Market Frictions, Allocative Efficiency and Aggregate Productivity in the Manufacturing Sector: Evidence from Zimbabwe

By

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Abstract

Underdevelopment arises not only from the lack of production resources such as capital and labour but also as a consequence of the inefficient allocation of available resources. Reducing the misallocation of resources is, therefore, seen as one of the channels through which substantial increases in aggregate productivity and incomes of emerging economies can be achieved.

This thesis analyses how market distortions contribute to the misallocation of resources within and between the formal and informal manufacturing sectors in Zimbabwe. The thesis is guided by three broad shortcomings in the available literature. First is the exclusion of the informal sector, a major source of economic activity in emerging economies, in the analysis of misallocation. Second is the paucity of studies that isolate the distinct factor market distortions that drive misallocation in emerging economies. Third, notwithstanding the importance of allocative efficiency in aiding aggregate TFP and the abundant informal sector activities in emerging economies, few studies have analysed misallocation in sub-Saharan Africa. A key reason for the above is the lack of detailed firm and employee data.

The thesis is structured around three main research objectives. Firstly, it quantifies the extent of allocative inefficiency within and between the formal and informal manufacturing firms in Zimbabwe. Secondly, it investigates the extent to which financial access constraints contribute to misallocation and hinder firm performance. Finally, it tests for labour market segmentation within and between formal and informal manufacturing sectors as a source of labour misallocation.

To conduct the analysis, the thesis draws on the recently available Matched Employer-Employee manufacturing firm-level survey dataset for formal and informal sector firms and workers that was conducted between 2015 and 2018 as part of this thesis. These surveys provide unique data on firm production activities and on worker wages and characteristics that allow for the analysis of resource misallocation and its sources in Zimbabwe.

The thesis comprises of three main chapters apart from the general introduction and conclusion chapters. Chapter 2 draws on the Hsieh & Klenow (2009) approach to measure the extent of allocative inefficiency within and between the formal and informal manufacturing sector firms in Zimbabwe. The results reveal a high degree of misallocation that is more pronounced in informal sector firms. Output and capital market distortions both contribute substantially to

resource misallocation, but it is the capital distortions that are strikingly large for the informal sector firms. Further, there is a positive correlation between firm productivity and indicators of misallocation, implying that the more productive firms face relatively high distortions preventing them from growing to their optimal level, thus exacerbating aggregate TFP losses. Specifically, the results show that by removing misallocation of resources, aggregate TFP gains of 153.6 percent can be realised.

Chapter 3 empirically tests how financial access constraints affect the efficient allocation of resources. The focus of this chapter is on informal firms, given the availability of data, and the presence of relatively high capital distortions that these firms are found to be facing. While the direct impact of financial access constraints on firm performance has been studied extensively, the indirect effect on aggregate productivity via the allocation of resources across firms has received less attention. This is important, as financial constraints can attenuate or exacerbate aggregate TFP losses through misallocation.

The empirical analysis is conducted using two approaches. Firstly, regression analysis is used to assess the extent to which financial access constraints exacerbate or attenuate the misallocation effects arising from capital market distortions. Secondly, in order to explore the channels through which factor market distortions affect misallocation, productivity-enhancing re-allocation regressions (following Bartelsman et al., 2017) are estimated to test how initial financial access constraints faced by firms affect subsequent investment and employment growth.

The analysis reveals a significant positive association between financial access constraints and indicators of misallocation, suggesting that financial access constraints are an important source of misallocation. Further, the interaction of financial constraints and firm productivity is positive, implying that these constraints amplify the aggregate TFP losses due to misallocation. Disaggregating the analysis further shows that financial access constraints affect misallocation through both capital and output distortions. Finally, the productivity-enhancing reallocation regressions indicate that financial access constraints affect firm investment negatively but are not significant in constraining employment growth. The findings indicate that the negative effects of financial access constraints on firm growth, allocative efficiency and hence aggregate TFP operate through the investment channel.

Chapter 4 investigates the extent, type and sources of labour market segmentation within and between the formal and informal manufacturing sectors. The chapter exploits the panel dimension of the formal and informal worker surveys in the Matched Employer-Employee dataset. Wage differentials between labour market subgroups are used to test for the extent and types of segmentation. The rent-sharing model is then used to test for the importance of profit-per-worker as a source of labour market segmentation. We find evidence of labour market segmentation between the regulated formal sector and the unregulated informal sector, with a conditional wage gap of 25 percent. The results also reveal segmentation between permanent and contract workers within the formal sector, but no evidence of wage differentials between contract and informal sector workers after controlling for human capital endowments. Further, a significant positive association between wages and profits-per-worker is estimated in the formal sector. The results suggest that labour markets are segmented due to rigidities in labour markets regulations and institutions that are associated with registered formal sector firms.

Overall, the thesis underscores the importance of idiosyncratic distortions and factor market frictions, such as access to finance constraints and labour market regulations, as a source of inefficiencies and reductions in aggregate TFP. It shows that market distortions in Zimbabwe curtail the efficient allocation of production resources and constrain the performance of manufacturing sector firms, particularly in the informal sector. Thus, a policy framework that aims at reducing market frictions and distortions may substantially enhance allocative efficiency and firm performance, and through this, boost aggregate TFP.

Declaration

I, *Godfrey Paradzai Kamutando*, declare that this thesis is my original work and that other sources have been acknowledged through referencing. I also declare that the thesis has not been submitted for the award of a PhD degree at any other university.

Signature: Signed by candidate

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Dedication

To my loving wife, Tsungai, my kids, Taneisha and Aiden, and my parents.

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List of Acronyms

ARPK	Average Revenue Product of Capital
CZI	Confederation of Zimbabwe Industries
EU	European Union
GDP	Gross Domestic Product
HK	Hsieh & Klenow
IV	Instrumental Variable
LFS	Labour Force Surveys
LMS	Labour Market Segmentation
MRPK	Marginal Revenue Product of Capital
MRPL	Marginal Revenue Product of Labour
OLS	Ordinary Least Square
OP	Olley and Pakes
PSM	Propensity Score Matching
RIF	Re-centred Influence Function
SMEs	Small and Medium Enterprises
SSA	Sub-Sahara Africa
TFP	Total Factor Productivity
TFPQ	Total Factor Productivity Output
TFPR	Total Factor Productivity Revenue
UK	United Kingdom
UNDP	United Nations Development Programme
US	United States
WB	World Bank
WBES	World Bank Enterprise Survey
WEF	World Economic Forum

Chapter 1

1. General Introduction

1.1. Introduction and Motivation

This thesis analyses how market distortions contribute to the misallocation of resources within and between the formal and informal manufacturing sectors in Zimbabwe. In doing so, the thesis estimates the aggregate TFP losses associated with misallocation, as well as the relative importance of product and factor market distortions in driving the misallocation of resources in an emerging economy.

Assessing the effects of misallocation on aggregate TFP is very important, particularly for emerging economies. Two sources of aggregate TFP have been articulated in literature. First is productivity within firms. Rising productivity within firms raises aggregate productivity of a country. Second is the efficiency in which the available resources are (re)allocated across firms. Misallocation of production resources has been singled out as one of the main sources of aggregate TFP loss (David & Venkateswaran, 2019; Restuccia & Rogerson, 2017; Bartelsman, Haltiwanger & Scarpetta, 2013; Hsieh & Klenow, 2009). The argument is that underdevelopment arises not only from the lack of production resources (such as capital and labour) and their efficient use by firms, but also as a consequence of the inefficient allocation of available resources across firms and industries. Reducing the misallocation of resources is therefore seen as one of the channels through which substantial increases in aggregate productivity and incomes of emerging economies can be achieved, despite the constraints they face in accessing technology, capital, and other productive resources.

This issue is particularly relevant for the manufacturing sector in Africa for several reasons. First, the manufacturing sector is a key contributor towards productivity-driven growth. This contribution is driven by rising productivity within firms, as well as structural shifts of the economy towards manufacturing (Timmer, de Vries & De Vries, 2015; McMillan, Rodrik & Verduzco-Gallo, 2014). The manufacturing sector thus lends itself to research on productivity and allocative efficiency – a core focus of this thesis. Second, the manufacturing sector bridges the primary agricultural sector with the tertiary service industry. Hence, the performance of the manufacturing sector results in spillovers to other industries. The productivity growth of other sectors in the economy can, therefore, be directly or indirectly driven by productivity growth in the manufacturing sector. Lastly, the sector makes a significant contribution to the GDP and can be a source through which sustained economic growth can be anchored in emerging economies. Within Africa, the contribution of the manufacturing sector to aggregate output and employment has been declining (Bigsten & Söderbom, 2011; Söderbom, Teal & Harding, 2006; Söderbom & Teal, 2004). One source of this relative decline may be the presence of severe frictions and distortions inhibiting the re-allocation of resources to manufacturing, as well as towards relatively efficient firms within manufacturing.

Three broad potential sources of misallocation have been emphasised in mainstream literature (Restuccia & Rogerson, 2017). First are factor and product market imperfections that arise as a result of institutional and policy regulations. Second, statutory provisions such as regulations and tax codes may create misallocation, particularly when they are heterogeneous across firms. For example, labour market regulations that are more restrictive for larger efficient firms may distort the re-allocation of labour to these firms. Lastly, distortionary policies by the government such as selective enforcement of regulations or preferential access to markets and/or subsidies may impede efficiency of resource allocation across firms. These sources generate market frictions or idiosyncratic distortions that can have severe consequences for the optimal allocation of resource across firms and thus generate aggregate TFP loss (Wu, 2018; Midrigan & Xu, 2014; Hsieh & Klenow, 2009).

Much literature has estimated the size of the allocative efficiency using different approaches (see Restuccia and Rogerson, 2017; Bartelsman, 2013; Hsieh & Klenow, 2009). In general, these studies find substantial productivity losses associated with misallocation (e.g. Hsieh & Klenow (2009) for India and China, and Cirera, Fattal Jaef & Maemir (2017) for Ethiopia, Kenya, Ghana and Ivory Coast). There are three broad shortcomings of the available literature that guide the focus of this thesis. First is the exclusion of the informal sector in the analysis of misallocation. There is growing debate regarding whether informality reflects an inefficient allocation or may actually reflect an efficient outcome, in the face of barriers or distortions inhibiting entry into the formal sector (see Ulyssea, 2018). By excluding the informal sector, the analysis of emerging economies' efficiency may be rendered incomplete. To our knowledge, no studies have incorporated the informal sector in the analysis of allocative efficiency in Africa despite the stylised fact that most African economies are characterised by the presence of large informal sector. The major constraint has been the availability of plausible data for the informal manufacturing sector firms.

Second, while there is a growing literature documenting the extent of resource misallocation and its impact on aggregate TFP, including for emerging economies (Cirera et al., 2017; Asker, Collard-Wexler & De Loecker, 2014), what is missing from much of this research is a detailed study of the particular market distortions that are driving these outcomes. One example of this is the unresolved debate in the literature on the relative role of financial access in constraining resource allocation (Wu, 2018; Moll, 2014; Midrigan & Xu, 2014; Gilchrist, Sim & Zakrajšek, 2013). In part, this outcome is driven by the difficulty in measuring financial access constraints at the firm level. This requires detailed firm-level survey data that are is readily available for many emerging economies. Lack of proper measurement and identification of financial access constraints makes it challenging for previous studies to provide reliable quantification of the impact of financial access on misallocation and aggregate TFP.

Third, notwithstanding the importance of allocative efficiency in aiding aggregate TFP and the abundant informal sector activities in emerging economies, it is still surprising that there are very few studies on this topic in sub-Sahara Africa, perhaps due to the paucity of firm-level panel datasets.

This thesis draws on the matched employer-employee dataset of Zimbabwean manufacturing firms that we collected under the "Matched Employee-Employer Data for Labour Market Analysis in Zimbabwe" 2015 project.[1] As part of this thesis, I was actively involved in the data collection for the formal firms and workers, and also supervised the collection of the informal sector firm and worker data under this project. Building on this project, I extended the time dimension (through re-interviews) and the sample size (through new surveys) of informal sector firms and workers. The data include the panel dimension for workers and informal sector firms. For a more comprehensive data description of the sample and collection procedure, see the Appendix for Chapter 1. This new unique data contribute to our understanding of inefficiencies as it includes the informal sector dimension and detailed information on the firm production process and employee characteristics.

By drawing on the firm-level employer-employee matched data that we collected, this research strives to fill the gaps in the literature by examining the (in)efficiencies within and between the formal and informal manufacturing firms in an emerging economy, namely Zimbabwe. The thesis is structured around identifying and analysing how factor market distortions contribute to misallocation and the implication on aggregate TFP. By doing so, the thesis offers some key

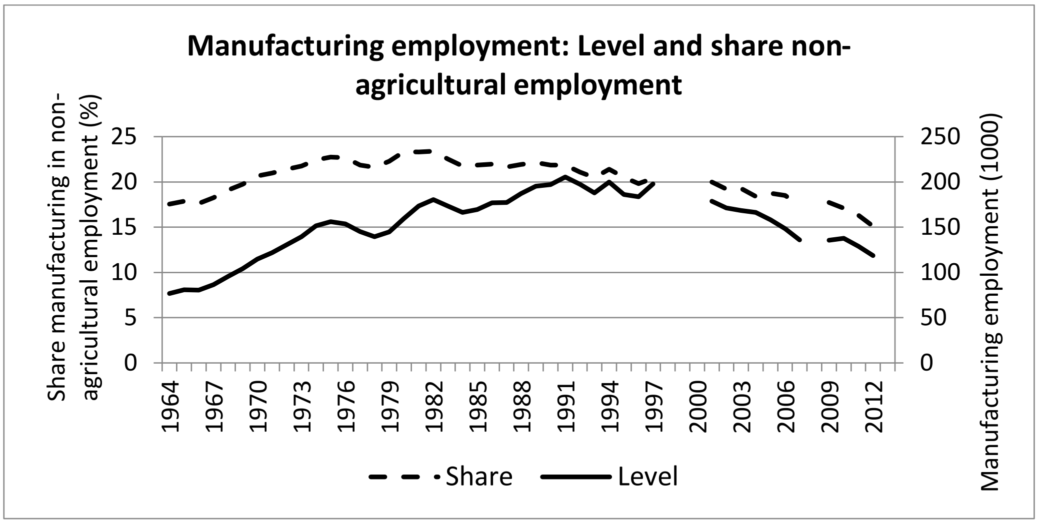
[1] For access to the data, please see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/702/study-description .

contributions to the literature. First is the incorporation of the informal sector into the analyses of allocative efficiency, a subject that has been marginalised in the mainstream literature. Second is the test of a specific source of misallocation associated with financial access constraints. The thesis draws on detailed firm-level survey information regarding financial access to assess the extent to which financial access constraints limit firm performance and productivity-enhancing re-allocation of resources. Our dataset allows us to offer explicit measures of financial access constraints directly from the information from the survey – as opposed to the use of balance sheet information as done in conventional literature. Third, our study focuses on a low-income country, Zimbabwe, thereby contributing to the misallocation literature for emerging economies. There is generally a lack of studies on misallocation in low-income countries, particularly in sub-Sahara Africa (SSA), due to the paucity of firm-level panel data.

The Zimbabwean economy provides a relevant case for the conduct of this study. First, Zimbabwe, like many other emerging economies, is characterised by extensive factor and product market frictions and distortions (CZI, 2012; World Bank, 2016). Key among them is lack of access to finance, including foreign currency, restrictive government regulations such as labour legislation, and lack of infrastructures such as water, power and energy (WEF, 2017). Such market frictions are expected to negatively affect allocative efficiency, firm performance and aggregate TFP of the manufacturing sector. Thus, Zimbabwe provides a suitable context for studying the link between market frictions and misallocation.

Second, there is a large informal manufacturing sector base in Zimbabwe. It is argued that in response to the many economic crises the country faced over the past few decades, Zimbabwe has experienced structural reversal, with the acceleration of deindustrialisation and informalisation of the economy (CZI, 2012; World Bank, 2012). This is shown in Figure 1.1, which plots formal manufacturing sector employment levels and its share of total non-agricultural employment in Zimbabwe over the period of 1964 to 2012. Both the level of employment in the formal manufacturing sector and its share of total employment has declined since the early 1990s. For instance, the manufacturing share of non-agricultural employment fell from 22 percent in 1992 to 15 percent in 2012.

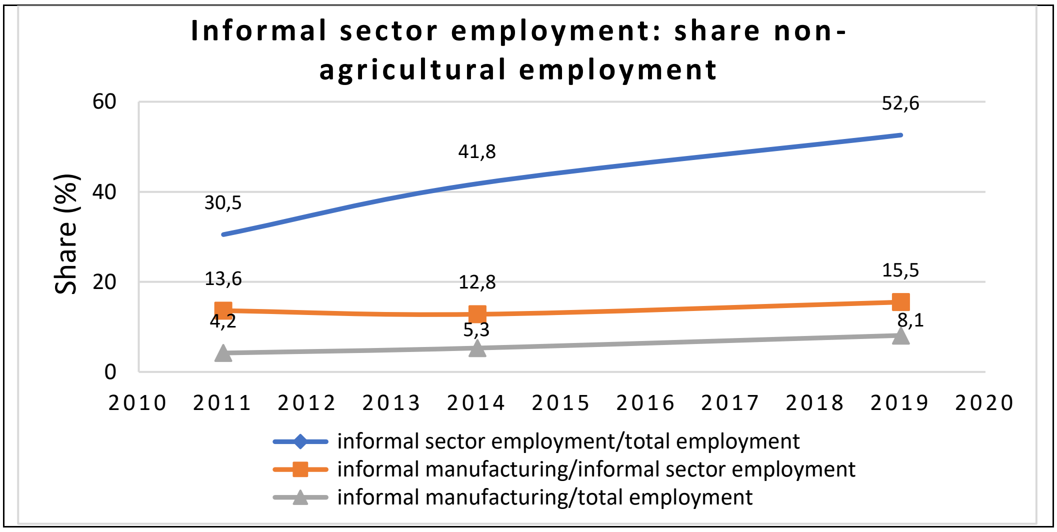
Figure 1. 1. The contribution of the formal manufacturing sector to employment



Source: Author computations from Zimstats data (1964-2012)

On the contrary, the informal sector's contribution to employment has been increasing (Medina & Schneider, 2018). Drawing on Zimstats data for the period 2011-2019, Figure 1.2 plots the contribution of the informal (manufacturing) sector to employment. The data reveals a rise in share of the informal sector in total employment from 30.5 percent in 2011 to 52.6 percent in 2019.[2]

Figure 1. 2. Contribution of the informal sector manufacturing to employment



Source: Author computations from Zimstats LFPS, 2011, 2014 and 2019

[2] Informal employment in manufacturing accounts for between 13.6 and 15.5 percent of total informal employment, with its share rising slightly from 2014 to 2019. The effect is that employment in the informal manufacturing sector as a share of total employment almost doubled from 4.2 percent in 2011 to 8.1 percent in 2019.

Figures 1.1 and 1.2 demonstrate the informal (manufacturing) sector is large and deserves to be included in the analysis of allocative efficiency and aggregate TFP. There is growing recognition that the informal manufacturing sector forms an integral part of the economy in many emerging countries. These firms, on one hand, may be less constrained by some of the regulations, including restrictive labour laws that impose rigidities on formal firms. On the other hand, the informal status of these firms may also impose some constraints that limit their ability to realise their full potential. For example, they may have limited access to formal sources of finance, formal contracts, and some government-specific assistance. The informal sector could play an important role in realising the government's declared policy imperative of boosting manufacturing output as part of their recovery strategy.

Third, Zimbabwe suffers from substantial adverse shocks through which we expect reallocation of resources. Such shocks may create frictions and distortions in the product and factor markets, and these rigidities affect firm performance and hence TFP, particularly in the manufacturing sector.

Fourth, Zimbabwe has a deep manufacturing base. The key source of productivity-driven growth is in the manufacturing sector. The manufacturing sector activities also lend themselves easily to issues related to TFP and allocative efficiency. Like many African economies, the manufacturing sector performance in Zimbabwe is still lagging compared to developed countries, hence the importance of assessing how allocative inefficiency constrain TFP.

Lastly, to our knowledge, no studies have been done concerning allocative efficiency of the formal and informal sector firms in Zimbabwe – perhaps due to data challenges. We have collected robust data for formal and informal sector firms and employees that allow us to provide a robust assessment of the performance of the manufacturing sector in line with the theoretical and empirical literature on allocative efficiency and aggregate TFP. The results of the thesis can also easily be generalised to other emerging economies with similar characteristics to Zimbabwe.

1.1. The Thesis Objective

The prime objective of this thesis is to analyse how market frictions and distortions contribute to aggregate TFP loss through the misallocation channel. The study pays particular attention to the extent and sources of allocative inefficiency in the manufacturing sector using Zimbabwe as the case study. There are three specific objectives of this thesis that are addressed in separate chapters.

Objective 1

The first specific objective of this thesis is to investigate and quantify the extent of allocative inefficiency within and between the formal and informal manufacturing firms. This objective is dealt with in chapter 2 of the thesis. The idea is to visualise and characterise the formal and informal firms in terms of market distortions and misallocation of resources. Further, the aim is to determine the relative importance of capital and output distortions in contributing to allocative inefficiency and estimate the aggregate TFP gains that can be realised if misallocation is corrected.

To achieve objective 1, the study draws on the firm-level data for formal and informal firms collected in 2015. The study then derives the overall measures of misallocation that affect output and factor market prices by using the Hsieh Klenow (2009) model. By decomposing the total factor revenue productivity (TFPR), which is a composite measure of misallocation, and looking at distortions to factor inputs individually, the study provides an important step towards identifying the nature and the source of distortions.

Objective 2

Given the importance of misallocation in constraining aggregate TFP, objective 2 of this thesis investigates the extent to which financial access constraints contribute to misallocation and hinder firm performance. This objective is addressed in chapter 3. It complements objective 1 by identifying a specific source of distortions – financial access constraints – and analysing the extent to which they contribute to misallocation and productivity-enhanced firm performance. While available literature on emerging economies has shown that substantial TFP gains can be realized by removing distortions (Cirera et al., 2017; León-Ledesma & Christopoulos, 2016; Nguyen, Taskin & Yilmaz, 2016; Hsieh & Klenow, 2009), it remains unsettled on what specific source of distortions contributes chiefly to misallocation, and its consequences for firm performance. Hence, the chapter addresses the following two questions: What is the link between financial constraints and informal manufacturing firm performance in Zimbabwe? Do financial constraints attenuate or exacerbate aggregate TFP losses through misallocation?

Using the panel dataset of the informal manufacturing sector firms that we collected between 2015 and 2018, chapter 3 analyses the implication of financial access constraints on allocative efficiency following two approaches: first, we use regression analysis to study the relationship between firm-specific indicators of financial access and our measures of misallocation. This allows us to assess the extent to which financial access constraints exacerbate or attenuate the misallocation effects arising from capital market distortions. Second, we use the panel of data to study how initial financial access constraints faced by firms affect subsequent growth through aggregate productivity. In particular, we follow Bartelsman et al. (2017) and estimate productivity-enhancing re-allocation regressions. The measures of misallocation are derived from the theoretical framework of Hsieh & Klenow (2009), and Wu (2018) while the measures of financial access constraints are directly derived from rich information on firm financing activities in the dataset.

Objective 3

Objective 3 of the thesis, which is addressed in chapter 4, pays attention to the extent to which labour market inefficiency may account for allocative inefficiency within the Zimbabwean manufacturing sector. The approach taken is to study the extent to which labour markets are segmented, and through this, infer the inefficiency of labour allocations within the labour market (Deakin, 2013). While there is a general consensus that labour markets in SSA are segmented (Fields, 2011), there is still debate on the underlying sources of this segmentation (Pratap & Quintin, 2006; Maloney, 1999). We test the importance of a specific source of segmentation that is associated with profit-per-worker (rent-sharing).

The chapter exploits the panel dimension of the formal and informal worker surveys in the Matched Employer-Employee dataset. The advantage of the dataset is that we can control for both firm and employee characteristics in the wage-setting processes, thus overcoming some of the omitted variable and selection bias challenges faced by other studies in this field. Wage differentials between labour market subgroups are first used to test for the extent and nature of segmentation within and between the formal and informal manufacturing sectors. The rent-sharing model is then used to test for the importance of profit-per-worker as a source of labour market segmentation. The Recentered Influence Function (RIF), also known as the unconditional quantile regression approach, is used to provide a more comprehensive analysis of the extent and sources of labour market segmentation.

1.2. Structure of the thesis

The rest of the thesis is structured as follows: Chapter 2 provides an analysis of the extent and allocative efficiency within and between the formal and informal manufacturing firms. Chapter 3 investigates the extent to which financial access constraints contribute to misallocation and hinder firm performance. Chapter 4 assesses the efficiency of labour markets by examining the extent and sources of labour market segmentation. Finally, chapter 5 presents the general conclusion, policy implications and areas of further research for this thesis.

Chapter 2

2. Allocative Efficiency Within and Between Formal and Informal Manufacturing Sectors in Zimbabwe

2.1. Introduction

International literature has underscored the importance of differences in aggregate total factor productivity (TFP) in explaining cross-country differences in incomes and development (David & Venkateswaran, 2019; Gopinath et al., 2017; Collard-Wexler, Asker & De Loecker, 2011; Hsieh & Klenow, 2009; Hall & Jones, 1999). The striking question, which is still a topic of much debate, is what gives rise to these differences in aggregate TFP across countries. Traditional literature points to differences in technologies and factor inputs accumulation (such as labour and capital) as the key reason for differences in cross-country aggregate TFP (Howitt, 2000; Hall & Jones, 1999).

A new approach in recent literature, however, emphasises the role of resource misallocation in determining the observed disparities in cross-country aggregate TFP (David & Venkateswaran, 2019; Restuccia & Rogerson, 2017; Hsieh & Klenow, 2009). The proposition is that misallocation of resources – which arises when firms, industries or sectors face idiosyncratic distortions due to institutional, policy or market rigidities – may reduce aggregate TFP. This is because distortions prevent the efficient (re)allocation of resources across firms, causing high-productivity firms to be inefficiently small while low productivity firms become inefficiently large. This depresses aggregate TFP. Eliminating misallocation is, therefore, seen as one of the important channels through which aggregate TFP can be enhanced. This is particularly important for emerging economies[3].

For instance, Hsieh & Klenow (2009) illustrate that by eliminating resource misallocation, aggregate TFP gains of up to 50% and 60% could be realised in China and India respectively when these countries become as efficient as the US. Inklaar, Lashitew & Timmer (2017), for several developing and developed countries, show that developing countries have a higher presence of misallocation when compared to advanced economies. What these studies show is that idiosyncratic distortions could lead to substantial reduction in aggregate TFP via misallocation. The correction of misallocation may, therefore, result in larger TFP gains in

[3] Emerging economies are generally constrained from accumulating technology and production resources relative to developed economies. They are also characterised by market distortions and frictions (Leon-Ledesma & Christopoulos, 2016).

emerging countries despite the impediments they face in accessing technology, capital, and other productive resources.

Whereas the empirical evidence on misallocation and aggregate productivity has been well documented (Restuccia & Rogerson, 2017; Bartelsman et al., 2013; Syverson, 2011; Hsieh & Klenow, 2009; Restuccia & Rogerson, 2008), there is still little attention given to allocative efficiency in developing and emerging economies. This is despite the fact that misallocation predominantly affects developing economies, as they are more commonly characterised by factor market distortions and underdevelopment relative to advanced economies (Inklaar, et al., 2017).

Another area that has not received sufficient attention in the international literature is the role of the informal sector in driving misallocation. There are two different positions in this regard. The dualists model portrays the informal production sector as a backward traditional sector with high market frictions, low productivity, a highly segmented labour market, and limited scope to drive aggregate productivity growth. On the other hand, the structuralist model portrays the formal and informal sectors as two competitive and integrated economic systems wherein the informal sector is able to trigger aggregate productivity and growth (Benjamin & Mbaye, 2012; Fields, 2011; Maloney, 1999; Mcpherson, 1996).

This is particularly relevant for emerging economies such as Zimbabwe. Firstly, the informal sector accounts for a high proportion of domestic economic activity in many emerging economies. Secondly, the informal sector co-exists with the formal sector and there are strong distribution and production linkages between the two sectors (ZEPARU, 2014). Thirdly, in the case of Zimbabwe, the economy has experienced a process of de-industrialisation and informalisation with the apparent reallocation of resources from the formal to the informal manufacturing sector (World Economic Forum, 2017; Davies, Kumar & Shah, 2012; Confederation of Zimbabwe Industries, 2012; World Bank, 2012). Should the structuralist model apply, then these features would not necessarily denote a severe misallocation of resources and a consequent reduction in aggregate TFP. Rather, the informal sector could play a key role in driving economic growth and manufacturing production within emerging economies, including Zimbabwe.

