Guven et al., 2020; Lemieux et al., 2020; Aum et al., 2021; Khamis et al., 2021; Blundell et al., 2022; Bundervoet et al., 2022; Casarico & Lattanzio, 2022; Immel et al., 2022; Lariau & Liu, 2022; Soares & Berg, 2022; Webster et al., 2022; Angelov & Waldenström, 2023; Autor et al., 2023; Cortes & Forsythe, 2023a; Kugler et al., 2023; Oyenubi, 2023; Schotte et al., 2023). Broadly, this has been attributed to unfavourable occupational distributions. Similarly, the literature in South Africa documents a notably regressive distribution of effects (for instance, see Ranchhod & Daniels, 2021; Shifa et al., 2021, 2022; Casale & Shepherd, 2022; Daniels & Casale, 2022; Espi-Sanchis et al., 2022; Rogan & Skinner, 2022; Turok & Visagie, 2022; Bassier et al., 2023; Yu et al., 2023). Thus, one of the pandemic's overarching outcomes was a reinforcement or, in some cases, exacerbation of pre-existing labour market inequalities.

Despite its large size, the South African literature remains limited in scope. As shown in Chapter 2, existing studies tend to focus on the immediate impact of the pandemic. For the few which do consider a longer time horizon, attention is given only to one or a limited set of worker groups. Moreover, few pay any attention to adjustments on the intensive margin, such as working hours among job retainers, which were widely used by firms to manage costs and avoid layoffs in response to reduced demand. No study in South Africa documents the evolution of working hours throughout the course of the pandemic, either on average or across most worker groups. Gender serves as the single exception, but only until one year following the pandemic's onset (Casale & Posel, 2021; Hill & Köhler, 2021; Casale & Shepherd, 2022; Mosomi & Thornton, 2022). It is this context which this chapter seeks to contribute.

This chapter's analysis comprises a comprehensive, descriptive micro-econometric analysis of the aggregate and between-group adjustments to the pandemic on South African labour market outcomes on both the extensive and intensive margins. Unlike much of the literature, the analysis considers a relatively long time horizon covering the pre-pandemic period in 2019, the first two years of the pandemic in 2020 and 2021, as well as the 'medium'-term covering the first half of 2022 when all remaining pandemic-related restrictions were repealed. By making use individual-level, nationally representative labour force household survey data, a range of uni-, bi-, and multivariate statistical techniques are employed to examine the dynamics of three extensive margin outcomes - labour market participation, employment, and unemployment by both the narrow and broad definitions - and one intensive margin outcome - working hours conditional on employment. One other key intensive margin outcome of interest – wages – is exclusively considered in Chapter 4.

The analysis is structured in four sections. First, I estimate and examine trends in each of the four outcomes of interest on aggregate from before to after the pandemic's onset and as it progressed. Thereafter, to gain a more nuanced insight, I conduct a disaggregated analysis of temporal variation in two of the outcomes – one extensive margin outcome (employment) and one intensive margin outcome (working hours) – both within and between three broad sub-groups which together account for a wide range of characteristics. These include demographic characteristics such as gender, age, and education; employment characteristics such as industry, occupation, and employment formality; and labour market institutional characteristics such as trade union membership, public versus private sector status, and unemployment insurance fund contribution status. I additionally consider pandemic-specific characteristics, such as remote work ability and 'essential' worker status. In the third section, to analyse how the pandemic affected the structure of the labour market, I estimate a series of multivariate, non-linear regressions to model the evolution of the determinants of outcomes over time. Fourth and finally, I exploit the unique but temporary panel nature of the data to examine labour market churn; that is, temporal transitions between mutually exclusive labour market states. Here I consider 15 different 'inter-state' and 'intra-state' extensive-margin and intensive margin transitions, such as the probabilities of transitioning from employment into inactivity or remaining employed but becoming furloughed. I first analyse churn descriptively using transition matrices, and thereafter model their conditional probabilities.

The remainder of the chapter is organised as follows. Section 3.2 provides a description and assessment of the data, while in Section 3.3 I discuss the chapter's methodology in detail. The results are presented in Section 3.4, organised as per the four subsections described above.

Finally, I conclude with a discussion in Section 3.5.

3.2 Data

3.2.1 The Quarterly Labour Force Survey

The analysis here makes use of three and a half years' worth (or 14 waves) of individual-level, nationally representative, sample-based household survey microdata from the QLFS. Conducted by StatsSA, the data comprises nearly 800,000 observations during the period of interest: a pre-pandemic reference period (the first quarter of 2019, or 2019Q1, to 2019Q4 and 2020Q1) and the first two years of the pandemic (2020Q2 – 2022Q2). The QLFS is a nationally representative, cross-sectional (with a rotating panel component) household-based sample survey conducted every quarter since 2008 that contains detailed information on a wide array of demographic and socioeconomic characteristics and labour market activities for individuals aged 15 years and older who live in South Africa. Serving as the country's official source of labour market statistics, the primary objective of the survey is to collect regular information about individuals in the labour market (Statistics South Africa, 2008). Considering its use of household survey data, the analysis here adopts a labour supply perspective. The survey follows a stratified two-stage sampling design, with probability proportional to size sampling of primary sampling units (PSU) in the first stage and sampling of dwelling units with systematic sampling in the second stage (Statistics South Africa, 2008). As such, the sampling unit is the dwelling and the unit of observation is the household. The sample includes the non-institutionalised population, except for workers' hostels,[1] and is designed to be representative at the national level, provincial level, metro/non-metro level within provinces, and the geography-type level within metro areas (for example, urban areas).

As noted above, the QLFS additionally has a rotating panel element. Specifically, the sample is equally divided into four groups, usually of 7,500 dwelling units, and by design one of these groups will rotate out of the sample each quarter of the year and replaced by new dwellings from the same PSU or the next PSU on the master sampling list. Prior to the pandemic, the survey's sample in a given quarter consisted of approximately 67,000 individuals living in approximately 30,000 dwelling units, with data collected via face-to-face interviews. The sampling weights for the data collected account for original selection probabilities and non-response and are benchmarked to known population estimates of the entire civilian population of South Africa. In this analysis, the sample is restricted to working-age individuals (15 to 64 years) and all estimates throughout this analysis are weighted using the survey sampling weights and account for the complex survey design by making use of the cluster (PSU in the case of the QLFS), sampling weight, and strata variables in the data. Standard errors are clustered at the PSU level unless specified otherwise.

[1] However, individuals living in private dwelling units within institutions are included, such as teachers' accommodation within school compounds (Statistics South Africa, 2008).

3.2.2 Pandemic-induced changes to the survey

Towards the end of March 2020, StatsSA suspended face-to-face data collection due to the onset of the pandemic and legislation on restricted movement of persons. This decision was made to ensure that StatsSA field staff and respondents were not exposed to risk of exposure to the virus (Statistics South Africa, 2020e,g). Because of this, 621 sampled dwelling units (or 2 percent of the intended sample) were not interviewed in the 2020Q1 dataset (Statistics South Africa, 2020f). To adjust for this missing data, StatsSA used the rotating panel component of the survey and made imputations where possible using data for respondents from the previous quarter. Additionally, however, several changes were made to the survey design to facilitate the collection of labour market statistics during the pandemic, which are worth noting in detail. This section outlines these changes, specifically with respect to survey mode and sampling design.

3.2.2.1 Survey mode

From 2020Q2 until 2021Q1 inclusive, StatsSA changed its data collection mode from face-to-face interviews to CATI. To facilitate this, and unlike in previous quarters, the sample that was surveyed in 2020Q1 and for which StatsSA had contact numbers was surveyed again in 2020Q2. The result was that the 2020Q2 data included 71 percent of the 2020Q1 sample because not all dwelling units had valid contact numbers. Additionally, amongst those households who StatsSA did have contact numbers for, some contact numbers were found to be invalid or were not answered during data collection, and some households indicated that they were no longer residing at the dwelling units they had occupied during 2020Q1. StatsSA regarded all of these cases as non-contact households. From 2021Q2, the easing of pandemic-related restrictions allowed for the resumption of sample rotation and face-to-face collection of telephone numbers, however CATI as the interview mode remained in place. Only from 2022Q1 did StatsSA reintroduce face-to-face interviews (Statistics South Africa, 2022e).

Table 3.1 presents the wave-specific sample sizes for this paper's period of analysis and the accompanying survey response rates (RR). Prior to the pandemic (2019Q1 - 2020Q1), the survey obtained an RR of 88.8 percent and sample of 67,403 individuals on average. The marginal decrease to 87.7 percent in 2020Q1 is likely attributable to StatsSA's suspension of data collection at the end of the quarter described above. At the onset of the pandemic when StatsSA began using the CATI survey mode (2020Q2), the RR reduced substantially to just above 57 percent, resulting in a nearly 30 percent smaller sample (a contraction of nearly 20,000 individuals). For the next year, the RR remained low and varied only marginally between 57 – 61 percent. The increase in the sample to just under 54,000 in 2021Q2 is likely attributable to StatsSA being permitted to resume sample rotation again. Unfortunately, in the period thereafter, the RR and sample size decreased to their lowest levels in the entire period at the end of 2021: 44.6 percent (equivalent to approximately half the pre-pandemic average) and just over 39,000 individuals, respectively. Response rates during this quarter

Table 3.1: Sample sizes and response rates, 2019Q1 – 2022Q2

Wave	RR	Total sample		Working-age sample	
		n	Relative to 2020Q1 (%)	n	Relative to 2020Q1 (%)
2019Q1	89.0	67,480	1.2	42,024	0.5
2019Q2	89.0	67,626	1.5	42,210	0.9
2019Q3	89.2	67,975	2.0	42,497	1.6
2019Q4	88.9	67,277	0.9	42,257	1.0
2020Q1	87.7	66,657	0.0	41,827	0.0
2020Q2	57.1	47,103	-29.3	29,495	-29.5
2020Q3	57.6	47,167	-29.2	29,467	-29.6
2020Q4	60.9	48,990	-26.5	30,508	-27.1
2021Q1	57.4	45,702	-31.4	28,510	-31.8
2021Q2	60.0	53,940	-19.1	33,791	-19.2
2021Q3	53.7	43,837	-34.2	27,336	-34.6
2021Q4	44.6	39,073	-41.4	24,572	-41.3
2022Q1	64.7	49,808	-25.3	31,184	-25.4
2022Q2	78.7	57,244	-14.1	35,897	-14.2
Total		769,879		481,575	

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Response rates (RR) are at the national-level and expressed in percentages. Working-age defined as those between 15 and 64 years inclusive.

varied considerably at the sub-national level, ranging from 61.3 percent for the Eastern Cape to 23.8 percent for Gauteng (Statistics South Africa, 2021e). The reintroduction of face-to-face interviews from 2022Q1 yielded a large increase in both the RR and sample size, and as of 2022Q2, both were at their highest levels yet during the pandemic, however they remained below their pre-pandemic levels. Considering the analysis here makes use of the working-aged sample, it should be noted that the evolution of this sub-sample closely follows that of the total sample.

3.2.2.2 Sample selection

The fact that only a select subset of the 2020Q1 sample could be surveyed for 2020Q2 to 2021Q1 raises the concern that estimates produced during this period will suffer from selection bias. That is, it is likely that the underlying characteristics of 'telephone' and 'non-telephone' households are different, which threatens the representativity of the sample and consequently the accuracy of population estimates. For example, in the 2020Q1 data, individuals in 'non-telephone households' were significantly more likely to be unemployed relative to those in 'telephone households'. To address this source of bias, StatsSA adjusted the calibrated survey weights using bias adjustment factors based on respondent's 2020Q1 data. These factors were computed as the ratio between the estimates for each cell of a given variable for the combined (telephone and non-telephone) sample of households and telephone-only households and were computed at the national level and individual metropolitan and non-metropolitan area levels within provinces (Statistics South Africa, 2020f). The variables selected for this process included various labour market characteristics (employment status, sector, main industry, and main occupation) and demographic characteristics (age, race, and gender), and were chosen because they are marker variables which exhibit strong correlation with the final data of interest (Statistics South Africa, 2021). The weights were then adjusted to achieve consistency with the known total population aged 15 and over to compute the final survey weights (Statistics South Africa, 2020f).

These bias-adjusted weights for the period appear to be appropriately computed. Table 3.2 presents an overview of the sample sizes and weighted population estimates of several labour market groups for 2020Q1 and 2020Q2. The relevant estimates for the same period one year prior (2019) are included for comparison. From an unweighted sample of over 66,000 individuals, the South African population estimate in 2020Q1 of 57.8 million is neither economically nor statistically significantly different from the 2020Q2 estimate, despite the latter sample consisting of nearly 20,000 fewer observations. In contrast, the weighted estimates of specific labour market groups are statistically significantly different in size between quarters, which is expected given the onset of the pandemic. These differences between quarters in 2020 are similar to the year-on-year differences within quarter two, and considering the first quarter, the between-year sample sizes are similar, and the weighted estimates are not statistically significantly different from one another, apart from the broad unemployed sample size and population estimate which have grown by 6 and 8 percent year-on-year, respectively. The smaller samples from 2020Q2 result in expectedly less precise estimates, as reflected by the larger standard errors. Despite the above similarities, it should be noted that StatsSA's bias-adjustment procedure relied on observable characteristics; however, respondents may still be unobservably different from non-respondents and hence possibly from the broader population. The possibility of this outcome was confirmed by StatsSA through a telephone interview (Statistics South Africa, 2021). At the time of writing, an explicit external review of the construction of these weights had yet to be conducted and would require more information than is available in the public QLFS documentation.

3.2.2.3 Cross-sectional to longitudinal

The decision to sample individuals from 2020Q2 to 2021Q1 whom StatsSA had valid contact numbers for has notable implications for the nature of research that had previously been infeasible with the available data. Unlike the data prior to the pandemic, this decision resulted in the survey changing from a cross-sectional survey with a rotational panel element to an (unbalanced) longitudinal survey. It is important however to ensure that individuals in the panel sample can indeed be identified. This is relevant not only for any longitudinal study of the data, but also for this chapter's final section which examines temporal transitions between mutually exclusive labour market states from 2020Q1 to 2020Q2. To do so,

Table 3.2: Sample sizes and weighted population estimates, by year and quarter

	2019Q1		2019Q2		2020Q1		2020Q2	
	n	Weighted	n	Weighted	n	Weighted	n	Weighted
Total	67,480	57,071,059	67,626	57,251,253	66,657	57,792,395	47,103	57,973,917
		(548,901)		(551,886)		(575,263)		(803,347)
Working-age	42,024	38,282,909	42,210	38,432,975	41,827	38,873,945	29,495	39,021,017
		(379,362)		(380,014)		(39,488)		(547,142)
Employed	17,490	16,291,436	17,414	16,312,706	17,044	16,382,555	10,001	14,148,215
		(185,895)		(191,220)		(196,425)		(246,679)
Unemployed	10,959	9,994,457	11,244	10,226,485	11,577	10,796,924	7,624	10,259,336
		(161,116)		(160,964)		(169,914)		(221,937)
Inactive	13,575	11,997,016	13,552	11,893,784	13,206	11,694,466	11,870	14,613,465
		(178,093)		(171,581)		(168,282)		(263,776)

[a] Author's own calculations. Source: QLFS 2019Q1, 2019Q2, 2020Q1, 2020Q2 (Statistics South Africa, 2019a,b, 2020a,b).
[b] Notes: Relevant estimates weighted using sampling weights. Labour market groups restricted to the working age (15 to 64 years). Unemployed and economically inactive expressed using the broad definition. Standard errors presented in parentheses and account for the complex survey design.

I identify unique observations by making use of household and person numbers in the data. The anonymisation of the data prohibits one from making use of more sensitive identifiers such as names and birth dates. During this period, there are 113,760 observations in total (irrespective of age): 66,657 and 47,103 in each quarter, respectively, as shown in Table 3.2 above. Of the identified unique observations, 42,912 are observed in the balanced panel, 23,745 are only observed in 2020Q1, and the remainder (4,191) only in 2020Q2. However, considering the sample for 2020Q2 was drawn from the 2020Q1 sample, one would think that the number of unique observations in the balanced panel sample would equal the number of observations in the 2020Q2 sample, and that no unique observations should be observed only in 2020Q2. This suggests that a simple combination of household and person numbers in this data does not yield credible personal identifiers for the panel sample.

If the above combination of data did yield credible personal identifiers, certain characteristics of a given panel observation should be time-invariant. To examine this, I analyse the extent of inconsistency in three characteristics for panel observations between 2020Q1 and 2020Q2: sex, race, and age. For the latter, I allow for a one-year difference in age between quarters in either direction to account for ageing or possible measurement error. In total, 1,816 unique observations are inconsistent in either gender, race, or age over this period. Of these observations, 766 exhibit inconsistent data with respect to gender, 191 with respect to race, and 1,399 with respect to age. This suggests that two observations of the same household-person personal identifier over time need not represent the same individual. These inconsistencies may be explained by the fact that the survey is designed as a household-based (as opposed to an individual-based) survey. For instance, the onset of the national lockdown in South Africa at the end of March 2020 abruptly changed the short- and long-term living arrangements of many individuals. These include tertiary-level students returning home following education institution and residence closures, but also adults who lost employment and relied on relatives and other social networks as a means of social and economic support. Posel & Casale (2020) estimate that during the beginning of the pandemic between 5 and 6 million adults had moved into a different household, with 70 percent of movement occurring at the end of March 2020 before the beginning of the national lockdown. The implication of this is that, because household compositions changed, when StatsSA contacted the relevant households to survey their members in 2020Q2, some households had new members not previously living in the household, and not all members who were surveyed in the previous quarter could be surveyed again.

Considering these inconsistencies, in this chapter's panel analysis I restrict the sample to the balanced sample of observations present in 2020Q1 and 2020Q2 who exhibited 'consistent' values of the above three time-invariant characteristics. By doing so, I explicitly assume that the same individual is observed over time if their household number, person number, race, gender, and age (allowing for a one-year change in age across quarters) remains constant. With these adjustments, I arrive at a sample of 24,475 working-age unique individuals each observed twice in the period, equivalent to only a marginal reduction of the sample from 25,114 working-age unique individuals prior to these adjustments. Later in Chapter 5, I show that despite these adjustments, the panel sample remains relatively representative of the broader South African working-age population.

3.3 Methodology

This chapter adopts a quantitative, descriptive econometric approach to gain insight into the aggregate and between-group effects of the pandemic on South African labour market outcomes on both the extensive and intensive margins. As previously stated, the analysis employs a range of uni-, bi-, and multivariate statistical techniques and focuses on four outcomes: labour market participation (and inversely labour market inactivity), employment conditional on participation, unemployment conditional on participation (using both the narrow and broad definitions), and working hours conditional on employment. The period of analysis comprises four distinct periods: a pre-pandemic reference period (2019Q1 – 2019Q4 and 2020Q1), the first year of the pandemic or the 'immediate'-term (2020Q2 – 2021Q1), the second year of the pandemic or the 'short'-term (2021Q2 – 2022Q1), and the 'medium'-term (2022Q2).

The pre-pandemic period provides a useful benchmark of the state of the labour market prior to the pandemic's onset, while comparisons of outcomes between the latter periods allows one to examine the labour market's evolution as the pandemic and associated lockdown restrictions progressed. As such, throughout, I make the implicit assumption that changes from just prior to after the pandemic's onset are substantially attributable to the pandemic shock, inclusive of government-mandated mitigation measures or sector-specific restrictions as well as voluntary reductions in economic activity and other pandemic conditions. Later analysis in Chapter 5 attempts to decompose this shock and isolate the effect due to sector-specific restrictions alone. Temporal changes across quarters and years are considered to account for seasonality, and where appropriate, I conduct adjusted Wald tests to determine the statistical significance of any outcome change, and include 95 percent confidence intervals in all relevant figures to disclose degrees of statistical precision. All estimates of changes in cross-sectional employment levels over time refer to changes on net, and as such, caution is issued regarding the interpretation of these estimates given potential compositional effects brought about through transitions between labour market states or 'churn'.[2]

The analysis is structured in four sections. First, I estimate trends in aggregate labour market statistics for each outcome from before to after the pandemic's onset. These include estimates of the levels of varied labour market sub-populations, labour market rates, as well as the distribution of working hours. Second, to gain a more nuanced insight, I conduct a disaggregated analysis of variation in two of the outcomes – one extensive margin outcome (employment) and one intensive margin outcome (working hours conditional on employment) – over time both within and between three broad sub-groups of interest which, together, account for a wide range of characteristics: by demographic characteristics, employment characteristics, and labour market institutional characteristics. Demographic characteristics include age group, gender, racial population group, highest level of education, area of residence (urban or rural), and province of residence. Employment characteristics include economic sector,[3] main industry at the one-digit level, main occupation at the one-digit level, skill-level,[4] and sectoral formality of employment. Employment is defined as per StatsSA's conventional definition of working for at least one hour in the reference week prior to the survey or not working because of a temporary absence but still having a job to return to, which is consistent with the labour force framework in the relevant international guidelines (Hussmanns, 2007). To distinguish the formal and informal sectors, I again follow StatsSA's definitions which are based on two criteria: tax registration status and the size classification of enterprises. Specifically, the formal sector here only includes workers (regardless of

[2]For example, it is not appropriate to interpret a reduction in net employment from one period to the next using cross-sectional data as job loss solely, but rather as the combination of job loss and gain where the former exceeds the latter. On the other side of the same coin, recovery in net employment levels following such a reduction ought not be interpreted as the same individuals who previously experienced job loss returning to employment.

[3]Classifications by economic sector are derived using data on workers' main industry using one-digit Standard Industrial Classification (SIC) codes. The primary sector comprises workers in the agriculture, hunting, forestry, and fishing industry and the mining and quarrying industry; the secondary sector comprises workers in the manufacturing industry, utilities industry, and construction industry; and the tertiary sector comprises workers in the wholesale and retail trade industry, transport, storage, and communications industry, financial intermediation, insurance, real estate, and business services industry, community, social, and personal services industry, and workers in private households.

[4]Classifications by skill-level are derived using data on workers' main occupation using one-digit South African Standard Classification of Occupations codes. Specifically, high-skilled workers include legislators, senior officials, managers, and professionals; semi-skilled workers include technical and associate professionals, clerks, service workers and shop and market sales workers, skilled agricultural and fishery workers, craft and related trades workers, and plant and machine operators and assemblers; and less-skilled workers include domestic workers and workers in elementary occupations.

type) who are registered for personal income tax, while the informal sector only includes (i) employees who are not registered for personal income tax and work in establishments that employ fewer than five workers and (ii) all other workers (employers, the self-employed, and persons helping unpaid in their household business) who are not registered for any tax.[5]

Finally, regarding labour market institutional characteristics, the choice of covariates was guided by both data availability and the literature. Following Berg (2015), I adopt a broad set of labour market institutions which include those that regulate the workplace, such as trade union membership and the type of employment relationship and contract, as well as those that redistribute labour income, such as mandated income support for the unemployed and benefits such as pension fund contributions. Specifically, I consider outcome variation by public versus private sector status, trade union membership, employment relationship (wage worker, employer, self-employed, or unpaid household worker), contract type (written or verbal) and duration, unemployment insurance fund (UIF)[6] contribution status, and pension or retirement fund contribution status.

In the third section, I adopt a production function approach and estimate a series of multivariate, binary and continuous outcome, non-linear regression models to gain insight into how the pandemic affected the determinants or correlates of labour market outcomes over time. Importantly, I explicitly do not seek to establish causality here but rather conditional associations. By employing Maximum Likelihood Estimation (MLE), I estimate probit models of the following specification in a setting with $i = 1, ..., N$ individuals and $t = 1, ..., T$ time periods:

$$Pr(status_{it} = 1 \mid x_{it}) = \delta + \boldsymbol{\beta} \boldsymbol{D_{it}} + \phi_t + \varepsilon_{it} \tag{3.1}$$

where $status_{it}$ is a binary outcome representing either labour market participation or, conditional on participation, employment or unemployment (according to the narrow definition), with each outcome being modelled separately. Regarding participation, $status_{it}$ is equal to one for all individuals that are either employed or unemployed according to the narrow definition in period t and zero otherwise. Regarding employment and unemployment, $status_{it}$ is equal to one for all individuals that they are employed and zero otherwise, or unemployed and zero otherwise, respectively. These outcomes are regressed on a vector of demographic observable covariates $\boldsymbol{D_{it}}$ which includes age group, a female binary indicator, race, highest level of education, marital status, area of residence measured by a binary urban indicator, and province of residence. Additionally, I control for time fixed effects (FE) ϕ_t. Five models are estimated for each outcome: a pooled model which includes data from all periods from 2019Q1 to 2022Q2 and year-specific models for 2019 to 2022. ϕ_t represents

[5]It should be noted that StatsSA's definition of informal sector employment differs from that of the International Labour Organization, who define informal sector employment (as opposed to informal employment more broadly) as workers engaged in the production of goods or services in unincorporated enterprises with the primary objective of generating employment and incomes to the persons concerned.

[6]South Africa's UIF is a form of social insurance which provides income relief to the formally employed for up to one year in the event of unemployment, maternity, adoption and parental leave, or illness.

year-quarter FE and quarter FE in the pooled and year-specific models, respectively. δ represents the regression constant term and ε_{it} the error term.

It would be inappropriate to model the intensive margin outcome of interest, weekly working hours, using such a model given the variable's continuous nature. Linear regression using Ordinary Least Squares (OLS) estimation could alternatively be used; however, such an approach would also be inappropriate considering working hours is counts-based data (that is, values only include non-negative integers). As discussed by Wooldridge (2010), fitting an OLS-based linear regression on such data has shortcomings similar to those for binary outcomes. Because $working\, hours_{it} \geq 0$, $E(working\, hours_{it}|x_{it})$ should be non-negative for all x_{it}, however using OLS can result in negative predicted values. One could alternatively employ OLS after using the log transformation of $working\, hours_{it}$ if the variable only had strictly positive values, but such an approach would be inappropriate here given the presence of a nontrivial subset of observations with zero values (shown later in Section 3.4). A Poisson regression model could alternatively be used to ensure non-negative predicted values. However, this approach explicitly requires equality of the conditional variance and mean – referred to as the 'Poisson variance assumption'. Using the pooled sample, the unconditional sample variance (220.12) is more than five times larger than the mean (41.12), which is indicative of overdispersion and the invalidity of this assumption here, at least in an unconditional environment.[7] To formally test for overdispersion in a conditional environment, I conduct a likelihood ratio test of the overdispersion parameter α obtained through a negative binomial regression of working hours on the vector of covariates specified in equation 3.1 using the pooled sample. Specifically, I conduct a one-tailed test of $H_0 : \alpha = 0$.[8] When $\alpha = 0$, the mean and variance are equal so the negative binomial distribution is equivalent to the Poisson distribution. However, the likelihood ratio test here outputs an estimated $\alpha = 0.163$ with a standard error of 0.004, making it highly statistically significant (p = 0.000). This result holds when year-, quarter-, or wave-specific samples are alternatively used and is thus strongly suggestive of overdispersion. As such, the Poisson model is inappropriate. Given that negative binomial models allow for such overdispersion as they explicitly include an extra parameter, α, to model it, I make use of them to model the evolution of the determinants of working hours using the following specification on the employed sub-sample:

$$working\, hours_{it} = \delta + \boldsymbol{\beta D_{it}} + \boldsymbol{\gamma L_{it}} + \phi_t + \varepsilon_{it} \tag{3.2}$$

where $working\, hours_{it}$ represents weekly working hours. Here, given that working hour data is modelled conditional on employment, I additionally am able to include a vector of observable labour market covariates $\boldsymbol{L_{it}}$ which include main industry at the one-digit level, main occupation at the one-digit level, sectoral formality of employment, a public sector dummy variable, trade union membership, and contract type.

[7] This disparity holds when year-, quarter-, or wave-specific samples are alternatively used.

[8] The test is one-tailed as α cannot be less than zero.

In the fourth and final section, I make use of the unique panel nature of the data between 2020Q1 and 2020Q2 described in Section 3.2 to analyse and model temporal transitions between mutually exclusive labour market states – in other words, labour market churn. Such an examination is useful as it allows one to overcome a key limitation of prior approaches in this analysis: aggregate and between-group temporal changes in net employment mask underlying temporal variation in labour market states. For instance, a reduction in net employment can be decomposed into a subset of individuals transitioning out of and into employment, whereas the former simply outweighs the latter. Additionally, this approach allows me to model the correlational determinants of various labour market trajectories at the pandemic's onset. I define three sets of 15 individual transitions. 'Intra-state' extensive margin transitions comprise the first four: remaining inactive, remaining a labour market participant (defined as above as being employed or unemployed by the narrow definition), remaining employed, and remaining searching unemployed. 'Inter-state' extensive margin transitions comprise the following seven: inactivity to participation, inactivity to employment, inactivity to searching unemployment, employment to searching unemployment, employment to inactivity, searching unemployment to inactivity, and searching unemployment to employment. The remaining four comprise intensive margin transitions: remaining employed but moving from formal to informal sectoral employment, remaining employed but moving from informal to formal sectoral employment, remaining employed but becoming 'furloughed' (defined as remaining employed but working zero hours per week), and remaining employed but experiencing a reduction in working hours of a magnitude of at least 10 percent of a given individual's pre-pandemic working hours. After generating several transition matrices to examine the magnitudes of these transitions descriptively, I estimate multivariate probit models of the following specification on the balanced panel sample:

$$Pr(state_{it-1} \rightarrow state_{it} \mid x_{it-1}) = \delta + \boldsymbol{\beta D_{it-1}} + \boldsymbol{\gamma L_{it-1}} + \varepsilon_{it-1} \tag{3.3}$$

where $state_{it-1} \rightarrow state_{it}$ is a binary variable which references a given transition from period $t-1$ to period t. This outcome is set equal to one for all individuals who experienced a given transition and, for inter-state transitions, zero if they remained in the pre-pandemic state in period $t-1$, or for intra-state transitions, did not remain in their state in period $t-1$. I model these transitions using a vector of pre-pandemic (2020Q1) demographic ($\boldsymbol{D_{it-1}}$) and labour market ($\boldsymbol{L_{it-1}}$) characteristics as defined above, where the latter is again only included for employed individuals in period $t-1$. $_{it-1}$ is again the error term.[9]

For ease of interpretation, I transform all coefficients obtained from all models in equations 3.1, 3.2, and 3.3 into average marginal effect (AME) estimates which are presented in the sections to follow. As with the descriptive results, all regressions are weighted using sampling weights and account for the complex survey design. Standard errors are clustered at the PSU level to allow for correlation in the error term for the same enumeration area

[9]Due to small sub-sample sizes for some transitions, the data becomes unfortunately too sparse for some covariates to be effectively included in the models. These are explicitly mentioned later.

over time.

3.4 Results

3.4.1 Aggregate trends

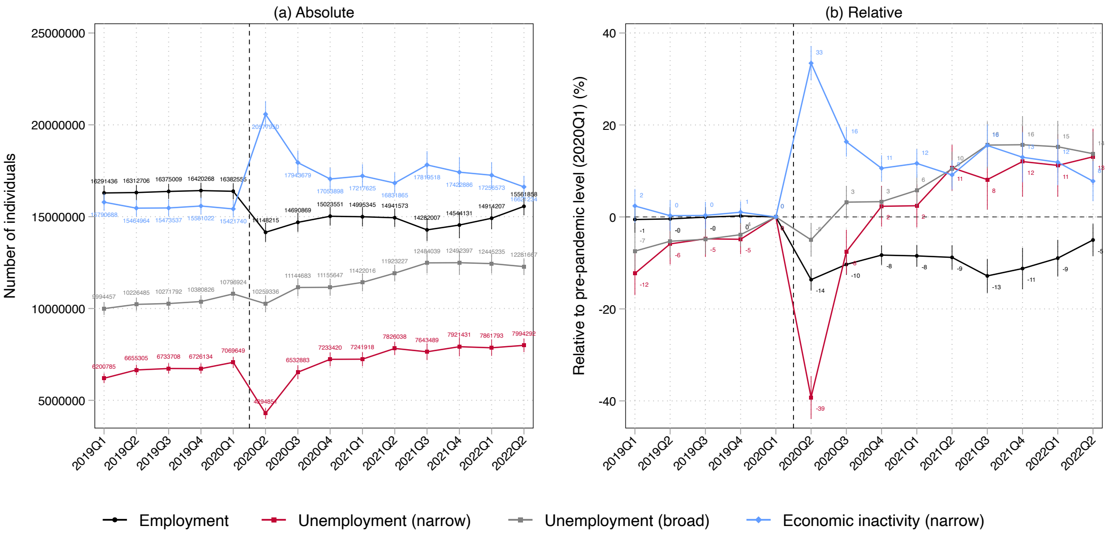
In this section, I present the estimates of trends in aggregate labour market outcomes from before to after the pandemic's onset. Figure 3.1 presents trends in extensive margin outcomes from 2019Q1 to 2022Q2 in both absolute and relative terms in panels (a) and (b), respectively.[10] The latter refer to levels relative to the respective level just prior to the onset of the pandemic in 2020Q1 (hereafter referred to as the pre-pandemic period). Additionally, Table A2 in the appendix presents estimates of outcome levels for the second quarter of each year and their respective temporal changes to account for seasonality.

It is immediately clear that the pandemic had a substantially large and, in some cases, persistent effect on the South African labour market. On net, the immediate impact saw employment fall by 2.2 million (14 percent) quarter-on-quarter from 16.4 million to 14.2 million workers from 2020Q1 to 2020Q2, respectively. This contraction is highly statistically significant and equivalent to the relevant year-on-year change using second quarter estimates. The 2020Q2 level is similar to 2011 levels, where employment varied from 13.9 million to 14.3 million (Statistics South Africa, 2022b) which suggests that the magnitude of job loss was equivalent to approximately a decade's worth of jobs growth. Up to the end of 2020, employment recovered at a gradual pace to 15 million workers or 8 percent below the pre-pandemic level, equivalent to recovering 39 percent of all jobs lost on net. However thereafter the recovery stalled with employment levels remaining statistically unchanged for three quarters. Moreover, in 2021Q3 any recovery thus far was completely reversed. Employment contracted by 660 000 to 14.3 million workers, or 13 percent below the pre-pandemic level and was statistically insignificantly different from the level at the beginning of the pandemic in 2020Q2. It is plausible that such a contraction is at least in part attributable to the quarter being characterised by another wave of COVID-19 infections, associated lockdown restrictions, as well as a wave of socio-political social unrest that was characterised by the looting of businesses and destruction of public and private properties (Vhumbunu, 2021). Since then, employment levels partially recovered to 15.6 million as of 2022Q2 – just 5 percent below the pre-pandemic level – the closest such level at the time of writing. Given these developments, in terms of employment levels the South African labour market exhibited a weak W-shaped trajectory, in contrast to an optimistic V-shaped recovery – that is, a rapid and almost-immediate recovery – which many governments had hoped for.

Unlike the W-shaped employment trajectory, unemployment appears to have consistently risen during both the pre-pandemic and pandemic periods, with the exception of a temporary

[10] The former estimates are also presented in Table A1 in the appendix.

Figure 3.1: Absolute and relative trends in aggregate labour market outcomes: 2019Q1 - 2022Q2



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Spikes represent 95 percent confidence intervals. Relative estimates calculated using adjusted Wald tests. Sample restricted to those of working age. Vertical line represents the onset of the COVID-19 pandemic in South Africa.

reduction at the pandemic's onset. In 2020Q2, unemployment by the narrow definition fell sharply by 39 percent (or 2.8 million individuals) from a pre-pandemic level of 7.1 million. It does not appear that the unemployed simply transitioned from a searching to a non-searching state during this period, but transitioned into economic inactivity (which comprises those outside the labour force such as students and home-makers). During the same period, unemployment by the broad definition, which additionally includes the non-searching unemployed due to discouragement or other reasons, also fell but by a far less severe rate (5 percent or 540 000 individuals). The fall in unemployment appears explained by the substantial quarter-on-quarter growth in economic inactivity which expanded by 33 percent or nearly 5.2 million individuals to 20 million individuals in 2020Q2 – a highly statistically significant change. Year-on-year, the change in this estimate is similar (5.1 million).

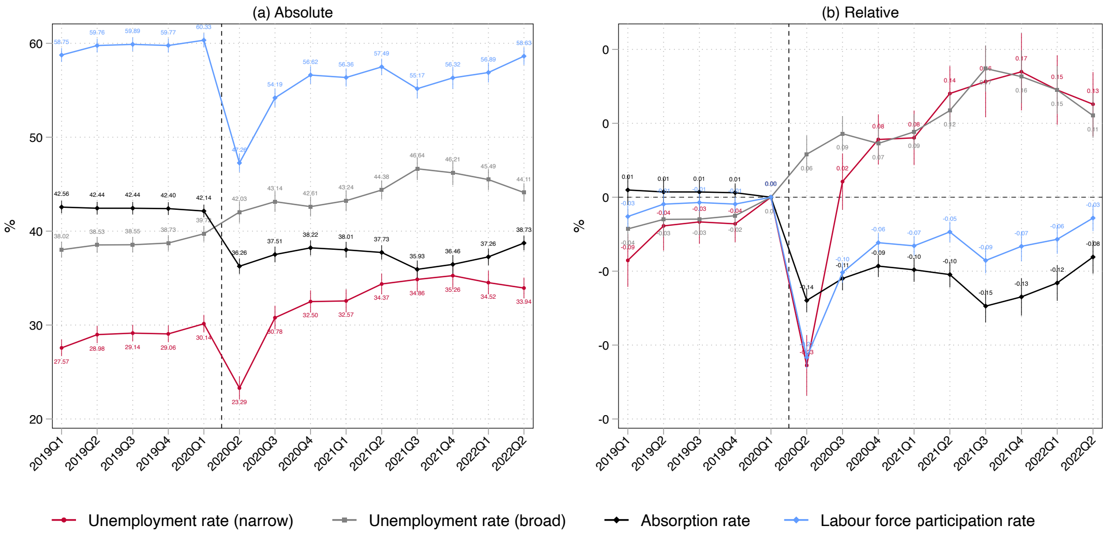
This expansion in inactivity is not explained by a surge in discouragement among inactive individuals, considering that the level of discouraged unemployed reduced from 2.9 million to 2.5 million during this period. Rather, the expansion was driven by individuals not being able to participate in the labour market due to lockdown restrictions which largely prohibited them from leaving their household for any non-essential activities. When those who reported discouragement were asked "*What was the main reason you did not want to work last week?*", just under 30 percent reported an "Other" reason and specified the national lockdown or COVID-19 (Statistics South Africa, 2020f). This increased from just 6 percent in the pre-pandemic period, and accounts for nearly all (98 percent) of the total change in the extent of inactivity. This large contraction in the number of jobseekers accompanied by a surge in inactivity represents a key characteristic of lockdown policy in the beginning of the pandemic which restricted both those with jobs and jobseekers from labour market participation.

The observed inverse temporal association between inactivity and unemployment persists into the remainder of the period. In 2020Q3 and relative to the preceding quarter, as lockdown restrictions were eased and the economy re-opened, economic inactivity decreased substantially by 2.6 million, equivalent to 51 percent of the prior growth in inactivity. This was accompanied by a significant increase in the number of jobseekers by 2.2 million, equivalent to the majority (81 percent) of the prior contraction. Thereafter, inactivity and unemployment continued to fall and rise respectively albeit non-linearly. By the end of 2020 narrow unemployment had statistically returned to the pre-pandemic level, and by 2022Q2 it reached a peak of nearly 8 million jobseekers. Controlling for seasonality, this represents an expansion of 1.4 million individuals relative to 2019Q2, a highly statistically significant difference. This post-2020Q1 trajectory does not appear to be pandemic-specific. Relative to just prior to the pandemic, in 2019Q1 narrow unemployment was 12 percent lower (comprising 6.2 million individuals) and by then end of 2019 just 5 percent lower. Despite the difference in levels within a given period, unemployment by the broad definition resembles a similar trend albeit reaches a peak in 2021Q3 and, despite declining marginally thereafter, remained 14 percent above the pre-pandemic level as of 2022Q2.

The inferences from the above trends in outcome levels are similar to those from labour market rates, notwithstanding further nuance in some instances. Similar to Figure 3.1, I present estimates of trends in labour market rates in both absolute and relative terms in Figure 3.2. First considering participation, the (narrow) labour force participation rate (LFPR), calculated as the share of the working-age population who are in the labour force (either employed or narrow unemployed), provides an indication of the size of labour supply available. During the pre-pandemic period, the LFPR marginally increased from 58.8 percent in 2019Q1 to over 60 percent in 2020Q1 – a statistically significant difference at the 1 percent level. This gradual improvement was, however, reversed in its entirety following the pandemic's onset. In 2020Q2 the LFPR fell to 47.3 percent which reflects a 22 percent decline from the preceding quarter and was driven by a contraction in both employment and narrow unemployment, but more so the latter (which decreased by nearly 23 percent) than the former (14 percent). Labour market participation improved during the remainder of 2020 and the first half of 2021, but again contracted in 2021Q3 which was characterised by another wave of COVID-19 infections, lockdown restrictions, and socio-political social unrest, as noted above. Thereafter, the LFPR gradually improved and reached a peak of 58.6 percent as of 2022Q2, equivalent to just 2.8 percent below the pre-pandemic level. Although this difference in terms of magnitude is relative small, it remains statistically significant at the 1 percent level.

The absorption rate, calculated as the share of the working-age population employed,

Figure 3.2: Absolute and relative trends in aggregate labour market rates: 2019Q1 - 2022Q2



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Spikes represent 95 percent confidence intervals. Relative estimates calculated using adjusted Wald tests. Sample restricted to those of working age. Vertical line represents the onset of the COVID-19 pandemic in South Africa.

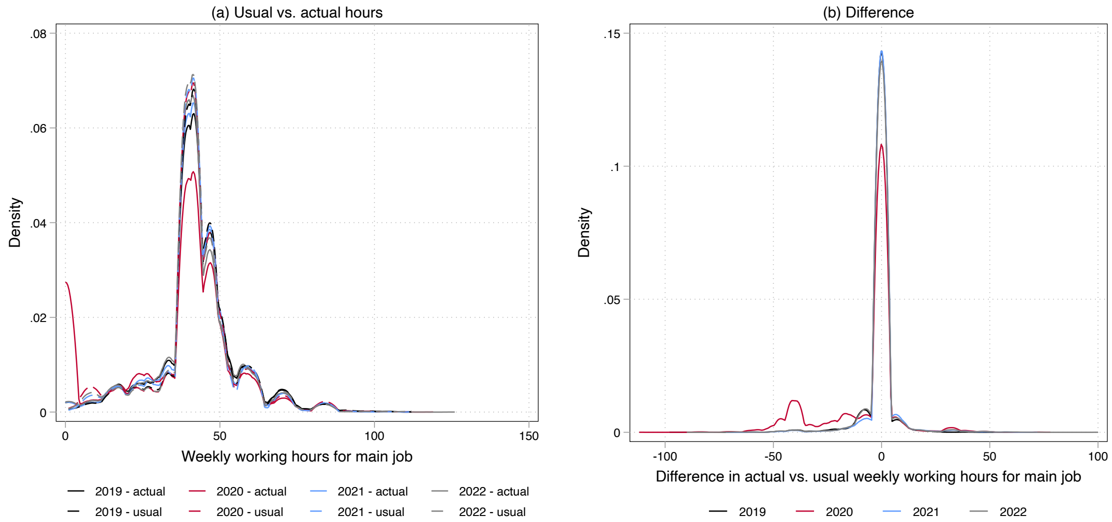
closely mirrors employment in Figure 3.1 due to the analysis sample's working-age restriction. Despite this, the rate is still useful as it is indicative of the relative size of the employed population compared to the working-age population. Pre-pandemic, the rate implies that 42 percent of working-aged individuals were employed, maintaining parity with working-age population growth during 2019. Following the pandemic's onset, it closely followed the weak W-shaped employment trend, hitting lows of 36.3 percent in 2020Q2 (a 14 percent drop from 2020Q1) and 35.9 percent in 2021Q3 (15 percent). Importantly, this calculation includes all employed individuals, regardless of their hours worked, but understates labour absorption without accounting for zero-hour or furloughed workers, as I show later. As of 2022Q2, the absorption rate reached 38.7 percent, equivalent to 8 percent below pre-pandemic levels. In contrast, as shown in Figure 3.1, employment remained 5 percent lower. This difference reflects the 3.4 percent increase in the working-age population during the pandemic (40.2 million versus 38.9 million, as shown in Table A1), a statistically significant difference at the 5 percent level.

The absorption rate's trajectory mirrors employment, while the unemployment rate also largely reflects unemployment levels, with some exceptions. Before the pandemic, both narrow and broad unemployment rates gradually rose. In 2019Q1, narrow and broad unemployment stood at 27.6 percent and 38 percent, respectively, 8.5 percent and 4.3 percent below the pre-pandemic (2020Q1) levels of 30.1 percent and 39.7 percent. In 2020Q2, narrow unemployment fell sharply to 23.3 percent, while broad unemployment rose to just over 42 percent. This divergence is simply a consequence of definitions: narrow considers only those actively seeking work, while the number of such individuals dropped by 39 percent from 2020Q1 to 2020Q2, affecting both the numerator and denominator. The consequent fall in the unemployment rate can then be explained by the accompanying 14 percent contraction in employment which solely affects the denominator. Broad unemployment fell by a less severe 5 percent, again affecting both the numerator and denominator of the formula, but because the denominator also includes employment which decreased, the ratio increased. After 2020Q2, both narrow and broad unemployment rates exceeded pre-pandemic levels, peaking in 2021Q4 and 2021Q3, respectively, and continued to rise until the second half of 2021. In 2021Q4, the narrow unemployment rate reached over 35 percent – the highest level on the QLFS record – but has since decreased during the first half of 2022. With reduced unemployment rates, increased employment, and higher labour force participation, the South African labour market showed consistent recovery starting late 2021.

I now analyse aggregate trends in the intensive margin outcome of interest: weekly working hours. Figure 3.3 presents kernel density estimates of the distribution by year, using Q2 data to adjust for seasonality. The QLFS collects a variety of data on working hours which vary by a given worker's number of jobs and "usual" vs. "actual" hours during a reference day or week. First, items are asked separately for those with one job and those with multiple jobs. Multiple job workers make up a small share, ranging from 0.3 to 0.7 percent during the period. Second, "usual" vs. "actual" hours are distinguished in the survey questions, where the item for the former is "*How many hours do you usually work each week (Monday to Sunday)?*" and that of the latter is "*How many hours did you actually work on x?*" which is repeated for each weekday x (including Saturday and Sunday) and then summed to arrive at a weekly value. I primarily use data on "actual" weekly working hours for a worker's main job, where the main job is the one with the most weekly hours, regardless of the number of jobs. Although "usual" working hours have the advantage of being unaffected by special features of a reference period, such as public holidays, arguably measuring "actual" working hours is more appropriate during pandemic when lockdown regulations created or affected the disparity between hours usually and actually worked. However, I also analyse "usual" hours for completeness.

Figure 3.3 reveals a significant shift in the 2020 "actual" working hours distribution, primarily at the lower end. While other years show similar distributions with equivalent values around the 10$^{\text{th}}$ percentile (25 hours), median (40 hours), mean (42 hours), and 90$^{\text{th}}$ percentile (56 to 60 hours), 2020 stands out with 0 hours at the 10$^{\text{th}}$ percentile and 35 hours at the mean. The median remains at 40 hours and the 90$^{\text{th}}$ at 55 hours. Kolmogorov-Smirnov equality-of-distributions tests confirm that the 2020 "actual" hours distribution differs significantly from all other years (p-values < 0.000). Overall, the 2020 distribution suggests that at the pandemic's onset, many individuals remained employed but not "actively" employed (that is, they worked zero hours per week), akin to the concept of furloughed workers. This aligns with findings from other studies which, although used an alternative dataset as documented in Chapter 2, document a substantial reduction of "active" employment in South

Figure 3.3: Distributions of actual and usual weekly working hours, 2019 - 2022



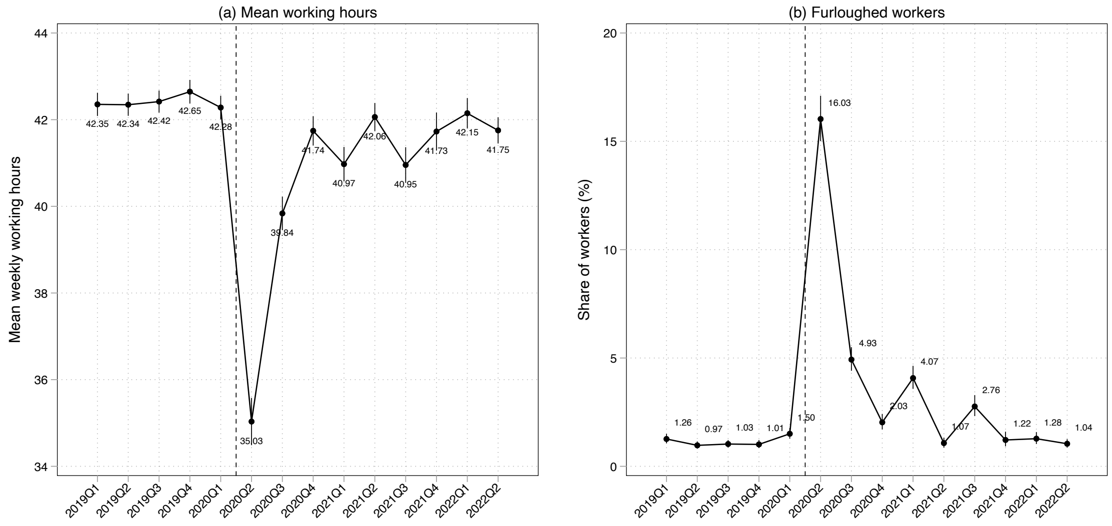
[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Estimates weighted using sampling weights. Epanechnikov kernel function with a half-width of 2 used. Sample restricted to those of working age. Densities plot data on actual or usual weekly working hours for workers with one job as well as multi-job workers for their main job. Difference = actual less usual hours.

Africa (Ranchhod & Daniels, 2021; Bassier et al., 2023).

Comparing "actual" and "usual" hours yields several interesting observations. As shown in panel (a), "usual" hour distributions consistently share a similar shape across years, with Kolmogorov-Smirnov tests showing no significant differences, including 2020. This is not necessarily surprising and aligns with the argument favouring "actual" hours during the pandemic. As shown in panel (b), the majority of workers (82 to 84 percent) in all years have zero differences between "actual" and "usual" hours, except in 2020 where large disparities in terms of prevalence and depth are observed. Just 63 percent of workers exhibited equivalence in "actual" and "usual" working hours – 20 percentage points below the respective shares for other years. Among those workers who exhibit a disparity, most (78.4 percent) have their "usual" hours exceeding "actual" hours, by an average of 28.4 hours per week. Among these, most (55.6 percent) were furloughed or zero-hour workers, with all furloughed workers experiencing "actual" hours less than "usual" hours during this period.

Although the pandemic initially led to a significant decrease in "active" employment, this was temporary. Figure 3.4 presents the estimated mean weekly working hours and the share of furloughed workers (employed but working zero hours) over time, all using "actual" hours. Pre-pandemic, the average worker worked about 42 hours. Only 1 percent worked zero hours, mostly due to temporary reasons like vacation or parental leave (over 65 percent cited these reasons). After the pandemic's onset, the average worker clocked 35 hours, a 7.3-hour drop (17.3 percent). Panel (b) shows this decrease was driven by a surge in furloughed

Figure 3.4: Mean actual weekly working hours and share of furloughed or zero-hour workers, 2019Q1-2022Q2



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights. Spikes represent 95 percent confidence intervals. Sample restricted to those of working age. Working hours data based on actual weekly working hours for workers with one job as well as multi-job workers for their main job. Vertical line represents the onset of the COVID-19 pandemic in South Africa.

workers, rising to over 16 percent in one quarter.[11] In other words, "active" employment fell by 26.5 percent (4.3 million workers) from 16.1 million to 11.2 million workers, almost double the overall employment contraction rate. This corresponds to a 27.8 percent decrease in the absorption rate, dropping from 42.1 percent to 30.4 percent (compared to 36.3 percent with the conventional employment definition in Figure 3.2 above). These estimates align with Ranchhod & Daniels (2021) who, using the NIDS-CRAM data, found a slightly higher absorption ratio reduction of 33.9 percent, which is not surprising given their similar estimated rise in the share of furloughed workers from 2.9 percent in February 2020 to 19.4 percent in April 2020. This suggests these findings have some external validity. Again, this development was temporary. After 2020Q2, the working hours distribution returned to its pre-pandemic shape. As of 2020Q3, mean weekly working hours and the furloughed worker share approached pre-pandemic levels and remained relatively stable throughout the period, with minor fluctuations.

3.4.2 Between-group variation in employment

In this second section, I provide detailed insights into the pandemic's labour market impacts by presenting disaggregated estimates of cross-sectional and temporal variation in one extensive margin outcome of interest – employment – for the three broad sub-groups of

[11]Importantly, these changes in the working hours distribution are not observed when using the "usual" hours data, as implied by Figure 3.4.

individuals described in Section 3.3. To address seasonality, I again use Q2 data for each of the four years in the study. I analyse net employment levels and shares to understand how the pandemic affected not only the number but also the composition of specific worker groups. I also calculate group-specific temporal differences and generate a unique statistic which speaks to the incidence of job loss referred to as the "job loss burden ratio", defined as the ratio of a given group's share of net employment change to their pre-pandemic (2019) employment share. Values above one indicate disproportionate job loss. I focus on two temporal differences: 2019 vs. 2020 to capture the immediate pandemic impact and 2019 vs. 2022 to assess any cumulative recovery over medium-term. I start with demographic characteristics followed by employment and labour market institutional characteristics.

3.4.2.1 Demographic characteristics

Table 3.3 presents cross-sectional employment estimates by demographic group from 2019 to 2022, while Table 3.4 presents net employment changes for the two indicated periods. In terms of gender, men initially experienced a slightly larger employment contraction from 9.2 million in 2019 to 8 million in 2020, accounting for 55 percent of net job losses. Women saw a smaller absolute drop (960 000) but the relative change (13.1 versus 13.5 percent) was similar, reflecting their smaller pre-pandemic share. The data then suggests that women were disproportionately affected, but only marginally, representing 44.5 percent of net employment change despite being 43.7 percent of pre-pandemic workers. This gender disparity is largely consistent with the international literature (for instance, see Adams-Prassl et al., 2020; Soares & Berg, 2022; Casarico & Lattanzio, 2022; Craig & Churchill, 2021; Lariau & Liu, 2022; Morales et al., 2022; Schotte et al., 2023; Bundervoet et al., 2022) and South African studies which make use of the NIDS-CRAM data (Ranchhod & Daniels, 2021; Casale & Posel, 2021; Casale & Shepherd, 2022; Mosomi & Thornton, 2022; Bassier et al., 2023). However, these studies document a much larger difference as discussed in Chapter 2, likely due to differences in sampling design, reference periods, and job attachment measurements (Daniels et al., 2022). Despite women's slight job loss disadvantage, they had recovered faster than men with employment about 3 percent below pre-pandemic levels by 2022 – an insignificant difference – while that of men's was nearly 6 percent below – a still significant difference at the one percent level.

By age, the youth (15 to 34 years) were most likely to experience job loss in 2020, with employment contracting by 18.4 percent and contributing to over 50 percent of net employment loss, despite comprising 36.6 percent of the employed population pre-pandemic. Again, this is consistent with the NIDS-CRAM data (Ranchhod & Daniels, 2021; Espi-Sanchis et al., 2022; Yu et al., 2023), suggestive of some external validity, as well as the international literature as documented in the preceding chapter (for instance, see Adams-Prassl et al., 2020; Béland et al., 2020; Blundell et al., 2022; Soares & Berg, 2022). Other age groups also had notable employment reductions but to a lesser extent. This shift in the composition of the employed towards older workers is reflected in the youth's employment share dropping from

36.6 to 33.8 percent over a year, although it partially recovered by 2022. However, youth employment remained over 8 percent lower than pre-pandemic levels. In contrast, workers aged 35 to 59 years, who account for the majority of workers, had fully recovered (the estimated magnitude of the difference coefficient is negative but is statistically insignificant). Older workers (at least 60 years) showed no significant improvement, with employment even lower in 2022 than 2020. Despite these dynamics, the youth still accounted for the majority (61.4 percent) of net employment loss remaining in 2022.

By race,[12] all racial groups experienced significant job losses, with African/Black and Coloured individuals disproportionately affected. African/Black workers, representing about 75 percent of the employed pre-pandemic, accounted for 78.3 percent of net job losses from 2019 to 2020. Coloured workers were more disproportionately affected, making up just 10 percent of pre-pandemic employment, saw a 16.3 percent decline and contributed to 12.7 percent of net job losses, resulting in a job loss burden ratio of 1.23 (compared to 1.04 for African/Black individuals). By 2022, the employment levels of both groups remained statistically significantly lower (at the 10 percent level) than the pre-pandemic period. However, Coloured individuals lagged in recovery, regaining only 43 percent of lost jobs while African/Black individuals recovered 73 percent. Employment levels among Indian/Asian and White workers showed no significant difference over the period, however this is at least partially due to small sub-sample sizes.[13]

In terms of education, I estimate a steep negative gradient in net job loss in both the short and medium terms. In other words, after accounting for differences in pre-pandemic employment shares, less formally educated workers were disproportionately affected by job loss. This is again in line with the NIDS-CRAM data (Ranchhod & Daniels, 2021; Yu et al., 2023). From 2019 to 2020, employment among those with primary education or less fell by 30 percent (despite representing 11.5 percent of pre-pandemic employment). In contrast, those with incomplete secondary education (32.9 percent of pre-pandemic employment) saw a 17 percent decline, complete secondary education (32.8 percent of pre-pandemic employment) experienced a 9 percent decline, and post-secondary education (21.5 percent of pre-pandemic employment) a 3.5 percent decline. This latter change in net employment is statistically insignificant. This development altered the composition of the employed population towards higher-educated workers. From 2019 to 2020, workers with primary education or less shrunk to represent 9.4 percent of employment while complete secondary and post-secondary education expanded to account for 34.3 percent and just under 24 percent, respectively. In 2022, those with a complete secondary education grew further to 36.6 percent, and those with primary education or less shrank to 8.7 percent. Notably, there was no statistically significant recovery in employment for this latter group, with only 5 percent of net jobs lost having

[12] Race as a form of classification in South Africa is still widely used in the literature with the four largest race groups being African/Black, Indian/Asian, Coloured (mixed-race), and White. As noted by Spaull (2013), it is important to note that this serves a functional rather than normative purpose.

[13] n = 498 and 1568 for Indian/Asian and White individuals, respectively, for 2019, while n = 272 and 1 017 for Indian/Asian and White individuals, respectively, for 2020.

Table 3.3: Employment levels and composition by demographic group, 2019 - 2022

	2019		2020		2021		2022	
	Level	Share (%)	Level	Share (%)	Level	Share (%)	Level	Share (%)
Total	16,312,706	100.00	14,148,215	100.00	14,941,573	100.00	15,561,858	100.00
	(211,024)		(264,005)		(256,165)		(248,838)	
Gender								
Male	9,179,612	56.27	7,977,963	56.39	8,461,781	56.63	8,641,544	55.53
	(132,618)		(168,925)		(161,475)		(154,320)	
Female	7,133,094	43.73	6,170,252	43.61	6,479,792	43.37	6,920,314	44.47
	(109,503)		(134,007)		(128,740)		(131,091)	
Age (years)								
15-34	5,964,514	36.56	4,869,685	34.42	5,047,111	33.78	5,480,637	35.22
	(110,381)		(130,334)		(125,821)		(125,335)	
35-59	9,881,895	60.58	8,881,014	62.77	9,467,400	63.36	9,698,014	62.32
	(145,599)		(179,928)		(178,714)		(168,999)	
60+	466,296	2.86	397,517	2.81	427,061	2.86	383,206	2.46
	(23,996)		(27,837)		(27,407)		(25,444)	
Race								
African/Black	12,250,320	75.10	10,554,996	74.60	11,263,839	75.39	11,789,286	75.76
	(175,803)		(209,721)		(205,775)		(208,497)	
Coloured	1,686,611	10.34	1,412,289	9.98	1,416,347	9.48	1,530,588	9.84
	(76,821)		(99,702)		(90,830)		(75,138)	
Indian/Asian	530,391	3.25	488,224	3.45	487,255	3.26	543,354	3.49
	(45,881)		(50,607)		(49,798)		(59,607)	
White	1,845,384	11.31	1,692,706	11.96	1,774,131	11.87	1,698,631	10.92
	(89,313)		(103,413)		(111,085)		(102,967)	
Education								
Primary	1,879,845	11.52	1,329,658	9.40	1,424,912	9.54	1,356,068	8.71
	(51,034)		(58,719)		(56,186)		(48,908)	
Secondary incom.	5,360,983	32.86	4,443,230	31.40	4,892,020	32.74	4,815,286	30.94
	(96,774)		(121,995)		(115,952)		(113,355)	
Secondary com.	5,346,917	32.78	4,846,446	34.25	5,144,362	34.43	5,698,234	36.62
	(106,601)		(126,713)		(125,492)		(126,196)	
Post-secondary	3,511,214	21.52	3,389,699	23.96	3,358,654	22.48	3,495,640	22.46
	(98,679)		(115,372)		(116,454)		(117,029)	
Area								
Rural	3,837,240	23.52	3,385,932	23.93	3,613,570	24.18	3,659,191	23.51
	(102,281)		(134,130)		(114,354)		(111,699)	
Urban	12,475,465	76.48	10,762,283	76.07	11,328,003	75.82	11,902,667	76.49
	(191,043)		(231,657)		(234,156)		(227,640)	
Province								
Western Cape	2,497,453	15.31	2,179,400	15.40	2,256,332	15.10	2,343,554	15.06
	(89,694)		(134,477)		(114,837)		(103,801)	
Eastern Cape	1,387,666	8.51	1,169,357	8.27	1,234,848	8.26	1,342,916	8.63
	(54,093)		(66,717)		(57,672)		(63,578)	
Northern Cape	301,370	1.85	255,328	1.80	256,440	1.72	318,221	2.04
	(22,636)		(25,611)		(25,026)		(25,748)	
Free State	808,403	4.96	637,576	4.51	722,889	4.84	806,961	5.19
	(38,864)		(43,484)		(44,176)		(51,812)	
KwaZulu-Natal	2,634,837	16.15	2,297,138	16.24	2,420,775	16.20	2,481,251	15.94
	(81,693)		(94,523)		(91,836)		(101,473)	
North West	918,032	5.63	873,620	6.17	978,809	6.55	923,960	5.94
	(45,787)		(62,568)		(67,314)		(55,963)	
Gauteng	5,065,933	31.06	4,473,200	31.62	4,648,295	31.11	4,786,778	30.76
	(125,714)		(153,652)		(160,553)		(147,307)	
Mpumalanga	1,243,042	7.62	1,111,877	7.86	1,165,951	7.80	1,166,977	7.50
	(54,422)		(58,317)		(59,563)		(56,061)	
Limpopo	1,455,970	8.93	1,150,720	8.13	1,257,234	8.41	1,391,239	8.94
	(63,256)		(68,972)		(65,106)		(74,065)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).

[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Incom. = incomplete; com. = complete. Rural areas include traditional areas.

Table 3.4: Year-on-year net employment change by demographic group, 2019 - 2022

	Change (2019-2020)				Change (2019-2022)			
	Absolute	%	Share of change (%)	Job loss burden ratio	Absolute	%	Share of change (%)	Job loss burden ratio
Total	-2 164 490*** (265,541)	-13.27	100.00	1.00	-750 848** (299,081)	-4.60	100.00	1.00
Gender								
Male	-1 201 649*** (174,500)	-13.09	55.52	0.99	-538 068*** (189,952)	-5.86	71.66	1.27
Female	-962 842*** (143,240)	-13.50	44.48	1.02	-212,780 (159,394)	-2.98	28.34	0.65
Age (years)								
15-34	-1 094 829*** (146,362)	-18.36	50.58	1.38	-483 877*** (158,215)	-8.11	64.44	1.76
35-59	-1 000 882*** (186,411)	-10.13	46.24	0.76	-183,881 (204,691)	-1.86	24.49	0.40
60+	-68 780** (34,564)	-14.75	3.18	1.11	-83 090** (35,435)	-17.82	11.07	3.87
Race								
African/Black	-1 695 324*** (215,537)	-13.84	78.32	1.04	-461 035* (242,421)	-3.76	61.40	0.82
Coloured	-274 322*** (89,967)	-16.26	12.67	1.23	-156 023* (84,648)	-9.25	20.78	2.01
Indian/Asian	-42,167 (47,949)	-7.95	1.95	0.60	12,963 (63,594)	2.44	-1.73	-0.53
White	-152,677 (107,672)	-8.27	7.05	0.62	-146,752 (128,793)	-7.95	19.54	1.73
Education								
Primary	-550,188*** (67,522)	-29.27	25.42	2.21	-523,777*** (67,181)	-27.86	69.76	6.05
Secondary incom.	-917,753*** (129,291)	-17.12	42.40	1.29	-545,697*** (138,544)	-10.18	72.68	2.21
Secondary com.	-500,471*** (144,798)	-9.36	23.12	0.71	351,317*** (155,395)	6.57	-46.79	-1.43
Post-secondary	-121,516 (124,882)	-3.46	5.61	0.26	-15,574 (145,208)	-0.44	2.07	0.10
Area								
Rural	-451,308*** (126,409)	-11.76	20.85	0.89	-178,050 (129,915)	-4.64	23.71	1.01
Urban	-1,713,182*** (233,389)	-13.73	79.15	1.03	-572,798** (269,491)	-4.59	76.29	1.00
Province								
Western Cape	-318,053*** (123,206)	-12.74	14.69	0.96	-153,899 (124,669)	-6.16	20.50	1.34
Eastern Cape	-218,309*** (69,108)	-15.73	10.09	1.19	-44,750 (77,071)	-3.22	5.96	0.70
Northern Cape	-46,042** (24,917)	-15.28	2.13	1.15	16,851 (24,053)	5.59	-2.24	-1.21
Free State	-170,827*** (50,198)	-21.13	7.89	1.59	-1,442 (58,439)	-0.18	0.19	0.04
KwaZulu-Natal	-337,699*** (100,731)	-12.82	15.60	0.97	-153,586 (120,850)	-5.83	20.46	1.27
North West	-44,413 (64,344)	-4.84	2.05	0.36	5,928 (70,443)	0.65	-0.79	-0.14
Gauteng	-592,733*** (156,060)	-11.70	27.38	0.88	-279,155 (177,909)	-5.51	37.18	1.20
Mpumalanga	-131,165** (56,037)	-10.55	6.06	0.80	-76,065 (67,970)	-6.12	10.13	1.33
Limpopo	-305,250*** (75,058)	-20.97	14.10	1.58	-64,730 (90,195)	-4.45	8.62	0.97

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2022d).

[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Incom. = incomplete; com. = complete. Rural areas include traditional areas. Job loss burden ratio for a given period = ratio of a given group's share of net employment change to the group's pre-pandemic (2019) employment share. Differences estimated using adjusted Wald tests. *** p<0.01, ** p<0.05, * p<0.10.

been recovered two years later by 2022. Given the well-documented strong and positive relationship between levels of education and employment and earnings in the South African labour market (Acquah, 2009; Bhorat & Mayet, 2012; Leibbrandt et al., 2012; Branson & Leibbrandt, 2013; Branson et al., 2013; Lam et al., 2013), these findings are strongly suggestive of the regressive nature of job loss and recovery during the pandemic in the country. This is again largely consistent with the international experience as discussed in Chapter 2.

Finally, by geographic area, urban areas were harder hit in terms of employment during the pandemic in both absolute and relative terms. Urban employment decreased by 13.7 percent from 2019 to 2020, accounting for nearly 80 percent of net job losses, slightly exceeding its pre-pandemic share of 76.5 percent. Rural employment fell by a slightly lower rate of 11.8 percent. By 2022, urban areas had recovered 66.6 percent of net job losses, and rural areas 60.6 percent, however the latter is not statistically significantly different from 100 percent. In 2022, both urban and rural employment remained 4.6 percent below pre-pandemic levels, with only urban employment being statistically significant at the 5 percent level. The composition of employment in this regard appears largely unchanged. Regarding provinces, net job losses were observed in all provinces except the North West, which however represented a minority of workers (less than 2 percent). Gauteng, KwaZulu-Natal, and the Western Cape accounted for most net job losses nationally (57.7 percent), consistent with their large collective pre-pandemic employment share (62.5 percent). In relative terms, the Free State and Limpopo had the highest net job losses, with both contracting by approximately 21 percent from 2019 to 2020. Despite representing only 5 and 9 percent of pre-pandemic employment, the Free State and Limpopo accounted for 8 percent and 14 percent of net jobs lost, respectively. By 2022, there were no statistically significant differences in employment levels for any province relative to 2019, indicative of a recovery. However, most estimates were negative, averaging 2.8 percent below pre-pandemic levels. This suggests full recovery in all provinces if only statistical significance is considered, but only partial recovery if economic significance is also taken into account.

3.4.2.2 Employment characteristics

Similar to before, by employment characteristic, Table 3.5 presents cross-sectional employment levels and shares estimates while Table 3.6 presents net employment change estimates in absolute and relative terms. By sector, the secondary sector saw the most severe employment decline from 2019 to 2020, contracting by 20.3 percent or about 670 000 workers – significant at the 1 percent level. This sector accounted for 30.9 percent of all net job losses, disproportionately high compared to its pre-pandemic employment share of 20.3 percent. All industries within the sector contributed to this contraction, with each exceeding their pre-pandemic employment shares in job losses, but manufacturing was affected the most. The tertiary sector also experienced a significant contraction but less severely (12.4 percent), accounting for two-thirds of net job losses (67.7 percent or 1.5 million individuals) which is not very dissimilar for the industry's pre-pandemic employment share (72.2 percent).

All industries within the sector contributed to the contraction, with private households and wholesale/retail trade driving it. Private household workers were most affected, with their share of net job losses significantly exceeding their pre-pandemic employment share (11.4 percent and 7.7 percent, respectively). In contrast, the primary sector's net employment level appears to have been largely insensitive to the pandemic, with an estimated reduction of just 51 000 individuals or 4.2 percent, but not statistically significant at any conventional level. This lack of significance doesn't mask any intra-sector industry-specific changes: employment changes in agriculture and mining/quarrying were also statistically insignificant. These estimates are also neither economically significant given their relatively small magnitudes and the sector's larger pre-pandemic employment share.

By 2022, net primary sector employment remained similar to pre-pandemic levels, while that of the secondary sector was significantly lower (15.6 percent). Employment in all secondary sector industries was markedly lower than pre-pandemic levels. The secondary sector's recovery was slow, regaining only 23 percent of lost jobs compared to the tertiary sector's 79 percent recovery. The tertiary sector's employment level in 2022 was statistically unchanged from pre-pandemic levels, indicating a potential full recovery. However, a closer look reveals that the trade and private household industries had lower employment, while community, social, and personal services grew by over 5 percent (significant at the 10 percent level). This led to a shift in the sectoral composition of the labour market: a 3 percent contraction in the secondary sector, no significant change in the primary sector, and a 1.6 percent expansion in the tertiary sector.[14] This shift aligns with the pre-pandemic trend of services-led structural transformation and premature deindustrialization of the post-apartheid South African economy (Bhorat et al., 2016; Busse et al., 2019; Bhorat et al., 2020b, 2022). While this analysis doesn't definitively reveal what sectoral changes would have happened in the absence of the pandemic, these results suggest the shock may have accelerated the country's ongoing path of structural transformation.

Among skill-levels, semi- and less-skilled occupations saw the most significant employment declines from 2019 to 2010, at 15.6 percent and 16.5 percent, respectively. High-skilled occupations showed no significant aggregate change, but variations existed within the group. Semi-skilled jobs accounted for 66.5 percent of total net job losses, exceeding their pre-pandemic employment share by 10 percentage points. Less-skilled jobs made up the remaining 36 percent of losses despite representing 28.9 percent of pre-pandemic employment. As discussed in Chapter 2, this regressive incidence of job loss is consistent with the NIDS-CRAM data (Ranchhod & Daniels, 2021; Daniels & Casale, 2022; Bassier et al., 2023; Yu et al., 2023). Among semi-skilled jobs, craft and related trades workers had the sharpest drop, down 22.3 percent, accounting for 20.2 percent of net job losses despite representing 12 percent of pre-pandemic employment. Less-skilled occupations saw a significant drop,

[14]Despite the overall expansion of the tertiary sector, I observe some industry-specific heterogeneity within: while the employment shares of the wholesale and retail trade, transport, storage and communication, and private households industries have contracted, those of the finance and CSP services industries have grown.

Table 3.5: Employment levels and composition by employment characteristic, 2019 - 2022

	2019		2020		2021		2022	
	Level	Share (%)	Level	Share (%)	Level	Share (%)	Level	Share (%)
Total	16 312 706	100.00	14 148 215	100.00	14 941 573	100.00	15 561 858	100.00
	(211 024)		(264 005)		(256 165)		(248 838)	
Industry								
Primary	1 223 144	7.50	1 172 236	8.30	1 259 999	8.45	1 281 225	8.24
	(55 874)		(89 804)		(68 954)		(60 265)	
Agriculture	842 062	5.16	799 033	5.65	861 634	5.77	873 820	5.62
	(47 830)		(80 306)		(55 984)		(51 581)	
Mining	381 082	2.34	373 203	2.64	398 365	2.67	407 404	2.62
	(29 717)		(40 498)		(40 184)		(31 458)	
Secondary	3 303 486	20.26	2 634 571	18.66	2 755 111	18.47	2 787 560	17.93
	(76 599)		(86 995)		(83 159)		(81 608)	
Manufacturing	1 789 388	10.97	1 455 825	10.29	1 414 755	9.47	1 506 973	9.68
	(55 882)		(63 108)		(57 728)		(59 914)	
Utilities	151 339	0.93	112 926	0.80	118 213	0.79	103 806	0.67
	(17 657)		(15 741)		(17 731)		(14 700)	
Construction	1 362 759	8.35	1 065 820	7.53	1 222 144	8.18	1 176 781	7.56
	(45 509)		(50 077)		(52 467)		(49 083)	
Tertiary	11 780 270	72.24	10 314 562	73.04	10 899 606	73.08	11 474 616	73.82
	(168 763)		(201 584)		(202 244)		(204 564)	
Trade	3 428 621	21.02	2 946 463	20.83	3 086 956	20.66	3 163 150	20.33
	(78 490)		(90 335)		(92 969)		(86 533)	
TSC	982 502	6.02	884 683	6.25	968 547	6.48	906 120	5.82
	(37 513)		(46 702)		(47 310)		(45 166)	
Finance	2 495 239	15.30	2 234 281	15.79	2 248 440	15.05	2 460 140	15.81
	(68 663)		(77 474)		(76 039)		(82 171)	
CSP services	3 622 492	22.21	3 243 976	22.93	3 401 388	22.76	3 821 327	24.56
	(78 943)		(92 473)		(93 748)		(94 835)	
Private households	1 251 415	7.67	1 005 159	7.10	1 194 274	7.99	1 123 879	7.22
	(40 255)		(50 255)		(50 330)		(47 015)	
Occupation								
High-skilled	2 367 575	14.51	2 360 096	16.68	2 398 196	16.05	2 418 669	15.54
	(78 618)		(96 981)		(100 399)		(91 494)	
Managers	1 527 944	9.37	1 287 769	9.10	1 405 744	9.41	1 252 700	8.05
	(59 869)		(68 446)		(67 116)		(61 722)	
Professionals	839 631	5.15	1 072 327	7.58	992 452	6.64	1 165 969	7.49
	(39 695)		(55 016)		(56 864)		(57 796)	
Semi-skilled	9 228 963	56.58	7 790 407	55.06	8 000 580	53.55	8 637 165	55.50
	(137 889)		(162 834)		(158 932)		(161 279)	
TA professionals	1 436 393	8.81	1 213 133	8.57	1 319 603	8.83	1 369 104	8.80
	(47 426)		(52 123)		(52 517)		(54 455)	
Clerks	1 708 008	10.47	1 470 386	10.39	1 473 953	9.86	1 600 738	10.29
	(52 096)		(56 436)		(55 176)		(60 188)	
Service workers	2 687 359	16.47	2 301 782	16.27	2 321 880	15.54	2 581 863	16.59
	(62 607)		(73 651)		(69 003)		(71 173)	
Skilled agriculture	53 782	0.33	67 454	0.48	45 092	0.30	72 071	0.46
	(8 051)		(11 079)		(8 046)		(10 386)	
Craft	1 957 006	12.00	1 520 915	10.75	1 598 532	10.70	1 673 171	10.75
	(53 650)		(61 731)		(59 172)		(59 177)	
Plant operators	1 386 415	8.50	1 216 737	8.60	1 241 519	8.31	1 340 218	8.61
	(43 456)		(54 140)		(50 718)		(50 338)	
Less-skilled	4 715 050	28.90	3 935 253	27.81	4 497 000	30.10	4 506 024	28.96
	(92 378)		(119 243)		(115 634)		(105 480)	
Elementary occup.	3 720 516	22.81	3 190 566	22.55	3 605 283	24.13	3 648 285	23.44
	(81 276)		(107 183)		(100 485)		(93 071)	
Domestic workers	994 535	6.10	744 687	5.26	891 716	5.97	857 740	5.51
	(33 809)		(38 064)		(40 615)		(37 631)	
Formality								
Formal sector	11 884 180	72.85	10 754 818	76.02	10 940 291	73.22	11 329 557	72.80
	(177 741)		(224 354)		(213 733)		(203 776)	
Informal sector	3 177 110	19.48	2 388 238	16.88	2 807 008	18.79	3 108 422	19.97
	(74 586)		(78 355)		(81 988)		(88 683)	
Private households	1 251 415	7.67	1 005 159	7.10	1 194 274	7.99	1 123 879	7.22
	(40 255)		(50 255)		(50 330)		(47 015)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).

[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. TSC = transport, storage and communication; CSP = community; social and personal services; TA = technical and associate; managers = legislators, senior officials, and managers; occup. = occupations. Industries and occupations classified as 'other' are excluded for brevity.

driven by domestic workers, with a 25.1 percent net job loss, double their pre-pandemic employment share. Employment in elementary occupations also contracted, but their share of net job losses matched their pre-pandemic employment share. Interestingly, high-skilled employment experienced no significant change on aggregate, but significant heterogeneity is evident within this group. Legislators, senior officials, and managers decreased by 15.7 percent, while professionals increased by 27.7 percent, both statistically significant at the 1 percent level. This positive change for professionals was unique in this period. Absolute employment changes for both groups were similar (around 230 000 to 240 000 individuals), leading to no variation in high-skilled jobs on aggregate at the pandemic's onset.

High-skilled employment changes from 2019 to 2022 suggest a lasting trend. By 2022, legislators, officials, and managers' employment remained 18 percent below pre-pandemic levels, while professionals were almost 40 percent above. High-skilled employment on aggregate remained statistically unchanged. Semi-skilled employment on aggregate had only partially recovered, regaining 59 percent of lost jobs and remaining 6.4 percent below pre-pandemic levels. Most occupations in this group have statistically recovered, except craft and related trades workers, down 14.5 percent. Less-skilled occupations remained 4.4 percent below pre-pandemic levels, primarily due to domestic workers, recovering by only 45 percent. Overall, these developments have led to a marginal but persistent change in the skills structure of the labour market towards higher-skilled occupations, with their share growing by over 1 percentage point from 2019 to 2022, while semi-skilled occupations shrank similarly and less-skilled occupations remained relatively constant.

It is clear that by formality of employment, the informal sector and workers in private households suffered the most significant net employment losses at the pandemic's onset.[15] Although the formal sector contracted by 9.5 percent and accounted for 52.2 percent of all net job losses, the sector represents the majority of workers in the labour market (73 percent just prior to the pandemic) and hence did not exhibit disproportionate job loss incidence. Conversely, the informal sector, comprising 19.5 percent of all workers in the pre-pandemic period, experienced a net job loss rate of 24.8 percent, accounting for 36.5 percent of all net job losses and displaying the highest job loss burden ratio. Private household workers also experienced a significant contraction but not as severe as the informal sector. As discussed in the preceding chapter, this concentration of job loss among informal sector workers is in line with the existing South African and international literature (Rogan & Skinner, 2020; Fox & Signe, 2020; International Labor Organisation, 2020; Benhura & Magejo, 2020; Balde et al., 2020; Krafft et al., 2021; Schotte et al., 2023; Soares & Berg, 2022; Rogan & Skinner, 2022; Oyenubi, 2023), and has been argued to be attributable to factors which characterise the sector, such as a concentration in contact-intensive occupations and a lower probability of being able to work remotely and access legal protections such as paid leave and unemployment

[15] As discussed in Section 3.2, to distinguish the formal from the informal sector I follow the definition employed by StatsSA, which considers workers in private households as an additional independent category of formality, but which is equivalent to the private households main industry category.

Table 3.6: Year-on-year net employment change by employment characteristic, 2019 - 2022

	Change (2019-2020)				Change (2019-2022)			
	Absolute	%	Share of change (%)	Job loss burden ratio	Absolute	%	Share of change (%)	Job loss burden ratio
Total	-2 164 490*** (265,541)	-13.27	100.00	1.00	-750 848** (299,081)	-4.60	100.00	1.00
Industry								
Primary	-50,908 (78,614)	-4.16	2.35	0.31	58,081 (67,198)	4.75	-7.74	-1.03
Agriculture	-43,029 (70,174)	-5.11	1.99	0.39	31,759 (55,433)	3.77	-4.23	-0.82
Mining	-7,879 (36,209)	-2.07	0.36	0.16	26,322 (37,105)	6.91	-3.51	-1.50
Secondary	-668,915*** (101,362)	-20.25	30.90	1.53	-515,925*** (105,383)	-15.62	68.71	3.39
Manufacturing	-333,564*** (74,288)	-18.64	15.41	1.40	-282,415*** (74,587)	-15.78	37.61	3.43
Utilities	-38,412* (21,336)	-25.38	1.77	1.91	-47,532** (22,524)	-31.41	6.33	6.82
Construction	-296,939*** (62,336)	-21.79	13.72	1.64	-185,978*** (65,620)	-13.65	24.77	2.96
Tertiary	-1,465,708*** (215,409)	-12.44	67.72	0.94	-305,654 (245,866)	-2.59	40.71	0.56
Trade	-482,158*** (105,008)	-14.06	22.28	1.06	-265,471** (110,617)	-7.74	35.36	1.68
TSC	-97,819* (54,837)	-9.96	4.52	0.75	-76,382 (56,571)	-7.77	10.17	1.69
Finance	-260,958*** (91,005)	-10.46	12.06	0.79	-35,100 (103,966)	-1.41	4.67	0.31
CSP services	-378,517*** (105,122)	-10.45	17.49	0.79	198,835* (116,163)	5.49	-26.48	-1.19
Private households	-246,256*** (57,777)	-19.68	11.38	1.48	-127,536** (58,255)	-10.19	16.99	2.21
Occupation								
High-skilled	-7,479 (102,944)	-0.32	0.35	0.02	51,094 (113,575)	2.16	-6.80	-0.47
Managers	-240,175*** (76,247)	-15.72	11.10	1.18	-275,244*** (82,674)	-18.01	36.66	3.91
Professionals	232,696*** (62,613)	27.71	-10.75	-2.09	326,339*** (66,316)	38.87	-43.46	-8.44
Semi-skilled	-1,438,555*** (178,699)	-15.59	66.46	1.17	-591,798*** (197,068)	-6.41	78.82	1.39
TA professionals	-223,259*** (62,158)	-15.54	10.31	1.17	-67,288 (70,734)	-4.68	8.96	1.02
Clerks	-237,622*** (69,756)	-13.91	10.98	1.05	-107,270 (76,548)	-6.28	14.29	1.36
Service workers	-385,577*** (87,190)	-14.35	17.81	1.08	-105,496 (89,416)	-3.93	14.05	0.85
Skilled agriculture	13,671 (13,300)	25.42	-0.63	-1.92	18,289 (13,061)	34.01	-2.44	-7.39
Craft	-436,091*** (73,533)	-22.28	20.15	1.68	-283,835*** (78,443)	-14.50	37.80	3.15
Plant operators	-169,678*** (61,301)	-12.24	7.84	0.92	-46,197 (63,546)	-3.33	6.15	0.72
Less-skilled	-779,797*** (123,553)	-16.54	36.03	1.25	-209,026* (125,837)	-4.43	27.84	0.96
Elementary occup.	-529,950*** (109,492)	-14.24	24.48	1.07	-72,231 (112,010)	-1.94	9.62	0.42
Domestic workers	-249,847*** (44,874)	-25.12	11.54	1.89	-136,795*** (48,247)	-13.75	18.22	2.99
Formality								
Formal sector	-1,129,362*** (228,370)	-9.50	52.18	0.72	-554,624** (251,756)	-4.67	73.87	1.01
Informal sector	-788,872*** (92,538)	-24.83	36.45	1.87	-68,688 (106,318)	-2.16	9.15	0.47
Private households	-246,256*** (57,777)	-19.68	11.38	1.48	-127,536** (58,255)	-10.19	16.99	2.21

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2022d).

[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Job loss burden ratio for a given period = ratio of a given group's share of net employment change to the group's pre-pandemic (2019) employment share. TSC = transport, storage and communication; CSP = community; social and personal services; TA = technical and associate; managers = legislators, senior officials, and managers; occup. = occupations. Industries and occupations classified as 'other' are excluded for brevity. Differences estimated using adjusted Wald tests. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

insurance. By 2022, the informal sector had fully recovered in net employment, with a small and statistically insignificant difference estimate. In contrast, the formal sector only regained 51 percent of its lost jobs, remaining 4.7 percent below pre-pandemic levels. As shown later in Chapter 5, the informal sector was on a consistent trajectory of recovery since 2020Q2, while the formal sector followed a weak W-shaped trajectory similar to aggregate employment, which is unsurprising given the concentration of labour in the sector. These changes briefly shifted the composition of employment towards the formal sector, but over time, the labour market reverted to its pre-pandemic composition.

3.4.2.3 Labour market institutional characteristics

I present the cross-sectional estimates of employment levels and shares by labour market institution from 2019 to 2022 in Table 3.7, while in Table 3.8 I present the relevant net employment change estimates. In 2020, it is notable that, statistically, all net employment loss occurred in the private sector, which accounted for 82.7 percent of pre-pandemic employment. Conversely, the public sector saw a negative net employment change of 5.1 percent which however wasn't statistically significant. This suggests public sector workers were relatively protected from pandemic-related employment effects, aligning with the typical pattern of public sector stability during economic crises (Colley et al., 2022). Possible reasons include increased demand for public sector healthcare workers, job security due to remote work options, and legal protections (Organisation for Economic Co-operation and Development, 2020; International Labor Organisation, 2021b). By 2022, public sector employment remained similar to pre-pandemic levels, while private sector employment had only partially recovered, standing at 5.7 percent below pre-pandemic levels. Initially, the pandemic shifted employment toward the public sector, but by 2022, the private sector employment share rebounded to 81.75 percent while that of the public sector decreased to 18.25 percent, only marginally different from the pre-pandemic shares.

I find significant differences in employment trends based on trade union membership. Non-union members, who constituted just two-thirds (67.8 percent) of workers before the pandemic, accounted for all the net employment loss from 2019 to 2020, with an employment contraction of over 22 percent. In contrast, union members saw a 6.6 percent increase in employment. This suggests that union membership may have provided protection against job loss during the pandemic, similar to public sector workers, again at least on aggregate and on net. Possible reasons include the provision of protection against uninsurable labour market risks, and the ability to mobilise industrial action and negotiate in favour of their members (Checchi & Lucifora, 2002; Bhorat et al., 2015). The International Labor Organisation (2021a) notes that, globally, unions supported their members particularly by proposing outstanding responses to the pandemic at the workplace in order to help workers retain decent employment and fair work. By 2022, non-member employment partially recovered but remained 5.3 percent below pre-pandemic levels.

The employment protection provided to union members and public sector workers suggested by the data here need not be unrelated. High unionisation or 'union density' has been long documented in the South African public sector (Bhorat et al., 2015). Before the pandemic (2020Q1), only 20 percent of private sector workers were union members, compared to 65 percent in the public sector—a highly significant difference ($p < 0.000$). The absence of net job loss for these two worker groups may again be indicative of the pandemic's regressive employment effects considering the well-documented wage premium for both groups in the South African labour market (Bhorat et al., 2015; Kwenda & Ntuli, 2018; Kerr & Wittenberg, 2021). Importantly however, Bhorat et al. (2015) emphasise the interaction between economic sector and union membership in South Africa, and show that unionised workers have large wage premiums regardless of sector. I similarly observe this interaction but with respect to net employment changes at the pandemic's onset. As shown in Table A3 in the appendix, regardless of sector, net employment of union members remained statistically unchanged, however within both the private and public sectors I estimate a significant contraction among non-members. These contractions are relatively large (22 percent and 30 percent for private and public sectors, respectively), suggesting that union membership rather than public-private sectoral division played a key role in pandemic job protection. This development however appears to have been temporary. However, by 2022, non-unionised private sector employment remained 7.4 percent below pre-pandemic levels, while unionised public sector employment also fell below pre-pandemic levels, while non-unionised public sector employment surpassed it.

By type of employment relationship, wage workers, accounting for 89.3 percent of net job losses from 2019 to 2020 but the majority (83.7 percent) of the pre-pandemic employed, experienced a significant 14.2 percent contraction. However, the self-employed, with a pre-pandemic share of just over 10 percent, were most severely impacted, with a 20.7 percent net job loss. On the other hand, employers' employment level increased by 12 percent (about 110 000 individuals), marginally statistically significant at the 10 percent level. By 2022, wage workers still dominated cumulative net job losses while other worker groups showed no statistically significant differences from pre-pandemic levels. Employer growth was short-lived, but the self-employed fully recovered from their contraction by 2022. I find no significant evidence of a change in employment among unpaid household workers over the entire period.

Regarding contract types, workers with verbal contracts suffered more in relative terms. Employment for them dropped by nearly 37 percent, despite representing the minority (20.2 percent) of pre-pandemic employment, compared to an 8.4 percent reduction for those with written contracts. By 2022, about 59 percent of verbal contract job losses were recovered, but accounted for all remaining net job losses. The consequence was a shift in labour market composition toward workers with written contracts. By contract duration, those with unspecified durations (who may be referred to as 'casual' workers) experienced the most significant net job losses, with a 30 percent drop, accounting for 53 percent of all losses despite representing just 25 percent of pre-pandemic employment. Workers with limited-duration

Table 3.7: Employment levels and composition by labour market institutional characteristic, 2019 - 2022

	2019		2020		2021		2022	
	Level	Share (%)	Level	Share (%)	Level	Share (%)	Level	Share (%)
Total	16,312,706	100.00	14,148,215	100.00	14,941,573	100.00	15,561,858	100.00
	(211,024)		(264,005)		(256,165)		(248,838)	
Sector								
Private	13,486,125	82.67	11,447,311	80.91	12,311,537	82.40	12,721,617	81.75
	(187,428)		(234,912)		(228,790)		(223,182)	
Public	2,826,581	17.33	2,683,395	18.97	2,627,544	17.59	2,840,241	18.25
	(73,622)		(84,354)		(80,602)		(82,253)	
Trade union membership								
Member	3,930,691	28.79	4,188,103	35.74	4,125,192	33.11	3,787,078	29.04
	(92,624)		(114,532)		(113,245)		(106,331)	
Non-member	9,250,165	67.75	7,211,612	61.53	8,032,362	64.47	8,763,964	67.21
	(151,453)		(182,228)		(167,780)		(174,386)	
Do not know	472,267	3.46	320,010	2.73	302,187	2.43	488,832	3.75
	(30,392)		(26,467)		(38,414)		(36,586)	
Employment relationship type								
Wage worker	13,653,123	83.70	11,719,724	82.84	12,459,741	83.39	13,039,874	83.79
	(187,451)		(232,435)		(222,301)		(217,683)	
Employer	901,395	5.53	1,010,504	7.14	883,331	5.91	806,278	5.18
	(39,743)		(50,673)		(48,403)		(42,957)	
Self-employed	1,656,532	10.15	1,312,924	9.28	1,495,116	10.01	1,627,636	10.46
	(48,346)		(54,804)		(58,591)		(60,194)	
Unpaid household	101,657	0.62	105,062	0.74	103,385	0.69	88,070	0.57
	(11,860)		(15,535)		(15,621)		(13,671)	
Contract type								
Verbal	2,753,258	20.17	1,738,282	14.83	2,057,385	16.51	2,334,300	17.90
	(70,001)		(67,946)		(69,273)		(73,663)	
Written	10,899,865	79.83	9,981,443	85.17	10,402,355	83.49	10,705,575	82.10
	(165,785)		(211,717)		(200,214)		(195,297)	
Contract duration								
Limited	1,826,090	13.37	1,396,028	11.91	1,681,205	13.49	1,945,349	14.92
	(59,636)		(60,691)		(64,728)		(67,107)	
Permanent	8,402,539	61.54	7,923,984	67.61	7,785,687	62.49	7,925,328	60.78
	(143,642)		(186,499)		(171,352)		(163,779)	
Unspecified	3,424,494	25.08	2,399,713	20.48	2,992,849	24.02	3,169,198	24.30
	(77,892)		(79,573)		(89,672)		(88,733)	
UIF contribution status								
Contributor	8,302,742	60.81	7,518,686	64.15	7,874,720	63.20	7,894,247	60.54
	(144,942)		(180,269)		(171,088)		(167,655)	
Non-contributor	5,059,551	37.06	3,986,772	34.02	4,449,258	35.71	4,796,734	36.79
	(98,202)		(106,888)		(110,057)		(111,293)	
Do not know	290,830	2.13	214,266	1.83	135,763	1.09	348,894	2.68
	(23,478)		(20,779)		(15,499)		(31,673)	
Pension fund contribution status								
Contributor	6,596,680	48.32	6,328,998	54.00	6,081,584	48.81	5,852,322	44.88
	(125,872)		(155,770)		(146,103)		(135,742)	
Non-contributor	6,757,796	49.50	5,175,990	44.16	6,165,620	49.48	6,800,038	52.15
	(121,444)		(144,643)		(141,682)		(145,841)	
Do not know	298,648	2.19	214,736	1.83	212,536	1.71	387,515	2.97
	(23,491)		(22,519)		(22,204)		(30,399)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Estimates by trade union membership, contract type, contract duration, UIF contribution status, and pension fund contribution status only include employees.

contracts were also affected, though not as severely as 'casual' workers, with a 23.6 percent employment reduction. Permanent contract workers, who represented the pre-pandemic majority at 61.5 percent, experienced significant net job loss but were the least affected, with a 5.6 percent reduction and accounting for 25 percent of total net job losses. By 2022, while limited-duration contract workers had fully recovered, 'casual' workers had only partially recovered, but permanent contract workers showed no net employment recovery, remaining at 2020 levels.

I find significant differences in employment trends based on coverage of unemployment insurance. From 2019 to 2020, UIF non-contributors experienced a larger employment decline of 21.2 percent compared to 9.4 percent for UIF contributors, accounting for 55.5 percent of total job losses. Pre-pandemic, 60.8 percent had unemployment insurance, making non-contributors disproportionately affected. By 2022, the composition of employment by contribution status returned to pre-pandemic state but levels remained lower for both contributors and non-contributors by a similar rate. As such, because non-contributors were more severely initially affected, they recovered at a greater pace, having recovered over 75 percent of lost jobs compared to 47.9 percent for contributors. Consequently, contributors accounted for over 66 percent of cumulative net job losses by 2022. These findings closely align with employment formality trends, reflecting the strong, positive correlation between social insurance coverage and formal employment in the country (Woolard et al., 2011; Seekings & Matisonn, 2012; World Bank, 2021). In 2020Q1, 71 percent of formal sector workers and 23 percent of informal sector workers were UIF contributors. This again highlights the regressive distribution of job loss in the South African labour market at the pandemic's onset.

Finally, I examine employment changes based on pension contribution status, a form of voluntary social insurance. Among contributors, who constituted nearly half of all workers before the pandemic, I estimate no statistically significant change in net employment at the pandemic's onset. In contrast, non-contributors saw a highly significant 23.4 percent employment contraction. The temporal difference for contributors is negative but not statistically significant. These results align with the regressive employment effects of the pandemic previously noted, given the strong, positive correlation between pension fund contribution and labour market earnings in South Africa (Donaldson, 2021). Interestingly, by 2022, non-contributors' employment recovered to pre-pandemic levels, while contributors were 11.3 percent lower, statistically significant at the 1 percent level. Examining year-specific trends, employment among contributors gradually declined from 2019 to 2022, possibly indicating job losses or a composition effect with fewer workers contributing to pension funds.

Recall, as discussed in Chapter 2, the international literature highlights that remote work ability and 'essential' worker status - two defining features of pandemic labour markets globally - were both particularly strong predictors of job loss at the pandemic's onset (for instance, see Adams-Prassl et al., 2020; Béland et al., 2020; Borjas & Cassidy, 2020; Dingel & Neiman, 2020; Guven et al., 2020; Craig & Churchill, 2021; Zimpelmann et al.,

Table 3.8: Year-on-year net employment change by labour market institutional characteristic, 2019 - 2022

	Change (2019-2020)				Change (2019-2022)			
	Absolute	%	Share of change (%)	Job loss burden ratio	Absolute	%	Share of change (%)	Job loss burden ratio
Total	-2 164 490***	-13.27	100.00	1.00	-750 848**	-4.60	100.00	1.00
	(265,541)				(299,081)			
Sector								
Private	-2,038,814***	-15.12	94.19	1.14	-764,508***	-5.67	101.82	1.23
	(236,715)				(265,930)			
Public	-143,186	-5.07	6.62	0.38	13,660	0.48	-1.82	-0.10
	(92,802)				(99,532)			
Trade union membership								
Member	257,411**	6.55	-13.31	-0.46	-143,613	-3.65	23.42	0.81
	(125,518)				(129,838)			
Non-member	-2,038,553***	-22.04	105.44	1.56	-486,200**	-5.26	79.28	1.17
	(191,204)				(212,817)			
Do not know	-152,257***	-32.24	7.88	2.28	16,565	3.51	-2.70	-0.78
	(37,343)				(44,030)			
Employment relationship type								
Wage worker	-1,933,399***	-14.16	89.32	1.07	-613,249**	-4.49	81.67	0.98
	(239,476)				(263,030)			
Employer	109,110*	12.10	-5.04	-0.91	-95,116	-10.55	12.67	2.29
	(56,193)				(58,068)			
Self-employed	-343,607***	-20.74	15.87	1.56	-28,896	-1.74	3.85	0.38
	(64,375)				(72,829)			
Unpaid household	3,406	3.35	-0.16	-0.25	-13,587	-13.37	1.81	2.90
	(17,881)				(18,267)			
Contract type								
Verbal	-1,014,977***	-36.86	52.50	2.60	-418,958***	-15.22	68.32	3.39
	(83,822)				(95,961)			
Written	-918,422***	-8.43	47.50	0.60	-194,291	-1.78	31.68	0.40
	(217,356)				(235,884)			
Contract duration								
Limited	-430,062***	-23.55	22.24	1.66	119,258	6.53	-19.45	-1.45
	(74,504)				(82,887)			
Permanent	-478,556**	-5.70	24.75	0.40	-477,212**	-5.68	77.82	1.26
	(190,191)				(201,452)			
Unspecified	-1,024,781***	-29.93	53.00	2.11	-255,296**	-7.45	41.63	1.66
	(96,432)				(111,520)			
UIF contribution status								
Contributor	-784,056***	-9.44	40.55	0.67	-408,494**	-4.92	66.61	1.10
	(187,536)				(204,012)			
Non-contributor	-1,072,779***	-21.20	55.49	1.50	-262,817*	-5.19	42.86	1.16
	(123,838)				(136,087)			
Do not know	-76,564***	-26.33	3.96	1.86	58,063	19.96	-9.47	-4.44
	(29,757)				(38,996)			
Pension fund contribution status								
Contributor	-267,682	-4.06	13.85	0.29	-744,358***	-11.28	121.38	2.51
	(164,555)				(172,107)			
Non-contributor	-1,581,806***	-23.41	81.81	1.65	42,242	0.63	-6.89	-0.14
	(154,039)				(172,259)			
Do not know	-83,912***	-28.10	4.34	1.98	88,867**	29.76	-14.49	-6.62
	(30,094)				(37,474)			

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2022d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Job loss burden ratio for a given period = ratio of a given group's share of net employment change to the group's pre-pandemic (2019) employment share. Differences estimated using adjusted Wald tests. Estimates by trade union membership, contract type, contract duration, UIF contribution status, and pension fund contribution status only include employees. *** p<0.01, ** p<0.05, * p<0.10.

2021; Casarico & Lattanzio, 2022; Morales et al., 2022). Prior to examining adjustments to working hours in the next section, I consider variation in job loss in South Africa by remote work ability and 'essential' worker status. For the latter, similar to the approach used in Chapter 5, I cross-reference the country's industry-specific lockdown regulations in the Government Gazettes to over 150 three-digit SIC codes in the data to identify 'essential' and non-'essential' workers.[16] For the former, unfortunately data on remote work arrangements were not collected in the survey. As such, I follow the approach adopted by Kerr & Thornton (2020) who use four-digit occupation codes in the QLFS to identify workers who can plausibly work remotely by following Dingel & Neiman (2020) and classifying occupations based on occupational context and activities using data from the O*NET dataset.[17,18] The interested reader is referred to Kerr & Thornton (2020) for a detailed discussion of their approach. Table A4 in the appendix shows that, relative to those who cannot, those who can work remotely are more likely to be older, have a tertiary education, reside in urban areas, and work in the tertiary sector, the formal sector, and in a high-skilled occupation. This worker profile is largely consistent with that implied by the NIDS-CRAM data (Benhura & Magejo, 2020; Nwosu et al., 2022). Additionally, relative to non-'essential' workers, 'essential' workers are more likely to comprise men, those with a tertiary education, those who reside in rural areas, and those working in the primary sector, the formal sector, and the public sector.

Table 3.9 presents the relevant net employment change estimates. Consistent with the international literature, job loss at the pandemic's onset was concentrated among those who could not work remotely and those who were in non-'essential' industries. Those who could not work remotely, representing the majority (86 percent) prior to the pandemic, accounted for nearly all (94 percent) net jobs lost with their net employment level contracting by 14 percent from 2019 to 2020. In contrast, I find no statistically significant evidence of any change in employment among those who could work remotely. Similarly, net employment of non-'essential' workers contracted by nearly 19 percent, accounting for 91 percent of all net jobs lost. Those regarded as only 'partially essential'[19] experienced a smaller but still significant 12 percent contraction, while in contrast, the employment level of 'essential' workers remained statistically unchanged. Moreover, this distribution of job loss persisted as the pandemic progressed and the labour market partially recovered. As of 2022, the employment levels of both those who could not work remotely as well as non-'essential' workers remained 5 and 6 percent below pre-pandemic levels, respectively. Employment among those who could work remotely and 'essential' or 'partially essential' workers remained statistically un-

[16] The categorised list of industries are presented in Table A14 in Chapter 5's appendix. As described earlier, South Africa's lockdown regulations were however not time-invariant. Here, I assign 'essential' worker status based on the most stringent lockdown level in place during April 2020.

[17] Given that the O*NET is an occupational survey in the US, the authors' approach thus assumes equivalence in a given job's ability to be done from home in the US versus in South Africa. Because this need not be the case for certain jobs, such as teaching, the authors adjust the classification based on their own judgement of the South African context.

[18] Due to missing occupation data, remote work status could not be generated for a very small minority of observations - 0.16 percent or 26, 16, and 21 observations in 2019Q2, 2020Q2, and 2022Q2, respectively.

[19] This refers to workers in industries which were permitted to operate but only at a limited employment capacity. These are listed in Table A14 in Chapter 5's appendix.

Table 3.9: Year-on-year net employment change by remote work ability and essential worker status, 2019 - 2022

	Change (2019-2020)				Change (2019-2022)			
	Absolute	%	Share of change (%)	Job loss burden ratio	Absolute	%	Share of change (%)	Job loss burden ratio
Total	-2 164 490*** (265,541)	-13.27	100.00	1.00	-750 848** (299,081)	-4.60	100.00	1.00
Remote work ability								
Can work-from-home	-138,881 (95,906)	-6.24	6.42	0.47	-94,166 (107,290)	-4.23	12.45	0.91
Cannot work-from-home	-2,022,720*** (234,920)	-14.39	93.58	1.08	-662,488** (258,742)	-4.71	87.55	1.01
Essential worker status								
Non-essential	-1,904,933*** (195,642)	-18.53	91.04	1.33	-661,845*** (219,246)	-6.44	97.53	1.43
Partially essential	-221,451*** (74,498)	-11.60	10.58	0.83	-84,542 (78,413)	-4.43	12.46	0.98
Essential	33,964 (108,298)	1.19	-1.62	-0.09	67,748 (100,644)	2.37	-9.98	-0.53

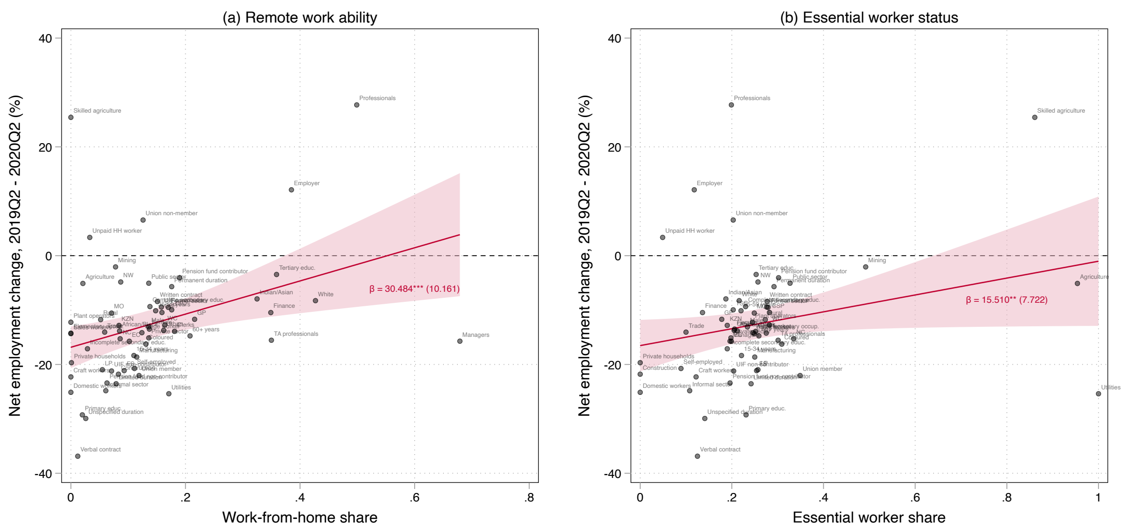
[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2022d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Job loss burden ratio for a given period = ratio of a given group's share of net employment change to the group's pre-pandemic (2019) employment share. Differences estimated using adjusted Wald tests. Estimates may not sum to total due to missing data. *** p<0.01, ** p<0.05, * p<0.10.

changed.

Also discussed in Chapter 2, the international literature also shows that inequalities in job loss probabilities across groups of varying demographic or labour market characteristics has been largely attributed to inequalities in remote work ability and 'essential' worker status. To examine whether this holds in the South African context, in Figure 3.5 I present scatterplots of each worker group's net employment change at the pandemic's onset against their shares who can work remotely and are regarded as 'essential'. In both cases, I estimate a statistically significant and positive relationship with job loss, indicating that groups with larger shares of workers who could work remotely or who regarded as 'essential' tended to experience less severe rates of job loss.[20] Interestingly, the magnitude of the coefficient from a simple OLS bi-variate regression in panel (a) is twice as large as that in panel (b), indicating that remote work ability is a stronger predictor of job loss. Overall, these estimates indeed suggest that inequalities in job loss probabilities across worker groups in South Africa can at least partially be explained by differences in remote work ability and 'essential' worker status, in line with the international literature.

[20]These relationships hold if each group's share of total net employment change or job loss burden ratio are used as alternatives to their net employment change. Moreover, the relationship is panel (b) remains positive, significant, and becomes slightly stronger if potential outliers - the skilled agriculture occupation, the agriculture industry, and the utilities industry - are excluded.

Figure 3.5: Group-specific net employment change by remote work ability and essential worker status, 2019Q2 - 2020Q2



[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2 (Statistics South Africa, 2019b, 2020b).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Sample restricted to those of working age.

3.4.3 Between-group variation in working hours

In this third section, I provide disaggregated estimates of cross-sectional and temporal variation in the intensive margin outcome of interest – mean working hours – for the three described sub-groups. I use "actual" weekly working hours for a worker's main job, as discussed in Section 4.1. As before, I focus on Q2 data over four years to account for seasonality, examine estimates in both absolute and relative terms, and again focus on two distinct periods: 2019 vs. 2020 and 2019 vs. 2022. I again begin with demographic characteristics and thereafter consider employment and labour market institutional characteristics.

3.4.3.1 Demographic characteristics

Table 3.10 presents mean weekly working hours for the employed by demographic group from 2019 to 2022 and estimated changes for the two mentioned periods. By sex, both men and women saw reductions from 2019 to 2020. Women's reduction was greater in absolute (8 vs. 6.8 hours) and relative terms (20.2 percent vs. 15.2 percent), a highly statistically significant difference. This is despite women working 5 fewer hours per week before the pandemic. As documented in Chapter 2, this larger adjustment among women is consistent with the NIDS-CRAM data (Casale & Posel, 2021; Casale & Shepherd, 2022; Daniels & Casale, 2022; Mosomi & Thornton, 2022) as well as the international literature (for instance, see Collins et al., 2021; Craig & Churchill, 2021; McDermott & Hansen, 2021; Couch et al., 2022; Hanzl & Rehm, 2023). By 2022, their hours had recovered to pre-pandemic levels, while that of men remained 1 hour (2 percent) lower, a significant difference. Unlike these disparities, I find no significant differences are evident across age groups. Youth workers (15-34 years) worked more hours before the pandemic, with reductions of 7.3 to 7.5 hours (16.8 to 18.7 percent) from 2019 to 2020, however not statistically significant. By 2022, the working hours of youth and workers aged 35 to 59 years remained at least half an hour (1.3 to 1.5 percent) below pre-pandemic levels on average. Workers aged 60 years and older had a negative but statistically insignificant change, possibly due to a small sub-sample size.[21]

Across racial groups, Coloured workers suffered the largest reductions at the pandemic's onset, despite already exhibiting the lowest number of hours on average before the pandemic. From 2019 to 2020, these workers experienced a 23 percent reduction (9.5 hours). Other groups also saw significant reductions ranging from 13.4 to 17.2 percent. By 2022, Coloured workers' hours returned to pre-pandemic levels, but White and African/Black workers remained 2.4 percent and 1.6 percent below their respective levels. By education level, I observe an inverse U-shaped pattern in working hour losses from 2019 to 2020. Workers with primary education or less experienced a 20 percent reduction on average, just slightly more than post-secondary-educated workers (18.2 percent). Pre-pandemic, both groups worked similar hours. By 2022, the pattern shifted, with primary education or less experiencing the most significant decrease (4.4 percent, 1.8 hours per week, significant at 1 percent) compared to 2.2 percent, 1.2 percent, and 0.1 percent cumulative reductions for incomplete secondary education, complete secondary education, and post-secondary education workers, respectively. The latter however isn't statistically significant, suggesting a full recovery of working hours for this group only.

In terms of geographic residence, both urban and rural workers saw significant working hour losses from 2019 to 2020 of similar magnitudes (7.3 and 7.5 hours per week, respectively) and relative changes (17.2 percent and 17.5 percent, respectively). This trend persisted over time; by 2022, both groups had recovered somewhat but still worked 1.2 to 2.1 percent fewer hours relative to pre-pandemic levels. I observe substantial variation in working hour changes across provinces. All saw statistically significant reductions, with Mpumalanga and the North West experiencing the largest losses of approximately 23 percent or nearly 10 hours per week each. In contrast, Limpopo, the Northern Cape, and Gauteng had smaller but still significant reductions of 13.4 percent, 14.3 percent, and 15.2 percent, respectively. By 2022, only five of the nine provinces had mean working hour levels statistically similar to pre-pandemic levels. Exceptions, in order of relative reductions from pre-pandemic levels, include the Eastern Cape (5.2 percent), North West (3.6 percent), Mpumalanga (3 percent), and Limpopo (2.7 percent), with the latter two estimates being only marginally significant.

3.4.3.2 Employment characteristics

I now consider cross-sectional mean weekly working hour estimates as well as the estimated changes by employment characteristic. As shown in Table 3.11, workers in the secondary

[21] In the second quarter of 2019 (2022), n = 574 (369) for workers aged at least 60 years with non-missing actual working hour data, in contrast to n = 6 347 (4 426) for youth and n = 10 493 (8 151) for workers aged between 35 and 59 years.

Table 3.10: Mean levels and changes in weekly working hours by demographic group, 2019 - 2022

	2019	2020	2021	2022	Change 2019-2020 Absolute	Change 2019-2020 %	Change 2019-2022 Absolute	Change 2019-2022 %
Total	42.35	35.03	42.06	41.75	-7.31***	-17.26	-0.59***	-1.39
	(0.13)	(0.28)	(0.16)	(0.15)	(0.29)		(0.19)	
Gender								
Male	44.37	37.61	43.99	43.49	-6.76***	-15.24	-0.88***	-1.98
	(0.17)	(0.35)	(0.21)	(0.20)	(0.37)		(0.25)	
Female	39.74	31.71	39.54	39.58	-8.03***	-20.21	-0.16	-0.40
	(0.17)	(0.35)	(0.22)	(0.20)	(0.38)		(0.25)	
Age (years)								
15-34	43.22	35.99	42.58	42.59	-7.24***	-16.75	-0.63**	-1.46
	(0.20)	(0.45)	(0.28)	(0.24)	(0.48)		(0.30)	
35-59	41.91	34.61	41.88	41.37	-7.30***	-17.42	-0.54**	-1.29
	(0.16)	(0.32)	(0.19)	(0.18)	(0.35)		(0.23)	
60+	40.30	32.78	39.95	39.36	-7.52***	-18.66	-0.94	-2.33
	(0.71)	(1.34)	(0.77)	(0.85)	(1.47)		(1.12)	
Race								
African/Black	42.51	35.22	42.14	41.83	-7.29***	-17.15	-0.68***	-1.60
	(0.15)	(0.31)	(0.19)	(0.18)	(0.33)		(0.22)	
Coloured	41.20	31.69	41.07	41.10	-9.51***	-23.08	-0.1	-0.24
	(0.34)	(0.87)	(0.51)	(0.37)	(0.88)		(0.45)	
Indian/Asian	43.50	37.67	44.31	44.44	-5.83***	-13.40	0.93	2.14
	(0.68)	(1.16)	(0.70)	(0.80)	(1.35)		(1.03)	
White	41.96	35.89	41.74	40.94	-6.07***	-14.47	-1.02**	-2.43
	(0.32)	(0.83)	(0.46)	(0.42)	(0.86)		(0.52)	
Highest education								
Primary	40.88	32.70	39.95	39.08	-8.17***	-19.99	-1.79***	-4.38
	(0.38)	(0.87)	(0.57)	(0.55)	(0.90)		(0.64)	
Secondary incomplete	42.65	35.49	42.16	41.72	-7.16***	-16.79	-0.93***	-2.18
	(0.24)	(0.48)	(0.30)	(0.28)	(0.51)		(0.36)	
Secondary complete	43.33	36.36	42.97	42.82	-6.97***	-16.09	-0.51*	-1.18
	(0.19)	(0.39)	(0.25)	(0.22)	(0.43)		(0.29)	
Post-secondary	40.99	33.53	41.40	41.03	-7.46***	-18.20	0.04	0.10
	(0.20)	(0.52)	(0.24)	(0.23)	(0.56)		(0.31)	
Area								
Rural or traditional	42.48	35.02	41.96	41.57	-7.46***	-17.56	-0.91**	-2.14
	(0.30)	(0.62)	(0.35)	(0.34)	(0.65)		(0.41)	
Urban	42.30	35.04	42.09	41.81	-7.27***	-17.19	-0.50**	-1.18
	(0.14)	(0.31)	(0.19)	(0.17)	(0.33)		(0.21)	
Province								
Western Cape	41.96	34.39	41.57	41.71	-7.57***	-18.04	-0.25	-0.60
	(0.32)	(0.83)	(0.44)	(0.38)	(0.82)		(0.47)	
Eastern Cape	42.10	34.26	39.74	39.91	-7.84***	-18.62	-2.19***	-5.20
	(0.50)	(1.02)	(0.58)	(0.51)	(1.03)		(0.69)	
Northern Cape	39.05	33.49	40.58	39.63	-5.57***	-14.26	0.58	1.49
	(0.71)	(1.39)	(0.77)	(0.74)	(1.45)		(0.95)	
Free State	40.17	33.01	40.17	40.64	-7.15***	-17.80	0.47	1.17
	(0.51)	(1.10)	(0.62)	(0.67)	(1.21)		(0.82)	
KwaZulu-Natal	43.22	35.93	43.31	43.15	-7.29***	-16.87	-0.07	-0.16
	(0.35)	(0.65)	(0.43)	(0.39)	(0.69)		(0.47)	
North West	42.01	32.33	42.08	40.47	-9.68***	-23.04	-1.53**	-3.64
	(0.54)	(1.33)	(0.55)	(0.53)	(1.40)		(0.74)	
Gauteng	42.60	36.11	42.48	42.31	-6.49***	-15.23	-0.29	-0.68
	(0.22)	(0.49)	(0.30)	(0.28)	(0.54)		(0.34)	
Mpumalanga	41.98	32.11	41.56	40.72	-9.87***	-23.51	-1.25*	-2.98
	(0.48)	(0.87)	(0.52)	(0.61)	(0.90)		(0.73)	
Limpopo	43.20	37.40	43.12	42.04	-5.80***	-13.43	-1.16*	-2.69
	(0.48)	(0.78)	(0.64)	(0.58)	(0.88)		(0.69)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).

[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Differences estimated using adjusted Wald tests. *** p<0.01, ** p<0.05, * p<0.10.

and tertiary sectors saw the largest reductions in mean working hours at the pandemic's onset, both in absolute (7.5 and 7.6 hours per week) and relative terms (18 percent each). The secondary sector's contraction was driven by construction and manufacturing workers, with the former decreasing slightly more (20.7 percent vs. 17 percent). The utilities industry showed no statistically significant reduction on average. In the tertiary sector, CSP services and trade workers had notable reductions of 23.2 percent (9.1 hours per week) and 18.4 percent (8.5 hours) on average, although all industries in the sector experienced significant reductions. Primary sector workers saw a 10.3 percent reduction, driven by mining and quarrying (16.7 percent or 7.3 hours) and agriculture (7.4 percent or 3.3 hours). By 2022, working hours in all industries had mostly returned to pre-pandemic levels, except for finance and private households which decreased by about 3 percent, with the latter being only marginally statistically significant.

By skill-level, all workers experienced similar reductions in working hours in both magnitude and statistical significance. Less-skilled workers saw an 18.3 percent decrease (7.2 hours), high-skilled workers 18 percent (7.7 hours), and semi-skilled workers 16.7 drop (7.3 hours). Among high-skilled workers, professionals' hours contracted by over 21 percent while legislators, senior officials, and managers' hours reduced by 14.2 percent. Within semi-skilled workers, the largest adjustments were experienced by technical and associate professionals (19.7 percent or 7.9 hours), clerks (19.1 percent or 7.4 hours), and craft and related trades workers (18.3 percent or 7.6 hours). Mean working hours in all occupations within this group significantly decreased, with that of skilled agricultural workers however being only marginally significant. Among less-skilled workers, elementary occupations saw an 18.1 percent reduction (7.3 hours) and domestic workers a slightly larger 21 percent reduction (7.3 hours). This adjustment, along with professional occupations, marked the largest contraction across industries during this period. By 2022, nearly all groups except service and sales workers (4.9 percent or 2.3 hours below) and domestic workers (4.9 percent or 1.7 hours below) had returned to pre-pandemic working hour levels.

Regarding formality, similar to aggregate net employment trends, informal sector workers were most impacted on the intensive margin, in line with the international literature (for instance, see Krafft et al., 2021). Pre-pandemic, informal sector workers averaged 1.14 more hours per week than formal sector workers. At the pandemic's onset, informal workers saw a 19 percent reduction (8.3 hours) compared to a 17 percent reduction (7.3 hours per week) for formal workers. These contractions, however, are not statistically different from each other. By 2022, informal sector workers worked 2.6 percent fewer hours, while formal sector workers worked 1.1 percent fewer, but these differences remain statistically insignificant. Overall then, the pandemic led to similar working hour adjustments for both sectors on average, but informal workers were marginally more severely affected in magnitude, both immediately and in the medium-term.

Table 3.11: Mean levels and changes in weekly working hours by employment characteristic, 2019 - 2022

	2019	2020	2021	2022	Change 2019-2020 Absolute	Change 2019-2020 %	Change 2019-2022 Absolute	Change 2019-2022 %
Total	42.35	35.03	42.06	41.75	-7.31***	-17.26	-0.59***	-1.39
	(0.13)	(0.28)	(0.16)	(0.15)	(0.29)		(0.19)	
Industry								
Primary	44.32	39.73	44.47	43.68	-4.58***	-10.33	-0.64	-1.44
	(0.37)	(0.84)	(0.45)	(0.46)	(0.90)		(0.57)	
Agriculture	44.47	41.18	44.46	44.27	-3.29***	-7.40	-0.20	-0.45
	(0.46)	(0.99)	(0.58)	(0.58)	(1.04)		(0.71)	
Mining	43.98	36.65	44.47	42.42	-7.33***	-16.67	-1.56	-3.55
	(0.65)	(1.28)	(0.69)	(0.75)	(1.54)		(0.96)	
Secondary	41.51	34.04	40.67	41.07	-7.47***	-18.00	-0.45	-1.08
	(0.20)	(0.52)	(0.30)	(0.27)	(0.55)		(0.33)	
Manufacturing	42.32	35.14	41.68	42.09	-7.18***	-16.97	-0.24	-0.57
	(0.23)	(0.68)	(0.37)	(0.32)	(0.71)		(0.40)	
Utilities	41.87	38.85	41.35	43.43	-3.02	-7.21	1.56	3.73
	(0.70)	(1.89)	(1.44)	(0.97)	(2.06)		(1.15)	
Construction	40.41	32.03	39.43	39.56	-8.38***	-20.74	-0.86	-2.13
	(0.36)	(0.83)	(0.46)	(0.48)	(0.88)		(0.58)	
Tertiary	42.37	34.76	42.14	41.70	-7.61***	-17.96	-0.67***	-1.58
	(0.16)	(0.32)	(0.20)	(0.18)	(0.34)		(0.23)	
Trade	46.03	37.58	45.43	45.42	-8.45***	-18.36	-0.61	-1.33
	(0.29)	(0.55)	(0.37)	(0.35)	(0.61)		(0.46)	
TSC	48.97	41.54	49.09	49.15	-7.43***	-15.17	0.18	0.37
	(0.56)	(1.16)	(0.70)	(0.68)	(1.23)		(0.89)	
Finance	43.80	38.19	43.63	42.53	-5.62***	-12.83	-1.28***	-2.92
	(0.31)	(0.55)	(0.35)	(0.34)	(0.61)		(0.45)	
CSP services	39.06	30.00	39.26	38.97	-9.06***	-23.20	-0.09	-0.23
	(0.23)	(0.53)	(0.26)	(0.25)	(0.56)		(0.33)	
Private households	33.94	28.27	33.40	32.78	-5.67***	-16.71	-1.16*	-3.42
	(0.40)	(0.94)	(0.55)	(0.49)	(0.98)		(0.62)	
Occupation								
High-skilled	42.59	34.91	42.69	42.21	-7.68***	-18.03	-0.38	-0.89
	(0.30)	(0.65)	(0.34)	(0.31)	(0.71)		(0.43)	
Managers	44.32	38.06	43.95	44.30	-6.27***	-14.15	-0.02	-0.05
	(0.39)	(0.82)	(0.50)	(0.46)	(0.90)		(0.59)	
Professionals	39.43	31.13	40.91	39.96	-8.30***	-21.05	0.53	1.34
	(0.37)	(0.83)	(0.38)	(0.39)	(0.88)		(0.53)	
Semi-skilled	43.83	36.53	43.71	43.25	-7.30***	-16.66	-0.58**	-1.32
	(0.16)	(0.34)	(0.21)	(0.20)	(0.36)		(0.24)	
TA professionals	40.31	32.39	40.54	40.64	-7.92***	-19.65	0.33	0.82
	(0.32)	(0.77)	(0.33)	(0.37)	(0.81)		(0.49)	
Clerks	41.78	33.81	41.08	42.05	-7.97***	-19.08	0.27	0.65
	(0.25)	(0.62)	(0.29)	(0.26)	(0.66)		(0.36)	
Service workers	47.11	39.71	46.95	44.81	-7.40***	-15.71	-2.29***	-4.86
	(0.32)	(0.63)	(0.43)	(0.40)	(0.70)		(0.50)	
Skilled agriculture	49.50	42.26	46.82	46.02	-7.24*	-14.63	-3.48	-7.03
	(2.05)	(3.13)	(2.55)	(1.44)	(3.73)		(2.59)	
Craft	41.70	34.06	41.15	41.01	-7.64***	-18.32	-0.69	-1.65
	(0.29)	(0.67)	(0.40)	(0.45)	(0.70)		(0.52)	
Plant operators	46.43	40.71	47.35	46.99	-5.72***	-12.32	0.56	1.21
	(0.40)	(0.82)	(0.54)	(0.46)	(0.87)		(0.60)	
Less-skilled	39.32	32.12	38.78	38.64	-7.20***	-18.31	-0.68*	-1.73
	(0.25)	(0.50)	(0.30)	(0.28)	(0.53)		(0.35)	
Elementary occup.	40.58	33.23	40.05	39.98	-7.34***	-18.09	-0.60	-1.48
	(0.28)	(0.56)	(0.34)	(0.31)	(0.59)		(0.40)	
Domestic workers	34.60	27.34	33.65	32.91	-7.27***	-21.01	-1.69**	-4.88
	(0.43)	(0.96)	(0.61)	(0.54)	(0.99)		(0.69)	
Formality								
Formal sector	42.80	35.54	42.59	42.36	-7.27***	-16.99	-0.45**	-1.05
	(0.13)	(0.31)	(0.16)	(0.15)	(0.32)		(0.19)	
Informal sector	43.94	35.61	43.71	42.79	-8.34***	-18.98	-1.15*	-2.62
	(0.39)	(0.68)	(0.49)	(0.47)	(0.74)		(0.59)	
Private households	33.94	28.27	33.40	32.78	-5.67***	-16.71	-1.16*	-3.42
	(0.40)	(0.94)	(0.55)	(0.49)	(0.98)		(0.62)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).

[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. TSC = transport, storage and communication; CSP = community; social and personal services; TA = technical and associate; managers = legislators, senior officials, and managers; occup. = occupations. Industries and occupations classified as 'other' are excluded for brevity. Differences estimated using adjusted Wald tests. *** p<0.01, ** p<0.05, * p<0.10.

3.4.3.3 Labour market institutional characteristics

I now examine the cross-sectional and temporal change estimates in mean weekly working hours by labour market institution, presented in Table 3.12. By sector, there were significant reductions in working hours for both public and private sector workers at the pandemic's onset. Public sector workers however experienced a more severe decline (20.8 percent, 7.9 hours) compared to private sector workers (16.3 percent, 7.1 hours), despite the private sector being primarily affected by net employment changes. Interestingly, by 2022, public sector workers had returned to pre-pandemic working hours, while private sector workers remained 1.5 percent (0.6 hours per week) below pre-pandemic levels. However, the differences in sector contractions is not statistically significant for either the 2019-2020 or 2019-2022 periods. Regarding trade union membership, both members and non-members experienced significant working hour reductions, with non-members facing a greater decrease from 2019 to 2020 (17.3 percent vs. 13.9 percent). By 2022, unionised workers had recovered to pre-pandemic levels, but non-members remained over 1.5 percent below. Given the positive correlation between union membership and sector in the South African labour market described in the previous section, it is not surprising that both union non-members and private sector workers experienced similar trajectories in working hours during the period.

Unpaid household workers saw the most significant working hour reduction from 2019 to 2020, with an average decrease of 33.4 percent (14.2 hours or approximately two full-time days' worth). Other worker types also experienced statistically significant reductions but not as pronounced as unpaid household workers. Employers had a substantial contraction of nearly 27 percent (12.2 hours per week), followed by self-employed individuals (20.1 percent, 8.6 hours per week), and wage workers (16 percent, 6.7 hours per week), the latter of whom represent the majority of workers (see Section 3.4.2). By 2022, unpaid household workers and employers had returned to pre-pandemic levels, while wage workers and the self-employed remained 1.1 percent and 3.6 percent below theirs.

Unlike relationship type differences, contract type showed similar reductions for workers of either written or verbal contracts. Workers with written or verbal contracts saw reductions of 16.3 and 15 percent, or 6.9 and 6.2 hours, respectively. Notably, by 2022 only workers with verbal contracts remained below pre-pandemic levels by 3 percent (1.3 hours). With respect to contract duration, limited-duration contract workers suffered the most with a 22 percent reduction (8.6 hours). Permanent and 'casual' workers also experienced significant but less severe contractions of 15.4 and 15.8 percent, respectively. By 2022, only 'casual' workers' hours remained below pre-pandemic levels, by 2.5 percent (1.1 hours) on average, while other workers had recovered.

Similar to the aggregate net employment estimates, workers without unemployment insurance faced marginally more substantial effects on the intensive margin. At the pandemic's onset, non-contributing UIF workers experienced an 18.6 percent reduction in weekly hours

(7.4 hours less) while contributing UIF workers saw a 15 percent reduction (6.5 hours less). However, this difference is not statistically significant. In 2022, both groups worked significantly fewer hours relative to before the pandemic, differing by 0.3 to 0.6 hours per week at the 10 percent level. I also observed significant reductions in mean working hours for both pension fund contributors and non-contributors, however the latter experienced a higher reduction (17.7 percent vs. 14.8 percent), statistically significant at the 10 percent level. By 2022, both groups worked fewer hours by a similar magnitude of 0.8 to 1.2 percent, equivalent to about 0.5 fewer hours per week.

As in the case of employment, the international literature highlights that remote work ability and 'essential' worker status served as strong predictors of intensive margin adjustments, including working hours, at the pandemic's onset. Using the same approach as before to identify 'essential' workers and those who could work remotely, Table 3.13 presents the relevant estimates of mean working hour changes. Consistent with the literature, I estimate larger working hour reductions among non-'essential' workers relative to 'essential' workers. I also document a similar reduction among those regarded as 'partially-essential'. At the pandemic's onset, working hours among non-'essential' and 'partially-essential' workers contracted by 22 and 19 percent on average, respectively, compared to a much milder contraction of 8 percent among 'essential' workers. In contrast, I do not find evidence of a difference in working hour adjustments by remote work ability status at the pandemic's onset. Among both those who could and could not work remotely, I estimate significant and similarly-sized average reductions of approximately 17 percent. Similar to employment, while the magnitude of these adjustments reduced over time, its distribution largely persisted. By 2022, the average working hours of non-'essential' workers remained 2 percent below their pre-pandemic level, while those of 'partially-essential' had fully recovered and those of 'essential' workers remained unchanged. On the other hand, the lower hours of those who could not work remotely had only partially recovered while the hours of those who could had fully recovered to their pre-pandemic level, statistically-speaking.

Similar to employment and consistent with the international literature, I find that inequalities in working hour adjustments across worker groups can be at least partially attributed to inequalities in 'essential' worker status. However, I do not find such evidence with respect to remote work ability. In Figure 3.6 I present scatterplots of each worker group's mean working hour change at the pandemic's onset against their shares who can work remotely and are regarded as 'essential'. I estimate a statistically significant and positive relationship with respect to 'essential' worker status, suggesting that groups with larger shares of workers who are regarded as 'essential' tended to experience less severe mean working hour reductions.[22] In contrast, the estimated gradient with respect to remote work ability is relatively flat and statistically insignificant. This is consistent with the estimates in Table 3.13. Overall, this indicates that inequalities in extensive margin adjustments can be explained by differences

[22] Again, this relationship holds if potential outliers - the skilled agriculture occupation, the agriculture industry, and the utilities industry - are excluded.

Table 3.12: Mean levels and changes in weekly working hours by labour market institutional characteristic, 2019 - 2022

	2019	2020	2021	2022	Change 2019-2020 Absolute	Change 2019-2020 %	Change 2019-2022 Absolute	Change 2019-2022 %
Total	42.35	35.03	42.06	41.75	-7.31***	-17.26	-0.59***	-1.39
	(0.13)	(0.28)	(0.16)	(0.15)	(0.29)		(0.19)	
Sector								
Private	43.27	36.20	42.94	42.63	-7.07***	-16.34	-0.64***	-1.48
	(0.15)	(0.30)	(0.19)	(0.17)	(0.32)		(0.22)	
Public	37.94	30.06	37.97	37.80	-7.88***	-20.77	-0.13	-0.34
	(0.24)	(0.56)	(0.28)	(0.25)	(0.59)		(0.33)	
Trade union membership								
Member	42.42	36.52	42.69	42.42	-5.89***	-13.88	0.00	0.00
	(0.17)	(0.41)	(0.21)	(0.19)	(0.43)		(0.25)	
Non-member	41.86	34.65	41.25	41.23	-7.22***	-17.25	-0.63***	-1.51
	(0.16)	(0.36)	(0.21)	(0.19)	(0.38)		(0.24)	
Do not know	43.75	35.75	43.70	42.90	-8.00***	-18.29	-0.85	-1.94
	(0.56)	(1.65)	(0.51)	(0.49)	(1.73)		(0.74)	
Employment relationship type								
Wage worker	42.09	35.35	41.79	41.64	-6.74***	-16.01	-0.45**	-1.07
	(0.13)	(0.28)	(0.16)	(0.14)	(0.30)		(0.18)	
Employer	45.47	33.23	45.84	44.56	-12.24***	-26.92	-0.91	-2.00
	(0.57)	(1.20)	(0.65)	(0.72)	(1.32)		(0.91)	
Self-employed	42.76	34.16	42.26	41.22	-8.60***	-20.11	-1.53*	-3.58
	(0.58)	(0.87)	(0.72)	(0.67)	(0.99)		(0.86)	
Unpaid household	42.47	28.29	39.70	42.69	-14.19***	-33.41	0.22	0.52
	(2.04)	(2.33)	(2.55)	(2.78)	(3.09)		(3.43)	
Contract type								
Verbal	41.51	35.29	39.76	40.26	-6.22***	-14.98	-1.25**	-3.01
	(0.36)	(0.81)	(0.52)	(0.44)	(0.85)		(0.54)	
Written	42.23	35.36	42.19	41.94	-6.88***	-16.29	-0.30	-0.71
	(0.12)	(0.30)	(0.15)	(0.15)	(0.31)		(0.18)	
Contract duration								
Limited	38.62	30.03	38.37	37.89	-8.59***	-22.24	-0.74	-1.92
	(0.34)	(0.80)	(0.45)	(0.36)	(0.83)		(0.47)	
Permanent	42.90	36.30	42.98	42.86	-6.60***	-15.38	-0.04	-0.09
	(0.13)	(0.33)	(0.15)	(0.15)	(0.34)		(0.20)	
Unspecified	41.93	35.30	40.61	40.88	-6.64***	-15.84	-1.06**	-2.53
	(0.30)	(0.65)	(0.39)	(0.36)	(0.68)		(0.45)	
UIF contribution status								
Contributor	43.35	36.83	43.07	43.01	-6.52***	-15.04	-0.34*	-0.78
	(0.13)	(0.32)	(0.17)	(0.16)	(0.34)		(0.21)	
Non-contributor	40.03	32.60	39.53	39.46	-7.43***	-18.56	-0.58*	-1.45
	(0.24)	(0.51)	(0.30)	(0.26)	(0.54)		(0.34)	
Do not know	41.89	34.57	41.45	40.70	-7.32***	-17.47	-1.19	-2.84
	(0.91)	(1.75)	(1.09)	(0.75)	(1.97)		(1.18)	
Pension fund contribution status								
Contributor	42.92	36.57	42.78	42.56	-6.35***	-14.79	-0.36*	-0.84
	(0.14)	(0.35)	(0.17)	(0.16)	(0.36)		(0.21)	
Non-contributor	41.17	33.88	40.75	40.68	-7.29***	-17.71	-0.49*	-1.19
	(0.21)	(0.43)	(0.26)	(0.22)	(0.45)		(0.29)	
Do not know	44.44	34.65	43.41	44.57	-9.79***	-22.03	0.13	0.29
	(0.69)	(1.84)	(0.74)	(0.69)	(1.97)		(0.96)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Differences estimated using adjusted Wald tests. *** p<0.01, ** p<0.05, * p<0.10.