The main objective of this chapter is to analyse the extent of misallocation and its impact on aggregate total factor productivity (TFP) within and between the formal and informal manufacturing sectors in Zimbabwe. The analysis of this chapter is structured around the following questions:

- To what extent are resources misallocated between and within the formal and informal manufacturing sectors?
- What is the impact of resource misallocation on aggregate TFP?

This chapter provides three key contributions to the misallocation literature. First is the incorporation of the informal sector measuring resource misallocation. Making a distinction between informal and formal manufacturing activities may have crucial implications in deepening our understanding of allocative efficiency in emerging economies. Second, the chapter measures the extent of misallocation in the *aggregate* (formal and informal) manufacturing economy. Several studies in the literature have only focused on a part of the manufacturing economy – the formal sector. Third, it offers the first quantification of misallocation in Zimbabwe – an emerging economy. Existing studies in Zimbabwe have predominantly presented a descriptive overview of the characteristics of the formal and informal sectors without an in-depth analysis of productivity and misallocation (Luebker, 2008; McPherson, 1991).

The analysis of this chapter is based on the measurements of misallocation constructed from the Hsieh & Klenow (2009) empirical framework. Using this approach, we derive the composite measure of misallocation as the dispersion of total factor revenue productivity (TFPR). By decomposing TFPR and looking at distortions to factor inputs individually, the study provides an important step towards identifying the extent, nature and source of the distortions contributing to misallocation. Hsieh & Klenow (2009) model allows us to calculate the aggregate TFP gains achieved should misallocation be corrected.

To conduct the empirical analysis, this chapter draws on newly available firm-level survey data on formal and informal manufacturing firms in Zimbabwe that was collected in 2015. More details of the data are provided in the Appendix for Chapter 1 of this thesis.

The rest of the study is structured as follows: Section 2.2 provides a theoretical and empirical literature review, while section 2.3 presents the methodology. Results are discussed in section 2.4 and the conclusion is presented in section 2.5.

2.2. Theory and Empirical Evidence

2.2.1 Theoretical Concept

The question that guides the discussion in this section is what drives misallocation, and what the mechanisms through which misallocation reduces aggregate TFP are. The concept behind misallocation, as hypothesised by Hsieh & Klenow (2009), is that in competitive markets with no frictions, firms will pay common factor prices, and consequently the marginal revenue product (MRP) of factor inputs will be equal across firms with similar production functions. Should MRP for a particular factor differ across firms, then the higher MRP firms will bid for these factors, leading to a re-allocation from low to high marginal revenue product firms. A further consequence of this (see later for formal derivation) is that in efficient markets, firms within the same industry should have the equivalent total factor productivity revenue (TFPR)[4].

Factor and product market distortions, however, impede the (re)allocation of given production resources across heterogeneous firms. This will happen, for example, if the output of firms within the same industry are taxed differently or when distortions affect the cost of inputs across firms differently. These distortions impede the equalisation of marginal revenue products of capital and labour across all firms, thereby generating misallocation (Hsieh & Klenow, 2009). Further, they give rise to dispersion in TFPR across firms, with high TFPR firms being inefficiently small, while those with TFPR below the industrial average would be inefficiently large. Empirically, therefore, the dispersion of TFPR across firms within the same industry has been used to determine the presence and extent of resource misallocation (Hsieh & Klenow, 2009).

Resource misallocation has an adverse effect on aggregate TFP. Conceptually, there are three channels through which misallocation may reduce aggregate TFP. First is the *selection* channel, which determines the choice of firms that operates on the extensive margins (Restuccia & Rogerson, 2017). The concept is that if markets are efficiently allocating resources, we expect more productive firms to expand, while less productive firms shrink and eventually exit production, thereby leaving resources to more productive firms. This is the first-best equilibrium that increases aggregate TFP. The presence of misallocation, therefore, discourages the exit of less productive firms while at the same time constraining the entry and growth of productive firms. This leads to a reduction in aggregate TFP. Negative distortions

[4] The argument is that firms with high (low) MRP will produce more (less) output, and high (low) output maps in low (high) prices and TFPR is equalized across firms.

constrain the growth of some firms below the optimal level while inducing some firms to expand beyond their optimal size in an efficient market.

The second channel reflects how markets characterised by a wide range of idiosyncratic distortions reduce the efficient allocation of resources across firms. Theory suggests that more productive firms should be able to attract more resources (capital and labour) relative to less productive firms (Restuccia & Rogerson, 2008; Olley and Pakes, 1996). Distortions, however, prevent such flow of resource to productive firms. This would result in more productive firms growing below their optimal size while less productive firms grow above their optimal size, leading to total output being lower than it should otherwise be. Consequently, aggregate TFP (aggregate output per factor input) would be lower. Hsieh & Klenow (2009) show that the greater the variation in the distortions, the larger the aggregate TFP losses.

Third, the standard neoclassical model by Restuccia and Rogerson (2008) shows that the aggregate TFP losses will be exacerbated if negative distortions penalise more efficient firms relative to less efficient ones. In this case, production of the efficient firms is constrained, while production of less efficient firms is stimulated beyond efficient levels. The implication is an aggregate shift of resources away from efficient firms towards less efficient firms, further reducing aggregate TFP. Thus, as predicted by the Restuccia and Rogerson (2008) model, misallocation would be costly to aggregate TFP if idiosyncratic distortions are correlated with firm productivity.

The factors that drive misallocation emanate from several sources. Restuccia & Rogerson (2017) grouped potential sources into three categories. The first category includes market imperfections. These include market frictions, property rights, and monopoly power. Second, are government or institutional discretionary provisions that may favour some firms while disregarding others. Third, are statutory regulations. These, for instance, include product market regulations that limit access to the market and labour market regulations such as employment protection. These regulations, even if applied uniformly to all firms in the same sector, may create misallocation when they punish expanding firms relative to contracting firms.

In summary, high dispersion of TFPR potentially indicates the presence of misallocation in product and factor markets. Constrained firms (denoted by high TFPR firms) produce too little relative to the efficient benchmark. The aggregate output given factor endowments, or aggregate productivity, is consequently lower than the efficient outcome. Aggregate TFP is further reduced if there is a positive correlation between negative distortions and firm productivity. Such a relationship implies that misallocation acts as a tax to more productive firms, thereby reducing their size below the optimal level while increasing the size of the inefficient firms beyond their optimal size. This results in an output weighted composition of firms that has a lower aggregate TFP than otherwise.

2.2.2 Review of Empirical Literature

The effects of market frictions and distortions on resource misallocation and aggregate TFP has been the focus of much research in the mainstream literature (Restuccia & Rogerson, 2017; Nguyen et al., 2016; Bartelsman et al., 2013; Busso, Madrigal & Pagés, 2013; Syverson, 2011; Hsieh & Klenow, 2009; Foster, Haltiwanger & Syverson, 2008). Two broad approaches have been adopted in the empirical literature. First is the direct approach that identifies and isolates specific factors that give rise to the misallocation of resource (see Restuccia & Rogerson, 2017). Such factors in the literature include regulations, financial frictions, and corruption, amongst others. Second is the indirect approach that quantifies the extent of misallocation without locating the underlying sources of it. Given the central focus of this chapter in measuring the extent of misallocation, the theoretical and empirical approach adopted draws upon the indirect approach in the literature.

The indirect method has been formalised by Hsieh & Klenow (2009). In their most cited paper, Hsieh & Klenow (2009) used manufacturing firms' data for China (1998-2005) and India (1987-1994) to analyse cross-country differences in misallocation and total factor productivity (TFP). They developed a method that identifies the extent of resource misallocation and the associated TFP losses based on the variation in marginal revenue products of inputs. In their study, they argue that in perfectly competitive markets without distortions, and assuming Cobb-Douglas production functions, marginal revenue products (MRP) for capital and labour will be equalised across all firms, even if their productivity levels differ. A further implication of this is that Total Factor Revenue Products (TFPR) will also be equalised across firms. However, factor and product market distortions that affect firms differently result in deviations in MRP, and consequently Total Factor Revenue Products (TFPR), across firms.

To conduct their empirical analysis, Hsieh & Klenow (2009) use the functional forms of their model to calculate MRP and TFPR for India and China. They reveal wide variations in both these measures across manufacturing firms in both countries, providing evidence of widespread misallocation of resources. Their measures imply that manufacturing TFP can increase 30% to 50% in China and 40% to 60% in India if labour and capital are reallocated so that marginal products are equalised to the extent observed in the United States (US).

Several other studies in the literature have subsequently applied the methodology of Hsieh & Klenow (2009) to a wide range of (mostly developed) countries. These studies include Calligaris (2015) for Italy; Dias et al. (2016) for the Eurozone; Gopinath et al. (2017) for South Europe; Bartelsman et al. (2013) for EU countries; Asker et al. (2014) for some developed countries[5]; and Foster et al. (2016) for the US. While fewer studies have been conducted for emerging economies, the literature is growing. Examples include Kalemli-Ozcan and Sorensen (2014) for a sample of 10 African countries[6]; León-Ledesma (2016) for 62 developing countries; Nguyen et al. (2016) for Turkey; and Cirera et al. (2017) for Ivory Coast, Ethiopia, Ghana and Kenya. The general findings from these studies is that market frictions lead to large aggregate TFP losses via the misallocation channel, particularly in emerging economies.

However, the existing literature faces two challenges. First, the measurement of misallocation is contested. For example, the use of the dispersion of marginal products as evidence of misallocation, as in Hsieh & Klenow (2009), has been criticised. Restuccia & Rogerson (2017) argue that whereas Hsieh & Klenow (2009) assume that firms within the same industry have the same production function such that deviations in capital-to-labour ratios are directly inferred as misallocation, these deviations may be alternatively interpreted as a reflection of heterogeneity of the production function. Alternatively, Haltiwanger, Kulick & Syverson (2018) and Bartelsman et al. (2013) argue that the dispersion in marginal revenue products of capital and labour may simply reflect differences in adjustment costs across producers rather than misallocation. Measurement error in the data can also drive dispersion in marginal revenue products.

One method in the literature that provides an alternative to the Hsieh & Klenow (2009) model is the Olley and Pakes (1996) (OP) decomposition technique used by Bartelsman et al. (2013). The OP decomposition separates an index of industry-level productivity (weighted firm-level

[5] These include US, France, Spain, Romania and Slovenia
[6] They included a sample of the following African countries, Burundi, Kenya, South Africa, Senegal, Botswana, Nigeria, Uganda, Ghana, Tanzania and Zambia.

productivity) into unweighted firm-level average productivity and the *covariance term*. The covariance term (known as the OP covariance) measures the covariance between firm size and firm productivity. The context of this model, just like Hsieh & Klenow (2009), is that within an industry, more productive firms demand more resources and hence grow faster and produce more output. By contrast, less productive firms demand fewer factors of production and should shrink in size as compared to high-productivity firms. If this relationship between productivity and size is not realized or is weak, then resource misallocation is confessed.

Using this technique, Bartelsman et al. (2013) investigated the impact of firm size on productivity and resource allocation in the US and selected European countries. The researchers find industry productivity and size of the firm to be correlated, with the direction of their relationship varying across countries. The relationship was found to be positive and stronger in more advanced economies. In some countries, small firms were more productive than large firms, raising questions about the dualists' notions that small firms are unproductive. Similarly, Inklaar et al. (2017), using data for 52 countries (for both developed and developing countries), find corroborating results that more advanced economies have a lower presence of misallocation than developing economies. This is evidenced by the higher and positive sign of the OP covariance for developing economies as benchmarked to developing economies. León-Ledesma (2016) uses firm-level data for 62 developing countries to measure misallocation using the HK model and the OP decomposition technique. The author finds results suggesting very small sizes of the OP covariance term that are distributed around zero with the maximum magnitude being 6 percent. These results suggest a weak relationship between productivity and firm size, thus indicating evidence of high presence of misallocation in developing countries.

A second limitation of the empirical research is that there has been little analysis of allocative efficiency between formal and informal manufacturing sector firms. Several studies, including those from developing economies, have only paid attention to the formal sector (David & Venkateswaran, 2019; Bento & Restuccia, 2017; David, Hopenhayn & Venkateswaran, 2016; Busso et al., 2013). Such analysis has been constrained by the lack of firm-level microdata in the informal manufacturing sector. Because the informal sector is significantly large in developing countries (Medina & Schneider, 2018), by not incorporating it in the analysis of misallocation, researchers may bias the aggregate effect of misallocation on aggregate TFP.

The role of the informal sector in contributing to aggregate TFP is still a topic of much debate in the literature (Lopez-Martin, 2019; La Porta & Shleifer, 2014; Fields, 2011; Fields, 1990). Some studies are in support of the 'dualist' theories (Baez-Morales, 2015; La Porta & Shleifer, 2014; Benjamin & Mbaye, 2012; Fajnzylber, Maloney & Montes-Rojas, 2011). These studies conclude that most informal sector firms are too small to become efficient and productive. Other studies have argued that the informal sector can trigger aggregate productivity and growth (Chen, 2012; Potts, 2008; Chen, 2005).

La Porta and Shleifer (2008) provide a useful review of different propositions on the informal sector. Using data from World Bank Informal and Micro Surveys, they assess the role of the informal sector in developing countries. Analysing labour productivity as measured by value-added per worker (VA/L), they find evidence that supports the dualists' view that the informal sector is comprised of low labour productivity firms. The authors find large productivity gaps between the formal and the informal sectors in developing economies and conclude that informal sector firms are less productive economic units as compared to formal firms. They conclude that resources should be moved from the informal sector to the formal sector to increase aggregate TFP. The results of their study should be taken with caution before accepting them as they use VA/L as a measure of labour productivity. The problem with VA/L is that it does not account for the contribution of capital stock. The lower VA/L of informal firms could just reflect lower K/L ratios given access to credit constraints by informal firms and not that the lower VA/L reflects a misallocation of resources towards informal firms. There is also broad literature that shows that disparities in revenue productivities, such as value-added per worker, reveal distortions differences rather than the disparity in true productivity (Asker et al., 2014; Hsieh & Klenow, 2009; Foster et al., 2008).

Using data for formal and informal manufacturing sector firms in India and applying the stochastic frontier analysis to assess the efficiency of the informal sector, Kathuria et al. (2013) find that the formal sector firms are more significantly efficient than the informal sector firms. These results are in line with the dualists' views of informality. In the study, the authors advocate for policies that reduce the informal sector's size to realise overall growth. While these studies have concentrated on technical efficiency, our study is more interested in allocative efficiency, which is an important source of productivity, especially in emerging economies.

In line with the informal sector misallocation literature and more related to our approach in this chapter are studies by Lopez-Martin (2019) and Busso et al. (2012). In their study, Busso et al. (2012) apply the Hsieh & Klenow (2009) model to assess resource misallocation and productivity between the formal and informal sectors using firm-level microdata in Mexico. In their study, they find the informal sector to be less productive than the formal sector, despite the informal sector commanding a large share of production resources. They conclude that informality plays a significant role in resource misallocation by creating labour markets distortions that reduce total factor productivity.

Likewise, Lopez-Martin (2019) uses firm-level data to determine the extent of misallocation in the informal sector in Mexico, Egypt, and Turkey. The author concludes that large aggregate productivity losses arise from the large informal sectors in developing countries. The author finds that improvement in access to credit for formal sector firms and reduction of informal sector size increase aggregate TFP, wages and employment. The study argues that the informal sector is an inferior sector that should be eliminated to enhance growth. The findings of Lopez-Martin (2019) and Busso et al. (2012) provide support for the dualist view of advocating for policies that eliminate the informal sector to enhance aggregate productivity.

In conclusion, the above reviewed empirical literature can be summed up in this way. First, misallocation reduces aggregate TFP. This literature is of particular importance to developing countries, where most economies are largely characterised by high product and factor market distortions in addition to underdevelopment. However, empirical literature for emerging economies, especially in Sub-Sahara Africa (SSA) is still limited.

Second, there is very little empirical literature on misallocation that has covered the informal sector. Such studies have largely been constrained by the paucity of data. This is despite the observation that the informal sector commands a large portion of production, especially in developing economies (Medina & Schneider, 2018). This chapter, therefore, tests for misallocation for formal and informal manufacturing sector using the case study of Zimbabwe, an emerging economy in the SSA.

2.3. Methodology

2.3.1 Empirical Framework

This chapter draws on the widely used Hsieh & Klenow (2009) (HK) theoretical framework to measure misallocation. This methodology allows one to analyse the importance and impact of capital and output distortions on allocative efficiency.

The HK framework assumes an economy with heterogeneous manufacturing firms, operating under a monopolistic competition market structure. Assuming an economy with many industrial sectors,s, aggregate output is given by a Cobb Douglas production technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta s}$$

where θ_s is the value-added share of the industry s, and $\sum_{s=1}^{S} \theta_s = 1$. Each industry output Y_s is the total of individual firm's production Y_{si}, with a CES technology, such that:

$$Y_s = \left(\sum_{i=1}^{Ms} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where Y_{si} is a differentiated product of firm i in industry s, and Ms is the number of firms in each industry. Each firm produces a differentiated product using Cobb-Douglas production technology:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \qquad (2.1)$$

where A_{si} is firm-specific productivity (TFP), K_{si} and L_{si} are capital and labour inputs respectively. The key assumption is that firms in the same industry have the same production technologies. Each firm maximises profits,

$$\pi_{si} = (1 - \tau_{Ysi}) P_{si} Y_{si} - wL_{si} - (1 + \tau_{Ksi}) RK_{si} \qquad (2.2)$$

where $P_{si}Y_{si}$ is the firm's value-added (firm's revenue less cost of raw materials), w and R are the unit cost of labour and capital respectively. The term τ_{Ysi} shows firm-specific distorts of output which reduces revenue (e.g transport costs, taxes, corruption) and τ_{Ksi} denotes firm-specific capital distortions which increase the cost of capital (e.g. access to credit, credit rationing)[7]

[7] The list of factors that causes distortions varies and is long. For example, inefficient financial markets may offer credits to selective producers based on non-economic factors, causing misallocation. Government may

Following the Hsieh & Klenow (2009), the first-order condition from profit maximisation can be used to derive firm distortions and productivity as:

$$1 + \tau_{Ksi} = \frac{a_s}{1 - a_s} \frac{wL_{si}}{RK_{si}} \tag{2.3}$$

$$1 - \tau_{Ysi} = \frac{\delta}{1 - \delta} \frac{wL_{si}}{(1 - a_s) P_{si} Y_{si}} \tag{2.4}$$

$$A_{si} = \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma - 1}}}{K_{si}^{a_s} (wL_{si}^{1 - \alpha_s})} \tag{2.5}$$

Equation (2.3) shows the distortions in input choice relative to the optimal level of factor input. It shows that an establishment faces a high capital distortion (larger τ_{Ksi}) when the ratio of labour to capital is high benchmarked to the efficient allocation of input. It is worth emphasizing that τ_{Ksi} measures capital market distortion relative to labour market distortion. Thus, high capital distortion (larger τ_{Ksi}) should be interpreted as a low labour distortion, and vice versa.

Note that in our computation, following Hsieh & Klenow (2009), we use an establishment's total wage bill (including benefits) instead of employment to account for differences in the quality of labour across establishments.

Marginal revenue product of capital (MRPK) and labour (MRPL) are affected by distortions as follows:

$$MRPK_{si} = \alpha \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = R \frac{1 + \tau_{Ksi}}{1 - \tau_{Ysi}} \tag{2.6}$$

$$MRPL_{si} = (1 - \alpha_s) \frac{\sigma - 1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = w \frac{1}{1 - \tau_{Ysi}} \tag{2.7}$$

Based on Foster et al. (2008), we then make a crucial distinction between two measures of productivity one in monetary value (TFPR) and the other in physical units (TFPQ)[8];

provide contracts, special taxes and subsides to selected firms. Labour regulations may restrict firms from firing and hiring, driving up the cost of labour in the formal sector more than in the informal sector.

[8] Note that what we observe in the data are the MRPKi and TFPRi and not MPKi and TFPQi for every firm as we do not observe individual firm prices. This is the reason the HK make an assumption about market structure to infer prices as a function of firm productivity and distortions.

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s}(L_{si}^{1-\alpha_s})}$$

$$TFPR_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}(L_{si}^{1-\alpha_s})} = P_{si}TFPQ$$

In this framework, in the absence of distortions, TFPR should be equal across firms in the same industry. The argument is that (assuming monopolistic competition) lower-productivity firms produce less and charge high prices while higher-productivity firms produce more and charge lower price. Hsieh & Klenow (2009) argued that in the absence of distortions, more labour and capital should be allocated to firms with higher TFPQ which will result in lower prices and have the same TFPR as small firms.[9] Hence any difference in TFPR within the same industry denotes distortions. TFPR can be expressed as a weighted average of marginal revenue products:

$$TFPR_{si} = \frac{\sigma}{1-\sigma}\left(\frac{MRPK_{si}}{a_s}\right)^{a_s}\left(\frac{MRPL_{si}}{(1-a_s)}\right)^{1-a_s} \qquad (2.8)$$

Substituting $MRPK_{si}$ and $MRPL_{si}$ in $TFPR_{si}$ we get a measure of TFPR at the firm level as;

$$TFPR_{si} = \frac{\sigma}{1-\sigma}\left(\frac{R}{a_s}\right)^{a_s}\left(\frac{w}{1-a_s}\right)^{1-a_s}\frac{(1+\tau_{Ksi})^{a_s}}{1-\tau_{Ysi}} \qquad (2.9)^{10}$$

In this framework, TFPR at the industry level can be calculated as follows:

$$\overline{TFPR_s} = \frac{\sigma}{1-\sigma}\left(\frac{R}{a_s\sum_{i=1}^{Ms}\left(\frac{1-\tau_{Ysi}}{1+\tau_{Ksi}}\right)\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)}\right)^{a_s}\left(\frac{w}{(1-a_s)\sum_{i=1}^{Ms}(1-\tau_{Ysi})\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)}\right)^{1-a_s} \qquad (2.10)$$

Once $TFPR_{si}$ has been calculated for all firms, aggregate misallocation in the economy can be measured as the dispersion of its distribution across firms. In this study, we are interested in assessing how misallocation (as measured by the variance of TFPR) varies between sectors (formal vs informal), industrial sectors (e.g., wood, clothing, metal) as well as firm size and within these groups. We, therefore, categorise firms not only by sector but also by industry and firm size they belong to.

[9] It is not market power that makes less productivity firms charge high prices, but rather economies of scale. More productive firms are able to produce more output and hence reduce production cost (due to economies of scale). Thus, productive firms may charge less price while still making economic profits. The flip side is true for less productive firms, who produce less and charge higher prices.

[10] Note that the estimates are based on the corrected version for TFPR presented in Hsieh and Klenow (2013). Hsieh and Klenow (2013) corrected some of the equations in HK (2009), which includes footnotes 10 & 11 and other specifications used to construct TFPR. See Hsieh and Klenow (2013) for more details.

From equation (2.9) and (2.10) it can be shown that in the absence of distortions (i.e. when τ_{Ksi} = 0 and τ_{Ysi}=0) for all i, the right-hand side of (9) equals the right-hand side of (10), which means that TFPR does not differ for firms within the same industry. This implies that in the absence of distortions, production resources will be allocated to more productive establishments with higher TFP and less to productive firms with lower TFP[11]. By contrast, with distortions, TFPR may not be equalised across firms-a symptom of resource misallocation. A firm with higher TFPR than the average industry is taxed more - that is, it suffers from more obstacles than other firms. Hence, the deviation of the firm's TFPR from the average industry TFPR represents distortions that indicate resource misallocation and allocative inefficiency. This can be represented as scaled TFPR $\left(\frac{TFPR_{si}}{\overline{TFPR_s}}\right)$. If the scaled TFPR for a given firm is greater than one it means that the firm is being taxed so that if distortions are removed the firm increases production. We use the scaled (log) TFPR as a measure of resource misallocation in our empirical analysis.

With both revenue and physical productivity for establishments in the sample, we can calculate industry level TFP. Since TFPR is regarded as the main source of distortions and TFPQ shows the actual productivity, industry actual TFP can be found by an average of firms' TFPQ weighted by firms' level deviations of TFPR from industry mean. It is also crucial to relate TFPQ to firms' distortions and productivities. Firms with lower TFPR than the industry average (i.e., with fewer distortions) will have higher weight - hence higher TFPQ - than those with higher values of TFPR. Industry aggregate TFPQ is given by:

$$TFP_s^{act} = A_s = \left[\sum_{i=1}^{Ms}\left(A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \quad (2.11)$$

As discussed above, in the absence of distortion (in an efficient economy) firm-level and industry TFPR will be equal such that the efficient level of industry TFP will be given by:

$$TFP_s^{eff} = \bar{A}_s = \left[\sum_{i=1}^{Ms}(A_{si})^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \quad (2.12)$$

In equation (2.12) resources are reallocated from less productive firms to more productive ones, hence TFPQ will be highest. Therefore, the deviation of equation (2.11) from (2.12) can be used to calculate output costs that occur because of distortions.

[11] This reallocation of resources continues to a point where prices start lowering for firms with higher output and rising for firms with lower output until their TFPR is equalised.

To calculate productivity loss due to distortions at the industry level, HK used the ratio of actual TFP to the efficient level of TFP[12] as shown in equation (2.13).

$$\frac{TFP^{actual}}{TFP^{efficient}} = \prod_{S=1}^{S} \left[\sum_{i=1}^{Ms} \left(\frac{A_{si}\overline{TFPR_s}}{\bar{A}_s TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta s}{\sigma-1}} \quad (2.13)$$

Equation (2.13) shows the gap between the distorted and efficient level of TFPQ. Aggregate productivity gains across all industries are calculated using the Cobb-Douglas aggregator as:

In the model, if there is no misallocation, more productive firms should produce more output and should be large. If there exist size-depended policies such that $TFPQ_{si}$ and $1 + \tau_{Ksi}$ are positively correlated or $TFPQ_{si}$ and $1 - \tau_{Ysi}$ are negatively correlated, more productive firms will produce less than optimal and less productive firms will produce more than optimal. This entails that efficient distribution is more dispersed and spread out than the actual size distribution in the presence of distortions.

To this end, this study employs the Hsieh & Klenow (2009) methodology in estimating allocative efficiency between and within the formal and informal manufacturing sectors. The dispersion of output and capital distortion and scaled TFPR help us to assess and compare the extent of resource misallocation across industries between and within the formal and informal manufacturing sectors. We also estimate TFP gain that can be achieved if resources are efficiently allocated at the industry level within each sector. We incorporated the informal sector in the same production function with the formal sector to determine the aggregate implications.

We are motivated to use the Hsieh & Klenow (2009) framework for two reasons. First, the model allows us to quantitatively measure misallocation from the data we have. The Hsieh-Klenow method combines considerable empirical power and flexibility with a straightforward measurement algorithm. Second, the framework has been widely used in several empirical studies (both in developed and developing economies) and therefore allows us to compare our results with others in the international literature.

[12] Note that productivity loss (gains) is zero if $\frac{\overline{TFPR_s}}{TFPR_{si}} = 1$ for all establishments. This is achieved if there are no distortions such that dispersion of $\frac{\overline{TFPR_s}}{TFPR_{si}}$ is zero.

2.3.1.1 Limitations of the Hsieh and Klenow (2009) model

Notwithstanding the strength of the Hsieh & Klenow (2009) model in measuring misallocation, several studies have identified the caveats of this model (Bills et al., 2020; David & Venkateswaran, 2019; Haltiwanger et al., 2018; Wu, 2018; Bartelsman et al., 2013). These caveats span from the model assumptions about the heterogeneity and nature of production functions to the issues related to measurement errors. The Hsieh and Klenow (2009) model hinges on several fundamental assumptions that allow this model to hold. However, theoretically and empirically these assumptions have a tentative quality. The only technology and demand structure that upholds the Hsieh and Klenow (2009) model is the CES demand with Cobb-Douglas constant returns to scale (CRS) technology. If these assumptions do not hold, then dispersion in TFPR is likely to be correlated with demand shocks and TFPQ even in the unavailability of distortions (Haltiwanger et al., 2018). In practice, most firm production functions may not in line with the fundamental assumptions of this model.[13] Restuccia and Rogerson (2017) point out that there may be adjustment costs or transitory firm-specific shocks that cause deviations in optimal. The HK model being an autarky model and does not account for how TFPR responds to shocks such as import competition. Lastly, as pointed in Newman et al. (2019) paper, inefficiencies may be a result of measurement error, which is common in firm-level data sets, especially in developing countries (Bils et al. 2020).