Table 3.13: Year-on-year mean working hours change by remote work ability and essential worker status, 2019 - 2022

	2019	2020	2021	2022	Change 2019-2020 Absolute	Change 2019-2020 %	Change 2019-2022 Absolute	Change 2019-2022 %
Total	42.35	35.03	42.06	41.75	-7.31***	-17.26	-0.59***	-1.39
	(0.13)	(0.28)	(0.16)	(0.15)	(0.29)		(0.19)	
Remote work ability								
Can work-from-home	42.03	34.94	42.05	41.46	-7.09***	-16.87	-0.56	-1.33
	(0.27)	(0.62)	(0.34)	(0.30)	(0.67)		(0.41)	
Cannot work-from-home	42.39	35.05	42.05	41.79	-7.34***	-17.32	-0.60***	-1.42
	(0.14)	(0.30)	(0.18)	(0.17)	(0.31)		(0.21)	
Essential worker status								
Non-essential	40.85	31.91	40.30	40.11	-8.94***	-21.88	-0.73***	-1.79
	(0.17)	(0.36)	(0.21)	(0.19)	(0.38)		(0.24)	
Partially essential	44.95	36.28	45.15	44.67	-8.68***	-19.31	-0.28	-0.62
	(0.35)	(0.81)	(0.44)	(0.42)	(0.84)		(0.54)	
Essential	43.83	40.30	43.54	43.54	-3.53***	-8.05	-0.29	-0.66
	(0.23)	(0.42)	(0.29)	(0.27)	(0.45)		(0.35)	

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Differences estimated using adjusted Wald tests. *** p<0.01, ** p<0.05, * p<0.10.

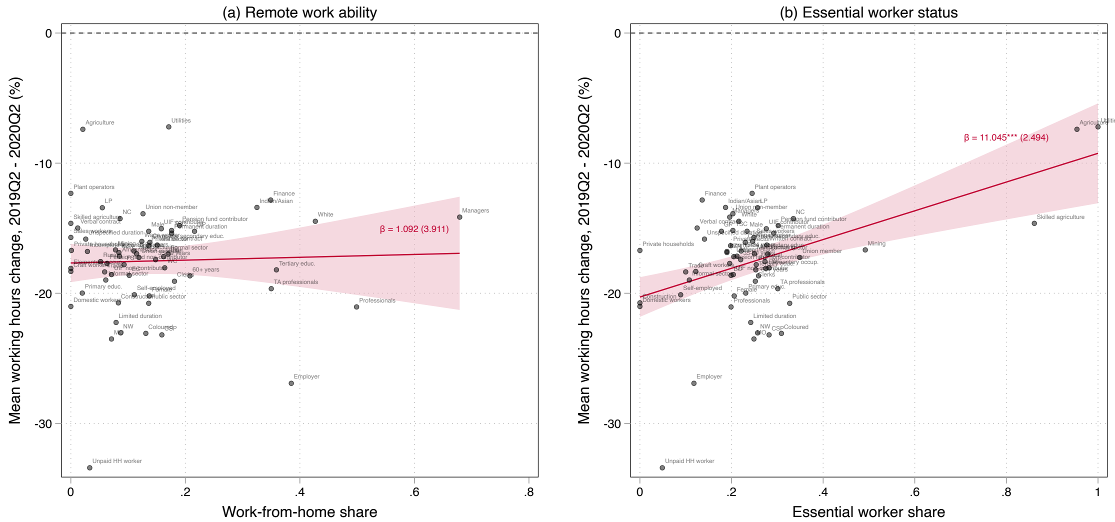
in both remote work ability and 'essential' worker status, but inequalities on the intensive margin (at least with respect to working hours) appear only explained by differences in 'essential' worker status.

3.4.4 Modelling the evolution of outcome determinants

In this section, I present the results from the multivariate non-linear regression models described earlier to examine the pandemic's impact on the determinants of labour market outcomes over time. I present AME estimates obtained from pooled and year-specific probit and negative binomial models of the extensive and intensive margin outcomes, respectively. Together, these models yield nearly 400 estimates. For brevity, I visually present them using coefficient plots but include them in Tables A5, A6, A7, and A8 in the appendix for completeness.[23] Figure 3.7 presents the estimates for demographic factors across all outcomes, excluding labour market covariates in the working hours models which are included in Figure 3.8. Here, "all else equal" is used to refer to the other observable covariates in the model being held constant.

[23]While all models control for province and time fixed effects as discussed in Section 3.3, for brevity I omit these estimates from the coefficient plots, with the exception of the event study models where the coefficients on the time dummies are of central interest. No estimates are omitted from the relevant tables reported in the appendix.

Figure 3.6: Group-specific working hours change by remote work ability and essential worker status, 2019Q2 - 2020Q2



[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2 (Statistics South Africa, 2019b, 2020b).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Sample restricted to those of working age.

3.4.4.1 Labour market participation

Regarding labour market participation in panel (a), correlates remained consistent in sign and statistical significance throughout the pre- and post-pandemic periods. This suggests that the structure of the labour market in terms of participation remained relatively rigid despite the historically large magnitude of the shock. However, the coefficients on certain covariates changed in magnitude. Notably, men, younger individuals, those with higher education, urban residents, married or cohabiting individuals, and African/Black and Coloured individuals exhibited higher probabilities of participation both before and after the pandemic. Age was the strongest predictor. Pre-pandemic, prime-age individuals (35-59 years) were 42.1 percentage points more likely to participate than those aged 60 or older, followed by youth who were 22.6 percentage points more likely, all else equal. These estimates slightly reduced immediately after the pandemic but remained statistically similar. Subsequently, they increased by about five percentage points each, significantly differing from 2019 at the 1 percent level in both cases.

By education, I estimate a clear positive gradient with respect to participation. In 2019, compared to individuals with primary education or less, those with incomplete secondary, complete secondary, and post-secondary education had 6.4, 21.1, and 37 percentage point higher participation probabilities, respectively, all else equal. At the pandemic's onset in 2020, these estimates remained constant or slightly decreased but thereafter, like age, increased to 6.8, 22.9, and 39.6 percentage points, respectively, with the first two being statistically significant changes. In contrast, the coefficients on the married and urban indicators remained positive and significant but reduced over time. In 2019, married individuals had a 12.2 percentage point higher participation probability than the unmarried, reducing to 10.9 percentage points from 2020 to 2022, a statistically significant change. Similarly, urban individuals had an 8.6 percentage point higher participation probability than their rural counterparts in 2019, decreasing to 5.1 percentage points in 2020 but rising to 7.2 percentage points by 2022.

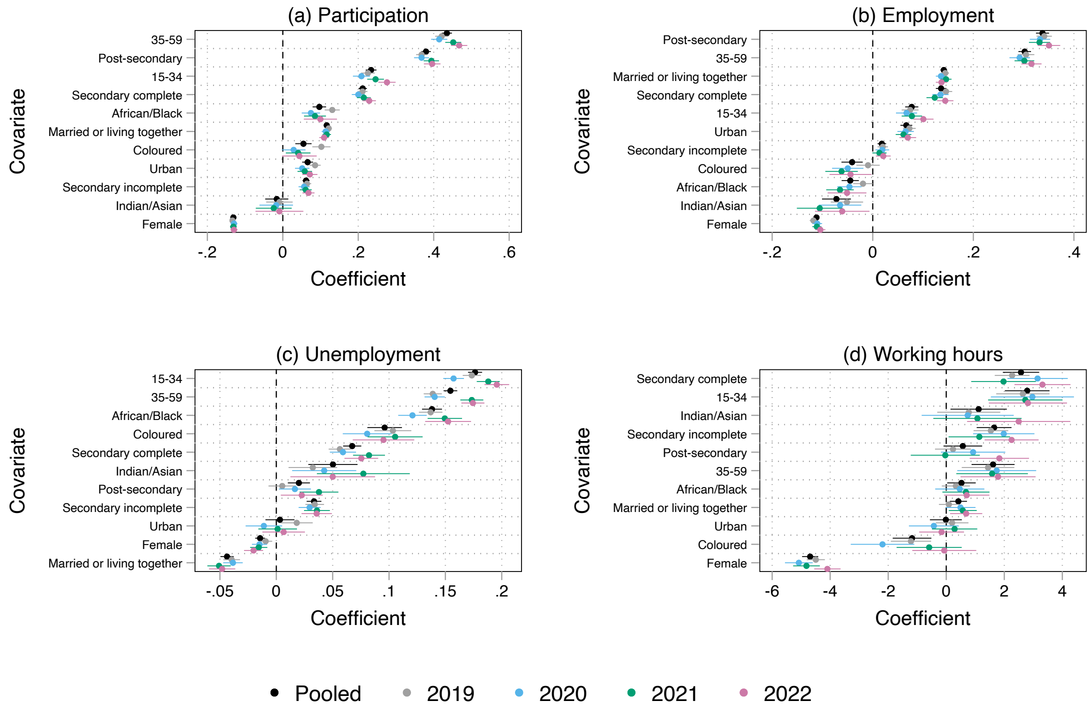
Regarding gender and race, the female indicator's coefficient remained constant throughout the period with respect to sign, magnitude, and significance. Throughout the period, women were 13 percentage points less likely to participate than men on average. Notably, these estimates are very precise (standard errors ranging from 0.004 to 0.005). By race, before the pandemic African/Black and Coloured individuals were statistically more likely to participate in the labour market by 13.1 and 10.2 percentage points compared to White individuals. Indian/Asian individuals had similar probabilities to White individuals. At the pandemic's onset, the strength of the African/Black coefficient decreased by about half to 7.4 percentage points but remained statistically significant, and increased to 10 percentage points two years later. Coloured individuals' conditional probabilities followed a similar but more severe trajectory, decreasing by nearly 72 percent to 2.9 percentage points in 2020 and increasing to 4.4 percentage points by 2022. Throughout, Indian/Asian individuals had similar conditional participation probabilities to White individuals.

3.4.4.2 Employment

Regarding employment (panel b), similar to participation, the correlates remained consistent in sign and statistical significance throughout the pre- and post-pandemic periods, with slight changes in covariate magnitudes. Before and after the pandemic, men, younger individuals (relative to those aged at least 60 years), those who have higher levels of education, those who reside in urban areas, and those who are married or living together with a partner were associated with a higher probability of employment. This closely resembles the predictors of participation, except for race. While African/Black and Coloured individuals had higher conditional participation probabilities than their White and Indian/Asian counterparts, White individuals had significantly higher employment probabilities than all other groups, with some variation post-pandemic. Pre-pandemic, White individuals were 2 and 5 percentage points more likely to be employed than African/Black and Indian/Asian individuals, respectively, and had similar employment probabilities to Coloured individuals. From 2020 onwards this relative difference grew to 4.6 to 6.5 percentage points with respect to African/Black individuals and 6.1 to 10.5 percentage points for Indian or Asian individuals. Moreover, a statistically significant difference of 5 percentage points with respect to Coloured individuals emerged in 2020 and persisted over time.

Education remains the strongest predictor of employment among the covariates here, both before and after the pandemic. Individuals with a post-secondary education had a 33

Figure 3.7: Coefficient plot of average marginal effect estimates of demographic covariates on labour market outcomes: 2019 - 2022



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Spikes represent 95 percent confidence intervals. Sample restricted to those of working age. Average model effect estimates presented. All models control for province fixed effects. Pooled model controls for year-quarter fixed effects and year-specific models control for quarter fixed effects. Reference groups for categorical variables as follows: White, 60+ years, primary education or less.

to 35 percentage point higher conditional employment probability relative to individuals with a primary education level or less, while those with complete secondary education had a 12 to 15 percentage point higher probability. The difference between primary education or less and incomplete secondary education was statistically significant, but very small (1-2 percentage points). Unlike the participation estimates, I find no evidence that the pandemic affected these education-related returns; the order and magnitudes of education estimates persistent throughout the period, with no significant differences between before and after the pandemic.

Considering other covariates, like the participation estimates, I find a persistent gender gap in conditional employment probabilities. On average, women were 10 to 12 percentage points less likely to be employed than men, a highly statistically significant relationship throughout the period. However, this gap reduced marginally after the pandemic's onset, from 2019 to 2020 (11.8 to 11 percentage points, significant at the 5 percent level) and further to 10.4 percentage points by 2022. Although these changes are marginal, they are suggestive of an improvement in women's employment prospects which cannot be accounted for by inter-gender differences in age, race, education, area of residence, or marital status. On this latter covariate, I estimate a persistent, unchanged significant conditional employment probability gap. Married individuals were 14 percentage points more likely to be employed than unmarried ones on average, both before and during the pandemic. A rural-urban gap also persists, with individuals in urban areas being 6 to 7 percentage points more likely to be employed. Differences in this gap over time are not significant at any conventional level. Lastly, unsurprisingly, individuals younger than 60 years were consistently more likely to be employed than their older counterparts. Prime-aged individuals (35 to 59 years) exhibited between 29 and 32 percentage points higher conditional employment probabilities. The youth were much less likely than this group to be employed, however over the period this gap reduced. From 2019 to 2021, the youth were just 7 to 8 percentage points more likely to be employed than those aged 60 years and above, but in 2022 this probability grew to over 10 percentage points – a statistically significant difference. From 2020, the conditional employment probabilities among prime-aged individuals also grew, but only marginally.

3.4.4.3 Unemployment

Regarding unemployment in panel (c), it should first be noted that, with the narrow definition used, these estimates pertain to labour market participation through job search, not inactivity or discouragement. Most correlates again remained consistent in sign and statistical significance over the period both before and after the pandemic's onset. Some estimates gained or lost significance, while few experienced a marginal growth in magnitude. Throughout the period, men, younger individuals, individuals of all other racial groups relative to White individuals, and non-married individuals were more likely to be unemployed and actively searching. I observe interesting variation in these probabilities by education level both within and across periods. In 2019, those with a post-secondary education had similar conditional unemployment probabilities as their primary-level counterparts, while those with an incomplete or complete secondary education were 3 to 6 percentage points more likely to be unemployed. This can at least partially be explained by the prior observation that post-secondary individuals are significantly more likely to be employed than other groups, as observed in panel (b), and hence less likely to be searching for work, while 'primary level or less' individuals are among the least likely to participate in the labour market, as observed in panel (a). The pandemic's onset in 2020 mostly kept these estimates constant, except for post-secondary education which grew slightly in magnitude and became significant. This estimate grew even larger one year later, with post-secondary education individuals being nearly 4 percentage points more likely to be unemployed and searching for work compared to their primary-level counterparts. Conditional probabilities for those with a complete secondary education also increased, likely due to a relatively unchanged employment probability as shown in panel (a). By 2022, these conditional probabilities decreased slightly in magnitude but remained statistically larger than pre-pandemic levels.

Regarding gender, women consistently show slightly lower but statistically significant conditional unemployment probabilities compared to men. Before the pandemic, this gender gap was just under 1 percentage point, increasing to 1.5 points at the pandemic's onset (a significant difference at the 5 percent level). From 2020 to 2022, it grew further to 2 percentage points, double its pre-pandemic size. This aligns with the increased conditional employment probabilities for women in panel (c), again indicative of improved labour market prospects for women post-2020. In terms of race, African/Black individuals exhibited the highest conditional unemployment probability, followed by Coloured and Indian/Asian individuals. This ranking persisted throughout the pandemic, however the trajectories of the coefficients varied. At the pandemic's onset in 2020, African/Black and Coloured individuals' probabilities decreased from 14 to 12 and 10 to 8 percentage points, respectively, with both differences being statistically significant at the 1 percent level. This trajectory appears however short-lived. From 2020 to 2022, both groups' probabilities returned to their pre-pandemic levels.

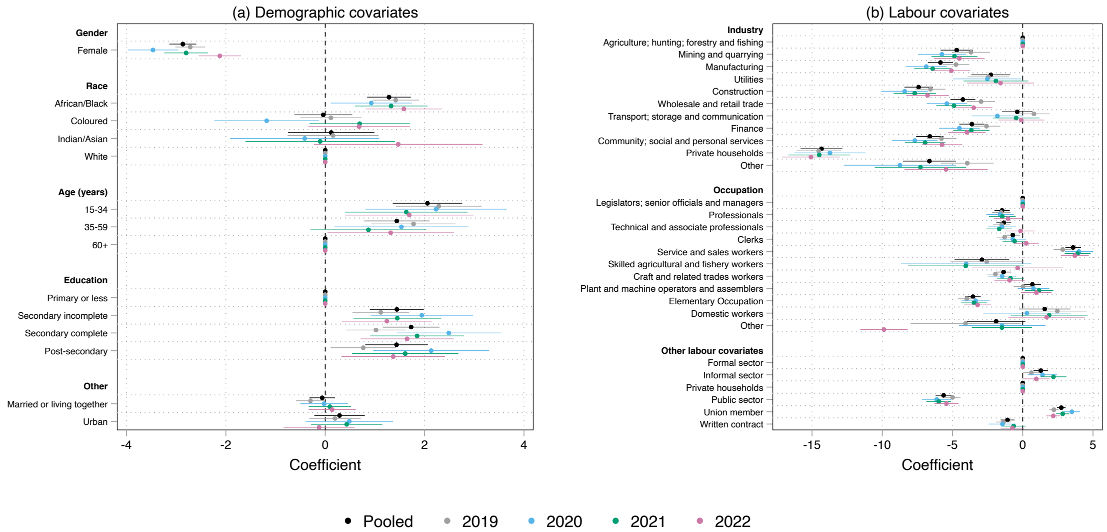
The youth consistently exhibited higher conditional unemployment probabilities than other age groups, a gap which widened post-pandemic. Pre-pandemic, they were 17.3 percentage points more likely to be unemployed compared to those aged 60 years or more, while prime-aged individuals were 14 percentage points more likely. After the pandemic's onset, this latter probability remained unchanged while that of youth's decreased to 15.7 percentage points (a significant difference). This may reflect a transition for many youth individuals from searching unemployment into inactivity rather than into employment, given the group's constant employment probability coupled with a reduced participation probability, as shown in panels (a) and (b). Subsequently, youth's relative unemployment probability surpassed its pre-pandemic level and grew to nearly 20 percentage points by 2022, accompanied by a similar growth for prime-aged individuals. Both groups saw conditional employment and participation probability increases, indicative of both rising job search and gain.

Regarding the remaining covariates, married individuals consistently had lower conditional unemployment probabilities than unmarried individuals throughout the period, with a relatively stable difference of 4 to 5 percentage points. On the other hand, during the pandemic, there was no significant difference between urban and rural individuals. Prior to the pandemic, urban individuals were about 2 percentage points more likely to be unemployed compared to rural individuals, all else equal. This difference disappeared from 2020 to 2022. This suggests that the drop in urban participation from 2019 to 2020 was driven by reduced job search activity.

3.4.4.4 Working hours

Finally, I examine the correlates of the intensive margin outcome of interest – working hours – in panel (d). I regress the outcome on the same vector demographic covariates as before, but additionally I include the vector of observable labour market covariates $\boldsymbol{L_{it}}$ as described in Section 3.3. As before, these coefficients are presented visually in coefficient plots in Figure 3.8. Not accounting for $\boldsymbol{L_{it}}$ results in larger coefficients for most common covariates, as expected, given their association with working hours in the South African literature (Yu &

Figure 3.8: Coefficient plots of average marginal effect estimates of demographic and labour market covariates on working hours: 2019 - 2022



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Spikes represent 95 percent confidence intervals. Sample restricted to those of working age. Average model effect estimates presented. All models control for province fixed effects. Pooled model controls for year-quarter fixed effects and year-specific models control for quarter fixed effects. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Agricultural industry, Managers occupation group, Formal sector (including agriculture).

Bosch, 2012). First regarding gender, before the pandemic, women worked 4.5 fewer hours per week than men, controlling for demographic covariates. After including $\boldsymbol{L_{it}}$, this gap reduces to 2.7 hours but remained statistically significant. At the pandemic's onset in 2020, this conditional gap briefly increased to 3.5 percentage points and thereafter declined, approaching but not reaching gender parity. By 2022, the gap was 22 percent lower than the pre-pandemic level at 2.1 fewer hours weekly. Despite differences in the estimate before and after controlling for $\boldsymbol{L_{it}}$, the gender gap trajectories are similar. For the remainder of the analysis of the correlates of working hours, I focus on the conditional estimates from these latter models.

By race, before the pandemic Coloured, Indian/Asian, and White workers had statistically similar conditional weekly hours, while African/Black workers worked approximately 1.4 hours more, all else equal. In 2020, this difference reduced but wasn't statistically significant. Coloured workers averaged 1.2 hours less than White workers, significant at the 5 percent level. One year later, this difference however became insignificant. By 2022, the Indian/Asian indicator grew and became marginally significant. Regarding age, I observe a consistent inverse relationship with hours worked. Pre-pandemic, compared to those aged at least 60 years, the youth worked 2.3 more hours and prime-aged workers 1.8 more hours, both significant at the 1 percent level. At the pandemic's onset, these estimates remained largely unchanged but became marginally less significant. In 2021, prime-aged workers matched older individuals while the youth worked 1.6 more hours, persisting in 2022. Concurrently, prime-aged workers returned to pre-pandemic levels.

Regarding education, I estimate a positive but decreasing non-linear relationship with working hours which persisted throughout the period. Pre-pandemic, an incomplete secondary education was associated with 1.1 more weekly hours than primary education or less, while complete secondary and post-secondary education were associated with 1 and 0.8 additional hours, respectively, with no statistical difference between incomplete and complete secondary education. At the pandemic's onset, the relationship strengthened for all groups, with complete secondary education becoming associated with the highest number of hours. From 2020 to 2022, these correlations reduced but remained above pre-pandemic levels, except for incomplete secondary education which didn't significantly differ from its pre-pandemic estimate. By marital status, married workers worked less than non-married individuals pre-pandemic, but only marginally so (0.3 hours, 18 minutes per week). This difference however disappeared after 2020. Similarly, I also estimate no significant urban-rural differences in weekly working hours both before and after the pandemic's onset.

Regarding labour market covariates, before the pandemic workers in every industry worked fewer hours than those in agriculture, except for the transport, storage, and communication (TSC) industry where hours were statistically similar, all else equal. The largest difference was between private household workers and agriculture or TSC workers, with the former working approximately 14.5 fewer hours per week. In 2020, these differences generally increased, and the average TSC worker worked slightly fewer hours than agricultural workers, marginally significant at the 10 percent level. By 2021, most estimates decreased but remained above pre-pandemic levels, and TSC workers again worked statistically similar hours to agricultural workers. By 2022, mean conditional working hours in most industries returned to pre-pandemic levels, with few exceptions. Workers in mining and quarrying and finance still worked fewer hours than those in agriculture, with differences over one hour larger than the pre-pandemic period. Additionally, the average worker in the utilities industry now worked a statistically similar number of hours to those in agriculture, all else equal.

Occupations exhibit substantial variation in conditional working hours both within and between periods. Pre-pandemic, most groups worked 1.3 to 4 hours less per week compared to legislators, senior officials, and managers (hereafter 'managers'). Service and shop sales workers and domestic workers worked 2.8 and 2.5 hours more per week, respectively. In 2020, these differences remained largely consistent with few exceptions. Clerical workers and domestic workers matched managers, while service and shop sales workers worked 4 more hours and skilled agricultural workers 4 less. In 2021, the pattern remained intact with the exception of plant and machine operators now working more than managers. By 2022, technical and associate professionals, clerical workers, skilled agricultural workers, and domestic workers matched managers in working hours. Conversely, service and shop sales workers and plant and machine operators and assemblers worked a greater number of hours, in contrast to the groups' pre-pandemic states.

Considering the remaining labour market covariates, informal sector and unionised workers worked more hours than their formal sector and non-unionised counterparts on average, all else equal. Pre-pandemic, informal sector workers worked 0.6 more hours (36 minutes) weekly than formal sector workers. At the pandemic's onset, this association increased to 1.4 additional hours, now significant at the 1 percent level, and later to 2.2 hours. By 2022, it returned to pre-pandemic levels. This trend was similar for union members and public sector workers compared to their respective counterparts. Conversely, workers with written contracts worked 1.4 hours less per week than those with verbal contracts, an association which remained constant from before to after the pandemic's onset. In 2021, no significant difference was found, while in 2022, the estimate halved but was only marginally significant.

3.4.5 Modelling labour market churn

In this section, I present the results of the descriptive and multivariate analysis of labour market churn at the pandemic's onset. As described in Section 3.3, I exploit the unique panel nature of the data to analyse three sets of 15 temporal transitions between mutually exclusive labour market states on the balanced panel sample. I begin with the 'intra-state' extensive margin transitions, followed by the 'inter-state' extensive margin and intensive margin transitions. For each set, I first present transition matrices to examine the degree of these transitions descriptively and thereafter report the results from the multivariate regressions which seek to uncover the correlates of different transition probabilities.

3.4.5.1 Intra-state extensive margin transitions

Table 3.14 presents the transition matrix of extensive margin outcomes over time, including standard errors and sub-sample sizes. It is clear that there was a significant amount of labour market churn during this period, consistent with prior studies which made use of the NIDS-CRAM data (Ranchhod & Daniels, 2021; Espi-Sanchis et al., 2022). Most churn involves transitions into inactivity in particular. About 80 percent of the employed in 2020Q1 remained employed the following quarter, while the majority of those who lost their job (15 percent of the employed in 2020Q1, or 74 percent of those who lost their job) transitioned out of the labour force entirely and into inactivity. Only a minority of the previously employed (5.3 percent) were searching for work in the next quarter. For the searching unemployed in 2020Q1, the majority (56 percent) also shifted into inactivity, while 34.3 percent remained unemployed and just under 10 percent gained employment. Inactivity remained the dominant state for those already inactive in 2020Q1, with over 91 percent remaining inactive in 2020Q2. In summary, intra-state transitions were dominant for the employed or inactive before the pandemic, while inter-state transitions were dominant for the searching unemployed.

In Figure 3.9, I present the AME coefficients from the probit models for the four intra-state, extensive margin transitions. Regarding sex, women exhibited a nearly 3 percentage

Table 3.14: Transition matrix of intra- and inter-state extensive margin labour market churn, 2020Q1 – 2020Q2

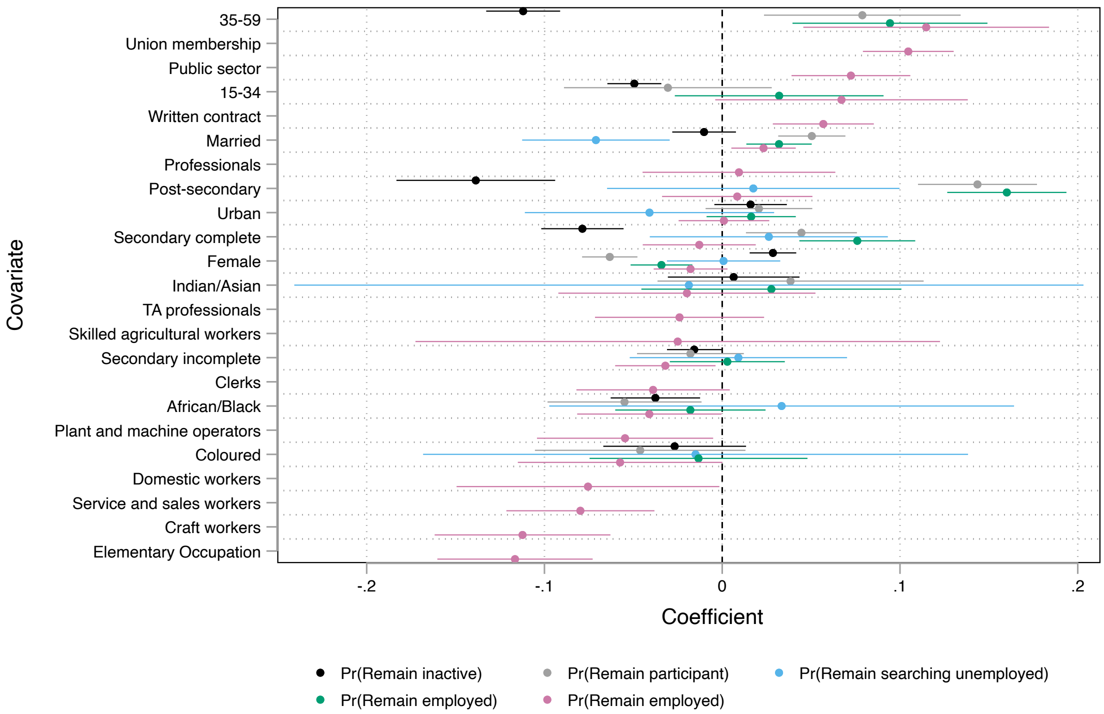
		Status, 2020Q2			
		Employed	Searching unemployed	Inactive	Total
Status, 2020Q1	Employed	80.01 (0.50) *n=7 975*	5.26 (0.29) *n=528*	14.73 (0.44) *n=1 571*	100.00 *n=10 074*
	Searching unemployed	9.63 (0.52) *n=401*	34.36 (1.25) *n=1 410*	56.01 (1.30) *n=2 411*	100.00 *n=4 222*
	Inactive	3.49 (0.23) *n=331*	5.16 (0.34) *n=512*	91.35 (0.41) *n=9 235*	100.00 *n=10 078*
	Total	37.34 (0.42) *n=8 707*	10.31 (0.35) *n=2 450*	52.36 (0.51) *n=13 217*	100.00 *n=24 374*

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Estimates weighted using 2020Q1 sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to the balanced panel working-age sample from 2020Q1 to 2020Q2.

point higher likelihood of remaining inactive compared to men. Conditional on already participating in the labour market, women were over 6 percentage points less likely to remain participants and 3.4 percentage points less likely to remain employed (2 percentage points when additionally controlling for labour market covariates). Women and men had similar conditional probabilities of remaining unemployed by the narrow definition. African/Black individuals had similar probabilities to their White counterparts, while Coloured and Indian/Asian individuals had comparable probabilities for all transitions. Regarding age, the youth were about 5 percentage points less likely to remain inactive and 6.7 percentage points more likely to remain employed than those aged at least 60 years (marginally significant at the 10 percent level), all else equal. All age groups had similar probabilities of remaining labour market participants. Due to data sparsity, I am unable to estimate the conditional probabilities of remaining unemployed by the narrow definition for all age groups. Prime-aged individuals were the least likely to remain inactive (by 11.2 percentage points compared to those aged at least 60 years), most likely to remain participants (by nearly 8 percentage points), and most likely to remain employed (by 11.5 percentage points).

I observe a strong, inverse relationship between education and the conditional probability of remaining inactive, and a positive one for remaining a participant. Compared to those with primary education or less, individuals with incomplete secondary, complete secondary, and post-secondary education had a 1.6, 7.9, and 13.9 percent lower probabilities of remaining

Figure 3.9: Coefficient plot of average marginal effect estimates on intra-state extensive margin transitions in labour market states



[a] Author's own calculations. Source: QLFS 2020Q1 - 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Sample restricted to those of working age and to the 2020Q1 sample. Average model effect estimates presented. All models control for province fixed effects. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Agricultural industry, Managers occupation group, Formal sector (including agriculture). Spikes represent 95 percent confidence intervals. Estimates presented in tabular form in Table A9 in the appendix.

inactive, all significant at the 5 percent level. Those with an incomplete secondary education had similar probabilities of remaining participants than their primary level counterparts, but those with a complete secondary or post-secondary education had 4.5 percent and 14.3 percent higher probabilities. All education groups exhibited similar probabilities of remaining narrowly unemployed. Before controlling for the vector of labour market covariates, higher education levels were associated with higher probabilities of remaining employed, but after, this finding mostly disappears, with most education groups now exhibiting statistically similar conditional probabilities of remaining employed, with the exception of those with an incomplete secondary education who exhibit a 3.2 percentage point lower probability than their primary level counterparts.

Regarding the remaining demographic covariates, I find no significant difference in the conditional probabilities of any intra-state, extensive margin transition for individuals in urban versus rural areas. However, married individuals, while having similar inactivity probabilities as their non-married counterparts, were 5 percentage points more likely to remain participants. This appears driven by a 3.2 percentage point higher chance of remaining employed, which reduces slightly to 2.3 percentage points when controlling for labour market covariates but remains statistically significant. Additionally, married individuals ere 7.1 percentage points less likely to remain unemployed by the narrow definition.

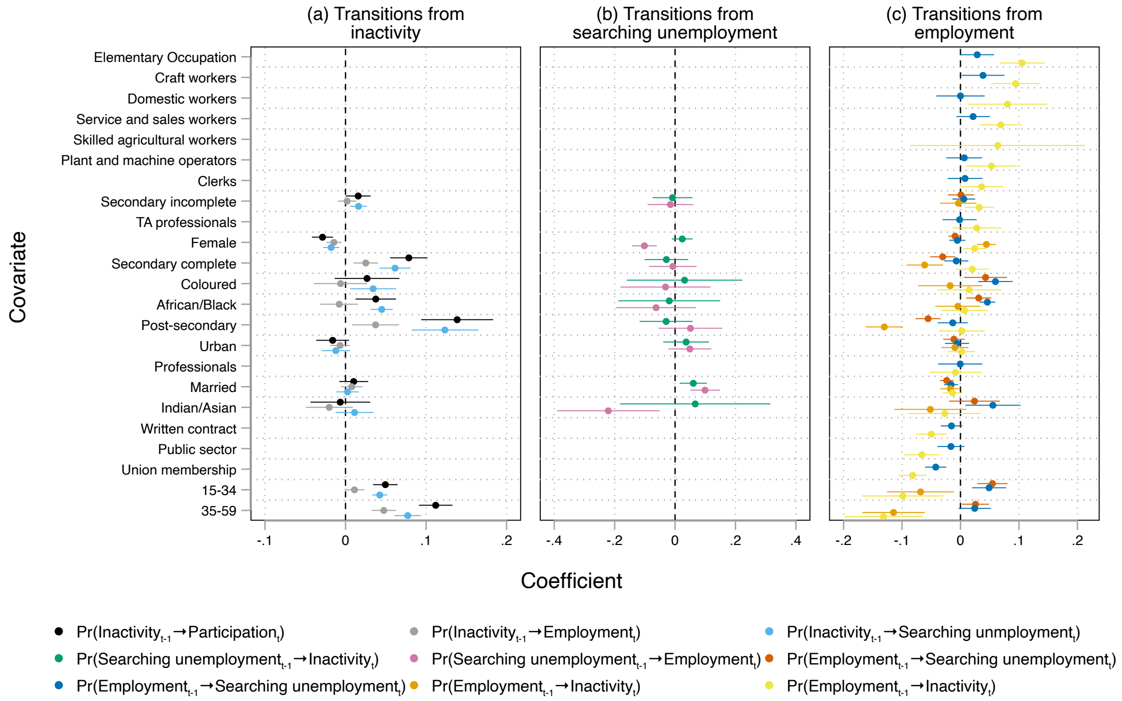
I identify several notable associations between the conditional probability of remaining employed and labour market covariates, which can only be included in this specification as previously discussed. Regarding occupation groups, most workers had lower chances of remaining employed compared to managers, except for professionals, technical and associate professionals, and skilled agricultural workers who exhibited similar probabilities. In particularly, elementary and craft-related trade workers had the lowest chances: 11 to 12 percentage points below managers. This aligns with my previous finding of craft-related trade workers being the most affected occupation group with respect to net job loss. I also find that written contract holders, public sector employees, and union members had 5.7, 7.2, and 10.5 percentage point higher probabilities of remaining employed compared to verbal contract, private sector, and non-union counterparts, respectively. These results are significant at the 1 percent level, and are consistent with the heterogeneous net employment trajectories observed prior.

3.4.5.2 Inter-state extensive margin transitions

The estimates from the probit models of the seven inter-state transitions are presented in Figure 3.10. For ease of interpretation the models are grouped according to pre-pandemic labour market state. Regarding sex, women had a 3 percentage point lower likelihood of transitioning out of inactivity and into a state of participation compared to men, and hence were less likely to shift from inactivity into either employment or narrow unemployment. Concurrently, jobseekers' probability of transitioning into inactivity didn't significantly differ by sex or other demographic factors, apart from marital status. Married jobseekers had a 6 percentage point higher probability of becoming inactive. I further find that women who were employed before the pandemic were no more likely than their male counterparts to transition into narrow unemployment, but were 4.4 percentage points (2.4 after additionally controlling for labour market covariates) more likely to transition out of the labour market entirely.

By race, I observe a substantial degree of variation in inter-state labour market churn. Compared to White individuals, Indian/Asian individuals had similar probabilities for most transitions except for moving from employment to searching unemployment, where the latter group had a 5.5 percentage point higher likelihood. Coloured individuals also faced statistically similar probabilities for most transitions with two exceptions: those inactive or employed pre-pandemic had 3.4 and 6 percentage point higher chances of transitioning into searching unemployment, respectively. The largest number of significant differences in transitions were between African/Black and White individuals. African/Black individuals who were inactive prior to the pandemic were 3.8 percentage points more likely to transition into a state of participation, however this appears driven by job search rather than employ-

Figure 3.10: Coefficient plot of average marginal effect estimates on inter-state extensive margin transitions in labour market states



[a] Author's own calculations. Source: QLFS 2020Q1 - 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Sample restricted to those of working age and to the 2020Q1 sample. Average model effect estimates presented. All models control for province fixed effects. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Agricultural industry, Managers occupation group, Formal sector (including agriculture). Spikes represent 95 percent confidence intervals. Estimates presented in tabular form in Table A10 in the appendix.

ment. African/Black individuals who were already employed prior to the pandemic were also more likely to shift into narrow unemployment, but their probabilities of transitioning from employment to inactivity were statistically similar to their White counterparts, even after adjusting for labour market covariates. Similarly, there were no statistically significant differences in the chances of transitioning out of narrow unemployment into either employment or inactivity between African/Black and White individuals.

By age, compared to individuals aged at least 60 years, both youth and prime-aged individuals had higher chances of moving from inactivity to participation, through either job search or employment. Among those employed before the pandemic, more youth transitioned into narrow unemployment than prime-aged individuals (4.9 vs. 2.4 percentage points – a significant difference). However, both age groups were less likely than older individuals to move from employment into inactivity, with youth being 10 percentage points less likely and prime-aged 13 percentage points less likely. Unfortunately, due to sparse data, I am unable to estimate age's association with transitioning from narrow unemployment to either inactivity or employment. Similar to the intra-state extensive margin transitions, urban and rural individuals showed no significant differences in extensive margin transitions on average. Among married individuals, jobseekers had a 6 percentage point higher chance of transitioning into inactivity and were even more likely (10 percentage point) to transition into employment. Among pre-pandemic employed individuals, non-married individuals were rather more likely to move out of employment and into narrow unemployment, but had a similar probability of transitioning into inactivity as married individuals.

I observe a positive association between education levels and transitions out of inactivity into participation, especially through job search. Compared to those with primary education or less, individuals with incomplete secondary, complete secondary, and post-secondary education levels had 1.6, 7.9, and 13.9 percentage point higher chances of transitioning out of inactivity and into participation. Probabilities of transitions into employment and narrow unemployment were higher for post-secondary and complete secondary education, surpassing less educated groups. Among those employed pre-pandemic, there's no significant difference in transitions into narrow unemployment by education. Regarding transitioning from employment into inactivity, individuals with an incomplete secondary education had a 3.2 percentage point higher likelihood than others. I do not find any evidence of a significant difference in the conditional probabilities of transitioning out of narrow unemployment into any other state across education levels.

Regarding the associations between the varied labour market covariates and the probability of transitioning out of employment, most occupation groups exhibited similar probabilities of shifting into narrow unemployment. Craft and elementary occupation workers had a 4 and 3 percentage point higher likelihood than managers, respectively. While public vs. private sector workers and written vs. verbal contract workers had similar transition probabilities into narrow unemployment, unionised workers had a 4.3 percentage point lower likelihood than non-unionised workers. Unionised workers were also 8.2 percentage points less likely to transition out of employment into inactivity, aligning with the net job loss incidence observed previously. Also consistent with the descriptive analysis is that public sector and written contract workers had lower probabilities of transitioning into inactivity (6.6 and 5 percentage points less) than private sector and verbal contract workers. For other employment-inactivity transitions, most occupation groups were more likely to experience such transitions compared to managers, except for professionals, technical and associate professionals, and skilled agricultural workers, who exhibited statistically similar probabilities.

3.4.5.3 Intensive margin transitions

Table 3.15 presents a transition matrix of the intensive margin outcome transitions with respect to employment formality, accompanied by standard errors and sub-sample sizes. As such, the sample here is restricted to those who remained employed from before to after the pandemic's onset. Notably, a significant transition occurred from the informal to the formal sector, with nearly 23 percent of informal workers transitioning after the pandemic's onset. Conversely, nearly all (96.3 percent) formal sector workers remained in that sector

Table 3.15: Transition matrix of intensive margin labour market churn, by employment formality, 2020Q1 – 2020Q2

		Employment formality, 2020Q2		
		Formal sector	Informal sector	Total
Employment formality, 2020Q1	Formal sector	96.25 (0.27) *n=5,886*	3.75 (0.27) *n=237*	100.00 *n=6,123*
	Informal sector	22.83 (1.48) *n=270*	77.17 (1.48) *n=986*	100.00 *n=1,256*
	Total	84.33 (0.51) *n=6,156*	15.67 (0.51) *n=1,223*	100.00 *n=7,379*

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to the balanced panel working-age employed sample from 2020Q1 to 2020Q2. StatsSA's additionally category of workers in private households is omitted.

post-pandemic, with just under 4 percent moving to the informal sector.

Table 3.16 presents a transition matrix of intensive margin outcome changes with respect to working hours. I report the relative frequencies within columns, as opposed to before, to allow for an examination of pre-pandemic hours based on post-pandemic hours. In line with Figures 3.3 and Figure 3.4, significant intensive margin adjustments occurred at the pandemic's onset. In 2020Q2, the majority (70 percent) of furloughed workers previously worked fewer than 40 hours per week, mainly in the 25-40 hour range. However, some 'high-hour' workers – that is, they worked more than 40 hours per week, an arbitrary but useful threshold – also became furloughed. Among non-furloughed workers, roughly 70 percent of those working up to 24 hours were previously working more hours. Conversely, I also find evidence of shifts up the working hours distribution. A quarter of those working 40-60 hours in 2020Q2 previously worked fewer hours. Similarly, 42 percent of those working over 60 hours previously worked fewer hours, mostly in the 40-60 hour range. Together, these findings highlight substantial intensive margin adjustments alongside the previously observed extensive margin churn.

Figure 3.11 reports the transformed coefficients from the probit models of the four intensive margin transitions. I report estimates for two specifications: one with demographic covariates only and another with both demographic and labour market covariates. Considering the formal-to-informal sector transitions, initially, women had a 1.3 percentage point

Table 3.16: Transition matrix of intensive margin labour market churn, by weekly working hours, 2020Q1 – 2020Q2

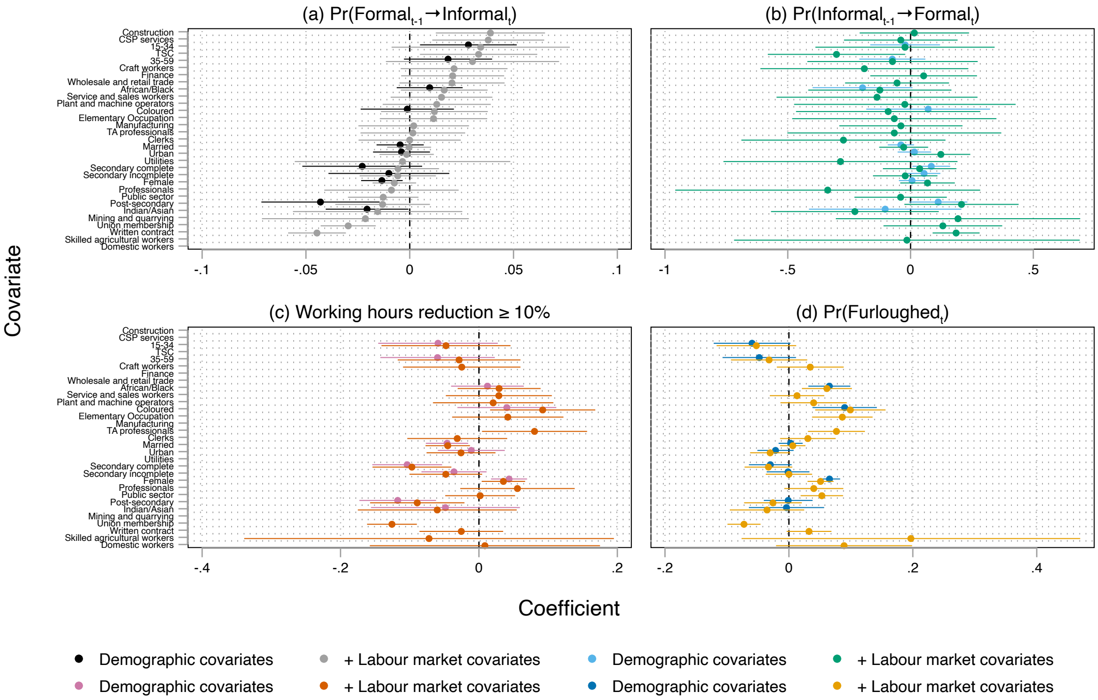
		Hours, 2020Q2					
		Furloughed	$0 < x \leq 24$	$25 \leq 40$	$41 \leq 60$	$x > 60$	Total
Hours, 2020Q1	Furloughed	2.45 (0.46) *n=38*	2.19 (0.62) *n=15*	0.96 (0.21) *n=31*	1.14 (0.23) *n=29*	0.40 (0.29) *n=2*	1.35 (0.15) *n=115*
	$0 < x \leq 24$	13.84 (1.10) *n=210*	28.65 (1.92) *n=231*	2.59 (0.30) *n=85*	1.75 (0.28) *n=45*	1.75 (0.68) *n=8*	6.45 (0.31) *n=579*
	$25 \leq 40$	52.07 (1.61) *n=722*	47.24 (2.06) *n=340*	68.87 (1.08) *n=2,073*	21.91 (1.02) *n=548*	11.74 (1.75) *n=45*	46.83 (0.73) *n=3,728*
	$41 \leq 60$	27.78 (1.43) *n=374*	19.54 (1.70) *n=141*	25.71 (1.01) *n=752*	69.50 (1.13) *n=1,673*	28.15 (2.61) *n=105*	39.42 (0.72) *n=3045*
	$x > 60$	3.85 (0.65) *n=53*	2.38 (0.59) *n=20*	1.87 (0.27) *n=62*	5.71 (0.51) *n=152*	57.96 (2.97) *n=213*	5.94 (0.31) *n=500*
	Total	100.00 *n=1,397*	100.00 *n=747*	100.00 *n=3,003*	100.00 *n=2,447*	100.00 *n=373*	100.00 *n=7,967*

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to the balanced panel working-age employed sample from 2020Q1 to 2020Q2.

lower probability of remaining employed but moving from the formal to the informal sector relative to men, all else equal. However, this difference disappears after controlling for labour market covariates. Similarly, there was no significant differences by race, age, education, marital status, or urban/rural residence with respect to transitioning from formal to informal employment in the fully adjusted model. This finding largely holds when modelling the transition in the opposite direction, with two exceptions. Relative to those with a primary education or less, workers with a post-secondary education had a 20.7 percentage point higher probability of transitioning from the informal to the formal sector, all else equal. Similarly, urban residents were 12.3 percentage points more likely to experience this transition.

Considering the labour market covariates for these transitions, I find that construction, TSC, and CSP services industry workers were 3 to 4 percentage points more likely to shift

Figure 3.11: Coefficient plot of average marginal effect estimates on intensive margin transitions in labour market states



[a] Author's own calculations. Source: QLFS 2020Q1 - 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Sample restricted to those of working age and to the 2020Q1 sample. Average model effect estimates presented. All models control for province fixed effects. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Agricultural industry, Managers occupation group, Formal sector (including agriculture). Spikes represent 95 percent confidence intervals. Estimates presented in tabular form in Table A11 in the appendix.

from formal to informal sector employment compared to agriculture workers. All other industries had statistically similar probabilities to agriculture. Considering the informal to formal sector transition, all industries showed similar probabilities except TSC, where the likelihood was substantially (30.2 percentage points) lower than agriculture. However, this lack of statistical significance among several covariates in this model may be explained by the relatively small sample of individuals experiencing this transition. By occupation groups, no significant differences in sector transitions were observed, regardless of transition. Private and public workers also had similar transitions, but unionised workers were 3 percentage points less likely to shift from the formal to the informal sector. However, no difference is observed regarding the informal to formal sector transition. Finally and notably, workers with written contracts displayed exhibited a significant trajectory towards the formal sector. Those in the formal sector before the pandemic were 4.5 percentage points less likely to switch to the informal sector than verbal contract workers, while informal sector workers before the pandemic were 18.6 percentage points more likely to transition to the formal sector. Both of these estimates are highly significant at the 1 percent level.

I now consider the intensive margin transitions with respect to working hours, the estimates of which are presented in panels (c) and (d). Women had a 4.3 percentage point higher likelihood of experiencing a working hours reduction (defined as at least 10 percent) compared to men, which reduces only marginally to 3.5 points after adjusting for differences in labour market covariates. Women were also more likely than men to become furloughed (working zero hours) by approximately 5 percentage points, highly significant at the 1 percent level. These findings align with the larger reduction in mean working hours among women observed prior. Regarding race, only Coloured workers had a significantly higher chance of experiencing a reduction in working hours. However, both Coloured and African/Black workers were more likely to become furloughed than their White and Indian or Asian counterparts. After controlling for both vectors of covariates, African/Black and Coloured workers had approximately 6 and 10 percentage point higher conditional probabilities of become furloughed. By age, there were no statistically significant differences in either outcome across age groups after adjusting for all covariates.

I find a negative association between education levels and the likelihood of a reduction in working hours. Workers with an incomplete secondary, complete secondary, and post-secondary education had 4.8, 9.7, and 8.9 percentage point lower probabilities of a reduction in hours compared to those with a primary education or less, all else equal. These latter two estimates aren't statistically different. However, no such relationship exists for the probability of becoming furloughed among all education groups, except for workers with a complete secondary education who were 3.3 percentage points less likely to become furloughed. This estimate is however only marginally significant at the 10 percent level. Considering marital status, married workers were 4.5 percentage points less likely to experience a reduction in hours than unmarried workers, but both had similar probabilities of becoming furloughed. Conversely, urban and rural workers had similar chances of experiencing a working hours reduction, but urban workers were 3 percentage points less likely to become furloughed, an estimate which is however only marginally significant at the 10 percent level.

Regarding the labour market covariates, unfortunately data sparsity prevents the estimation of working hour-related conditional probabilities by main industry. However, by occupation, all groups except technical and associate professionals had similar conditional probabilities of a reduction in working hours. This latter group were 8 percentage points more likely to experience this outcome compared to managers. Most occupation groups also faced similar conditional probabilities of becoming furloughed, with three exceptions: professionals, technical and associate professionals, and those in elementary occupations were 4, 7.7, and 8.6 percentage points more likely to become furloughed, respectively. Workers with written versus verbal contracts had similar probabilities of a working hours reduction, but those with written contracts were slightly (3.2 percentage points) more likely to become furloughed, though this was only marginally statistically significant at the 10 percent level. Unionised workers had a lower probability of a working hours reduction and becoming furloughed by 12.6 and 7.2 percentage points, respectively, compared to non-unionised workers. On the other hand, private and public sector workers had similar conditional probabilities of working hours reductions but differed with respect to becoming furloughed, with the latter being over 5 percentage points more likely to be furloughed. It can then be said that while unionised and public sector workers were much more likely than their counterparts to remain employed, this protection on the extensive margin may have come at cost of a significant intensive margin adjustment.

3.5 Conclusion

The empirical literature of the labour market effects of the COVID-19 pandemic is substantial in size and still evolving, both internationally and in the South African context. However, despite its large size, the latter remains limited in scope. Existing studies either largely focus on the pandemic's immediate impact or give attention to one or a limited set of worker groups. Very few consider any adjustment on the intensive margin, such as working hours among job retainers, with none documenting either the average or heterogenous evolution of working hours as the pandemic progressed. Gender serves as the single exception but such studies are limited to a relatively short time horizon. In this context, this chapter sought to provide a comprehensive, descriptive micro-econometric analysis of aggregate and between-group adjustments in the South African labour market. By making use individual-level, nationally representative, cross-sectional and panel labour force household survey data, a range of uni-, bi-, and multivariate statistical techniques are employed to examine the dynamics of three extensive margin outcomes - labour market participation, employment, and unemployment - and one intensive margin outcome - working hours conditional on employment. Building on existing literature, the analysis considers a relatively long time horizon spanning the pre-pandemic period in 2019 through to the middle of 2022 when all remaining pandemic regulations were repealed.

Several findings stand out. On aggregate, the pandemic had a substantial and in some cases a persistent effect on extensive margin outcomes. At its onset, labour supply contracted by 22 percent driven by both job loss – equivalent to a decade's worth of jobs growth – as well as a loss in the number of jobseekers. Reflecting a key characteristic of the pandemic and associated lockdown policy, most job-losers and seekers exited the labour market entirely as reflected by a surge in economic inactivity. This is strongly consistent with the panel analysis which highlights that most churn relates to transitions toward inactivity. On the intensive margin, the average individual who remained employed worked seven fewer hours per week, driven by both 16 percent of workers becoming furloughed as well as many working fewer non-zero hours. A very small minority of workers experienced a shift up the hours distribution, plausibly reflecting increased demand in some industries. These adjustments were however temporary. Beyond 2020Q2 as the economy re-opened, the working hours distribution quickly recovered to its pre-pandemic shape, and a partial, slow, and non-linear employment recovery ensued. Only after the recovery completely reversed during 2021 did the labour market show consistent signs of recovery, but remained 5 percent below the pre-pandemic level halfway through 2022.

The pandemic's effects differed greatly across workers of varied characteristics, both at its onset and as it progressed. Those who exhibited greater labour market vulnerability were disproportionately affected in the short- and longer-terms, thus reinforcing pre-existing labour market inequalities. This includes women, the youth, those with lower levels of education, informal sector workers, less-skilled workers, the non-unionised, the self-employed, 'casual' workers, and those without written contracts. Strongly consistent with the international literature, I show that this regressive pattern of job loss can at least partially be explained by two defining features of the pandemic labour market: remote work ability and 'essential' worker status. Job loss disproportionately affected those who could neither work remotely nor were in 'essential' industries, who largely comprise the aforementioned vulnerable groups. On the intensive margin, inequalities in working hour adjustments can also be attributed to inequalities in 'essential' worker status, but not remote work ability. In addition to these two characteristics, the analysis here suggests that other factors, such as employer preferences, union bargaining power, and access to legal protections, may also partially explain these adjustments. Over time, the trajectories of recovery were also heterogenous. Some groups recovered at a faster rate than their relevant counterparts, but few had fully recovered by the middle of 2022. Finally, despite the large magnitude of the shock, the determinants of both extensive and intensive margin outcomes were relatively rigid, with few exceptions such as those which relate to sectoral composition. Although marginal, these latter changes are suggestive of a persistent change to the structure of South Africa's labour market.

Chapter 4

Wages and wage inequality during the COVID-19 pandemic in South Africa

4.1 Introduction

The empirical literature on the effects of the COVID-19 pandemic in South Africa largely focus on extensive margin outcomes, such as employment. As documented in Chapter 2, this has resulted in a relative scarcity of evidence on intensive margin adjustments. Wages serve as one particular intensive margin outcome of interest, as well as how they are distributed. However, by simultaneously affecting the supply, demand, and nature of work, the pandemic introduced unusual complications in the interpretation of the wage distribution over time, with respect to both compositional and structural dynamics. First, in times of crisis, aggregate measures of wages can be skewed by significant changes to the composition of the workforce, such as through job loss which effectively removes workers from the distribution entirely. Average wages may then mechanically rise, reflecting not an improvement to the labour market but a concentration of job loss among lower-wage workers, as documented in a wide array of labour markets globally (Béland et al., 2020; Cajner et al., 2020; International Labour Organisation, 2020; Economic Commission for Latin America and the Caribbean, 2022; Gáspár & Reizer, 2020; Gherghina, 2022; Grigsby, 2022; Autor et al., 2023). Second, as an alternative to layoffs, firms may reduce their workers' wages in response to reduced demand due to government-mandated restrictions and voluntary contractions in economic activity, another widely-documented outcome (Balde et al., 2020; de Mahieu & Lastunen, 2023; Djoumessi, 2021; Webster et al., 2022; Khamis et al., 2021). Firms may alternatively adjust working hours without adjusting hourly wages, with a reduction in monthly earnings serving as the consequence. Third, government support measures such as job retention programmes, wage subsidies, and short-time work schemes may have mitigated such changes on both the extensive and intensive margins, resulting in little to no change in observed wages or earnings. Finally, it is plausible that through these and other mechanisms, the pandemic affected the returns associated with various individual-level characteristics for those who remained employed. Given these dynamics, the implications for wage inequality are *ex ante* unclear. For instance, because industry-specific economic activity restrictions may have shielded some worker groups at the bottom of the wage distribution, such as agricultural workers, more than other groups further up the distribution, such as hospitality workers, wage inequality may decrease. On the other hand, wage inequality may increase if 'essential' or 'remote' occupations are concentrated towards the top of the wage distribution and exhibit lower job loss or wage reduction probabilities than their counterparts – a reasonable conjecture supported by empirical evidence (Adams-Prassl et al., 2020; Béland et al., 2020; Borjas & Cassidy, 2020; Dingel & Neiman, 2020; Guven et al., 2020; Zimpelmann et al., 2021; Casarico & Lattanzio, 2022; Craig & Churchill, 2021). Arguably then, both structural and compositional dynamics ought to be considered in any analysis of wages during the pandemic.

Such dynamics are particularly important in the South African context, which is characterised by extreme levels of income inequality driven by labour market inequality (Finn et al., 2016; Wittenberg, 2017; Bhorat et al., 2020c; Díaz Pabon et al., 2021; Kerr & Wittenberg, 2021; Leibbrandt et al., 2012, 2020; Bhorat et al., 2022; Leibbrandt & Díaz Pabón, 2022). This is due both to a large share of the population lacking access to labour market incomes (unemployment) and a very unequal distribution of these incomes among the employed. This latter component has, however, been shown to play a more dominant role (Leibbrandt et al., 2012; Kerr & Wittenberg, 2021). As such, a better understanding of the pandemic's effects on wage inequality is critical in aiding one's understanding of South Africa's aggregate income inequality. However, at the time of writing, these consequences of the pandemic were not yet fully understood. The empirical literature is very limited, relative to both the literature on other labour market outcomes in the country as well as the international literature on wage adjustments, primarily a consequence of a lack of access to adequate wage data. Using the NIDS-CRAM data, at the pandemic's onset Ranchhod & Daniels (2021) find that 12 percent of workers earned zero wages, while Bassier et al. (2023) estimate no significant change in average earnings for those who remained actively employed relative to February 2020, but a small negative change among those who became furloughed. Using the same data, few studies document the unequal impact of the pandemic on earnings by gender (Casale & Posel, 2021; Casale & Shepherd, 2021; Hill & Köhler, 2021). While insightful, these analyses are limited by a relatively short time period and small samples characterised by relatively high amounts of imprecision and representivity issues (Daniels et al., 2022). To the author's knowledge, no study has analysed the evolution of wages as the pandemic progressed beyond its first year, either on average or among specific worker groups. Moreover, none have examined changes in either the magnitude or drivers of wage inequality.

In this chapter, I conduct a micro-econometric analysis of the evolution of the level and nature of wages and wage inequality and its drivers during the two years of the pandemic using a representative and relatively large sample of workers in South Africa. By doing so, I seek to answer three key research questions. First, what describes the pre-pandemic wage distribution and hence wage inequality in the South African labour market? Second, how did the wage distribution change in response to the pandemic, both at its onset and as it progressed over time? Third, what were the drivers of the change of the wage distribution in response to the pandemic, both at its onset and as it progressed over time? To address these questions, I use nationally representative, individual-level household survey data from StatsSA's QLFS from 2019 to 2022. Importantly, to avoid significant data quality issues documented in the literature which are attributable to StatsSA's approach to address non-random missing wage values in the survey, I make use the raw, unimputed QLFS wage data provided by StatsSA not available in the public domain to produce reliable estimates of the wage distribution.

This analysis employs a range of techniques categorised into three components. First, by placing a focus on measurement, I examine the quality of the raw, unimputed wage data by making several analytical comparisons to the public domain data and interrogating the quality of the imputations in the latter. Thereafter, I adopt two parametric techniques to address outliers and impute for non-random missing data using a method which explicitly accounts for the implicit uncertainty which characterises imputations, and conduct a multitude of diagnostic tests to examine the quality and sensitivity of these imputations. Second, I analyse both aggregate and within-worker variation in real hourly wages across the distribution from before to after the pandemic's onset, and estimate several descriptive and normative wage inequality indices which vary in sensitivity to changes in different parts of the distribution, before and after explicitly accounting for the pandemic-induced change in the composition of workers. Third, I conduct decomposition analyses to identify the drivers of the temporal changes in wages from before to after the pandemic's onset. I examine these drivers both at the mean and across the entire distribution using Oaxaca-Blinder (OB) and Recentered Influence Function (RIF) decomposition, respectively, to isolate the extent changes in wages can be explained by changes in the characteristics of the employed population versus changes in the returns to these characteristics.

The remainder of this chapter proceeds as follows. In Section 4.2 I synthesise the empirical literature on wage inequality in South Africa prior to the pandemic. In Section 4.3 I describe the data used as well as the wage data quality adjustments I undertake for the analysis, and present the results from the diagnostic tests undertaken to examine the quality of these adjustments. Thereafter, I outline the methodologies adopted in the latter two components of my analysis in Section 4.4. I then present the results for these components in Section 4.5. In Section 4.6 I conclude.

4.2 Pre-pandemic wage inequality in South Africa

Income inequality in South Africa has remained stubbornly high in the post-apartheid period. Such persistence serves as a key challenge during this period when the institutional underpinnings of discrimination have and continue to be removed (Wittenberg, 2017). There is a broad consensus in the literature that the labour market continues to dominate and drive the country's aggregate income inequality (Finn et al., 2016; Wittenberg, 2017; Bhorat et al., 2020c; Díaz Pabon et al., 2021; Kerr & Wittenberg, 2021; Leibbrandt et al., 2012, 2020; Bhorat et al., 2022; Leibbrandt & Díaz Pabón, 2022). Labour market income has been estimated to account for between 84 and 90 percent of the aggregate per capita household income Gini coefficient (Leibbrandt et al., 2012; Díaz Pabon et al., 2021). This influence is partially because labour market income represents the dominant source of household income in the country (Bhorat et al., 2022). South Africa's labour market inequality is due to both a lack of access to labour market incomes (that is, extreme unemployment) as well as the distribution of these incomes among those who are employed. In this way, the labour market can be regarded as notably segmented in that it reproduces the advantage of a minority of high-paid and high-skilled individuals who are employed in secure and well-regulated jobs which are relatively easily obtained, while reproducing the disadvantage of the more vulnerable majority who compete for jobs in a loose labour market among high unemployment which are often characterised as having inadequate job security and benefits (Bhorat et al., 2020c; Díaz Pabon et al., 2021). Importantly however, while South Africa's large amount of unemployment (in other words, zero-income earners) explains a large proportion of aggregate income inequality, wage inequality among the employed explains a larger proportion (Leibbrandt et al., 2012; Kerr & Wittenberg, 2021). It is unsurprising then that, like aggregate income inequality, the country has one of the most unequal wage distributions in the world (Díaz Pabon et al., 2021). Hence, a better understanding of wage inequality is critical in aiding one's understanding of aggregate income inequality in the country.

There is a large literature on the levels, patterns, and determinants of wage inequality in South Africa, most of which makes use of representative household survey data. Overall, there seems to be a consensus that wage inequality has remained high, and may have even increased, during the post-apartheid period. Leibbrandt et al. (2012) estimate a rise in the Gini coefficient from 0.60 in 1993 to 0.64 for 2008, suggestive of a monotonic rise in wage inequality in the post-apartheid period, however the authors can only make use of two comparable cross-sectional datasets and thus cannot account for variation within this period. Wittenberg (2017) addresses this by stacking 29 cross-sectional household surveys to analyse the entire series from 1994 to 2011. Using several inequality measures, they show that while wage inequality fluctuated over time, it does appear to have increased over the period. Their estimated Gini coefficient for 1994 is approximately 0.47 compared to 0.55 in 2011. Apart from different time periods, the differences compared to that of Leibbrandt et al. (2012) are at least partially explained by a different analytical sample. Whereas Leibbrandt et al. (2012) estimate a household-level Gini (that is, using household income per capita for people living in households with labour income), Wittenberg (2017) estimates an individual-level Gini using a sample of wage earners. In addition to sample differences, differences in inequality estimates in South Africa can also be explained by methodological differences both within and between surveys, making it challenging to draw definitive conclusions on temporal patterns. Despite this, Shifa et al. (2023) take stock of such differences between 1993 and 2017 and show that all datasets consistently measure extremely high levels of wage inequality in the international context, which appears to have indeed increased during the post-apartheid period.