In light of the HK model caveats, this study uses other alternative robust measures to counter the weaknesses of the Hsieh & Klenow (2009) methods. First, the chapter uses the World Bank enterprise survey as an alternative dataset to check for the consistency of the survey and test on survey measurement error. However, although we have the World Bank survey for informal sector firms, we are limited to use this as it does not contain key variables that allow us to construct the production function for informal sector firms. For example, the survey does not have information on the value of capital. For this reason, we only use the World Bank enterprise surveys for formal micro firms (those with less than 5 workers) and larger formal firms (with more than five workers) for robustness. Second, the chapter utilises the OP covariance decomposition technique (as used in Bartelsman et al. (2013) as an alternative measure to check the robustness of the HK method. Third, the chapter uses the alternative measures of

[13] This is particularly important given the challenges of merging formal and informal firms in the same production function. One the key challenges is differences in capital and labour structures of the formal and informal sector firms; given that informal firms are relatively labor intensive. However, we overcome this constraint by using alternative measures of misallocation that do not rely on production function assumptions such as Wu (2018) to test for the HK robustness.

misallocation based on Wu (2018) methodology. David & Venkateswaran (2019) also propose interesting alternative measures of misallocation to HK[14]. However, we are constrained by our data to implement their approaches.

2.3.2 Data

This chapter draws on the firm-level data for formal and informal manufacturing sector firms we collected in 2015 under the "Matched Employee-Employer Panel Data for Labour Market Analysis in Zimbabwe" project. The dataset consists of 195 formal manufacturing firms and 130 informal manufacturing firms that were surveyed in 2015. For the formal survey, three different size strata were defined for the survey, namely 'small' (5-9 employees), 'medium' (10-99 employees), and 'large' (100+ employees). The survey covered all manufacturing industries based on the 2-digit ISIC Rev.2: food, beverages and tobacco; wood and furniture; metal, machinery and equipment; textile and leather; and chemical and rubber. The survey was done in four main industrial cities: Harare and surrounds; Bulawayo; Gweru, Kwekwe and Redcliff (in Midlands); and Mutare (in Manicaland). A stratified sampling procedure was used with size, industry and location strata. Weights were then constructed for two reasons. First, the desired sample purposively oversampled the larger firms as well as firms in the locations outside Harare and surrounds and Bulawayo. Second, the actual sample differs from the desired sample because of non-response. It worth noting that the sample for the formal sector survey is representative of the formal sector firms in Zimbabwe. Detailed data description has been presented in the Appendix for Chapter 1.

For the informal sector, surveys were done for the metal; wood and furniture; and textile industries. These are industries in which the bulk of informal manufacturing takes place. Data collection was done in Harare and Bulawayo, the largest urban cities in Zimbabwe which constitute the bulk of informal manufacturing activities. A two-stage sampling process was followed in selecting informal manufacturing firms, based on our own constructed sample

[14] David & Venkateswaran (2019) methodology is based on a structural general equilibrium model of firm dynamics to estimate misallocation. Their methodology disentangles sources of capital misallocation, by looking at dispersion in average revenue product of capital. The methods measure the contributions of technological/informational frictions and some firm-specific factors. The extended the HK model by including the firm dynamics. The model, being dynamic is based on AR (1) processes. Given that this is a dynamic model, and our data is cross-sectional, we are not able to implement the David & Venkateswaran (2019) methodology in a convincing way. We thus use approached that use static models such as Wu (2018) as robustness.

frame.[15][16] Survey imperfections such as the selection of units with unequal probabilities cause bias and departure of the sample from the reference population. Thus, sampling weights were constructed to make the survey data representative of our targeted population. It should be noted that the misallocation measure is an aggregate national measure and thus the data should reflect the population of firms in the country. We use weights to construct nationally representative measures of misallocation. Because we followed a two-stage sampling design, base weights were constructed to reflect the selection probabilities at each stage. See Appendix for Chapter 1 for a detailed explanation of the data collection procedure.

It is worth noting that we constructed sampling weights to make the survey data representative of our targeted population (see Appendix for Chapter 1 for details). Because we followed a two-stage sampling design, base weights were constructed to reflect the selection probabilities at each stage. There are two issues that we need to express concerning the use of weights. First, the survey for the informal sector is not representative of the total population of informal manufacturing sectors in Zimbabwe but informal enterprises in the respective geographical areas surveyed. Second, guided by the literature, we used weighted estimations only in the non-parametric analysis, as there is inconclusive econometric debate on the use of weights in regression analysis (Lohr, 2019; Cochran, 2007; Deaton, 1997; DuMouchel & Duncan, 1983). These studies argue that the use of weights in regression analysis may impose additional noise to the standard errors, leading to inefficient estimates.

Our analyses of the formal and informal sector results are based on industrial sectors that match both sectors, that is, metal; wood; and textile. While this may affect the aggregate representativeness of our data (because we drop other industries) this provides a nuanced comparison between formal and informal sector firms with the same industry category. Since this Chapter is based on non-parametric analysis, weights were used for both formal and informal sector analysis.

[15] In the first stage, the two main (or main area where informal production is located in a single area) informal areas for each of the industry strata were selected. Where it is possible or sensible these areas were then divided into blocks (enumerating areas) with roughly equal numbers of firms based on spatial area or building complex. Blocks were then randomly selected. In the second stage, firms within each of these randomly selected blocks were listed. A random sample of firms was then selected for interviewing purposes from the listed firms in each randomly chosen block.

[16] Our sampling procedure rules out a likelihood of the informal firms being a select sample of the informal firms; for example, that they constitute the upper end of the productivity distribution of the population of informal firms.

The data contains essential information that allows us to construct the measure of markets distortions and misallocation. The information includes data on sales and production, raw material costs, indirect costs, capital stock and labour inputs among other important information. In our analysis, labour input is measured by the wage bill[17] (rather than employment) to account for differences in human capital and hours worked (as in Hsieh & Klenow, 2009). The capital stock is measured by netbook and market value of fixed assets, summed across vehicles, machinery and equipment, and land and buildings. Value-added is computed as the difference between sales and cost of raw materials, overhead expenses, and energy costs (electricity, fuel, gas).

To implement the Hsieh & Klenow (2009) framework, we also need information on the elasticity of substitution (σ), interest rate (R) and industry level of labour and capital share (α_s). There is little consensus in the literature on which effective magnitude on this parameter. Following the HK framework, we fixed this parameter at σ = 3[18] in our baseline computations as this is the value most used in similar empirical approaches. The value of the elasticity of substation is likely to impact the results of TFP gains, thus we will consider a robustness check using alternative values of σ. We also set R = 12.5% drawing from the average interest rate reported in our data for the formal and informal firms. We calculate capital share by subtracting the industry mean of labour expenditure as a share of value-added at firm level from one, that is, $a_s = 1 - \frac{wL_{si}}{P_{si}Y_{si}}$). In literature, most studies have widely used the US capital share, which is set at one third. In our sample, we dropped all observations where value-added could not be calculated because of either missing variables or those where value-added was negative (14 firms). Having considered overlapping industries between formal and informal sector, as discussed above, this left a sample of 107 out of 195 formal firms and 128 out of 130 informal sector firms. Table 2.1 below provides some key variables in our analysis.

[17]The sum of wages, bonuses, and benefits.
[18] This parameter does not alter our measures of distortions, but rather their effect on aggregate productivity.

Table 2. 1. Summary statistics for key variables

	Formal Sector			Informal Sector		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Value added per worker (log)	100	8.44	1.24	122	7.74	0.86
Value added per capital (log)	95	-0.08	1.80	121	2.24	1.33
Capital/Labour ratio (log)	95	8.52	1.37	121	5.51	1.22
Labour costs (log)	95	11.56	1.85	113	8.24	1.03
Firm Size (employment)	100	66.03	92.19	122	3.12	1.50
Firm age	100	34.48	23.23	117	8.55	6.41

Notes: For the formal sector, the summary statistics are only for overlapping industries with the informal sector (Metal, Textile and Wood) for plausible comparisons.

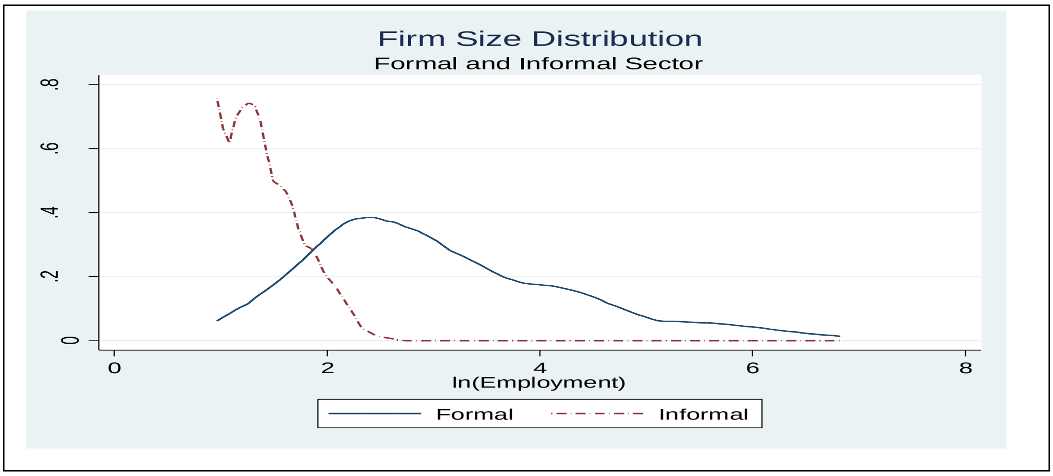
The summary statistics in Table 2.1 shows differences in firm size between the formal and informal sector firms, with the formal sector having average employment of 66 as compared to the informal sector of 3. Firms in the informal sector are on average younger than those in the formal sector. However, value-added per worker (labour productivity) is comparably the same in the two sectors. Noticeably, the formal sector firms have a lower value-added per capital as compared to informal sector firms. This signals that firms in the formal sector produce using substantially higher capital-labour ratios.

2.3.3 Stylised Facts from the Data

This section presents some key facts depicted in the dataset. Figure 2.1 shows the distribution of firm size between the formal and informal sector firms. These distributions corroborate the results in Table 2.1 that there is a large difference in firm size between formal and informal sector firms.

Informal sector firms in our data consist of very small firms with less than 5 workers on average, while formal sector firms averaged 66 workers. One concern in comparing these two samples is that we may be comparing very different samples of firms. Consequently, to better enable comparisons with informal firms, formal sector firms are split into groups with less than 20 workers (small firms) and firms with 20 or more workers (large firms).

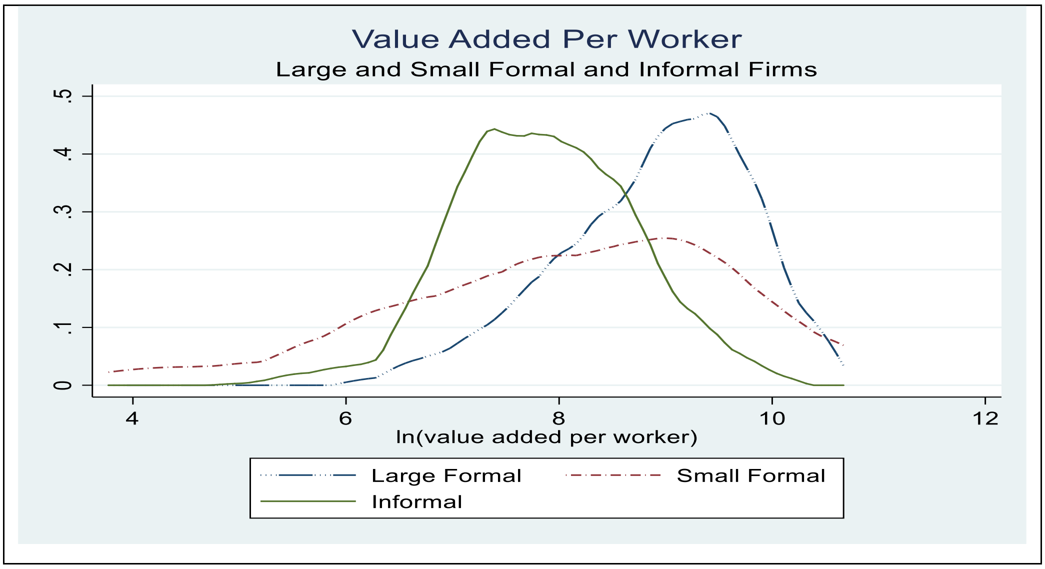
Figure 2. 1. Distribution of firm size for formal and informal sector firms



Notes: Kernel density plot for the firm size as measure by the log of employment. The solid density is for the formal sector while the dashed one is for the informal sector.

Figure 2.2 presents the distribution of value-added per worker (labour productivity) between formal and informal sectors. Several features are evident in the data. There is a wide distribution of value-added per worker across formal and informal firms, reflecting a high degree of firm heterogeneity within each sector. The distributions show that the formal sector firms are, on average, more productive than the informal sector firms as shown by the rightward location of the kernel density function for formal sector firms. Finally, there is a large overlap in productivity between formal and informal sector firms.

Figure 2. 2. Formal and Informal sector valued-added per worker



Notes: Kdensity plot for log value-added per worker for large and small formal firms as well as informal firms. The purpose is to show that productivity overlaps between the formal and informal sector firms.

The overlap in productivity shows that many informal sector firms are as productive as their counterparts in the formal sector. There are nevertheless many informal firms that have very low levels of value-added per worker. This again points to substantial heterogeneity in the sample, but also that many firms in the informal manufacturing sector comply with the structuralist view of the informal sector. Lastly, the formal sector distribution has a long tail skewed to the left. Many large firms, therefore, remain in operation despite low levels of productivity.

Market frictions or obstacles are theoretically and empirically well known to be an important source of allocative inefficiency. Table 2.2 presents the proportion of firms within each sector that declare the given obstacles as constraining the growth of their businesses. The results in Table 2.2 demonstrate that financial inaccessibility is one of the major challenges hindering the growth of firms. Unsurprisingly, 57 percent and 78 percent of firms in the formal and informal sector, respectively, declared inaccessibility to finance as a major challenge constraining business growth. The Zimbabwean economy has been, for the past two decades, suffering from high liquidity and credit constraint, such that firms have limited access to lines of credits to boost their business. Interest rates on loans are also very high, discouraging firms from borrowing (Mujeyi, 2016). This obstacle is much prevalent in the informal sector where most firms do not have the required documents to source formal loans from banks.

Table 2. 2. Prevalence of obstacles in the formal manufacturing sector

	Formal Sector		**Informal Sector**	
Variable	N	Mean	N	Mean
Financial Inaccessibility	100	0.57	122	0.78
Electricity Shortages	100	0.14	122	0.18
Lack of government initiatives	100	0.18	122	0.33
Raw materials Inaccessibility	100	0.16	122	0.10
Unfair Competition	100	0.34	122	0.51
Bad Debtors	100	0.06	122	0.03
Insufficient Demand	100	0.39	122	0.56
Labour Regulations	100	0.20	-	-
Obsolete Equipment	100	0.10	-	-
Lack of Space to Operate		-	122	0.20

Notes: Proportions of firms with underlying obstacles in the formal and informal sectors.

Table 2.2 also illustrates that 34 percent of formal sector firms and 51 percent of informal sector firms have unfair competition as one of the challenges affecting their business operations negatively. Unfair competition largely constitutes competition from cheap imports which are flooding the markets, especially in the textile industry, thereby reducing the competitiveness of domestic firms. Formal sector firms also highlight the informal sector firms as having an unfair competitive advantage over them, as informal sector firms do not pay regulated taxes, and hence are able to lower their prices without incurring much loss. Empirically, unfair competition can reduce the aggregate productiveness of the economy, especially from imports. Noticeably, there is a strong relationship between unfair competition as a constraint, and firms declaring as having insufficient demand.

Only 18 percent of formal sector firms declare lack of government initiatives as affecting their operations negatively, as compared to 33 percent for informal sector firms. Lack of government initiatives includes government policy inconsistency, counterproductive policies, bureaucracy and other government policies that reduce the ease of doing business by firms. These policies may have a distortionary effect on the market.

Stringent labour market regulations are also a source of hindrances to business growth in the formal sector where firms adhere to regulative legislation. 20 percent of formal firms reported being constrained by labour regulations. These regulations do not allow firms to retrench workers whenever firms deem necessary. The costs of doing so are prohibitively high, resulting in firms employing more workers than is optimal, leading to productivity losses and constraining effective allocation of resources. Some informal sector firms are constrained by a lack of space to operate their business and operate in open spaces with no permanent structures. They end up incurring huge losses and increased business costs as they try to safeguard their equipment and output from weather conditions and theft. Other constraints facing firms include the shortage of electricity and the inaccessibility of raw materials.

In the next section, we present the empirical results from the HK non-parametric model to determine how the stylised facts presented above fit together to explain the extent of misallocation within and between the formal and informal sector firms and the implied TFP losses.

2.4. Results

This section presents the results of the Hsieh & Klenow (2009) model applied to Zimbabwe manufacturing sector data to analyse the extent of resource misallocation between the formal and informal sectors. The analysis is structured in three parts. First, we present the results on the dispersion of productivity (TFPQ) and the measure of misallocation (TFPR). As argued in the earlier sections, the presence of misallocation leads to the survival of many least productivity firms that should otherwise be exiting operations and release resources to more productive firms (Restuccia & Rogerson, 2008). The existence of many less productive firms is the first evidence indicating the prevalence of misallocation. Likewise, high TFPR denotes firms that produce too little relative to the efficient benchmark. This implies that too few resources have been allocated towards production in the firm, therefore giving rise to misallocation.

Second, the chapter presents the results on the correlation between indicators of misallocation and productivity (TFPQ). Theoretically, a positive correlation implies that misallocation affects more productive firms relative to less productive firms, thus leading to higher aggregate TFP losses.

Third and last, we calculate the aggregate TFP gains that can be achieved if misallocation is eliminated.

2.4.1 Productivity and Misallocation

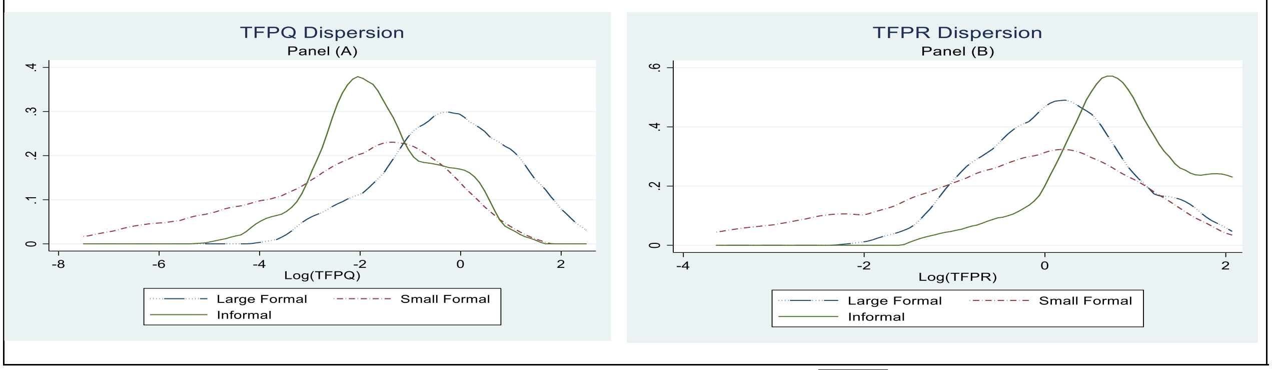
Figure 2.3 shows the distribution of plant TFPQ (in panel A) and TFPR (in panel B) demeaned by industry averages for the formal and informal sector in Zimbabwe. TFPR and TFPQ distributions are respectively calculated as $log(TFPR_{si}/\overline{TFPR_s})$ and $log(TFPQ_{si}/\overline{TFPQ_s})$. As mentioned above, to ensure a comparable analysis, formal sector firms are split into small and large size categories. We then compare informal sector firms across the formal sector size categories.

Results in Figure 2.3 in panel (A) illustrate that larger formal sector firms are more productive as compared to informal and small formal sector firms as expected, but there are large productivity overlaps between formal and informal sector firms. Theoretically and empirically, we expect large firms to be more productive than small firms. However, the results in panel (A) also show not much difference in productivity between small formal and informal sector firms. This suggests that informal sector firms are as productive as (small) formal sector firms, as the structuralist view suggests. A thick tail to the left for small formal firms' plot suggests that some small firms are less productive although they are not exiting operations. A significant proportion of small firms survive regardless of low productivity. This shows the possibility of the existence of policies and regulations that prompt firms in the formal sector to continue operating at low productivity levels rather than exiting or shrinking operations.

Figure 2.3 panel (B) shows the distribution of TFPR; our measure of allocative inefficiency. In efficient economies with no resource misallocation, we expect the distributions of demeaned TFPR to be spiked around zero. The high dispersion of the TFPR distributions shows evidence of allocative inefficiency in both the formal and informal manufacturing sector. Allocative inefficiency seems more of a problem in the small formal sector firms, which have a relatively wide dispersion. Comparing the formal and informal sector firms shows that the TFPR distribution for the informal sector lies towards the right of the diagram. This shows that production by informal sector firms is constrained relative to formal firms.

Figure 2. 3. Distribution of TFPQ and TFPR

Panel A | Panel B



Notes: The left panel plots the distribution of TFPQ, $\log(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}}_s)$ for the formal and informal manufacturing sector; the right panel plots the distribution of TFPR, $\log(\mathrm{TFPR}_{si}/\overline{\mathrm{TFPR}}_s)$ for the formal and informal manufacturing sector. Distributions are weighted using sampling weights.

Table 2.3 provides supporting evidence on the dispersion of various measures of misallocation between the formal and the informal sectors. It shows the standard deviation of TFPQ, TFPR, and two components of TFPR: output and capital distortions, the difference between the 75th and 25th percentiles, and the difference between the 90th and 10th percentiles for the informal and formal manufacturing sector in Zimbabwe.

The finding shows notable firm-level heterogeneity in productivity across the two sectors. The standard deviation of TFPQ (1.76 for formal firms against 1.07 for informal firms) presented in Table 2.3 shows larger productivity dispersion in the formal sector than in the informal sector. In the formal sector, firms in the 90^{th} percentile of the productivity distribution are 435 log points more productive than those in the 10^{th} percentile, while the gap is 285 log points in the informal sector. This, combined with information in Figure 2.3, reveals the coexistence of many less productive firms with more productive ones in the Zimbabwe manufacturing sector. This suggests evidence of the existence of 'zombie' firms that should otherwise be exiting production in the absence of product and market distortions.

Table 2. 3. Dispersion of TFPR and TFPQ

	log (TFPQ)	log (TFPR)	log (MPKR)	log (1+ τ_k)	log (1- τ_y)
		Formal			
sd	1.76	0.99	1.78	1.61	0.68
p75-p25	2.32	1.21	2.40	2.16	0.81
p90-p10	4.35	2.53	4.51	4.29	1.82
Corr. with TFPQ	1.00	0.87	0.86	0.70	-0.59
N	94	94	94	94	94
		Informal			
sd	1.07	0.77	1.33	1.46	0.71
p75-p25	1.22	0.94	1.78	2.17	0.63
p90-p10	2.85	2.06	3.25	3.94	1.84
Corr. with TFPQ	1.00	0.90	0.78	0.45	-0.55
N	112	112	112	112	112

Notes: For each firm i, in industry s TFPRsi=$\frac{P_{si}Y_{si}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$, TFPQsi =$\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$, $1+\tau_{Ksi}=\frac{a_s}{1-a_s}\frac{wL_{si}}{RK_{si}}$ and $1-\tau_{Ysi}=\frac{\delta}{1-\delta}\frac{wL_{si}}{(1-a_s)P_{si}Y_{si}}$. The statistics for log(TFPQ) and log(TFPR) are deviations from respective industry means. S.D is the standard deviation, p75-p25 is the difference between the 75^{th} and 25^{th} percentiles p90-p10 is the difference between the 90^{th} and 10^{th} percentiles. N is the number of firms.

We now turn the analysis to indicators of misallocation: TFPR, MRPK, capital distortions, and output distortions. Dispersion of product and factor market distortions across producers has widely been used to assess the extent of resource misallocation (Hsieh & Klenow, 2009). Without distortions, marginal products of inputs should be the same for firms within the same industry and variation of marginal products should be zero, as discussed above. Looking at the dispersion indicators of misallocation, Table 2.3 indicates results consistent with the prevalence of high distortions. For example, the ratio of the 90^{th} and 10^{th} percentiles of TFPR are 2.53 in the formal sector and 2.06 in the informal sector. The results of the dispersion of marginal product of capital revenue, capital distortions and output distortions in Table 2.3 are also consistent with the prevalence of high distortions that impedes effective allocation of resources leading to allocative inefficiencies.

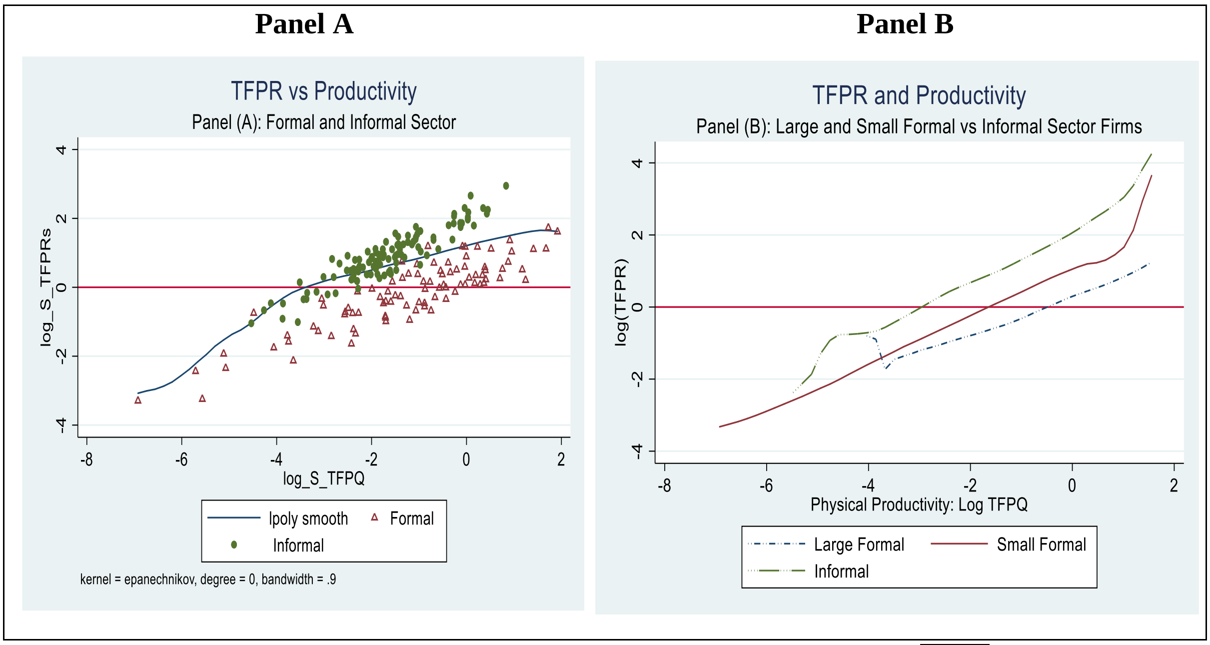
2.4.2 Correlation between Misallocation and Productivity

Thus far, we have shown evidence pointing to a high prevalence of misallocation, as shown by the dispersion of an indicator of misallocation. But to what extent does misallocation reduce or cost aggregate TFP? In efficient markets, where TFPR is equalised across industries, more productive firms with high TFPQ are expected to acquire more resources, leading to high output. A high positive correlation between productivity and indicators of misallocation, therefore, signifies that the negative effects of resource misallocation impact more productive firms relative to least productive firms. This means that distortions act as a tax to high-productivity firms, thereby constraining them from growing to their potential optimal size while promoting the growth of less productive firms beyond their optimal size. The consequence would be a reduction in aggregate TFP.

Figure 2.3 plots the local polynomial regression for TFPQ against TFPR to explore the relationship between distortions and productivity. In an economy with no distortions, the dispersion of $log(TFPR_{si}/\overline{TFPR}_s)$ should be zero, as discussed in the above sections. Hence, all firms should be placed along the zero TFPR line. Along this line, firms would only differ in their TFPQ. If we see a positive relationship between TFPQ and TFPR, it shows the existence of distortions that inhibit production by more productive firms. The results in Figure 2.4 illustrate a strong positive correlation between TFPR and productivity in both the formal and informal sector firms. These results are supported by the findings in Table 2.3, which reports a highly positive correlation between the TFPR and TFPQ in both sectors but marginally higher in the informal sector (0.87 in the formal sector and 0.90 in the informal sector).

Comparing the plots for formal (small and large) and informal firms, the results indicate that misallocation is higher in the informal sector. This is consistent with the above arguments that the informal sector firms face more barriers as compared to formal sector firms.

Figure 2. 4. TFPR vs Productivity



Notes: The plots show the relationship between TFPQ, $\log(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}}_s)$ and TFPR, $\log(\mathrm{TFPR}_{si}/\overline{\mathrm{TFPR}}_s)$. Distributions are weighted using sampling weights. Panel A shows the aggregate manufacturing sector. Panel B shows a comparison between the formal and informal sectors.

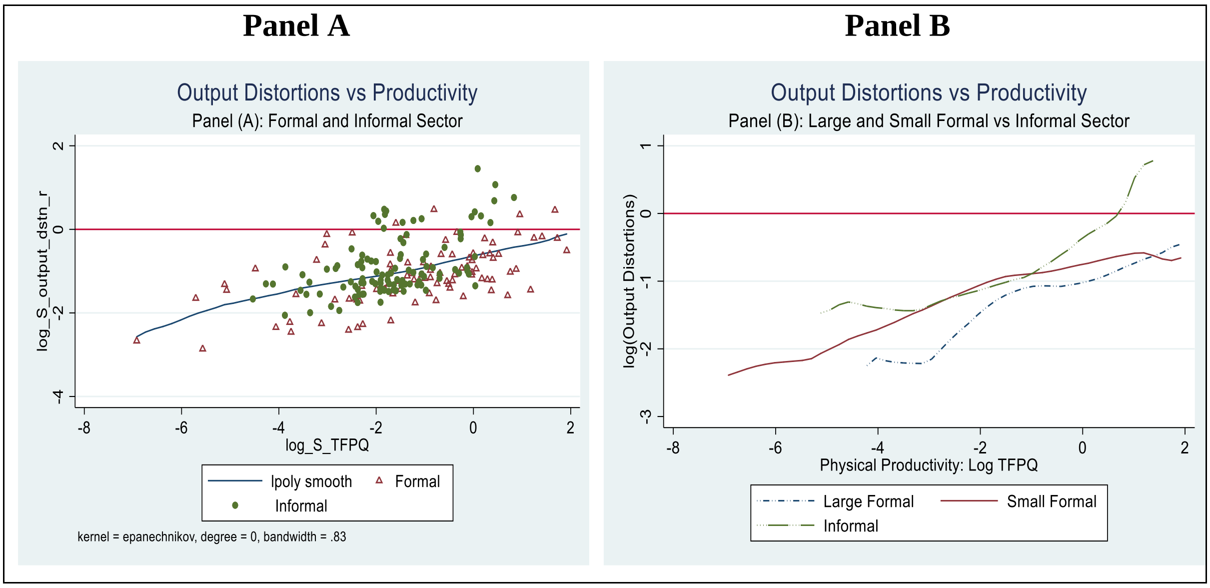
These results are not a surprise given the challenges the Zimbabwean economy, including the manufacturing sector, has been facing for the past two decades. For example, distorted financial markets as a result of lack of financial access (including foreign currency) have resulted in credit rationing of available funds. However, access to such limited finance by firms is not related to the performance or productivity of firms, but rather how well-connected these firms are to government and service providers. This, therefore, deprives more productive firms of resources that should have been channelled to them if economic systems were efficient, resulting in loss of productivity and output. This suggests that both within and between sectors' allocative inefficiency may have a substantial part to play in declining activities within the manufacturing sector.

2.4.3 Output and Capital Distortions vs Productivity

To understand the sources and nature of distortions, it is important to decompose TFPR into capital distortions $log(1 + \tau k)$ and output distortions $log\left(\frac{1}{1-\tau y}\right)$. Capital distortions reflect government discretionary policies that impede equal access to capital and raise the cost of capital for other firms. Examples include subsidised interest rates granted to specific firms, targeted investment incentives, firm-specific or capital-specific depreciation rates for tax purposes. Output distortions reflect obstacles that affect firm sales and prices in the market. These could include price controls (as were commonly used in Zimbabwe during hyper-inflation), output subsidies, price support, government controls over production, government procurement laws (e.g., local procurement, black economic empowerment requirements as in the context of Zimbabwe), and preferential market access. The relationship between these output and capital distortions and TFPQ are shown respectively in Figure 2.5 and Figure 2.6. The results indicate that both capital and output distortions are highly correlated with firm productivity in all sectors. The results suggest that, on average, firms in both the formal and informal sector have negative values of output distortions. Negative values of $log\left(\frac{1}{1-\tau y}\right)$ implies that output distortions are large and are acting as a tax on firms.

The results in Figure 2.5 imply that productive firms face high output distortions which induce them to produce a lower output than optimal while less productive firms produce more output than their optimal level in both sectors. This relationship between distortions and productivity is an indication of inefficient allocation of resources that lowers aggregate TFP via misallocation. Comparing the formal and informal sector distributions suggests insignificant differences in the prevalence of output distortions between these two sectors.

Figure 2. 5. Output distortions vs Productivity

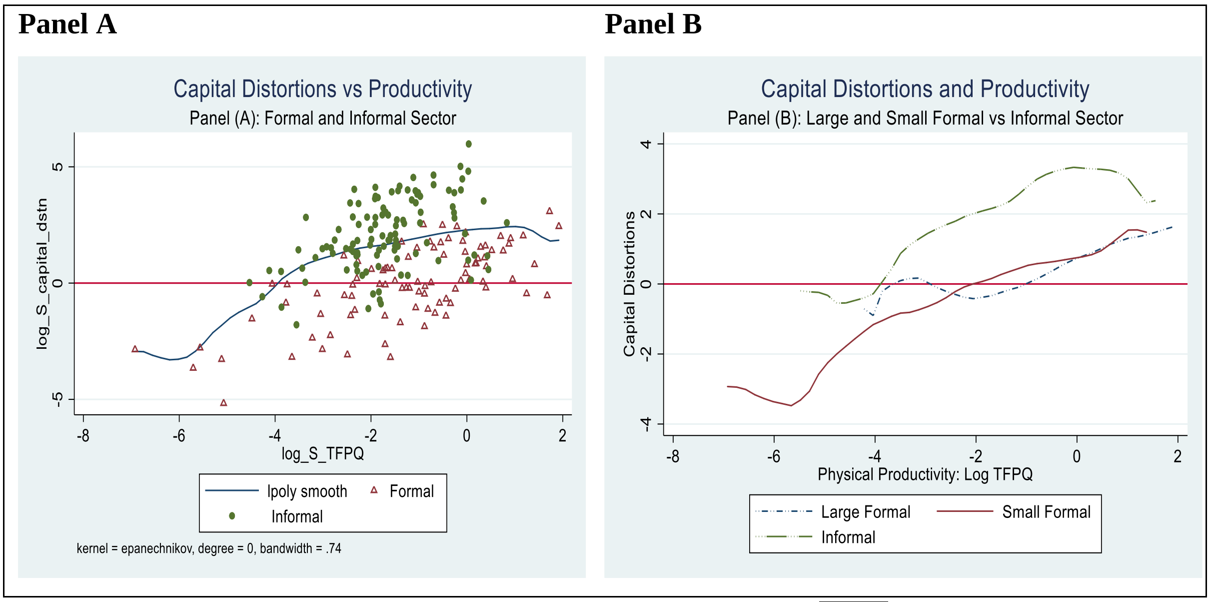


Notes: The plots show the relationship between TFPQ, $(\log(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}_s}))$ and output distortions, $\log\left(\frac{1}{1-\tau y}\right)$. Distributions are weighted using sampling weights. Panel A shows for the aggregate manufacturing sector. Panel B shows a comparison between the formal and informal sector.

Looking at the plots for capital distortions in Figure 2.6, the results show a positive correlation between capital distortions and productivity, suggesting they act as a tax on more productive firms. The results also illustrate that the impact of capital distortions is significantly high in the informal sector relative to the formal sector firms, as shown by a high outward shift of the informal sector plot.

The above findings provide evidence of severe resource misallocation in both the formal and informal manufacturing sectors in Zimbabwe. A possible explanation for these results is that policies and institutions play a central role in preventing more productive firms from growing while allowing less productive firms to operate above their optimal size. Similar results have been found in developing countries, at least for formal sector firms (for example Cirera et l., 2017; León-Ledesma & Christopoulos, 2016; Kalemli-Ozcan & Sørensen, 2014; Busso et al., 2013).

Figure 2. 6. Capital distortions vs Productivity.



Notes: The plots show the relationship between TFPQ, $\log(\mathrm{TFPQ}_{si}/\overline{\mathrm{TFPQ}_s})$ and capital distortions, log (1+ τk). Distributions are weighted using sampling weights. Pane A shows for the aggregate manufacturing sector. Panel B shows a comparison between the formal and informal sector.

2.4.4 Productivity Gains

Given the existence of resource misallocation in the manufacturing sector in Zimbabwe shown above, it is vital to assess potential gains in total factor productivity that can be realised if idiosyncratic distortions are eliminated.[19] To calculate gains, the study compares the actual

[19] Note that the estimates are based on the corrected version for TFPRs presented in Hsieh and Klenow (2013)

level of output to a situation where there are no distortions that is a situation where variation in TFPR is zero. This is calculated as $\left(\frac{TFP_s{}^{efficient}}{TFP_s{}^{actual}} - 1\right)100$. Table 2.4 presents the TFP gains achieved by equalising TFPR across firms for our baseline results, where σ=3. In column 1, we use sampling weights to account for representativeness. The results show that by efficiently allocating resources, aggregate TFP can be boosted by 153.6% for the entire manufacturing sector, based on our weighted baseline results in column (1). The weighted results are slightly higher than the unweighted results in column 2 (121.6%). This justifies the importance of accounting for weights. The results also indicate that elimination of distortions at the firm level in the manufacturing sector would improve productivity by 156.6% in the formal sector and 151.2% in the informal sector, and these results are consistent when compared to unweighted results in column 2.

Table 2. 4. TFP gains from Reallocation of resources: baseline results.

	Total TFP Gains	
	(1) Weighted	**(2) Unweighted**
Aggregate	153.6	121.6
Formal	156.6	125.4
Informal	151.2	120.4

Notes: Entries are $\left(\frac{\mathrm{TFP_s}^{\mathrm{efficient}}}{\mathrm{TFP_s}^{\mathrm{actual}}} - 1\right) * 100$, where $\frac{\mathrm{TFP_s}^{\mathrm{actual}}}{\mathrm{TFP_s}^{\mathrm{efficient}}} = \prod_{s=1}^{S}\left[\sum_{i=1}^{Ms}\left(\frac{A_{si}\overline{\mathrm{TFPR_s}}}{\bar{A}_s \mathrm{TFPR}_{si}}\right)^{\sigma-1}\right]^{\frac{\theta s}{\sigma-1}}$ and $\mathrm{TFPR}_{si} = \frac{P_{si}Y_{si}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$. For weighted results, we have used sampling weights to account for representativeness. The elasticity of substitution σ=3

Our analysis of potential gains has focused on the removal of distortions within the manufacturing industries, separating from between industry productivity gains. Cirera et al. (2017) argued that removing distortions between industries may lead to higher TFP gains. In addition, our analysis has focused on static TFP gains. Efficiency resource allocation in the manufacturing sector may have important implications in the economy through its linkages with other sectors.

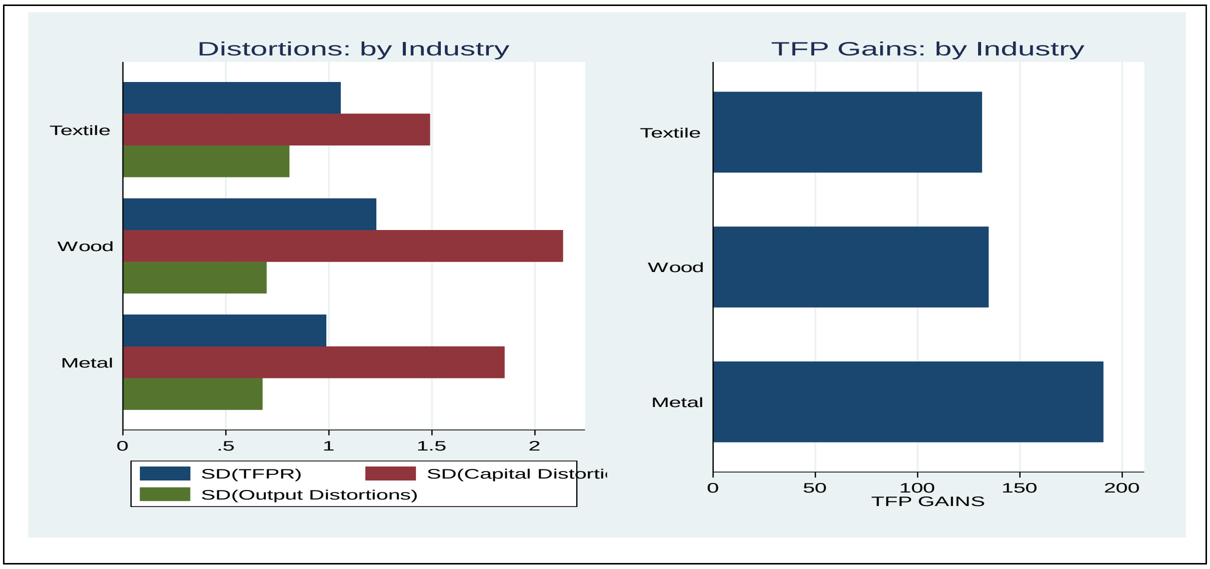
Next, we compare our results with other studies on misallocation that have applied the Hsieh and Klenow (2009) methods in the context of developing countries. First, Cirera et al. (2017) found that TFP gains of 66.6%, 75.7% and 162.6% can be realised in Ethiopia, Ghana, and Kenya respectively if misallocation is corrected, based on the World Bank Enterprise Survey

(WBES) data. Relatedly, using the WBES for developing countries, Fossati et al. (2020) found average TFP gains of 30.1% in Latin American countries and 76.9% for African countries. Interestingly, they found TFP gains of 120.91% for Zimbabwe, which is highly comparable to our results portrayed in Table 2.4. The above-average TFP gains they found suggest a huge presence of misallocation in Zimbabwe. Busso et al. (2013) find reallocation gains between 40% and 122% for developing countries in Latin America. It should be noted that Latin American countries share many similar characteristics with Zimbabwe, for example, high presence of informality and hence provides a good comparison to the Zimbabwean case. Finally, Kalemli-Ozcan and Sorensen (2012), using WBES, found significant levels of capital misallocation for the selected African countries. It should be noted that studies that have incorporated the informal sector are limited literature, hence we cannot compare our informality results.

2.4.5 Industry level of Misallocation

To explore the extent of misallocation, it is useful to look at industry-level results, as aggregate outcomes may conceal significant differences in misallocation across industries. Figure 2.7 shows the dispersion of TFPR, capital distortions and output distortions by the industrial sector. The right panel shows potential TFP gains achieved by the efficient allocation of resources by industry. These results indicate that industry-specific characteristics are linked to misallocation. On average, there is high misallocation in all sectors (metal, textile, and wood). Capital distortions seem to be high in all sectors, but slightly higher in the wood industry. Figure 2.7 shows that TFP gains differ by industry sector. Elimination of distortions can increase TFP by 100 percent in the textile and wood industries, as compared to 150% in the metal sector.

Figure 2. 7. Distortions by Industry



Notes: TFPR, TFPQ, capital distortions and output distortions are deviations from industry averages. Industries are weighted by shares of value-added. Industry TFP gain is calculated as $\left(\frac{\mathrm{TFP_s}^{\mathrm{efficient}}}{\mathrm{TFP_s}^{\mathrm{actual}}} - 1\right) * 100$, where $\frac{\mathrm{TFP_s}^{\mathrm{actual}}}{\mathrm{TFP_s}^{\mathrm{efficient}}}$ corresponds to equation (2.13). Distributions are weighted using sampling weights.

2.4.6 Robustness Check

Following our earlier argument, the HK model succumbs to several caveats. We conclude our analysis in this section by conducting several robustness checks to the above HK results. We first use alternative values of elasticity of substitution. Second, we use an alternative dataset. Third, we use the OP covariance measure as an alternative indicator of misallocation. Lastly, we construct alternative measures of misallocation based on Wu (2018) approach.

2.4.6.1 Alternative elasticity of substitution

As discussed earlier, the values of the elasticity of substitution may affect the TFP gains. We perform a robustness check by setting set the value of σ to 4 and 5 respectively to test the robustness of our baseline results. See the results in Table B2.1 in Appendix for Chapter 2. As expected, the TFP gains increase from 153.6 to 223.6 and 302.8 when we increase the value of σ to 4 and 5 respectively. Other studies in the literature have also found that gains are inflated once one uses higher values of σ (Dias et al., 2016; Ryzhenkov, 2016). Intuitively, when σ is larger, TFP gaps are closed more slowly in response to the reallocation of inputs and in this case, gains are higher (Hsieh and Klenow, 2009). The results are consistently showing a high presence of misallocation in the Zimbabwe manufacturing sector.

2.4.6.2 Alternative Dataset: The World Bank Enterprise Survey (WBES) of 2016

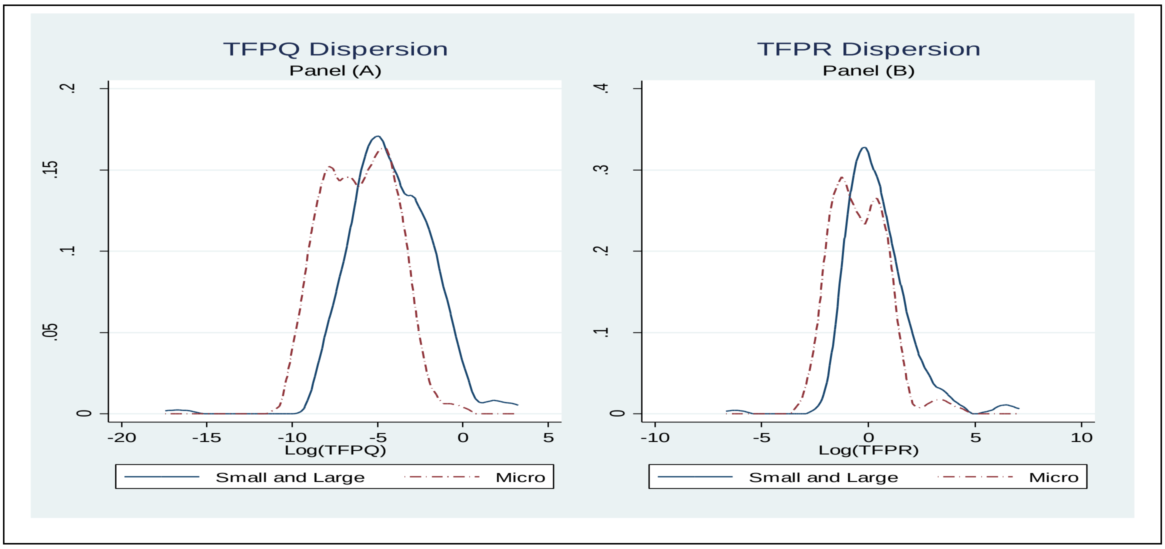
One of the critical issues that arise as a result of the underlying assumptions of the Hsieh & Klenow (2009) method is that the variation of the marginal products of inputs may depict (survey) measurement error rather than misallocation. In this section, we use the World Bank Enterprise Survey (WBES) as an alternative dataset to measure misallocation using the same exercise as in the above sections. One reason to use the WBES is that sampling is enormously difficult in Zimbabwe given the poor firm register. Consequently, the WBES data provides us with an alternative sample of firms to test the sensitivity of our results.

The WBES for Zimbabwe shares several similarities with our Matched Employer-Employee data, especially on the sampling process and coverage. The WBES is a World Bank ongoing project that seeks to collect enterprise-level datasets from several middle and low-income countries since 2002. In Zimbabwe, two rounds of survey have so far been collected, in 2011 and 2016. The 2011 WBES only included firms with more than five employees, but the 2016 Zimbabwe WBES includes micro establishments (those with five or fewer employees).

The major difference between our dataset and the WBES is that in our data we have comprehensive information for both the formal and informal manufacturing sector firms. The WBES only includes detailed information for formal sector firms. For informal firms, the WBES lacks crucial information, such as the value of capital, that is vital for the calculation of TFPR. The WBES also includes the service sector while in our survey we only concentrated on the manufacturing sector. For these reasons, we only use the WBES for the analysis of the large, small and micro firms in the formal manufacturing sector.

We, therefore, compute the indicators of misallocation using the WBES and determine if they pose similar results to those we find above. Figure 2.8 shows the distribution of TFPQ and TFPR for micro, small and large firms. In this figure, micro firms are those with five and fewer employees while small and large firms are those with greater than five workers. Consistent with our results above, the WBES shows the presence of many less productive firms in the manufacturing sector in Zimbabwe as shown in Panel (A). Results in panel (B) also show a dispersion in TFPR which according to Hsieh & Klenow (2009) confirms resource misallocation. However, the dispersion is quite small as compared to the results we found in Figure 2.3 above.

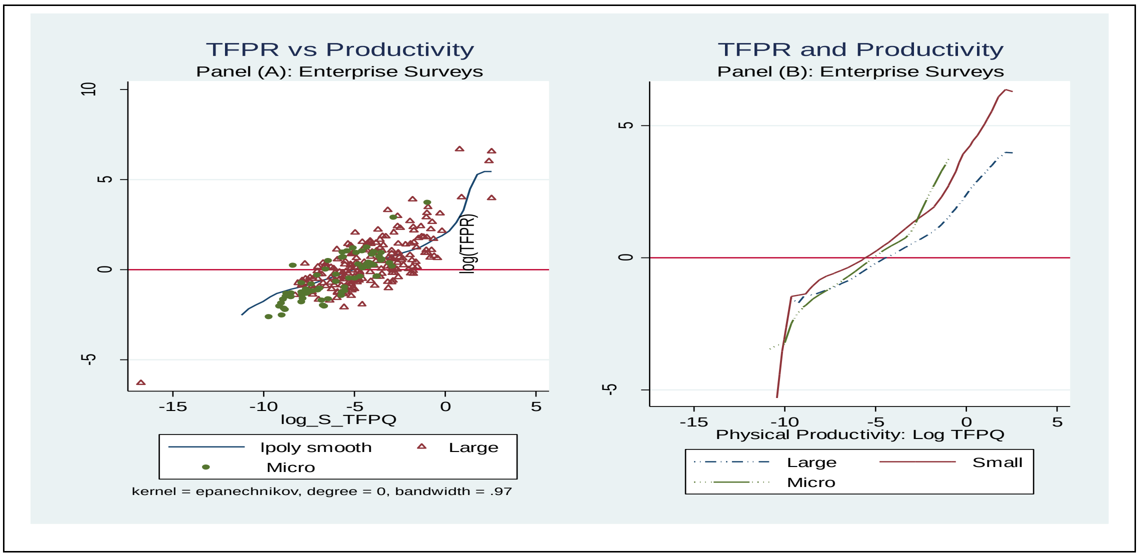
Figure 2. 8. Distribution of TFPQ and TFPR using ES Data 2016



Notes: Distribution constructed using Word Bank Enterprise Survey 2016

Figure 2.9 provides the relationship between misallocation and productivity. The positive correlation between our misallocation measure (TFPR) and productivity in Figure 2.9 provides robust arguments to the conclusion we find in Figure 2.4 above. These results provide evidence of resource misallocation which stifle the growth of more productive firms.

Figure 2. 9. Distortions vs Productivity using the WBES Data 2016



Notes: Distribution constructed using Word Bank Enterprise Survey 2016

2.4.6.3 An alternative measure of misallocation: The OP Covariance

Olley and Pakes (1996) formulated an aggregate productivity decomposition technique to quantitatively measure resource misallocation. They derived the covariance term (OP covariance) that depicts the presence of allocative inefficiency. The covariance term depicts whether high productive firms have more than average market shares as compared to less productive firms. The context of their model is that, within an industry, more productive firms demand more resources and hence grow faster and produce more output. By contrast, less productive firms demand less factors of production and should shrink in size as compared to high productivity firms. If this relationship between productivity and size is not realized, then resource misallocation is confessed.

$$A_t = \sum_{k=1}^{K} \theta_{it} A_{it} = \bar{A}_t + \sum_{k=1}^{K} (\theta_{it} - \bar{\theta}_t)(A_{it} - \bar{A}_t) = \bar{A}_t + \sum_{k=1}^{K} \tilde{\theta}_{it} \tilde{A}_{it}$$

where A is a measure of productivity such as labour productivity or TFP and θ is a measure of firm size, k is used to index firms, a bar over a variable is used to indicate the arithmetic mean of that particular variable and a tilde over a variable represent deviations from the mean value. In the model above, aggregate productivity (which is equal to the weighted average of firm-level productivity, with the firm size used as weights) is decomposed into two components: unweighted mean of firm-level productivities and sample covariance between firm size and productivity. The second component (covariance term) is key as it exhibits the market selection mechanism. In an efficient market system selection only depends on a market-oriented mechanism such as demand and productivity shocks and input cost. In this regard, less productive firms shrink their activities while more productive firms expand. The covariance is, therefore, an ideal tool to measure allocative inefficiencies. Markets and policy distortions constrain the role of market mechanisms and productivity on market selection and hence influence the magnitude and sign of the OP covariance term.

The OP covariance term is zero if all firms have the same relative size or productivity and/or firm size and performance are uncorrelated. The covariance term is positive (negative) if firms with higher-than-average productivity have also a larger (smaller) size than average firm size and firms with below-average productivity have smaller (larger) than average firm size. A positive (negative) OP covariance term, therefore, signifies a positive (negative) relationship between productivity and firm size. A larger covariance term shows that a higher proportion of economic resources goes towards more productive firms, hence higher aggregate productivity.

Although the underlying assumptions of the OP model are different from the HK model, the intuition of the two models are the same; more productive firms within an industry should demand more production resources, produce more output and grow faster. By contrast, less productive firms shrink in size as they demand less resources and produce less output.

Table 2.5 presents the results for sectorial and the industry OP covariance. The results show positive but small values of the OP covariance term. This suggests that economic resources are not flowing to more productive firms, thus indicating misallocation across sectors and industries. These results corroborate with our previous findings using the Hsieh & Klenow (2009) framework. These findings are generally in line with other results in the literature. For example, Masiyandima & Edwards (2018) found small overall OP covariance of -0.047 in Zimbabwe using the 2011 RPED. They also concluded that the misallocation of resources in Zimbabwe has worsened since 1995. In their study, they showed that the OP covariance ranges from -0.047 to 0.237 points in Zimbabwe, Kenya and Ghana. Although Ghana and Kenya have improved in allocative efficiency of resources between 1993 and 2013, Zimbabwe's efficiency is on a declining path.

Table 2. 5. Sectorial and Industry OP Covariance

Sector	**OP Covariance**
Formal Sector	0.238
Informal Sector	0.219
Aggregate	0.224
Industry	**OP Covariance**
Metal	0.294
Textile	0.140
Wood	0.233

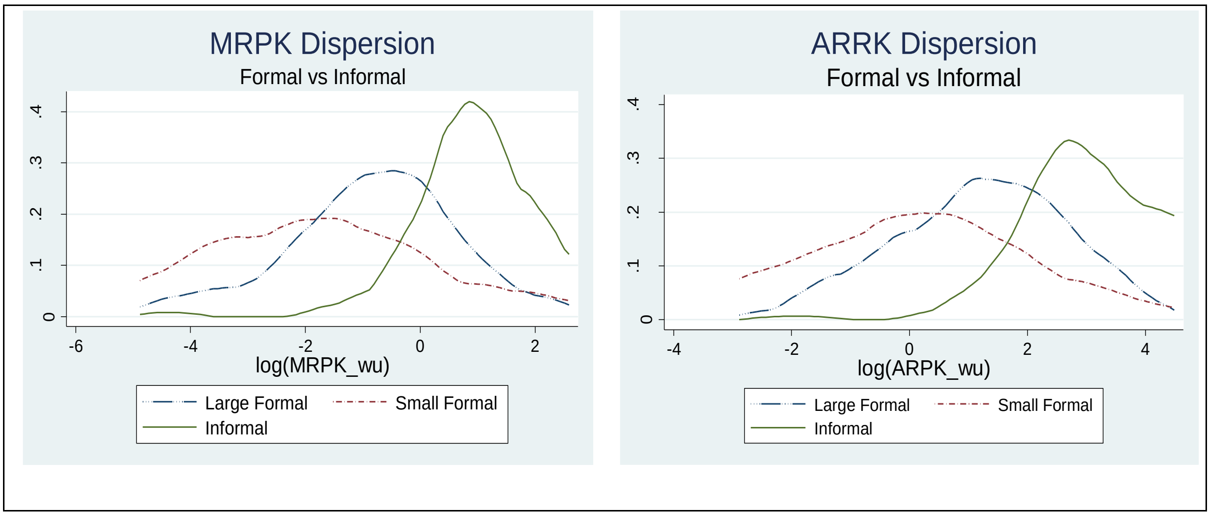
Notes: Results for the covariance between firm size and firm productivity. We use labour productivity (value-added per worker) as a measure for firm productivity. Firm size is measured by the number of employees. For the formal sector, we consider only small-sized firms (with less than 20 employees).