The Gini coefficient certainly appears to be the dominant measure in the literature. However, when analysing inequality dynamics, the choice of measure matters due to variation in sensitivity to changes in different parts of the wage distribution. Additional measures can also then help shed light on the drivers of changes in inequality. Wittenberg (2017) uses several measures to show that the increase in overall wage inequality from 1994 to 2011 appears driven by a compression of the distribution below the median combined with a widening above it. In other words, wage inequality decreased at the bottom but increased at the top. The compression at the bottom appears driven by a growth of wages at the bottom relative to the middle of the distribution. Extending the period to 2014 and using an alternative method, Wittenberg (2018) similarly finds that the observed increase in mean real wages over this period was driven by an increase (decrease) in inequality in the top (bottom) half of the distribution. These findings are in line with those of Leibbrandt et al. (2012) above as well as Finn & Leibbrandt (2018) who use wage data from StatsSA's labour force surveys in 2000, 2011, and 2014. These latter authors find that between 2000 and 2011, real wage growth across the distribution exhibits a distinct U-shape, but trends beyond 2011 are less clear due to data quality issues. Evidence of such wage polarisation was however also found by Bhorat et al. (2020c) who examine real wage changes between 2000 and 2015, however the data used for the latter period also suffers from the same data quality issues as in Finn & Leibbrandt (2018), discussed in detail in Section 4.3.

Several studies have also sought to identify the reasons behind the persistence and rise in wage inequality during the post-apartheid period. These studies primarily focus on the roles of institutional change, compositional change, and structural change. Wittenberg (2018) discusses how wage setting through collective bargaining and minimum wage determinations may explain the observed compression in the bottom half of the distribution. Finn & Leibbrandt (2018) and Bhorat et al. (2020c) both use a distributional decomposition method – one of the methods employed in this chapter's analysis – to explain the rise in inequality. Consistent with the argument put forward by Wittenberg (2018), their findings suggest that minimum wages may indeed explain the observed growth in wages at the bottom, while increasing returns to education and non-routine-intense jobs largely explain the growth at the top. At this latter part of the distribution, Finn & Leibbrandt (2018) find that growing returns to education, specifically tertiary education, in addition to experience, appears to explain wage growth and hence serve as a dominant driver of increasing inequality.[1] For the middle, the authors find that wage growth was undermined by reduced returns to routine-intense jobs and a change in the composition of workers, particularly in mining and manufacturing. In addition to worker characteristics, firm characteristics are also relevant.

[1] These findings, however, ought to be interpreted with a degree of caution given the data quality issues mentioned above and discussed below.

Using administrative tax micro-data on the universe of formal sector workers and firms, Foster (2023) estimates that, while worker characteristics explain over a third (35 percent) of wage inequality in the country, firm characteristics explain a non-negligible 18 percent. Using similar data, Bassier (2023) estimates a similar worker component of 37 percent but a larger firm component of 28 percent. Both sets of estimates are consistent with the broader literature which highlights worker characteristics as the dominant driver of wage inequality in developing countries (Alvarez et al., 2018; Messina & Silva, 2019; Rodríguez-Castelán et al., 2022), and despite a discrepancy in the magnitude of the firm component, both also point to the significant role that firms play in South Africa.[2]

Other studies have also shown that the persistence of wage inequality in South Africa can be partially explained by very low intergenerational mobility. Although the correlation between the wages of parents and that of their adult offspring is usually positive in the international literature, South Africa exhibits an extremely strong correlation. Using a representative sample of males aged 20 to 44 years old, Piraino (2015) estimates an intergenerational earnings elasticity for the country of between 0.62 and 0.68. In other words, more than 60 percent of the wage advantage (or disadvantage) of South African fathers is passed on to their sons. This is in line with the notion of the 'Great Gatsby Curve' which suggests that countries with higher levels of inequality tend to have lower levels of intergenerational mobility. Finn et al. (2016) expand on the analysis by Piraino (2015) to find estimates of a similar magnitude, but additionally find that immobility is particularly strong at the bottom of the distribution. While this is in line with the international literature, the magnitude of the estimate is unusually high at approximately 0.90. Such strong correlations are often understood to be indicative of unequal opportunities in the labour market, with inherited circumstances playing an influential role in determining outcomes. Concerningly, Piraino (2015) finds that race serves as one of the strongest predictors of mobility – a particularly discouraging finding more than two decades after the end of apartheid.

4.3 Data

4.3.1 The Quarterly Labour Force Survey

The analysis in this chapter makes use of over three years' worth (or 14 waves) of individual-level household survey data from StatsSA's QLFS for all four quarters of 2019, 2020, and 2021 and the first half of 2022. As discussed in the preceding chapter, the QLFS is a nationally representative, cross-sectional (with a rotating panel component) household-based sample survey conducted every quarter since 2008 that contains detailed information on a wide array of demographic and socioeconomic characteristics and labour market activities for individuals aged 15 years and older who live in South Africa. The reader is referred to the preceding chapter for a detailed description of the survey design as well as changes to

[2]In addition to using a longer time period, Foster (2023) attributes this discrepancy to differences in the structure of the datasets used.

its mode and sample following the onset of the pandemic in the country in March 2020.

Importantly, the public domain versions of the QLFS data do not include wage data. This data are typically released with a lag in a separate annual publication entitled the 'Labour Market Dynamics of South Africa'. As is the case with many household surveys, the QLFS exhibits non-negligible rates of item non-response for questions related to earnings. While it is common for statistical agencies to impute or assign values in such cases to avoid non-response bias, a recent literature has highlighted the notably poor quality of the public domain QLFS wage data due to StatsSA's imputation approach, discussed in more detail below. To overcome this issue, in this analysis I merge in the raw, unimputed wage data privately provided by StatsSA for each wave and adopt two parametric statistical techniques to address both outliers and missing data, discussed in detail below. Given this chapter's focus on wages, the primary sample here is restricted to working-age (15 to 64 years) employed individuals, resulting in a sample of over 180 000 observations in total or 13 000 in the average wave. The wage estimates in this analysis include all forms of wages from labour market activities, including self-employment, and are measured before taxation and deductions. All estimates are weighted using the survey sampling weights and the standard errors are adjusted for the complex survey design through the use of the cluster and strata variables available in the data.

To account for inflation, throughout this analysis I deflate and express the nominal wage data in June 2022 Rands using StatsSA's headline Consumer Price Index data. Additionally, I express wages earned for each hour worked. As discussed in the preceding chapter, the QLFS includes several items relating to working hours which vary by a given worker's number of jobs and their "usual" versus "actual" working hours during a reference day or week. The reader is referred to the preceding chapter for a detailed discussion of these items. Consistent with my argument in that chapter that "actual" working hours is more appropriate than "usual" working hours in the context of the pandemic when various regulations created or affected the disparity between hours usually and actually worked, here I make use of data on "actual" working hours for a given worker's main job. Main job is defined as the job where a worker usually works the most hours per week, regardless of the number of jobs they have, with one exception. Adopting this approach for furloughed workers (that is, workers who remained employed by reported zero "actual" working hours but a positive wage value in a given period) would result in undefined hourly wage values and hence bias the wage distribution estimates. I retain these workers in the sample but make the explicit assumption that furloughed workers received their "usual" hourly wage (calculated using "usual" working hours data) in a given period, and hence regard being furloughed as a special type of paid leave under such circumstances.[3] This approach may result in a degree of measurement error; however, given the absence of more detailed data on wages in the survey, it is arguably

[3]An alternative option would be to focus exclusively on the actively employed sample (that is, non-zero hour workers). However, doing so would exclude a non-negligible share of workers from the wage distribution – a weighted 16 percent of workers in 2020Q2 as shown in the preceding chapter.

amongst the most appropriate of approaches. As a robustness test, I examine the sensitivity of this chapter's findings by excluding furloughed workers from the sample.

4.3.2 Wage data quality

My use of the raw, unimputed QLFS wage data provided by StatsSA is important to discuss in brief given the recent debate surrounding the quality of the public release QLFS wage data, which includes imputations, which has played out among labour market researchers in South Africa (Wittenberg, 2017; Kerr & Wittenberg, 2019b; Kerr, 2021; Kerr & Wittenberg, 2021; Köhler et al., 2023). First, the survey collects data on wages before taxation and deductions from all employees, employers, and own-account workers.[4] These workers are first asked to report their exact wages in South African Rands, and those that do not are then asked to report the bracket or range that their wage falls into. A substantive issue exists in this regard: in the public QLFS wage data from 2010 onwards, StatsSA have included problematic imputations for the wages of workers who did not report them. These include those who neither reported their wage in exact terms nor in a bracket, as well as those who only reported their bracket.[5] Unfortunately, the public release documents do not include an explanation on how these imputations were conducted. In fact, wage imputations are never even mentioned.

An internal document examined by Kerr & Wittenberg (2021) suggests that StatsSA employed a hot deck imputation method – in which the reported wage of a given respondent or 'donor' is assigned to a given non-respondent with an identical set of observable characteristics – which the authors argue results in imputations of a notably low quality. Specifically, this approach made use of just four variables: gender, race, seven education categories, and three occupation categories. Moreover, StatsSA's approach accounts for bracket responses in a very crude way by making use of only two bracket response categories: less than R6 000 per month and more than R6 000 per month. This strongly contrasts with the survey's 19 possible bracket response categories[6] and can result in very inaccurate imputations. For example, a worker who reported earning between R6 000 and R8 000 per month could be given an imputed wage of any value above R6 000. Unfortunately, the publicly released data does not make it possible to distinguish between the imputed and actual responses. Overall, this suggests that any analysis which makes use of the public QLFS wage data in its current form is erroneous to some degree.

[4]During the beginning of the pandemic in 2020Q1, the wages reported by employees may include benefits received from the government's TERS policy. As discussed in Chapter 2, the TERS was a wage subsidy which provided income relief to employees who suffered income loss due to a full or partial closure of their employer's operations. Initially, employees received benefits via their employer or bargaining council who applied and received benefits on their behalf, but from May 2020 benefits were paid directly into employee bank accounts (Köhler & Hill, 2022). Unfortunately, because the survey instrument did not include any items relating to the policy, it is not possible to isolate TERS benefits from wages or prove that they are included in wage responses.

[5]Kerr & Wittenberg (2021)'s analysis suggests that, from 2010Q1 to 2012Q2, imputations were made for complete refusals and all bracket responses including refusals and don't knows; however, from 2012Q3 refusals were no longer imputed for.

[6]Excluding the 'don't know' and 'refusal' category.

Several studies have highlighted how the use of this public release wage data produces implausible results. In two unpublished presentations, Khanyile & Kerr (2022) and Kerr (2022) compare the unimputed QLFS wage data for a select few years to the public domain data, highlighting the poor quality of the imputations in the latter. Kerr & Wittenberg (2019b) and Kerr (2021) show that these imputations result in unreliable trends in several measures of wage inequality. Comparing estimates from the unimputed data to public release data in 2011 and 2012, Kerr & Wittenberg (2021) find that while the public release data produces unreliable results, the results appear to be much more reliable when the underlying unimputed data is used. This suggests that although the quality of the imputations done by StatsSA is questionable, the underlying wage data is not. Unfortunately, at the time of writing, the unimputed data has not been made publicly available. Considering the poor quality of the public release wage data, my use of the raw, unimputed data resolves the data quality issues pertaining to their imputations discussed above.

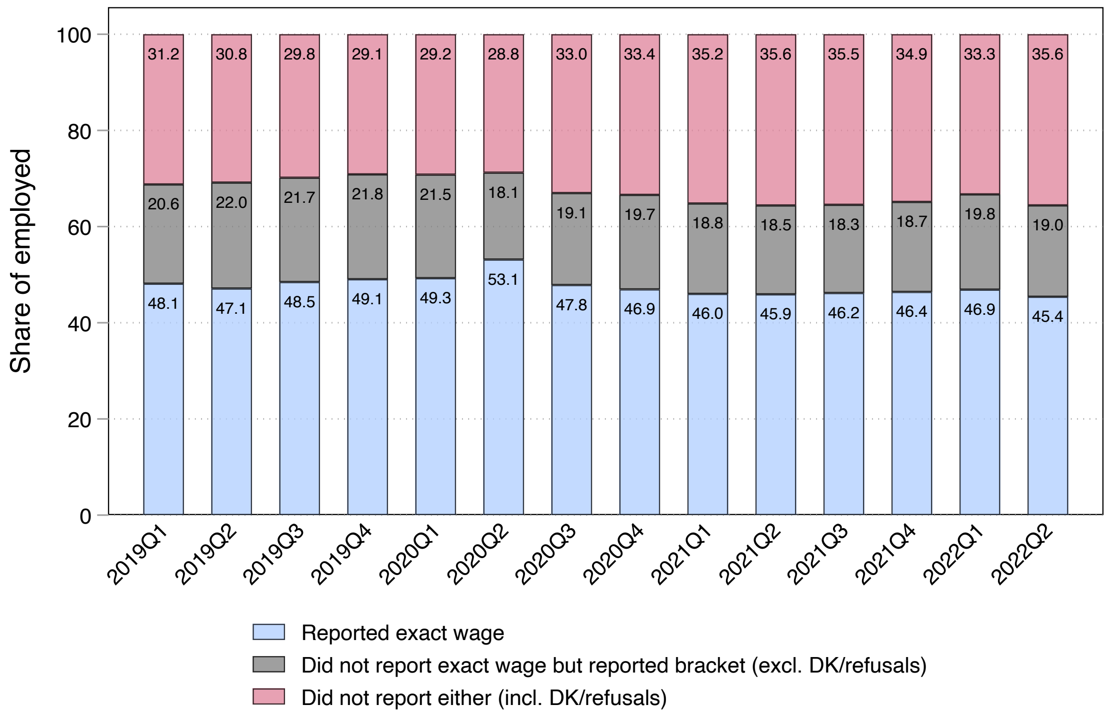
To examine the quality of these imputations, I merge the raw, unimputed wage data with the public QLFS wage data.[7] By doing so, I am able to examine the distribution of responses among the employed and how this has varied over time, generate imputation flags to distinguish the imputed from the reported data, and analyse the quality of StatsSA's imputations. Between 2019Q1 and 2020Q4,[8] about 32 percent of all employed in the public QLFS sample have imputed wages, and nearly 40 percent of all wages in the public file are imputed.[9] Of these imputations, most (56 percent) are for cases of completely missing wage data (that is, both exact and bracket responses are missing) while the remainder are for bracket responses. Figure 4.1 presents the unweighted distribution of wage responses among the employed from 2019Q1 to 2022Q2 using the unimputed data. It should be noted that such a decomposition is not possible with the public QLFS data. The distribution is quite stable over time. Between 45.4 and 53.1 percent of employed individuals in the sample reported an exact wage value in Rand terms, while an additional 18.1 – 22 percent did not report their exact wage but did report a bracket. This latter finding is quite consistent with Kerr & Wittenberg (2021)'s analysis of the 2011 and 2012 unimputed data which showed bracket responses comprised 20 – 23 percent of employed individuals. Together, this implies that the average wave tends to have non-missing wage data of some kind for nearly two-thirds of all workers, with missing wage data then for over one-third of workers. While the survey instruments of course differ in design, this missing data rate is not dissimilar from the US Current Population Survey (CPS) which typically contains missing earnings data for

[7]It should be noted that, since 2020Q2, the item in the QLFS instrument which asks respondent workers to report the exact value of their wage included an explicit instruction to enumerators to enter the value zero if the respondent did not state their wage. This instruction is not included in the instrument for any waves prior to 2020Q2. The implication of this instruction is that researchers would be unable to distinguish true zero values from non-responses, which is particularly relevant at the pandemic's onset when many workers became furloughed. However, all waves of raw data provided by StatsSA do not include any zero values, which implies that such values were recoded as missing.

[8]This merge can only be done using the public QLFS wage data for 2019 and 2020 given that the public data beyond this period was not yet made available at the time of writing.

[9]These two shares are not equivalent because the public QLFS wage data does not include imputations for all workers with missing wage data.

Figure 4.1: Distribution of wage responses among the employed in the QLFS, 2019Q1 – 2022Q2



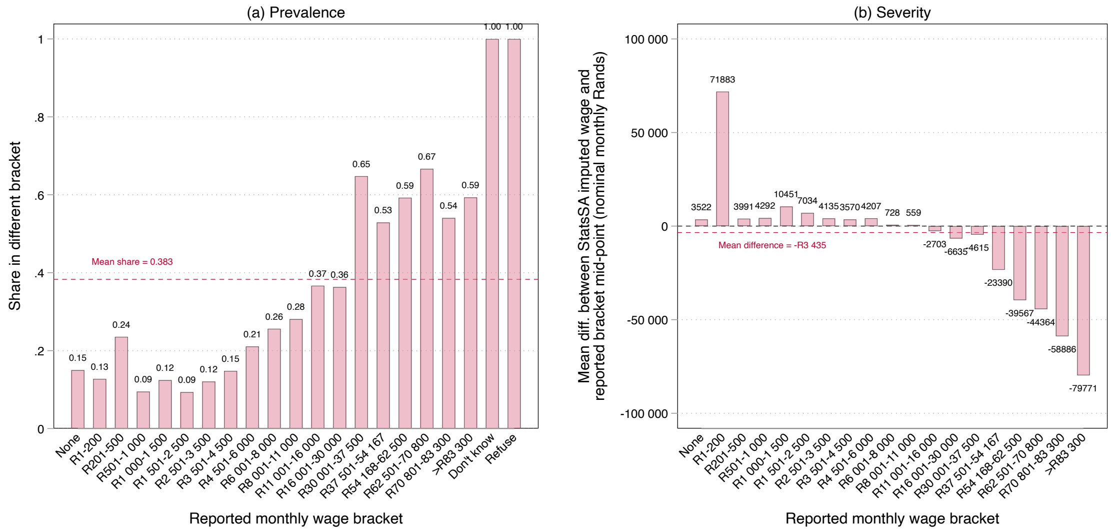
[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Unweighted estimates presented. DK = Don't know bracket responses.

around 30 percent of the employed (Bollinger & Hirsch, 2006; Kerr & Wittenberg, 2021).

Expectedly, this missing data does not appear to be distributed randomly but instead is associated with several observable covariates. As shown in Table A12 in the appendix, relative to workers who only reported bracket data or neither bracket nor exact data, the average worker who did report their exact wage value is statistically significantly younger, have fewer years of education, more likely to be female, African/Black, work in the informal sector, live in a rural area, work in the private sector, and not be a trade union member. Such differences are also reflected in a more conditional environment. Table A13 presents pooled Linear Probability Model (LPM) estimates of the predictors of non-response. Given that all of these characteristics are associated with lower wages in the South African labour market, this indicates that wage non-response is non-random and is likely concentrated towards the top of the wage distribution, which is consistent with the literature (Wittenberg, 2017).

The quality of the public QLFS wage imputations is apparent when analysing the imputation values among those who did not report their exact wage value but did report the

Figure 4.2: Inaccuracy measures of public QLFS wage imputations, 2020Q1



[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed who reported bracket wage data. Unweighted estimates presented. Panel (a) considers the share of imputations in the public QLFS data which fall into a different bracket other than the reported one. Panel (b) considers, among those in a different bracket, the absolute difference between the imputed value and the bracket mid-point.

bracket within which their wage lies. For such responders, one would expect a reasonable imputation procedure to bound their imputed values within their reported bracket. However, in two unpublished presentations, Khanyile & Kerr (2022) and Kerr (2022) showed that the imputations for bracket responders are largely outside the brackets individuals actually reported. Building on their work, in Figure 4.2 I present two measures of 'inaccuracy' of these imputations for 2020Q1: the 'Prevalence' measure in panel (a) considers the share of imputations which fall into a different bracket other than the reported one, while the 'Severity' measure in panel (b) considers, among those in a different bracket, the absolute difference between the imputed value and the bracket mid-point.

The two panels indeed strongly suggest that the public QLFS wage imputations are of a poor quality. Excluding don't knows and refusals, 38.3 percent of imputations for bracket responders are outside the bracket which the respondent reported their wage lies in.[10] This is consistent with the analysis by Khanyile & Kerr (2022) referred to above. Notably, this share varies considerably across the reported bracket distribution, with larger shares among higher-wage workers. For example, while 12 percent of imputations for workers who reported earning between R2 501 and R3 500 per month are outside this range, the equivalent share for workers who reported earning between R62 501 and R70 800 per month is 67 percent. The degree these imputations lie outside reported brackets is not negligible. As shown in panel

[10]The figure also shows that StatsSA also imputed wages for all workers who refused to report their bracket or reported that they did not know their wage. This contrasts Kerr & Wittenberg (2021)'s analysis which showed that refusals were no longer imputed for in 2012Q3, which suggests that StatsSA changed their imputation approach sometime thereafter.

(b), excluding bracket don't knows and refusals, the average imputation outside a reported bracket is R3 435 lower than the bracket mid-point. Notably, there are very severely inaccurate imputations for the R1 – R200 bracket, within which the average imputed monthly wage outside the bracket is nearly R72 000 larger than the bracket mid-point.[11] The data is also indicative of a growing discrepancy towards the top of the bracket distribution.

The unimputed wage data by itself is, of course, also not immune to non-random item non-response. To prepare the unimputed data for analysis, I follow Wittenberg (2017) and Kerr & Wittenberg (2019a) and adjust the data to (i) identify outliers and (ii) address missing values. I discuss these two approaches in detail below.

4.3.3 Outlier detection

I employ a studentised regression residual approach to identify outlying wage values and recode them as missing. While there are several outlier detection algorithms available, the studentised regression residual approach is advantageous in that it addresses outliers in both tails of the distribution, not only at the top end. This approach entails estimating an expanded Mincerian wage regression of the logarithm of monthly wages[12] on a vector of observable covariates using Ordinary Least Squares (OLS), predicting the residuals, and flagging observations with large residuals as outliers. Conceptually then, outlying wage values are considered as those which deviate significantly from what would be expected as implies by the parameters in a model of the determinants of wages. Here, the vector of observable covariates includes the usual Mincerian covariates – years of education and potential experience[13] (and its squared term) (Mincer, 1974; Lemieux, 2006; Patrinos, 2016) – as well as age, sex, racial population group, province, an urban indicator, marital status, main industry and occupation, a public sector indicator, a formal sector indicator, a trade union membership indicator, and survey wave fixed effects.[14,15] As shown in panel (a) of Figure 4.3, the residuals are concentrated around zero and appear randomly distributed across the fitted values, which suggests that both linearity and homoscedasticity hold. However, a few larger residuals are evident, but making a judgement on their magnitude is difficult because

[11] Strikingly, for one observation in 2020Q1 who did not report their exact wage but reported a bracket of R1 – 200 per month, StatsSA imputed a monthly wage of R404 434. This seems like a very implausible wage given this discrepancy, but additionally given that a worker of this set of characteristics (a 53-year old woman with seven years of education working in a sales and services occupation in the informal sector in rural Limpopo) is not associated with such a high wage. As an illustration, an expanded Mincerian regression model on the observed (exact) wage data for the wave predicts a wage of just R279 per month for this worker. Despite being outside, this prediction is much closer to the reported bracket range.

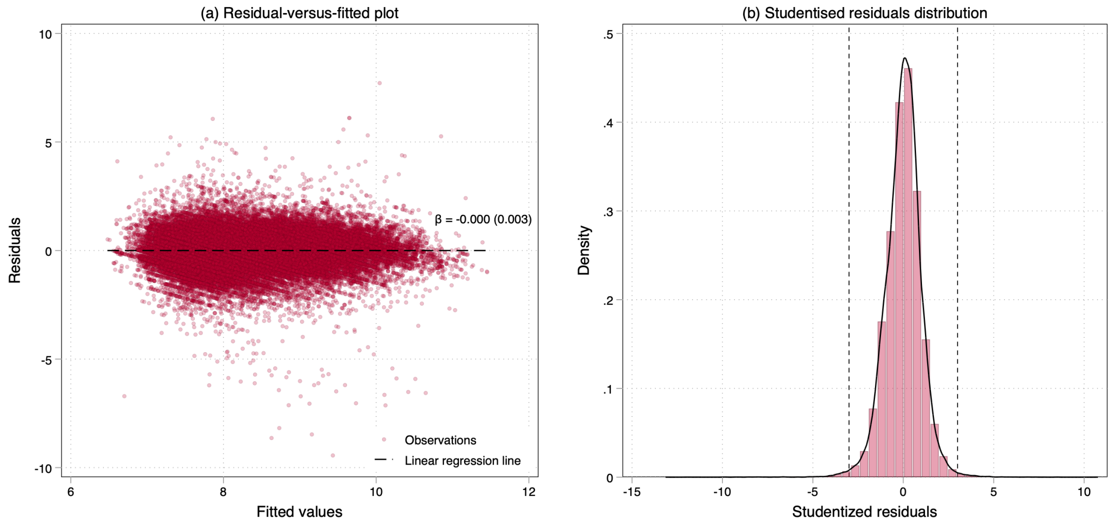
[12] There are no workers in any period in the dataset who exhibit zero monthly wages, so taking the logarithmic transformation does not result in a smaller or more select sample.

[13] Experience is not observed in the data, so potential experience is derived as age - 6 - years of education.

[14] Of course, the model will only include observations with non-missing data on all the included covariates. The extent of missing data for one covariate in particular – trade union membership status – is non-negligible at about 16 percent of worker observations in the period. To retain these workers in the sample, they are assigned the wave-specific mean of trade union membership status and a binary 'missing trade union membership status' variable is included as an additional control to flag these observations.

[15] Although the original specification by Mincer (1974) proposed modelling wages parsimoniously as a linear function of years of schooling and a quadratic function of years of potential experience, it is common in the contemporary literature to expand the model to include additional covariates of interest.

Figure 4.3: Residuals-versus-fitted-values plot and the studentised residuals distribution



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Residuals and fitted values obtained by estimating an expanded Mincerian wage regression of the logarithm of monthly wages on a vector of observable covariates using OLS. Model is unweighted. Vertical lines in panel (b) correspond to a value of three in absolute terms.

residuals depend on the unit of measurement. Additionally, points of high leverage tend to be associated with smaller residuals. Studentised residuals address these problems by adjusting each residual by an estimate of its standard deviation. The studentised residual for individual i – r_i – is defined as follows:

$$r_i = \frac{\varepsilon_i}{\sqrt{s^2_{(i)}\left(1 - h_i\right)}} \tag{4.1}$$

where ε_i is the unstandardised residual, $s^2_{(i)}$ is the estimated variance of the residual with the i^{th} observation removed, and h_i is the leverage. As expressed by Wittenberg (2017), r_i can be interpreted as a t-statistic for testing the significance of a dummy variable equal to one in a given observation and zero elsewhere, so such a variable effectively absorbs the observation and remove its influence on the other coefficients in the model. The distribution of the studentised residuals is presented in panel (b) in Figure 4.3. Following Stevens (1984), outliers are defined as observations with absolute studentised residuals in excess of three, which then detects about one percent (n = 894) of reported exact wages as outliers. These outliers are evenly distributed across survey waves. These wages are recoded as missing and then imputed for along with other observations with missing wage data using the approach discussed below.

4.3.4 Multiple imputation

Wittenberg (2017) discusses how there are two broad approaches for dealing with missing data: re-weighting non-missing values to account for missing ones or imputing for the missing data. While several methods are available, in my analysis here I employ a multiple imputation (MI) approach. First proposed by Rubin (1987), MI is now considered as one of the most effective methods for addressing item non-response (Daniels, 2022). The approach is similar to stochastic imputation which first imputes a single value, parametrically or non-parametrically, and then adds a random error term to the predicted value. One key issue with stochastic imputation is that subsequent statistical analysis treats the imputed value as the true value, even though it is the sum of the true value and some measurement error. In other words, the imputed value does not reflect any of the uncertainty implicit in the imputation process. MI is advantageous in that it repeats the imputation process multiple times to produce multiple values of what the true data might have been. Appropriate point estimates and standard errors are then obtained using Rubin (1987)'s rules, which state that standard complete-data techniques should be used to estimate the variance of estimators within all of the complete datasets while accounting for differences in estimates between datasets. Formally, Rubin (1987)'s rules are defined as follows, following the exposition by Daniels (2022). For the estimated parameter θ, the mean is simply computed as:

$$\bar{\theta}_M = \frac{1}{M}\sum_{m=1}^{M}\hat{\theta}_m \tag{4.2}$$

where $\hat{\theta}_m$ is a complete-data estimate for $m = 1, \ldots, M$ imputations. The within and between components of the variance, $\bar{W}_M$ and B_M respectively, are:

$$\bar{W}_M = \frac{1}{M}\sum_{m=1}^{M} W_m \tag{4.3}$$

$$B_M = \frac{1}{M-1}\sum_{m=1}^{M}\left(\hat{\theta}_m - \bar{\theta}_M\right)^2 \tag{4.4}$$

The total variance, T_M, can then be obtained by combining 4.3 and 4.4 as follows:

$$T_M = \bar{W}_M + \frac{M+1}{M}B_M \tag{4.5}$$

Confidence intervals can be calculated, and significance tests conducted, using a t distribution, $\left(\theta - \bar{\theta}_M\right) T_M^{-1/2} \sim t_v$ with $v = (M-1)\left(1 + \frac{1}{M+1}\frac{W_M}{B_M}\right)^2$ degrees of freedom. Following this approach, I impute exact wage values for workers who (i) neither reported their exact wage nor their bracket (including here those who reported the 'refusal or 'don't know' bracket), (ii) only reported their bracket, and (iii) were identified as outliers as discussed in the previous section. Imputations are not generated for those who reported exact wage values and were not detected as outliers. Because the missing wage data in the QLFS has a monotone pattern – that is, if bracket wage data is missing then exact wage data is missing – due to the questionnaire's skip logic, imputations here are generated by specifying a sequence of independent univariate conditional imputation methods.

Specifically, separately for each wave and following Wittenberg (2017), I first multiply impute a bracket for those in group (i) or (iii) by estimating an ordered logit model on a vector of observable covariates, and thereafter multiply impute log monthly wages based on the imputed bracket and the same vector of observable covariates using predictive mean matching (PMM) with 10 nearest neighbours.[16] For observations in group (ii), the imputation process of course skips the first step and proceeds with multiply imputing log monthly wages as described above. This process is repeated iteratively to arrive at 10 imputations, and I set the seed to ensure reproducibility. A similar approach was followed by Kerr & Wittenberg (2019a) in their generation of the Post-Apartheid Labour Market Series (PALMS) dataset – a compilation of individual-level microdata from household surveys conducted between 1993 and 2019 in South Africa. Following Van Buuren et al. (1999), the selection of observable covariates to be included is based on those which are required in the complete data model of interest, those which appear to determine missingness (see the relevant LPM estimates presented in Table A13), and those which explain a considerable amount of the variance of log monthly wages. These are included in both imputation models, following the recommended procedure (Rubin, 1987), and include age, sex, racial population group, years of education, potential experience (and its squared term), province, an urban indicator, marital status, main industry and occupation, a public sector indicator, a formal sector indicator, frequency of wage payments, and a trade union membership indicator.[17]

Table 4.1 presents information on sample sizes, extent of missing data, and number of imputations for both bracket and exact value responses over the period. In the pooled sample, 52 percent of workers do not report exact wage data, while 32 percent do not report bracket wage data, which implies that nearly 40 percent of those that do not report exact wage data do report bracket wage data. In other words, the average wave tends to have non-missing wage data (either exact or bracket responses) for nearly two-thirds of workers, with missing wage data then for over one-third of workers. This is, expectedly, consistent with the estimates presented in Figure 4.1. As previously discussed, the extent of missing data is relatively constant over time. Finally, as shown in columns (5) and (9), imputations were successfully made for nearly all observations with missing bracket data and missing exact wage data (97 percent in both cases). As with the missing data rate, the imputation rate is also relatively constant over the period.

I conduct several diagnostic tests to assess the quality of the imputations, including comparing wage distributions across imputation iterations, examining how the distributions of complete (the sum of observed and imputed values) and imputed values only compare to

[16]PMM entails regressing log monthly wages on the (imputed or reported) bracket and the vector of observable covariates, and then matches observations with missing and non-missing wage data using their predicted log monthly wage. In other words, the actual wage from an observation with non-missing wage data is imputed for an observation with missing wage data but a similar predicted wage. As such, this process is defined even for workers with missing exact wage data provided they have non-missing explanatory variable data.

[17]Observations with missing trade union membership status data here are treated similarly as with the outlier detection model.

Table 4.1: Sample size, item non-response, and imputation information, 2019Q1 – 2022Q2

		Brackets				Exact values			
	Total employed (n)	Missing data, incl. DK/Refuse (n)	Missing data rate (%)	Imputations (n)	Imputation rate (%)	Missing data (n)	Missing data rate (%)	Imputations (n)	Imputation rate (%)
	(1)	(2)	(3) = (2)/(1)	(4)	(5) = (4)/(2)	(6)	(7) = (6)/(1)	(8)	(9) = (8)/(6)
2019Q1	17,490	5,464	31.2	5,243	96.0	9,072	51.9	8,722	96.1
2019Q2	17,414	5,372	30.8	5,136	95.6	9,208	52.9	8,817	95.8
2019Q3	17,597	5,251	29.8	5,042	96.0	9,068	51.5	8,708	96.0
2019Q4	17,422	5,078	29.1	4,913	96.8	8,876	50.9	8,575	96.6
2020Q1	17,044	4,976	29.2	4,805	96.6	8,646	50.7	8,340	96.5
2020Q2	10,001	2,879	28.8	2,795	97.1	4,686	46.9	4,526	96.6
2020Q3	10,464	3,456	33.0	3,370	97.5	5,457	52.2	5,320	97.5
2020Q4	11,008	3,677	33.4	3,574	97.2	5,841	53.1	5,684	97.3
2021Q1	10,200	3,590	35.2	3,498	97.4	5,508	54.0	5,364	97.4
2021Q2	11,827	4,211	35.6	4,097	97.3	6,397	54.1	6,227	97.3
2021Q3	8,938	3,170	35.5	3,130	98.7	4,810	53.8	4,726	98.3
2021Q4	8,041	2,804	34.9	2,736	97.6	4,309	53.6	4,210	97.7
2022Q1	10,448	3,479	33.3	3,397	97.6	5,549	53.1	5,405	97.4
2022Q2	12,947	4,608	35.6	4,468	97.0	7,068	54.6	6,859	97.0
Total	180,841	58,015	32.1	56,204	96.9	94,495	52.3	91,483	96.8

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).

[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Horizontal dashed line refers to the onset of the COVID-19 pandemic in South Africa. Number of observations in columns (5) and (12) in a given wave refers to the minimum number of observations for which wage data was imputed for among the 10 imputation iterations.

the distributions of observed values only and the distribution implied by the public QLFS data, comparing the complete distributions across different types of responders (for example, those who only reported bracket responses to those who neither reported exact nor bracket values), and analysing how estimates of the complete distribution vary by the number of imputations and alternative imputation model specifications.

First, using data for 2020Q1[18] and following Abayomi et al. (2008), I estimate and plot kernel density estimates of the wage distributions separately using the observed, imputed, and complete (the sum of the observed and imputed) data for each of the 10 imputations. I plot these estimates in Figure 4.4. Differences between the observed and imputed distributions are expected here given the assumption that the wage data is missing not at random (MNAR) – that is, the probability of reporting wages varies across the wage distribution, and in particular tends to have an inverse relationship with wages (Wittenberg, 2017). As such, it may be expected that the distribution of the imputed data is located more rightwards relative to the observed data. Indeed, this appears to be the case for each imputation iteration. The imputed data distributions are all towards the right of the observed distributions, and the p-values of Kolmogorov–Smirnov tests of the equality of these distributions are all close to 0.000, implying significantly different distributions. Moreover, the imputed data distributions all exhibit a similar shape to one another and are not indicative of unreasonable wage values.

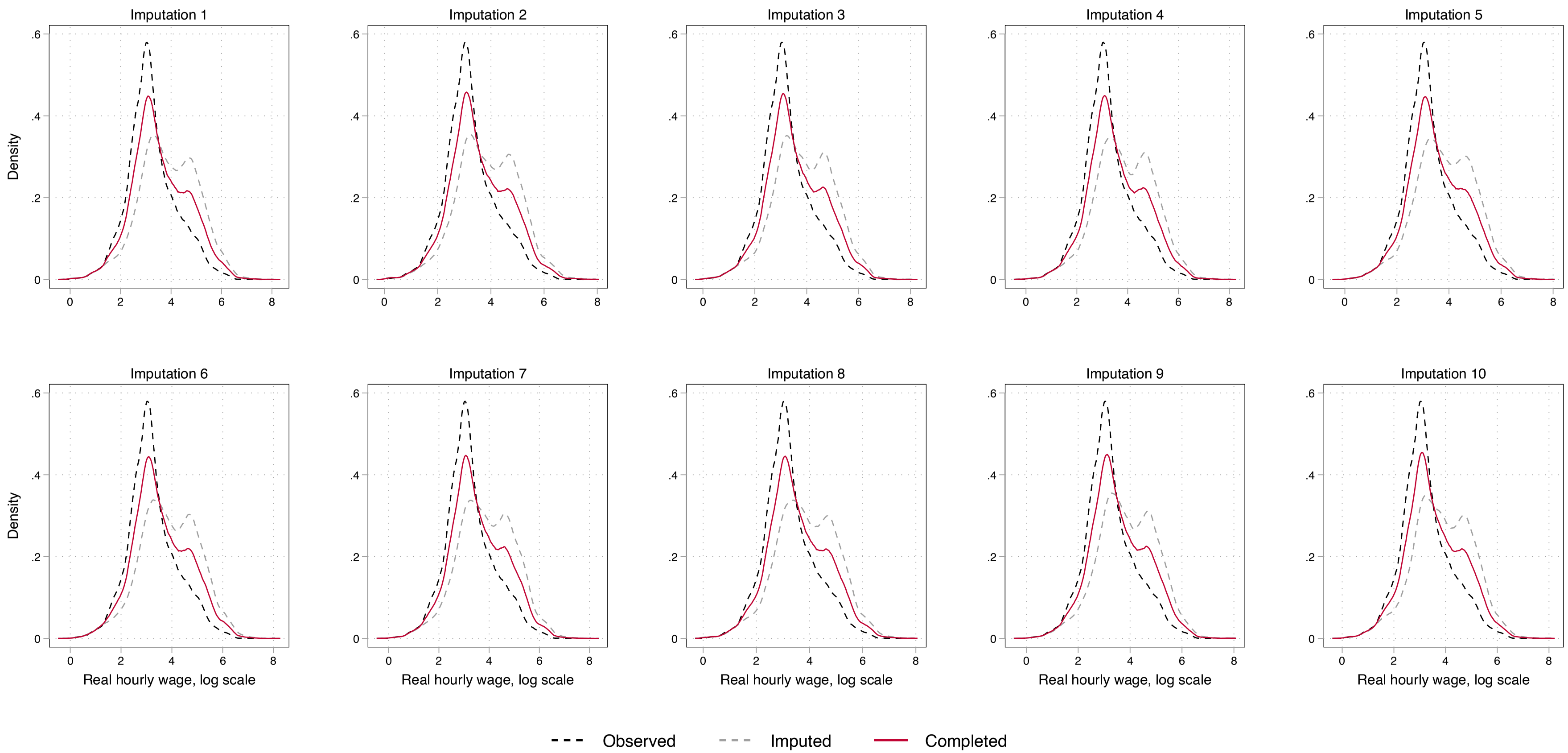
Another simple diagnostic for the MI approach entails the examination of mean and median estimates using the data before and after the inclusion of the imputed data – that is, the observed and complete data. I present the relevant estimates in Table 4.2, along with the equivalent estimates using the public QLFS wage data for comparison.[19] Overall, the table suggests that this study's approach results in a larger sample and more precise estimates in a given period which are less volatile over time. This is indicative that the imputed values obtained from the MI model are reasonable. As shown in columns (7) to (9), using the pooled complete data results in an estimated mean of R74 and median of R33, which appear to be relatively constant over time.[20] These estimates are notably higher than those obtained using only the observed data, as shown in columns (4) to (6), which is expected given the MNAR nature of the wage data and the relationship between wages and the probability of reporting wages discussed above. The larger standard errors of the complete relative to the observed data estimates are also expected given that the MI procedure explicitly incorporates additional uncertainty into the estimates. Using the public QLFS wage data, as shown in columns (1) to (3), the smaller sample sizes imply that StatsSA's approach imputed wages

[18]The relevant distributions for other survey waves are not shown for brevity; however, the distributions in all pre- and post-pandemic waves exhibit similar characteristics to the 2020Q1 data.

[19]For the public QLFS wage data, real hourly wages could only be estimated for 2019Q1 to 2020Q4 given that the public wage data for both 2021 and 2022 were not yet available in the public domain at the time of writing.

[20]Apart from a spike at the onset of the pandemic in 2020Q2. Notably, this is evident in all datasets here and as such is arguably not a consequence of either imputation process. An examination of this outcome is deferred to the detailed discussion in Section 4.5.

Figure 4.4: Diagnostic plot of real hourly wage distributions by sample and imputation iteration, 2020Q1



[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).

[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Unweighted estimates presented. Wages adjusted for inflation and expressed in June 2022 Rands. Observed = non-imputed wage data only; Imputed = imputed wage data only; Completed = combination of observed and imputed data.

for a smaller share of workers in the sample, which may be the reason behind the inflated standard errors. Relative to the complete case, while the data results in a lower median of R25 but a similar mean of R73, the latter appears to be influenced by a subset of extremely high values in 2019Q4. This outcome is presumably a consequence of StatsSA's imputation approach given that it is not evident in either the complete or observed data. Disregarding the 2019Q4 data however reduces the mean to between R60 and R69 over the period.

The characteristics described above suggest that the use of either the public QLFS wage data or the observed data alone results in an underestimation of wages. This appears to be the case not only when considering mean and median values but also across the entire distribution, as presented in Figure 4.5. Relative to the complete data distribution which includes the imputations here, both the distributions of the observed data only and the public QLFS data are positioned towards the left. At the bottom, the public QLFS data exhibits 10$^{\text{th}}$ and 25$^{\text{th}}$ percentiles of the lowest values (R7 and R14, respectively), as reflected by the distribution's longer bottom tail. These estimates are lower than the equivalent estimates using either the observed data (R9 and R15) or the complete data (R12 and R19). Towards the top of the distribution, the complete data percentiles also exceed those of both the observed data and public QLFS data.[21] Analysing the distributions of imputed values using the public QLFS data versus those obtained through the MI approach here, presented in Figure 4.6, reveals that while both approaches exhibit similar means of R94 and R96 respectively, StatsSA has imputed more extreme wage values at both tails of the distribution. The distribution's 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles are approximately R0.37 and R1 182 respectively, compared to those of R5 and R534 in the alternative distribution, resulting in a 50 percent lower median of R29.

Next, I disaggregate the distribution presented in Figure 4.6 to examine the subsets of the multiply imputed wage data; that is, the imputed data for workers who did not report their exact wage but did report their bracket and those who did not report either. These distributions are presented in Figure 4.7 along with the distributions of the complete and observed (exact wage) data for comparison. It is apparent that the imputed wage distributions of both sources of missing data are relatively similar. The distribution for those who reported bracket information (excluding 'don't know' and 'refusal' responses) exhibits a mean and median of R100 and R57 respectively, compared to R92 and R60 for those who neither reported their exact wage nor their bracket (including 'don't know' and refusal' responses), in other words 'complete missings'. Both distributions also exhibit similar degrees of positive skewness, however the kurtosis of the distribution for bracket responders is higher at 51.7 compared to 33.2 for 'complete missings', as reflected by the former distribution's longer tails. Importantly, the figure shows that the densities of imputations lie to the right of the exact data distribution. This is consistent with Daniels (2022)'s findings, who uses an MI approach on alternative labour force survey data for South Africa in the late 1990s and early 2000s, and is expected given the positive correlation between wages and the probability

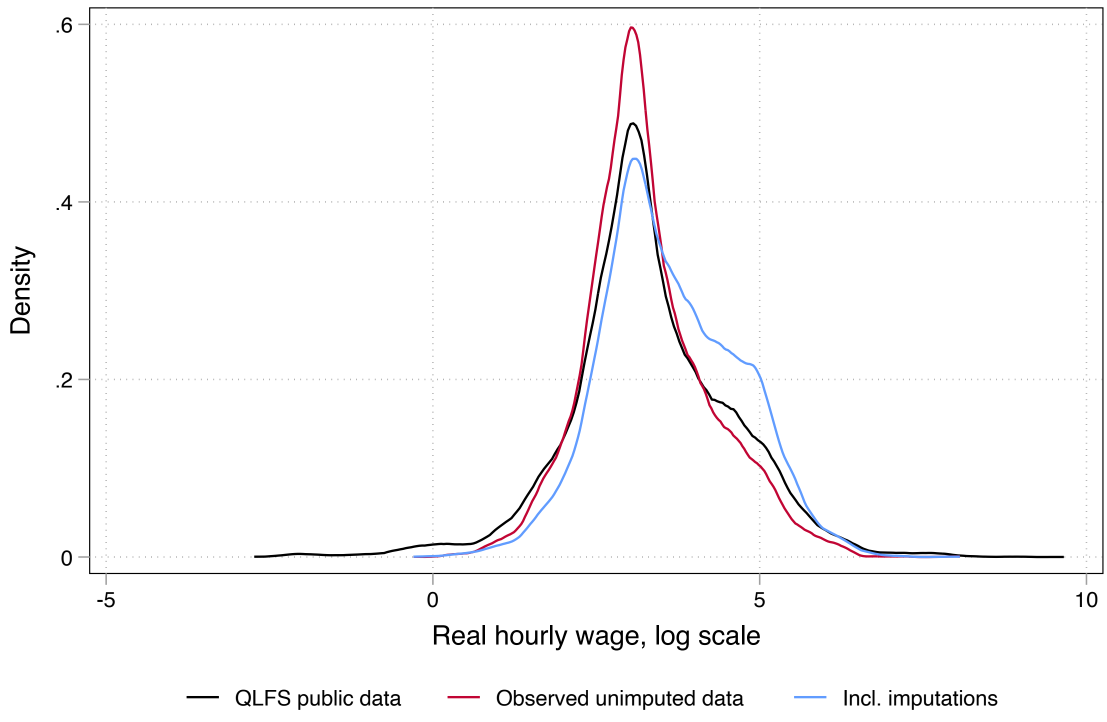
[21] The 75$^{\text{th}}$ and 90$^{\text{th}}$ percentile values for each distribution are as follows, respectively: R88 and R169 for the complete data; R58 and R142 for the public QLFS data; and R46 and R104 for the observed data.

Table 4.2: Mean and median real hourly wage estimates by dataset, 2019Q1 – 2022Q2

	QLFS public data					Observed unimputed data					Incl. imputations				
	n	Mean		Median		n	Mean		Median		n	Mean		Median	
	(1)	(2)		(3)		(4)	(5)		(6)		(7)	(8)		(9)	
2019Q1	14,571	68.61	(2.56)	24.45	(0.27)	8,419	48.39	(1.00)	23.52	(0.28)	17,124	73.43	(1.46)	32.96	(0.62)
2019Q2	14,499	66.51	(2.24)	24.01	(0.25)	8,205	48.52	(1.05)	23.10	(0.25)	17,014	74.79	(1.51)	32.51	(0.71)
2019Q3	14,640	66.76	(2.17)	24.40	(0.25)	8,529	48.16	(1.02)	22.89	(0.25)	17,220	74.43	(1.58)	33.02	(0.56)
2019Q4	14,421	89.19	(22.66)	24.45	(0.24)	8,548	47.75	(1.29)	23.04	(0.24)	17,105	75.43	(1.98)	32.91	(0.57)
2020Q1	14,103	66.18	(2.08)	24.36	(0.24)	8,399	45.57	(1.03)	22.74	(0.23)	16,721	71.72	(1.58)	32.49	(0.55)
2020Q2	8,430	101.78	(26.02)	28.94	(0.44)	5,314	56.78	(1.51)	26.04	(0.41)	9,841	86.85	(2.74)	37.02	(1.02)
2020Q3	5,479	63.31	(3.12)	24.99	(0.40)	5,008	49.80	(1.14)	24.62	(0.39)	10,327	74.91	(1.61)	36.26	(1.03)
2020Q4	8,912	60.45	(2.25)	26.43	(0.38)	5,168	50.02	(1.40)	24.31	(0.38)	10,851	74.49	(1.89)	34.61	(0.90)
2021Q1	.	.	.	.	.	4,692	50.25	(1.36)	23.96	(0.36)	10,056	77.08	(2.10)	35.16	(1.05)
2021Q2	.	.	.	.	.	5,430	47.98	(1.44)	23.68	(0.32)	11,655	73.43	(2.10)	33.33	(0.79)
2021Q3	.	.	.	.	.	4,127	48.14	(1.73)	23.30	(0.40)	8,854	76.67	(3.24)	34.15	(1.09)
2021Q4	.	.	.	.	.	3,732	44.08	(1.67)	23.04	(0.40)	7,942	67.86	(2.58)	31.90	(0.91)
2022Q1	.	.	.	.	.	4,900	45.28	(1.51)	23.85	(0.33)	10,304	65.89	(2.01)	31.66	(0.97)
2022Q2	.	.	.	.	.	5,878	51.20	(1.80)	23.49	(0.28)	12,738	70.76	(1.70)	31.94	(0.69)
Total	95,055	73.12	(4.45)	25.37	(0.11)	86,349	48.74	(0.36)	23.58	(0.08)	177,752	74.07	(1.03)	33.34	(0.43)

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Horizontal dashed line refers to the onset of the COVID-19 pandemic in South Africa. Wages adjusted for inflation and expressed in June 2022 Rands. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses. QLFS public wage data only available for 2019 and 2020 at the time of writing.

Figure 4.5: Real hourly wage distributions by dataset, 2020Q1

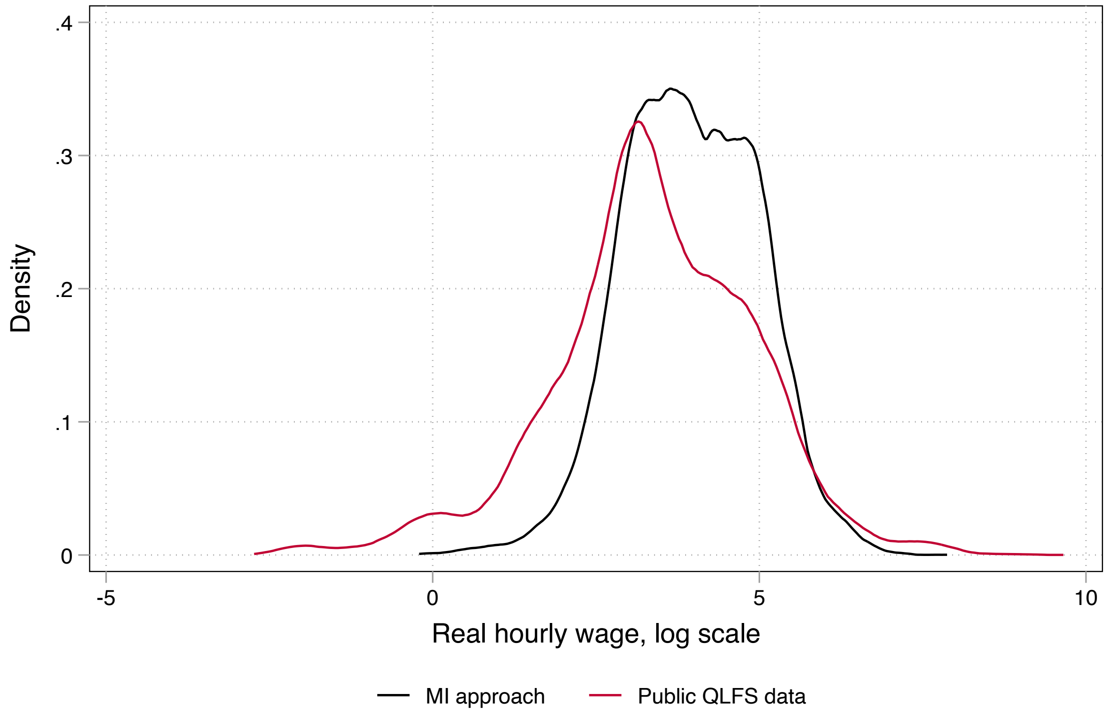


[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates weighted using sampling weights. Wages adjusted for inflation and expressed in June 2022 Rands.

of non-response discussed prior. Finally, while higher wages are typically imputed for, the figure makes it clear that both the minimum and maximum wage values in the complete distribution stem from the exact as opposed to imputed draws.

I next analyse the stability of the mean and median wage estimates by varying the number of imputations. I consider the cases of two, five, and 20 imputations, compared to my primary estimates which makes use of 10 imputations. These estimates are presented in Table 4.3. Again, following Rubin (1987)'s rules, the estimates for a given individual are computed as the mean of their multiply imputed values. It is clear that, regardless of the number of imputations here, both the mean and median estimates are almost identical across the number of imputations. This holds both within a given survey wave and over time, both before and after the onset of the pandemic. The sudden rise in estimates at the onset of the pandemic in 2020Q2 is also evident. While the discussion of this increase is deferred to Section 4.5, the observation that it occurs regardless of the number of imputations again suggests that it is not a consequence of the imputation process. The precision of the estimates, as reflected by the standard errors, also do not vary considerably as the number of imputations increase. In other words, the relationship between the number of imputations and inference does not appear to be strong in this data. As such, it can be concluded that

Figure 4.6: Distributions of imputed real hourly wages by dataset, 2020Q1

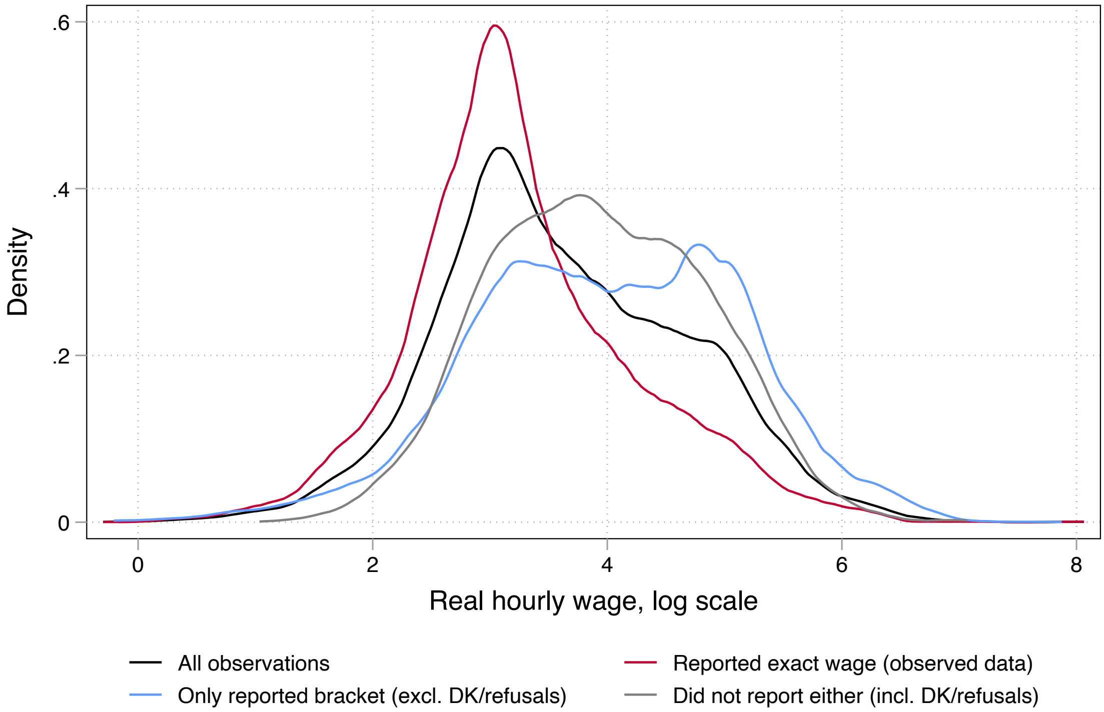


[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed whose wages were imputed. Estimates weighted using sampling weights. Wages expressed in June 2022 Rands.

the estimates here are very stable across varied number of imputations and, in line with Daniels (2022), stability of multiply imputed income data can be achieved with as little as two imputations.

As a final diagnostic for the MI approach adopted here, I test the sensitivity of estimates to a range of varied specifications of the prediction models in the imputation algorithm. Four models are developed for this purpose. First, an intentionally-misspecified model is estimated which only includes gender and province as predictors in the observable covariate vector. Second, a model which only includes covariates which predict missing wage data is estimated. As shown in Table A13, this includes wage frequency, age (and its squared term), gender, years of education, racial population group, province, main industry and occupation, and urban and public sector employment indicators. Third, a model which only includes Mincerian wage function covariates is estimated, which includes years of education and potential experience (and its squared term). Finally, the fourth model is estimated using covariates from both a Mincerian wage function and those which predict missing wage data. As described by Daniels (2022), the first model serves as a baseline to provide insight into the importance of covariate misspecification in the imputation algorithm; the second model generates imputations which are "uncongenial" in nature – that is, the imputation

Figure 4.7: Real hourly wage distributions by type of wage response, 2020Q1



[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates weighted using sampling weights. Wages expressed in June 2022 Rands.

model differs from the intended complete analysis model; the third model then generates imputations which are more "congenial" to analysing wages even though covariates which are associated with the response process are absent; while the fourth model, a-priori, is most similar to the main imputation specification described earlier in this section and hence is treated as first-best as it conforms to the recommendations of Van Buuren et al. (1999).[22]

Estimates of mean and median wages for each survey wave obtained using the four alternative multiple imputation algorithm specifications are presented in Table 4.4. For a given wave, the estimates from the second model – which only include covariates which predict missingness – and the fourth model – which also includes these covariates along with those from a typical Mincerian wage function which are more "congenial" to analysing wages – are similar to one another as well as to those obtained using the main imputation specification in this chapter's main analysis. In contrast, both the intentionally-misspecified model and that which only includes Mincerian wage function covariates produce notably smaller mean and median wage estimates. Given that the only difference between models

[22]Three covariates are not included in this model's specification but are in the main imputation specification: marital status, a formal sector indicator, and a trade union membership indicator. The reason for this discrepancy is that they neither predict missingness nor are typical Mincerian covariates, but they are required in the complete data model of interest.

Table 4.3: Mean and median real hourly wage estimates by number of imputations, 2019Q1 – 2022Q2

	m=2				m=5				m=20			
	Mean (1)		Median (2)		Mean (3)		Median (4)		Mean (5)		Median (6)	
2019Q1	73.93	(1.49)	33.06	(0.59)	73.49	(1.63)	33.10	(0.58)	73.33	(1.43)	32.89	(0.61)
2019Q2	73.70	(1.36)	32.64	(0.93)	74.34	(1.60)	32.46	(0.71)	75.17	(1.76)	32.27	(0.63)
2019Q3	73.72	(1.47)	33.02	(0.55)	73.99	(1.46)	33.02	(0.55)	74.28	(1.46)	33.02	(0.55)
2019Q4	76.40	(2.15)	32.91	(0.58)	75.55	(2.01)	32.91	(0.57)	76.24	(2.35)	32.91	(0.57)
2020Q1	72.83	(2.33)	32.49	(0.55)	72.05	(1.90)	32.49	(0.55)	71.93	(1.60)	32.49	(0.55)
2020Q2	87.70	(2.94)	37.61	(0.94)	87.48	(2.85)	37.38	(1.00)	86.91	(2.92)	37.32	(0.99)
2020Q3	74.48	(1.91)	36.25	(1.07)	75.01	(1.86)	36.37	(1.04)	75.25	(1.85)	36.31	(1.01)
2020Q4	75.32	(2.25)	34.54	(0.79)	74.77	(1.85)	34.63	(0.84)	74.74	(1.89)	34.64	(0.98)
2021Q1	76.36	(1.80)	34.99	(1.03)	76.22	(1.77)	34.86	(0.92)	76.56	(1.97)	35.11	(0.96)
2021Q2	73.40	(1.62)	33.39	(0.87)	74.15	(2.30)	33.50	(0.80)	73.73	(2.01)	33.36	(0.82)
2021Q3	76.34	(2.53)	34.24	(1.00)	76.56	(2.66)	34.35	(1.14)	76.40	(2.67)	34.38	(1.15)
2021Q4	67.34	(2.45)	31.76	(0.84)	67.61	(2.87)	31.85	(0.88)	67.19	(2.44)	31.98	(0.93)
2022Q1	64.99	(2.52)	31.30	(0.74)	66.06	(2.78)	31.64	(1.08)	65.92	(2.35)	31.59	(0.86)
2022Q2	72.17	(2.45)	32.35	(0.81)	71.59	(1.99)	32.29	(0.68)	71.85	(1.96)	32.23	(0.70)
Total	74.14	(1.10)	33.35	(0.43)	74.15	(1.03)	33.36	(0.43)	74.20	(1.03)	33.34	(0.43)

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Horizontal dashed line refers to the onset of the COVID-19 pandemic in South Africa. Wages adjusted for inflation and expressed in June 2022 Rands. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses.

2 and 4 is the inclusion of potential experience and its squared term, it should be noted that many of the covariates which predict missingness also explain a non-negligible share of the variation in wages in an 'expanded' Mincerian wage function, such as main occupation and industry. These results then suggest that covariate selection based on explaining the response process, as well as the outcome variable of interest (wages here), are particularly crucial for drawing plausible wage values using the data here. This is consistent with Daniels (2022) who notes that specifying MI algorithms using covariates which explain the response process alone is suboptimal. Additionally, it should be noted that the rise in wages in 2020Q2 is again evident regardless of model specification, which strongly suggests that the rise is not a consequence of the imputation procedure.

4.4 Methodology

4.4.1 Trends in wages and wage inequality

The remainder of this chapter's analysis is structured in two components. In the first, I estimate and analyse trends in real hourly wages and several commonly-used wage inequality indices for the weighted sample of workers in the South African labour market from the

Table 4.4: Mean and median real hourly wage estimates across alternative imputation model specifications, 2019Q1 – 2022Q2

	(i) Intentionally misspecified		(ii) Predict missingness only		(iii) Mincer		(iv) Mincer + predict missingness	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2019Q1	66.53 (1.58)	28.57 (0.44)	74.46 (1.53)	33.16 (0.63)	68.30 (1.39)	30.50 (0.49)	74.79 (1.61)	33.19 (0.66)
2019Q2	67.20 (1.64)	28.02 (0.44)	76.13 (1.64)	32.78 (0.74)	69.67 (1.46)	29.99 (0.57)	75.91 (1.73)	32.57 (0.83)
2019Q3	67.07 (1.60)	28.58 (0.39)	75.22 (1.68)	33.02 (0.55)	69.48 (1.48)	30.44 (0.49)	75.16 (1.56)	33.02 (0.55)
2019Q4	65.79 (2.29)	28.29 (0.53)	76.36 (2.27)	32.91 (0.57)	70.62 (2.08)	30.20 (0.52)	76.26 (2.50)	32.91 (0.56)
2020Q1	64.19 (1.44)	28.32 (0.49)	72.33 (1.55)	32.49 (0.55)	68.58 (1.77)	30.49 (0.54)	72.49 (1.59)	32.49 (0.55)
2020Q2	76.40 (2.39)	32.46 (0.71)	86.91 (2.80)	37.33 (0.96)	80.77 (2.46)	34.77 (0.79)	86.79 (2.58)	37.20 (1.07)
2020Q3	66.49 (2.10)	30.61 (0.94)	76.32 (1.91)	36.66 (0.96)	69.88 (2.01)	32.98 (0.99)	76.12 (1.66)	36.60 (1.05)
2020Q4	65.92 (1.84)	29.37 (0.68)	75.27 (1.77)	34.68 (0.93)	68.05 (1.72)	31.90 (0.63)	75.71 (1.85)	34.67 (0.87)
2021Q1	67.75 (1.83)	29.53 (0.87)	77.04 (2.05)	35.44 (1.14)	70.71 (2.13)	31.62 (0.74)	76.82 (2.01)	35.01 (0.94)
2021Q2	62.11 (1.81)	27.71 (0.47)	74.43 (2.45)	33.10 (0.83)	66.79 (2.01)	30.59 (0.68)	73.75 (2.15)	33.13 (0.79)
2021Q3	64.04 (2.40)	28.52 (0.74)	76.28 (2.53)	34.15 (1.08)	69.01 (2.38)	30.57 (0.70)	76.38 (2.46)	34.04 (1.11)
2021Q4	56.76 (1.97)	27.31 (0.61)	69.01 (3.26)	31.76 (0.95)	61.18 (2.11)	29.68 (0.85)	69.42 (2.48)	31.96 (0.95)
2022Q1	56.73 (1.82)	26.65 (0.48)	66.88 (2.73)	31.51 (1.03)	59.52 (1.91)	29.06 (0.71)	66.40 (2.17)	31.18 (0.91)
2022Q2	62.88 (2.37)	27.22 (0.48)	73.45 (2.07)	32.25 (0.71)	66.08 (1.79)	29.27 (0.50)	73.68 (1.90)	32.42 (0.67)
Total	65.00 (0.79)	28.57 (0.27)	74.96 (1.05)	33.37 (0.44)	68.46 (0.87)	30.70 (0.34)	74.93 (1.05)	33.36 (0.45)

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).

[b] Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Horizontal dashed line refers to the onset of the COVID-19 pandemic in South Africa. Wages adjusted for inflation and expressed in June 2022 Rands. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses.

pre-pandemic baseline period (2019Q1 – 2020Q1) through to after the onset of the pandemic (2020Q2) and during its first two years (up to and inclusive of 2022Q2). For the analysis of wages, I adopt a distributional analysis by explicitly examining cross-sectional estimates and temporal changes across the entire wage distribution. I additionally exploit the panel nature of the data at the pandemic's onset to estimate within-worker variation; that is, wage changes among those who remained employed. For the analysis of wage inequality, I again make use of both the cross-sectional and panel samples. To gain a comprehensive understanding of wage dispersion across the entire distribution, I make use of both descriptive and normative measures; that is, ones which are calculated using only mathematical formulae and ones which are additionally derived from a social welfare function, respectively. I primarily use measures which are relative rather than absolute in nature. The former are generally preferred to the latter because they have the advantage of being scale invariant – that is, if all wages were multiplied by one positive scalar, the relative inequality measure will remain unchanged – which is a desirable property because it ensures that the inequality measure is insensitive to the units in which wages is measured (Allison, 1978; Shorrocks, 1984; Sen, 1997; Atkinson & Brandolini, 2010; Shifa & Ranchhod, 2019). Specifically, I estimate and examine the following indices: the Gini coefficient, the Atkinson index, Theil's T index, as well as various percentile ratios and quantile shares. While all of these measures try to describe the distribution of wages in some way, they vary in the level of importance placed at different parts of the distribution. These are described in more detail below.