2.4.6.4 An alternative measure of capital misallocation: The Wu (2008) approach.

We further provide some robustness checks to the HK measures by using alternative measures of capital misallocation proposed by Wu (2018). These measures are based on the marginal revenue product of capital ($MRPK_{i,t}$) (constructed differently as above) and average revenue product of capital ($ARPK_{i,t}$). The constructed measures are based on the linear relationship between ARPK and MRPK (refer to Wu (2018) for a detailed approach).[20]

The advantages of using the Wu (2018) measure of MRPK over the HK is that, first, it takes into account heterogeneities in production functions and market power as compared to other measures in literature and it only displays the cost of capital. Second, the measure being a residual has a sample mean and some interesting economic interpretation (Wu, 2018). For example, if $logMRPK_{i,t}$= 0.15 then the MRPK for that particular firm is 15 percent higher than the average MRPK in the economy. Figure 2.10 presents the distribution of the log of $MRPK_{i,t}$ and log of $ARPK_{i,t}$ for the formal and informal sector firms.

Figure 2. 10. The Distribution of Wu (2018) indicators of misallocation: MRPK and ARPK



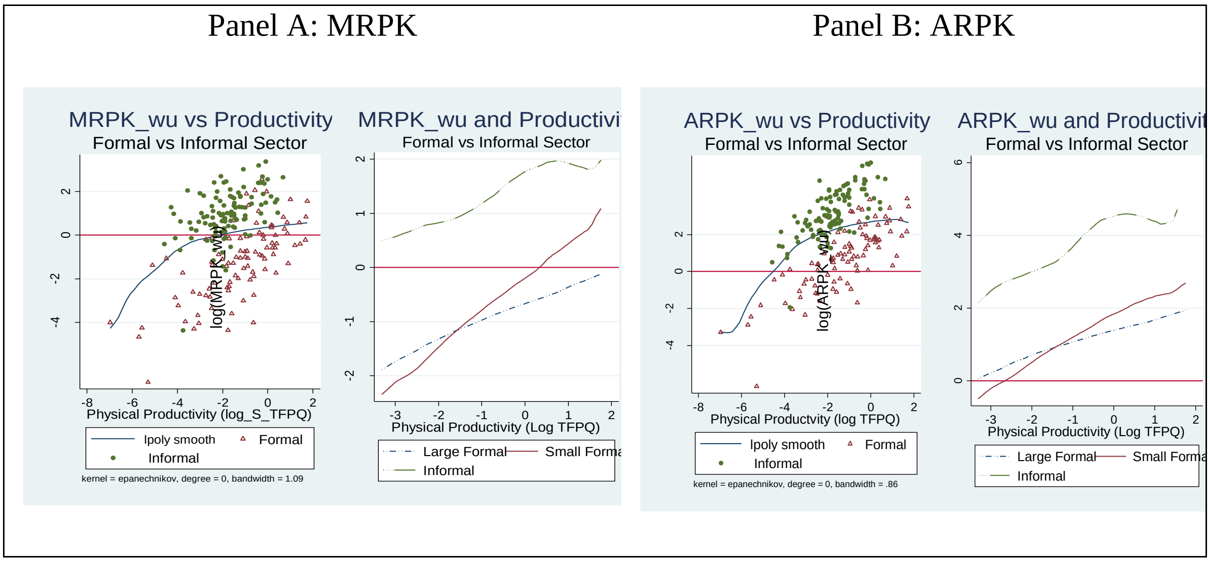
Notes: The left panel plots the distribution of MRPK for the formal and informal manufacturing sector; the right panel plots the distribution of ARPK for the formal and informal manufacturing sector. Distributions are weighted using sampling weights.

The results presented in Figure 2.10 corroborate our previous findings, based on the HK framework, that misallocation is huge in the Zimbabwe manufacturing sector. This is confirmed by the large dispersion of both MRPK and ARPK distributions as shown.

[20] The linear relationship is given by, $MRPK_{i,t} \equiv \frac{\partial R_{i,t}}{\partial K_{i,t}} = \alpha_i(1-\eta_i)\frac{R_{i,t}}{K_{i,t}} \equiv \alpha_i(1-\eta_i)ARPK_{i,t}$, where η and α are the average of the inverse of the demand elasticity and capital-output elasticity respectively. Using the first-order Taylor expansion, Wu derived the approximation of for log $MRPK_{i,t}$ as; $logMRPK_{i,t} \backsimeq logARPK_{i,t} + log\frac{\pi_{i,t}}{R_{i,t}} - \eta_i\frac{R_{i,t}}{\pi_{i,t}}$. They then obtain, the estimate of log $MRPK_{i,t}$ as the residuals from the regression model.

We then assess the link between Wu (2018) indicators of misallocation to firm productivity. The results are presented in Figure 2.11. The results in Figure 2.11 also substantiate our previous findings, first, by a strong positive relationship between indicators of capital misallocation and firm productivity, implying that misallocation acts as a tax that reduces aggregate TFP. Second, the results also confirm that indeed capital misallocation is particularly high for the informal sector firms.

Figure 2. 11. Capital Misallocation and Productivity.



Notes: Panel A provides the correlation between MRPK and productivity. Panel B presents the correlation between ARPK and firm productivity. Firm productivity is constructed based on the HK framework since Wu (2018) did not propose any new measure of firm productivity.

2.5. Conclusion

This study assesses the extent of resource misallocation between and within the formal and informal manufacturing sectors in Zimbabwe. The study applied the widely used Hsieh & Klenow (2009) models to measure resource misallocation using firm-level data for formal and informal sector firms collected in 2015. The key contribution of the study is the inclusion of the informal sector in the resource misallocation analysis. The informal sector in Zimbabwe is huge and contributes significantly towards employment and GDP. We measure misallocation using the dispersion of TFPR, capital distortions and output distortions.

The results show evidence of a large degree of idiosyncratic distortions to both output and factor markets in both the formal and the informal sector in Zimbabwe, as indicated by large dispersion of the measures of misallocation. In both the formal and informal sectors, distortions act as a tax, and their existence constraints the growth of firms especially large and more productive firms. Misallocation is found to be relatively higher in the informal sector than in the formal sector. The study revealed that by efficiently allocating resources, aggregate TFP can boost by about 153.6 percent. Looking at the correlation between productivity and measures of distortions, the chapter shows that, compared to frictionless markets, more productive firms suffer more from distortions relative to less productive firms in both sectors, causing them to produce lower than optimal while less productive produce more than their optimal level resulting in inefficient allocation of resources and thus lower aggregate productivity.

Overall, the findings indicate evidence of misallocation, which suggests the presence of product and factor market frictions inhibiting efficient allocation of resources across firms. Capital distortions are found to be high in the informal sector relative to the formal sector while there is not much difference in output distortions.

The results provide a path to understand the type of obstacles whose correction can boost important productivity gains and increase potential growth. These results entail that the Zimbabwean economy can achieve substantial growth by reducing misallocation in both sectors. Thus, policy measures that focus on eliminating market frictions and distortions can go a long way in reducing misallocation and bolster aggregate TFP in Zimbabwe. Resource misallocation arises due to poor economic policies that prevent the expansion of productive firms and promote the survival of less efficient firms. Eliminating misallocation is a difficult task that needs all policy levers. Structural policies may play a critical role in reducing misallocation.

While this chapter sheds some light on the extent of misallocation, there is a need for future research in this area to look at the dynamic of misallocation between and within the formal and informal sector over time by using panel datasets. Panel datasets would also allow one to consider the effects of misallocation on the extensive margins (exit and entry of firms). Future studies can compare misallocation in Zimbabwe with other regional countries' manufacturing sectors. This will provide more information on the extent of misallocation in emerging countries. To this end, the findings in this chapter point to the importance of misallocation in constraining aggregate TFP. The next chapter focuses on how financial access constraints, as a specific source of misallocation, affect the efficient allocation of resources and give rise to misallocation.

Chapter 3

3. Financial Access Constraints, Misallocation and Aggregate Total Factor Productivity in the Zimbabwean Informal Manufacturing Sector

3.1. Introduction

Financial access constraints severely impede firm performance, particularly within emerging economies. According to World Bank Enterprise data, 25% of firms in all countries identify access to finance as a major constraint to their business operations. The proportion is substantially higher amongst sub-Saharan African firms (39%) compared to East Asia and the Pacific (11.9%).[21] These constraints are one of the salient distortions that may cause allocative inefficiency as a result of capital market failure. Such distortions prevent the optimal allocation of resources across firms leading to lower than otherwise aggregate total factor productivity (TFP) (Hsieh & Klenow, 2009). Therefore, to the extent that financial access constraints affect firms differently, it may give rise to allocative inefficiencies.

There are two mechanisms through which financial access constraints affect firm performance and aggregate total factor productivity (TFP). First is the direct approach that stipulates that lack of financial access restricts investment and hiring decisions of firms, and hence directly reduces firm output and growth. Financial access constraints can, therefore, reduce aggregate productivity by lowering the mean productivity of all firms. This approach has received wide attention in the literature (Campello, Graham & Harvey, 2010; Beck & Demirguc-Kunt, 2006).

What firm-level studies often ignore is an indirect ‘reallocation’ effect of financial access on firm growth and TFP via the allocative efficiency effect. The literature on allocative efficiency shows that aggregate productivity is negatively affected by the variance in factor (and product) market distortions across firms. Rising variance in capital market constraints across firms can thus reduce aggregate productivity through misallocation (see Hsieh & Klenow, 2009).

It is not only the variance in capital markets distortion that matters. Financial access constraints are not independent of firm characteristics – not all firms are equally affected by financial access constraints. In general, larger and more established firms with collateral and established relationships with banks are better able to access finance than smaller new firms (Wu, 2018;

[21] Data sourced from https://www.enterprisesurveys.org/data/exploretopics/finance#2 [Accessed 7 July 2019].

Beck & Demirguc-Kunt, 2006). This unequal access to finance has an ambiguous effect – it can attenuate or exacerbate aggregate TFP losses through misallocation. For example, preferential access to finance for incumbent firms may contribute to resource misallocation and dampen aggregate TFP if these firms are relatively inefficient (Buera & Moll, 2015; Restuccia & Rogerson, 2013; Caballero, Hoshi & Kashyap, 2008; Banerjee & Duflo, 2005). Alternatively, to the extent that more productive firms are better able to overcome financial constraints to access scarce capital, the misallocation effects from the distortion can be ameliorated. Consequently, the correlation between firm characteristics and financial access constraints is a further contributing factor.

The indirect channel is likely to be more relevant to emerging economies than advanced economies given their thin capital markets and distortions. It is, however, surprising that the 'reallocation' effect of financial constraints of aggregate TFP has not received much attention in the literature, particularly for emerging economies. Further, within emerging economies, we would anticipate stronger effects within informal sectors, as they have limited access to formal capital markets (D'Erasmo & Boedo, 2012; Amaral & Quintin, 2006; Beck & Demirguc-Kunt 2006). As shown in the prior chapter, in Zimbabwe at least, constraints to the growth of informal manufacturing firms have relatively large adverse effects on aggregate TFP associated with misallocation. The data shows that the capital distortion faced by informal firms is the major contributory factor towards this outcome.

This chapter uses the informal manufacturing industry in Zimbabwe to analyse the extent to which financial access constraints contribute to misallocation and thus hinder aggregate TFP. In particular, the chapter addresses the following specific questions:

- What is the link between financial constraints and indicators of misallocation amongst informal manufacturing firms?
- Do financial constraints attenuate or exacerbate aggregate TFP losses through misallocation?
- What is the association between financial constraints and changes in employment and capital within firms?

Zimbabwe presents a relevant and interesting case study for the analysis of the effects of financial constraints on aggregate TFP through the misallocation channel. First, the Zimbabwean economy is characterised by a large informal sector that contributes significantly to the country's economic outcomes such as employment and income. It is believed to account for about 60.6 percent of the national economy and about 94.6 percent of national employment (Medina & Schneider, 2018; Zimstats, 2014). Second, Zimbabwe is an economy where lack of financial access is identified by owners and managers as a major constraint to firm operations - 56% of all firms, according to the World Bank (2016). Third, as shown in the previous chapter, the informal sector faces large capital constraints relative to the formal sector, and these constraints are severely detrimental to aggregate TFP. The study can thus provide some insight into the extent to which financial access constraints explain aggregate TFP losses through the capital market distortions. Fourth, we have unique panel data available for the informal sector that allows us to contact this study. Lastly, the results of this chapter are also relevant to other African or emerging economies that have large informal manufacturing sectors.

To analyse the link between firm performance and financial constraints, we use the survey data to present a picture of financial access constraints faced by Zimbabwean informal manufacturing firms. This provides insight into the severity and heterogeneity of these constraints across firms. The implication of financial access constraints on allocative efficiency is studied using two approaches: firstly, regression analysis is used to study the relationship between firm-specific indicators of financial access constraints and misallocation using the Wu (2018) (henceforth -WU) measures of misallocation. In addition to the Wu (2018) measures, we use the Hsieh and Klenow (2009) (henceforth - HK) measures to test for robustness. The advantage of the WU measure is that it considers firm heterogeneity and market power, which the HK measures do not take into account. This allows us to assess the extent to which financial access constraints exacerbate or attenuate the misallocation effects arising from capital market distortions. Secondly, panel data is used to study how initial financial access constraints faced by firms affect subsequent firm growth through aggregate productivity. In this approach, we follow Bartelsman et al. (2017) and estimate productivity-enhancing re-allocation regressions.

This study provides some key contributions and innovations to the growing literature on the effects of financial access constraints on firm growth and aggregate TFP in the presence of misallocation. First, the chapter contributes to the literature by providing objective measures of financial access constraints that are derived from detailed firm-level survey data. Often studies in the literature use subjective measurements of financial access constraints derived from firm balance sheets and income statements (Ferrando & Ruggieri, 2018; Kalemli-Ozcan and Sorensen, 2014; Beck & Demirguc-Kunt, 2006, 2005). Lack of proper measurement and identification of financial access constraints makes it challenging for previous studies to provide reliable quantification of the impact of financial access on misallocation and aggregate TFP. In this study, these constraints are overcome by using a range of indicators regarding access to finance constraints provided by firm owners or managers. Second, the chapter contributes to the literature by incorporating the informal sector, which is shown to large and important in emerging economies.

The rest of the chapter is structured as follows: Section 3.2 presents the overview of theoretical insights and related empirical literature review on financial access constraints and misallocation. Section 3.3 discusses the methodological framework, which includes discussion on the theoretical model, estimation strategy and describes the data. The discussion of the empirical findings is done in section 3.4 and finally, section 3.5 concludes.

3.2. Theory and Empirical Evidence

3.2.1 Theoretical Insights

This chapter is guided by the theoretical models that link the relationship between financial access constraints and total factor productivity (TFP) through misallocation, also known as the 'indirect' channel. Through the 'indirect' channel, financial frictions can influence aggregate TFP through two main mechanisms. The first is the dispersion of the financial frictions across firms. The second is the correlation between financial frictions and firm productivity.

Economic theory suggests that more productive firms should have a greater incentive and be able to attract production inputs (capital and labour) relative to less efficient firms. Thus, over time, less efficient firms are either forced to go out of the business or become more efficient. This process results in resource reallocation that increases aggregate TFP and fosters productivity. However, in the presence of frictions and distortions, this adjustment process may fail to hold. For example, Mortensen & Pissarides (1994) and Hopenhayn & Rogerson (1993) present models where market distortions (such as financial access frictions) hinder effective resource reallocations and sequentially lead to lower firm productivity and aggregate TFP due to misallocation.

Several models have been developed to specifically isolate the channels through which financial frictions cause aggregate TFP loss through misallocation. Wu (2018) develops a model where the aggregate TFP loss from financial constraints is proportional to the variance of the marginal revenue product of capital (MRPK) that is used as a measure of capital misallocation. Wu (2018) argues that in the first-best equilibrium with no market distortions or frictions, MRPK is equalised across firms. Financial frictions and distortions that affect firms differently induce dispersion of MRPK. Specifically, the model predicts that capital misallocation (variance of MRPK) depends on the variance of the distortions, the variance of the financial frictions, the covariance between distortions and financial frictions, and the state of firm productivity. Accordingly, the larger the variance of financial frictions the greater is the impact on misallocation.

Midrigan and Xu (2014) build a model to predict the effects of financial access constraints on aggregate TFP in the presence of misallocation. In the model, they argued that financial frictions reduce aggregate TFP through two channels, first by distorting entry into the modern sector and, secondly, by generating losses from misallocation. The model allows the computation of the size of the aggregate TFP loss that arises due to misallocation on the intensive margins. They show that TFP losses as a result of financial frictions are proportion to the variance of the average product of capital (APK). As such, efficient allocations entail equalisation of marginal (in their case average) product of capital. Dispersion in the average product of capital, therefore, generates TFP losses. The higher the financial frictions, the higher the dispersion of the average product of capital, the higher is the misallocation and the higher is the aggregate TFP loss.

Gilchrist et al., (2013) argue that financial frictions distort resource allocation among productive units. Firms whose financial choice are affected by financial frictions face higher financial access costs than firms with ease of access to capital markets. As such, inputs choice may differ systematically across firms in a way that is not related to firm productivity. As a result, this creates misallocation that causes aggregate TFP loss. In their theoretical model, aggregate TFP loss is an increasing function of the dispersion of capital and labour distortions, as well as the covariance between firm-level productivity and the capital and labour distortions. A high correlation between firm-level productivity and market distortions reduces the aggregate TFP due to resource misallocation. The last point is explained by the fact that the high correlation between capital and labour distortions is associated with increased scale distortions but less variation in input mix across firms. In their model, the efficiency gain from reduced variation in the input mix outweighs the efficiency loss owing to increased variation in firm size. The model predicts a positive association between financial frictions and misallocation and thus leading to aggregate TFP losses.

Restuccia & Rogerson (2008) determine the effects of misallocation on aggregate TFP using a standard neoclassical growth model with heterogeneous firms, such as in Melitz (2003). In their model, they consider firm-specific idiosyncratic distortions that create wedges in prices. They underscore that productivity losses due to misallocation would be huge if distortions are positively correlated with firm productivity. This prediction implies that financial access constraints reduce aggregate productivity if these constraints affect relatively more productivity firms.

In conclusion, this chapter is premised on the theoretical insights provided by these models. Financial constraints inhibit firm productivity and through this aggregate productivity. Economies with high levels of financial constraints are expected to have firms with lower average productivity and thus lower aggregate productivity. This is well established and unambiguous. But financial constraints, because they do not affect all firms equally, can affect aggregate firm TFP through a second channel, namely allocative efficiency. The effect of this channel depends crucially on the *correlation* between financial access constraints and firm productivity. These misallocation effects can either attenuate or exacerbate the aggregate productivity effects arising from the average impact of financial constraints on firm productivity. Testing this is an empirical exercise.

3.2.2 Review of Related Empirical Literature

There are two main strands of literature on the channels through which financial access constraints affect firm productivity and hence aggregate TFP. The first strand focuses on the *direct* effect of financial access constraints on firm investment and employment decisions, and hence directly on firm productivity. This has received much attention in the literature (see Campello et al., 2010; Beck & Demirguc-Kunt, 2006; Clementi & Hopenhayn, 2006).

The second strand, which is the main focus of this chapter, concentrates on the *indirect* or 'reallocation' effect of financial access constraints on aggregate TFP via the misallocation channel (Wu, 2018; Kinghan, Newman & O'Toole, 2018; Restuccia & Rogerson, 2017; Buera & Moll, 2015; Midrigan & Xu, 2014; Chen & Song, 2013). Such literature argues that the extent to which financial access constraints affect aggregate TFP depends on the variance of financial constraints across firms and the correlation between financial access constraints and firm productivity in stimulating misallocation. Empirical studies remain limited on the 'indirect' effect of financial access constraints, particularly for emerging economies, as well as on the informal sector.

Two broad methods have been used to identify the effects of financial access constraints on aggregate TFP via the misallocation channel. First is the use of structural econometric models with simulations (Buera & Moll, 2015; Midrigan and Xu, 2014; Moll, 2014; Gilchrist et al., 2013; Banerjee & Duflo, 2005). Second, is the use of the regression approach, where financial access constraints are regressed on measures of misallocation (Cirera et al., 2017; Kalemli-Ozcan & Sorensen, 2014; Leon-Ledesma & Christopoulos, 2016).

Using Korean plant-level panel data, Midrigan and Xu (2014) estimated calibrated structural models with financial frictions and use them to quantify the impact of and mechanisms through which financial frictions affect aggregate TFP in the presence of misallocation. They find that financial frictions, as measured by collateral constraint, only account for a moderately small impact of between 5 and 10 percent on the TFP losses but find sizeable TFP losses to be due to entry and exit of firms. Thus, their results suggest that financial frictions do not have a compelling effect in exacerbating aggregating TFP losses through the misallocation channel, but rather through the inefficient entry and exit of firms. Gilchirst et al. (2013) follow the same approach but use firm borrowing cost as a measure of financial constraints in U.S manufacturing firms. They find corroborating evidence with a small loss of up to 3.5 percent of aggregate TFP as a result of financial constraints. Similarly, Udry (2012), in his review of the literature, argues that financial frictions do not play a dominant role in affecting misallocation.

Contrary to these results, Wu (2018) develops an identification strategy that unpacks the impact of financial frictions and policy distortions on capital misallocation and aggregate TFP in China using firm-level panel data from the China Annual Industrial Survey. The strategy identifies how the variance of the distortions and the covariance between distortions and firm characteristics can attenuate or exacerbate capital misallocation, which is the subject line of our study. Wu (2018) finds that financial frictions account for about 30 percent of observed capital misallocation in China, which results in up to a 9.4 percent loss in aggregate TFP.

The key advantage of the Wu (2018) approach, and the constructed measure of MRPK, is that it takes into account heterogeneities in production functions and market power as compared to other measures in the literature (such as Hsieh & Klenow, 2009). What is interesting about the Wu (2018) study is that the researcher is able to determine the contribution of the financial access distortions to the aggregate TFP by using propensity score matching (PSM), a semi-parametric technique. The advantage of the PSM method is that it solves some econometric issues (such as selection bias and misspecification) that are associated with the regression approach (Chang and Lee, 2011; Angrist and Kuersteiner, 2011; Campello et al., 2010; Rubin & Thomas, 2000).

Other studies finding large effects include Buera et al. (2011) who apply a structural quantitative model with financial frictions to services and manufacturing in 18 OECD countries. They argue that lack of access to finance impedes poor, but productive entrepreneurs, from entering the market, while enabling rich less productive entrepreneurs to remain operating. On aggregate they estimate that financial frictions result in a 35 percent loss in TFP (90 percent in services, 50 percent in manufactures) amongst the sample of countries, with 25 percent of this loss accounted for by the misallocation channel. Importantly, they find that financial access constraints affect relatively productive firms with a larger scale of operations, thus amplifying the costs of misallocation. Their results confirm the theoretical prediction that financial access distortions contribute to misallocation and aggregate TFP losses if they act as taxes to more efficient firms (see Restuccia & Rogerson, 2008) and if they vary across firms.

Alternative approaches using regression analysis include Kinghan et al. (2018), who estimate the impact of financial access constraints on efficient allocation of capital small and micro enterprises (SMEs) in Vietnam. In particular, they test if firms with higher marginal revenue product of capital (MRPK) have more or less access to finance. They constructed the measure of capital (mis)allocation based on HK MRPK. They test whether financial frictions (as measured by whether a firm is (1) credit constrained, (2) discouraged from borrowing and (3) face credit rationing) restrain capital allocation by hindering employment and investment activities of a firm. In essence, they tested the reallocation effect of financial constraints. They find that firms with high MRPK have the greatest likelihood of being constrained. Further, they reveal that capital misallocation hinders firm investment activities with not much impact on employment. They did not, however, unpack the contribution of financial constraints to aggregate TFP losses.

Empirical Evidence from Africa

Although much empirical literature exists for developed countries, evidence of the link between financial constraints and aggregate TFP is still very scarce in sub-Sahara Africa (SSA). Using the cross-sectional World Bank Enterprise Survey Data for formal firms, Leon-Ledesma & Christopoulos (2016) test the quantitative importance of access to finance on misallocation in 45 developing economies (including some SSA countries). They draw on two measures of financial access constraints: (1) firm self-declared financial access obstacles[22], and (2) the ability for firms to access government and private credit. They construct the measures of misallocation based on the Hsieh & Klenow (2009) framework and use the regression approach to test the significance of access to finance in exacerbating misallocation. In addition, they use the Fields (2002) decomposition technique to depict whether access to finance variables decrease or increase the dispersion of misallocation measures. They show that access to finance constraints increases the dispersion of both the factor market and size distortions. They also show that financial constraints contribute about 21 percent of the total dispersion in capital distortions and about 43 percent of all other observable obstacles, highlighting that financial constraints are important in increasing misallocation. However, similar to Kinghan et al. (2018), they did not show how financial access constraints affect aggregate TFP losses.

Kalemli-Ozcan and Sorensen (2014) use the World Bank Productivity and Investment Climate Survey for formal firms and the HK approach on 10 African countries to determine the role of access to finance on capital misallocation. The results from their study show that financial access constraints (as measured by firms' self-declared financial obstacles) are significant in explaining misallocation. They find that financially constrained firms have a 45 percent higher MRPK than unconstrained firms – a signal that access to finance is a source of capital misallocation. Conditional on access to finance, small firms have lower MPK and they conclude that efficiency gains can be attained if more capital is allocated to productive firms. Benchmarking their results using similar data for some developed countries such as Germany, they find that financial constraints affect misallocation in Africa and not in developed countries. Within Africa, they find heterogeneous effects of financial access on misallocation.

However, according to Banerjee and Moll (2010), differential access to finance may not necessarily prompt serious misallocation if firms with higher MPK invest more than their

[22] Firms were asked 'how much of an obstacle is financial access for the operation of the firm?', with responses; 'no obstacles', 'low obstacles', 'moderate obstacles', and 'high obstacles.

counterparts. This result is quite useful because it emphasises the channel through which access to finance can result in misallocation and aggregate TFP. It is not clear cut if the removal of access to finance constraints will lead directly to aggregate TFP gains. Removal of constraints is likely to have larger effects on aggregate TFP if the relatively productive firms are constrained as a theory of misallocation predicts.

Using comparable firm-level manufacturing census data in three sub-Sahara African countries (Kenya, Ghana, Ivory Coast and Ethiopia), Cirera et al. (2017) explore factors that account for misallocation. Using a similar approach as in Leon-Ledesma and Christopoulos (2016), they examine specific factors that contribute to allocative inefficiency. In their regression model, the determinants of misallocation (measured by (1) TFPR, (2) MRPK, (3) capital distortions and (4) output distortions – derived using the HK approach) include financial frictions (whether a firm has a line of credit or loan, and the interest rate charged), lack of access to electricity, corruption and red tape. Their results show that financial access frictions are more important explanatory factors for misallocation in all three countries than other obstacles. The results of Cirera et al. (2017) corroborate other studies that follow the HK framework in emerging countries (e.g. Leon-Ledesma & Christopoulos, 2016 and Kalemli-Ozcan & Sorensen, 2014).

In conclusion, while the empirical literature provides some important insights, it shows that the link between financial access constraints, misallocation and aggregate TFP is far from settled. First, while all studies acknowledge that financial frictions could explain part of the aggregate TFP losses, findings are not homogeneous with regard to the magnitude of the impact and the mechanism behind it. Further, the impact of financial constraints on misallocation and aggregate TFP differs across countries, industries and firms. In some cases, removal of financial access constraints exacerbates misallocation, especially in cases where inefficient firms are granted easy access to finance, thereby crowding out more efficient firms (Restuccia & Rogerson, 2017).

Second, one of the contentious issues in the literature is the measurement of financial constraints. Several studies have derived the measure of the extent to which a firm is financially constrained using firm balance sheet and income statement (Ferrando & Ruggieri, 2018; Moll, 2014; Midrigan & Xu, 2014; Buera, Kaboski & Shin, 2011). However, whether a firm is financially constrained is often not directly observed from business-level data. Authors of such studies often resort to collateral borrowing (constructed by utilising the debt-to-asset ratio) and firm characteristics (such as size and age) as a proxy to measure the likelihood of a firm being financially constraint. These proxy variables may fail to assert the true extent to which a firm is constrained (Abel & Eberly, 2011; Alti, 2003; Cooper & Ejarque, 2003; Kaplan & Zingales, 1997). Access to firm-level dataset has allowed researchers to construct more objective measures of financial constraints based on survey information (Kinghan et al., 2018; Leon-Ledesma & Christopoulos, 2016).

Third, a variety of methods have been used to test the impact of financial access constraints on misallocation and the associated TFP losses. Some researchers have used structural models with simulations (e.g., Midrigan & Xu, 2014; Gilchrist et al., 2013; Buera et al., 2011). Others have used the regression approach (Cirera et al., 2017; Leon-Ledesma & Christopoulos, 2016). Thus, it is difficult to compare results across studies. Even amongst studies that have used the structural model approach, differences in model assumptions and parameterisation make comparisons difficult.

Fourth, much of the empirical literature focuses on advanced economies. Evidence of the link between financial constraints and aggregate TFP via the misallocation channel is still very scarce in sub-Sahara Africa (SSA). Such studies have been constrained by the availability of plausible datasets.

Fifth and last, according to our knowledge, no studies have been done for the informal sector despite the abundant presence of the informal sector in most emerging economies. Such studies have been constrained by the unavailability of firm-level panel datasets for informal sector firms. The informal sector firms have been argued to be more financially constrained than the formal sector counterparts (Amaral & Quintin, 2006; Beck & Demirguc-Kunt, 2006). Thus, the gains to aggregate TFP from alleviating financial constraints to these firms could be potentially large, particularly if, as is found in Zimbabwe, these are relatively constrained firms.

3.3. Theoretical Framework and Estimation Strategy

3.3.1 The Theoretical Model

This section presents the theoretical model showing how financial constraints cause misallocation and reduce aggregate TFP. The theoretical model is motivated by the Wu (2018) framework that captures how capital market distortions, plus firm-specific financial frictions and policy distortions, affect a firm's optimal choice of capital giving rise to misallocation of capital across firms.

The model presents a scenario where a firm desire to purchase capital (K_i) (as part of its investment maximising strategy) but lacks sufficient internal funds (W_i) to fund it. Therefore, it is required to access finance ($K_i - W_i$) externally. The problem is that there are both specific financial frictions (associated with firm characteristics that influence the cost of borrowing) and policy distortions that also affect the cost of borrowing. It is the joint distribution of these factors that ultimately affect the cost of capital.

In the model, the degree to which a firm is financially constrained is measured by the firm-specific cost parameter θ_i. The parameter θ_i depends on firm characteristics. For example, young and smaller firms without credit histories are expected to have larger θ_i as they pay higher costs in accessing finance. It also depends on the extent of policy distortions affecting a firm – governments for example may offer cheaper finance to state-owned enterprises. Hence the cost of accessing finance by firm *i* can be denoted as $\theta_i = \theta(\theta_i^f, \theta_i^p)$, where θ_i^f and θ_i^p represents firm-specific financial frictions and policy distortions respectively in determining the cost of accessing finance.

To quantify the overall effect of financial frictions on capital misallocation and aggregate TFP, Wu (2018) uses a cost-constrained model and a quantity constrained model.

Cost Constrained model

The external financing cost model entails the following capital investment optimisation problem that maximises gross profits, (Z_i, K_i) .

$$\max_{K_i} V_i = \pi(Z_i, K_i) - (1 + \tau_i)K_i - \theta_i \Lambda(K_i, W_i) \qquad (3.0)$$

where K_i is capital stock, Z_i is a stochastic investment opportunity represented by the state of firm productivity, W_i is the amount of internal funds available for investment, $(1 + \tau_i)$ is the price of capital normalised to 1 with τ_i measuring the firm-specific rate of investment tax credit [23]. $\theta_i \Lambda(K_i, W_i)$ is a function for the cost of accessing finance.

By maximising equation 3.0, the first-order condition for optimal capital investment that maximises gross profit is given by,

$$\pi_K(Z_i, K_i) = (1 + \tau_i) + \theta_i \lambda(K_i, W_i) \qquad (3.1)$$

[23] If $\tau_i < 0$ a firm *i* enjoys a subsidy for its investment expenditure and if $\tau_i > 0$ then a firm suffers a tax on its investment expenditure.

where $\theta_i\lambda(K_i, W_i) \equiv \theta_i\Lambda_K(K_i, W_i) > 0$ is the marginal costs of external financing, with $\lambda_K > 0$ and $\lambda_W < 0$. Equation 3.1 implies that the optimal capital depends on the firm-specific price of capital, $(1 + \tau_i)$, and the marginal cost of accessing external finance, $\theta_i\lambda(K_i, W_i)$. A high value of $\theta_i\lambda(K_i, W_i)$ reduces the optimal capital investment. Firms choose capital such that MRPK equals the general cost of capital, which as per equation (3.1) is influenced by distortions $(1 + \tau_i)$ and the cost of accessing finance. Firms that face implicit taxes on capital (τ_i) plus high costs in accessing finance will have lower levels of capital and, consequently, higher MRPK.

Quantity Constraint Model

In the quantity-constrained model, firms seek to raise finance in the capital markets but the amount they can raise is limited to a certain point. The maximisation problem of the firm is given by,

$\max_{K_i} V_i = \pi(Z_i, K_i) - (1 + \tau_i)K_i$ subject to the quantity constraint,

$K_i - W_i \leq (1 - \phi_i)K_i$

where ϕ_i is a firm-specific constraint parameter that measures the extent of restrictions on how much a firm can raise $K_i - W_i$ finance externally, where $0 \leq \phi_i \leq 1$. If ϕ_i=1 then a firm faces credit rationing. According to Wu (2018), the first-order condition for the optimal capital investment is given by,

$$\pi_K(Z_i, K_i) = (1 + \tau_i)K_i + \phi_i\mu(Z_i, W_i) \quad (3.2)$$

The micro-foundations of the quantity constrained model entails that the firm-specific constraint parameter ϕ_i depends on the volatility of the firm's revenue and pledgeability of firm's assets. ϕ_i also depends on policy distortions, for example, firms that face negative policy distortions are expected to have higher ϕ_i. As thus, $\phi_i = \phi(\phi_i^f, \phi_i^p)$, where ϕ_i^f and ϕ_i^p presents firm-specific factors operating through financial frictions and policy distortions in explaining the quantity encountering firm *i*.

Both the cost-constrained and the quantity constrained models are relevant in the context of Zimbabwe, particularly the informal sector. For example, based on the quantity constrained model, often that the informal sector has limited pledgeability of their assets, thus constrained from securing formal sources of finance. In the same vein, high interest rates and other cost-related factors have increased the cost of accessing external finance and deter many informal sector players from accessing the much need capital (Fafchamps, 199).

Financial Frictions, Misallocation and aggregate TFP

To deduce the mechanism through which financial frictions are the sources of misallocation, Wu (2018) rewrites equation (3.1) and (3.2) respectively as,

$$MRPK_i \equiv \pi_K(Z_i, K_i) = (1+\tau_i) + \theta_i \lambda(K_i, W_i) \qquad (3.3a)$$

$$MRPK_i \equiv \pi_K(Z_i, K_i) = (1+\tau_i) + \phi_i \mu(Z_i, W_i) \qquad (3.3b)$$

The left-hand side of the equation (3.3a) and (3.3b) depicts the firm MRPK. Hence different forms of financial constraints (whether cost or quantity constraint) have similar repercussions on misallocation. A firm's optimal choice of capital stock is set by the equality of its MRPK with its generalised cost of capital. The cost of capital, in turn, depends on policy distortions $(\tau_i, \theta_i^p, \phi_i^p)$ and financial frictions (θ_i^f, ϕ_i^f) encountering the firm, productivity and internal funds (Z_i, W_i).

In an efficient economic system with no frictions or distortions, that is in first-best equilibrium, $\tau_i = \theta_i = \phi_i = 0$ and MRPK=1, given the normalised capital goods prices. Hence optimal capital stock assures that MRPK is the same across all firms. On the other hand, in the presence of financial frictions and policy distortions, Wu(2018) argues that the actual allocation is influenced by firm-specific user cost of capital which depends on the joint distribution $G(\tau_i, \theta_i^p, \phi_i^p, \theta_i^f, \phi_i^f, Z_i, W_i)$.

Wu (2018) shows that aggregate TFP loss can be approximated as proportional to the variance of the logarithm of the $MRPK_i$ which is the function of G, as follows:

$$\Delta logTFP = \frac{1}{2}\frac{\alpha(1-\eta)(1-(1-\alpha)(1-\eta))}{\eta} Var(logMRPK_i) \qquad (3.4)$$

where η and α are the average of the inverse of the demand elasticity and capital-output elasticity respectively.

Using this model, we can link how distortions or frictions can lead to dispersion in the MRPK and thus attenuate or exacerbate aggregate TFP losses. If we take equation 3.3b, for instance, the $Var(MRPK_i)$ is given by,

$$Var(MRPK_i) = Var(1+\tau_i) + var(\phi_i \mu(Z_i, W_i)) + 2cov(1+\tau_i, \phi_i \mu(Z_i, W_i)) \qquad (3.5)$$

Accordingly, the dispersion of MRPK, and thus aggregate TFP losses, depends on the variation in the generalised cost of capital across firms, which, in turn, depends on the variation and covariance of policy distortions, financial frictions encountering by the firm. These, in turn, are influenced by firms' productivity and the availability of internal funds (Z_i, W_i).

If financial constraints correlate with firm productivity, then aggregate TFP losses will be amplified through misallocation in a similar way as hypothesised by Restuccia and Rogerson (2008). The argument is that if high productive firms are those with high $\phi_i\mu(Z_i, W_i$, given, for example, government policy constraints (e.g., biasing policies towards inefficient state-owned enterprises), or bank selection by only giving credit to large inefficient firms or to firms that are part of a network, then the TFP losses will be amplified.

It is the combination of variation and covariance in distortions in the price of capital (τ_i) plus distortions in the cost of finance that drive variation in $MRPK_i$. In particular, high variance in both these elements reduces the efficient allocation of capital. But if the price of capital is positively correlated with the cost of finance, then the variation in MRPK, and hence aggregate TFP loss is heightened.

It is important to note that this Wu (2018) model can also replicate that of Restuccia and Rogerson (2008). If the cost of accessing finance, through firm characteristics and/or policy distortions, is relatively high for efficient firms, then we find similar results to Restuccia and Rogerson (2008). For instance, in the context of Zimbabwe, credit by banks or other institutions is offered on the basis of networkers rather than firm productivity or performance (Fafchamps, 1997; Fafchamps, Pender & Robinson, 1995). Government policy can distort the efficiency of capital markets, for example, by providing cheap finance or access to foreign currency to purchase capital to government-related firms that may not be efficient. The overall effect would be misallocation as a result of constrained access to finance by more productive firms and thus reduces aggregate TFP.

To this end, the theoretical model presented above provides three important pillars on which to base our hypothesis. First, the model links aggregate TFP loss to the variance in firm-specific distortions. The higher the variance across firms, the greater the aggregate loss in TFP. This outcome is similar to that of Hsieh and Klenow (2009). Second, aggregate TFP loss is higher if the variation in the marginal cost of external finance (which is a function of firm financial frictions and policy distortions) is high. Third, aggregate TFP losses can be amplified if there exists a covariance between distortions and the marginal cost of external finance (which directly depends on firm TFP as shown in equations 3.3b).

The model, therefore, predicts a positive link between misallocation and financial distortions and large aggregate TFP losses if distortions are positively correlated with firm productivity. As such, we derive the following testable hypothesis.

H1: There is a positive relationship between misallocation (MRPK) and financial constraints.

H2: Financial constraints amplify or attenuate aggregate TFP losses through their correlation with firm productivity.

H3: Financial access constraints increases the cost of capital and negatively affects productivity reallocations of firm investment opportunities.

3.3.2 Estimation Strategy

Based on the above theoretical framework linking financial frictions to aggregate TFP loss in the presence of misallocation, the empirical analysis approaches the research question in two parts: First, we test the association between financial access constraints and misallocation using the regression approach. The second part tests for the channel through which financial access constraints may affect productivity losses using the Bartelsman et al. (2017) regression approach. We first start by discussing how Wu (2018) estimated the measures of misallocation empirically.

Measuring Misallocation: Wu (2018) Approach

Wu (2018) constructed a measure of capital misallocation ($MRPK_{i,t}$) based on firm $ARPK_{i,t}$. The constructed the measure based on the linear relationship between ARPK and MRPK as presented in equation (6) below.

$$MRPK_{i,t} \equiv \frac{\partial R_{i,t}}{\partial K_{i,t}} = \alpha_i(1-\eta_i)\frac{R_{i,t}}{K_{i,t}} \equiv \alpha_i(1-\eta_i)ARPK_{i,t} \qquad (6)$$

They argued that although ARPK has been used to infer misallocation in literature it is a biased measure in the presence of unobserved heterogeneity and argued that MRPK is a sufficient measure of capital misallocation. Wu (2018) attested that ARPK can only be a valid proxy for MRPK if $\alpha_i(1-\eta_i)$ in equation (6) is similar across firms and this may not hold in cases where other firms have market power due to product distortions or frictions or where firms differ in terms of capital intensiveness due to frictions or distortions in technology adoption. Using the first-order Taylor expansion, Wu derived the approximation of for log $MRPK_{i,t}$ as;

$$logMRPK_{i,t} \backsimeq logARPK_{i,t} + log\frac{\pi_{i,t}}{R_{i,t}} - \eta_i \frac{R_{i,t}}{\pi_{i,t}} \quad (7)$$

Compared to ARPK, this measure of MRPK is not contaminated with frictions or distortions highlighted earlier. They then obtain, the estimate of log $MRPK_{i,t}$ as the residuals from the regression model in equation (8).

$$logARPK_{i,t} = \beta_0 + \beta_1 log\frac{\pi_{i,t}}{R_{i,t}} + \beta_2 \frac{R_{i,t}}{\pi_{i,t}} + \beta_3 industry_{i,t} + \beta_4 location_{i,t} + \zeta_{i,t} \quad (8)$$

Where $logARPK_{i,t}$, is the log of revenue-capital ratio, $log\frac{\pi_{i,t}}{R_{i,t}}$ is the log of profit-to-revenue ratio, $\frac{R_{i,t}}{\pi_{i,t}}$ is a revenue-to-profit ratio, and $industry_{i,t}$ and $location_{i,t}$ are dummies for firm industry and location respectively.

The advantages of this measure of MRPK are that: It takes into account heterogeneities in production functions and market power as compared to other measures in literature and it only displays the cost of capital. In addition, this measure being a residual it has a sample mean and some interesting economic interpretation (Wu, 2018). For example, if $logMRPK_{i,t}$= 0.15 then the MRPK for that particular firm is 15 percent higher than the average MPRK in the economy. The weakness of this measure as illustrated by Wu (2018) emanates from misspecification. Hence ARPK will be more usefully measure if the misspecification problem is higher than the heterogeneity problem.

Understanding the link between financial access constraints and misallocation

The first part of the empirical analysis tests the effect of financial access constraints on measures of misallocation derived using the Wu (2018) measures of capital misallocation (MRPK and average revenue product of capital (ARPK) discussed above. We further use the Hsieh and Klenow (2009) measures of misallocation discussed in the preceding chapter to provide robustness. We test the hypothesis that there is a positive relationship between misallocation and financial constraints. To achieve this, the study utilises the panel dimension of the data and regresses the measures of misallocation on initial financial access constraints, initial firm TFP and the interaction between the two and a set of firm characteristics controls. The model is specified in equation (3.6). i

$$lnD_{ist} = \beta_0 + \beta_1 FA_{ist_0} + \beta_2 TFP_{ist_0} + \beta_3 FA_{ist_0} \times TFP_{ist_0} + X_{ist_0}{}'\gamma + \varepsilon_{ist} \quad (3.6)$$

where $ln\mathrm{D}_{ist}$ represents the log of measures of misallocation, MRPK and ARPK (based on Wu (2018). FA is the measure of financial access constraint, X_{is} a vector of firm characteristics which) includes firms size (measured by the number of employees), firm age, firm industry and location, ε_{is} is the white noise error term. The coefficient of interest is β_1 , β_2 and β_3.

Following Leon-Ledesma (2016), a positive sign on the coefficient of financial access variable, β_1, stipulates that the presence of financial constraints results in increasing MRPK or ARPK. This implies that financial constraint acts as a tax on capital relative to labour. On the other hand, a negative coefficient is interpreted as lowering MRPK such that output distortions are relatively high compared to capital distortions, that is, a firm uses more labour relative to capital than optimal. In an efficiently operating system with no distortions, the coefficient on financial access constraints should be insignificant. Thus, a significant β_1 shows that financial access constraints are a source of misallocation.

If misallocation is high for more productive firms, we expect $\beta_2 > 0$. Restuccia & Rogerson (2008) argued that misallocation is costly if there is a positive correlation between firm productivity and misallocation. Bartelsman et al. (2013) also echoed the same sentiments, highlighting that distortions are costly to aggregate TFP if the presence of distortions reduces the firm's productivity. If financial access constraints are affecting more productive firms, we expect $\beta_3 > 0$, thus exacerbating aggregate TFP losses.

Channels through which financial constraints may exacerbate productivity loss.

The second part of the empirical analysis focuses on exploring the channels through which financial constraints reduce firm productivity. We do this by estimating the productivity-enhancing reallocation of resources (labour and capital) model. To achieve this, the study estimates whether changes in employment and investment are influenced by initial financial access constraints faced by firms. We follow the approach by Bartelsman et al. (2017) and estimate the model,

$$\Delta Y_{ist} = \alpha + \beta TFP_{ist_0} + \gamma' FA_{ist_0} + \delta TFP_{ist_0} \times FA_{ist_0} + \rho X_{ist_0} + \upsilon_{ist} \qquad (3.7)$$

where ΔY_{ist} is the average growth rate in employment, or investment in firm i, in industry s at time t. TFP is firm-level (log) total factor productivity at time t_0 relative to industry mean, FA is a measure of financial access constraint at time t_0. The coefficients of interest are β, γ and

δ. The coefficient β determines if productivity-enhanced growth is achieved in the informal sector. A positive coefficient, β, implies that more productive firms are associated with higher growth rates, hence factor reallocation is productivity-enhancing. The coefficient γ shows the association between financial constraints and firm growth and it is expected to be negative. The coefficient, δ, of the interaction term between initial TFP with the measures of financial access constraints signifies the extent to which financial access frictions are constraining the growth of high-productivity firms. In other words, it indicates the impact of financial constraints in restraining productivity enhanced growth, that is the extent to which financial constraints impede (or promote) productivity-enhancing reallocation.

One criticism of using a firm level-based measure of financial access constraints is that they are endogenous to firm activities and may also be endogenous to variation in firm investment opportunities (Duchin, Ozbas & Sensoy, 2010). We use the initial measures of financial constraints and firm TFP and subsequent waves to take into account some of the endogeneity concerns associated with including level values of financial constraints and TFP in the estimation.

The below paragraphs explain how the dependent variables (employment growth and capital growth) were constructed. These variables have been borrowed from theory and empirical literature and can be constructed from the available data. Following Davis & Haltiwanger (1992) and Davis et al. (1996) models, employment growth, g_{ist} at a firm-level between time t and t-n is given by equation (3.8).

$$\boldsymbol{g_{ist}} = \frac{\Delta X_{ist}}{m_{ist}} = \frac{X_{ist}-X_{ist-1}}{0.5(X_{ist}+X_{ist-1})} \qquad (3.8)$$

where X_{ist} is the number of workers in firm *i*, in industry *s* at time *t*, m_{ist} is the average firm size between time *t* and *t-n*. The employment growth in equation (3.8) is computed by dividing the change in employment by average firm size between period *t* and *t-n*. This measure of growth rate has become the standard measure in the analysis of firm dynamics (Foster et al., 2016). Note that we use the average firm size rather than the initial firm size, as is usually done. Using the average firm size has several advantages. The key advantage is that it reduces measurement errors that are associated with transitory high or low initial and ultimate firm's sizes that may induce overestimation of growing small firms. [24] In this study, growth is considered from *t-2* and *t-1* for firms initially interviewed in 2015 and 2017 respectively.

We derive our measure of capital growth (investment) based on the questionnaire of whether firms purchased equipment or machinery, and if so, how much. However, one of the challenges in estimating investment models especially for informal sector firms is the considerable number of zero values of investment. This is because many informal sector firms invest on a lumpy and infrequent basis. Given this concern, a poisson estimator may be better than if the level of investment is used. We, therefore, generate a binary indicator for investment as,

$$\boldsymbol{I} = \begin{cases} \mathbf{1}\ \boldsymbol{if}\ \boldsymbol{I}^* > \mathbf{0} \\ \mathbf{0}\ \boldsymbol{if}\ \boldsymbol{I}^* \leq \mathbf{0} \end{cases} \qquad (3.9)$$

The variable I takes a value of 1 if the firm purchased equipment and machinery ($I^* > 0$) and zero if no purchases were made. This variable has been coded this way because for some firms the value of the investment is zero. This implies that the regression model for investment on financial obstacles and lagged TFP is a discrete probability model and the probit model is used. Testing the effects of financial constraints on investment, as in the case of employment growth outline above, is subject to concerns about endogeneity. In our case, we have an additional problem that both the independent variable of our interest and the dependent variable is binary. The standard approach suggested in the literature to deal with this issue is to use the bivariate probit model (Gerlach-Kristen, O'Connell & O'Toole, 2015; Nichols, 2011; Chiburis, Das & Lokshin, 2011).

3.3.3 Data and Measuring of Key Variables

This chapter exploits the informal sector firms' panel dataset collected between 2015 and 2018, as part of this thesis, and the "Matched Employee-Employer Panel Data for Labour Market Analysis in Zimbabwe" project. More details of the data are presented in the Appendix for Chapter 1.

The data consists of three panels of data for firms that were initially interviewed in 2015, two panels of data for firms that were initially interviewed in 2017, and one wave of the dataset for firms that were initially interviewed in 2018. The first wave of the data that was collected in

[24] Note that we use the average firm size rather the initial firm size, as is usually done. Using the average firm size has several advantages. The key advantage is that it reduces measurement errors that are associated with transitory high or low initial and ultimate firm's sizes that may induce overestimation of growing small firms.

2015 consists of 130 firms. In a follow-up survey done in 2016 out of 130 firms interviewed in 2015, 99 firms were successfully re-interviewed. In 2017, a new dataset was collected consisting of 74 new manufacturing informal sector firms. In 2018, we re-interviewed firms that were initially surveyed in 2015 and managed to successfully re-interview 108 firms. Re-interviews were also done with firms that were initially interviewed in 2017, and 68 firms out of 74 firms were successfully contacted. The follow-up interviews were conducted using telephones rather than face-to-face. The data consists of firms drawn from three key manufacturing industries in the informal sector: namely the Metal, Textile and Wood industries. The data was collected from two major urban cities in Zimbabwe, namely Harare and Bulawayo.

The panel data on the informal sector firms used in this paper is unique, and to our knowledge, it is the first of its kind regarding the informal manufacturing sector in Zimbabwe. The data consists of key variables that allow us to explore the study research questions. The data include information on production costs, sales, employment, capital and investment, obstacles affecting firm growth among other key variables. The data is recent, and one advantage is that we are able to determine the dynamics of the informal sector in terms of financial frictions, firm performance and misallocation. The data contains a rich set of information on financial access. This is a major advantage of this study over others in the literature.

Notwithstanding the strength of our dataset, it is necessary to mention its weaknesses. First, the data only contains continuing firms, thus we are not able to determine the link between financial constraints and indicators of misallocation due to entry or exit of firms, commonly known in the literature as the selection channel. Second is the issue of attrition[25] in the data. The major reasons for attrition were that some respondents' phones were unreachable, while some phones went unanswered even after several attempts during re-interviews. Some respondents refused to take part in the surveys. We have shown, however, that attrition is not a major concern in this study as the non-response firms are not significantly and systematically different from firms that responded (see Table C3.0 in Appendix for Chapter 3). Third, the data does not include previous values of some key variables for the base surveys' periods (2015 and 2017). Lastly, our sample size is small relative to other studies in the literature. This is because

[25] The problem with attrition is that it may bias the analysis and the results of the study, especially when the respondents that were not contacted are systematically different from those successfully surveyed. The assumption is that those we fail to contact may be the one that has exited operations ideally because were less productive than those firms we were able to contact.

we have used survey data; the small sample size to some extent reflects the low number of informal manufacturing firms[26] (see Table A2b in the Appendix for Chapter 1 for detailed sample frame and the actual sample size). We acknowledge that the small sample size may affect the precision of our estimates. However, our data is representative of the manufacturing sector in Harare and Bulawayo, and being representative implies that the small sample may have little effect on the precision of our estimates.

Measurement of Key Explanatory Variables

This study is interested in exploring how financial access constraints affect firm performance through misallocation. As such, our key variables are a measure of financial access constraints, firm-level productivity, firm size and firm age. These variables are borrowed from theory and empirical literature).

Financial Access Constraint

A firm is financially constrained if it demands but unable to secure finance (formal or informal) due to market constraints defined in Table 3.4. Our financial access constraints measure covers access to both formal and informal finance (from the interviews we know that formal firms also access finance through informal channels, e.g., family networks) and is thus not restricted to just formal financial sector financing. Usually, informal firms are constrained to access formal finance due to the limited pledgeability of their assets. Our measures of financial access constraints consist of both subjective and objective measures. We provide standard definitions of objective and subjective measures as borrowed from literature (Kinghan et al.,2018; Ayyagari, Demirguc-Kunt & Maksimovic, 2008; Beck & Demirguc-Kunt, 2006). The subjective measure is obtained from the respondents stating whether or not financial access constraints are one of the three major obstacles affecting their growth of businesses. This variable is coded 1 if a firm states financial access constraint as one of the three major obstacles affecting firm performance and 0 otherwise.

The subjective measures can offer useful insights into the business environment. However, they have some limitations. The first limitation is that they are based on firm owner perception about the business environment and could reflect pessimism or optimism of the respondent

[26] Table A2b in the Appendix shows that in Harare we surveyed about 16% of the firms while in Bulawayo we interviewed about 23% of the firms. The sample frame also shows that the total number of firms is relatively small.

(Aterido, Hallward-Driemeier & Pagés, 2011; Ayyagari, Demirguc-Kunt & Maksimovic, 2008; Beck & Demirguc-Kunt, 2006). Secondly, self-reported responses are likely to be influenced by firm performance and experience, and hence may be endogenous.

Therefore, we construct objective measures of financial access constraints from the information on financing and investment activities of the firm collected on the questionnaire. Table 3.1 below summarizes how the objective measures were constructed from the available data[27]. These different measures are correlated to each other (see Table C3.1 in the Appendix for Chapter 3).

Table 3. 1. Indicators of Financial Access Constraints

Indicator	Definition
Objective Measures	
Fin_Acess1: Credit rationed /Discouraged Borrowers	Variable = 1 if the firm has been rejected for a loan and 0 otherwise Variable = 1 if the firm did not apply for a loan due to a) possible rejection, b) the process was too difficult or c) the interest rates were too high and 0 otherwise
Fin_Access2: Cannot obtain Credit Purchases	Variable = 1 if firms do not purchase raw materials on credit and do not owe suppliers and 0 otherwise
Subjective Measure	
Fin_Access3	Variable = 1 if firm mentioned lack of finance as of the three major constraints affecting the growth of business and 0 otherwise
Fin_Access4	Variable = 1 if firm mentioned that it has problems in sourcing finance and 0 otherwise

Notes: Measures of financial access constraints derived from the questionnaire information.

Firm productivity

The productivity variables are constructed from information on output, employment, capital and raw materials. The output is measured as value-added. Value added is computed as the difference between sales and cost of raw materials, overhead expenses, and energy costs (electricity, fuel, gas). Capital is measured by netbook and market value of fixed assets, summed across vehicles, machinery and equipment, and land and buildings. Raw materials

[27] We acknowledge that while our definitions are standard from the literature, one might argue the objectivity of these measures. For example, how the firm assesses the possibility of rejection surely is largely subjective. Further, there are many possible reasons for a loan application to be rejected, some of which may not be indicative of "financial access constraint", for instance, quality of application or application accompanied by a very weak or no business plan. While we acknowledge this, our objective measures are derived based on financial information summarised in Table 3.1, which has high degree of objectivity.

represent the costs of inputs used in producing goods. Employment is measured as the number of workers.

Several methods have been suggested in the empirical literature on measuring productivity based on the estimation of the production function. These include the Olley & Pakes (1996), Levinson & Petrin (2003), and the Ackerberg et al. (2015). The productivity measure produced from these models is revenue-based. Productivity can be measured using total factor productivity (TFP) or using partial productivity measures which take into account the contribution of inputs such as capital and labour.

Consistent with the literature in this field, we built our measure of productivity based on firm TFP. Our measure of TFP draws on the approach adopted by Foster et al. (2008) model and applied by Hsieh & Klenow (2009). Foster et al. (2008) constructed an alternative measure of TFP that is based on physical productivity rather than the ubiquitous revenue-based productivity. This measure of TFP does not require inference from econometrics, but rather it can be constructed from available firm-level data. Physical TFP, according to Foster et al. (2008) and modified by Hsieh & Klenow (2009), can be computed as:

$$TFPQ_{si} = A_{si} = \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s}(L_{si}^{1-\alpha_s})} \tag{3.10}$$

where A_{si} is firm-specific productivity (TFP), $P_{si}Y_{si}$ represents the firm value-added, K_{si} and L_{si} are the capital and labour inputs respectively, σ is the elasticity of substitution. All these variables are observed from the available data except for elasticity, which we will calibrate from literature (studies commonly use $\sigma = 3$). Based on the argument of Hsieh & Klenow (2009), we use the wage bill instead of the units of labour to take into account the quality of the workers. As an alternative measure of productivity, we also use value-added per worker. For robustness check, we construct an alternative measure of productivity based on Levinson and Petrin (2003) approach.