4.4.1.1 The Gini coefficient

The Gini coefficient is one of the most commonly used measures of inequality. Formally, it is calculated as follows, following Shifa & Ranchhod (2019):

$$\text{Gini} = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{|y_i - y_j|}{2N^2\mu} \tag{4.6}$$

where y_i and y_j represent the wages of workers i and j, respectively, μ the mean wage, and N the size of the population of workers. The coefficient ranges between 0 and 1 with higher values indicating higher inequality. It can be visualised as a Lorenz curve – a graphical representation of a distribution (in this case, wages) which plots the cumulative share of wages earned by the poorest x percent of a population for all possible values of x. A 'curve' of a 45-degree line represents perfect equality; that is, when wages are shared equally among all individuals, however these curves tend to exhibit a convex shape given the generally unequal distribution of wages (the poorest x percent of a population earn less than x percent of total income). The Gini coefficient can then be calculated as the area between the Lorenz curve and the 45-degree line as a proportion of the total area under the 45-degree line. An advantage of the coefficient is that it uses data from the entire distribution to generate a summary statistic, but it places greater weight on the middle of the distribution. However, an important limitation of the index is that a similar coefficient between different groups or time periods need not imply similar distributions.[23]

4.4.1.2 The Atkinson index

The Gini coefficient is a descriptive measure, implying that its calculation does not entail the incorporation of an explicit social welfare function. Atkinson (1970) however argued that such a measure does assume some implicit value judgement because they are used in policymaking processes. To allow for a measure which explicitly incorporates a social welfare function, Atkinson (1970) proposed the Atkinson class of inequality measures which are one of the most commonly-used normative inequality measures in the literature. These measures reflect the welfare loss to a society due to inequality (Shifa & Ranchhod, 2019). They do so by explicitly including an inequality aversion parameter which can vary between zero and infinity, with greater values implying that a society more heavily weights a given transfer towards the lower end of the distribution relative to an equivalent transfer towards the top. The measures are computed as follows:

$$\text{Atkinson}(\varepsilon) = 1 - \left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\mu}\right)^{(1-\varepsilon)}\right]^{\frac{1}{(1-\varepsilon)}} \tag{4.7}$$

where y_i, μ, and N take on the same definitions as in equation 4.6. ε represents the inequality aversion parameter. Although the choice of which is somewhat arbitrary, the most-commonly used values in the literature are 0.5, 1, 1.5, and 2 (Sen, 1997; Atkinson & Brandolini, 2010; Shifa & Ranchhod, 2019). In my analysis here I incorporate $\varepsilon = 1$, which makes the measure sensitive to changes in inequality at the bottom of the distribution. Like the Gini coefficient, values of the measure vary between 0 and 1, regardless of the choice of parameter, and is interpreted with respect to an equal income distribution. In the case of wages, a value of 0.80 implies that 80 percent of all wages is 'wasted' due to inequality, or alternatively, just 20 percent of all wages is needed to achieve a level of social welfare equivalent to one with an equal wage distribution.

4.4.1.3 The Theil T index

While the Atkinson class of measures have the advantage that they make the social welfare function in a given context explicit, they can result in different rankings of income distributions depending on the choice of the inequality aversion parameter (Cowell, 2011; McGregor et al., 2019). An alternative set of measures – the class of Generalised Entropy (GE) measures – overcomes this disadvantage. At their core, these measures are based on ratios of incomes to the mean income, and as such can be useful in understanding which part of

[23] As an illustration, in a context where half a population earning zero wages while the other half shall all wages equally, compared to a context where 75 percent of a population earns 25 percent of wages shared equally while the remaining quarter earn 75 percent of wages shared equally, it would be reasonable to consider the latter context as more equal than the former because half of the population in the former earn nothing. However, both contexts will exhibit the same Gini coefficient of 0.5.

the distribution drives an observed change in inequality. These measures are calculated as follows:

$$GE(\alpha) = \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\mu}\right)-1\right] \tag{4.8}$$

where y_i, μ, and N again take on the same definitions as in equation 4.6. α is a parameter which represents the weight given to inequality at different parts of the distribution. The greater a positive α value, the more sensitive the GE measure is to changes in inequality at the top of the distribution. This parameter can be of any real value, although the most commonly-used values are 0, 1, and 2 (Shifa & Ranchhod, 2019). When $\alpha = 1$, the measure is often referred to as the Theil T index – one of the most popular GE measures – which is sensitive to changes in inequality at the top of the distribution, unlike the Atkinson index which is sensitive to changes at the bottom when $\varepsilon = 1$ and the Gini coefficient which is sensitive to changes in the middle. In the analysis here I employ this specific GE measure. Unlike the Gini and Atkinson index, the values of the GE measures themselves are not restricted to vary between 0 and 1 but instead vary between 0 and ∞, with higher values again representing higher levels of inequality.

4.4.1.4 Percentile ratios and quantile shares

While the above measures make use of the entire income distribution, percentile ratios and quantile shares focus only on specific parts of the distribution. Percentile ratios serve as a comparison of incomes at different parts of the distribution, and quantile shares serve as a measure of income concentration in a particular part of the distribution. The fact that they only make use of two parts of the distribution at a time can be regarded as both a disadvantage – because they do not reflect information from the entire distribution – as well as an advantage – because they are transparent about which part of the distribution is driving any observed changed in a summary inequality measure. However, one can overcome the aforementioned disadvantage by simply computing a multitude of ratios and shares. To calculate them, I first order the population of workers in a given period from poorest to richest and then categorise them into specific quantile groups (for example, quintiles or deciles). Thereafter, to calculate quantile shares I estimate the proportion of total wages that accrue to each quantile group in a given period. In my analysis here, I estimates quantile shares for the bottom 50 percent, the middle 40 percent (workers who earn between the 30^{th} and 70^{th} percentile of the distribution), the top 10 percent, and the top 5 percent of workers. To calculate percentile ratios, I simply divide the wage at a particular percentile (for instance, the 90^{th} percentile or p90) by the wage at another percentile (for instance, the 10^{th} percentile or p10). As such, values can range between zero and ∞ and the higher the value, the greater the level of inequality. I calculate ratios for p90 to p10 (the 90/10 ratio), p90 to p50 (the 90/50 ratio), and p50 to p10 (the 50/10 ratio) to analyse wage disparities between the upper end and the bottom, the upper end and the middle, and the middle and the lower end, respectively.

4.4.2 Decomposition analysis of temporal wage variation at the mean and across the distribution

The second component of this chapter's remaining analysis consists of an examination of the drivers of the temporal changes in wages from before to after the onset of the pandemic in South Africa. In other words, I seek to decompose wage inequality over time, and hence this component is dynamic in nature. I do so both at the mean and across the entire distribution, and in doing so I seek to understand how and to what extent such changes can be explained by the relative contributions of changes in the characteristics of the employed population and changes in the returns to these characteristics. I first conduct the analysis at the mean using a twofold OB decomposition, introduced by Oaxaca (1973) and Blinder (1973), and thereafter employ RIF regression (also known as unconditional quantile regression) and decomposition for the distributional analysis, which was introduced by Firpo et al. (2009) and expanded by Fortin et al. (2011) as a means of generalising the OB decomposition to any unconditional quantile of an outcome distribution. I outline both these procedures in more detail below.

Regarding the twofold OB decomposition, I am interested in comparing wages between two time periods, $t \in (1, 2)$. OB decomposition is related to the earlier developed Kitagawa decomposition and has the same objective; however, OB decomposition is more general and is only identical to Kitagawa decomposition under very specific circumstances (Oaxaca & Sierminska, 2023). Following Oaxaca (1973) and Blinder (1973), assuming wages can be expressed as a linear function of observable and unobservable covariates:

$$wage_{it} = \boldsymbol{X}_{it}\beta_t + \varepsilon_{it}, \text{ for } t \in (1, 2) \tag{4.9}$$

A model which pools data for both periods can then simply be expressed as follows:

$$wage_i = \boldsymbol{X}_i\beta + \varepsilon_i \tag{4.10}$$

If an indicator variable $T = 0$ for $t = 1$ and $T = 1$ for $t = 2$, then the following can represent difference in wages at the mean across periods:

$$\begin{aligned}
&E\left[wage_i \mid T = 1\right] - E\left[wage_i \mid T = 0\right] \\
&= E\left[\boldsymbol{X_i} \mid T = 1\right]' (\beta_2 - \beta) + E\left[\boldsymbol{X_i} \mid T = 0\right]' (\beta - \beta_1) \\
&+ \left(E\left[\boldsymbol{X_i} \mid T = 1\right] - E\left[\boldsymbol{X_i} \mid T = 0\right]\right)' \beta
\end{aligned} \tag{4.11}$$

Equation 4.9 can then be estimated as follows, where horizontal bar accents represent sample means:

$$\begin{aligned}
\overline{wage}_{i2} - \overline{wage}_{i1} &= \left[\overline{\boldsymbol{X}}'_{\boldsymbol{i2}} \left(\hat{\beta}_2 - \hat{\beta}\right) + \overline{\boldsymbol{X}}'_{\boldsymbol{i1}} \left(\hat{\beta} - \hat{\beta}_1\right)\right] + \left(\overline{\boldsymbol{X}}'_{\boldsymbol{i2}} - \overline{\boldsymbol{X}}'_{\boldsymbol{i1}\beta}\right) \hat{\beta} \\
&= \widehat{\Delta}^{\mu}_{S} + \widehat{\Delta}^{\mu}_{X}
\end{aligned} \tag{4.12}$$

The first term in equation 4.12, $\widehat{\Delta}_S^\mu$, is referred to the estimated wage structure effect which speaks to the relative contribution of changes in the returns to characteristics in the vector $\boldsymbol{X_{it}}$ to temporal wage changes at the mean μ. The second term, $\widehat{\Delta}_X^\mu$, is referred to the estimated composition effect which speaks to the relative contribution of changes in the characteristics of the employed (again those in the vector $\boldsymbol{X_{it}}$) to temporal wage changes at the mean. These components are sometimes alternatively referred to as the 'price' and 'quantity' components, respectively. While the estimated coefficients can be used to obtain overall structure and composition effects for all covariates, it also provides estimates of the structure and composition effects for each covariate j as follows:

$$\widehat{\Delta}_S^\mu = \sum_{j=1}^{k} \bar{X}'_{2,j} \left(\hat{\beta}_{2,j} - \hat{\beta}_j\right) + \bar{X}'_{1,j} \left(\hat{\beta}_j - \hat{\beta}_{1,j}\right) \tag{4.13}$$

$$\widehat{\Delta}_X^\mu = \sum_{j=1}^{k} \left(\bar{X}'_{2,j} - \bar{X}'_{1,j}\right) \hat{\beta}_j \tag{4.14}$$

The RIF decomposition approach to analyse these temporal changes beyond the mean and across the entire distribution operates in a similar way to the OB decomposition. The exception is that the outcome variable in a RIF regression is the RIF of any functional of the outcome instead of the outcome itself. These functionals may be specific quantiles of the outcome distribution, or specific distributional statistics such as the Gini coefficient or percentile ratios. If f is the functional of the distribution, then $\widehat{\Delta}_S^\mu$ and $\widehat{\Delta}_X^\mu$ in the case of the mean μ can be expressed in the case of f as follows:

$$\widehat{\Delta}_S^f = \sum_{j=1}^{k} \widehat{\Delta}_{S,j}^f = \sum_{j=1}^{k} \bar{X}'_{2,j} \left(\hat{\beta}_{2,j}^f - \hat{\beta}_j^f\right) + \bar{X}'_{1,j} \left(\hat{\beta}_j^f - \hat{\beta}_{1,j}^f\right) \tag{4.15}$$

$$\widehat{\Delta}_X^f = \sum_{j=1}^{k} \widehat{\Delta}_{X,j}^f = \sum_{j=1}^{k} \left(\bar{X}'_{2,j} - \bar{X}'_{1,j}\right) \hat{\beta}_j^f \tag{4.16}$$

A comparison of equations 4.13 and 4.14 in the OB decomposition case to 4.15 and 4.16 in the RIF case makes it clear that the latter is identical to the former when the functional f is the mean μ, as discussed by Canavire-Bacarreza & Rios-Avila (2017).

In my analysis, I begin with the overall and detailed OB decomposition of the logarithm of real hourly wages at the mean, and thereafter conduct overall and detailed RIF decompositions along the percentiles of the distribution. I analyse three periods of interest: the pre-pandemic baseline (2019Q2) to the onset of the pandemic (2020Q2), the pre-pandemic baseline to one year after the pandemic's onset (2021Q2), and the pre-pandemic baseline to two years after the pandemic's onset (2022Q2). I follow Finn & Leibbrandt (2018) and Bhorat et al. (2020c)'s[24] choice of covariates to consider the relative contributions of the

[24]With the exception that I do not include Bhorat et al. (2020c)'s five task content variables coded using an alternative dataset.

following possible drivers: age, race, sex, urbanisation, education (years of schooling), industry, experience (included its squared term), unionisation, and sector of employment (public versus private). I further expand from those included in these studies by additionally including occupation, formality of employment, and province, bringing the total number of drivers considered to 12.[25] Lastly, it should be noted that I continue to make use of the multiply imputed wage data described in Section 4.3 in this analysis.

4.5 Results

4.5.1 Aggregate trends in real wages

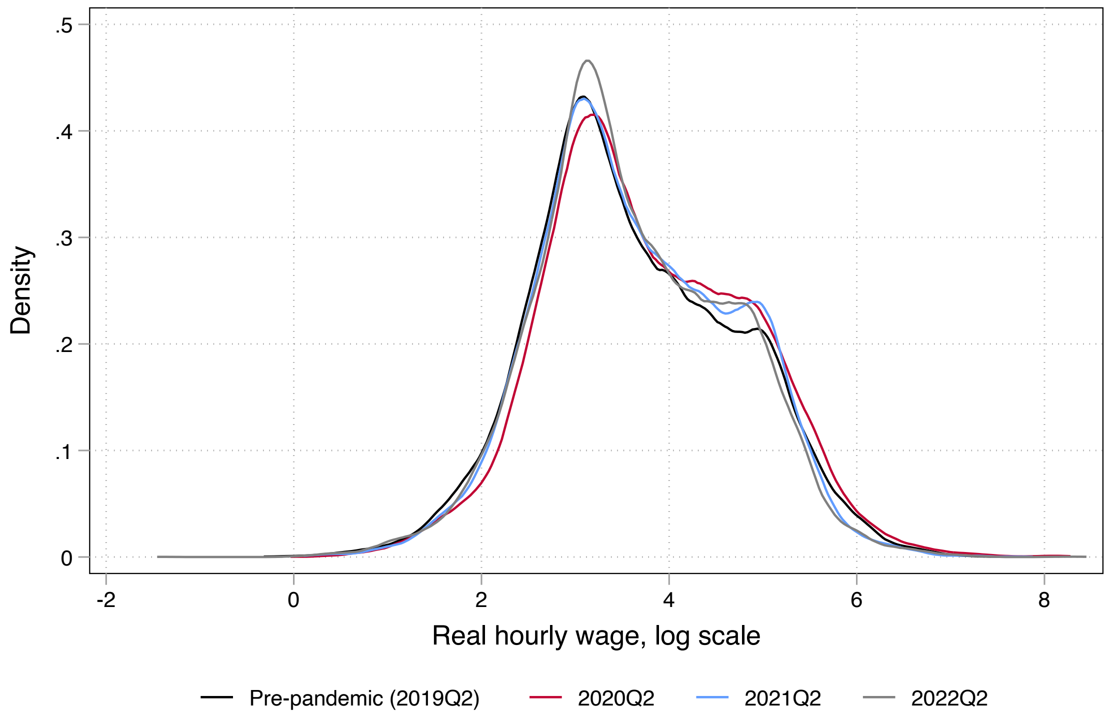
In this section I present the results from my analysis of aggregate trends of real hourly wages from the pre-pandemic baseline period through to the pandemic's onset and during its first two years. To begin, in Figure 4.8 I present kernel density estimates of the real hourly wage distributions over the period. To control for seasonality, I present the quarter 2 distributions for each year. Overall, I observe a clear rightwards but transient shift in the distribution at the onset of the pandemic accompanied, however, by a very marginal change in the shape of the distribution. This shift is reflected by variation in the mean wage (other points of the distribution are explored later). Prior to the pandemic, the estimated mean wage was R74.79 (s.e.[26] = R1.51) per hour worked, or R12 754.60 (s.e. = R248.67) per month. At the onset of the pandemic, these estimates increased to R86.85 (s.e. = R2.74) and R13 387.74 (s.e. = R360.48) respectively, with each difference being statistically significant by at least the 5 percent level. These represent substantially large real year-on-year increases of 16 and 5 percent, respectively. Two-sample Kolmogorov–Smirnov tests indicate that these distributions are statistically different from each other (p = 0.000).

One year later in 2021Q2, the distribution returned to a more similar shape compared to the pre-pandemic period, as reflected by the similar means of real hourly and monthly wages of R73.43 (s.e. = R2.10) and R12 521.46 (s.e. = R360.14), respectively. KS test results do not suggest the 2021Q2 and pre-pandemic distributions are statistically different from one another. These estimates remained relatively stable through to the end of the period another year later in 2022Q2, with marginally lower mean real hourly and monthly wages of R70.76 (s.e. = R1.70) and R11 826.42 276.458 (s.e. = R276.46), respectively, however these estimates are not statistically different from their pre-pandemic equivalents. Considering the shapes of the distributions, they are all similarly positively skewed with skewness coefficients ranging between 0.16 and 0.23 over the period, however the 2020Q2 distribution

[25] Firpo et al. (2018) note that, with respect to categorical variables, the contribution of a given covariate to the wage structure effect for both OB and RIF decomposition is sensitive to the choice of the reference group. Unfortunately, the authors also show that there is no simple solution to this problem. For transparency, the reference groups for categorical variables in the analysis here are as follows: youth (aged 15-34 years), men, those not married or living together with a partner, rural areas, self-reported Black/African individuals, the agriculture industry group at the one-digit level, the managers occupation group at the one-digit level, union non-membership, the private sector, and the informal sector.

[26] The estimated standard error.

Figure 4.8: Kernel density estimates of the real hourly wage distribution, 2019 – 2022

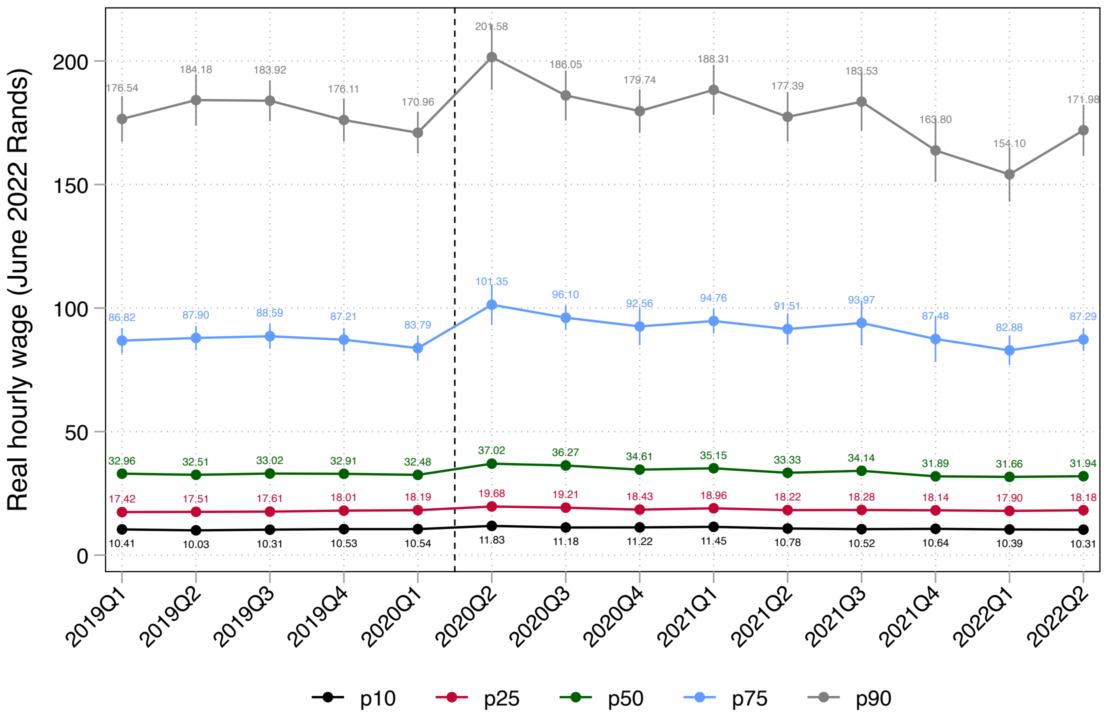


[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Wages adjusted for inflation and expressed in June 2022 Rands.

exhibits the highest degree thereof. Kurtosis coefficients are relatively constant with coefficients ranging between 2.67 and 2.83, apart from the 2022Q2 distribution which exhibits a marginally higher coefficient of 2.90, as reflected by the longer bottom tail. The variances are largely unchanged and vary between 1.06 and 1.16, suggestive of a little to no change in wage inequality among the employed over the period.

The observed rise in wages at the onset of the pandemic does not appear to be restricted to the mean but instead is observed across the entire wage distribution. Additionally, this change in wages appears to have been regressively distributed. Figure 4.9 presents the evolution of different percentiles of the wage distribution. First, the figure makes clear the extreme extent of wage inequality in the South African labour market even before the COVID-19 pandemic. Just prior to the pandemic, workers at the 10th percentile earned just R10.54 per hour, in contrast to the workers in the middle who earned more than 3 times more (R32.48 per hour). Inequality in the bottom half of the distribution is however far less severe than inequality in the top half, as documented in the literature. Workers at the 90$^{\text{th}}$ percentile of the distribution earned R170.96 per hour – more than 5 times that of the median worker. At the onset of the pandemic, while wages increased at all percentiles considered, the change in wages was marginally higher towards the top of the distribution. At the top of the distri-

Figure 4.9: Real hourly wage percentiles, 2019 – 2022

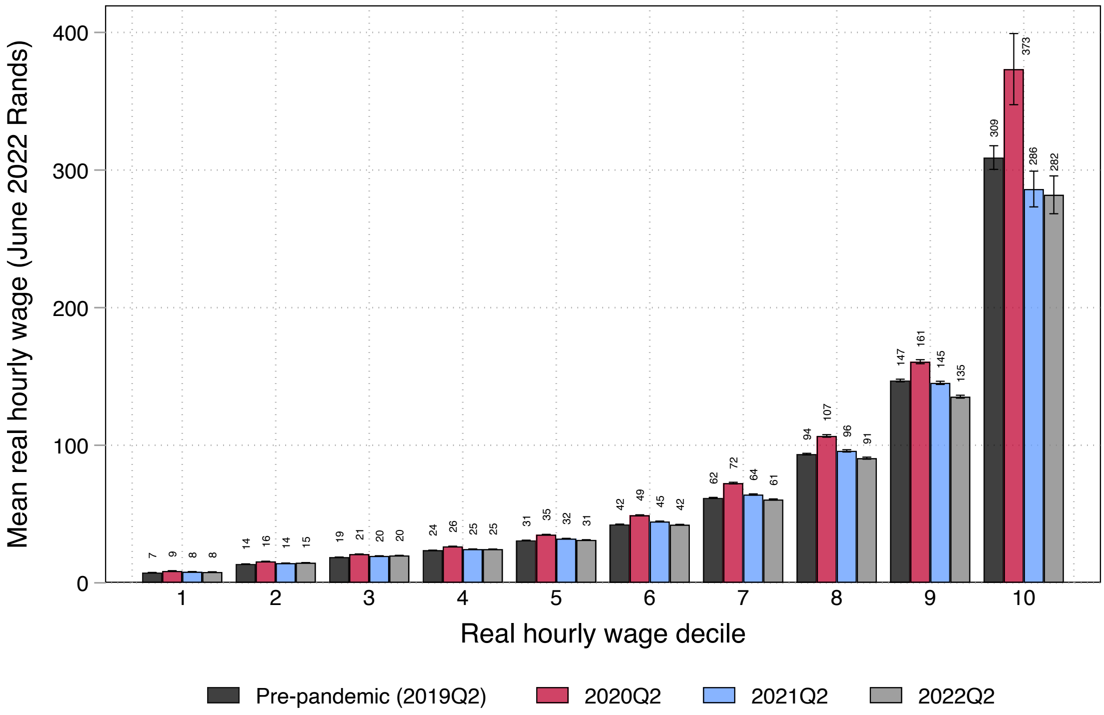


[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

bution, wages at the 90$^{\text{th}}$ percentile rose by 18 percent, in contrast to the middle where the median wage rose by 14 percent and the bottom where wages at the 10$^{\text{th}}$ percentile rose by 12 percent. All these differences are statistically significant by at least the 5 percent level. Thereafter, wages at all percentiles considered contracted towards their pre-pandemic levels and remained relatively stable for the remainder of the series.

Figure 4.10 plots estimates of decile-specific mean real hourly wages across the distribution and over time. The estimates again first describe the extreme extent of extreme wage inequality in the labour market, especially in the top half of the distribution. One year prior to the onset of the pandemic, the average worker among the poorest 10 percent of workers earned just R7 per hour, in contrast to the average worker in the middle who earned more than 4 times more (R31 per hour). As described above, inequality in the bottom half of the distribution is however far less severe than inequality in the top half. The average worker among the top decile of workers earned R309 per hour prior to the pandemic – nearly 10 and 44 times that of the average worker in the middle and bottom of the distribution. At the onset of the pandemic in 2020Q2, mean wages in all deciles rose but to varying degrees. Relative increases ranged between 8 to 29 percent in the bottom half and 10 to 21 percent in the top half. All of these increases are statistically significant by at least the 5 percent

Figure 4.10: Mean real hourly wages across the wage distribution, 2019 – 2022



[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Capped spikes represent 95 percent confidence intervals.

level. During this quarter, however, the dispersion of the distribution was not considerably different. The ratio of mean wages at the middle compared to the bottom 10 percent remained at about 4, while that of the top 10 percent to the middle increased only marginally from 10 to 10.66. During the two years thereafter, these ratios remained relatively constant while most decile-specific mean wages reduced back to their pre-pandemic levels and were not statistically significantly different from them, however among the top 30 percent of workers, mean wages reduced further in real terms marginally below their pre-pandemic levels. Overall, these dynamics are consistent with the rightwards but transient shift in the distribution observed above and are suggestive of little to no change in wage inequality among the employed during the period.

In brief, these estimates also point to a relatively large amount of minimum wage non-compliance in the labour market. Adjusted for inflation and using the National Minimum Wage (NMW) and relevant sectoral minimum wages for agriculture workers and domestic workers in place in January 2020, I estimate that just under one third (32.1 percent; s.e. = 0.6 percent) of employees earned sub-minimum wages just prior to the pandemic in 2020Q1.[27] A

[27]The NMW came into effect in January 2019, was set at R20 per hour excluding any allowances, bonuses, tips, or in-kind payments. It was applied across all sectors with the exceptions of agriculture workers, domestic workers, and public works programmes workers who were then entitled to minimum wages of R18, R15, and R11

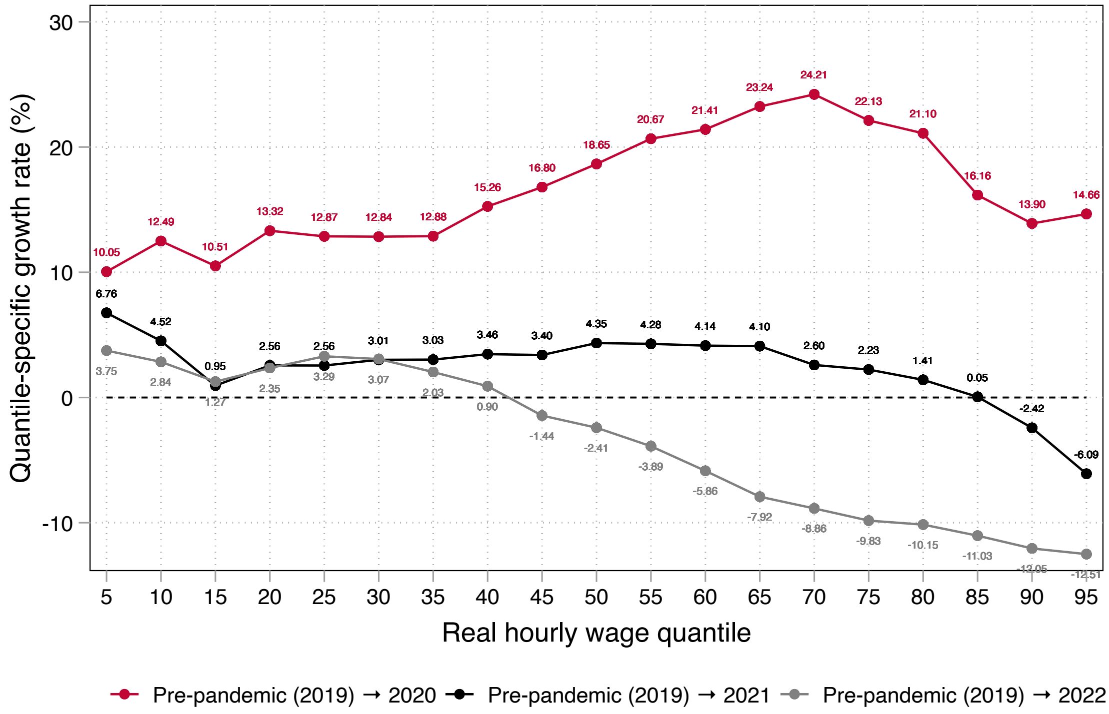
large amount of non-compliance has also been reported by Bhorat et al. (2021a) who however estimate a notably higher rate of 43.5 percent for the last quarter of 2019. This latter estimate is likely biased due to the use of the public QLFS wage data which includes StatsSA's imputations discussed in Section 4.3. This discrepancy suggests that the public QLFS data significantly overestimates minimum wage non-compliance, in line with Kerr (2022)'s analysis in an unpublished presentation. A more detailed analysis of minimum wage compliance during the pandemic in South Africa using the unimputed wage data here is beyond the scope of this chapter, but certainly serves as an important area for future research.

The marginally regressive distribution of changes in real wages at the onset of the pandemic is again observed through the use of growth incidence curves – that is, a visual representation of quantile-specific growth rates across the wage distribution. I plot these curves in Figure 4.11 for three distinct periods to compare the evolution of unequal wage changes as the pandemic progressed. Considering the pre-pandemic period to the onset of the pandemic, all estimated growth rates are positive and exceed 10 percent after accounting for inflation, which is consistent with the previously observed rightwards shift in the distribution. During this period, growth rates were relatively constant up to the 35$^{\text{th}}$ quantile and thereafter rise until and inclusive of the 70$^{\text{th}}$ quantile. Growth rates reduce beyond this point but remain higher than those observed towards the bottom of the distribution. Real wages across most of the distribution were only marginally higher one year after the pandemic's onset relative to the pre-pandemic period. One year thereafter in 2022, wages for approximately the bottom half of the distribution remained elevated but only marginally so, while those for the top half were lower. It should be noted that, to some extent, this contraction can be explained by relatively high consumer price inflation experienced during 2022 (Statistics South Africa, 2022a). Together, these dynamics reflect the temporary rightwards shift in the distribution at the pandemic's onset, followed by a relatively quick return to the pre-pandemic position thereafter.

The increase in real wages at the pandemic's onset begs the questions of whether this was driven by within-worker wage raises or alternatively a compositional change in the employed population – that is, selection into remaining employed or conversely experiencing job loss across the wage distribution. I explore these mechanisms by exploiting the unique panel nature of the QLFS data from 2020Q1 to 2020Q2. This panel sample is described in detail in Chapter 3. First, to examine the presence of a composition effect, I estimate job loss probabilities (defined as being either unemployed, discouraged, or economically inactive in 2020Q2 conditional on being employed in 2020Q1) using the balanced panel sample across the pre-pandemic wage distribution. I present these estimates for each decile in Figure 4.12.

per hour, respectively. Employers are also permitted to apply for exemptions in certain cases. My calculation here accounts for both the NMW and sectoral minimum wages for agriculture workers and domestic workers. It however neither accounts for the public works minimum wage nor workers whose employers successfully applied for exemption. As such, the estimate may be biased upwards to some degree.

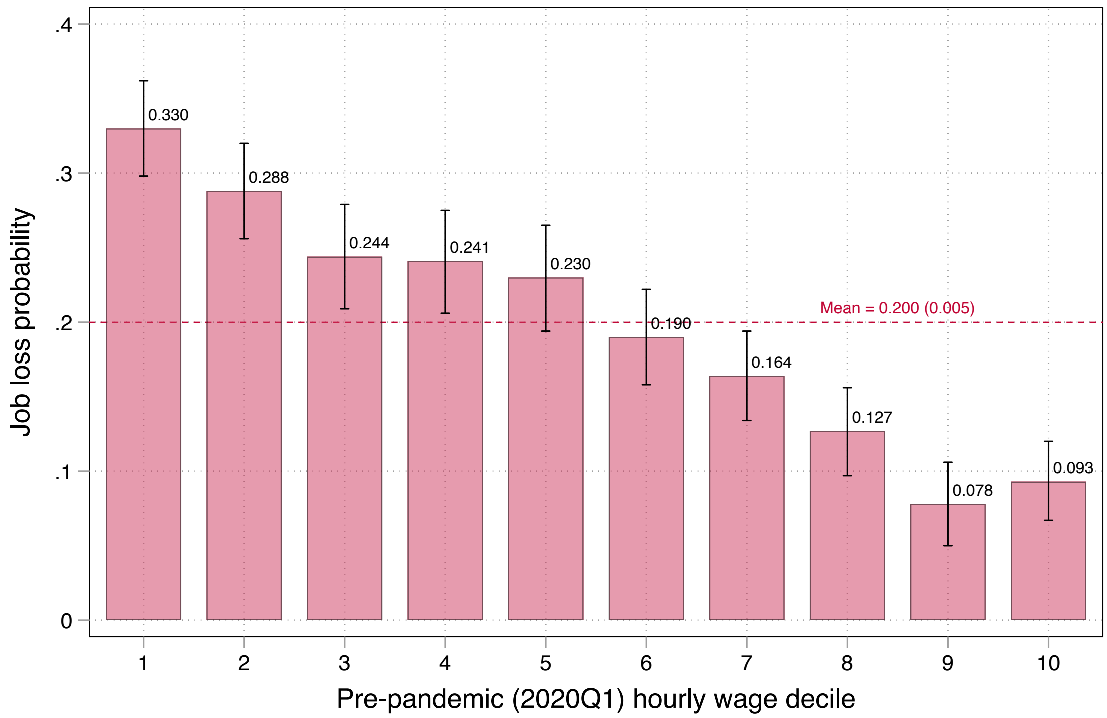
Figure 4.11: Growth incidence curves of real hourly wages, 2019 – 2022



[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Wages adjusted for inflation and expressed in June 2022 Rands.

First, it is apparent that workers across the entire distribution experienced job loss over this period. Second, job loss probabilities were notably heterogenous and regressive across the distribution. While the average worker faced a 20 percent chance of job loss, the steep and negative gradient with respect to pre-pandemic wages in the figure highlights the much greater vulnerability among lower-wage workers. A third (33 percent) of workers at the bottom of the distribution lost their jobs, in contrast to 23 percent of workers in the middle and 9 percent of workers at the top. The differences in these estimates are all statistically significant by at least the 5 percent level. This suggests that the observed increase in real wages was partially due to regressive selection into remaining employed; hence, a 'composition' effect. In other words, higher-earning workers were more likely to remain employed relative to lower-earning workers who dropped out of the wage distribution. As discussed in Chapter 2, this finding does not appear to be a consequence of the QLFS data but instead is externally valid. Using the NIDS-CRAM data, Ranchhod & Daniels (2021) show that lower-wage workers (according to their wage in February 2020) were significantly more vulnerable to job loss in April 2020. Also previously discussed, this is consistent with the large number of studies which, using either the NIDS-CRAM or QLFS, show that job losses in the country were disproportionately borne by other workers who tend to largely comprise low-wage workers, such as the less-educated, the youth, those in less-skilled occupations,

Figure 4.12: Job loss probabilities by pre-pandemic real hourly wage decile, 2020Q1 – 2020Q2



[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) in the balanced panel sample who were employed in 2020Q1 but any labour market status in 2020Q2. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design. Capped spikes represent 95 percent confidence intervals.

urban informal settlement residents, and informal workers (Ranchhod & Daniels, 2021; Espi-Sanchis et al., 2022; Rogan & Skinner, 2022; Turok & Visagie, 2022; Bassier et al., 2023; Yu et al., 2023). Again, South Africa is not unique in this regard. Such composition effects have been documented in the US (Cajner et al., 2020; Grigsby, 2022; Autor et al., 2023), Canada, France, Italy, and Norway (International Labour Organisation, 2020; Béland et al., 2020; Gherghina, 2022), Romania (Gherghina, 2022), Hungary (Gáspár & Reizer, 2020), and many Latin American countries including Brazil, Chile, and Mexico (Economic Commission for Latin America and the Caribbean, 2022).

What mechanism explains the higher job incidence among lower-wage workers observed above? As discussed in Chapter 2, the international literature provides strong evidence that this relates to the distribution of workers in 'essential' jobs largely not subjected to government-mandated sector-specific restrictions and those whose jobs allow them to work-from-home (Adams-Prassl et al., 2020; Béland et al., 2020; Borjas & Cassidy, 2020; Dingel & Neiman, 2020; Guven et al., 2020; Baek et al., 2021; Craig & Churchill, 2021; Juranek et al., 2021; Schotte et al., 2023; Zimpelmann et al., 2021; Casarico & Lattanzio, 2022; Morales et al., 2022). Similarly in South Africa, remote work ability has been shown to be strongly inversely correlated to labour market vulnerability (Benhura & Magejo, 2020; Bhorat et al., 2020d; Kerr & Thornton, 2020; Nwosu et al., 2022). As noted in Chapter 3, while industry codes can be used to identify 'essential' workers in the data, unfortunately prior to the pandemic no household survey in South Africa contained items related to a given worker's ability to work remotely. As done in the preceding and proceeding chapters, to identify 'essential' workers I cross-reference the country's industry-specific lockdown regulations in the Government Gazettes to over 150 three-digit SIC codes in the data.[28] To identify those who could plausibly work remotely, I again adopt the approach used by Kerr & Thornton (2020) and Dingel & Neiman (2020) as described in Chapter 4. Figure 4.13 presents the relevant estimates across the pre-pandemic wage distribution in 2020Q1.[29] First, it is clear that lower-wage workers were significantly less likely than their high-earning counterparts to work in either 'essential' jobs or be able to work remotely. Over 84 percent of the poorest decile of workers neither worked in 'essential' jobs nor could work-from-home, compared to 38 percent of the richest decile of workers. Remote work ability is also significantly higher among higher earners, likely related to the nature of tasks undertaken in these jobs (Dingel & Neiman, 2020). Overall, these estimates support the notion that the regressive distribution of job loss can be, at least in part, explained by lower-wage workers being less likely to work in 'essential' jobs or being able to work remotely.

4.5.2 Within-worker variation in real wages

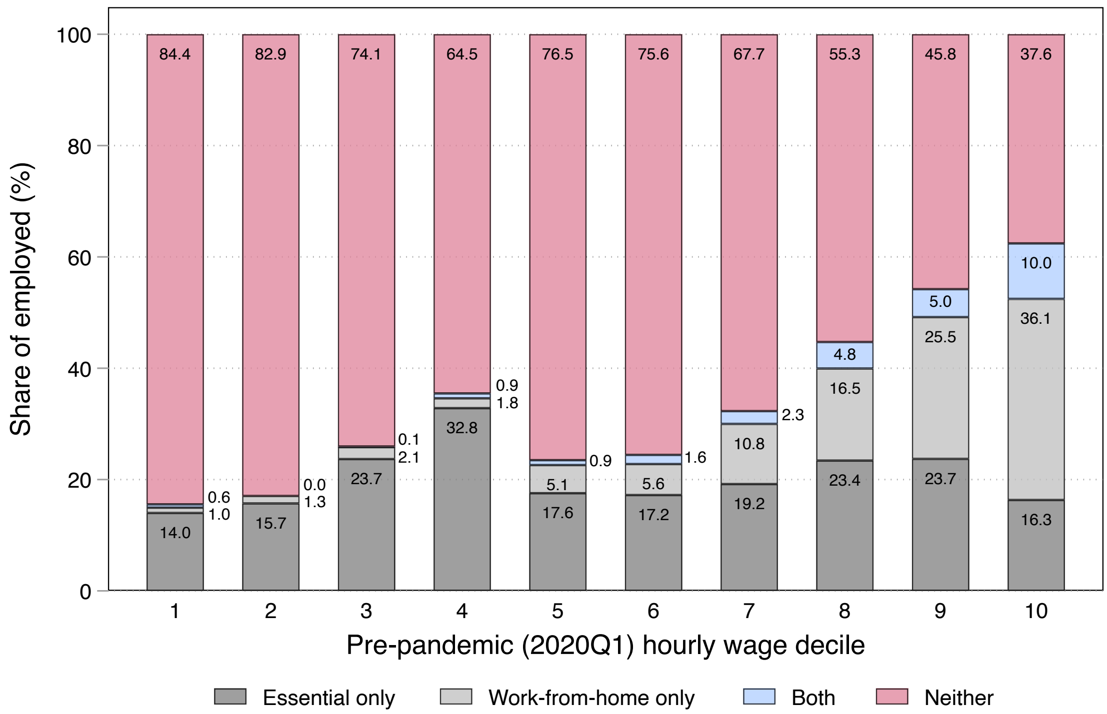
The above analysis shows that cross-sectional estimates of real wage changes at the pandemic's onset are significantly skewed by a composition effect. Of course, these estimates also mask wage changes among those who remained employed; that is, within-worker variation. To examine whether the observed increase in wages was also influenced by within-worker wage increases, I again make use of the balanced panel sample from 2020Q1 to 2020Q2 to estimate hourly and monthly wage changes, in real and relative terms, for all workers who remained employed as well as select groups of interest. The estimates are presented in Figure 4.14. Overall, I observe highly statistically significant increases - 26 percent in real monthly wages and 45 percent in real hourly wages on average - for workers who remained employed at the pandemic's onset. The larger change for hourly wages can be explained by the concurrent 17 percent (s.e. = 0.78) decrease in weekly working hours within this group. These increases do not appear explained by either two key intensive margin adjustments: individuals remaining employed but transitioning between jobs[30] or becoming furloughed. Average wage increases were significant both for those who remained in the same job as well as those who changed jobs, but were larger for the latter (34 versus 23 percent using monthly wages). Those who remained actively employed, defined as working positive hours as per

[28] Again, the categorised list of industries are presented in Table A14 in Chapter 5's appendix. I again assign 'essential' worker status based on the most stringent lockdown level in place during April 2020.

[29] Kerr & Thornton (2020) also examine the distribution of workers by 'essential' and work-from-home status across the wage distribution. However, the advantage of adopting their method here is that they could only make use of the inaccurate public QLFS wage data, whereas the analysis here uses the raw or observed QLFS wage data with multiple imputations.

[30] Job changes are measured using one-digit South African Standard Classification of Occupations and Standard Industrial Classification codes available in the data.

Figure 4.13: Essential worker and work-from-home status by pre-pandemic real hourly wage decile



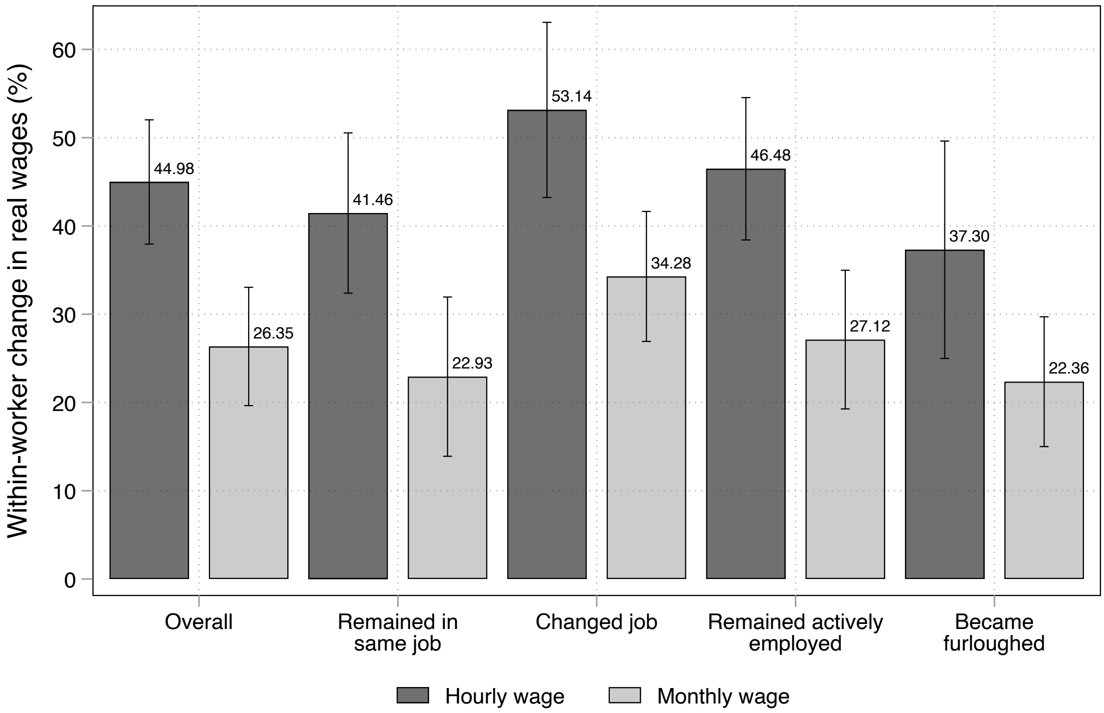
[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years). Estimates weighted using sampling weights. Categorisation of jobs by work-from-home status follows the approach employed by Kerr & Thornton (2020) and Dingel & Neiman (2020).

Chapter 3, experienced marginally higher wage increases than those who became furloughed. However, given the wide confidence intervals, I cannot reject the hypothesis that these two groups experienced the same wage change. Importantly, these observed increases are not driven by the imputation procedure adopted here. Figure A1 in the appendix presents the equivalent estimates using varied samples of workers depending on whether their wage was reported or imputed in a given or both survey waves. While the magnitudes vary, in all cases the estimated within-worker changes are highly statistically significant and positive and the hourly wage increases exceed the monthly wage increases.[31]

This evidence of within-worker wage increases stands in contrast to Bassier et al. (2023)'s analysis which, as mentioned previously, uses the NIDS-CRAM data to find no significant change in wages on average among those who remained actively employed, and a decrease on average among those who became furloughed. This discrepancy may be due to the use of different datasets which differ with respect to sample size, sampling design, and reference periods. Alternatively, this may be related to their decision to only consider wage changes

[31] The largest estimated increases are for the sample who wages were reported in 2020Q1 but imputed for in 2020Q2, while the smallest increases are for the sample whose wages were reported in both periods.

Figure 4.14: Within-worker wage changes, 2020Q1 - 2020Q2



[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) in the balanced panel sample who were employed in both 2020Q1 and 2020Q2. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design. Capped spikes represent 95 percent confidence intervals.

among a more select sample: workers who reported the exact value of their earnings, as opposed to bracket responses or cases of complete non-response. The increases documented here may appear counterintuitive but have been documented in other contexts. For instance, as discussed in Chapter 2, in the US Autor et al. (2023) attribute stronger wage growth at the bottom of the distribution after the pandemic's onset to increased labour market competition which led to a reallocation of jobs from low-wage to higher-wage employers. The higher wage growth rates among those who changed jobs relative to those who remained in the same job shown in Figure 4.14 lends suggestive support to this argument in the South African context. Also discussed previously, the literature documents a rise in demand for a subset of workers, such as 'essential' workers and those who could work remotely, in response to increased workloads which may translate into wage gains (McDermott & Hansen, 2021; Zimpelmann et al., 2021).

Alternatively, these wage increases can also plausibly be due to a distinct characteristic of the country's wage subsidy scheme - the TERS, described in Chapter 2 - introduced in response to the pandemic. As discussed by Köhler & Hill (2022) and Köhler et al. (2023), the policy's progressive design meant that some low-wage workers were eligible to receive subsidies greater than their usual wage. For instance, a worker earning approximately R1 500 per month prior to the pandemic would be eligible for a monthly subsidy of R3 500 - more than double their usual wage - assuming their employer could not make any contributions. This was not the case for higher-wage workers.[32] This implies the presence of higher wage growth rates at the bottom of the distribution.[33] In Figure 4.15 I plot the equivalent estimates as in Figure 4.14 but across the pre-pandemic wage distribution. Both hourly and monthly real wage increases are evident across most of the distribution, with the exception of the top decile of workers who exhibit a 9.5 percent *decrease* in monthly wages. As in the average case, hourly wage increases exceed monthly wage increases across all deciles, again explained by significant working hour reductions throughout. Notably, I estimate substantial working hour reduction inequality, with lower-wage workers experiencing reductions up to four times larger than their higher-wage counterparts. On the other hand and importantly, for both hourly and monthly wages, within-worker wage growth was highest towards the bottom. Among the poorest 10 percent of workers, hourly wages nearly tripled while monthly wages more than doubled over the period. While a more thorough analysis is required to arrive at a conclusive statement, this progressive distribution of wage growth is consistent with Köhler & Hill (2022) and Köhler et al. (2023)'s description of the TERS policy design.

Overall, while the exact mechanism driving the within-worker variation is unclear, these results suggest that the rise in cross-sectional wage estimates at the pandemic's onset is attributable to both a composition effect and wage gains among those who remained employed, with both primarily affecting low-wage workers. This is consistent with the results from the decomposition analysis to follow in Section 4.5.4, which additionally seeks to estimate each component's relative contribution.

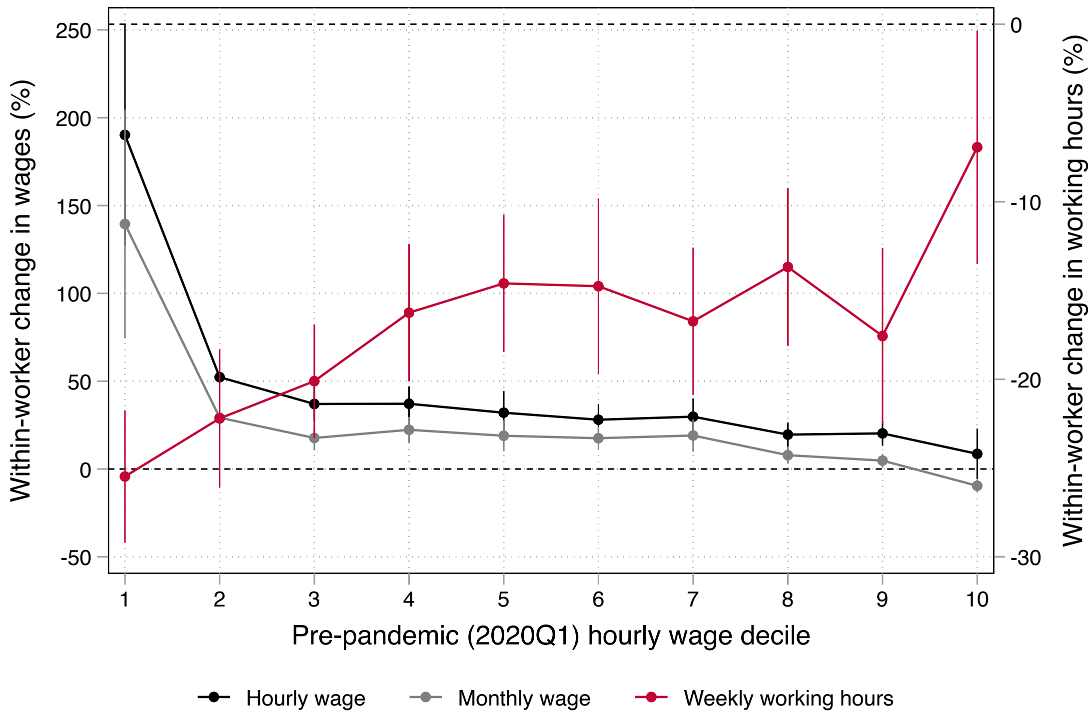
4.5.3 Trends in wage inequality

The above analysis shows that both extensive and intensive margin adjustments - an unequal distribution of job loss alongside within-worker wage increases - drove the significant but transient rise in real wages across the distribution at the pandemic's onset. However, because both were concentrated on lower-wage workers, the implications of these adjustments on wage inequality are unclear. Lower-wage workers experienced greater rates of job loss which effectively removed them from the distribution (inequality-enhancing) while conditional on remaining employed experienced stronger wage increases (inequality-reducing). To explore these inequality dynamics further, I now turn to estimating the aforementioned inequality indices across the series. Figure 4.16 presents the evolution of the estimated Gini coefficient, Atkinson index, and Theil T index. The estimates in the figure make is clear that, as described above, wage inequality prior to the pandemic was extremely high regardless of the measure, with estimated Gini, Atkinson, and Theil T coefficients of 0.585, 0.473, and 0.649 in 2020Q1, respectively. In the year prior to the pandemic, inequality remained

[32] See Köhler & Hill (2022) and Köhler et al. (2023) for a detailed description of the policy design.

[33] Recall that, as disccused in Section 4.3, wages reported by employees in the survey may be inclusive of these subsidies.

Figure 4.15: Within-worker wage and working hour changes across the pre-pandemic wage distribution, 2020Q1 - 2020Q2



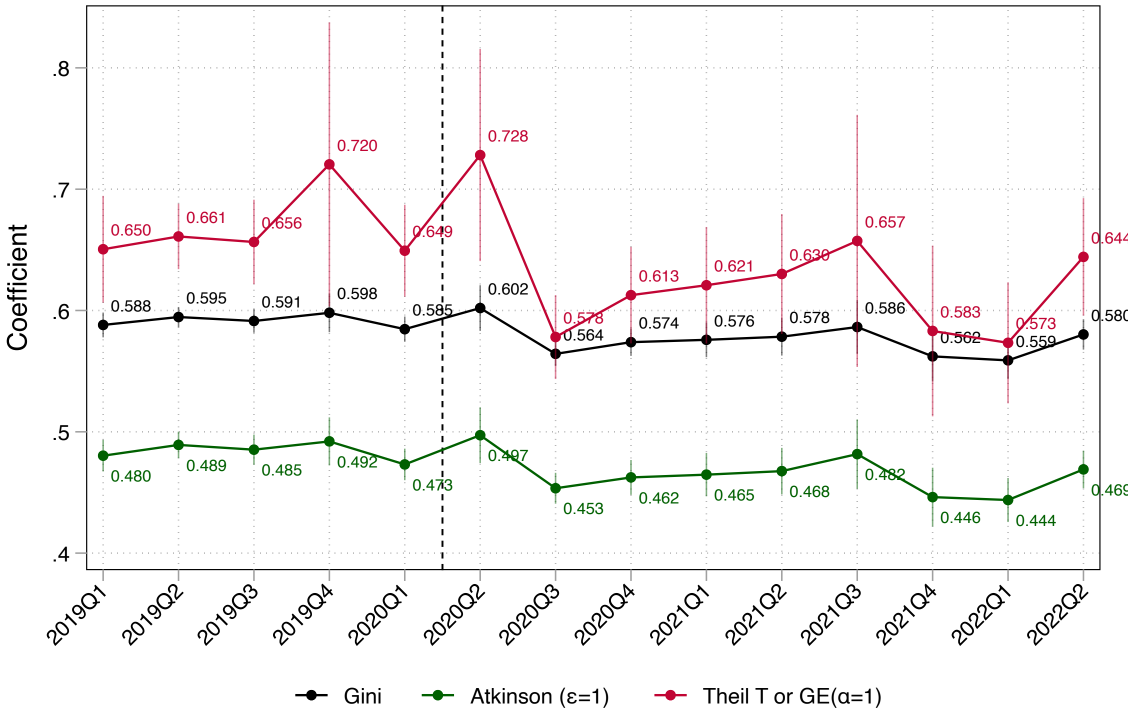
[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) in the balanced panel sample who were employed in both 2020Q1 and 2020Q2. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

relatively constant and only experienced marginal fluctuations, which is not necessarily surprising given that inequality indices are generally very slow-moving statistics (Cornia, 2014; Finn & Leibbrandt, 2018; Furceri et al., 2022). The Theil T index serves as an exception given the large spike exhibited in 2019Q4.[34] However, this spike appears to be driven by the inclusion of one observation with a particularly large, self-reported wage value.[35] While this wage was not detected as an outlier by the model described in Section 4.3, its influence is notable. When this observation is excluded from the sample, the Gini and Atkinson indices remain relatively constant at 0.591 and 0.483, respectively, while the Theil T index reduces considerably to 0.666 – a level similar to the immediate preceding and proceeding survey waves. This latter estimate is also much more precisely estimated, with a confidence interval of a magnitude similar to neighbouring waves. Such outlying values are not evident in any other wave during the period, including at the pandemic's onset in 2020Q2 when the Theil T

[34]Such a dynamic is not however shared by the other inequality indices. The estimate is also much less precisely estimated, as indicated by the wide confidence intervals, and is not statistically significantly different from the immediate preceding or proceeding estimates.

[35]The referenced worker reported an hourly wage of approximately R5 792 in real terms, which significantly exceeds the maximum self-reported wage for both the preceding and proceeding periods (R2 134 and R4 664, respectively).

Figure 4.16: Relative wage inequality estimates by measure, 2019Q1 – 2022Q2



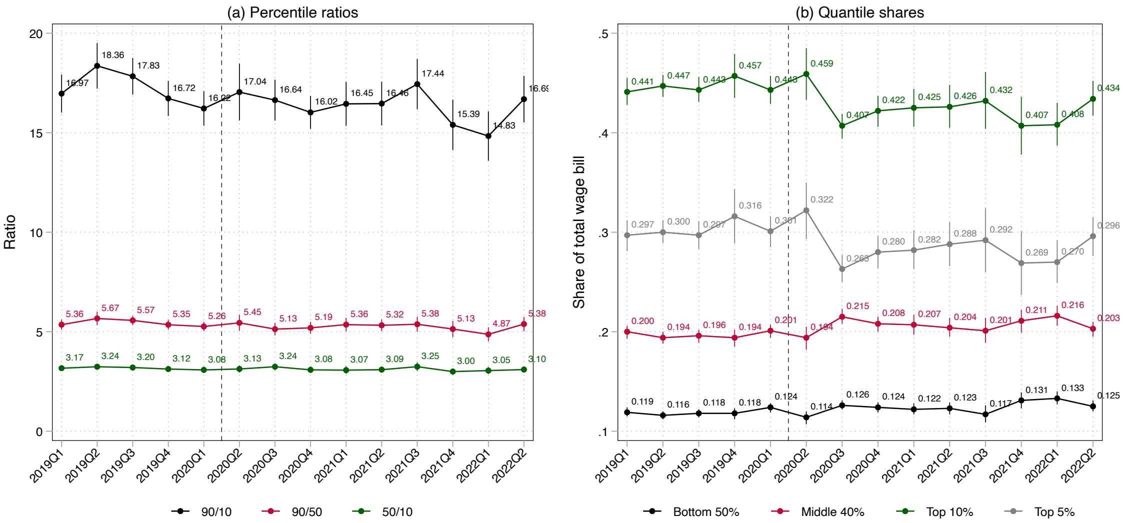
[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

exhibits another increase.[36] Overall, this suggests that wage inequality prior to the pandemic was both relatively high and quite stable in the year preceding the pandemic.

At the pandemic's onset, the values of all indices rose but to varying degrees.[37] The Gini and Atkinson indices rose only marginally by 3 and 5 percent, respectively. These increases are however only marginally larger than those observed one year prior. On the other hand, the Theil T index experienced a larger jump of 12 percent – seven times larger than the increase during the equivalent period one year prior. Considering the sensitivity of this measure to wage changes towards the top of the distribution, these dynamics are consistent with the prior observation of larger wage changes towards the top. Thereafter, all indices indicate that wage inequality reduced to below pre-pandemic levels in the following quarter (2020Q3) before gradually rising at similar rates thereafter. This points to the transient nature of the rise in wage inequality at the pandemic's onset. Inequality experienced another reduction from 2021Q3 to 2022Q1 before rising to again to the pre-pandemic level again by the end of the period. It should be noted that these levels and trends are very insensitive to my treatment of furloughed workers, as shown in Figure A2 in the appendix which presents the equivalent estimates when these workers are excluded from the sample.

[36] The maximum self-reported wage in 2020Q2 is R2 604.
[37] Recall that higher values for all indices indicate greater inequality.

Figure 4.17: Wage percentile ratios and quantile shares, 2019Q1 – 2022Q2



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

I now focus on specific parts of the distribution by estimating percentile ratios and quantile shares, presented in Figure 4.17. First, panel (a) again highlights the greater amount of inequality in the top half of the distribution relative to the bottom half. Just before the pandemic, workers at the 90th percentile earned more than 16 times that of workers at the bottom (10th percentile) of the distribution and more than 5 times that of workers in the middle. These latter workers earned just over 3 times that of workers at the 10th percentile, highlighting the relative compression of wages towards the bottom. Notably, these estimates suggest that wage inequality was gradually reducing during the year preceding the pandemic, particularly inequality between the bottom and top of the distribution. From 2019Q2 to 2020Q1, the 90/10 ratio contracted by 13 percent from 18.4 to 16, while the 90/50 ratio also reduced but at a nearly 50 percent slower rate. Panel (b) tells a similar story of extreme and persistent wage inequality but from the perspective of income concentration. Prior to the pandemic, the top 10 percent of workers accounted for 44 percent of all wages earned in the labour market, while the bottom 50 percent accounted for just 12 percent. Within the top 10 percent, wages were concentrated among the top 5 percent who accounted for 30 percent of all wages, or over two-thirds percent of all wages within the top decile.

At the pandemic's onset, the gap between workers at the top and bottom widened marginally, with 90th percentile workers now earning 17 times that of 10th percentile workers. However, this difference is not statistically significant. Statistically insignificant changes are also observed for the 90/50 and 50/10 ratio. It is unsurprising then that the quantile shares of workers towards the top of the distribution grew, albeit insignificantly, while those towards the bottom shrunk.[38] As the pandemic progressed into the next quarter (2020Q3), wage inequality reduced to below pre-pandemic levels as previously observed in Figure 4.16. This transient contraction is particularly evident when considering the quantile shares as opposed to percentile ratios. From 2020Q2 to 2020Q3, the top decile's share reduced by 46 to 41 percent, while concurrently, the bottom 50 percent's share grew from 11 to 13 percent and the middle 40 percent's from 19 to 22 percent. Thereafter, wage inequality gradually returned to levels similar to the pre-pandemic period, again as observed in Figure 4.16 and again highlighting the transient nature of the rise in wage inequality. As such, these estimates make it clear that extreme wage inequality persisted even as the labour market was recovering with respect to job loss.

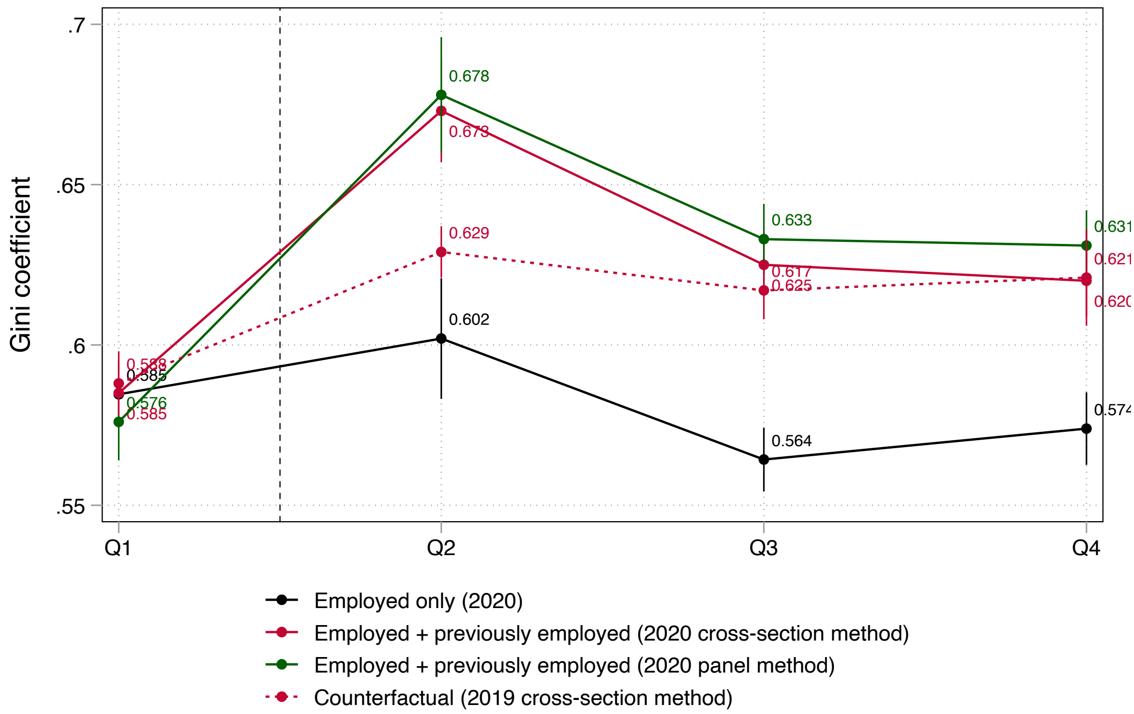
Importantly, because the inequality estimates presented in Figures 4.16 and 4.17 are based on cross-sectional samples of the employed, they do not explicitly account for selection into experiencing job loss or conversely remaining employed at the pandemic's onset; in other words, the composition effect referred to earlier. Accounting for this effect entails retaining the previously employed in the sample and regarding them as zero wage earners. While unconventional, doing so seeks to explicitly account for the role of job loss as a driver of inequality during the pandemic period. To do so, I adopt two approaches. First, I make use of a cross-sectional recall item in the survey – which asks the unemployed, conditional on having ever worked before, how long ago it was since they last worked – to identify those who were employed in 2020Q1 just prior to the pandemic but unemployed thereafter.[39] I consider data up to 2020Q4 inclusive, while observations beyond then are not considered because the available response items do not allow one to identify those previously employed just prior to the pandemic. Second, I exploit the temporary panel nature of the survey from 2020Q1 to 2021Q1, as discussed previously, to identify those who were employed in 2020Q1 but unemployed thereafter.[40] While attrition results in this sample not including all respondents surveyed in 2020Q1, which may be cause for concern for bias, the estimates are very similar in both magnitude and precision to those obtained using the cross-sectional approach described above, as shown later. For both these approaches then, the sample in a given wave comprise the employed and those previously employed just prior to the pandemic, with the latter's wages being set to zero.

[38] This latter contraction in the bottom 50 percent's share of one percentage point is statistically significant at the 5 percent level.

[39] Possible responses to this item include "less than 3 months"; "3 months to less than 6 months"; "6 months to less than 9 months"; "9 months to less than 1 year"; "1 year to less than 3 years"; "3 years to 5 years"; "more than 5 years"; and "don't know". Here, unemployed observations in 2020Q2 were regarded as employed prior to the pandemic if they reported being employed either "less than 3 months" or "3 months to less than 6 months" ago, those in 2020Q3 were regarded as employed prior to the pandemic if they reported being employed either "3 months to less than 6 months" or "6 months to less than 9 months" ago, and those in 2020Q3 were regarded as employed prior to the pandemic if they reported being employed either "6 months to less than 9 months" or "9 months to less than 1 year" ago.

[40] Because of the anonymity of observations in the survey, covariates in addition to household and person identifiers were used to ensure the same individual was being observed over time. These included self-reported race, sex, and age. Age was permitted to vary by one year across a given quarter-by-quarter pair. This approach resulted in 19 943 unique observations observed four times from 2020Q1 to 2020Q4.