Other variables

Firm age is measured as the difference between the current year and the year the firm was established. Firms are classified as falling into one of three industries: metal, textile and wood products. Firm location is a dummy variable that is coded one for Harare and zero for Bulawayo. Table 3.2 contains the summary statistics for the variables of interest.

Summary overview of data

The data reveals a wide variation in the key indicators across firms. The average firm productive is 6.18 (in natural logarithms) but widely ranges from 2.64 to 10.44 (in natural logarithms). The same can also be revealed for firm productivity relative to industry mean with a mean of 6.8 (in natural logarithms) but also widely ranges. The natural logarithm of value-added per worker averages 7.78 (2392 US dollar) but ranges from (5.35) (210 US dollars) to 9.82 (18398 US dollars). The variation in the capital is even wider, ranging from 3.4 to 9.62 (in natural logarithms). The average age of firms is just under 10 years, with the oldest firm in existence for 28 years. The high average age reflects the permanency of these firms, despite their informal status. On average, firms employ 3 workers ranging from 1 to 10 workers.

Table 3. 2. Summary statistics for key variables (in base periods for 2015 and 2017 sample firms)

Variable	Obs	Mean	sd	Min	Max
Firm TFP (log)	167	6.81	1.58	2.64	10.44
Firm TFP (log) relative to industry	167	0.99	0.58	0.39	1.52
Value added per worker (log)	167	7.78	0.82	5.35	9.82
Capital (log)	172	6.41	1.19	3.40	9.62
Output (log)	170	9.65	0.83	7.09	11.72
Firm age (years)	169	9.86	7.10	0.00	28.00
Employment	172	3.06	1.50	1.00	10.00
Labour costs (log)	165	8.21	1.00	4.97	10.35
Profit Margin (ratio)	170	0.23	0.23	-1.17	1.00

Source: Author Computations from the Dataset.
Notes: The values are for the base period (the year of first interviews-2015 and 2017) for firms that we able to follow up in 2018. Profit Margin is a ratio computed as a proportion of firm profits to sales.

3.3.4 Stylized Facts Emerging from the Data

In this section, we present and discuss the observable features that are characterised by our dataset on the relationship between financial access constraints, misallocation and firm performance. We start by assessing the extent to which access to finance is a constraint in the informal manufacturing sector in Zimbabwe. Given our definition of financial access constraints and various measures of these constraints, Table 3.3 shows the prevalence of financial access constraints between 2015 and 2018 for both the objective and subjective measures.

Table 3. 3. Prevalence of financial access constraints

year	2015	2017	2018
Objective Measures			
Fin_Access1: (Credit rationed and Discouraged borrowers)	0.66	0.88	0.88
Fin_Access2: (Cannot obtain Credit Purchases)	0.87	0.97	-
Subjective Measures			
Fin_Access3: (self-declared as one of three major obstacles)	0.79	0.86	0.84
Fin_Access4: (self-declared problems in sourcing finance)	0.93	0.54	0.65

Notes: The Table shows the prevalence of our measures financial access constraints as defined in Table 1. For *Fin_Access2* we only have data for base years (2015 and2017)

In Table 3.3, we observe that financial access constraints have remained high. For example, if we look at Fin_Acess1, 88 percent of firms in 2018 had either their loans applications denied or did not apply for loans or borrow money due to financial rationing or discouraged borrowing. This figure is higher in 2018 compared to 2015 (66 percent). Similar results are also observed from the other variables measuring financial constraints. For example, looking at Fin_Access3, a measure of subjective financial constraints, 84 percent of firms reported that financial access constraints limit the growth of their business in 2018 as compared to 79 percent in 2015. The main important fact from Table 3.3 is that financial access constraints are very high within the informal manufacturing sector.

In light of the results in Table 3.3, we explore the reasons why firms are not able to access finance. The reasons may be supply or demand-oriented. The extent to which financial access constraints originate from the supply-side highlights that market frictions are an important source of financial access constraints. Table 3.4 presents the reasons associated with why firms are were not able to apply or access some lines of credit.

What the results in Table 3.4 indicate is that 34.2 percent of firms are not able to borrow due to too many collateral requirements. This is not surprising as most informal sector firms do not have adequate collateral needed to secure a line of credit. Further, 19 percent of firms cited high interest rate as the reason why they are not able to access finance. Other reasons include complicated procedures when applying for finance (17.68 percent) and no availability of institutions or individuals to borrow from (12.8 percent). A very small proportion of firms (7.93 percent) did not need a loan. The results in Table 3.4 imply that supply-side barriers to financial access are a major problem constraining firms from accessing finance, thus indicating the presence of factor market frictions in constraining access to finance.

Table 3. 4. The main reasons why informal sector firms are not able to borrow finance.

Main Reason	Freq	Percentage
Procedures Complicated	29	17.68
High Interest Rates	31	18.90
Too Much Collateral	56	34.15
None to Borrow from	21	12.80
No need for a Loan	13	7.93
Other	14	8.54
Total	164	100

Notes: The table shows what firms reported as the main reasons why they are constrained to access finance. Most of the reasons are from the supply side.

Now that we have characterised the prevalence and source of financial access constraints, we determine the correlation between financial access constraints and firm characteristics. Theoretically, the heterogeneity in access to finance by firms generates misallocation of resources, a theory supported by the literature. Table 3.5 presents the breakdown of financial constraint conditioned to firm size, firm age, and industry sector for the pooled base periods 2015 and 2017.

We observe that young firms (2 years or less) are more constrained than old firms (those aged 20 years and above). For example, if we look at the objective variable *Fin_Acess1* we find that 88 percent of those age 2 or less are financially constrained compared to 75 percent of firms aged 20 years and above. Similar results can be found on the subjective measures of financial constraints variable *Fin_Access4* where 94 percent of firms aged 2 years or less are constrained compared to 66 percent of firms aged 20 and above. These results are in line with the literature, which suggests that young firms are more likely to be constrained than large firms (Beck & Demirguc-Kunt, 2006). Financial constraints are however high across all age groups (above 75 percent on average).

Table 3.5 also shows that the prevalence of financial constraints differs with firm size. We find that the proportion of firms with financial access constraints is higher for smaller firms across all measures. For instance, we can observe that 75 percent of firms with less than 5 workers are constrained, as compared to 67 percent of firms with 5 or more workers. The same can be deduced from other measures. The results that small firms are more financially constrained is also supported by the literature (Ayyagari et al., 2008; Beck, Demirgüç-Kunt & Maksimovic, 2005). The reason is that small firms usually lack the collateral need to secure finance. The prevalence of financial access constraints seems to be, on average, not systematically different across the industrial sector.

Table 3. 5. The proportion of financially constrained firms in the sample by firm age, firm size and industry sector for 2015 and 2017

	Measures of Financial Access Constraints			
	Fin_Access1	Fin_access2	Fin_access3	Fin_Acess4
By Firm Age				
2 or less	0.88	1.00	0.81	0.94
3-5	0.73	0.90	0.82	0.82
5-10	0.73	0.87	0.78	0.80
10-20	0.71	0.92	0.86	0.78
20+	0.75	0.94	0.84	0.66
By Firm Size				
4 or less	0.75	0.92	0.84	0.88
5+	0.67	0.91	0.63	0.78
By Firm Industry				
Metal	0.71	0.86	0.86	0.80
Textile	0.70	0.95	0.80	0.69
Wood	0.81	0.90	0.78	0.86

Notes: The table shows how our four measures of financial constraints vary with firm characteristics. The general conclusion is that there is some firm heterogeneity in terms of access to finance.

We have, thus far, established the extent to which firms are financially constrained. The next step is to assess how these constraints are a source of misallocation. From our theoretical model, there are two ways of assessing this. The first is to find how financial constraints correlate with indicators of misallocation. The second is to find the extent to which financial access constraints affect relatively better-performing firms. Table 3.6 presents the descriptive analysis of the relationship between financial constraints, average firm performance measures, and indicators of misallocation for base periods 2015 and 2017. We speculate that, in the first best equilibrium, firms with no financial constraints invest more, are more productive and achieve high growth rates than constrained firms.

Table 3. 6. Heterogeneity in firm performance, misallocation and firm characteristics between constrained and non-constrained firms using the sample for base periods (2015 and 2017)

	Financial Access Constraints	
	No	Yes
Key Indicators of firm performance		
Investment (proportion)	0.51	0.33
employment growth	0.06	0.06
TFP (log)	6.57	6.89
Value Added per Worker (log)	7.71	7.78
Capital/L (log)	5.55	5.33
Profit Margin (ratio)	0.28	0.21
Measures of Misallocation		
ARPR (log)	3.11	3.31
MRPK (log)	0.07	0.11

Notes: The table shows the differences in firm performance between constrained and non-constrained firms. The measure of financial constraint is Fin_Access1 which is our main objective measure of financial constraints. Profit margin is measured as a ratio of firm profits to revenue. Misallocation measures are based on the HK framework discussed in Chapter 2.

Table 3.6 illustrates that the levels of investment are, on average, different between constrained and non-constrained firms. It shows that 51 percent of non-constrained firms invested in new equipment and machinery while only 33 percent of the constrained firms managed to carry out investments. There is, however, no difference in average employment growth between constrained and unconstrained firms. Table 3.6 indicates that more constrained firms are more productive than unconstrained ones as measured by TFP (6.57 vs. 6.89) and labour productivity (7.71 vs. 7.78). To the extent that more productive firms are more financially constrained, this may signal that financial constraints are a source of allocative inefficiency-a hypothesis we will test in the below sections. Financially constrained firms have lower profit margins as compared to unconstrained ones. This shows that financial access constraints on average reduce the profitability of firms. Finally, Table 3.6 indicates that more constrained firms have a higher average prevalence of misallocation as measured by ARPK (3.11vs 3.31), and MRPK (0.07vs 0.11).

Having established the extent of financial constraints, we lastly by assessing the distribution of our misallocation measures. As deduced from the theoretical model, the high dispersion of log MRPK implies misallocation. Table 3.7 shows the dispersion of Wu (2018) and Hsieh and Klenow (2009) measures of misallocation.

Table 3. 7. Variance of logarithms of MRPK, ARPK and TFPR and Aggregate TFP losses

year	2015	2016	2017	2018	Average
(1) Var(mrpk_WU)	1.180	0.940	1.502	1.179	1.201
(2) Var(arpk_WU)	1.739	1.284	1.830	1.178	1.508
(3) Var(mrpk_HK)	1.924	1.673	1.545	1.438	1.645
(4) Var(TFPR_HK)	0.755	0.821	0.421	0.635	0.658

Notes: Row (1) and Row (2) shows the variance of Wu (2018) measure of capital misallocation (MRPK and ARPK). Row (3) and Row (4) shows the variance of HK measures of misallocation (MRKK and TFPR). TFP loss is computed from equation (4). We have set $\alpha = 1/3$ and $\eta = 0.15$ as borrowed from mainstream literature.

Row (1) and (2) provides the dispersion of the Wu (2018) measures of misallocation and row (3) and (4) provides HK measures of misallocation. The results in Row (1) suggests high dispersions in log MPRK, with an average variance of 1.20 across years. Compared to results in Row (1), the HK measure of MRPK in Row (3) also shows high variance across years with an average of 1.65. The dispersion of the misallocation measures seems to be persistent over time, with no evidence of significant reduction. The table further presents the results for the variance of log ARPK in Row (2). As pointed by Wu (2018) and Song and Wu (2015) the differences between Row (1) and Row (2) suggest the existence and importance of market power and firm-specific production technology. There are no huge differences in the dispersion of the Wu (2018) measures and HK MRPK, suggesting that these measures are comparable.

To this end, the data shows the huge presence of financial access constraints that may induce allocative inefficiency in the informal manufacturing sector. There is also much heterogeneity on firm characteristics between constrained firms and unconstrained firms. The data further shows that high performing firms are the ones that are relatively constrained by financial access constraints. This, therefore, implies that financial markets are inefficiently allocating finance, and this may have the effect of reducing aggregate TFP as per the theoretical model. In the next section, we present econometric results to support our stylised facts above. The end result of this study is to unpack the extent to which financial constraints explain the presence of misallocation.

3.4. Empirical Results

The descriptive analysis above suggests that financial access constraints attenuate aggregate TFP losses. This is in line with our theoretical predictions. We now test empirically the mechanisms through which financial access constraints affect aggregate TFP through the misallocation channel. Our empirical analysis is conducted in two parts.

We first test the underlying hypothesis that financial access constraints increase the misallocation measures. We estimate our model using an OLS regression. The measures of misallocation are regressed on financial access constraints and firm productivity as specified in equation (3.6). The results are shown in Table 3.8. The table presents the results for our measures of misallocation (based on Wu (2018), namely: MRPK and ARPK.

We first look at the association between initial TFP and our indicators of misallocation. Theoretically, as argued by Restuccia & Rogerson (2008) and Wu (2018), the losses in aggregate TFP due to misallocation are compounded if there is a positive correlation between firm productivity and the indicators of misallocation. The results confirm such a relationship for informal manufacturing firms in Zimbabwe. Looking at column 1, a positive and significant correlation between initial firm productivity and MRPK is estimated. This shows that more productive firms have a higher MPRK suggesting that they suffer more from misallocation than lower productivity firms and therefore under-produce relative to an allocative efficient outcome. This result is consistent with our earlier findings in the preceding chapter.

To assess whether financial access constraints impose an additional source of misallocation, we look at the coefficients on the variables, including the dummy, for the objective measure of financial constraints. In line with the theoretical predictions, the results in column 2 and column 3 indicate a positive and significant correlation between financial access constraints and MPRK, signifying that financial access constraints impede the efficient allocation of resources.

To assess whether financial access constraints compound the misallocation of resources via its association with initial firm productivity, we look at the coefficient on the variable interacting financial access and TFP. The results in column 3 show a positive significant association between MPRK and the interaction term. The coefficient on TFP also falls from column 2 results (from 0. 447 to 0. 385). This illustrates that it is the interaction of high TFP and financial constraints that compounds the aggregate TFP losses due to misallocation.

Thus far, the results in columns 1-3 of Table 3.8 illustrate that financial constraints are associated with the misallocation of resources. In subsequent columns (4-6) we present regressions for ARPK. Column 4 indicates a positive correlation between initial TFP and

APRK, confirming our expectation that aggregate TFP losses as a result of capital misallocation are magnified. In column 5 we include variable for financial constraints. As per our hypothesis, the correlation between financial constraints and APRK is positive, strong and statistically significant (at 1 percent level). This suggests that financial access constraints act as a tax on capital relative to labour, leading to firms using relatively less capital than labour than they would if markets were allocative efficient. In column 6 we add the interaction term TFP and financial constraints and we get two interesting results. First, the interaction term is significant (at 1 percent level) and positively correlated to APRK, suggesting financial constraints magnify TFP losses through capital misallocation. Second, the coefficient of TFP reduces from 0. 609 log points to 0. 555 log points, again, pointing that it is the interaction of high TFP and financial constraints that further compounds the aggregate TFP losses due to the capital misallocation.

Overall, it can be concluded that firms facing financial constraints are smaller than they should be and employ less capital than they should. Equally, misallocation affects the most productive firms the most as shown by the positive coefficient on TFP in all specifications. These results suggest that distortions worsen the effect on aggregate productivity via the misallocation channel as indicated by the fact that the coefficient on financial constraint is positive and that there is a positive correlation between TFP and the interaction term.

Table 3. 8. Correlations between Misallocation and Financial Access constraints using Wu (2018) measures.

	MRPK			ARPK		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fin Constraint		0.103*	0.267**		0.374***	0.514***
		(0.055)	(0.105)		(0.094)	(0.105)
TFP_{t0}	0.447***	0.447***	0.385***	0.608***	0.609***	0.555***
	(0.045)	(0.045)	(0.053)	(0.042)	(0.041)	(0.053)
Fin Constraint×TFP_{t0}			0.175**			0.150**
			(0.083)			(0.070)
Constant	0.565***	0.529***	0.466***	3.619***	3.486***	3.432***
	(0.130)	(0.135)	(0.141)	(0.125)	(0.130)	(0.136)
Observations	276	276	276	276	276	276
R-squared	0.363	0.365	0.380	0.583	0.601	0.608
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The measures of misallocation are based on the Wu (2018) approach. We have used an objective measure (Fin_Acess2) as our main measure of financial access constraint. Firm Controls include industry and location dummies, firm size and firm age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05 and * p<0.1 represents 1%, 5% and 10% levels of statistical significance.

3.4.1 Robustness Check

We conduct a couple of robustness checks to the results reported above. The underlying assumption in Wu (2018) when estimating misallocation is that with a large number of firms, the aggregate TFP loss can be approximated as proportional to the variance of the logarithm of the MRPK. Given that our sample size is relatively small, we provide some robustness checks to the Wu (2018) measures by using alternative measures of misallocation proposed by Hsieh and Klenow (2009). These measures are TFPR, MRPK, capital distortions, and output distortions as discussed in the preceding chapter.[28]

The results that Table 3.9 provides corroborate our previous results that financial access constraints are a major source of capital misallocation. This is confirmed, first, by a positive significant correlation between firm productivity and TFPR suggesting, as above, that aggregate TFP losses are magnified. Second, a statistically significant positive correlation between financial constraints and TFPR, in column 3 also confirms our previous findings that financial constraints impose an additional source of misallocation. The subsequent columns are columns 4-6 for capital misallocation as measured by MRPK; columns 7-9 for capital distortions; and columns 10-12 for output distortions. As per our hypothesis, the correlation between financial constraints and MRPK is positive, strong and statistically significant (at 1 percent level). This suggests that financial access constraints act as a tax on capital relative to labour, leading to firms using relatively less capital than labour than they would if markets were allocative efficient. In column 6 we add the interaction term TFP, and financial constraints and we get two interesting results. First, the interaction term is significant (at 1 percent level) and positively correlated to MRPK, suggesting financial constraints magnify TFP losses through capital misallocation. The same results can be said for capital distorts and output distortions. The results in Table 3.9 are robust to our main findings in Table 3.8. Therefore, financial constraints attenuate aggregate TFP through misallocation as predicted by our theoretical model

[28] The HK measures are firm level measures demeaned at industrial levels. But because they are in logarithms, they naturally measure the dispersion of firm level measures from industrial levels. That dispersion is what HK refer as misallocation because in efficient markets firm TFPR is equal to industry TFPR.

Table 3. 9 Correlations between indicators of Misallocation and Financial Access Constraints

	Dependent Variables											
	TFPR			MRPK			Capital Distortions			Output Distortions		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fin Constraint		0.097*	0.250**		0.180**	0.335***		1.523***	1.466***		-1.896***	-2.071***
		(0.056)	(0.110)		(0.090)	(0.101)		(0.153)	(0.173)		(0.107)	(0.102)
TFP_{t0}	0.648***	0.649***	0.589***	0.727***	0.728***	0.668***	0.538***	0.542***	0.564***	-0.235***	-0.250***	-0.183***
	(0.036)	(0.037)	(0.051)	(0.039)	(0.039)	(0.056)	(0.057)	(0.067)	(0.076)	(0.055)	(0.047)	(0.056)
Fin Constraint × TFP_{t0}			0.165**			0.167***			-0.060			-0.191**
			(0.067)			(0.060)			(0.126)			(0.090)
Constant	1.182***	1.146***	1.087***	2.460***	2.392***	2.332***	6.706***	6.151***	6.173***	1.074***	1.777***	1.844***
	(0.115)	(0.127)	(0.132)	(0.118)	(0.133)	(0.140)	(0.195)	(0.234)	(0.237)	(0.139)	(0.142)	(0.143)
Observations	273	273	273	273	273	273	276	276	276	277	277	277
R-squared	0.594	0.595	0.605	0.627	0.630	0.638	0.214	0.366	0.367	0.076	0.459	0.469
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The measures of misallocation are based on the HK model. *Fin Constraint* is a dummy for an objective measure of financial constraints which takes a value of 1 if a firm faced credit rationing or discouraged from borrowing as defined in Table 3.1. TFP_{t0} is the measure of firm initial productivity. Firm Controls include industry and location dummies, firm size and firm age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05 and * p<0.1 represents 1%, 5% and 10% levels of statistical significance.

Our results are comparable to other existing studies in the literature. For example, Cirera et al. (2017) for sub-Sahara Africa find that financial access constraints increase misallocation by increasing the costs of capital than optimal. Likewise, Kalemli-Ozcan & Sorensen (2014) find that access to finance is significant sources of misallocation. They find that firms with high financial constraints have high MRPK, signalling the significant association between financial constraints and capital misallocation. Kinghan et al. (2018) find evidence of capital misallocation as a result of financial constraints. They also find that firms with the highest returns have a lower likelihood of accessing finance.

Second, we use an alternative objective measure of financial access constraints (*Fin_Acess1*) that is richly available in our dataset, following Leon-Ledesma & Christopoulos (2016), to test for the robustness of the results reported in Table 3.9. The results presented in Table C3.2 (in the Appendix for Chapter 3) are robust to our previous findings that financial access constraints are a source of misallocation.

Third and finally, we test for robustness using an alternative measure of firm productivity based on Levinson and Petrin (2003) approach. One concern in the regressions where we identify whether financial constraints through their correlation with TFP amplifies the misallocation is that we use a constructed TFP measure on the right-hand side (RHS), which is closely related to the distortion measure on the left-hand side (LHS). Though the Levinson and Petrin (2003) measure is revenue-based and is associated with endogeneity concerns, it allows us to test the robustness of our results. The results are presented in Table C3.3 (in the Appendix for Chapter 3). Again, these results generally corroborate our previous results.

3.4.2 Channels through which financial constraints may exacerbate productivity loss.

In the section above, we establish that financial access constraints are an important source of misallocation. In this section, we test for the channels through which financial constraints may affect allocative inefficiency. We do this by testing for productivity enhanced reallocations (PER) using the investment and employment growth, as specified in equation 3.7.

Theoretically, a positive relationship between firm productivity and firm investment or employment growth implies productivity-enhanced reallocation of resources. We hypothesise a negative relationship between financial access constraints and investment as constraints increase the cost of capital and undermine investment initiatives. The link between financial constraints and employment growth is ambiguous–it depends on whether investment and employment are substitutes or complements[29].

The results for the investment regression model are presented in columns 1– 4 of Table 3.10. In column 1 we first test PER by regressing a dummy for firm investment on initial firm productivity controlling for initial firm characteristics (firm age, firm size, industry and location). The results indicate a negative and insignificant association between firm investment and firm initial productivity, suggesting that productivity-enhancing capital reallocations are not being achieved in the informal sector.

Column 2 provides the results for the link between financial access constraints and investment. The objective is to test if financial constraints depress investment. As theoretically expected, the results indicate that there is a negative relationship between financial access constraints and the probability of a firm investing, implying that financially constrained firms are, on average, less likely to invest as compared to non-constrained firms. In the earlier sections, we show that financial access constraints affect relatively more productivity firms. Through this channel more productivity firms are less likely to invest, as supported by the negative association between firm productivity and investment in column 3 even when we control for financial constraints. These findings are consistent with our previous results, which indicate that financial constraints have a direct influence on misallocation. In column 4 we test the extent to which financial access constraints accentuate misallocation via the interaction with initial firm productivity. While the financial constraint remains negative and significant, the interaction term is negative and insignificant. A negative sign of the interaction term implies that financial constraints reduce investment opportunities for productive firms and thus exacerbate misallocation.

[29] If the two are complements we expect a negative relationship, and if substitutes we expect a positive relationship.

Table 3. 9. Firm investment, Employment Growth and Financial Access Constraints

	Firm Investment				Employment Growth			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fin_Constraint		-0.192***	-0.191***	-0.141*		-0.020	-0.021	0.015
		(0.071)	(0.071)	(0.083)		(0.067)	(0.067)	(0.071)
TFP_{t0}	-0.023		-0.021	-0.057	0.007		0.007	-0.020
	(0.021)		(0.020)	(0.039)	(0.024)		(0.024)	(0.026)
Fin_Constraint × TFP_{t0}				-0.049				0.037
				(0.044)				(0.039)
Constant					0.142	0.154	0.160	0.137
					(0.094)	(0.106)	(0.109)	(0.108)
Observations	246	246	246	246	246	246	246	246
R-squared					0.046	0.046	0.047	0.049
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Results are from equation (3.7). *Firm investment* is a binary variable. Columns 1-4 presents the *Marginal Effects* of the investment model equation. Columns 5-8 presents results from the employment growth model. Columns 1 and 3 shows the baseline model. In Columns 2 and 5 and we control for initial firm productivity (TFP_{t0}). In columns 3 and 6 we control for the interaction between initial Fin Constraint and initial TFP. Firm controls include industry and location dummies, firm size and firm age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05 and * p<0.1 represents 1%, 5% and 10% levels of statistical significance.

We test for the robustness of the investment model results using valued-added per worker (following Bartelsman et al., 2017) demeaned at the industry level as an alternative measure of firm productivity. The results are presented in Table C3.4 in the Appendix for Chapter 3. The robustness results corroborate with the above results indicating the importance of financial access in reducing firm investment drive but no evidence of productivity-enhancing reallocations.

In columns 5–8 we repeat the same procedure, for the investment model as for the employment growth model. We test the link between firm employment growth, financial constraints and determining if productivity-enhancing reallocations are achieved by including firm initial productivity in the regressions. The results in columns 5-8 show a statistically insignificant relationship between employment growth and initial financial access constraints, initial firm productivity and the interaction term. These results signify that productive-enhancing reallocation of labour is not realised in the informal sector and that financial access constraints do not affect employment growth. We find similar results when we test robustness using an alternative measure of productivity based on Levinson and Petrin (2003)[30] as shown in Table C3.4 in the Appendix for Chapter 3.

Some studies in the literature have also similarly concluded that there is no relationship between access to finance and employment growth. For example, Kinghan et al. (2018) for micro-firms in Vietnam found an insignificant relationship between employment growth and financial access constraints. The literature argues that financial access has a direct effect on firm investment rather than employment (Kinghan et al. 2018). Financial access affects employment growth only through the investment channel; that is, as firms invest in capital and expand business, then they are expected to demand more labour. However, if investment and employment are substitutes, a decrease in investment as a result of more financial constraints can increase firm employment growth as firms substitute workers for machines.

To this end, we can synthesis our results as follows: First, we find support for the fact that financial access constraints reduce subsequent investment. This suggests that reduced investment is a key channel through which misallocation of resources occurs. Second, we do not find an association between TFP and subsequent investment, directly, or via its interaction with financial constraints. At least over the duration of the data, it is not investment that is

[30] We are limited to use Value added per worker as we did in the investment model due to collinearity of employment growth and valued added per worker.

driving the compounding of the misallocation shown earlier. But this could be explained by the fact that the association is driven by historical investment over a longer time period. Third, we find no relationship between financial constraints and employment growth, confirming theoretical literature that argues that the relationship may be ambiguous.

What these results, together with the prior results, seem to say, is that firms facing financial constraints are experiencing a declining capital-labour ratio as the investment is falling for these firms, but employment change is no different to other firms. This result is consistent with the positive coefficient on capital market distortion – which is a K/L market distortion.

3.5. Conclusion

The chapter presents evidence on the impact of financial access constraints on firm performance and aggregate productivity through the misallocation channel in the Zimbabwean informal manufacturing sector. Specifically, the study investigates how financial access constraints affect the efficient allocation of resources. We do so in two ways: first by looking at the association between financial constraints and indicators of misallocation, and secondly, by looking at the association between financial constraints and changes in employment and capital within firms and test for productivity-enhancing reallocation of resources. The study drew on the recent informal sector firm-level panel dataset. Measures of misallocation are constructed using the Wu (2018) framework. The study utilises both subjective and objective measures of financial access constraints present in our dataset.

We find evidence suggesting the following stylised facts. First, we find that a high proportion of firms are financially constrained in the informal manufacturing sector. In this regard, the study shows that financial access constraints emanate from the supply side, that is, there are insufficient funds in the market to match the high demand for such funds. Also, we find evidence suggesting that productive, young, and small firms are more financially constrained. Second, looking at the relationship between financial access constraints and firm performance, the study finds that the proportion of constrained firms that have carried out investment initiatives is lower as compared to unconstrained firms. Average employment growth is, however, no difference between constrained and unconstrained firms.

The empirical results reveal the following findings: first, we find a significant relationship between initial firm TFP and indicators of misallocation, suggesting that aggregate TFP losses from allocative inefficiency are magnified. Second, we find a significant and positive association between financial constraints and measures of misallocation, MPRK and ARPK. This indicates that financial constraints are one channel through which misallocation occurs. Third, the fall in the coefficient of the TFP after controlling for the interaction term illustrates that financial constraints explain part of the TFP association, and it is the interaction of financial constraints and that further compound the aggregate TFP losses due to misallocation.