Figure 4.18: Gini coefficient estimates accounting for a composition effect, by sample



[a] Author's own calculations. Source: QLFS 2019Q1 - 2020Q4 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) throughout but varies as follows: "Employed only (2020)" includes the employed for each cross-section; "Employed + previously employed (2020 cross-section method)" includes the employed for each cross-section as well as those previously employed during the pre-pandemic period (2020Q1) using the described cross-section method; "Employed + previously employed (2020 panel method)" includes the employed for each cross-section as well as those previously employed during the pre-pandemic period (2020Q1) using the balanced panel data; "Counterfactual (2019 cross-section method)" includes the equivalent sample for "Employed + previously employed (2020 cross-section method)" but using the 2019 data. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

Figure 4.18 presents estimates of these 'composition-controlled' Gini coefficients using the above two approaches. For comparison, these are plotted alongside estimates using cross-sectional samples of the employed only, equivalent to the sample used previously in Figures 4.16 and 4.17. However, inferring that any wave-specific difference between a 'composition-controlled' coefficient and the 'employed only' coefficient is attributable to pandemic-induced job loss may be inaccurate because of other events that would have happened in the pandemic's absence. For instance, the transition from employment just prior to the pandemic to unemployment thereafter may simply be the consequence of seasonality effects. To account for this, I include estimates from a sample derived using the cross-sectional method described above but using 2019 data. Because this sample comprises a similar sample as that obtained using the cross-sectional method for 2020 but just for one year prior, I explicitly assume that any difference between the 'composition-controlled' estimates across 2019 and 2020 is attributable to the pandemic. Hence, I refer to estimates obtained from 2019 as the counterfactual of the 'composition-controlled' Gini for 2020.

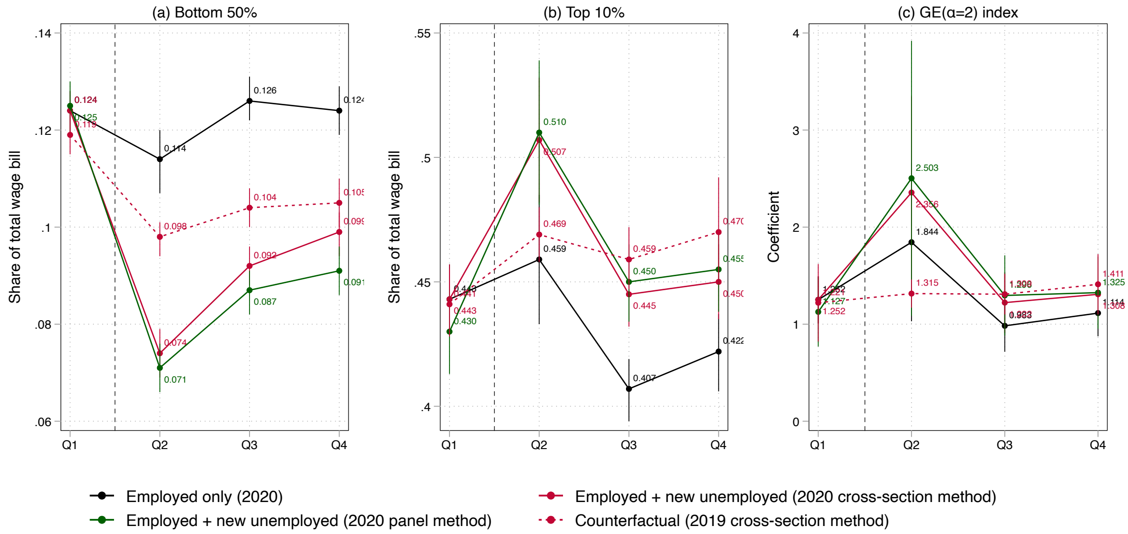
The estimates shows that, after accounting for a change in the composition of workers, the pandemic increased wage inequality significantly at its onset. While the Gini coefficient using the cross-sectional employed samples increased from 0.585 in 2020Q1 by just 3 percent to 0.602 in 2020Q2, as shown in Figure 4.16, the 'composition-controlled' coefficients rose by five to six times faster depending on the method. Using the cross-sectional method, the coefficient grew by 15 percent to 0.673, compared to a rise of 18 percent to 0.678 when the panel method is alternatively used.[41] These latter estimates for 2020Q2 are not statistically significantly different from one another. This partially reflects a reduction in the median hourly wage by 17 percent to R26.95 when the previously employed are included, as opposed to rising by 14 percent to R37.02 when they are excluded as shown in Figure 4.9. On the other hand, using the cross-sectional method but on data from the same period one year prior, the counterfactual estimate also rose from a similar base (in terms of both statistical significance and magnitude) but by a more than 50 percent lower rate (7 percent) during the same period.[42] Thereafter, the 'composition-controlled' coefficients gradually reduced toward their pre-pandemic levels while the counterfactual coefficient remained relatively constant. In both 2020Q3 and 2020Q4, while the 'composition-controlled' coefficients using the cross-sectional method were statistically insignificantly different from the counterfactual estimates, those derived using the panel method were higher but only marginally so. This observation is consistent with the prior finding that higher wage inequality at the pandemic's onset appears to have only been transient.

Assuming the 2019 'composition-controlled' Gini estimates serve as an appropriate counterfactual, the implications of these trends are four-fold. First, not accounting for the change in the composition of workers may lead to misinterpretations of wage inequality dynamics during this period. Second, wage inequality may have risen anyway in the pandemic's absence, but not to the same extent. Third, approximately half of the observed rise in the 'composition-controlled' Gini at the pandemic's onset is explained by the pandemic itself. In other words, the pandemic increased wage inequality by 7 − 8 percent or 4.4 − 4.9 Gini points in the immediate term. Finally, the rise in wage inequality appears to have been temporary, with estimates from 2020Q3 onwards being only marginally different than what they may have been in the pandemic's absence. These dynamics appear largely insensitive to the chosen measure of inequality. The trajectory of the 'composition-controlled' and counterfactual Gini estimates in Figure 4.18 closely mirror the equivalent trends for top 10 and bottom 50 percent quantile shares as well as the General Entropy (GE) measure presented in Figure 4.19. Regarding the latter, recall that the Theil T index, equivalent to GE($\alpha = 1$), exhibited a larger jump than other indices at the pandemic's onset as shown in Figure 4.16, implying larger wage changes towards the top of the distribution. While the Theil T cannot

[41] The 2020Q1 Gini coefficients using the 'employed only' and 'employed + previously employed (2020 cross-sectional method)' samples are identical because, by construction, both make use of the same sample of workers in the wave, while the coefficient using the 'employed + previously employed (2020 panel method)' sample is marginally but not statistically significantly lower because the balanced panel sample is used.

[42] This rate is of course more than twice the growth rate in the Gini when the employed cross-section samples are used.

Figure 4.19: Quantile share and General Entropy coefficient estimates accounting for a composition effect, by sample



[a] Author's own calculations. Source: QLFS 2019Q1 - 2020Q4 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) throughout but varies as follows: "Employed only (2020)" includes the employed for each cross-section; "Employed + previously employed (2020 cross-section method)" includes the employed for each cross-section as well as those previously employed during the pre-pandemic period (2020Q1) using the described cross-section method; "Employed + previously employed (2020 panel method)" includes the employed for each cross-section as well as those previously employed during the pre-pandemic period (2020Q1) using the balanced panel data; "Counterfactual (2019 cross-section method)" includes the equivalent sample for "Employed + previously employed (2020 cross-section method)" but using the 2019 data. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

be estimated here,[43] the equivalent trends using $\alpha = 2$ shown in panel (c) reveal an even larger increase at the pandemic's onset relative to the $\alpha = 1$ case. This is not necessarily surprising given the prior observation of larger observed wage changes towards the top of the distribution, and the positive relationship between positive α values and the sensitivity of this measure to such changes.

4.5.4 Decomposition analysis of temporal wage variation

4.5.4.1 At the mean: Oaxaca-Blinder estimates

In this final component of this chapter's analysis, I present the results of my decomposition analysis of the compositional and structural drivers of the changes in wages and wage inequality from before to after the onset of the pandemic, both at the mean and across the entire wage distribution using OB and RIF decomposition, respectively. I begin with the analysis at the mean and present the results from the overall and detailed OB decompositions in Tables 4.5, 4.6, and 4.7. Table 4.5 reports the mean real hourly wages (on a logarithmic scale) in a given first and second period, the temporal difference, and how much this difference is explained by composition (that is, changes in the distribution of covariates) and structure (that is, changes in the associated returns to these covariates) effects. Table 4.6 considers

[43] The Theil T index cannot be estimated because any GE measure with $\alpha < 2$ is undefined in the presence of non-positive wage values, which are explicitly included for the previously employed here.

Table 4.5: Overall Oaxaca-Blinder decomposition estimates of changes in mean real hourly wages, by period

	(1) Pre-pandemic (2019Q2) - 2020Q2	(2) Pre-pandemic (2019Q2) - 2021Q2	(3) Pre-pandemic (2019Q2) - 2022Q2
Pre mean log wage	3.645***	3.645***	3.645***
	(0.014)	(0.015)	(0.015)
Post mean log wage	3.778***	3.667***	3.628***
	(0.019)	(0.018)	(0.017)
Difference	0.133***	0.022	-0.017
	(0.020)	(0.021)	(0.020)
Composition effect	0.095***	0.056***	0.026*
	(0.015)	(0.016)	(0.016)
Structure effect	0.038***	-0.034**	-0.044***
	(0.014)	(0.014)	(0.013)
Observations	26,727	28,568	29,640

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses. Hourly wages adjusted for inflation and expressed in June 2022 Rands. * p<0.10; ** p<0.050; *** p<0.010.

the detailed decomposition of this full composition effect into the contributions from each group of covariates, while Table 4.7 does the same but for the full structure effect.

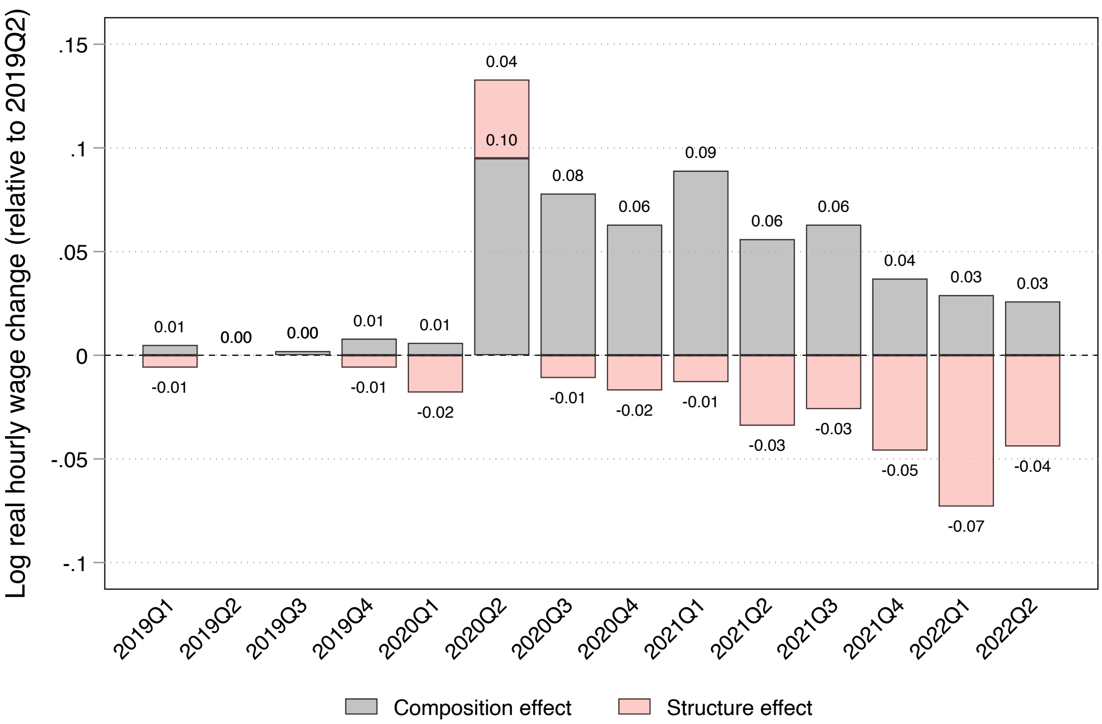
The overall decomposition results in Table 4.6 make it clear that the increase in the mean wage from the pre-pandemic period to after the pandemic's onset was primarily driven by a composition effect. As shown in column (1), the log mean wage increased by 0.133 log points, which is expected for reasons discussed in the preceding section, and while both a composition and structural effect together drive the mean wage upwards, most (71 percent) is explained by a composition effect. What is also notable, however, is the non-negligible magnitude of the structure effect. 29 percent of the increase in the average wage is explained by changes in the associated returns to individual-level characteristics, which plausibly relates to the within-worker wage gains observed previously. This suggests that both a regressive distribution of job loss alongside progressively distributed within-worker wage increases explain the rise in the mean wages at the pandemic's onset, which is consistent with the results from Sections 4.5.1 and 4.5.2. Importantly, however, the former mechanism is dominant. Because the composition and structure effects are both concentrated on lower-wage workers and hence the former is inequality-enhancing while the latter is inequality-reducing, as discussed previously, these results are also consistent with the estimates in Figures 4.18 and 4.19 which reveal an overall increase in inequality.

The results in columns (2) and (3) imply that as the pandemic progressed and the labour market partially recovered, the employed population started to return to a similar composition compared to the pre-pandemic period. However concurrently, the difference in associated returns to individual-level characteristics over the period grew. As shown in column (2) which compares wages one year after the pandemic's onset to those in the pre-pandemic period, the mean wage reduced to be marginally higher but insignificantly different than its pre-pandemic level. The composition effect, although less than half the magnitude of the effect in the preceding period, remained dominant, reflecting the compositional change in the employed population as the labour market recovered. On the other hand, the magnitude of the structure effect was relatively constant compared to the preceding period but became negative, and hence partially offset the positive compositional effect. Another year later, as shown in column (3), the mean wage marginally reduced further and the difference compared to the pre-pandemic level remained insignificant. The composition effect reduced further in magnitude and became only marginally significant, reflecting employment recovery, while the structure effect remained negative, grew by a further 30 percent, and remained highly significant, thus driving the mean wage downwards.

The above finding is insensitive to the specific wave-to-wave pairs selected above. Figure 4.20 presents estimates of the full composition and structure effects over the entire period. Each temporal change is relative to the same baseline period – 2019Q2 – to be consistent with the estimates above. The results show that the real mean wage was relatively constant prior to the pandemic, with both composition and structure effect estimates being statistically insignificant and close to zero in magnitude. As shown above, at the pandemic's onset both positive composition and structure effects drove the rise in the mean wage, however the former effect was dominant. During the two years thereafter the magnitude of the composition effect reduced in size, reflecting a growing similarity of the characteristics of workers compared to the pre-pandemic period as the labour market recovered and jobs were re-gained. Concurrently, the size of the structure effect became negative and gradually grew over time, driving the mean wage downwards. By the end of the period, this effect was larger than the only marginally significant composition effect and highly significant, indicative of a significant change in the associated wage returns to individual-level characteristics.

I now consider the detailed decomposition of this full composition effect into contributions from each group of covariates, as shown in Table 4.6. The estimates in column (1) show that at the pandemic's onset, five specific covariates – trade union membership, main occupation, years of education, formal sector employment, and public sector employment, in order of magnitude – explain about 95 percent of the full composition effect. Hence, these covariates explain over two-thirds (68 percent) of the rise in the real mean wage. It is notable that, with the exception of education, no demographic variable explains the composition effect at the mean. The coefficients on all covariate groups are positive and highly significant, indicating that after the pandemic's onset the profile of workers were more unionised, in typically higher-paying occupations, more educated, and more likely to work in the formal and public

Figure 4.20: Overall Oaxaca-Blinder decomposition estimates of changes in mean real hourly wages over the whole period



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights and are adjusted for the complex survey design. Hourly wages adjusted for inflation and expressed in June 2022 Rands.

sectors. These shifts are consistent with the employment shifts documented in Chapter 3 and, together with the substantial amount of job loss during the period, imply that workers with these characteristics were simply more likely to remain employed. During the two years thereafter, the real mean wage returned to the pre-pandemic level as employment recovered. The magnitude of the full composition effect approached zero, and the significance of all but one of these covariates - education - disappeared. This coefficient remained significant and of the same sign and similar magnitude to the preceding periods, reflecting a marginally but persistently more educated worker population.[44]

Table 4.7 presents the detailed decomposition of this full structure effect. The estimates in column (1) show that just one covariate had a statistically significant and positive coefficient at the pandemic's onset - main industry of employment - driving mean wages upwards. This is indicative of a change in sectoral wage premia during the period, at least at the mean, plausibly in response to the introduction of sector-specific restrictions at the pandemic's onset. As with the composition effect, it is notable that no demographic variable explains the

[44] Mean years of education was 11.39 years in 2022Q2 compared to 11.06 years in 2019Q2, a marginal but statistically significant difference at the 1 percent level.

Table 4.6: Detailed Oaxaca-Blinder decomposition estimates of composition effect, by period

	(1) Pre-pandemic (2019Q2) - 2020Q2	(2) Pre-pandemic (2019Q2) - 2021Q2	(3) Pre-pandemic (2019Q2) - 2022Q2
Race	0.003	0.000	-0.003
	(0.005)	(0.005)	(0.005)
Age	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Province	0.001	0.001	-0.001
	(0.002)	(0.002)	(0.002)
Female	0.000	0.000	-0.002
	(0.001)	(0.001)	(0.001)
Urban	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)
Education	0.024***	0.017***	0.027***
	(0.004)	(0.004)	(0.004)
Public sector	0.005***	0.000	0.002
	(0.002)	(0.001)	(0.001)
Formal sector	0.010***	0.000	-0.001
	(0.002)	(0.003)	(0.002)
Experience	0.002	0.005***	-0.002
	(0.002)	(0.002)	(0.002)
Unionisation	0.031***	0.022***	0.001
	(0.004)	(0.004)	(0.003)
Industry	0.001	0.003	-0.001
	(0.002)	(0.003)	(0.002)
Occupation	0.018***	0.007	0.004
	(0.007)	(0.007)	(0.006)
Observations	26,727	28,568	29,640

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses. Hourly wages adjusted for inflation and expressed in June 2022 Rands. Decomposition for categorical variables (industry, occupation, race, age, and province) based on "normalized" effects; that is, effects are expressed as deviation contrasts from the grand mean. Reference groups for categorical variables as follows: Province: Western Cape; Age: 15-34 years; Race: African/Black; Occupation: Managers; Industry: Agriculture, forestry, and fishing. * p<0.10; ** p<0.050; *** p<0.010.

structure effect at the mean. As shown in column (2), such varying returns however disappear one year later, and instead only the coefficient on the urban indicator is significant and negative. This however was short-lived. One further year later as shown in column (3), the significance of this estimate also disappears, leaving all estimates insignificant. Despite this, the full structure effect estimate in Table 4.5 is highly significant, implying the existence of significant differences in the associated returns to various characteristics in 2022Q2 relative to the pre-pandemic period. Solely considering coefficient magnitudes suggests this may be related to education and potential experience. However, the inflated standard errors do not allow me to arrive at such a conclusion confidently. As such, while differences in associated returns do appear to exist between the two periods, the data does not enable one to identify the covariates these differences pertain to.

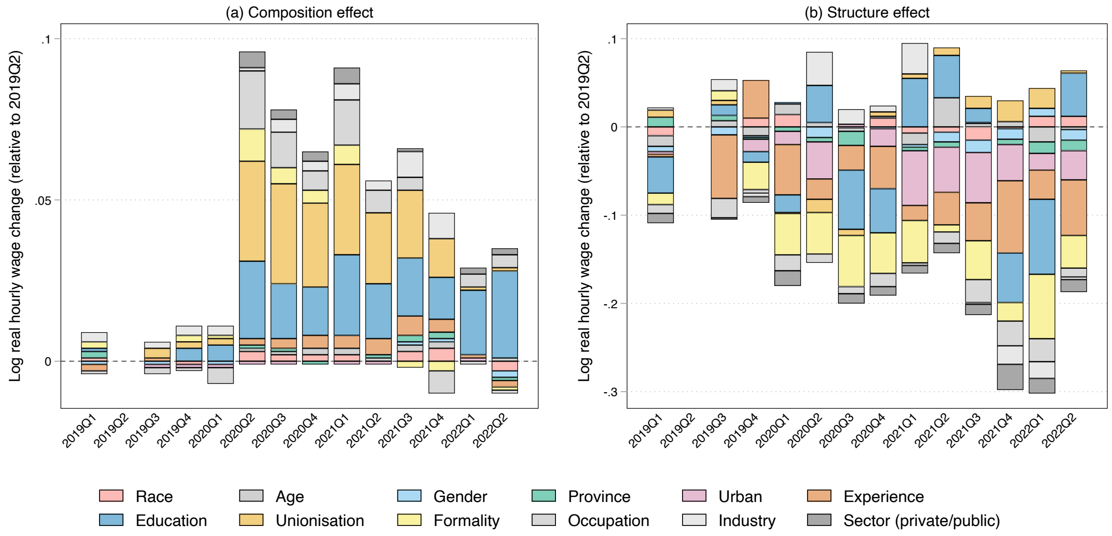
Table 4.7: Detailed Oaxaca-Blinder decomposition estimates of structure effect, by period

	(1) Pre-pandemic (2019Q2) - 2020Q2	(2) Pre-pandemic (2019Q2) - 2021Q2	(3) Pre-pandemic (2019Q2) - 2022Q2
Race	0.000	-0.006	0.012
	(0.022)	(0.027)	(0.033)
Age	0.005	0.033	-0.003
	(0.028)	(0.026)	(0.028)
Province	-0.005	-0.006	-0.012
	(0.010)	(0.009)	(0.010)
Female	-0.012	-0.011	-0.012
	(0.012)	(0.014)	(0.012)
Urban	-0.042	-0.051**	-0.033
	(0.026)	(0.023)	(0.025)
Education	0.042	0.047	0.049
	(0.075)	(0.074)	(0.066)
Public sector	0.000	-0.011	-0.014
	(0.008)	(0.007)	(0.009)
Formal sector	-0.047	-0.008	-0.037
	(0.035)	(0.036)	(0.032)
Experience	-0.023	-0.037	-0.063
	(0.070)	(0.074)	(0.074)
Unionisation	-0.015	0.009	0.003
	(0.012)	(0.013)	(0.013)
Industry	0.038**	0.000	-0.003
	(0.016)	(0.014)	(0.014)
Occupation	-0.010	-0.013	-0.010
	(0.023)	(0.019)	(0.018)
Observations	26,727	28,568	29,640

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses. Hourly wages adjusted for inflation and expressed in June 2022 Rands. Decomposition for categorical variables (industry, occupation, race, age, and province) based on "normalized" effects; that is, effects are expressed as deviation contrasts from the grand mean. Reference groups for categorical variables as follows: Province: Western Cape; Age: 15-34 years; Race: African/Black; Occupation: Managers; Industry: Agriculture, forestry, and fishing. Constant term omitted. * p<0.10; ** p<0.050; *** p<0.010.

These detailed decomposition estimates also appear to be insensitive to the specific wave-to-wave pairs selected above. Similar to Figure 4.20, Figure 4.21 presents estimates of the detailed composition and structure effects over the entire period, with each temporal change again being relative to the same baseline period (2019Q2). The estimates in panel (a) again

Figure 4.21: Oaxaca-Blinder detailed decomposition of composition and structure effects for the whole period



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design and are presented in parentheses. Hourly wages adjusted for inflation and expressed in June 2022 Rands. Decomposition for categorical variables (industry, occupation, race, age, and province) based on "normalized" effects; that is, effects are expressed as deviation contrasts from the grand mean. Reference groups for categorical variables as follows: Province: Western Cape; Age: 15-34 years; Race: African/Black; Occupation: Managers; Industry: Agriculture, forestry, and fishing. Constant term omitted from structure effect decomposition estimates.

show how trade union membership, main occupation, education, formal sector employment, and public sector employment primarily explain the full composition effect, both at the pandemic's onset and beyond. The influence of all other covariates were both economically and statistically insignificant. The influence of most of these covariates reduced meaningfully or fell away completely by the end of 2021, with the exception of education which served as the only covariate which persisted in influence throughout the period. This again reflects a marginally more educated worker population even two years after the pandemic's onset. The narrative pertaining to the detailed structure effects is less clear. As shown in panel (b), this is primarily because the majority of estimates are very small in magnitude and vary in sign.[45] The implication of this is that overall, as mentioned above, while differences in associated returns do appear to exist particularly between the end of the period and the pre-pandemic period, the data does not enable one to identify the specific covariates these returns are with respect to.

4.5.4.2 Across the distribution: Recentered Influence Function estimates

I now move beyond the mean and examine the results of the RIF decomposition of wage changes from before to after the onset of the pandemic across the entire wage distribution.

[45] It should be noted that each wave-specific constant term of the OB decomposition of the full structure effect is omitted from the figure here. In all waves the constant term is positive and relatively large, and hence the full structure effect is relatively small when summing the constant with covariate groups coefficients.

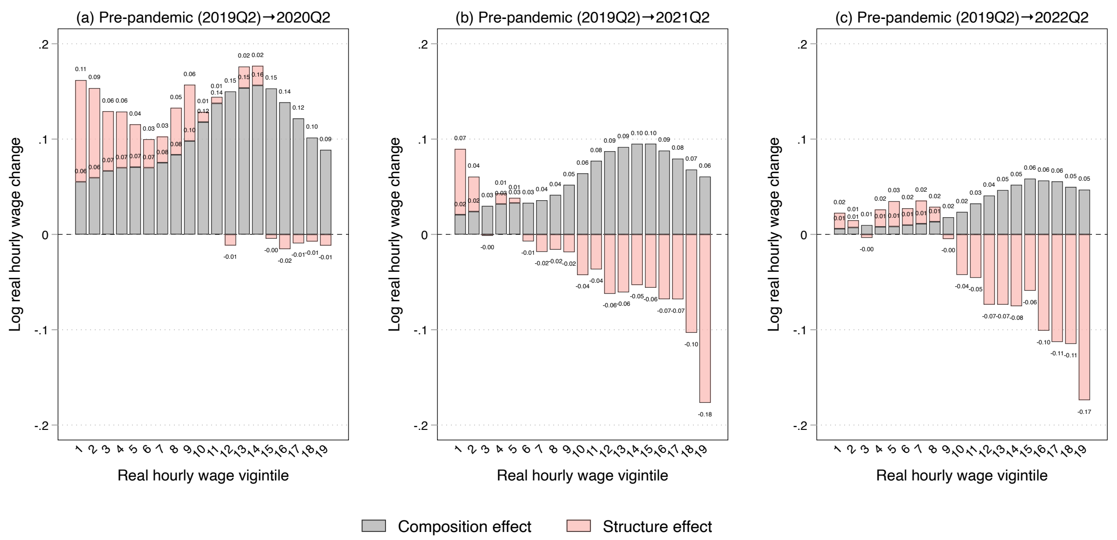
Figure 4.22 presents a visual representation of the estimates of the change in real hourly wages, again on a logarithmic scale, and the decomposed contributions of the full composition and structure effects for each quantile of the wage distribution, again for three distinct periods. The estimates are presented in the form of a stacked bar chart for ease of interpretation; that is, the net change in the log wage for a given quantile is equivalent to the sum of the individual components.

The estimates reveal significant heterogeneity in both the magnitude and direction of the full composition and structure effects across the wage distribution, highlighting an advantage of RIF decomposition over OB decomposition. Overall and as noted above, at the pandemic's onset a change in the characteristics of workers primarily explain the observed rise in real wages across most of the distribution – consistent with the analysis at the mean – apart from at the very bottom where the structure effect is dominant. As shown in panel (a), real wages were higher at the pandemic's onset relative to one year prior across the entire distribution, which is consistent with the growth incidence curve estimates in Figure 4.11, reflecting both the regressive distribution of job loss and within-worker wage gains during the period. In the average vigintile, the composition effect explains 80 percent of the rise in wages, from 52 percent in the 3rd vigintile at the bottom to 92 percent in the middle and exceeding 100 percent towards the top. As in the mean case, both the composition and structure effects are positive across most of the distribution.[46] The structure effect plays a relatively negligible role but appears to grow in magnitude with lower wages, and actually dominates the composition effect in the lowest decile. This suggests again that while changes in the composition of workers primarily explains wage increases across most of the distribution, changes in the returns to these characteristics explain wage increases at the very bottom. This is consistent with the stronger within-worker wage growth among lower-wage workers who remained employed, documented in the Section 4.5.2.

Panel (b) shows that, as the pandemic progressed and the labour market partially recovered one year following the pandemic's onset, the magnitude of the composition effect reduced, again reflecting fewer differences in the profile of workers relative to the pre-pandemic period. However, the composition effect remained dominant across most of the distribution but reduced in magnitude, consistent with the analysis at the mean. In other words, any remaining differences in wages were still primarily explained by characteristic differences in the profile of workers. The exceptions are at the very bottom and towards the top of the distribution where the structure effect is dominant. The sign of this effect is also now negative and its magnitude is larger than before, again consistent with the mean case. Additionally, the magnitude of the structure effect grows with wages, which indicates that higher-wage workers experienced larger changes in the returns to various individual-level characteristics, driving their wages downwards and hence reducing inequality. Panel (c) shows that, one additional year later, these dynamics with respect to the structure effect largely remained

[46] The structure effect is negative at top of the wage distribution, partially offsetting the composition effect. However, the estimates are negligible in magnitude and are statistically insignificant.

Figure 4.22: Recentered Influence Function decomposition of total wage change into composition and structure effects across the wage distribution, by period

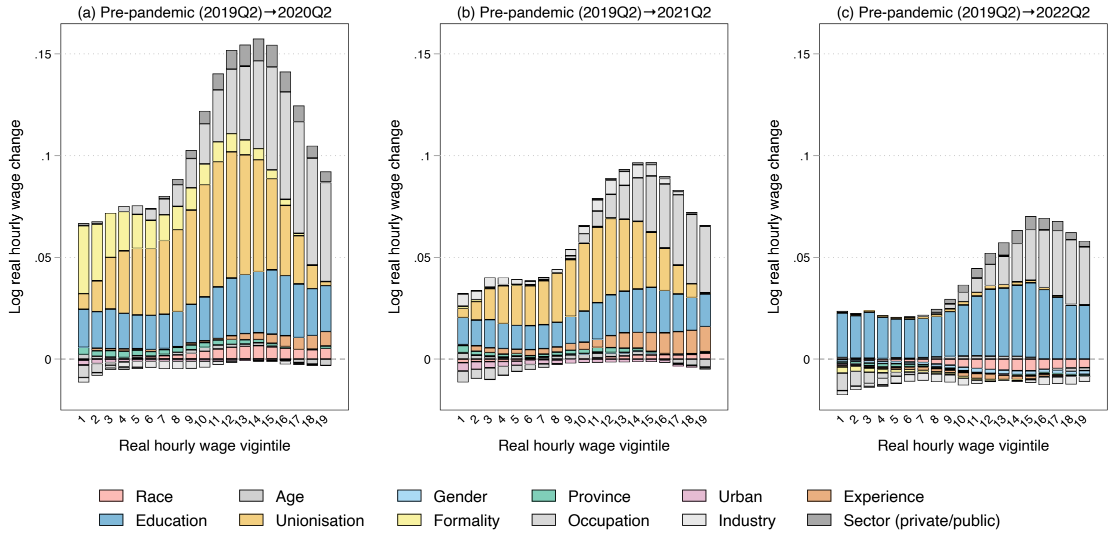


[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Hourly wages adjusted for inflation and expressed in June 2022 Rands. Decomposition for categorical variables (industry, occupation, race, age, and province) based on "normalized" effects; that is, effects are expressed as deviation contrasts from the grand mean.

intact. As of 2022Q2, the structure effect was now dominant across most of the distribution, which is consist with the mean case, while the magnitude of most composition effect estimates were relatively small – reflecting the partial employment recovery thus far and hence more similar profile of workers compared to the pre-pandemic period. The opposite signs of the effects imply that the increase in wages due to any remaining differences in the profile of workers partially offset the larger decrease in wages brought on by changes in the associated returns to individual-level characteristics. This reflects an overall reduction in inequality, considering the stronger and negative structure effect towards the top combined with smaller but positive effects at the bottom.

In Figure 4.23 I present the detailed decomposition of the full composition effects observed above across the wage distribution for each of the three periods of interest. As shown in panel (a), at the pandemic's onset the five dominant covariates observed in the mean case above – trade union membership, main occupation, years of education, formal sector employment, and public sector employment – are evident across most of the wage distribution, however the magnitudes of their respective influences varies. Towards the bottom of the distribution, changes in the characteristics of workers with respect to education, formal sector employment, and unionisation primarily explain the composition effect here. Because the full structure effect is dominant at this part of the distribution as shown in the preceding figure, these characteristic changes only partially explain the increase in real wages at the bottom. Instead, changes in the returns to certain characteristics primarily do so, examined

Figure 4.23: Recentered Influence Function detailed decomposition of the composition effect across the wage distribution, by period



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Hourly wages adjusted for inflation and expressed in June 2022 Rands. Decomposition for categorical variables (industry, occupation, race, age, and province) based on "normalized" effects; that is, effects are expressed as deviation contrasts from the grand mean.

in more detail later. Towards the middle, education, unionisation (now to a greater extent relative to the bottom), formal sector employment (now to a lesser extent), occupation, and to a small extent public sector employment explain the composition effect. The full composition effect is dominant here, and hence changes in the characteristics of workers with respect to these characteristics primarily explain the increase in wages at this point of the distribution. Towards the top, education and occupation remain influential as well as public sector employment to a lesser extent, while unionisation reduces in importance. Importantly, the magnitude of the education coefficient is relatively constant and positive across the entire distribution, suggesting that changes in the education profile of the employed population explained a similar absolute (but not relative[47]) amount of the increase in wages at the pandemic's onset regardless of the point of the wage distribution. Additionally, it is again notable that the composition effect is primarily explained not by demographics but instead by labour market characteristics, as in the mean case.

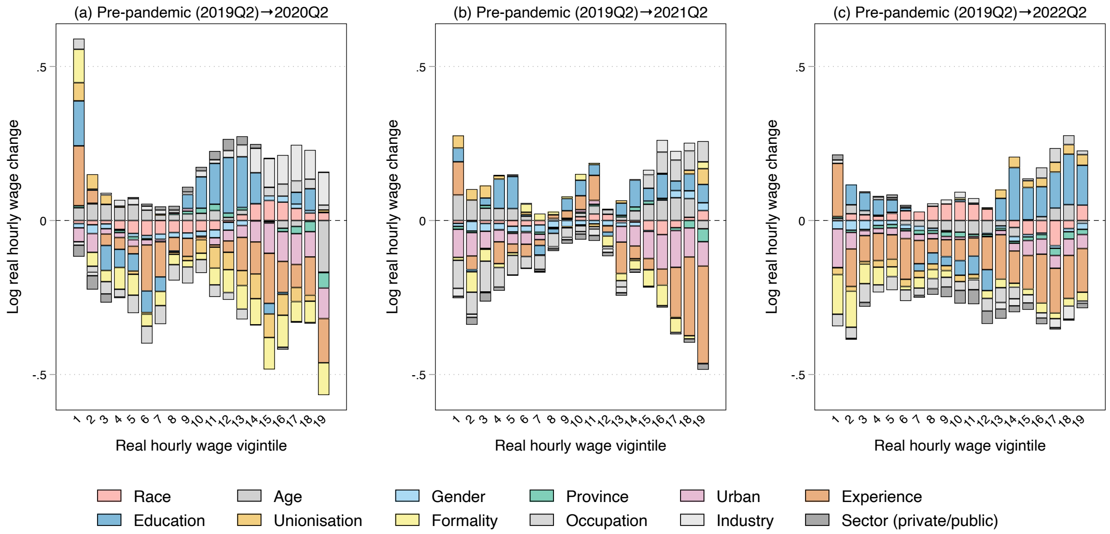
The estimates in panel (b) show that one year after the pandemic's onset, education remained an important contributor to the composition effect across the entire distribution, with the coefficient only marginally reducing in magnitude compared to the preceding period. This, in addition to union membership's continuing role, is consistent with the analysis at the mean. Unlike education however, union membership remains important in explaining

[47]This is simply because the size of the composition effect varies across the wage distribution, and hence the relative share of the composition effect explained by a relatively constant education coefficient varies.

the composition effect only towards the middle of the wage distribution and not at either the lower or upper tails, which is consistent with the preceding period. Towards the top, occupation increasingly explains the composition effect, as in the preceding period, but to a marginally-lower extent. This latter estimate is not uncovered in the mean analysis, which again highlights the advantage of the RIF approach. The magnitudes of the remaining covariates are all close to zero, reflecting the growing similarity of worker profiles relative to the pre-pandemic period as the labour market recovered. One additional year later, as shown in panel (c), education remained as an important and the dominant contributor to the composition effect across the entire distribution, which is consistent with the analysis at the mean, while occupation also remains important but again only towards the top. The magnitudes of the remaining covariates are negligible. This suggests that while characteristics of workers in 2022Q2 were more similar to those in the pre-pandemic period, some differences remained. Specifically, workers in the later period exhibited higher education levels and were more concentrated in higher-skilled occupations relative to those in the pre-pandemic period. However, because the full structure effect is dominant during this period, these differences in characteristics only partially offset the changes in the returns to various characteristics which drove real wages downwards at the end of the period.

In Figure 4.24 I present the detailed decomposition of the full structure effects observed above across the wage distribution for each of the three periods of interest. As in the mean case, the narrative pertaining to these detailed effects is less clear because the estimates for most covariates are very small in magnitude and are statistically insignificant. However, a few do stand out. As shown in panel (a), at the pandemic's onset, changes in the returns to education, experience, and formal sector employment placed upward pressure on wages at the bottom of the distribution – the only part of the distribution where the overall structure effect was dominant as shown above. The influence of these covariates is not evident when examining wage changes at the mean, again highlighting the existence of heterogeneities in the drivers of wage changes across the distribution. One year after the pandemic's onset, recall that the full, negative structure effects rise in importance from the middle to the top of the distribution but only partially offset the rise in wages driven by the dominant full composition effects. As shown in panel (b), from the middle to the top of the distribution changes in the associated returns to experience and residing in an urban area are largest in placing downward pressure on wages. This latter covariate is also evident in the mean case, but not the former. One additional year later, as shown in panel (c), the influence of the urban covariate fell away while that of potential experience not only persisted but spread to push downward pressure on wages across most of the distribution. Notably, this downward pressure from changes in the returns to experience at the top of the distribution was mostly offset by upward pressure induced by changes in the returns to education. Overall then, these estimates reveal a significant amount of heterogeneity in the drivers of the structure effect, both at a given part of the distribution, across the distribution, as well as over time as the pandemic progressed.

Figure 4.24: Recentered Influence Function detailed decomposition of the structure effect across the wage distribution, by period



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to those of working-age (15 to 64 years) employed. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Hourly wages adjusted for inflation and expressed in June 2022 Rands. Decomposition for categorical variables (industry, occupation, race, age, and province) based on "normalized" effects; that is, effects are expressed as deviation contrasts from the grand mean. Constant term omitted.

In summary, the decomposition analysis revealed a substantial degree of heterogeneity in the drivers of wage changes both at the mean and across the wage distribution over time. It is clear that the rise in wages both at the mean and across most of the distribution at the pandemic's onset is primarily explained by a change in the characteristics of workers, which itself is attributable to the regressive distribution of job loss observed prior. The specific characteristics which drive this change are trade union membership, main occupation, years of education, formal sector employment, and public sector employment, all of which are significant across the distribution but vary in influence. Importantly, changes in the returns to individual-level characteristics – specifically industry at the mean – played a more muted but non-negligible role in also driving wages upwards across most of the distribution. The bottom of the distribution serves as the exception where changes in the returns to such characteristics, specifically education, experience, and formal sector employment, explain a greater share of the rise in wages at the pandemic's onset compared to the composition effect. This is consistent with the stronger within-worker wage gains among those who remained employed at the bottom of the distribution, as documented in preceding sections. Together, the stronger, inequality-enhancing composition effect coupled with a weaker, inequality-reducing structure effect explains the rise in wage inequality at the pandemic's onset. As the pandemic progressed and employment partially recovered, the reduction in wages across the distribution toward pre-pandemic levels was only partially explained by the characteristics of workers more closely (but not completely) resembling those of the pre-pandemic period. Instead, persistent changes to the returns to various characteristics, which vary across the wage distribution, primarily explain this reduction in wages and, hence, inequality. The persistence of these changes is indicative of potential longer-term effects of the pandemic on the structure of the South African labour market.

4.6 Conclusion

This chapter provides a micro-econometric analysis of the evolution of the level and nature of wages, wage inequality, and their drivers during the full two years of the COVID-19 pandemic in South Africa. To do so, it makes use of nationally representative, individual-level household survey data collected from 2019 to 2022, including raw, unimputed wage data provided by StatsSA not available in the public domain. A range of statistical measures and econometric techniques were employed on both cross-sectional and panel samples to examine the quality of the wage data and answer three key research questions related to the level and nature of the pre-pandemic wage distribution, how it adjusted in response to the pandemic at its onset and as it progressed, and the compositional and structural drivers of these adjustments.

First, I show that the missing wage data in the survey is both non-negligible in magnitude, with over a third of workers in the average wave do not report any wage information at all, and is non-randomly distributed, with non-response being highly inversely correlated with wages itself. These two characteristics justify an imputation procedure, however I provide evidence that the imputations in the public QLFS data are of very poor quality and that the use of either this data or the observed reported data alone results in an underestimation of wages across the entire distribution with estimates from the former exhibiting greater volatility over time. This has substantial negative implications for any distributional analysis. I obtain reliable estimates of the wage distribution by adjusting the observed reported data for outliers using a parametric outlier detection model and missing data using an iterative, stochastic, and parametric imputation procedure which explicitly incorporates uncertainty inherent in the imputed values into the estimates, and thereafter conduct a battery of diagnostic tests to assess the quality of the imputations and sensitivity of the estimates.

Second, I find that wage inequality in the South African labour market was extremely high and stable in the year preceding the pandemic, regardless of the measure. Using cross-sectional samples of the employed, at the pandemic's onset the distribution experienced a significant rightwards shift accompanied however by a very marginal change in its shape, indicating little to no change in wage inequality. I show that this rise in wages across the distribution is primarily explained by a composition effect - a characteristic change in the employed population induced by a regressive distribution of job loss, plausibly due to lower-wage workers' lower propensities to work in 'essential' jobs and work-from-home - but additionally due to within-worker wage gains plausibly related to changes in the returns to various characteristics; in other words, a structure effect. Not accounting for such compositional changes may lead to misinterpretations of inequality dynamics during this period.

Because both of these extensive and intensive margin adjustments were concentrated among lower-wage workers, the composition effect was inequality-enhancing while the structure effect was inequality-reducing. Given that the former was dominant, explaining over 70 percent of the increased wage at the mean, overall inequality increased. A counterfactual exercise with composition-controlled indices indicates a significant 8 percent rise in wage inequality attributable to the pandemic. This rise was however transient, with wages quickly returning to their pre-pandemic levels as the labour market partially recovered.

Third and finally, I document substantial heterogeneity in the covariate drivers of wage changes both at the mean and across the wage distribution. At the pandemic's onset, five covariates primarily explain the dominant composition effect at the mean - trade union membership, main occupation, years of education, formal sector employment, and public sector employment - reflecting the correlates of job retention as documented in Chapter 3. The significance of these covariates is consistent across most of the distribution but the magnitudes of their individual influences vary. Changes in the returns to characteristics played a more muted but non-negligible role in driving wages upwards, particularly at the bottom. Industry was the only significant driver of this effect at the mean, which may reflect changes in sectoral returns in response to the government's sector-specific restrictions. As the labour market partially recovered, the reduction in wages across the distribution toward pre-pandemic levels was only partially explained by the characteristics of workers more closely (but not completely) resembling those of the pre-pandemic period. Instead, persistent changes to the returns to various characteristics, which vary across the distribution, primarily explain this reduction in wages and hence, owing to the inequality-reducing nature of this effect, inequality. The persistence of this latter adjustment is indicative of potential longer-term effects of the pandemic on the structure of the South African labour market. Future research ought to consider examining the existence of such persistence.

Overall, it is clear that the COVID-19 pandemic and associated regulations had a significant effect on wages and wage inequality in the South African labour market. Although these effects largely appear to have been transient in nature, it is concerning that extreme levels of wage inequality persisted for at least two years following the pandemic's onset. This is despite the repeal of all remaining restrictions together with a partial but notable labour market recovery with respect to employment and working hours as documented in Chapter 3.

Chapter 5

Lockdown stringency and employment formality during the COVID-19 pandemic in South Africa

5.1 Introduction

Like many governments around the world, in response to the COVID-19 pandemic the South African government implemented a national lockdown to prepare necessary health infrastructure as well as delay and minimise the spread of the virus. As discussed in preceding chapters, the country's initial lockdown lasted for five weeks and was relatively stringent by international standards (Bhorat et al., 2020a; Gustaffson, 2020). The regulations prevented any non-'essential' activities outside the home, imposed restrictions on all public gatherings, led to the closure of all schools, the introduction of a curfew, a prohibition on the sale of tobacco products and liquor, and strict domestic and international travel controls. Research using anonymised mobile phone data reveals a substantial reduction in population mobility in response to these regulations (Carlitz & Makhura, 2021), suggestive of a high degree of compliance. In the labour market, sector-specific restrictions meant that only workers in industries deemed 'essential' for economic function and pandemic response were permitted to continue working at their usual place of work during the period.

A lockdown of this severity was always expected to incur significant economic costs. As shown in Chapter 3, net employment contracted by 2.2 million or 14 percent, essentially erasing the prior decade of jobs growth in the economy. Importantly, the job axe did not fall evenly but was instead disproportionately borne by worker groups who already faced greater economic vulnerability prior to the pandemic, consistent with the international literature and plausibly driven by unfavourable occupation distributions. As discussed in Chapter 2, another global pattern evident in the South African context is with respect to employment formality. Informal workers suffered significantly greater job losses compared to their formal counterparts. As shown in Figure 5.1, at the pandemic's onset net informal sector employment contracted by double the rate experienced by the formal sector (22 vs. 11 percent).[1,2] More broadly, the informally employed, who operate both inside and outside the informal sector, accounted for 68 percent of all net jobs lost at the pandemic's onset (Rogan & Skinner, 2020, 2022).[3] Such a disproportionate incidence of job loss has characterised labour markets globally (Krafft et al., 2021; International Labour Organization, 2022; Soares & Berg, 2022) and across Sub-Saharan Africa in particular (Balde et al., 2020; Schotte et al., 2023; Oyenubi, 2023). As described in Chapter 2, this greater job loss vulnerability has broadly been attributed to the characteristics of informal sector jobs, such as a higher likelihood of being in contact-intensive industries, a lower likelihood of being able to work-from-home, and lower access to legal protections such as paid leave and unemployment insurance (Fox & Signe, 2020; International Labor Organisation, 2020; Benhura & Magejo, 2020; Balde et al., 2020; Schotte et al., 2023). Whatever the mechanism, informal sector employment appears to have served as a key predictor of job loss during the pandemic period.

Lockdown policy in South Africa and around the world was also, however, not time-invariant. Governments were required to make policy decisions in a context of significant uncertainty and a swiftly changing epidemiological situation, resulting in varying levels of lockdown stringency. In South Africa, as described in Chapter 1, following the initial 'hard' lockdown the government adopted a five-level strategy with lockdown stringency varying according to the severity of contagion. It is plausible that such variation may have heterogenous employment effects both on aggregate and by varied labour market characteristics, such as employment formality. Although existing studies provide causal evidence on the labour market effects of the pandemic and lockdown policies in both developed countries (for instance, see Aum et al., 2021; Baek et al., 2021; Juranek et al., 2021) and few developing countries (for instance, see Schotte et al., 2023; Morales et al., 2022), there is a lack of causal evidence on how variation in lockdown stringency affects labour market outcomes, both on aggregate and by employment formality. From a policy perspective, evidence of such heterogeneity not only provides a useful retrospective analysis, but also has the potential to inform future decisions regarding containment regulations and the optimal targeting of government support.

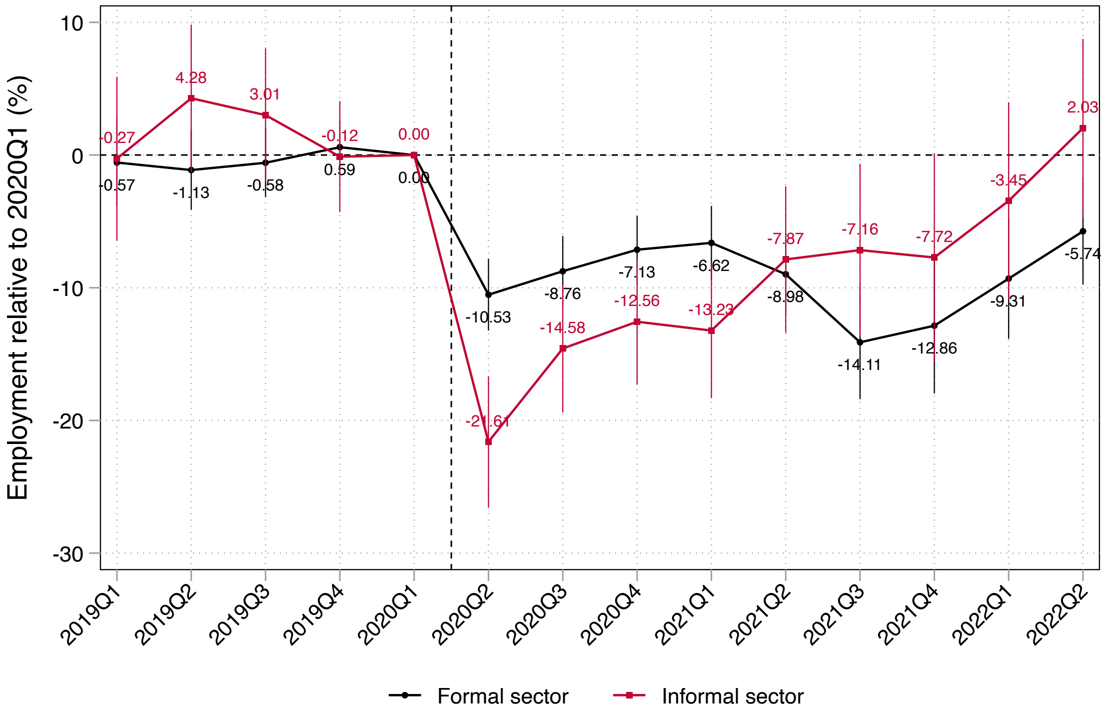
In this chapter, I estimate the causal effect of a core lockdown policy - sector-specific restrictions - on employment probabilities in the South African labour market and examine effect heterogeneity by lockdown stringency and employment formality. The analysis uses

[1] The evolution of net employment by sectoral formality is not the focus of this chapter but is examined in more detail in Chapter 3.

[2] Interestingly, these rates are approximately equivalent to the International Labour Organization (2022)'s estimates of global employment changes by formality.

[3] Informal employment is broader than informal sector employment in that it includes all workers in the informal sector as well as employees in the formal sector and persons employed in private households who are not entitled to a pension or medical aid and who do not have a written contract of employment.

Figure 5.1: Net employment by sectoral formality in South Africa, 2019Q1 – 2022Q2



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Spikes represent 95 percent confidence intervals. Sample restricted to those of working age (15 – 64 years). Vertical line represents the onset of the COVID-19 pandemic in South Africa.

nationally representative, individual-level, panel labour force data and, by cross-referencing lockdown regulations to over 150 industry codes in the data, I adopt a canonical DiD model to exploit temporal and between-industry variation in the employment probabilities of adults who were and were not permitted to work in their usual place of work, induced by these restrictions. I consider several levels of lockdown stringency over time, exploit the unique but temporary panel nature of the data to control for observable and unobservable time-invariant heterogeneity through individual fixed effects, and explore effect heterogeneity by employment formality. South Africa serves as an interesting case study in this regard for at least three reasons. First, the timing of changes in the country's lockdown levels coincide with labour force survey data collection periods which allows one the opportunity to exploit a natural experiment to isolate the effect of varying levels of lockdown stringency. Second, by isolating the effect of sector-specific restrictions from other pandemic-related factors, the analysis contributes to the empirical literature on how much labour market effects are attributable to restrictions versus voluntary reductions in economic activity, which remains particularly sparse in developing countries (Aum et al., 2021; Baek et al., 2021; Juranek et al., 2021; Schotte et al., 2023; Morales et al., 2022). Third, as an upper-middle-income country with a relatively small informal sector employment share, the findings may be externally valid to some extent for both developing countries (given South Africa's level of economic development) as well as more developed countries (given South Africa's low informal sector employment share).[4]

The remainder of this chapter is structured as follows. Section 5.2 first provides a description of the data and sample used. In Section 5.3 I describe the chapter's identification strategy and model specifications. The results are presented in Section 5.4, and thereafter the robustness tests in Section 5.6. Finally, I conclude in Section 5.7.

5.2 Data

5.2.1 The Quarterly Labour Force Survey

The analysis in this chapter uses individual-level household survey data from StatsSA's QLFS for the first two quarters of 2020. As described in the preceding chapters, the QLFS is a nationally representative, cross-sectional (with a rotating panel component) household-based sample survey conducted every quarter since 2008 that contains detailed information on a wide array of demographic and socioeconomic characteristics and labour market activities for individuals aged 15 years and older who live in South Africa. To avoid repetition, the reader is referred to Chapter 3 for a detailed description of the survey design as well as changes to its mode and sample following the pandemic's onset in the country. Throughout this analysis, the sample is restricted to those of working-age (aged 15 to 64 years) and all estimates are weighted using the survey sampling weights and the standard errors are adjusted for the complex survey design through the use of the cluster and strata variables available in the data.

Treatment assignment in the identification strategy here, detailed below, is a function of an individual's pre-pandemic (2020Q1) industry and therefore relies on observing individuals in both time periods, or in other words, panel data. The analysis here exploits the fact that, as discussed in Chapter 3, to facilitate the continued collection and provision of labour market statistics during the pandemic in 2020, the sample that was surveyed in 2020Q1 and for which StatsSA had valid contact numbers was surveyed again in 2020Q2. The result was that the survey changed from a cross-sectional to an unbalanced panel survey – a novel scenario in the survey's history. The 2020Q2 sample includes the majority (71 percent) of the 2020Q1 sample as not all dwelling units had valid contact numbers. The concern then is that estimates using the former sample may suffer from selection bias given characteristic differences between respondents which could and could not be surveyed. However, as shown in Chapter 3, StatsSA's adjustments to the calibrated survey weights appear to address this issue reasonably well.

[4] South Africa's informal sector accounts for less than 25 percent of total employment, compared to an average of 70 percent in developing and emerging countries and 89.2 percent in Sub-Saharan Africa (International Labour Organisation, 2014).

The sample is restricted to the balanced panel of individuals observed in both periods. Given that the QLFS is usually used as a cross-sectional survey, I make use of anonymised household and person identifiers in the data to ensure that the same individual is observed over time. However, as discussed in Chapter 3, even after doing so several instances emerge where a given individual has the same household and person identifiers between quarters but varies in other characteristics which plausibly should not exhibit such variation (for example, age changing from 41 years in 2020Q1 to 58 years in 2020Q2). To address this, although the anonymity of the data prohibits us from accessing other identifying variables such as names, surnames, and birth dates, in addition to household and person identifiers I make use of data on age (years), sex, and self-reported racial population group to identify the same individual over the period. While the latter two characteristics should be time-invariant, I allow for a one-year difference in age between 2020Q1 and 2020Q2 in either direction to account for ageing or measurement error. This procedure results in a balanced panel sample of 24 475 unique working-aged (as of 2020Q1) individuals, equivalent to 48 950 observations in total given that each is observed twice during the period.

5.2.2 Balanced panel sample representivity

To determine whether the balanced panel sample remains representative of those of working-age in South Africa, I estimate means for several observable covariates as well as the three outcomes of interest in the baseline period (2020Q1), for both the cross-sectional and balanced panel samples, and conduct t-tests to determine whether any observed differences are statistically and economically significant. To account for the fact that a minority of the 2020Q1 planned sample (2 percent, or 621 dwelling units) were not surveyed as a consequence of the suspension of data collection at the end of the quarter, I additionally include the relevant estimates in the same period one year prior (2019Q1). These estimates are presented in Table 5.1. Considering the statistically significant differences, individuals in the panel sample appear more likely to be older, female, African/Black, and have a post-secondary education, while being less likely to live in an urban area and have a highest education level of primary or less. Despite the statistical significance of these differences, they can be said to be economically insignificant given that their magnitudes are all relatively close to zero. This finding holds when considering differences between the balanced panel sample and cross-sectional estimates for either 2020Q1 or 2019Q1. As such, one can therefore be fairly confident that the panel sample remains relatively representative of the broader South African working-age population.

Table 5.1: Covariate balance table at baseline, by sample

	(1)	(2)	(3)	(1)-(3)	(2)-(3)
Sample:	Cross-sectional		Balanced panel	Difference	
Period:	2019Q1	2020Q1	2020Q1		
Observations:	42,024	41,827	24,475		
Demographics					
Age (years)	34.890	35.040	35.328	-0.437***	-0.287***
	(0.070)	(0.070)	(0.086)	(0.110)	(0.054)
Female	0.505	0.505	0.515	-0.010***	-0.011***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)
African/Black	0.806	0.808	0.829	-0.023***	-0.020***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)
Urban	0.677	0.680	0.658	0.019**	0.022***
	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)
Married	0.355	0.350	0.353	0.001	-0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Primary education or less	0.143	0.134	0.127	0.016***	0.007***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Incomplete secondary education	0.435	0.433	0.433	0.002	0.000
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)
Complete secondary education	0.297	0.306	0.308	-0.011**	-0.001
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)
Tertiary education	0.125	0.127	0.132	-0.007*	-0.005***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Occupation and sector					
Legislators and managers	0.076	0.075	0.076	0.000	-0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)
Professionals	0.047	0.050	0.053	-0.005*	-0.003**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)
Technical and associate professionals	0.080	0.077	0.080	0.000	-0.004**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Clerks	0.104	0.103	0.105	-0.001	-0.002
	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)
Service and shop workers	0.163	0.167	0.171	-0.008*	-0.004*
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)
Skilled agricultural workers	0.003	0.004	0.004	-0.001**	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Craft and related trades workers	0.127	0.127	0.125	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Plant and machine operators	0.082	0.081	0.085	-0.003	-0.004***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Elementary workers	0.249	0.249	0.235	0.014***	0.015***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)
Domestic workers	0.069	0.067	0.065	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Primary sector	0.080	0.079	0.067	0.012***	0.011***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Secondary sector	0.212	0.210	0.213	0.000	-0.002

Table 5.1 – continued from previous page

	(1)	(2)	(3)	(1) - (3)	(2) - (3)
Sample:	Cross-sectional		Balanced panel	Difference	
Period:	2019Q1	2020Q1	2020Q1		
Observations:	42,024	41,827	24,475		
	(0.003)	(0.004)	(0.004)	(0.005)	(0.002)
Tertiary sector	0.708	0.711	0.720	-0.012**	-0.009***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.003)
Province					
Western Cape	0.121	0.121	0.108	0.013**	0.013***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Eastern Cape	0.112	0.111	0.107	0.005	0.004
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)
Northern Cape	0.021	0.021	0.016	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Free State	0.050	0.049	0.048	0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
KwaZulu-Natal	0.185	0.185	0.212	-0.027***	-0.027***
	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)
North West	0.068	0.068	0.062	0.005	0.005**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)
Gauteng	0.269	0.270	0.253	0.016**	0.017***
	(0.005)	(0.004)	(0.006)	(0.007)	(0.004)
Mpumalanga	0.077	0.077	0.087	-0.011***	-0.011***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)
Limpopo	0.098	0.098	0.106	-0.008*	-0.008***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)
Outcome variables					
Employed	0.426	0.421	0.422	0.004	-0.001
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)
Formal sector employment	0.293	0.290	0.296	-0.003	-0.006**
	(0.003)	(0.003)	(0.004)	(0.005)	(0.002)
Informal sector employment	0.113	0.112	0.112	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)

[a] Author's own calculations. Source: QLFS 2019Q1, 2020Q1, and 2020Q2 (Statistics South Africa, 2019a, 2020a,b).
[b] Notes: This table presents estimates of mean values for observable covariates for the cross-sectional (either as of 2020Q1 or 2019Q1) and balanced panel sample (individuals observed in both 2020Q1 and 2020Q2; covariates values for this sample are as of 2020Q1) accompanied by difference estimates. Samples restricted to those of working-age (15-64 years). All estimates are weighted using sampling weights. Standard errors presented in parentheses and are clustered at the panel (individual) level. The magnitude and statistical significance of a given difference are estimated using t-tests. *** p < 0.01, ** p < 0.05, * p < 0.10.

5.3 Identification strategy

5.3.1 A canonical Difference-in-Differences model

My aim in this chapter is to estimate the causal effect of a core component of South Africa's lockdown – sector-specific restrictions which permitted certain individuals to work at their usual workplace but others not – on employment probabilities. The ideal approach to establishing a causal effect entails randomised assignment of treatment where, in the context of this study, a given worker group was legally obligated to adhere to the regulations while another characteristically similar worker group was not. South Africa's lockdown was of course, however, not randomly assigned across either time or space. It was implemented at the national level and as such legally obligated every worker to adhere to the regulations. However, being permitted to work was dependent on industry, as specified by legislation, which provides a neat division of 'treated' and 'untreated' individuals over time. I exploit this detail and cross-reference the sector-specific regulations in the Government Gazettes with over 150 three-digit SIC codes available in the data to identify individuals who were and were not permitted to work at the usual workplace; in other words, those subjected and not subjected to sector-specific restrictions. I then make use of the coincidental timing of the onset of the national lockdown levels and QLFS data collection periods to exploit cross-group (treatment and control) and cross-time (before and during the varying national lockdown levels) variation and estimate a DiD model. Simply put, I estimate the causal effect of this core component of the lockdown by comparing employment probabilities between permitted-to-work and not-permitted-to-work worker groups from before to after the onset of the lockdown.

Two points on this estimation strategy should be noted here. First, this estimation strategy does not allow me to estimate the effects of the country's lockdown policy in its entirety (that is, the cumulative effect of sector-specific restrictions, the curfew, school closures, and other restrictions on physical interaction and mobility), but rather the effect of one core component alone. In doing so, however, it isolates the effect of sector-specific restrictions from other pandemic-related factors. Morales et al. (2022) adopt a similar approach in the context of Columbia. Second, a new theoretical and empirical literature on the econometrics of DiD has developed over the last few years which has highlighted how, in practice, typical applications do not meet all requirements of the canonical DiD setup primarily due to the presence of more than two time periods and heterogenous or 'staggered' treatment timing; that is, when units are treated at different points in the post-treatment period – a common occurrence in empirical work. The consequence is that the estimates obtained using the canonical specification are often severely biased and do not correspond with interpretable causal parameters (Athey & Imbens, 2018; de Chaisemartin & d'Haultfoeuille, 2020; Borusyak et al., 2021; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Imai et al., 2021; Sun & Abraham, 2021; Roth et al., 2023). These concerns are not, however, relevant for this chapter's design given that only two data periods are used and every treated observation is treated at the same period (2020Q2). As such, I proceed with the canonical setup.

My treatment group comprises all individuals who were legally not permitted to work while my control group consists of those who were. In Table A14 I present the categorised list of industries, at the 3-digit SIC level, by treatment status and lockdown level based on my cross-referencing procedure. Importantly, South Africa's lockdown regulations were not time-invariant, as previously described. To account for this, I make use of interview month data in the post-period (2020Q2) provided to me by StatsSA which indicates whether an individual was surveyed in April, May, or June 2020. These periods fortunately coincide with changes in the country's lockdown levels, with level 5 in place from 1 to 30 April, level 4 from 1 to 31 May, and level 3 from 1 to 30 June 2020. As an example, individuals were included in the treatment group if they were not permitted to work under level 5 regulations and, in the post-treatment period, they were interviewed in April 2020 during level 5. Given that at the onset of the lockdown, this legislation affected individuals based on the industry they were already working in, treatment assignment for each observation in my analysis is a function of their pre-pandemic (2020Q1) industry. Therefore, my treatment variable is time-invariant within-individuals. In the pre-pandemic period, I have non-missing industry data for 13 143 of 24 475 observations, so as such it is only possible to code treatment for 26 286 (13 143 multiplied by two) observations in total in the two-quarter period. In some instances, certain industries were permitted to operate but only at a limited employment capacity (these industries are indicated in Table A14). My treatment assignment rule above would suggest coding these workers into the control group; however, at the firm-level they may not have been permitted to work given the capacity constraint. Although the data does not allow us to accurately identify these cases accurately, to address this I assign individuals in these 'limited capacity' industries to the control group if the legislated capacity was equal to or exceeded 50 percent. As a robustness test, I use alternative thresholds to examine the sensitivity of the results to this assumption.

5.3.2 Covariate balance and pre-treatment dynamics

The identifying assumption of my DiD approach implies that in the absence of these restrictions the average outcome trends of those not permitted to work in the lockdown period would have been similar to those who were permitted to work; in other words, the control group provides an appropriate counterfactual. Balanced mean levels of covariates or outcomes between the treatment and control group at baseline is not a requirement in a DiD strategy; however, the validity of this design may be threatened if the difference in the mean levels of covariates (but not outcomes) varies significantly from before to after treatment. To examine this, in Table 5.2 I present estimates of means for all observable covariates used my models as well as my outcomes of interest both in the pre-lockdown and lockdown period by treatment status, as well as estimates of between-group differences both within and across periods. For the covariates, these latter between-group between-period estimates are equivalent to those obtained through placebo falsification tests where the DiD model is estimated separately on covariates which, in theory, should not be affected. For the outcomes, these estimates are equivalent to unconditional DiD estimates.

Across most covariates, the mean levels for those permitted and not permitted to work within either period are not statistically significantly different from one another (see columns 3 and 6), and for the few that are, the magnitude and significance of the differences are stable from before to after the lockdown was introduced (see column 7). For instance, relative to those who would be permitted to work and in the pre-lockdown period, those that would not be permitted to work were approximately 2 percentage points more likely to be African/Black, 2 percentage points less likely to have a complete secondary education level, and just under 2 percentage points more likely to be a 'formality job mover' (defined as remaining employed over the period but transitioning from formal to informal sector employment or vice versa). The magnitudes and significance levels of all these differences in covariate values are similar during the lockdown period, and as indicated in column 7, the change in magnitude of all differences over time are close to zero and are statistically insignificant. Overall, these trends are supportive of the validity of the DiD design. On the other hand, regarding differences in mean values of my outcome variables, I do estimate a statistically and economically significant change in the size of the difference in employment probabilities from before to during the lockdown period. Specifically, significant differences are estimated for the probabilities of any employment and informal sector employment, but not formal sector employment. This however does not invalidate the validity of my empirical design but instead is indicative of significant and heterogenous treatment effects, which is explored in Section 5.4.

As noted above, similar mean levels of covariates between the treatment and control groups at baseline is not a requirement in a DiD strategy, but rather what is important is that any observed differences in covariates (but not outcomes) are stable from before the after treatment. Regarding outcomes, it is also important to determine that the two groups are comparable on outcome dynamics in the pre-treatment period; in other words, there are no pre-trends which would invalidate the credibility of the design. However, such an investigation requires multiple periods in the pre-treatment period. Given that treatment here is based on pre-pandemic industry and that I do not have panel data which precedes 2020Q1, I am unable to accurately conduct such a comparison. However, as an imperfect, approximate approach, I am able to make use of weighted cross-sectional data from previous waves of the survey to estimate mean outcome levels for the treatment and control groups over time in the pre-treatment period. Although this approach cannot make use of the same balanced panel sample used in my modelling approach described above, it seeks to provide some indication that my effect estimates to follow do not simply reflect pre-existing differences between those permitted and not permitted to work. I present these unconditional estimates for nine waves of pre-treatment data in Figure 5.2 for each of the three outcome variables and lockdown stringency levels.

For each outcome and treatment by lockdown level, the estimated trends are indicative that the treatment (not permitted to work) and control (permitted to work) groups are largely comparable on dynamics in the pre-treatment period. For individuals that would not be permitted to work in the future lockdown level 5, they exhibited a lower overall employment probability (approximately 76 percent on average) compared to those that would be permitted (80 percent), as shown in panel (a). Over the period, the levels of these individual probabilities, as well as the between-group difference, changed only marginally in terms of magnitude but not statistical significance. Similar can be said for this group for formal sector employment probability trends, as shown in panel (b). On the other hand,

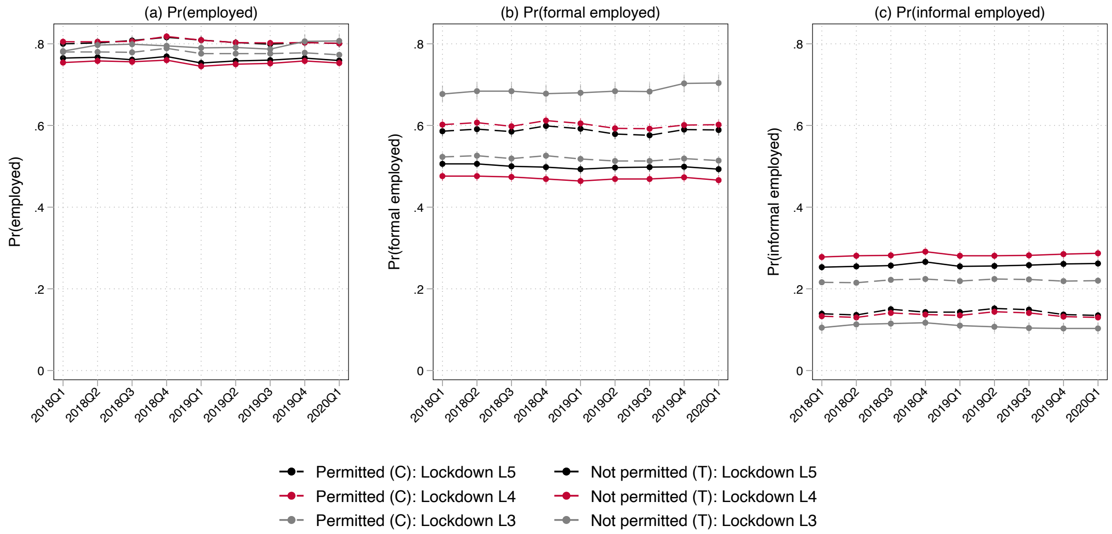
Table 5.2: Covariate balance table, by treatment status and period

Period	(1) 2020Q1 (pre-lockdown)	(2)	(3)	(4) 2020Q2 (lockdown)	(5)	(6)	(7)
Group:	Permitted to work (control)	Not permitted to work (treatment)	Diff: (2)-(1)	Permitted to work (control)	Not permitted to work (treatment)	Diff: (5)-(4)	Diff-in-diff: (6)-(3)
Observations:	7,620	5,523		7,620	5,523		
Covariates							
Age (years)	39.567	39.432	-0.135	39.652	39.645	-0.007	0.128
	(10.647)	(11.016)	(0.209)	(10.679)	(10.938)	(0.217)	(0.095)
Female	0.476	0.470	-0.007	0.464	0.460	-0.005	0.002
	(0.499)	(0.499)	(0.010)	(0.499)	(0.498)	(0.010)	(0.003)
African/Black	0.779	0.797	0.018**	0.756	0.776	0.020**	0.001
	(0.415)	(0.402)	(0.008)	(0.429)	(0.417)	(0.009)	(0.003)
Urban	0.735	0.729	-0.005	0.745	0.753	0.008	0.013
	(0.441)	(0.444)	(0.008)	(0.436)	(0.431)	(0.008)	(0.011)
Primary educ or less	0.106	0.109	0.003	0.109	0.106	-0.003	-0.006
	(0.308)	(0.312)	(0.006)	(0.312)	(0.307)	(0.006)	(0.004)
Secondary educ incomplete	0.343	0.370	0.027***	0.346	0.378	0.032***	0.005
	(0.475)	(0.483)	(0.009)	(0.476)	(0.485)	(0.010)	(0.006)
Secondary educ complete	0.346	0.325	-0.021**	0.348	0.325	-0.023**	-0.003
	(0.476)	(0.468)	(0.009)	(0.476)	(0.468)	(0.010)	(0.006)
Tertiary educ	0.205	0.196	-0.009	0.197	0.192	-0.005	0.004
	(0.404)	(0.397)	(0.008)	(0.398)	(0.394)	(0.008)	(0.005)
Wage employment	0.855	0.865	0.009	0.775	0.766	-0.010	-0.019
	(0.352)	(0.342)	(0.007)	(0.417)	(0.424)	(0.008)	(0.014)
Indus/occup job-mover	0.376	0.370	-0.007	0.381	0.377	-0.004	0.002
	(0.484)	(0.483)	(0.009)	(0.486)	(0.485)	(0.010)	(0.003)
Formality job mover	0.032	0.052	0.019***	0.032	0.051	0.019***	0.000
	(0.177)	(0.221)	(0.004)	(0.177)	(0.221)	(0.004)	(0.001)
Outcomes							
Employed	0.792	0.762	-0.030***	0.670	0.612	-0.058***	-0.028***
	(0.406)	(0.426)	(0.008)	(0.470)	(0.487)	(0.010)	(0.008)
Employed in formal sector	0.584	0.500	-0.084***	0.501	0.427	-0.075***	0.009
	(0.493)	(0.500)	(0.010)	(0.500)	(0.495)	(0.010)	(0.008)
Employed in informal sector	0.165	0.260	0.095***	0.118	0.180	0.062***	-0.033***
	(0.371)	(0.439)	(0.008)	(0.322)	(0.384)	(0.007)	(0.007)

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).

[b] Notes: This table presents estimates of mean values for observable covariates controlled for in my modelling to follow (excluding province for brevity) and outcomes by treatment group in the baseline and treatment periods accompanied by inter-group differences within and between periods for the balanced panel sample. Sample restricted to those of working-age (15-64 years). All estimates are weighted using sampling weights. Standard errors presented in parentheses and are clustered at the panel level. The magnitude and statistical significance of a given difference are estimated using t-tests. Diff. = Difference. *** p < 0.01, ** p < 0.05, * p < 0.10.

Figure 5.2: Pre-treatment outcome dynamics, by outcome and lockdown stringency level



[a] Author's own calculations. Source: QLFS 2018Q1 - 2020Q1 (Statistics South Africa, 2018a,b,c,d, 2019a,b,c,d, 2020a).
[b] Notes: This figure presents estimates of trends in mean outcome levels for the treatment (T) (not permitted to work) and control (C) (permitted to work) groups in the pre-treatment period by making use of cross-sectional data from 2018 to 2020. Estimates are presented for each lockdown stringency level which range from level 5 (L5) (most stringent) to L3 (most lenient). Sample restricted to those of working-age (15-64 years). All estimates are weighted using the sampling weights and account for the complex survey design. Spikes represent 95 percent confidence intervals.

panel (c) shows that those who would not be permitted to work were more likely to be employed in the informal sector relative to those that would be permitted. Despite this distinction, the groups follow similar trends: the estimates for each group are relatively constant over time in terms of magnitude and statistical significance. Regarding treatment with respect to lockdown level 4, the differences in overall, formal, and informal sector employment probabilities between those permitted and not permitted to work are similar to their lockdown level 5 counterparts. Finally, regarding treatment with respect to the least stringent lockdown level (3), the inverse holds: individuals that would not be permitted to work in this lockdown level exhibited higher (lower) overall and formal (informal) sector employment probabilities compared to those that would be permitted. Irrespective of this distinction, the pre-treatment outcome dynamics between those permitted and not permitted to work for a given employment type are similar. One exception where these trends do however diverge is in the first and last quarter of 2018 where the estimated probability of overall employment is similar in magnitude for both groups. Despite this, the between-group difference in every wave is statistically insignificant. Overall, these estimates provide some assurance that my treatment and control groups are comparable in outcome dynamics prior to the lockdown period, and explicitly assuming these dynamics would have continued in the absence of the pandemic lockdown, any observed divergence in the lockdown period can be attributed to the pandemic lockdown itself.

5.3.3 Model specification

In my modelling approach, I estimate effects on employment overall and thereafter explore heterogeneity by employment formality and lockdown stringency. Formally, I estimate the following canonical DiD model specification for individual i in industry j in quarter t using OLS:

$$y_{ijt} = \alpha + \beta treatment_j + \delta post_t + \gamma treatment_j \times post_t + \mu \boldsymbol{X}_{ijt} + \varphi_i + \varepsilon_{ijt} \tag{5.1}$$

where y_{ijt} is one of three binary employment indicators: employment; formal non-agricultural sector employment; and informal sector employment. Employment is defined as per StatsSA's conventional definition as working for at least one hour in the reference week or not working because of temporary absence but have a job to return to. As in Chapter 3, the distinction between formal and informal sector employment I use here is that followed by StatsSA.[5] Formal non-agricultural sector employment only includes tax-registered workers in all industries excluding agriculture, whereas informal sector employment consists of (i) employees who are not registered for personal income tax and work in establishments that employ fewer than five workers and (ii) employers, the self-employed, and persons helping unpaid in their household business who are not registered for any tax. As implied, this definition is based on two criteria: tax registration status and the size classification of enterprises, whereas the latter criterion only affects the categorization of employees but not other types of workers. Although in the literature tax registration status is often solely used to identify informal sector workers, I am not concerned about the inclusion of this 'smallness' criterion for two reasons. First and importantly, the categorisation here follows a two-step process: workers who are not registered for tax are first identified, and only thereafter is data on establishment size used to determine informality status on this subset of workers. Therefore, tax registration status remains the focus or primary criterion while 'smallness' is supplemental (Essop & Yu, 2008; Fourie & Kerr, 2017). Second, as a sensitivity check, I re-estimate all of my models using only the tax registration criterion to define informal sector employment and find near-identical estimates compared to those presented in the next section with respect to the coefficient magnitudes, levels of precision, and levels of statistical significance.[6]

$treatment_j$ is the binary, time-invariant treatment indicator, $post_t$ indicates whether quarter t is 2020Q2 considering the lockdown commenced at the end of March 2020, and $_{ijt}$ is the error term. I control for a vector of time-invariant and time-varying individual-level characteristics, $\boldsymbol{X}_{ijt}$, to reduce the residual variance and improve the precision of the estimates, enabling us to rule out a broader range of effect magnitudes. These characteristics include age, sex, racial population group, province of residence, a binary urban residence indicator, and highest education level. I also control for employment type which indicates whether an employed individual works for someone else for pay or not, where the latter group includes being an employer, self-employed, or an unpaid household worker, to control

[5] It should again be noted that StatsSA's informal sector employment definition differs to that used by the International Labor Organization.

[6] I do not present these results in this chapter; however, they are available upon request.

for differences in employment characteristics. Following the literature, I avoid controlling for time-varying characteristics which could be considered as outcomes themselves, such as marital status, occupation, and industry. However, my estimates are insensitive to their inclusion. I also exploit the unique panel nature of the data to control for 'industry or occupation job-movers' (individuals who remain employed over the period but change either occupations or industries at the one-digit level) and 'formality job movers' (individuals who remain employed over the period but transition from the formal to informal sector or vice versa). Where 'formality job movers' comprise just 2.1 percent (or 518 unique individuals) of my sample, 9.6 percent (or 2 360 unique individuals) are 'industry or occupation job-movers' and less than 1 percent are both.[7] I also exploit the panel to control for individual fixed effects (FE), represented by φ_i, which absorb any observable and unobservable time-invariant heterogeneity. When doing so, all time-invariant variables in $\boldsymbol{X}_{ijt}$ are of course automatically omitted from the model, as well as the time-invariant treatment indicator. However, I am still able to estimate γ – the coefficient of interest – due to prevailing variation in the DiD interaction term induced by within-individual variation in $post_t$ and between-individual variation in $treatment_j$ in the pre-treatment period (in other words, prevailing variation in the DiD interaction term). My approach here is equivalent then to a Two-Way Fixed Effects (TWFE) estimator with just two time periods. Equation 5.1 can then be alternatively specified in the following generic functional form:

$$y_{ijt} = \alpha + \varphi_i + \varphi_t + \gamma^{TWFE} D_{jt} + \mu \boldsymbol{X_{ijt}} + \varepsilon_{ijt} \tag{5.2}$$

where φ_t represents time fixed effects and D_{jt} is the DiD interaction term. When I examine effect heterogeneity by lockdown stringency, I continue to estimate the above specification but restrict the sample to treatment and control group individuals in a given lockdown level. Finally, all standard errors are clustered at the panel (individual) level to allow for correlation in the error for the same individual over time.

5.4 Results

5.4.1 Employment probabilities

Table 5.3 presents the effect estimates from specification 5.1 on the probability of employment. By pooling both data periods without controlling for any covariates, the model (1) results suggest that individuals who were not permitted to work were 4.6 percentage points less likely to be employed – statistically significant at the 1 percent level. Model (2) shows that this estimate remains similar in both magnitude and statistical significance when I control for the

[7] On average and relative to those who remain in the same sector, 'formality job movers' are older (39.5 years versus 36.3 years), more likely to be men (61 percent versus 45 percent), live in urban areas (72 percent versus 64 percent), and have at least completed a secondary education level or equivalent (49 percent versus 41 percent). On average and relative to those who do not switch industry or occupation, 'industry or occupation job-movers' are older (41 versus 36 years), more likely to be men (56 percent versus 44 percent), live in urban areas (78 percent versus 63 percent), and have at least completed a secondary education level or equivalent (62 percent versus 39 percent). All these between-sample differences are statistically significant by at least the 5 percent level.

lockdown period, and additionally that the average individual was 13.3 percentage points less likely to be employed during this period, regardless of legislated permission-to-work status. This is equivalent to the magnitude of net employment loss observed for the South African labour market during this period. When I control for $\boldsymbol{X}_{ijt}$ in model (3), the coefficients of both these variables reduce in magnitude but retain their signs and statistical significance levels. Expectedly, the consequence of the individual FE model (4) is the omission of the time-invariant treatment variable, but again highlights the significantly lower employment probability of individuals in the lockdown period, regardless of legislated permission-to-work status. The DiD estimates are presented in models (5) to (7). In the preferred model (7) which controls for $\boldsymbol{X}_{ijt}$ and individual FE φ_i, I find evidence of a significant and negative effect. Specifically, my main DiD estimate of interest – γ – suggests that this core lockdown component decreased the probability of employment for those not permitted to work by just under 3 percentage points relative to those who were permitted to work, significant at the 1 percent level. This is equivalent to a relative reduction of approximately 23 percent. Notably, the magnitude, precision, and statistical significance of the estimated effect are all largely insensitive to the inclusion of observable covariates and individual FE and is similar to the coefficient observed in Column 7 in Table 5.2.

Table 5.3: Model estimates of sector-specific restriction effects on employment probabilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.046***	-0.046***	-0.036***		-0.030***	-0.020***	
	(0.008)	(0.008)	(0.007)		(0.008)	(0.008)	
Post		-0.133***	-0.123***	-0.117***	-0.122***	-0.111***	-0.105***
		(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
Treatment×Post					-0.028***	-0.028***	-0.029***
					(0.008)	(0.008)	(0.008)
Time-varying $\boldsymbol{X}$	✗	✗	✓	✓	✗	✓	✓
Time-invariant $\boldsymbol{X}$	✗	✗	✓	✗	✗	✓	✗
Individual FE	✗	✗	✗	✓	✗	✗	✓
Constant	0.720***	0.799***	-0.259***	1.107*	0.792***	-0.267***	1.079*
	(0.005)	(0.005)	(0.053)	(0.603)	(0.005)	(0.053)	(0.602)
Observations	26,286	26,286	26,069	26,069	26,286	26,069	2,6069
R^2	0.002	0.023	0.193	0.800	0.023	0.193	0.800

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: This table presents estimates of specification 5.1 with a binary employment variable serving as the dependent variable. Sample restricted to those of working-age (15-64 years) as of 2020Q1. FE = fixed effects. Standard errors presented in parentheses and are clustered at the panel level. All estimates weighted using sampling weights. Time-varying controls include age, highest education level, and employment type. Time-invariant controls include sex, racial population group, province of residence, a binary urban residence indicator, an 'industry or occupation job-mover' indicator, and a 'formality job mover' indicator as described in Section 5.3.3. *** p < 0.01, ** p < 0.05, * p < 0.10.

Following the back-of-the-envelope approach used by Morales et al. (2022), I can approximate the aggregate impact of these restrictions and hence disentangle the share of total job loss attributable to them from other epidemiological and economic factors.[8] This is done by multiplying the estimated effect expressed in percentage terms (23 percent) by the share of the pre-pandemic (2020Q1) employed population affected by these restrictions (38 percent).[9] This exercise suggests that these restrictions were responsible for approximately 8.7 percentage points of the total 13.6 percent quarter-on-quarter decline in employment, equivalent to nearly two-thirds (64 percent). This finding is consistent with the literature discussed in Chapter 2 which shows adverse effects due to both government-mandated restrictions specifically as well as other factors (Aum et al., 2021; Baek et al., 2021; Juranek et al., 2021; Schotte et al., 2023; Morales et al., 2022). Additionally, it suggests that restrictions accounted for most of the employment decline in South Africa. In contrast, the literature points to more moderate impacts with restrictions accounting for up to half of the decline in South Korea (Aum et al., 2021) and the US (Baek et al., 2021) and a quarter in Denmark (Juranek et al., 2021) and Columbia (Morales et al., 2022). This may be explained by the relatively stringent nature of South Africa's initial lockdown by international standards (Bhorat et al., 2020a; Gustaffson, 2020), as discussed previously. However, it again implies that job loss would have still occurred in the absence of restrictions, suggesting that the primary culprit was the virus itself.

5.4.2 Effect heterogeneity by employment formality

I next investigate whether the estimated sector-specific restriction effect above is driven by effects in either the formal or informal sector, or both, in Tables 5.4 and 5.5. Beginning with the former, models (1) to (4) reflect findings similar to those for overall employment probabilities as observed in Table 5.3. Overall, individuals who were not permitted to work were less likely to be employed in the formal sector; and during the lockdown period in particular the average individual was less likely to be formally employed, regardless of legislated permission-to-work status, both before and after controlling for $\boldsymbol{X}_{ijt}$ and individual FE φ_i. My DiD estimates for formal sector employment in models (5) to (7) are, however, dissimilar from those for overall employment in both magnitude and statistical significance. In my preferred model (7), I do not find any evidence that this core lockdown component had any effect on the probability of formal sector employment for those not permitted to relative to those who were. This estimate is close to zero in magnitude and is not statistically significantly different from zero. This suggests that the significant, negative effect observed for overall employment in Table 5.3 is not explained by any such effects in the formal sector. Again, the magnitude, precision, and statistical significance of the DiD coefficients are all largely insensitive to the inclusion of observable covariates and individual FE.

[8] While insightful, it should be noted that this decomposition is however considered to be very approximate given concerns regarding extrapolating well-identified effects to aggregates because the shocks at the level used to identify effects may differ from those at the aggregate level (Beraja et al., 2019).

[9] Because restrictions varied over 2020Q2 with each of lockdown levels 5, 4, and 3 being in place for one month, as described earlier, this latter share is calculated as the equally-weighted share of pre-pandemic workers affected by lockdown levels 5 (55 percent), 4 (47.5 percent), and 3 (11.4 percent).

Table 5.4: Model estimates of sector-specific restriction effects on formal sector employment probabilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.078***	-0.079***	-0.062***		-0.084***	-0.068***	
	(0.009)	(0.009)	(0.007)		(0.010)	(0.008)	
Post		-0.079***	-0.050***	-0.055***	-0.082***	-0.055***	-0.053***
		(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Treatment×Post					0.009	0.011	-0.004
					(0.008)	(0.008)	(0.008)
Time-varying $\boldsymbol{X}$	✗	✗	✓	✓	✗	✓	✓
Time-invariant $\boldsymbol{X}$	✗	✗	✓	✗	✗	✓	✗
Individual FE	✗	✗	✗	✓	✗	✗	✓
Constant	0.535***	0.582***	-0.637***	1.365**	0.584***	-0.634***	1.361**
	(0.006)	(0.006)	(0.051)	(0.571)	(0.006)	(0.050)	(0.571)
Observations	26,286	26,286	26,069	26,069	26,286	26,069	26,069
R^2	0.006	0.012	0.308	0.869	0.012	0.308	0.869

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).

[b] Notes: This table presents estimates of specification 5.1 with a binary formal sector employment variable serving as the dependent variable. Sample restricted to those of working-age (15-64 years) as of 2020Q1. FE = fixed effects. Standard errors presented in parentheses and are clustered at the panel level. All estimates weighted using sampling weights. Time-varying controls include age, highest education level, and employment type. Time-invariant controls include sex, racial population group, province of residence, a binary urban residence indicator, an 'industry or occupation job-mover' indicator, and a 'formality job mover' indicator as described in Section 5.3.3. *** p < 0.01, ** p < 0.05, * p < 0.10.

In Table 5.5, I again examine effect heterogeneity by employment formality but focus on effects on informal sector employment. As opposed to my findings for overall or formal sector employment, models (1) to (2) reflect dissimilar estimates, neither in magnitude nor significance, but in sign. Although I continue to find that, regardless of legislated permission-to-work status, the average individual was less likely to be employed in the informal sector during the lockdown period in particular, I find here that individuals who were not permitted to work were more likely to be employed in the informal sector – statistically significant at the 1 percent level. The magnitude and significance of this latter estimate remains largely unchanged after I control for $\boldsymbol{X}_{ijt}$ in model (3). As observed in model (4), after controlling for individual FE φ_i I continue to find a significantly lower employment probability in the lockdown period, even in the informal sector, regardless of legislated permission-to-work status. My DiD estimates for informal sector employment in models (5) to (7) are, interestingly, dissimilar from those for overall and formal sector employment, and likely relates to my finding in model (2) that those who were not permitted to work were more likely to be employed in the informal sector. In my preferred model (7), I estimate a significant and negative sector-specific restriction effect on informal sector employment of 3.5 percentage points, significant at the 1 percent level. The magnitude of this estimate is similar to that for overall employment and is not statistically significantly different from it. It should be noted that, again, the magnitude, precision, and statistical significance of this estimate is largely insensitive to the inclusion of observable covariates and individual FE. This, combined with the observed zero effect on formal sector employment in both magnitude and significance, suggests that the significant, negative effect observed for overall employment in Table 5.3 is driven by a negative employment effect in the informal sector.

Table 5.5: Model estimates of sector-specific restriction effects on informal sector employment probabilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.076***	0.075***	0.067***		0.095***	0.089***	
	(0.006)	(0.006)	(0.006)		(0.008)	(0.007)	
Post		-0.061***	-0.081***	-0.059***	-0.047***	-0.066***	-0.045***
		(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Treatment×Post					-0.033***	-0.036***	-0.035***
					(0.007)	(0.007)	(0.007)
Time-varying $\boldsymbol{X}$	✗	✗	✓	✓	✗	✓	✓
Time-invariant $\boldsymbol{X}$	✗	✗	✓	✗	✗	✓	✗
Individual FE	✗	✗	✗	✓	✗	✗	✓
Constant	0.137***	0.173***	0.249***	0.068	0.165***	0.239***	0.034
	(0.004)	(0.004)	(0.037)	(0.482)	(0.005)	(0.037)	(0.482)
Observations	26,286	26,286	26,069	26,069	26,286	26,069	26,069
R^2	0.010	0.016	0.188	0.793	0.017	0.189	0.794

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: This table presents estimates of specification 5.1 with a binary informal sector employment variable serving as the dependent variable. Sample restricted to those of working-age (15-64 years) as of 2020Q1. FE = fixed effects. Standard errors presented in parentheses and are clustered at the panel level. All estimates weighted using sampling weights. Time-varying controls include age, highest education level, and employment type. Time-invariant controls include sex, racial population group, province of residence, a binary urban residence indicator, an 'industry or occupation job-mover' indicator, and a 'formality job mover' indicator as described in Section 5.3.3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4.3 Effect heterogeneity by lockdown stringency

In my analysis above, I find that the significant, negative employment effect of the sector-specific restrictions is driven not by an effect on formal sector employment but rather on informal sector employment. I next explore effect heterogeneity by varying levels of lockdown stringency for each of my three dependent variables as discussed in Section 5.3.3. I present the relevant DiD estimates in Table 5.6, where all models control for both $\boldsymbol{X}_{ijt}$ and individual FE φ_i. Considering overall employment probabilities in models (1) to (3), I consistently estimate a statistically significant and negative effect, at least at the 5 percent level. While the magnitude, statistical significance, and precision of the estimated effects for the most stringent lockdown levels (5 and 4) are identical, the estimated effect for the least stringent level (3) is slightly larger in magnitude but exhibits greater uncertainty given the larger standard error and hence lower degree of statistical significance. However, this latter estimate is not statistically significantly different from that of the more stringent levels 5 (p = 0.426) or 4 (p = 0.467). As such, although I observe negative effects for every level of lockdown stringency, I do not find evidence that these effects vary by lockdown stringency, at least for overall employment probabilities.

Models (4) to (9) present the relevant heterogeneous effect estimates on formal and informal sector employment probabilities by varying levels of lockdown stringency. Interestingly, my results suggest that informal sector employment is sensitive to higher degrees of lockdown stringency while formal sector employment is sensitive to lower degrees of lockdown stringency. Specifically, I find negative effects of 4.1 percentage points and 5.3 percentage points on the probability of informal sector employment for the most stringent lockdown levels 5 and 4, respectively, both significant at the 1 percent level. These estimates are not statistically different from one another ($p = 0.907$) and are statistically similar in magnitude to those in models (1) and (2) for overall employment probabilities for the same lockdown levels. However, I do not find evidence of any effect on informal sector employment for the least stringent lockdown level (3) – the coefficient is close to zero in magnitude and is not statistically significant. In contrast, I find no evidence of an effect on the probability of formal sector employment for the most stringent lockdown levels 5 and 4. The magnitudes of both coefficients here are close to zero and are not statistically significant. In contrast, I do however estimate a negative effect of 8.3 percentage points on the probability of formal sector employment for the least stringent lockdown level (3), significant at the 1 percent level and not statistically different from that in model (3) for the overall probability of employment for the same lockdown level.

5.5 Discussion

My estimates in this section suggest that employment probabilities in South Africa were adversely and significantly affected by sector-specific restrictions - a core component of the country's lockdown policy - for each of the three lockdown stringency levels assessed here. Moreover, these effects were heterogeneous by employment formality, where the initial, more stringent sector-specific restriction negatively affected informal sector employment while the least stringent restrictions negatively affected formal sector employment. What might explain this variation? One hypothesis is relates to between-sector variation in employment elasticities with respect to, what I refer to as, 'abrupt' versus 'accumulated' lockdown effects. As described prior, the initial 'hard' lockdown was implemented quickly and only permitted workers to continue working if they were in occupations deemed 'essential' to economic function or pandemic response, or if they could feasibly work from home. As shown in Chapter 3, informal sector workers were both less likely to be 'essential' workers or be able to work remotely relative to their formal sector counterparts. Moreover, nearly half (46.6 percent) of all informal sector workers are self-employed in contrast to just 1.9 percent of

Table 5.6: Model estimates of heterogenous effects on employment probabilities, by formality and lockdown stringency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var:	Pr(employment)			Pr(formal employment)			Pr(informal employment)		
Lockdown level:	5	4	3	5	4	3	5	4	3
Treatment×Post	-0.036***	-0.038***	-0.055**	0.008	0.003	-0.083***	-0.041***	-0.053***	0.022
	(0.013)	(0.013)	(0.027)	(0.012)	(0.011)	(0.026)	(0.011)	(0.011)	(0.018)
Time-varying $\boldsymbol{X}$	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Constant	0.740	0.840	2.230	1.583*	0.763	1.796	-0.626	0.378	0.956
	(0.909)	(0.993)	(1.357)	(0.863)	(0.934)	(1.261)	(0.759)	(0.771)	(1.078)
Observations	9,830	10,116	5,978	9,830	10,116	5,978	9,830	10,116	5,978
R^2	0.800	0.801	0.801	0.864	0.870	0.878	0.783	0.796	0.808

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).

[b] Notes: This table presents estimates of γ from specification 5.1 by lockdown level for varying binary dependent variables. Sample restricted to those of working-age (15-64 years) as of 2020Q1. Lockdown levels range from 5 (most stringent) to 3 (most lenient). FE = fixed effects. Standard errors presented in parentheses and are clustered at the panel level. All estimates weighted using sampling weights. 'Post' coefficient omitted for brevity. Time-varying controls include age, highest education level, and employment type. Each model controls for individual FEs and as such time-invariant observables are not included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

formal sector workers.[10] This suggests that a large proportion of the informal sector had to abruptly cease operations during the most stringent lockdown period. Over time, the easing of lockdown levels eventually permitted almost all sectors to operate thus allowing informal sector activities to resume. By contrast, at the start of the initial stringent lockdown which was at first expected to last for a few weeks, many formal sector workers were shielded from short-term job loss effects through formal employment relationships, a much higher ability to work from home, and access to job retention programmes introduced by the government. As the lockdown persisted, however, formal sector employers' capacities to retain workers may have waned over time. Hence, the job loss effects in this sector may have simply been delayed.

Alternatively, these heterogeneous effects may be explained by a combination of differential targeting and timing of two South African government's economic support policies during the beginning of the pandemic: the TERS (a wage subsidy) and the SRD grant (an unconditional cash transfer). As described in Chapters 1 and 2, the TERS was a wage subsidy which supported workers in firms who either fully or partially closed their operations due to the pandemic. The interested reader is again referred to Köhler & Hill (2022) and Köhler et al. (2023) for a detailed description of the policy. Importantly, during the policy's first two months (April and May 2020), eligibility was restricted to workers who were registered and contributing to the Unemployment Insurance Fund (UIF). Considering UIF contribution is concentrated in the formal sector in South Africa (as of 2020Q1, 88 percent of UIF-contributors were formal sector workers),[11] it can be said that during this period the policy mostly targeted formal sector workers while largely excluding those in the informal sector. Following legal challenges to this eligibility criterion, from the end of May 2020 onwards the policy was expanded to include all workers, whether they were UIF-contributors or non-contributors. This change in eligibility coincides with my employment effect estimates; that is, I find no evidence of any effect on formal sector employment for the most stringent lockdown levels 5 and 4 (in April and May 2020) during which the TERS targeted primarily formal sector workers, but I estimate a negative effect on formal sector employment for the least stringent lockdown level 3 (in June 2020) from which the policy was expanded to include all workers. This then also aligns with my null informal sector employment effect estimates for lockdown level 3 and the negative effects estimated for more stringent levels during which these workers were not eligible. This is supported by Köhler et al. (2023)'s analysis which exploits the aforementioned temporary eligibility criterion to find that the policy significantly increased the probability of job retention among formal, private sector employees during its first two months. Overall, this suggests that the TERS mitigated job loss in the formal sector during its initial period, and once the system expanded to include all workers it then possibly mitigated job loss in the informal sector, potentially at the expense of such mitigation in the formal sector.

A similar story may hold when considering an alternative policy during this period: the

[10] Own calculations using microdata from the QLFS for 2020Q1 (Statistics South Africa, 2020a).
[11] Own calculations using microdata from the QLFS for 2020Q1 (Statistics South Africa, 2020a).

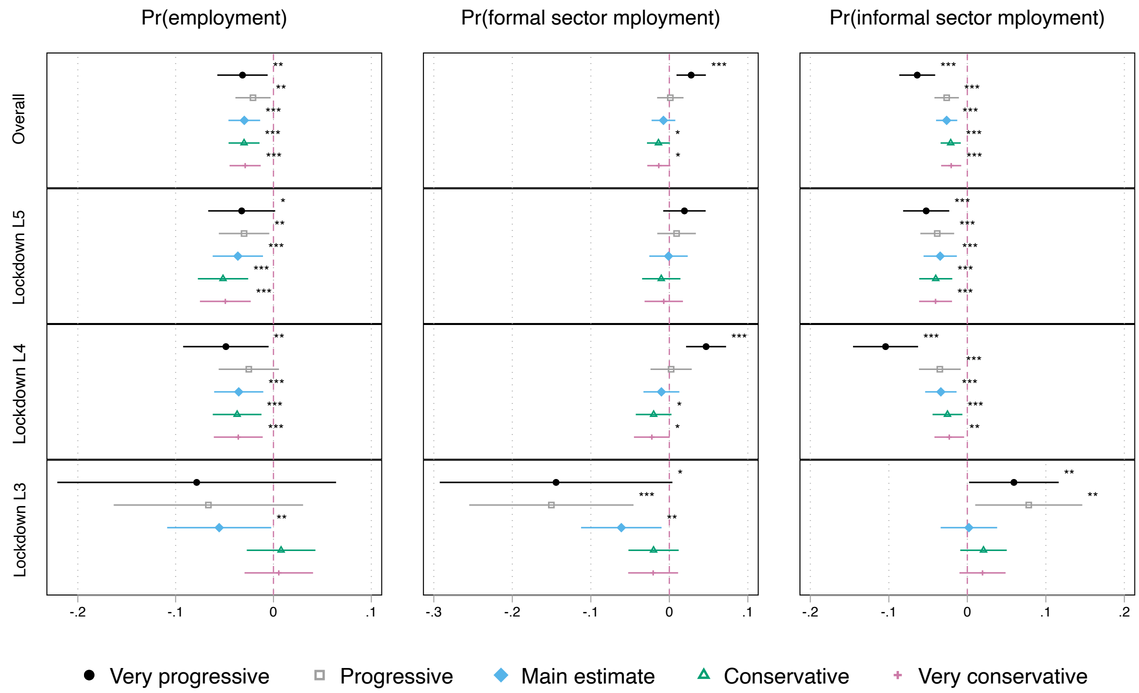
SRD grant. As previously described, the SRD grant is an unconditional cash transfer of R350 per person per month which targets unemployed adults. As previously mentioned, despite this criterion informal workers also benefited, which was not unexpected given the inability of the verification systems to distinguish these workers from the unemployed (Köhler & Bhorat, 2021). Importantly, although the transfer was announced in April 2020, payments only commenced at the end of May 2020. As such, the grant only largely provided support to the unemployed and informal sector workers from June 2020 but not during the two prior months. This aligns with the timing of my heterogeneous informal sector employment effect estimates by lockdown stringency; that is, I estimate negative effects for the most stringent lockdown levels 5 and 4 (in April and May 2020) during which the grant did not reach informal sector workers, but I find no evidence of any effects for the least stringent lockdown level 3 (in June 2020). This is in line with Bhorat et al. (2023)'s analysis which, through the use of a staggered DiD design, finds that receipt of the grant increased the employment probabilities of recipients in the short-term. Overall, this supports the hypothesis that the SRD grant may have mitigated the negative employment effects on informal sector workers once it had been rolled out. Taken together then, a combination of differential targeting and timing of these two core government support policies may explain the heterogeneous employment effects documented here.

5.6 Robustness tests

In this section, I conduct two robustness tests relating to (1) the assumptions of my empirical strategy and (2) accounting for a possibly confounding covariate. In my main estimation, I assume that individuals who work in 'limited capacity' industries were only permitted to work if their industry's legislated employment capacity was at least 50 percent and not otherwise. This is an arbitrary threshold and has implications for who is included in my control group. To examine the sensitivity of my results to this decision, I re-estimate specification (1) using four alternative threshold assumptions. The 'very progressive' assumption assumes a threshold of 0 percent (that is, permission-to-work is assumed if an individual's industry had any legislated capacity above 0 percent); the 'progressive' assumption assumes a threshold of 25 percent; the 'conservative' assumption assumes a threshold of 75 percent; and under the 'very conservative' assumption, permission-to-work is assumed only if 100 percent of employment within an individual's industry is permitted. My main results, which use the '50 percent' assumption, can be regarded as moderate in this regard. Intuitively, moving from the 'very progressive' assumption to the 'very conservative' assumption increases the size of my treatment group. This procedure of separately re-estimating specification (1) for each of my dependent variables and levels of lockdown stringency using each of these assumptions results in 60 DiD estimates. I present these estimates, including my main estimates for comparison, in a coefficient plot in Figure 5.3.

Considering effects on employment probabilities, for the overall model I consistently estimate a negative and statistically significant effect of a similar magnitude to my main

Figure 5.3: Coefficient plot of model estimates, by outcome, lockdown stringency level, and industry capacity assumption



[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q1 (Statistics South Africa, 2020a,b).
[b] Notes: This figure presents a coefficient plot of estimates of from specification 5.1 by dependent variable and lockdown level using varying industry capacity assumptions. 'Very progressive' = workers coded as being permitted to work if any share of the industry is permitted; 'progressive' = workers coded as being permitted to work if at least 25 percent of the industry is permitted; 'conservative' = workers coded as being permitted to work if at least 75 percent of the industry is permitted; 'very conservative' = workers coded as being permitted to work only if 100 percent of the industry is permitted. Markers represent point estimates and lines represent 95 percent confidence intervals. Lockdown levels range from 5 (most stringent) to 3 (most lenient). Sample restricted to those of working-age (15-64 years) as of 2020Q1. All model standard errors are clustered at the panel level. Estimated weighted using sampling weights. All models control for a vector of time-varying observable covariates including age, highest education level, and employment type. All models additionally control for individual fixed effects (FEs) and as such time-invariant observables are not included. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

estimate, regardless of assumption. This finding holds when I consider heterogenous effects for lockdown levels 5 and 4, where all estimates are not statistically significantly different from my main estimates and, for the latter lockdown level, the estimates for four out of five alternative assumptions are, at least at the 5 percent level, statistically significantly different from zero. While for lockdown level 3 only my main estimate is statistically significant, most estimates are negative in sign while two, which are estimated using the 'very conservative' and 'conservative' assumptions, are close to zero. None of these coefficients are however statistically different from my main estimate.

Considering effects on formal sector employment probabilities, for the overall model four of the five coefficients are close to zero and are not significant at least at the 5 percent level, in line with my main estimate. The 'very progressive' estimate represents the exception; however, it is not statistically significantly different from my main estimate, and I believe this assumption – that individuals were permitted to work if their industry had any legislated capacity – is very implausible. I find similar results for lockdown level 4, while all estimates for level 5 are not statistically significantly different from zero, in line with my main estimate. For level 3, all five coefficients are negative and, while most (three) are statistically significant, none are statistically significantly different from my main estimate.

Finally, considering effects on informal sector employment probabilities, for the overall model I consistently estimate a negative and statistically significant effect by at least the 5 percent level. This finding holds for both lockdown levels 5 and 4, all in line with my main estimates. For level 3, three of the estimates are not statistically different from zero, in line with my main estimate. The other two, estimated under the 'very progressive' and 'progressive' assumptions, exhibit a positive coefficient and are statistically significant. However, both are not statistically different from my main estimate. Considering these results, I can conclude that my main estimates largely hold, however some do exhibit a degree of sensitivity to the chosen 'limited industry' assumption in a few instances, particularly in the direction of more 'progressive' assumptions. However, as previously expressed, these progressive assumptions are arguably not as plausible relative to more moderate assumptions.

Considering South Africa's five-level risk-adjusted lockdown strategy was in part a function of transmission risk in the workplace (Ramaphosa, 2020), it is possible that my estimated causal effect of the permission-to-work component of the country's lockdown policy may be confounded by varying task content across occupations, specifically with respect to occupation-specific physical interaction. For instance, workers in occupations which tend to exhibit higher degrees of physical interaction may be less likely to be permitted to work during the lockdown period due to higher transmission risk, implying the potential existence of bias introduced through an omitted variable related to treatment. To account for such an identification threat, I follow Avdiu & Nayyar (2020), Lu (2020), and Bhorat et al. (2020d) to construct an occupation-level index of physical interaction (PI), which can be said to measure one aspect of transmission risk, and control for it in a re-estimation of specification 5.1. Unfortunately, neither the QLFS nor any other existing labour force survey in South Africa includes data on the task content of occupations. As such, to construct my index I merge my data here with occupational work context data from the O*NET database (National Center for O*NET Development, 2021). I make use of two components from this dataset which are relevant to physical interaction: physical proximity (P_o) and face-to-face discussions (F_o). Additionally, based on the assumption that workers who use public transport to get to work experience greater physical interaction relative to those using private transport, I merge in work travel data (T_o) from StatsSA's latest Time Use Survey conducted in 2010 (Statistics South Africa, 2014). Following the Multidimensional Poverty Index literature (Alkire & Foster, 2011), these three components are equally-weighted to generate scores for each four-digit level occupation o through the following specification:

$$PI_o = \frac{1}{3}P_o + \frac{1}{3}F_o + \frac{1}{3}T_o \tag{5.3}$$

In Table A15 in the appendix I provide information on definitions and the scoring method for each component of the index. Each of the components of the index are scaled to vary within the unit interval such that PI_o scores vary between 0 and 1 with higher values being indicative of higher levels of physical interaction.[12] To illustrate the degree of between-industry variation in physical interaction, in Table A14 in the appendix I include estimates of the mean index values by industry. Index values range between 0.118 and 0.934 and exhibit a median of 0.533 and a standard deviation of 0.102, indicative of a non-negligible degree of variation. By industry, physical interaction appears highest in Construction (0.579) and lowest in Private Households (0.457) and Agriculture, hunting, forestry, and fishing (0.467). By formality, physical interaction is higher among formal relative to informal sector workers (0.567 compared to 0.513), and with respect to my treatment groups, physical interaction is higher among those who were not permitted to work relative to those that were (0.564 compared to 0.545, or nearly 20 percent of a standard deviation), which is in line with my justification for controlling for this measure. Notably, within either the formal or informal sector, physical interaction is higher among those not permitted to work.[13] After re-estimating specification 5.1 with the inclusion of this index as a control, my model estimates are presented in Table 5.7. It should be noted that although this index is time-invariant within occupations during my period here, it is not time-invariant within individuals because some individuals change occupations over time (which I control for using my 'industry or occupation job-mover' variable as discussed in Section 5.3.3), and as such I am still able to control for individual FE in my modelling here.

The results suggest that my main findings are robust to the inclusion of this covariate in my specification with respect to magnitude, sign, and statistical significance of the estimated effects. Considering effects on employment probabilities, I observe a consistently negative and statistically significant effect overall and for each level of lockdown stringency with a range $[-0.030; -0.057]$, none of which are statistically significantly different from my main estimates. For formal sector employment effects, I observe no evidence of any effect overall and for the more stringent lockdown levels 5 and 4, but a statistically significant and negative effect for the least stringent level 3, in line with my main estimates. The results on informal sector employment effects are also in line with my main estimates: a significant and negative effect overall and for the more stringent lockdown levels 5 and 4, but no evidence of any effect for level 3. As a sensitivity test, I alternatively construct the index using Principal Component Analysis (PCA) and find that the estimates are very similar in terms of coefficient

[12] I adjust the generated score for one occupation to ensure the American O*NET data is relevant for the South African context. The initial scoring resulted in domestic workers exhibiting a low index value driven by a low physical proximity score. However, in South Africa domestic workers often perform a dual role of cleaning and child-minding (Du Plessis, 2018), leading us to believe this low physical proximity score was inappropriate for the South African context. I adjusted the physical proximity score for this occupation by replacing it with the mean of the physical proximity score for domestic workers and the physical proximity score for child-care workers.

[13] Within the formal sector, the physical interaction index is 0.583 for workers who were not permitted to work in a given lockdown level compared to 0.558 for those who were. Within the informal sector, the physical interaction index is 0.522 for workers who were not permitted to work in a given lockdown level compared to 0.503 for those who were.

Table 5.7: Model estimates, controlling for occupation-level physical interaction

	(1)	(2)	(3)	(4)
	Overall		Lockdown level	
		5	4	3
Panel A: Employment				
Treatment×Post	-0.030***	-0.035***	-0.037***	-0.057**
	(0.008)	(0.013)	(0.013)	(0.027)
PI index$_o$	-0.156**	-0.235**	-0.169*	-0.004
	(0.069)	(0.111)	(0.096)	(0.155)
Constant	1.946***	1.571*	2.143**	2.639*
	(0.621)	(0.917)	(0.992)	(1.427)
Observations	24,675	9,366	9,621	5,688
Panel B: Formal employment				
Treatment×Post	-0.006	0.001	-0.011	-0.056**
	(0.008)	(0.012)	(0.012)	(0.026)
PI index$_o$	0.029	-0.017	-0.000	0.210
	(0.067)	(0.116)	(0.094)	(0.138)
Constant	1.510**	2.023**	0.771	1.315
	(0.593)	(0.904)	(0.943)	(1.297)
Observations	24,675	9,366	9,621	5,688
Panel A: Informal employment				
Treatment×Post	-0.028***	-0.036***	-0.035***	-0.005
	(0.007)	(0.011)	(0.010)	(0.018)
PI index$_o$	-0.155**	-0.195*	-0.141*	-0.201
	(0.062)	(0.107)	(0.081)	(0.133)
Constant	0.313	-0.703	1.422*	0.960
	(0.485)	(0.718)	(0.775)	(1.133)
Observations	24,675	9,366	9,621	5,688

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b); National Center for O*NET Development (2021); Statistics South Africa (2014).
[b] Notes: This table presents estimates of specification 5.1, overall and by lockdown level, for varying binary dependent variables while additionally controlling for occupation-level workplace physical interaction. Sample restricted to those of working-age (15-64 years) as of 2020Q1. Lockdown levels range from 5 (most stringent) to 3 (most lenient). All models control for a vector of time-varying observable covariates including age, highest education level, and employment type, as well as individual fixed effects (FEs). PI index = Physical Interaction index generated by merging occupation-level data from National Center for O*NET Development (2021) and Statistics South Africa (2014) with the QLFS data. Standard errors presented in parentheses and are clustered at the panel level. Estimates weighted using sampling weights. 'Post' coefficient omitted for brevity. *** p < 0.01, ** p < 0.05, * p < 0.10.

magnitude as well as precision (see Table A16 in the appendix). Interestingly, considering panels A and C in Table 5.7, the coefficient on PI_o is negative and significant at the 5 percent level and appears the decrease with lower levels of lockdown stringency, suggesting that informal sector employment is less likely among workers in occupations which exhibit higher levels of physical interaction during periods of high lockdown stringency. I observe no evidence of such a relationship with respect to formal sector employment. In the context of my study here however, this variable is intended solely as an additional control, and as such any further analysis into this relationship is out of this chapter's scope.

5.7 Conclusion

Like many governments around the world, the South African government implemented a national lockdown in response to the COVID-19 pandemic. This initial lockdown was stringent by international standards and labour force data revealed significant job losses equivalent to the total number of net jobs created over the previous decade. Consistent with the international context, job loss disproportionately affected already vulnerable worker groups in the country, thus exacerbating pre-existing labour market inequalities. In particular, informal employment served as a strong predictor of job loss, which has been attributed to their lower abilities to work remotely, work in 'essential' industries, and have access to various legal protections. Additionally and importantly, lockdown policy was not time-invariant, and varying levels of lockdown stringency partially shape the nature of job losses across different labour market sub-groups over time. Although existing studies provide causal evidence on the labour market effects of the pandemic and lockdown policies in both developed and developing contexts, there is an absence of such evidence on how variation in lockdown stringency affects outcomes, particularly in developing countries. Plausibly, such variation may have heterogenous effects both on aggregate and by employment formality.

In this chapter, I sought to estimate the causal effect of a core lockdown policy - sector-specific restrictions - on employment probabilities in South Africa and examine effect heterogeneity by lockdown stringency and employment formality. To do so, I exploited temporal and between-industry variation induced by these restrictions through the use of a DiD design on representative, individual-level, panel labour force data. I show that these restrictions caused significant, negative effects on employment probabilities at every level of lockdown stringency. Applying an approximate decomposition technique, I estimate that these restrictions were responsible for nearly two-thirds of the total employment decline at the pandemic's onset, reflective of the stringency of the country's regulations but additionally that job loss would have still occurred in the absence of restrictions. This is strongly consistent with the international literature. I show that the negative employment effects were driven by effects on the informal sector, and highlight significant heterogeneity with more stringent lockdown levels having had large negative effects on informal sector employment but not formal sector employment, and vice versa. These results hold when subjected to robustness tests which control for varying task content across occupations as well as varying treatment group assumptions. I put forward two hypotheses to explain this heterogeneous relationship. First, regarding between-sector variation in employment elasticities with respect to 'abrupt' versus 'accumulated' lockdown effects; and second, regarding a combination of differential targeting and timing of two of the government's core economic support policies during the beginning of the pandemic.

In summary, this chapter's analysis provides empirical evidence on the differential effects of lockdown policies by level of stringency and employment formality in a large developing country economy. If governments continue to consider lockdown regulations as a policy response, whether to the COVID-19 pandemic or a future crisis, policymakers ought to be mindful of the existence of such heterogeneous effects in their efforts to target government support appropriately.

Chapter 6

Conclusion

Beyond its significant health implications, the COVID-19 pandemic severely disrupted nearly all aspects of social and economic life globally. Together with an almost universal adoption of government-mandated non-pharmaceutical interventions, the pandemic effectively paused economic activity both abruptly at its onset and intermittently as it progressed over time. Despite a rapid, far-reaching, and wide-ranging introduction of policies to provide important forms of support to firms and households, the pandemic and associated restrictions led to recessions deep and often unprecedented in both magnitude and nature. The consequence was a significant reduction in wellbeing, reflected perhaps most acutely in the one of the largest increases to global poverty and income inequality ever recorded. Effects on labour markets are of particular interest given their dominant role in determining various aspects of wellbeing, especially in developing country contexts. By simultaneously affecting the supply, demand, and nature of work, the pandemic labour market was characterised by substantial and often persistent job losses alongside varied adjustments to working hours and wages among those who remained employed. Contrary to the notion of a "great equaliser", unfavourable occupational distributions with respect to sector-specific restrictions and remote work ability meant that workers who were already in precarious, disadvantaged positions bore the brunt of these effects, thus reinforcing or exacerbating pre-existing inequalities.

The pandemic's labour market implications hold particular relevance in South Africa. At its onset, the government introduced one of the most stringent nationwide lockdowns globally, and already prior to the pandemic, the country was characterised as the most unequal in the world with respect to several pecuniary and non-pecuniary outcomes. Inequality within the labour market - the country's primary institution for determining socio-economic wellbeing - drives these extreme levels of aggregate inequality due to both extensive, structural unemployment as well as a very unequal income distribution among the employed. A better understanding of the pandemic's labour market effects are thus critical in gaining an understanding of its effects on overall wellbeing in the country. This thesis aimed to provide an in-depth, micro-econometric examination of the aggregate and heterogenous labour market effects of the COVID-19 pandemic in South Africa. To do so, it makes use of a range of descriptive and quasi-experimental econometric techniques applied on nationally representative, individual-level, cross-sectional and panel household survey data. Paying attention to the pandemic-induced series of distinct mechanisms including remote work ability and 'essential' worker status, it interrogates average and between-group dynamics of several extensive and intensive margin outcomes from a pre-pandemic baseline to when all remaining pandemic regulations were repealed in 2022.

6.1 Summary of findings

This thesis' analysis yields several notable findings. First, in Chapter 2 I facilitate a conceptual framework by providing a synthesised review of the vast and still evolving literature. I show that in both developed and developing countries, adjustments were far-reaching and substantial in magnitude. These were due to one or a combination of government-mandated mitigation measures; voluntary reductions in economic activity; occupational and sectoral compositions, specifically with respect to sector-specific restrictions and remote work ability; and government support policy. On the extensive margin, job losses were unprecedented in magnitude and characterised by both permanent separations and temporary furloughs. As alternatives to layoffs, intensive margin adjustments to working hours and wages were often larger in magnitude however more transient. Changes to working hours were driven not only by complete furloughs as well as reductions to lower non-zero, positive hours, but also shifts towards non-traditional hours in response to new demands. Similarly, many studies document large within-worker wage reductions while some highlight upward average wage spikes. This latter dynamic partially reflects the overarching finding throughout the literature that, both across and within countries, adjustments were regressively distributed, therefore reinforcing or exacerbating labour market inequalities. Largely, this has been attributed to inequality in remote work ability and 'essential' worker status. A subset of studies explicitly consider the role of the latter and conclude that while restrictions alone were responsible for a share of negative labour market effects, these effects remain evident in their absence, suggesting that the primary culprit was the virus itself. Many of these adjustments were mirrored in the South African context; however, the existing literature remains limited in scope.

In Chapter 3, I analyse aggregate and between-group adjustments with respect to employment and working hours in South Africa at the pandemic's onset and as it progressed. I estimate a substantial 14 percent aggregate contraction in employment, equivalent to a decade's worth of jobs growth, resulting in millions of both job-losers and seekers becoming inactive and exiting the labour market entirely. These adjustments were not however evenly distributed. In both the short- and longer-term, I estimate significant heterogeneity characterised by regressivity, with job loss being concentrated among those who exhibited greater labour market vulnerability, thus reinforcing pre-existing inequalities. Strongly consistent with the international context, I show that variation in between-group job loss probability can largely be explained by two defining features of the pandemic labour market: remote work ability and 'essential' worker status. Among those who remained employed, the average individual worked 17 percent fewer hours, driven by over two million becoming furloughed.

A minority experienced an increase in hours, plausibly reflecting increased demand in certain industries. While these adjustments were temporary, they were also regressively distributed. Like employment, I show that inequalities in working hour adjustments can largely be explained to inequalities in 'essential' worker status, however unlike employment, not remote work ability. Unlike working hours, over time employment experienced a slow, non-linear, and only partial recovery, with only a few groups having fully recovered by the middle of 2022. Notably, the determinants of both extensive and intensive margin outcomes were relatively rigid throughout the period with few exceptions, such as those which relate to sectoral composition. These latter changes are suggestive of a persistent change to the structure of South Africa's labour market.

Chapter 4 draws attention to wage dynamics. As a consequence of data availability, the South African literature was especially limited in this regard at the time of writing. In this chapter, I analyse the level and nature of wages and wage inequality and its drivers during the pandemic by employing descriptive and decompositional econometric techniques on cross-sectional and panel micro-data privately provided by South Africa's national statistics office - StatsSA. First, an interrogation of data quality reveals a non-negligible amount of missing data, with a third of workers not reporting any wage information at all in the average wave. Moreover, non-response is non-randomly distributed, being highly inversely correlated with wages itself, justifying imputation. I show that StatsSA's approach yields very poor quality imputations, resulting in an underestimation across the entire distribution. After obtaining reliable estimates using parametric outlier detection and imputation models, I estimate extremely high and stable wage inequality in the pre-pandemic period. At the pandemic's onset, I document a significant increase in real wages primarily explained by a composition effect - about 70 percent at the mean - and to a lesser but non-negligible extent a structure effect. The former was induced by a regressive distribution of job loss, again driven by inequalities in remote work ability and 'essential' worker status, and hence was inequality-enhancing. The latter was characterised by within-worker wage gains related to changes in the returns to various characteristics, primarily among lower-wage workers, and hence was inequality-reducing. The dominance of the composition effect meant that overall wage inequality increased. A counterfactual exercise with composition-controlled indices indicates a significant but transient 8 percent rise in wage inequality attributable to the pandemic. As the labour market recovered, persistent changes to the returns to various characteristics which vary across the distribution, rather than a more similar worker profile, explains the reduction in wages and wage inequality toward their pre-pandemic levels.

Finally, in Chapter 5, I exploit temporal and between-industry variation induced by a core pandemic policy - sector-specific restrictions - and adopt a quasi-experimental approach to estimate their causal effect on employment in South Africa. By isolating this effect, the analysis speaks to how much job loss was attributable to these restrictions as opposed to other pandemic-related factors. While similar studies exist in the international context, there is an absence of evidence on how variation in the stringency of these restrictions differentially affects employment. This variation shaped the extent and nature of job losses, both on average and across worker groups. I examine such heterogeneity by taking advantage of the coincidental timing of South Africa's policy changes and data collection periods, and also analyse how these effects vary between formal and informal workers, the latter of which were disproportionately affected globally. I show that these restrictions caused significant negative effects on employment at every level of lockdown stringency. I estimate that they were responsible for nearly two-thirds of the total employment decline at the pandemic's onset, reflective of the stringency of South Africa's regulations. Additionally, this suggests that job loss would have still occurred in the absence of restrictions, which is strongly consistent with the broader literature. These negative employment effects were driven by effects on the informal sector. Notably, more stringent lockdown levels had large negative effects on informal sector employment but not formal sector employment, and vice versa. I put forward two hypotheses which may explain this heterogeneous relationship. These results have significant policy implications. Namely, if policymakers continue to consider lockdown regulations as a response to a future crisis, they ought to be mindful of the existence of such heterogeneous effects in their efforts to target government support appropriately.

6.2 Limitations and implications for future research

This thesis is not without its limitations. First, with respect to data quality, the analyses primarily make use of the QLFS data and hence are subject to any threats to data quality evident during the pandemic period raised in Section 3.2. While the bias adjustment procedure made to the sampling weights by StatsSA appears to produce reasonable estimates, an explicit external review of these adjustments had yet to be conducted at the time of writing. Conditional on obtaining more information than is available in the public QLFS documentation, future work ought to consider undertaking such an exercise. In doing so, such work would also be able to validate the findings documented here. Beyond data quality, much scope remains to examine the short- and longer-term labour market effects of the pandemic in South Africa. Considering Chapter 3, while a wide range of worker groups are considered during the period under review, few others are not, may be of interest, and are available in the data. To name a few, this includes workers across specific municipalities, varying firm sizes, more disaggregated occupation and industry groups, and the underemployed. While these covariates are available in the data, several are however not, which emphasises the need for analyses beyond the QLFS. For any further examination of wage dynamics in particular, of particular interest would be datasets which allow for a wider range of firm characteristics to be considered, given the relevance of firms in explaining wage inequality in the country as discussed in Chapter 4.

Again regarding wage dynamics, the analysis here does not include an examination of between-group variation. The South African literature remains scarce in this regard, with the single exception being gender. Future research ought to consider such an analysis conditional on access to the unimputed wage data from StatsSA. Chapter 4's analysis can be further extended by examining the roles that remote work and 'essential' worker status play in explaining temporal wage variation, both at the mean and across the wage distribution using the decomposition techniques employed here. Additionally, future work can empirically investigate the mechanisms behind the observed within-worker wage increases, such as the design of the country's TERS policy or an increase in demand for a subset of workers, as previously discussed. Considering Chapter 5, the analysis specifically considers effects on employment probabilities as the only outcome of interest, and employment formality as the single between-group source of heterogeneity. Future research ought to consider an extension to other outcomes, such as working hours and wages, or other groups, such as remote and 'essential' workers. Finally, the period under investigation in this thesis is limited to when all remaining restrictions were repealed in June 2022. Analyses of aggregate and between-group adjustments beyond will provide important insights into the extent and nature of the likely heterogeneous paths of recovery in South Africa's post-pandemic economy.

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Appendix to Chapter 3

Table A1: Aggregate employment, unemployment, inactivity, and working age population levels, 2019Q1-2022Q2

	Employed (1)	Unemployed (narrow) (2)	Unemployed (broad) (3)	Inactive (4)	Working-age (5)
20191	16,291,436	6,200,785	9,994,457	15,790,688	38,282,909
	(206,169)	(135,414)	(178,598)	(243,746)	(425,787)
20192	16,312,706	6,655,305	10,226,485	15,464,964	38,432,975
	(211,024)	(145,532)	(178,123)	(231,479)	(425,594)
20193	16,375,009	6,733,708	10,271,792	15,473,537	38,582,254
	(209,716)	(142,853)	(177,401)	(233,925)	(427,017)
20194	16,420,268	6,726,134	10,380,826	15,581,022	38,727,424
	(216,284)	(142,266)	(176,059)	(236,720)	(427,511)
20201	16,382,555	7,069,649	10,796,924	15,421,740	38,873,945
	(223,670)	(154,366)	(187,909)	(240,453)	(451,487)
20202	14,148,215	4,294,851	10,259,336	20,577,950	39,021,017
	(264,005)	(152,809)	(235,134)	(367,157)	(589,549)
20203	14,690,869	6,532,883	11,144,683	17,943,679	39,167,432
	(264,223)	(194,705)	(245,838)	(336,803)	(593,534)
20204	15,023,551	7,233,420	11,155,647	17,053,898	39,310,870
	(259,932)	(194,867)	(235,472)	(308,495)	(563,056)
20211	14,995,345	7,241,918	11,422,016	17,217,625	39,454,887
	(269,552)	(199,475)	(248,423)	(326,749)	(588,580)
20212	14,941,573	7,826,038	11,923,227	16,831,865	39,599,476
	(256,165)	(185,754)	(228,926)	(291,655)	(542,879)
20213	14,282,007	7,643,489	12,484,039	17,819,518	39,745,014
	(311,608)	(231,346)	(293,475)	(380,756)	(708,943)
20214	14,544,131	7,921,431	12,492,397	17,422,886	39,888,448
	(366,659)	(266,121)	(332,015)	(417,941)	(821,469)
20221	14,914,207	7,861,793	12,445,235	17,256,573	40,032,574
	(307,527)	(226,891)	(277,733)	(362,403)	(680,214)
20222	15,561,858	7,994,292	12,281,667	16,621,234	40,177,384
	(248,838)	(190,575)	(229,397)	(307,907)	(538,135)

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Sample restricted to those of working age (15-64 years). Economically inactive include the discouraged unemployed. Standard errors presented in parentheses.

Table A2: Levels and year-on-year changes in aggregate labour market outcomes: 2019 - 2022

	2019	2020	2021	2022	Change			
					2019-2020	2020-2021	2021-2022	2019-2022
	(1)	(2)	(3)	(4)	(2) - (1)	(3) - (2)	(4) - (3)	(4) - (1)
Employed	16,312,706	14,148,215	14,941,573	15,561,858	-2 164 490***	793 357***	620 285**	-750 848**
	(211,024)	(264,005)	(256,165)	(248,838)	(265,541)	(268,698)	(307,921)	(299,081)
Unemployed (narrow)	6,655,305	4,294,851	7,826,038	7,994,292	-2 360 454***	3 531 186***	168,254	1 338 987***
	(145,532)	(152,809)	(185,754)	(190,575)	(182,449)	(193,799)	(228,288)	(217,252)
Unemployed (broad)	10,226,485	10,259,336	11,923,227	12,281,667	32,852	1 663 891***	358,440	2 055 183***
	(178,123)	(235,134)	(228,926)	(229,397)	(247,449)	(251,651)	(283,360)	(268,141)
Inactive (incl. discouraged)	15,464,964	20,577,950	16,831,865	16,621,234	5 112 986***	-3 746 085***	-210,631	1 156 270***
	(231,479)	(367,157)	(291,655)	(307,907)	(378,866)	(350,172)	(359,061)	(358,095)

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).

[b] Notes: Estimates for a given year are as per the second quarter of said year. Estimates weighted using sampling weights after accounting for the complex survey design. Standard errors presented in parentheses. Change estimates calculated using adjusted Wald tests. Sample restricted to those of working age. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Employment levels and year-on-year net employment change by sector-unionisation interaction, 2019 - 2022

	2019	2020	2021	2022	Change					
					2019-2020			2019-2022		
					Absolute	%	Share of change (%)	Absolute	%	Share of change (%)
Private, unionised	2,073,823	2,211,945	2,371,212	2,103,510	138,122	6.66	-7.08	29,687	1.43	-4.84
	(62,606)	(81,896)	(86,754)	(77,547)	(91,589)			(91,904)		
Private, non-unionised	8,756,297	6,851,355	7,470,122	8,106,762	-1,904,943***	-21.76	97.70	-649,535***	-7.42	105.92
	(147,586)	(175,580)	(166,292)	(169,121)	(183,408)			(205,763)		
Public, unionised	1,856,868	1,963,621	1,753,980	1,683,569	106,753	5.75	-5.47	-173,300**	-9.33	28.26
	(60,645)	(72,163)	(65,481)	(64,994)	(77,819)			(80,725)		
Public, non-unionised	966,134	676,360	861,935	1,146,034	-289,774***	-29.99	14.86	179,900***	18.62	-29.34
	(37,239)	(38,339)	(41,046)	(46,008)	(48,504)			(56,632)		

[a] Author's own calculations. Source: QLFS 2019Q2, 2020Q2, 2021Q2, 2022Q2 (Statistics South Africa, 2019b, 2020b, 2021b, 2022d).
[b] Notes: Quarter 2 data used for each year to account for seasonality. Estimates weighted using sampling weights and account for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to working-age employees. Differences estimated using adjusted Wald tests. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Worker characteristics by remote work ability and 'essential' worker status, 2020Q1

	Remote work status		Essential worker status		
	Cannot work remotely	Can work remotely	Non-essential	Partially-essential	Essential
	(1)	(2)	(3)	(4)	(5)
Female	44.16	44.41	46.70	35.63	43.44
	(0.43)	(1.08)	(0.50)	(1.19)	(1.00)
African/Black	79.64	46.72	74.29	82.70	69.41
	(0.65)	(1.57)	(0.82)	(1.10)	(1.33)
Youth (15-34 years)	37.20	29.12	36.62	31.43	36.26
	(0.48)	(1.20)	(0.57)	(1.17)	(1.06)
Tertiary education	16.17	57.23	21.17	24.91	26.48
	(0.44)	(1.41)	(0.61)	(1.25)	(1.07)
Urban	73.81	90.89	77.44	75.21	69.96
	(0.64)	(0.80)	(0.68)	(1.44)	(1.28)
Primary sector	8.85	2.35	0.46	21.82	27.59
	(0.39)	(0.40)	(0.09)	(1.58)	(1.26)
Secondary sector	20.05	14.71	25.95	0.00	18.36
	(0.42)	(0.92)	(0.54)	.	(0.93)
Tertiary sector	71.11	82.94	73.58	78.18	54.05
	(0.51)	(0.99)	(0.54)	(1.58)	(1.33)
High-skilled	6.66	65.31	15.54	16.43	13.98
	(0.27)	(1.20)	(0.53)	(0.96)	(0.82)
Semi-skilled	59.51	34.69	51.85	72.57	56.67
	(0.51)	(1.20)	(0.60)	(1.13)	(1.25)
Low-skilled	33.84	0.00	32.61	11.00	29.35
	(0.50)	.	(0.59)	(0.81)	(1.25)
Informal sector	29.23	8.33	34.93	20.43	8.98
	(0.48)	(0.69)	(0.61)	(1.08)	(0.60)
Public sector	17.53	17.44	13.35	28.94	28.33
	(0.41)	(0.96)	(0.42)	(1.22)	(1.06)

[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).
[b] Notes: Estimates weighted using sampling weights and account for the complex survey design. Sample restricted to those employed and of working age (15-64 years). Standard errors presented in parentheses.

Table A5: Average marginal effect estimates of demographic covariates on labour market participation: 2019 - 2022

	(1) Pooled	(2) 2019	(3) 2020	(4) 2021	(5) 2022
Female	-0.131***	-0.133***	-0.129***	-0.131***	-0.129***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
African/Black	0.097***	0.131***	0.074***	0.085***	0.100***
	(0.009)	(0.010)	(0.012)	(0.015)	(0.022)
Coloured	0.055***	0.102***	0.029*	0.041**	0.044*
	(0.011)	(0.012)	(0.016)	(0.017)	(0.023)
Indian/Asian	-0.016	-0.009	-0.017	-0.024	-0.009
	(0.016)	(0.018)	(0.023)	(0.024)	(0.032)
15-34	0.234***	0.226***	0.208***	0.246***	0.276***
	(0.007)	(0.009)	(0.012)	(0.011)	(0.012)
35-59	0.435***	0.421***	0.415***	0.452***	0.467***
	(0.007)	(0.009)	(0.011)	(0.011)	(0.011)
Secondary incomplete	0.062***	0.064***	0.057***	0.061***	0.068***
	(0.005)	(0.006)	(0.008)	(0.008)	(0.008)
Secondary complete (matric)	0.212***	0.211***	0.200***	0.215***	0.229***
	(0.006)	(0.007)	(0.009)	(0.009)	(0.009)
Post-secondary	0.380***	0.368***	0.368***	0.394***	0.396***
	(0.006)	(0.007)	(0.010)	(0.010)	(0.011)
Married or living together	0.116***	0.122***	0.114***	0.116***	0.109***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)
Urban	0.066***	0.086***	0.051***	0.058***	0.072***
	(0.007)	(0.008)	(0.010)	(0.010)	(0.010)
Eastern Cape	-0.042***	-0.070***	-0.030**	-0.024*	-0.048***
	(0.010)	(0.011)	(0.015)	(0.014)	(0.015)
Northern Cape	-0.082***	-0.061***	-0.068***	-0.112***	-0.093***
	(0.012)	(0.016)	(0.016)	(0.017)	(0.019)
Free State	-0.029**	-0.015	-0.033**	-0.030*	-0.048***
	(0.011)	(0.012)	(0.017)	(0.017)	(0.017)
KwaZulu-Natal	-0.098***	-0.095***	-0.100***	-0.097***	-0.104***
	(0.012)	(0.012)	(0.016)	(0.016)	(0.018)
North West	-0.087***	-0.095***	-0.080***	-0.074***	-0.116***
	(0.012)	(0.013)	(0.018)	(0.018)	(0.019)
Gauteng	-0.012	-0.003	-0.009	-0.013	-0.033**
	(0.009)	(0.010)	(0.013)	(0.013)	(0.014)
Mpumalanga	-0.014	0.017	-0.040**	-0.010	-0.027
	(0.012)	(0.013)	(0.017)	(0.017)	(0.018)
Limpopo	-0.105***	-0.109***	-0.114***	-0.111***	-0.063***
	(0.013)	(0.014)	(0.018)	(0.017)	(0.018)
Wave FE	✓	✗	✗	✗	✗
Quarter FE	✗	✓	✓	✓	✓
Observations	477,481	167,353	130,194	113,435	66,499

[a] Author's own calculations. Source: QLFS 2019Q1-2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Average model effect estimates presented and obtained after Probit estimation. Pooled model controls for year-quarter fixed effects (FE) and year-specific models control for quarter fixed effects; estimates of which are omitted for brevity. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Average marginal effect estimates of demographic covariates on the probability of employment: 2019 - 2022

	(1) Pooled	(2) 2019	(3) 2020	(4) 2021	(5) 2022
Female	-0.112***	-0.118***	-0.110***	-0.111***	-0.104***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
African/Black	-0.045***	-0.019*	-0.046***	-0.065***	-0.051***
	(0.009)	(0.010)	(0.012)	(0.014)	(0.020)
Coloured	-0.041***	-0.009	-0.050***	-0.062***	-0.044**
	(0.011)	(0.012)	(0.016)	(0.016)	(0.021)
Indian/Asian	-0.072***	-0.051***	-0.065***	-0.105***	-0.061**
	(0.015)	(0.016)	(0.022)	(0.023)	(0.028)
15-34	0.078***	0.074***	0.067***	0.078***	0.101***
	(0.007)	(0.009)	(0.011)	(0.010)	(0.010)
35-59	0.302***	0.305***	0.292***	0.302***	0.316***
	(0.006)	(0.008)	(0.010)	(0.010)	(0.010)
Secondary incomplete	0.018***	0.020***	0.019***	0.013*	0.021***
	(0.004)	(0.005)	(0.007)	(0.007)	(0.007)
Secondary complete (matric)	0.136***	0.146***	0.135***	0.123***	0.144***
	(0.005)	(0.006)	(0.008)	(0.008)	(0.008)
Post-secondary	0.338***	0.341***	0.333***	0.332***	0.350***
	(0.007)	(0.008)	(0.010)	(0.011)	(0.011)
Married or living together	0.141***	0.144***	0.136***	0.146***	0.137***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)
Urban	0.067***	0.073***	0.065***	0.061***	0.070***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Eastern Cape	-0.080***	-0.095***	-0.087***	-0.065***	-0.064***
	(0.009)	(0.010)	(0.014)	(0.013)	(0.014)
Northern Cape	-0.049***	-0.062***	-0.054***	-0.042**	-0.024
	(0.012)	(0.015)	(0.016)	(0.017)	(0.017)
Free State	-0.047***	-0.059***	-0.057***	-0.037**	-0.022
	(0.011)	(0.012)	(0.016)	(0.016)	(0.015)
KwaZulu-Natal	-0.043***	-0.051***	-0.046***	-0.030**	-0.044***
	(0.010)	(0.010)	(0.014)	(0.014)	(0.016)
North West	-0.059***	-0.082***	-0.059***	-0.041***	-0.049***
	(0.011)	(0.012)	(0.016)	(0.016)	(0.016)
Gauteng	-0.058***	-0.062***	-0.061***	-0.050***	-0.058***
	(0.008)	(0.009)	(0.012)	(0.013)	(0.013)
Mpumalanga	-0.018	-0.027**	-0.016	-0.008	-0.020
	(0.011)	(0.012)	(0.016)	(0.015)	(0.015)
Limpopo	-0.040***	-0.038***	-0.048***	-0.043***	-0.025
	(0.010)	(0.012)	(0.015)	(0.015)	(0.017)
Wave FE	✓	✗	✗	✗	✗
Quarter FE	✗	✓	✓	✓	✓
Observations	477,481	167,353	130,194	113,435	66,499

[a] Author's own calculations. Source: QLFS 2019Q1-2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).

[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Average model effect estimates presented and obtained after Probit estimation. Pooled model controls for year-quarter fixed effects (FE) and year-specific models control for quarter fixed effects; estimates of which are omitted for brevity. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Average marginal effect estimates of demographic covariates on the probability of unemployment: 2019 - 2022

	(1) Pooled	(2) 2019	(3) 2020	(4) 2021	(5) 2022
Female	-0.014***	-0.009***	-0.015***	-0.016***	-0.020***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
African/Black	0.138***	0.137***	0.121***	0.150***	0.152***
	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)
Coloured	0.096***	0.103***	0.081***	0.105***	0.095***
	(0.008)	(0.008)	(0.011)	(0.012)	(0.014)
Indian/Asian	0.050***	0.032***	0.042***	0.077***	0.050***
	(0.011)	(0.011)	(0.015)	(0.021)	(0.019)
15-34	0.176***	0.173***	0.157***	0.188***	0.196***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
35-59	0.154***	0.139***	0.140***	0.173***	0.174***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
Secondary incomplete	0.033***	0.034***	0.030***	0.036***	0.036***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
Secondary complete (matric)	0.067***	0.056***	0.059***	0.082***	0.075***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)
Post-secondary	0.020***	0.005	0.016**	0.038***	0.023**
	(0.005)	(0.006)	(0.007)	(0.009)	(0.010)
Married or living together	-0.044***	-0.040***	-0.038***	-0.051***	-0.048***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
Urban	0.003	0.018**	-0.011	0.001	0.007
	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)
Eastern Cape	0.035***	0.025***	0.054***	0.038***	0.013
	(0.009)	(0.010)	(0.012)	(0.013)	(0.014)
Northern Cape	-0.035***	0.004	-0.015	-0.077***	-0.072***
	(0.009)	(0.014)	(0.012)	(0.014)	(0.015)
Free State	0.023**	0.050***	0.029**	0.010	-0.021
	(0.010)	(0.011)	(0.014)	(0.015)	(0.016)
KwaZulu-Natal	-0.052***	-0.038***	-0.050***	-0.065***	-0.058***
	(0.009)	(0.009)	(0.012)	(0.013)	(0.015)
North West	-0.025**	-0.006	-0.019	-0.031**	-0.063***
	(0.010)	(0.011)	(0.014)	(0.015)	(0.016)
Gauteng	0.048***	0.061***	0.056***	0.038***	0.030**
	(0.008)	(0.008)	(0.012)	(0.013)	(0.014)
Mpumalanga	0.008	0.051***	-0.020	0.001	-0.003
	(0.012)	(0.015)	(0.014)	(0.016)	(0.017)
Limpopo	-0.057***	-0.063***	-0.058***	-0.065***	-0.030*
	(0.010)	(0.010)	(0.013)	(0.015)	(0.016)
Wave FE	✓	✗	✗	✗	✗
Quarter FE	✗	✓	✓	✓	✓
Observations	477,481	167,353	130,194	113,435	66,499

[a] Author's own calculations. Source: QLFS 2019Q1-2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Average model effect estimates presented and obtained after Probit estimation. Pooled model controls for year-quarter fixed effects (FE) and year-specific models control for quarter fixed effects; estimates of which are omitted for brevity. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Average marginal effect estimates of demographic and labour market covariates on working hours: 2019 - 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pooled		2019		2020		2021		2022	
Female	-4.691***	-2.865***	-4.494***	-2.717***	-5.079***	-3.468***	-4.816***	-2.800***	-4.096***	-2.122***
	(0.142)	(0.139)	(0.158)	(0.153)	(0.244)	(0.259)	(0.235)	(0.225)	(0.232)	(0.217)
African/Black	0.524**	1.284***	0.332	1.419***	0.466	0.928**	0.679	1.326***	0.705*	1.583***
	(0.251)	(0.224)	(0.247)	(0.239)	(0.432)	(0.416)	(0.414)	(0.374)	(0.398)	(0.392)
Coloured	-1.179***	-0.039	-1.217***	0.114	-2.196***	-1.178**	-0.588	0.693	-0.068	0.682
	(0.340)	(0.297)	(0.354)	(0.314)	(0.558)	(0.537)	(0.572)	(0.516)	(0.563)	(0.521)
Indian/Asian	1.117**	0.121	0.776	0.158	0.739	-0.414	1.075	-0.102	2.498***	1.470*
	(0.495)	(0.444)	(0.554)	(0.467)	(0.809)	(0.764)	(0.776)	(0.768)	(0.908)	(0.866)
15-34	2.789***	2.058***	2.641***	2.285***	2.969***	2.232***	2.725***	1.632***	2.815***	1.691**
	(0.392)	(0.357)	(0.468)	(0.441)	(0.730)	(0.726)	(0.654)	(0.630)	(0.687)	(0.658)
35-59	1.613***	1.441***	1.440***	1.778***	1.739**	1.534**	1.579**	0.871	1.785***	1.317**
	(0.378)	(0.336)	(0.462)	(0.432)	(0.694)	(0.688)	(0.629)	(0.595)	(0.660)	(0.649)
Secondary incomplete	1.650***	1.442***	1.538***	1.117***	1.982***	1.944***	1.140**	1.450***	2.253***	1.241***
	(0.306)	(0.277)	(0.305)	(0.291)	(0.539)	(0.527)	(0.541)	(0.451)	(0.475)	(0.463)
Secondary complete (matric)	2.576***	1.730***	2.271***	1.022***	3.148***	2.488***	1.974***	1.850***	3.316***	1.648***
	(0.320)	(0.291)	(0.306)	(0.305)	(0.531)	(0.536)	(0.569)	(0.481)	(0.492)	(0.478)
Post-secondary	0.571*	1.435***	0.234	0.766**	0.926	2.132***	-0.034	1.611***	1.830***	1.369**
	(0.339)	(0.321)	(0.317)	(0.335)	(0.565)	(0.595)	(0.607)	(0.546)	(0.521)	(0.531)
Married or living together	0.418***	-0.061	0.090	-0.297**	0.492*	-0.022	0.570**	0.093	0.686**	0.140
	(0.151)	(0.131)	(0.174)	(0.148)	(0.263)	(0.244)	(0.246)	(0.217)	(0.283)	(0.242)
Urban	-0.013	0.289	0.202	0.196	-0.427	0.484	0.288	0.432	-0.161	-0.123
	(0.281)	(0.259)	(0.287)	(0.263)	(0.438)	(0.449)	(0.398)	(0.366)	(0.394)	(0.366)
Eastern Cape	-1.839***	-1.194***	-0.861*	-0.361	-2.441***	-1.757***	-2.399***	-1.800***	-1.587***	-0.722
	(0.420)	(0.360)	(0.443)	(0.384)	(0.677)	(0.611)	(0.595)	(0.533)	(0.563)	(0.524)
Northern Cape	-3.239***	-2.244***	-3.288***	-1.869***	-4.509***	-3.809***	-2.631***	-1.572**	-1.900***	-1.361**
	(0.518)	(0.436)	(0.526)	(0.433)	(0.968)	(0.880)	(0.803)	(0.689)	(0.635)	(0.554)
Free State	-2.661***	-2.072***	-2.470***	-1.642***	-3.954***	-2.963***	-2.071***	-1.828***	-1.542**	-1.537**

Table A8 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pooled		2019		2020		2021		2022	
	(0.407)	(0.365)	(0.492)	(0.412)	(0.682)	(0.633)	(0.619)	(0.516)	(0.626)	(0.602)
KwaZulu-Natal	0.063	0.407	0.595	0.812**	-0.832	-0.199	0.019	0.430	0.885*	0.712
	(0.380)	(0.326)	(0.414)	(0.329)	(0.605)	(0.560)	(0.547)	(0.473)	(0.522)	(0.481)
North West	-1.680***	-1.103***	-1.349***	-0.786*	-3.051***	-2.082***	-0.634	-0.232	-1.475**	-1.271**
	(0.436)	(0.372)	(0.470)	(0.411)	(0.766)	(0.718)	(0.628)	(0.513)	(0.612)	(0.580)
Gauteng	-0.226	0.346	-0.110	0.492*	-0.705	0.137	0.091	0.371	-0.071	0.402
	(0.298)	(0.235)	(0.336)	(0.254)	(0.489)	(0.422)	(0.447)	(0.364)	(0.447)	(0.405)
Mpumalanga	-1.660***	-1.194***	-0.805	-0.314	-3.145***	-2.447***	-1.192*	-1.101**	-1.224*	-0.623
	(0.442)	(0.363)	(0.493)	(0.391)	(0.690)	(0.638)	(0.648)	(0.523)	(0.627)	(0.563)
Limpopo	-0.052	0.568	0.449	1.161***	-1.077	0.246	0.338	0.687	0.365	-0.139
	(0.463)	(0.397)	(0.495)	(0.417)	(0.692)	(0.663)	(0.667)	(0.589)	(0.685)	(0.614)
Mining and quarrying		-4.698***		-3.685***		-5.754***		-4.859***		-4.515***
		(0.587)		(0.693)		(0.870)		(0.833)		(0.920)
Manufacturing		-5.855***		-4.752***		-6.866***		-6.411***		-5.079***
		(0.459)		(0.485)		(0.745)		(0.674)		(0.678)
Utilities		-2.273***		-2.450***		-2.518**		-1.908		-1.580
		(0.708)		(0.755)		(1.241)		(1.178)		(1.213)
Construction		-7.410***		-6.566***		-8.401***		-7.689***		-6.776***
		(0.518)		(0.538)		(0.854)		(0.768)		(0.773)
Trade		-4.260***		-2.964***		-5.406***		-4.894***		-3.491***
		(0.451)		(0.510)		(0.729)		(0.641)		(0.677)
TSC		-0.384		0.798		-1.801*		-0.467		-0.100
		(0.555)		(0.576)		(0.933)		(0.845)		(0.840)
Finance		-3.620***		-2.576***		-4.505***		-3.656***		-3.973***
		(0.458)		(0.501)		(0.740)		(0.660)		(0.677)
CSP services		-6.616***		-5.783***		-7.685***		-6.945***		-5.740***
		(0.496)		(0.541)		(0.825)		(0.734)		(0.731)

Table A8 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pooled		2019		2020		2021		2022	
Private households		-14.323***		-14.530***		-13.724***		-14.485***		-15.075***
		(0.759)		(0.812)		(1.292)		(1.120)		(1.049)
Other		-6.644***		-3.946***		-8.743***		-7.280***		-5.454***
		(0.962)		(0.958)		(2.039)		(1.660)		(1.510)
Professionals		-1.467***		-1.530***		-1.611***		-1.455***		-1.043**
		(0.279)		(0.333)		(0.498)		(0.485)		(0.508)
TA professionals		-1.352***		-1.502***		-1.476***		-1.674***		-0.156
		(0.272)		(0.310)		(0.511)		(0.461)		(0.515)
Clerks		-0.704***		-1.291***		-0.701		-0.579		0.260
		(0.255)		(0.288)		(0.480)		(0.437)		(0.448)
Service workers		3.591***		2.844***		4.000***		3.906***		3.710***
		(0.284)		(0.325)		(0.512)		(0.470)		(0.505)
Skilled agricultural		-2.908***		-2.562*		-4.021*		-4.054*		-0.364
		(0.992)		(1.319)		(2.366)		(2.097)		(1.648)
Craft		-1.364***		-1.944***		-1.459***		-0.870*		-0.939*
		(0.280)		(0.314)		(0.511)		(0.487)		(0.552)
Plant operators		0.690**		0.025		0.765		1.161**		0.970*
		(0.310)		(0.345)		(0.573)		(0.517)		(0.556)
Elementary occupations		-3.540***		-3.981***		-3.349***		-3.464***		-3.212***
		(0.281)		(0.321)		(0.507)		(0.466)		(0.490)
Domestic workers		1.566*		2.465**		0.298		1.882		1.702
		(0.934)		(1.061)		(1.584)		(1.399)		(1.392)
Other		-1.890*		-4.068**		-1.467		-1.480		-9.876***
		(1.062)		(1.996)		(1.571)		(1.095)		(0.859)
Informal sector		1.284***		0.618**		1.407***		2.189***		0.965**
		(0.262)		(0.304)		(0.534)		(0.474)		(0.483)
Public sector		-5.634***		-4.993***		-6.126***		-5.974***		-5.428***

Table A8 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pooled		2019		2020		2021		2022	
		(0.292)		(0.285)		(0.533)		(0.449)		(0.438)
Union membership		2.746***		2.220***		3.499***		2.846***		2.178***
		(0.155)		(0.166)		(0.295)		(0.240)		(0.251)
Written contract		-1.082***		-1.371***		-1.443***		-0.649		-0.731*
		(0.253)		(0.273)		(0.504)		(0.437)		(0.427)
Wave FE	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
Quarter FE	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓
Observations	179,151	150,283	69,125	58,179	48,103	40,187	38,767	32,458	23,156	19,459

[a] Author's own calculations. Source: QLFS 2019Q1-2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).

[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age. Average model effect estimates presented and obtained after Poisson estimation. Pooled model controls for year-quarter fixed effects (FE) and year-specific models control for quarter fixed effects; estimates of which are omitted for brevity. TSC = transport, storage and communication; CSP = community; social and personal services; TA = technical and associate; managers = legislators, senior officials, and managers. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape, Agricultural industry, Managers occupation group, Formal sector (including agriculture).
*** p<0.01, ** p<0.05, * p<0.10.

Table A9: Average marginal effect estimates on intra-state extensive margin transitions in labour market states

	(1)	(2)	(3)	(4)	(5)
	Pr(Remain inactive)	Pr(Remain participant)	Pr(Remain unemployed)	Pr(Remain employed)	
Female	0.029***	-0.063***	0.001	-0.034***	-0.018*
	(0.007)	(0.008)	(0.016)	(0.009)	(0.011)
African/Black	-0.038***	-0.055**	0.033	-0.018	-0.041**
	(0.013)	(0.022)	(0.067)	(0.022)	(0.021)
Coloured	-0.027	-0.046	-0.015	-0.013	-0.057*
	(0.020)	(0.030)	(0.078)	(0.031)	(0.029)
Indian/Asian	0.006	0.038	-0.019	0.028	-0.020
	(0.019)	(0.038)	(0.113)	(0.037)	(0.037)
15-34	-0.049***	-0.031	n.e.	0.032	0.067*
	(0.008)	(0.030)	n.e.	(0.030)	(0.036)
35-59	-0.112***	0.079***	n.e.	0.094***	0.115***
	(0.011)	(0.028)	n.e.	(0.028)	(0.035)
Secondary incomplete	-0.016**	-0.018	0.009	0.003	-0.032**
	(0.008)	(0.015)	(0.031)	(0.016)	(0.014)
Secondary complete	-0.079***	0.045***	0.026	0.076***	-0.013
	(0.012)	(0.016)	(0.034)	(0.017)	(0.016)
Post-secondary	-0.139***	0.144***	0.017	0.160***	0.008
	(0.023)	(0.017)	(0.042)	(0.017)	(0.022)
Married	-0.010	0.050***	-0.071***	0.032***	0.023**
	(0.009)	(0.010)	(0.021)	(0.009)	(0.009)
Urban	0.016	0.021	-0.041	0.016	0.001
	(0.010)	(0.015)	(0.036)	(0.013)	(0.013)
Eastern Cape	-0.070***	-0.048*	-0.094	-0.020	-0.038*
	(0.016)	(0.025)	(0.059)	(0.024)	(0.021)
Northern Cape	-0.093***	-0.082**	-0.256***	-0.002	-0.002
	(0.024)	(0.036)	(0.071)	(0.029)	(0.025)
Free State	-0.041**	-0.106***	-0.175***	-0.010	-0.020

Table A9 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
	Pr(Remain inactive)	Pr(Remain participant)	Pr(Remain unemployed)	Pr(Remain employed)	
	(0.018)	(0.029)	(0.061)	(0.027)	(0.025)
KwaZulu-Natal	-0.023	-0.052**	-0.225***	0.020	0.006
	(0.015)	(0.024)	(0.057)	(0.023)	(0.021)
North West	-0.038**	-0.043	-0.207***	0.012	-0.027
	(0.018)	(0.029)	(0.064)	(0.028)	(0.028)
Gauteng	-0.086***	-0.046**	-0.072	-0.025	-0.034*
	(0.015)	(0.021)	(0.049)	(0.022)	(0.020)
Mpumalanga	-0.011	-0.097***	-0.337***	0.037	0.020
	(0.014)	(0.027)	(0.056)	(0.024)	(0.022)
Limpopo	-0.053***	-0.065**	-0.200***	-0.059**	-0.058**
	(0.017)	(0.028)	(0.071)	(0.027)	(0.026)
Mining and quarrying					n.e.
					n.e.
Manufacturing					n.e.
					n.e.
Utilities					n.e.
					n.e.
Construction					n.e.
					n.e.
Wholesale and retail trade					n.e.
					n.e.
TSC					n.e.
					n.e.
Finance					n.e.
					n.e.
CSP services					n.e.
					n.e.

Table A9 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
	Pr(Remain inactive)	Pr(Remain participant)	Pr(Remain unemployed)	Pr(Remain employed)	
Private households					n.e.
					n.e.
Other					n.e.
					n.e.
Professionals					0.009
					(0.028)
TA professionals					-0.024
					(0.024)
Clerks					-0.039*
					(0.022)
Service and sales workers					-0.080***
					(0.021)
Skilled agricultural workers					-0.025
					(0.075)
Craft workers					-0.112***
					(0.025)
Plant and machine operators					-0.055**
					(0.025)
Elementary occupations					-0.117***
					(0.022)
Domestic workers					-0.076**
					(0.038)
Other					n.e.
					n.e.
Informal sector					n.e.
					n.e.
Public sector					0.072***

Table A9 – continued from previous page

	(1) Pr(Remain inactive)	(2) Pr(Remain participant)	(3) Pr(Remain unemployed)	(4) Pr(Remain employed)	(5)
					(0.017)
Union membership					0.105***
					(0.013)
Written contract					0.057***
					(0.014)
Observations	9,996	14,191	4,201	9,981	8,322

[a] Author's own calculations. Source: QLFS 2020Q1 - 2020Q2 (Statistics South Africa, 2020a,b).

[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age and to the 2020Q1 sample. Average model effect estimates presented and obtained after Probit estimation. "n.e." = not estimable. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape, Agricultural industry, Managers occupation group, Formal sector (including agriculture). *** p<0.01, ** p<0.05, * p<0.10.

Table A10: Average marginal effect estimates on inter-state extensive margin transitions in labour market states

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pr(I → P)	Pr(I → E)	Pr(I → U)	Pr(E → U)		Pr(E → I)		Pr(U → I)	Pr(U → E)
Female	-0.029***	-0.014***	-0.018***	-0.009	-0.005	0.044***	0.024**	0.024	-0.102***
	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)	(0.018)	(0.021)
African/Black	0.038***	-0.008	0.045***	0.031***	0.046***	-0.004	0.007	-0.019	-0.063
	(0.013)	(0.012)	(0.007)	(0.011)	(0.007)	(0.020)	(0.020)	(0.086)	(0.067)
Coloured	0.027	-0.006	0.034**	0.043**	0.060***	-0.018	0.015	0.032	-0.032
	(0.020)	(0.017)	(0.015)	(0.019)	(0.015)	(0.028)	(0.028)	(0.098)	(0.076)
Indian/Asian	-0.006	-0.020	0.011	0.024	0.055**	-0.051	-0.027	0.067	-0.221**
	(0.019)	(0.015)	(0.012)	(0.022)	(0.024)	(0.031)	(0.032)	(0.127)	(0.087)
15-34	0.049***	0.011*	0.043***	0.055***	0.049***	-0.068**	-0.099***	n.e.	n.e.
	(0.008)	(0.006)	(0.005)	(0.013)	(0.015)	(0.029)	(0.035)	n.e.	n.e.
35-59	0.112***	0.048***	0.077***	0.026**	0.024*	-0.115***	-0.132***	n.e.	n.e.
	(0.011)	(0.008)	(0.008)	(0.012)	(0.014)	(0.027)	(0.034)	n.e.	n.e.
Secondary incomplete	0.016**	0.002	0.016***	0.001	0.006	-0.003	0.032**	-0.008	-0.015
	(0.008)	(0.006)	(0.005)	(0.011)	(0.010)	(0.016)	(0.013)	(0.034)	(0.039)
Secondary complete	0.079***	0.025***	0.061***	-0.030***	-0.007	-0.061***	0.020	-0.029	-0.007
	(0.012)	(0.008)	(0.010)	(0.011)	(0.011)	(0.016)	(0.015)	(0.037)	(0.040)
Post-secondary	0.139***	0.037**	0.123***	-0.055***	-0.013	-0.130***	0.002	-0.030	0.051
	(0.023)	(0.015)	(0.021)	(0.011)	(0.013)	(0.016)	(0.020)	(0.045)	(0.054)
Married	0.010	0.008	0.002	-0.024***	-0.016***	-0.017**	-0.014	0.060***	0.099***
	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)	(0.023)	(0.025)
Urban	-0.016	-0.007	-0.012	-0.011	-0.006	-0.010	0.002	0.037	0.049
	(0.010)	(0.006)	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)	(0.039)	(0.036)
Eastern Cape	0.070***	-0.001	0.079***	0.019	0.026*	0.009	0.027	0.100	0.027
	(0.016)	(0.010)	(0.014)	(0.015)	(0.014)	(0.023)	(0.021)	(0.064)	(0.041)
Northern Cape	0.093***	0.013	0.091***	-0.003	-0.002	0.009	0.010	0.278***	0.121
	(0.024)	(0.013)	(0.023)	(0.017)	(0.015)	(0.027)	(0.024)	(0.080)	(0.091)
Free State	0.041**	0.012	0.037***	0.005	0.007	0.010	0.020	0.192***	0.065

Table A10 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pr(I → P)	Pr(I → E)	Pr(I → U)	Pr(E → U)		Pr(E → I)		Pr(U → I)	Pr(U → E)
	(0.018)	(0.012)	(0.013)	(0.017)	(0.016)	(0.024)	(0.023)	(0.066)	(0.047)
KwaZulu-Natal	0.023	0.008	0.020*	-0.020	-0.016	-0.003	0.009	0.245***	0.086*
	(0.015)	(0.010)	(0.011)	(0.013)	(0.012)	(0.021)	(0.020)	(0.061)	(0.049)
North West	0.038**	0.015	0.028**	0.000	0.010	-0.012	0.024	0.215***	0.136**
	(0.018)	(0.014)	(0.013)	(0.017)	(0.018)	(0.026)	(0.026)	(0.071)	(0.068)
Gauteng	0.086***	0.024**	0.075***	0.036**	0.040***	0.003	0.008	0.066	0.048
	(0.015)	(0.011)	(0.012)	(0.014)	(0.013)	(0.020)	(0.019)	(0.053)	(0.032)
Mpumalanga	0.011	0.006	0.009	-0.022*	-0.017	-0.020	-0.007	0.369***	0.158**
	(0.014)	(0.011)	(0.009)	(0.013)	(0.012)	(0.022)	(0.021)	(0.060)	(0.069)
Limpopo	0.053***	0.024**	0.037***	0.008	0.014	0.063**	0.056**	0.203***	0.133*
	(0.017)	(0.012)	(0.013)	(0.017)	(0.017)	(0.025)	(0.024)	(0.077)	(0.068)
Mining and quarrying					n.e.		n.e.		
					n.e.		n.e.		
Manufacturing					n.e.		n.e.		
					n.e.		n.e.		
Utilities					n.e.		n.e.		
					n.e.		n.e.		
Construction					n.e.		n.e.		
					n.e.		n.e.		
Wholesale and retail trade					n.e.		n.e.		
					n.e.		n.e.		
TSC					n.e.		n.e.		
					n.e.		n.e.		
Finance					n.e.		n.e.		
					n.e.		n.e.		
CSP services					n.e.		n.e.		
					n.e.		n.e.		

Table A10 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pr(I → P)	Pr(I → E)	Pr(I → U)	Pr(E → U)		Pr(E → I)		Pr(U → I)	Pr(U → E)
Private households					n.e.		n.e.		
					n.e.		n.e.		
Other					n.e.		n.e.		
					n.e.		n.e.		
Professionals					-0.000		-0.008		
					(0.019)		(0.023)		
TA professionals					-0.001		0.028		
					(0.015)		(0.021)		
Clerks					0.008		0.036*		
					(0.015)		(0.019)		
Service and sales workers					0.022		0.069***		
					(0.015)		(0.018)		
Skilled agricultural workers					n.e.		0.064		
					n.e.		(0.076)		
Craft workers					0.039**		0.094***		
					(0.019)		(0.021)		
Plant operators					0.006		0.053**		
					(0.016)		(0.022)		
Elementary occupations					0.029*		0.105***		
					(0.015)		(0.020)		
Domestic workers					0.000		0.081**		
					(0.021)		(0.035)		
Other					n.e.		n.e.		
					n.e.		n.e.		
Informal sector					n.e.		n.e.		
					n.e.		n.e.		
Public sector					-0.016		-0.066***		

Table A10 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pr(I → P)	Pr(I → E)	Pr(I → U)	Pr(E → U)		Pr(E → I)		Pr(U → I)	Pr(U → E)
					(0.012)		(0.015)		
Union membership					-0.042***		-0.082***		
					(0.009)		(0.012)		
Written contract					-0.015		-0.050***		
					(0.009)		(0.013)		
Observations	9,996	9,488	9,667	8,432	7,149	9,459	7,910	3,800	1,808

[a] Author's own calculations. Source: QLFS 2020Q1 - 2020Q2 (Statistics South Africa, 2020a,b).

[b] Notes: P = participation; I = inactivity; E = employment; U = narrow unemployment. Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age and to the 2020Q1 sample. Average model effect estimates presented and obtained after Probit estimation. "n.e." = not estimable. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape, Agricultural industry, Managers occupation group, Formal sector (including agriculture). *** p<0.01, ** p<0.05, * p<0.10.

Table A11: Average marginal effect estimates on intensive margin transitions in labour market states

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(Formal → Informal)		Pr(Informal → Formal)		Pr(Hours reduced)		Pr(Furloughed)	
Female	-0.013***	-0.007	0.006	0.069	0.043***	0.035**	0.065***	0.051***
	(0.005)	(0.005)	(0.027)	(0.057)	(0.013)	(0.016)	(0.009)	(0.011)
African/Black	0.010	0.017	-0.195*	-0.125	0.012	0.029	0.065***	0.061***
	(0.008)	(0.011)	(0.104)	(0.149)	(0.027)	(0.031)	(0.017)	(0.021)
Coloured	-0.001	0.012	0.072	-0.091	0.040	0.092**	0.090***	0.099***
	(0.011)	(0.013)	(0.129)	(0.191)	(0.036)	(0.039)	(0.026)	(0.029)
Indian/Asian	-0.021**	-0.015	-0.103	-0.227	-0.048	-0.060	-0.004	-0.035
	(0.010)	(0.021)	(0.158)	(0.174)	(0.055)	(0.059)	(0.031)	(0.031)
15-34	0.028**	0.034	-0.022	-0.023	-0.059	-0.048	-0.059*	-0.052
	(0.012)	(0.022)	(0.073)	(0.186)	(0.044)	(0.048)	(0.032)	(0.033)
35-59	0.018*	0.030	-0.074	-0.073	-0.060	-0.029	-0.048	-0.032
	(0.011)	(0.021)	(0.069)	(0.177)	(0.042)	(0.045)	(0.030)	(0.031)
Secondary incomplete	-0.010	-0.006	0.055	-0.022	-0.036	-0.048*	-0.001	0.000
	(0.015)	(0.009)	(0.034)	(0.067)	(0.024)	(0.027)	(0.018)	(0.019)
Secondary complete	-0.023	-0.006	0.085**	0.037	-0.104***	-0.097***	-0.030*	-0.033*
	(0.015)	(0.010)	(0.039)	(0.076)	(0.026)	(0.029)	(0.018)	(0.020)
Post-secondary	-0.043***	-0.013	0.113*	0.207*	-0.117***	-0.089**	-0.001	-0.026
	(0.015)	(0.012)	(0.061)	(0.119)	(0.028)	(0.035)	(0.020)	(0.024)
Married	-0.005	-0.000	-0.039	-0.028	-0.046***	-0.045***	0.003	0.006
	(0.006)	(0.005)	(0.027)	(0.051)	(0.016)	(0.016)	(0.010)	(0.010)
Urban	-0.004	-0.001	0.016	0.123**	-0.011	-0.026	-0.022	-0.030*
	(0.007)	(0.007)	(0.035)	(0.061)	(0.025)	(0.025)	(0.015)	(0.017)
Eastern Cape	0.040***	0.036***	0.080	0.101	0.102***	0.109***	0.009	0.009
	(0.015)	(0.012)	(0.060)	(0.121)	(0.035)	(0.036)	(0.025)	(0.025)
Northern Cape	-0.010	-0.008	0.008	-0.416**	0.149***	0.171***	-0.007	-0.018
	(0.009)	(0.015)	(0.129)	(0.198)	(0.050)	(0.050)	(0.031)	(0.029)

Table A11 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(Formal → Informal)		Pr(Informal → Formal)		Pr(Hours reduced)		Pr(Furloughed)	
Free State	0.029**	0.038***	0.022	-0.047	0.047	0.060	-0.005	0.006
	(0.013)	(0.011)	(0.065)	(0.141)	(0.042)	(0.043)	(0.028)	(0.028)
KwaZulu-Natal	0.011	0.015	0.009	0.071	-0.001	-0.017	-0.013	-0.010
	(0.009)	(0.010)	(0.054)	(0.120)	(0.033)	(0.033)	(0.023)	(0.024)
North West	0.006	0.015	0.072	0.109	0.066	0.083*	0.094**	0.081**
	(0.011)	(0.013)	(0.079)	(0.145)	(0.047)	(0.048)	(0.041)	(0.041)
Gauteng	0.016*	0.016*	0.103*	0.058	0.035	0.019	-0.012	-0.003
	(0.008)	(0.009)	(0.055)	(0.121)	(0.029)	(0.030)	(0.022)	(0.023)
Mpumalanga	0.005	0.015	0.024	-0.001	0.104***	0.101***	0.044	0.043
	(0.010)	(0.012)	(0.059)	(0.125)	(0.038)	(0.038)	(0.028)	(0.029)
Limpopo	0.019	0.024**	0.011	0.023	0.082*	0.087*	-0.029	-0.027
	(0.012)	(0.011)	(0.061)	(0.141)	(0.043)	(0.044)	(0.026)	(0.027)
Mining and quarrying		-0.021		0.193		n.e.		n.e.
		(0.025)		(0.254)		n.e.		n.e.
Manufacturing		0.002		-0.039		n.e.		n.e.
		(0.014)		(0.128)		n.e.		n.e.
Utilities		-0.003		-0.285		n.e.		n.e.
		(0.026)		(0.243)		n.e.		n.e.
Construction		0.039***		0.015		n.e.		n.e.
		(0.013)		(0.114)		n.e.		n.e.
Trade		0.020		-0.055		n.e.		n.e.
		(0.013)		(0.108)		n.e.		n.e.
TSC		0.033**		-0.302**		n.e.		n.e.
		(0.014)		(0.143)		n.e.		n.e.
Finance		0.021		0.053		n.e.		n.e.
		(0.013)		(0.111)		n.e.		n.e.

Table A11 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(Formal → Informal)		Pr(Informal → Formal)		Pr(Hours reduced)		Pr(Furloughed)	
CSP services		0.038***		-0.040		n.e.		n.e.
		(0.014)		(0.118)		n.e.		n.e.
Private households		n.e.		n.e.		n.e.		n.e.
		n.e.		n.e.		n.e.		n.e.
Other		n.e.		n.e.		n.e.		n.e.
		n.e.		n.e.		n.e.		n.e.
Professionals		-0.009		-0.337		0.056		0.040*
		(0.017)		(0.317)		(0.042)		(0.024)
TA professionals		0.001		-0.066		0.080**		0.077***
		(0.013)		(0.222)		(0.039)		(0.023)
Clerks		-0.000		-0.273		-0.031		0.031
		(0.013)		(0.212)		(0.037)		(0.023)
Service workers		0.015		-0.136		0.029		0.013
		(0.012)		(0.209)		(0.039)		(0.022)
Skilled agricultural		n.e.		-0.015		-0.072		0.197
		n.e.		(0.359)		(0.136)		(0.139)
Craft workers		0.021		-0.188		-0.025		0.034
		(0.013)		(0.216)		(0.043)		(0.028)
Plant operators		0.013		-0.023		0.021		0.040
		(0.013)		(0.230)		(0.044)		(0.027)
Elementary occupations		0.011		-0.066		0.042		0.086***
		(0.013)		(0.212)		(0.041)		(0.025)
Domestic workers		n.e.		n.e.		0.009		0.089
		n.e.		n.e.		(0.085)		(0.056)
Other		n.e.		n.e.		n.e.		n.e.
		n.e.		n.e.		n.e.		n.e.

Table A11 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pr(Formal → Informal)		Pr(Informal → Formal)		Pr(Hours reduced)		Pr(Furloughed)	
Public sector		-0.013		-0.040		0.002		0.053***
		(0.009)		(0.096)		(0.026)		(0.017)
Union membership		-0.030***		0.132		-0.126***		-0.072***
		(0.007)		(0.123)		(0.018)		(0.014)
Written contract		-0.045***		0.186***		-0.025		0.032*
		(0.007)		(0.049)		(0.031)		(0.018)
Informal sector						n.e.		n.e.
						n.e.		n.e.
Observations	6,085	5,720	1,236	454	6,613	5,708	7,910	6,753

[a] Author's own calculations. Source: QLFS 2020Q1 - 2020Q2 (Statistics South Africa, 2020a,b).

[b] Notes: Estimates weighted using sampling weights after accounting for the complex survey design. Clustered standard errors presented in parentheses. Sample restricted to those of working age and to the 2020Q1 sample. Average model effect estimates presented and obtained after Probit estimation. "n.e." = not estimable. Reference groups for categorical variables as follows: White, 60+ years, primary education or less, Western Cape, Agricultural industry, Managers occupation group, Formal sector (including agriculture). *** p<0.01, ** p<0.05, * p<0.10.

Appendix to Chapter 4

Table A12: Balance table of observable covariates by wage reporting status, 2020Q1

	(1) Reported exact wage	(2) Reported bracket only	(3) Reported neither	(4) Diff: (1) - (2)	(5) Diff: (1) - (3)
Age (years)	38.893	40.141	39.725	-1.24***	-0.84***
	(0.133)	(0.207)	(0.193)	(0.246)	(0.237)
Female	0.460	0.437	0.417	0.02**	0.04***
	(0.006)	(0.008)	(0.007)	(0.010)	(0.009)
Years of education	10.237	11.923	11.902	-1.69***	-1.66***
	(0.047)	(0.069)	(0.054)	(0.083)	(0.071)
African/Black	0.846	0.724	0.625	0.12***	0.22***
	(0.009)	(0.015)	(0.013)	(0.017)	(0.015)
Urban	0.686	0.762	0.877	-0.08***	-0.19***
	(0.009)	(0.013)	(0.008)	(0.016)	(0.012)
Informal sector	0.224	0.150	0.148	0.07***	0.08***
	(0.006)	(0.008)	(0.006)	(0.010)	(0.009)
Public sector	0.147	0.239	0.172	-0.09***	-0.02***
	(0.005)	(0.009)	(0.007)	(0.010)	(0.009)
Union member	0.236	0.398	0.309	-0.16***	-0.07***
	(0.006)	(0.011)	(0.009)	(0.012)	(0.011)

[a] Author's own calculations. Source: QLFS 2020Q1 (Statistics South Africa, 2020a).

[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. All estimates are weighted using the sample weights. Wave-specific mean for trade union membership is assigned to individuals with missing trade union data. Standard errors are adjusted for the complex survey design and are presented in parentheses. * p<0.10; ** p<0.050; *** p<0.001.

Table A13: Linear probability model estimates of the correlates of having missing wage data

Outcome variable:	(1) =1 if missing exact value and bracket	(2)	(3) =1 if missing exact value only
	=0 if reported exact value or bracket	=0 if reported exact value	=0 if reported exact value
Salary interval (base = monthly)			
Weekly	-0.100***	-0.110***	-0.135***
	(0.004)	(0.004)	(0.004)
Fortnightly	-0.092***	-0.094***	-0.125***
	(0.006)	(0.005)	(0.006)
Daily	-0.088***	-0.110***	-0.174***
	(0.005)	(0.004)	(0.004)
Hourly	-0.150***	-0.193***	-0.239***
	(0.011)	(0.010)	(0.011)
Annually	-0.163***	-0.198***	-0.124***
	(0.021)	(0.021)	(0.020)
Refusal/DK	0.378***	0.670***	0.592***
	(0.003)	(0.003)	(0.002)
Age (years)	-0.002***	-0.002**	0.000
	(0.001)	(0.001)	(0.001)
Age squared	0.000**	0.000*	0.000
	(0.000	(0.000	(0.000
Female	-0.017***	-0.027***	-0.030***
	(0.002)	(0.002)	(0.002)
Years of schooling	0.005***	0.010***	0.013***
	(0.001)	(0.001)	(0.001)
Race (base = African/Black)			
Coloured	0.044***	0.080***	0.085***
	(0.004)	(0.004)	(0.004)
Indian/Asian	0.126***	0.098***	0.069***
	(0.006)	(0.006)	(0.006)
White	0.097***	0.112***	0.110***
	(0.004)	(0.004)	(0.004)
Province (base = WC)			
EC	0.000	0.092***	0.115***
	(0.004)	(0.004)	(0.004)
NC	0.019***	0.083***	0.099***
	(0.006)	(0.006)	(0.006)
FS	-0.064***	0.026***	0.087***
	(0.005)	(0.005)	(0.005)
KZN	-0.018***	0.118***	0.174***
	(0.004)	(0.004)	(0.004)
NW	-0.143***	-0.022***	0.027***
	(0.005)	(0.006)	(0.005)
GP	0.122***	0.246***	0.278***
	(0.004)	(0.004)	(0.004)

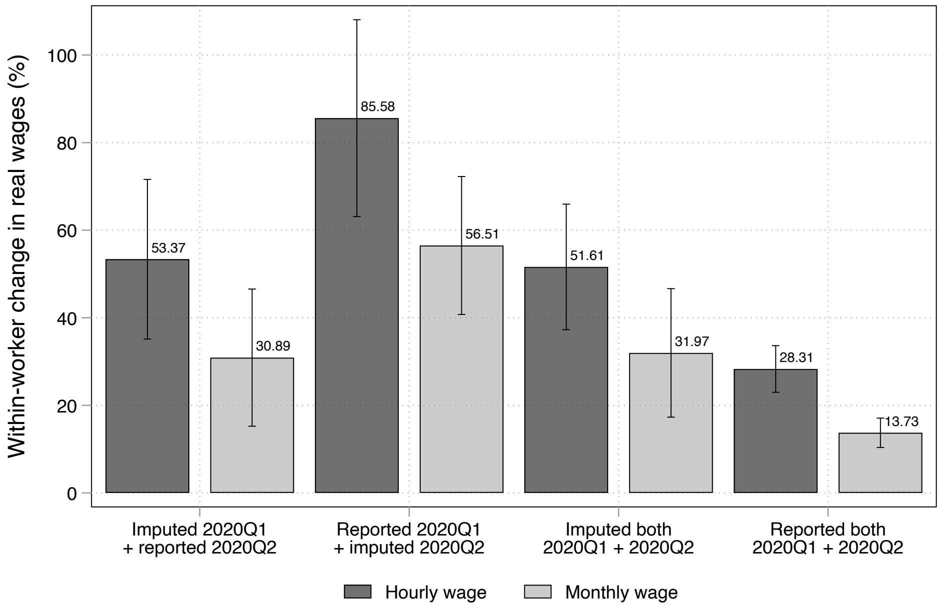
Table A13 – continued from previous page			
	(1)	(2)	(3)
	=1 if missing exact value and bracket		=1 if missing exact value only
Outcome variable:	=0 if reported exact value or bracket	=0 if reported exact value	=0 if reported exact value
MP	0.087***	0.219***	0.261***
	(0.005)	(0.005)	(0.005)
LP	-0.205***	-0.006	0.047***
	(0.005)	(0.005)	(0.005)
Industry (base = agriculture)			
Mining	0.074***	0.103***	0.132***
	(0.008)	(0.008)	(0.008)
Manufacturing	0.083***	0.090***	0.094***
	(0.006)	(0.006)	(0.005)
Utilities	0.110***	0.103***	0.079***
	(0.013)	(0.013)	(0.012)
Construction	0.064***	0.067***	0.073***
	(0.006)	(0.006)	(0.006)
Trade	0.071***	0.070***	0.078***
	(0.005)	(0.005)	(0.005)
Transport	0.101***	0.093***	0.094***
	(0.006)	(0.006)	(0.006)
Finance	0.063***	0.054***	0.057***
	(0.005)	(0.005)	(0.005)
Community and social services	0.042***	0.042***	0.052***
	(0.006)	(0.006)	(0.005)
Private households	0.015*	0.002	0.000
	(0.009)	(0.008)	(0.008)
Occupation (base = manager)			
Professional	-0.032***	-0.016***	0.000
	(0.006)	(0.006)	(0.005)
Technician	-0.001	0.004	0.007
	(0.005)	(0.005)	(0.005)
Clerk	0.003	0.005	0.001
	(0.005)	(0.005)	(0.005)
Sales and services	-0.056***	-0.077***	-0.076***
	(0.005)	(0.005)	(0.004)
Skilled agriculture	-0.052***	-0.073***	-0.090***
	(0.015)	(0.015)	(0.015)
Craft	-0.031***	-0.048***	-0.047***
	(0.005)	(0.005)	(0.005)
Plant and machine operator	-0.023***	-0.042***	-0.046***
	(0.005)	(0.006)	(0.005)
Elementary	-0.064***	-0.090***	-0.100***
	(0.005)	(0.005)	(0.004)
Domestic worker	-0.066***	-0.091***	-0.113***
	(0.010)	(0.009)	(0.009)

Table A13 – continued from previous page			
	(1)	(2)	(3)
	=1 if missing exact value and bracket		=1 if missing exact value only
Outcome variable:	=0 if reported exact value or bracket	=0 if reported exact value	=0 if reported exact value
Urban	0.065***	0.073***	0.050***
	(0.003)	(0.003)	(0.003)
Public sector	-0.022***	-0.007*	-0.006*
	(0.004)	(0.004)	(0.003)
Informal sector	-0.004	-0.006*	-0.016***
	(0.003)	(0.003)	(0.003)
Trade union membership	-0.001	0.049***	0.081***
	(0.003)	(0.003)	(0.003)
Trade union data missing	-0.046***	-0.066***	-0.042***
	(0.004)	(0.004)	(0.003)
Constant	0.132***	0.010	0.030
	(0.022)	(0.022)	(0.021)
Observations	177,183	141,083	177,183
R^2	0.250	0.461	0.406

[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).

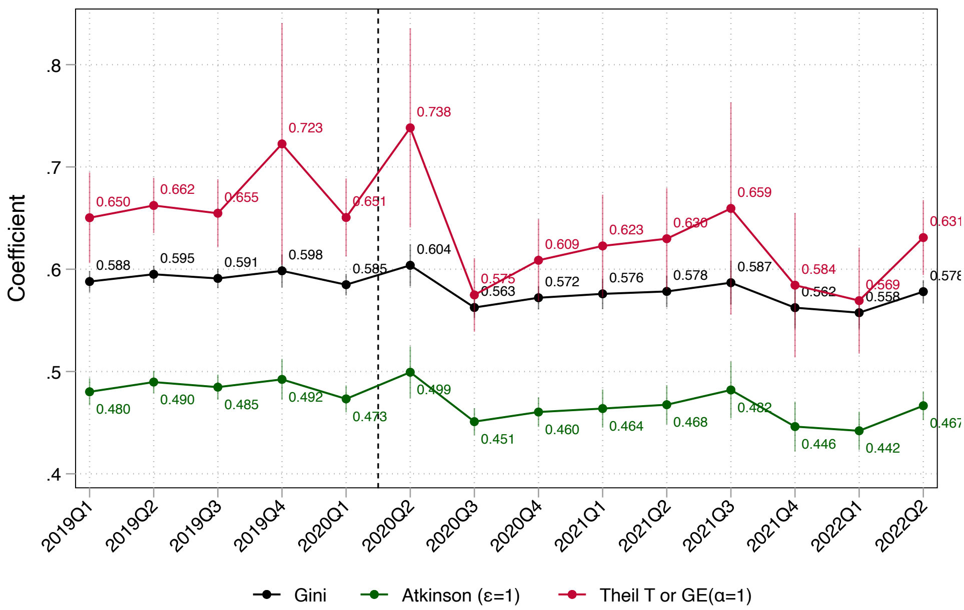
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Unweighted estimates presented. All models control for wave fixed effects. Binary indicator for missing trade union data included as a covariate, while the wave-specific mean for trade union membership is assigned to individuals with missing trade union data. Standard errors presented in parentheses. * p<0.10; ** p<0.050; *** p<0.001.

Figure A1: Within-worker wage changes by imputation status, 2020Q1 - 2020Q2



[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) in the balanced panel sample who were employed in both 2020Q1 and 2020Q2. Estimates weighted using sampling weights. Standard errors are adjusted for the complex survey design. Capped spikes represent 95 percent confidence intervals.

Figure A2: Relative wage inequality estimates by measure excluding furloughed workers, 2019Q1 – 2022Q2



[a] Author's own calculations. Source: QLFS 2019Q1 - 2022Q2 (Statistics South Africa, 2019a,b,c,d, 2020a,b,c,d, 2021a,b,c,d, 2022c,d).
[b] Notes: Unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed who reported working non-zero hours. Estimates are weighted using sampling weights. Standard errors are adjusted for the complex survey design. Spikes represent 95 percent confidence intervals.

Appendix to Chapter 5

Table A14: Industry-level variation in legislated permission to work, by lockdown level

SIC code	Industry description	Level 5	Level 4	Level 3	Mean PI index
10	**Private households**				0.457
10	Private households with employed persons	0	0	1	0.457
11	**Other**				0.477
20	Exterritorial organisations	1	1	1	0.453
30	Representatives of foreign governments	1	1	1	0.500
1	**Agriculture, forestry, and fishing**				0.510
111	Growing of crops; market gardening; horticulture	1	1	1	0.465
112	Farming of animals	1	1	1	0.470
113	Growing of crops combined with farming of animals (mixed farming)	1	1	1	0.451
114	Agricultural and animal husbandry services, except veterinary activities	1	1	1	0.449
115	Hunting, trapping and game propagation, including related services	1	1	1	0.382
116	Production of organic fertilizer	1	1	1	0.514
121	Forestry and related services	0	1	1	0.467
122	Logging and related services	0	1	1	0.505
131	Ocean and coastal fishing	1	1	1	0.591
132	Fish hatcheries and fish farms	1	1	1	0.806
2	**Mining and Quarrying**				0.581
210	Mining of coal and lignite	1	1	1	0.564
230	Mining of gold and uranium ore	0.25	0.5	1	0.577
240	Mining of metal ores, except gold and uranium	0.25	1	1	0.645
241	Mining of iron ore	0.25	1	1	0.560
242	Mining of non-ferrous metal ores, except gold and uranium	0.25	0.5	1	0.569
251	Stone quarrying, clay and sandpits	0.25	1	1	0.568
252	Mining of diamonds	0.25	1	1	0.615
253	Mining and quarrying not elsewhere classified	0.25	0.5	1	0.547
3	**Manufacturing**				0.557
301	Production, processing and preservation of meat, fish, fruit, vegetables, oils and fats	1	1	1	0.616
302	Manufacture of dairy products	1	1	1	0.575

SIC code	Industry description	Level 5	Level 4	Level 3	Mean PI index
	Table A14 – continued from previous page				
303	Manufacture of grain mill products, starches and starch products and prepared animal feeds	1	1	1	0.610
304	Manufacture of other food products	1	1	1	0.569
305	Manufacture of beverages	0.8	0.8	1	0.530
306	Manufacture of tobacco products	1	1	1	0.554
311	Spinning, weaving and finishing of textiles	0.25	0.5	1	0.591
312	Manufacture of other textiles	0.25	0.5	1	0.535
313	Manufacture of knitted and crocheted fabrics and articles	0.25	0.5	1	0.583
314	Manufacture of wearing apparel, except fur apparel	0.25	0.5	1	0.519
316	Tanning and dressing of leather; manufacture of luggage, handbag, saddlery and harness	0.25	0.5	1	0.504
317	Manufacture of footwear	0.25	0.5	1	0.573
321	Sawmilling and planing of wood	0	0.5	1	0.526
322	Manufacture of products of wood, cork, straw and plaiting materials	0	0.5	1	0.584
323	Manufacture of paper and paper products	1	1	1	0.550
324	Publishing	0	0.5	1	0.485
325	Printing and service activities related to printing	0	0.5	1	0.482
332	Petroleum refineries and synthesisers	1	1	1	0.585
333	Processing of nuclear fuel	1	1	1	0.488
334	Manufacture of basic chemicals	0	0.2	1	0.588
335	Manufacture of other chemical products	0	0.2	1	0.577
337	Manufacture of rubber products	0	0.5	1	0.524
338	Manufacture of plastic products	1	1	1	0.587
341	Manufacture of glass and glass products	1	1	1	0.577
342	Manufacture of non-metallic mineral products not elsewhere classified	0	0.2	1	0.547
351	Manufacture of basic iron and steel	0	0.5	1	0.563
352	Manufacture of basic precious and non-ferrous metals	0	0.5	1	0.571
354	Manufacture of structural metal products, tanks, reservoirs and steam generators	0	0.5	1	0.537
355	Manufacture of other fabricated metal products; metalwork service activities	0	0.5	1	0.532
356	Manufacture of general purpose machinery	0	0.5	1	0.566

Table A14 – continued from previous page

SIC code	Industry description	Level 5	Level 4	Level 3	Mean PI index
357	Manufacture of special purpose machinery	0	0.5	1	0.538
358	Manufacture of household appliances not elsewhere classified	0	0.2	1	0.599
359	Manufacture of office, accounting and computing machinery	0	0.2	1	0.581
361	Manufacture of electric motors, generators and transformers	0	0.2	1	0.550
362	Manufacture of electricity distribution and control apparatus	1	1	1	0.600
363	Manufacture of insulated wire and cable	0	0.2	1	0.584
364	Manufacture of accumulators, primary cells and primary batteries	0	0.2	1	0.557
365	Manufacture of electric lamps and lighting equipment	0	0.2	1	0.650
366	Manufacture of other electrical equipment not elsewhere classified	0	0.2	1	0.551
371	Manufacture of electronic valves and tubes and other electronic components	0	0.2	1	0.604
372	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy	0	0.2	1	0.460
374	Manufacture of medical appliances and instruments and appliances	1	1	1	0.557
375	Manufacture of optical instruments and photographic equipment	0	0.2	1	0.521
381	Manufacture of motor vehicles	0	0.5	1	0.554
382	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	0	0.5	1	0.572
383	Manufacture of parts and accessories for motor vehicles and their engines	0	0.5	1	0.563
384	Building and repairing of ships and boats	0	0.2	1	0.620
385	Manufacture of railway and tramway locomotives and rolling stock	0	0.2	1	0.549
386	Manufacture of aircraft and space-craft	0	0.2	1	0.545
387	Manufacture of transport equipment not elsewhere classified	0	0.2	1	0.519
391	Manufacture of furniture	0	0.2	1	0.548
392	Manufacturing not elsewhere classified	0	0.2	1	0.573
395	Recycling not elsewhere classified	0	0.2	1	0.511
4	**Electricity; gas and water supply**				0.559
411	Production, collection and distribution of electricity	1	1	1	0.582
412	Manufacture of gas; distribution of gaseous fuels through mains	1	1	1	0.512
420	Collection, purification, and distribution of water	1	1	1	0.582
5	**Construction**				0.545

Table A14 – continued from previous page

SIC code	Industry description	Level 5	Level 4	Level 3	Mean PI index
501	Site preparation	0.1	0.25	0.5	0.459
502	Building of complete constructions or parts thereof; civil engineering	0.1	0.25	0.5	0.573
503	Building installation	0.1	0.25	0.5	0.600
504	Building completion	0.1	0.25	0.5	0.589
505	Renting of construction of demolition equipment with operators	0.1	0.25	0.5	0.505
6	**Wholesale and retail trade**				0.580
611	Wholesale trade on a fee or contract basis	0.1	0.25	0.5	0.564
612	Wholesale trade in agricultural raw materials, livestock, food, beverages and tobacco	1	1	1	0.608
613	Wholesale trade in household goods	1	1	1	0.658
614	Wholesale trade in non-agricultural intermediate products, waste and scrap	1	1	1	0.553
615	Wholesale trade in machinery, equipment and supplies	0.1	0.25	1	0.490
619	Other wholesale trade	0.1	0.25	0.5	0.558
621	Non-specialised retail trade in stores	0.1	0.25	0.5	0.642
622	Retail trade in food, beverages and tobacco in specialised stores	0.75	0.8	0.9	0.619
623	Other retail trade in new goods in specialised stores	0.1	0.25	0.5	0.602
624	Retail trade in second-hand goods in stores	0.1	0.25	0.5	0.650
625	Retail trade not in stores	1	1	1	0.459
626	Repair of personal and household goods	0.1	0.25	1	0.560
631	Sale of motor vehicles	0	0	0.5	0.574
632	Maintenance and repair of motor vehicles	0.1	0.25	0.5	0.496
633	Sale of motor vehicle parts and accessories	0.1	0.25	0.5	0.578
634	Sale, maintenance and repair of motor cycles and related parts and accessories	0.1	0.25	0.5	0.609
635	Retail sale of automotive fuel	1	1	1	0.646
641	Hotels, camping sites and other provision of short-stay accommodation	0.1	0.1	0.1	0.553
642	Restaurants, bars and canteens	0	0.25	0.25	0.642
643	Shebeen	0	0	0.1	0.547
7	**Transport, storage and communication**				0.562
711	Railway transport	0.6	0.6	0.6	0.572

Table A14 – continued from previous page

SIC code	Industry description	Level 5	Level 4	Level 3	Mean PI index
712	Other land transport	0.1	0.25	0.5	0.580
721	Sea and coastal water transport	0.1	0.25	0.5	0.513
730	Air transport	0.1	0.25	0.5	0.582
741	Supporting and auxiliary transport	0.1	0.25	0.5	0.588
751	Postal and related courier activities	0.1	0.1	0.25	0.584
752	Telecommunication	1	1	1	0.516
8	**Finance**				0.501
811	Monetary intermediation	1	1	1	0.526
818	Cash loans	1	1	1	0.491
819	Other financial intermediation not elsewhere classified	1	1	1	0.468
821	Insurance and pension funding, except compulsory social security	1	1	1	0.475
831	Activities auxiliary to financial intermediation, except insurance and pension funding	1	1	1	0.449
841	Real estate activities with own or leased property	0	0	0.5	0.408
842	Real estate activities on a fee or contract basis	0	0	0.5	0.453
851	Renting of transport equipment	0.4	0.6	1	0.555
852	Renting of other machinery and equipment	0.4	0.6	1	0.495
853	Renting of personal and household goods not elsewhere classified	0.4	0.6	1	0.517
862	Software consultancy and supply	1	1	1	0.471
863	Data processing	1	1	1	0.521
864	Data base activities	1	1	1	0.513
865	Maintenance and repair of office, accounting and computing machinery	0	0	0.25	0.504
869	Other computer related activities	1	1	1	0.542
871	Research and experimental development on natural sciences and engineering	1	1	1	0.519
881	Legal, accounting, bookkeeping and auditing activities; tax, business, public-opinion consultancy	1	1	1	0.457
882	Architectural, engineering and other technical activities	1	1	1	0.534
883	Advertising	1	1	1	0.543
889	Business activities not elsewhere classified	1	1	1	0.582
9	**Community, social, and personal services**				0.544

SIC code	Industry description	Level 5	Level 4	Level 3	Mean PI index
	Table A14 – continued from previous page				
911	Central government activities	1	1	1	0.519
913	Local authority activities	1	1	1	0.528
914	Provincial administrations	1	1	1	0.500
915	SA Defence force	1	1	1	0.533
916	SA Police service	1	1	1	0.580
917	Correctional service	1	1	1	0.585
920	Education	0.1	0.1	0.25	0.605
931	Human health activities	1	1	1	0.620
932	Veterinary activities	1	1	1	0.575
933	Social work activities	0.5	1	1	0.597
940	Sewage and refuse disposal, sanitation and similar activities	1	1	1	0.487
951	Activities of business, employers and professional organisations	0.1	0.25	0.5	0.473
952	Activities of trade unions	0.1	0.25	0.5	0.516
959	Activities of other membership organisations	0	0	0	0.445
961	Motion picture, radio, television and other entertainment activities	0	0	0	0.519
962	News agency activities	1	1	1	0.495
963	Library, archives, museums and other cultural activities	0	0	0	0.545
964	Sporting and other recreational activities	0	0	0	0.585
990	Other service activities	0.1	0.25	0.5	0.621

[a] Author's own arrangement and calculations. Source: COVID-19 Risk Adjusted Strategy (Department of Health, 2020); QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b); Time Use Survey 2010 (Statistics South Africa, 2014); O*NET (National Center for O*NET Development, 2021).

[b] Notes: This table presents a list of industries using Standard industrial Classification (SIC) codes that were and were not permitted to work by legislation for each of South Africa's lockdown levels during the period of study (levels 5, 4, and 3). In columns (3) to (5), 1 = permitted to work; 0 = not permitted to work. If a given industry was permitted to work but at a limited employment capacity, (0;1) = the capacity in proportional terms. Column (6) presents the mean level of physical interaction for each industry according to the physical interaction index as described in Section 5.

Table A15: Physical interaction index component definitions

Component	Definition	Scoring method	Source
Physical proximity (P_o)	1. I don't work near other people (beyond 100 ft.). 2. I work with others but not closely (e.g., private office). 3. Slightly close (e.g., shared office). 4. Moderately close (at arm's length). 5. Very close (near touching).	O*NET spreads 100 points across five levels per occupation. My approach multiplies points by their category level and sums to get a score. I sum points in categories 3-5 only to reach a score out of 500 (the maximum feasible score). I rescale this to vary $[0; 1]$.	National Center for O*NET Development (2021)
Face-to-face discussions (F_o)	1. Never. 2. Once a year or more but not every month. 3. Once a month or more but not every week. 4. Once a week or more but not every day. 5. Every day.	O*NET spreads 100 points across five levels per occupation. My approach multiplies points by their category level and sums to get a score. I sum points in categories 4-5 only to reach a score out of 500 (the maximum feasible score). I rescale this to vary [0;1].	National Center for O*NET Development (2021)
Public transport (T_o)	Ever used any type of public transport to travel to work on a given day. Private transport is defined as walking, cycling, or private vehicle. Public transport is defined as bus, taxi, train, or other transport.	Share per occupation. Varies [0,1].	Statistics South Africa (2014)

[a] Author's own arrangement.

[b] Notes: This table presents a description of the three components of the occupation-level Physical Interaction index PI_o created using data from National Center for O*NET Development (2021) and Statistics South Africa (2014).

Table A16: Model estimates, controlling for occupation-level physical interaction using Principal Component Analysis

	(1)	(2)	(3)	(4)
	Overall		Lockdown level	
		5	4	3
Panel A: Employment				
Treatment×Post	-0.030***	-0.035***	-0.037***	-0.057**
	(0.008)	(0.013)	(0.013)	(0.027)
PI index$_o^{PCA}$	-0.007	-0.008	-0.018*	0.011
	(0.007)	(0.011)	(0.010)	(0.015)
Constant	1.868***	1.440	2.039**	2.644*
	(0.621)	(0.917)	(0.993)	(1.426)
Observations	24,678	9,368	9,621	5,689
Panel B: Formal employment				
Treatment×Post	-0.006	0.002	-0.011	-0.057**
	(0.008)	(0.012)	(0.012)	(0.026)
PI index$_o^{PCA}$	0.020***	0.026**	0.007	0.035***
	(0.006)	(0.011)	(0.009)	(0.013)
Constant	1.547***	2.039**	0.784	1.413
	(0.592)	(0.904)	(0.944)	(1.297)
Observations	24,678	9,368	9,621	5,689
Panel C: Informal employment				
Treatment×Post	-0.028***	-0.035***	-0.034***	-0.004
	(0.007)	(0.011)	(0.010)	(0.018)
PI index$_o^{PCA}$	-0.022***	-0.029***	-0.021***	-0.021
	(0.006)	(0.009)	(0.008)	(0.013)
Constant	0.217	-0.833	1.325*	0.873
	(0.487)	(0.728)	(0.776)	(1.128)
Observations	24,678	9,368	9,621	5,689

[a] Author's own calculations. Source: QLFS 2020Q1 and 2020Q2 (Statistics South Africa, 2020a,b); (National Center for O*NET Development, 2021); (Statistics South Africa, 2014).

[b] Notes: This table presents estimates of specification 5.1, overall and by lockdown level, for varying binary dependent variables while additionally controlling for occupation-level workplace physical interaction, similar to Table 5.7 but instead here the index is constructed using Principal Component Analysis. Sample restricted to those of working-age (15-64 years) as of 2020Q1. Lockdown levels range from 5 (most stringent) to 3 (most lenient). All models control for a vector of time-varying observable covariates including age, highest education level, and employment type, as well as individual fixed effects (FEs). PI index = Physical Interaction index generated by merging occupation-level data from National Center for O*NET Development (2021) and Statistics South Africa (2014) with the QLFS data. Standard errors presented in parentheses and are clustered at the panel level. Estimates weighted using sampling weights. 'Post' coefficient omitted for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.