We then test the channels through which financial access constraints exacerbate misallocation and attenuate aggregate TFP. We do this by empirically testing whether financial access constraints impeded productivity-enhancing reallocation of investment and employment across firms. The empirical results that financial constraints significantly reduce firms' appetite to invest but insignificantly affect employment growth. We find no evidence on the association between firm productivity and both investment and employment growth, suggesting that productivity enhanced reallocations are not realised. This result is further supported by an insignificant relationship between investment (and employment) and the interaction of financial constraints and firm productivity-which suggest that the effects of financial access constraints on investment do not differ with firm productivity. In standard neoclassical models, we would have expected more productive firms to have more access to finance, allowing them to embark on productivity-enhancing investments and growth.

The results of this study have important policy implications. However, care must be taken when designing such a policy as easy access to finance by all firms may create inefficiencies that could, in turn, attenuate the aggregate productivity improvements. Improved access to finance must be conditional on firm productivity-as supported by our finding that it is more productive firms that are financially constrained, thus exacerbating aggregate productivity losses through misallocation. There is a need to provide adequate information on the process needed to successfully apply for external finance to reduce access constraints.

Notwithstanding the study's potential contribution, we suggest that it would be useful in future to extend our analysis to the formal sector and give some insightful comparison between the formal and informal sector. Also, it would be informative if we would extend and compare our results to other informal sectors in developing economies. However, the major challenge is the availability of panel datasets on informal sector economies. Further, it would be also interesting in future if we extend out sample time dimension to give robust dynamics about informal sector efficient growth. Due to data limitations, we are only able to base our analysis on intensive margins. It would be important to assess how the exit and entry of firms affect misallocation and contribute to the productive growth of the informal sector. While the preceding chapters look at allocative efficiency from the firm perspective, henceforward we turn our attention to the efficiency of the labour markets by testing for the extent and sources of labour market segmentation. The extent of labour market segmentation has traditionally been used to test for the efficiency of the labour markets.

Chapter 4

4. Labour Market Segmentation within and between the Formal and Informal Manufacturing Sector in Zimbabwe

4.1. Introduction

There is growing evidence in the literature that labour markets in developing and emerging economies are highly segmented, as revealed by the presence of wage differentials between labour market sectors (Bigsten et al., 2003; Maloney, 1999; Velenchik, 1997a; Fields, 1990). The argument is that if the differences in the labour market outcomes, such as wages, cannot be fully accounted for by differences in worker productivity endowments, then this provides evidence against the hypothesis of competitive labour markets. This is of direct relevance to this thesis, as the extent to which labour markets are segmented can be used to make inferences about the efficiency of the labour markets in allocating resources[31].

Researchers commonly ascribe wage gaps as reflecting labour market segmentation. Typically, segmentation is associated with a dual labour market that is divided between the primary segment that offers 'standard' forms of employment and the secondary segment that provides 'atypical' forms of employment, with immobility of workers to the primary segment (Doeringer & Piore, 1971). This is too narrow a concept for emerging economies such as Zimbabwe, where labour markets are characterised by enormous heterogeneity.

Labour markets in emerging countries are characterised by the coexistence of formal and informal labour markets. Commonly, the literature argues that this coexistence reflects a segmentation of labour markets between low-wage informal workers and higher-wage regulated and protected formal sector workers (Günther & Launov, 2012; Heintz & Posel, 2008; Pratap & Quintin, 2006; Gindling, 1991). Yet, even within formal sector markets, employees differ with respect to wages and the protection they are afforded by contracts, e.g., permanent vs. contract workers. Such segmentation may arise from labour markets institutions such as unions that delineate permanent and contract workers. Workers often also work in both sectors, as is the case in Zimbabwe, undermining the notion of two distinct and separate labour markets as emphasised by early literature (Leontaridi, 1998; Thomas & Vallée, 1996;

[31] Labour market segmentation as a result of institutional and regulatory rigidity has been argued as one of the main sources of labour market inefficiencies that depresses employment growth and constrains adaptation of firms to business cycles (Deakin, 2013; Kalleberg, 2003).

Doeringer & Piore, 1971). Given the heterogeneity of workers, the productive characteristics of workers within each sector may differ, and this may explain the observed wage gaps.

Using a matched employer-employee dataset for the formal and informal manufacturing sectors in Zimbabwe, this chapter provides new empirical insights on the extent, types and sources of segmentation within and between the formal and informal manufacturing sectors in an emerging economy. We test the hypothesis that the labour market is competitive and contrast it with alternative segmentation narratives. The analysis is based on the following research questions.

- Are labour markets within and between the formal and informal sectors segmented in Zimbabwe and if so, why?
- How important is rent-sharing as a source of segmentation within the formal sector?

Studying the extent and sources of labour market segmentation using our unique and new matched employer-employee dataset in Zimbabwe provides many insights. The data allows us to control for individual-level and firm-specific characteristics that may be associated with wage levels in labour markets. To deal with the *presence* of segmentation, the paper, therefore, draws on simple descriptive representations of the wage data, as well as econometric estimates, using the Recentered Influence Function (RIF) regression approach, to control for individual firm characteristics.

The second research question relates to a potential *source* of labour market segmentation. International literature has highlighted rent-sharing as a key source of labour market segmentation (Card et al., 2018; Gürtzgen, 2009; Hildreth & Oswald, 1997; Blanchflower, Oswald & Sanfey, 1996). In these models bargaining between workers and owners over the sharing of rents at the firm level leads to a positive correlation between wages and firm profits, and the setting of wages above the competitive equilibrium, thus disproving the competitive theories of labour markets.

Zimbabwe provides a suitable case study to analyse the above research questions in the context of emerging economies. First, Zimbabwe has a large informal labour market that coexists with the formal labour market. Hence, we can take into account the multiplicity of the labour markets within and between sectors. Second, Zimbabwe shares many common characteristics with other emerging economies, such as the existence of distorted markets, the sectoral structure of employment, and unionism. The results of this chapter can easily be generalised to other emerging economies.

In addressing the above questions, this chapter makes three contributions to the literature. First, it contributes to the literature by examining labour market segmentation in the context of Africa, where such comprehensive studies that take into account the heterogeneity of labour markets have been marginal.

Second, it uses a recent employer-employee matched survey dataset on informal and formal manufacturing sector firms and employees. One of the challenges in the literature on the analysis of the wage gaps between the formal and the informal sectors' workers is the availability of comparable datasets. Although most studies in the literature have acknowledged the importance of firm characteristics in explaining wage gaps, most of these studies have failed to control for firm characteristics due to the limitations of the dataset they use (e.g., Gong and Van Soest, 2002). As such, in addition to individual characteristics, we are able to control for firm characteristics using our dataset. Further, our employer-employee matched dataset provides a solid base to analyse the heterogeneous nature of the labour markets in emerging economies. Our results can thus be generalised to other developing countries where formal and informal labour markets coexist.

Third, the study makes some methodological contributions by using the recently developed econometric methods to test the existence of the wage gap. A large body of literature has used the Oaxaca-Blinder decomposition and the Mincerian model to test the existence of wage gaps. We expand this literature by employing the Recentered Influence Function (RIF), also known as the unconditional quantile regression approach. This provides a more comprehensive analysis and assessment of the earnings differentials within and between the formal and informal sectors.

The rest of the chapter is structured as follows: Section 4.2 presents the overview of theoretical insights and related empirical literature review on sectorial wage differentials and rent-sharing. Section 4.3 discusses the methodological framework, which includes discussion on the theoretical model, estimation strategy and describes the data. The discussion of the empirical findings is done in section 4.4 and finally, section 4.5 concludes.

4.2. Theoretical and Empirical Literature Review

4.2.1 Theoretical Insights

Two broad theoretical models have been used in the literature to predict wage differentials between subgroups–the neo-classical model and the Segmented Labour Market (SLM) theory. These two models differ on the mechanism through which they explain the wage gaps.

The competitive neo-classical model, also known as the human capital theory of labour markets, hypothesises that differences in earnings amongst labour market subgroups are explained entirely by differences in human capital endowments and job characteristics (Mincer, 1974). Institutional factors such as unions, collective bargaining, firms and governments, therefore, do not play a role in determining the wages, as wages align with the worker's marginal productivity. The theory further asserts that the employee's choice to work in a given labour market (for example, in the informal sector) depends on rational decisions and preferences that maximise one's satisfaction. This implies that low-paying jobs are characterised by low-productivity workers who are unwilling or unable to acquire the necessary skills that allow them to access higher-paying jobs. Thus, the neoclassical labour markets outcomes are efficient.

The neo-classical models have, however, failed to predict real labour market outcomes that are characterised by market frictions and distortions (Loveridge & Mok, 2012; Leontaridi, 1998). Alternatively, the Segmented Labour Market (SLM) theory, presents a non-competitive model premised on the hypothesis that the wage differences among labour market segments are not as a result of differences in human capital attributes, but rather as a result of institutional rules that substitute market processes and prevent equal benefit from human capital. In this regard, wage structures are differentiated by the employer or institutional characteristics rather than the worker's human capital endowments.

The SLM posits that the labour markets revolve around four inter-connected presumptions (Doeringer & Piore, 1971). First, the labour market can be dichotomised into two segments: the primary and the secondary sectors of employment opportunities. Second, there are differences in wages and employment mechanisms between the primary and secondary sectors. Third, job mobility between the two sectors is highly limited and therefore workers are essentially trapped in the secondary sector. Finally, the secondary sector is characterised by under-employment. As such, the SLM theory puts much emphasis on ‘good jobs’ vs ‘bad jobs’ rather than ‘skilled’ vs ‘unskilled’ workers.

According to the SLM theory, the primary sector contains better-paying jobs, which are stable and are regarded as preferable in society. The workers in the primary sector possess secure jobs with opportunities for advancement, earning high wages, better working conditions and employment stability. In contrast, the secondary sector contains marginal jobs that are argued to be unattractive, self-terminating, provide little incentive for advancement, and pay low wages. The primary sector earning structures are insulated from the forces of supply and demand, while this is not the case with the secondary sector wage structures. Thus, the supply-side explanations of human capital theory regarding labour markets and wage structures are rejected in the SLM theory and are replaced with the demand-side-oriented theory.

Over the years, several complementary models to the SLM models have been developed to explain the sources of labour market outcomes such as wage differentials. One such model is the rent-sharing model (Hildreth & Oswald, 1997; Blanchflower et al.,1996). In these models, wages are influenced by the bargaining power of workers with more profitable firms paying higher wages to their workers in relation to the bargaining power of parties (Nickell & Andrews, 1983). The rent-sharing hypothesis, therefore, implies that workers with the same productivity attributes in different firms will be paid differently according to the firms’ ability to pay. Some firms may, therefore, pay wages that are higher than the equilibrium wage, unrelated to the individual workers’ marginal productivity.

This model can be insightful in explaining wages differentials within and between sectors. For, example formal workers may earner high wages than informal workers due to high union membership in the formal sector. At the same time, permanent workers may have a wage premium as compared to contract workers within the formal sector due to the fact that contract workers have weaker bargaining power.

The general prediction from the rent-sharing model is a positive correlation between firm profits and wages. However, possibilities other than rent-sharing may explain this positive relationship. For example, a wage-setting process where firms and workers share the risk may also be associated with correlations between profits and wages. Another possibility is the efficiency wage model, wherein firms may pay higher wages than equilibrium to retain productive workers, reduce shirking, and increase productivity. Hence, firm returns may also explain the positive correlation between firm profits and wages (Shapiro & Stiglitz, 1984). These other possibilities may reflect competitive efficient market outcomes. Thus, the extent to which rent-sharing models explain wage differentials is an empirical question.

4.2.2 Review of Related Empirical Literature

This section provides a review of the literature on labour market segmentation, covering the empirical methods used and some of the key findings, and is structured in two parts. First, it focuses on the strand of literature that estimates the wage gap as a measure of the extent of segmentation. Second, it provides a review of literature that analyses the rent-sharing channel as a source of segmentation.

Differences in the theoretical formulations of segmentation have lent themselves to differences in criteria and methodology used to identify types and causes of segmentation. While the segmentation hypothesis is based on the notion that the labour markets are divided into two separate parts -the primary and the secondary segments (Doeringer and Piore, 1971) - the literature does not contain any single testable empirical hypothesis for identifying the boundaries that separate the segments. Researchers have, therefore, resorted to using different criteria to identify the segments. In the context of emerging and developing economies, researchers have commonly tested the hypothesis that labour markets are segmented along the regulated formal sector and the unregulated informal sector by exploring wage differentials between the two segments (La Porta & Shleifer, 2014; El Badaoui, Strobl & Walsh, 2010; Maloney, 1999; Marcouiller, de Castilla & Woodruff, 1997).

The general approach followed is to estimate a Mincerian wage regression with an indicator variable that captures the wage gap. This approach allows one to identify the wage gap after controlling for a variety of factors that are thought to determine wages. These include human capital characteristics such as education, experience and age, as well as job characteristics and firm characteristics such as firm size and industry. A significant coefficient on the indicator variable would imply a significant wage, thus highlighting the existence of labour market segmentation.

Other studies have extended this approach using the Oaxaca-Blinder decomposition technique that decomposes the wage gap into the explained and unexplained part at the mean. This approach allows the identification of the wage gap after controlling for worker characteristics.

The relative importance of the unexplained component in explaining the wage is then used to confirm the existence of segmentation, where its significance implies segmentation.

The disadvantage of estimating the earnings gap at the mean is that differences in the earning gap along the wage distribution may be concealed. An alternative approach to deal with this concern is the quantile regressions method. This method allows one to estimate the wage gap at each quantile along the wage distribution, thereby giving more insights into the variations in the wage gap (Bargain & Kwenda, 2014; Nguyen, Nordman & Roubaud, 2013; Botelho & Ponczek, 2011).

One such approach is the recent RIF techniques by Fortin et al. (2011) that decompose the wage gap at each quantile. This method allows one to infer the contribution of each independent variable at different points of the wage distribution. The RIF decomposition answers the question of the extent to which wages differs if, for example, informal sector workers have the same characteristics as formal sector workers, thus providing the wage composition and structure effects. Again, the relative importance of the wage structure in explaining the wage gap is then used to confirm segmentation.

Different types of datasets have been used to analyse labour market segmentation. Commonly used datasets are the labour force and household datasets. For example, El Badaoui et al. (2008) in South Africa use the Labour Force Participation Survey panel data, while Carneiro and Henley (2001) use the 1997 Brazilian household survey data. However, as argued by Rand & Torm (2012), Arai (2003) and Gong and Van Soest (2002), the key problem of using such datasets in analysing segmentation is that they fail to take into account the role of firm characteristics in the analysis of factors contributing to segmentation. To the extent that segmentation theories highlight institutional characteristics as the key factors in explaining labour market outcomes, studies relying on such datasets may provide biased results in explaining segmentation. An alternative approach, and one followed in this chapter, is to use employer-employee matched data that includes both worker and firm characteristics in order to provide a robust analysis.

In general, the above-reviewed literature presents evidence of wage differentials between the formal and informal sector workers, highlighting the existence of segmented labour markets. For example, Carneiro and Henley (2001) use the 1997 Brazilian household survey data to assess factors that determine the selection of workers into informal or formal employment and the impact of labour market factors on wages in the two sectors. Gong and van Soest (2002), using data from Mexico, and Bargain & Kwenda (2014), using data from Brazil, Mexico and South Africa, find similar results corroborating the existence of labour segmentation between the formal and informal sectors. These studies are, however, criticised for not controlling for firm characteristics in determining the wage gap. Studies have generally shown a reduction in the wage gap once one controls for firm characteristics. For instance, Rand and Torm (2012) show that by adding firm characteristics, the formal-informal wage gap in Vietnam is reduced from 17 percent to 10 percent.

This chapter is further related to the strand of literature that has tested the importance of rent-sharing as a potential source of segmentation (Matano & Naticchioni, 2017; Rusinek & Rycx, 2013; Blanchflower eta l., 1996). Such literature argues that formal sector workers may have earn higher wages than informal workers because of differences in institutional arrangements, such as unions and bargaining power, that influence wage setting processes. This literature underscores the importance of demand-side (rather than supply-side) characteristics in determining wages, thus disproving the competitive labour markets hypothesis. The importance of rent-sharing is formally tested using Mincerian wage equations with the profit-per-worker as the main explanatory variable (Blanchflower et al., 1996). A positive relationship between profit-per-worker and wages is then interpreted as indicative of rent-sharing as a source of segmentation. The problem in the literature associated with the use of profits-per-worker is the treatment of firms with losses. To circumvent this issue, we follow conventional literature that has used sales-per-worker or value-added-per worker (Margolis & Salvanes, 2001; Hildreth & Oswald, 1997; Nickell, Stephen & Wadhwani, 1990).

However, as highlighted by Blanchflower et al. (1996), the major problem in estimating rent-sharing models is the endogeneity of profits. Some studies have attempted to solve this problem by using instrumental variables (IV) models by finding an instrument for profits and running a 2SLS model or used advanced methods such as the GMM (Blanchflower et al., 1996; Nickell & Andrews, 1983). Commonly used instruments in 2SLS estimations are values of the share of intermediates inputs costs to total output, amount of foreign borrowing per employee, cost of energy, capital-labour ratios and lagged values of profits-per-worker amongst other possible instruments (Matano & Naticchioni, 2017; Rusinek & Rycx, 2013; Card, Devicienti & Maida, 2013; Teal, 1996; Blanchflower et al., 1996). Our study uses the cost of electricity as instruments as they are readily available in our dataset.

Empirical evidence of rent-sharing as a source of wage differentials is still marginal for emerging economies. Such studies have been constrained by the unavailability of relevant datasets. Using matched employer-employee survey data with 200 firms collected in Ghana between 1991 and 1994, Teal (1995) tested a rent-sharing model for Ghana's labour markets. The author found strong evidence supporting a positive correlation between firm profits and wages. Similar results regarding rent-sharing were found by Velenchik (1997b) for Zimbabwe, Mazumdar and Mazaheri (1998) for Ghana, Kenya, Zambia and Zimbabwe, and Bigsten et al. (2003) for Cameroon, Ghana, Kenya and Zimbabwe, using the RPED matched employer-employee dataset. These studies only focus on segmentation in the formal sector, thereby neglecting the informal sector.

The reviewed empirical literature above has analysed labour market segmentation by focusing more attention on the formal-informal sector divide. The assumption is that workers within these sectors have homogeneous characteristics (Bargain & Kwenda, 2014; Günther & Launov, 2012; El Badaoui, Strobl & Walsh, 2008; Pratap & Quintin, 2006). Emerging literature has critiqued this assumption by recognizing the heterogeneity of workers, not only across firms within a sector but also across workers within firms (Cazes & de Laiglesia, 2015; Fields, 2011; Maloney, 1999). Workers in the same firm may have different wage-setting processes and maybe earning different wages, e.g. contract and casual and permanent workers. Controlling for heterogeneity of workers within and between sectors (and firms) is thus a key consideration in empirically testing for labour market segmentation.

While the literature has generally agreed that labour markets are segmented, what remains unsettled is the question of along what lines. This chapter argues that the types and causes of labour-market segmentation found in any given place vary with the form of the economy and its associated institutions. Beyond the formal/informal sector segmentation, we additionally investigate segmentation within formal firms by looking at the permanent and contract worker segments[32]. Permanent workers may earn higher wages than contract workers due to differences in labour market institutional and regulatory framework (such as union representation and bargaining power). Furthermore, the chapter identifies segmentation

[32] Contract workers in this thesis refers to formal sector workers with fixed contracts terms of employment (verbally or written). These workers are not liable for company employment benefits and security insurance, such as pensions. Such workers in the Zimbabwe context where there are high unemployment rates are easily manipulated by firms as they do not have security of tenure and are often paid very low wages compared to permanent workers.

between the contract workers in the formal sector and informal sector workers. The argument is that, although these forms of employment may not be governed by institutions such as unions, contract workers may earn higher wages due to regulations associated with being in registered firms in the formal sector. By analysing these different types of segmentation, the chapter offers some insight into the importance of regulations and labour market institutions (associated with registered firms) in driving the wage gaps.

4.3. Theoretical Framework and Estimation Strategy

4.3.1 The Theoretical Model

The empirical analysis of this chapter draws on the rent-sharing model developed by Blanchflower et al. (1996). Competitive labour markets imply that firms are wage-takers and their profitability does not affect wages, as wages are only determined by human capital endowments. The Blanchflower et al. (1996) bargaining model argues that rents are shared between the firms and their employees.

The model assumes that wages are determined at firm level through a generalised Nash bargaining problem in which unions maximise the expected gains from workers:

$$u(\omega, \overline{\omega}) = u(\omega) - u(\overline{\omega}) \qquad (4.1)$$

where $u(\omega)$ is the employee's utility from wage ω, $\overline{\omega}$ is the wage from other alternative sources such as temporary work in the case of a breakdown in bargaining. On the other side firms seek to maximise their profits π:

$$\pi = pf(n) - wn \qquad (4.2)$$

where p is the product market price, n is employment. The solution is to maximise,

$$log\{[u(\omega) - u(\overline{\omega})]n\} + (1 - \phi)log\pi \qquad (4.3)$$

where ϕ measures the bargaining power of workers. The model relies on the assumption that if the bargaining is delayed or failed then firms earn zero profits and employees receive $\overline{\omega}$. Solving the problem for wages ω and employment n produces the following first-order conditions:

$$\text{for } \omega: \frac{\phi u\prime(\omega)}{[u(\omega) - u(\overline{\omega})n]} - \frac{1-\phi}{\pi} = 0 \qquad (4.4)$$

$$\text{for } n: \frac{\phi}{n} + \frac{(1-\phi)[f'(n) - \omega]}{\pi} = 0 \qquad (4.5)$$

Solving equation (4.4) and simplifying produces;

$$\omega = \bar{\omega} + \left(\frac{\phi}{1-\phi}\right)\frac{\pi}{n} \tag{4.6}$$

Equation (4.6) is very important. It demonstrates that the equilibrium wage is determined by outside wage received in the case where bargaining is not achieved, the relative worker bargaining power and, of importance, the profit-per-worker. The determinants of the outside wage can be described by the function $g(\omega^0, b, U)$, where ω^0 is the wage rate in other sectors of the economy, b is the level of income when unemployed and U measures the unemployment rate for the type of workers employed by the firms. The conceptual interpretation is that $\bar{\omega}$ is expected income. Thus, the equilibrium wage can be written as;

$$\omega = g(\omega^0, b, U) + \left(\frac{\phi}{1-\phi}\right)\frac{\pi}{n} \tag{4.7}$$

The equilibrium wage is conceptually determined by external forces measured by $g(\omega^0, b, U)$ and internal forces measured by profit-per-employee π/n. The model predicts a positive partial correlation between wages and profits-per-employee and a negative correlation between wages and unemployment. The concept behind this is that when sector unemployment increases, the chances of getting a job elsewhere diminishes, and hence wages claim reduces. Thus, this model argues that firms' ability to pay is the main source of wage differentials. The greater the impact of profit-per-worker on wages, the stronger the bargaining power of workers. To this end, this chapter tests the hypothesis that there is a positive association between profit-per-worker and wages, suggesting that rent-sharing is an important source of segmented labour markets.

4.3.2 Estimation Strategy

The estimation strategy is twofold. First, we explore the extent to which the labour markets are segmented in Zimbabwe by estimating the wage gap between segments. This allows us to answer our first research question. Secondly, we incorporate the rent-sharing model discussed in the preceding section to analyse the extent to which differences in bargaining powers amongst labour market subgroups account for segmentation. This allows us to answer our second research question. To provide robust analysis, we complement our models with the Re-centred Influence Function (RIF) decomposition technique. This allows us to perform an in-depth analysis of the extent and sources of labour market segmentation along the wage distribution.

To estimate the wage gap within and between the formal and informal sectors, we use the standard OLS wage regression with an indicator dummy variable that captures different labour markets segments. The base or unadjusted earnings gap can be derived from estimating the below baseline wage regression model;

$$logW_{ij} = \delta + \beta_1 D_i + \xi_{ij} \tag{4.8}$$

where $logW_{ij}$ is the logarithm of hourly wages for worker i in firm j, δ is the intercept, D_i is an indicator dummy variable that indicates a worker's segment of employment, β_1 is the coefficient of importance that depicts the 'raw' wage gap, and ξ_i is the error term. A significant coefficient β_1 is indicative of the presence of labour market segmentation.

Although equation (4.8) is useful for estimating the wage gap, its weakness is that we do not know what accounts for that wage gap. As such, we expand equation (4.8) to control for other individual and firm variables that explain differences in wages for different types of segmentation. The resulting specifications are shown in equations (4.9) – (4.12). First, equation 4.9 shows the specification for the between sector segmentation, that is formal vs informal sector:

$$logW_{ij} = \alpha + \beta_1 Informal_i + X_i'\gamma + Z_j'\theta + \zeta_{ij} \tag{4.9}$$

where $logW_{ij}$, is the logarithm of hourly wages for worker i in firm j, $Informal_i$ is a dummy variable coded 1 if an employee works in the informal sector, X_i denotes a vector of individual, job and human capital characteristics for worker i, Z_j denotes the vector of firm industry and location dummies and ζ_{ij} is the error term. The coefficient β_1 captures the wage gap between formal and informal sector workers after controlling for other determinants of wages. If β_1 is negative and statistically significant, then the segmented labour market theory is confirmed.

Second, we test for the presence of wage gaps between contract and permanent workers within firms in the formal sector. The specification is presented as follows:

$$logW_{ij} = \alpha_2 + \beta_2 Contract_i + X_i'\gamma + Z_j'\theta + \lambda_j + \eta_{ij} \tag{4.10}$$

where $logW_{ij}, X_i$ and Z_j are defined as in equation (4.9), $Contract$ is a dummy variable coded 1 if a one is a contract worker and zero if is a permanent worker, λ_j are firm fixed effects (FE) and η_{ij} is the error term. β_2 signifies the presence of the wage gap between the contract and permanent workers. Equation 4.10 is used to test the hypothesis that there is segmentation within firms in the formal sector.

Lastly, we test the presence of the wage gap between contract workers in the formal sector and informal wage workers. We can think about short-term contract workers as a form of 'informalisation' within the formal sector. Thus, the need to compare contract formal sector workers with informal sector workers. The model is specified in equation 4.11,

$$logW_{ij} = \alpha_3 + \beta_3 Informal\_contr_i + X_i'\gamma + Z_j'\theta + \epsilon_{ij} \qquad (4.11)$$

where $logW_i, X_i$ and Z_j are defined as in equation (4.9), $Informal\_contr$ is an indicator variable coded 1 if the one in an informal sector worker and zero if is a contract worker in the formal sector. We hypothesise that there is across sector labour market segmentation. β_3 indicate the wage gap between the contract and informal sector workers. The sample firms are also restricted to small firms (employing fewer than 20 workers).

The second part of the analysis tests for the importance of rent-sharing, a source of segmentation within formal sector firms. We follow the theoretical model of Blanchflower et al. (1996) as applied by Rycx & Tojerow (2004). We are also interested in the importance of profit-per-worker in explaining segmentation within the formal sector. We hypothesise that there is a positive association between wages and profit-per-worker in the formal sector and that this should be higher for unionised or permanent workers as they have higher bargaining power. To test this, we estimate the equation specified below.

$$logW_{ijt} = \delta_0 + \delta_1 \frac{\pi}{n}_{jt-1} + \delta_2 \left(\frac{\pi}{n}_{jt-1} \times Bargaining_{jt0}\right) + \delta_3 Bargaining_{jt0} + Z_{jt0}'\theta + X_i'\gamma + \eta_{ij} \qquad (4.12)$$

where $logW_{ijt,}$, is the logarithm of hourly wages for worker i in firm j in period t, Z_{jt0} is a vector of firm characteristics in the base period and X_i is a vector of human capital, individual and $Bargaining_{jt0}$ represents the bargaining power of workers in the firm. We proxy it by three variables available in our data: share of union workers in the firm, the share of permanent workers, and individual employee working status (permanent vs contract). Our coefficients of interest are δ_1, δ_2 and δ_3.

Theoretically, we expect a positive coefficient of profits per-worker (δ_1). This shows that an increase in profits is associated with an increase in wages, ceteris paribus implying that workers have strong bargaining power, thus suggesting rent-sharing. This would imply that beyond human capital endowments and job characteristics, other non-market or institutional mechanisms explain wage differentials and thus provide evidence of segmented labour markets. A negative coefficient, on the other hand, implies that an increase in firm profits is associated with a decrease in wages, hence highlighting the importance of firm monopsony power in setting wages. Again, this provides evidence of segmentation. Hence, a significant association between profits and wages confirms non-competitive labour markets. δ_2 shows whether the effects of the rent-sharing differ between the firms with workers strong and weak bargaining powers. Theoretically, we expect δ_2 to be positive, indicating that the association between wages and profit will be stronger in firms where workers have higher bargaining power (Hildreth & Oswald, 1997). δ_3 is also expected to be positive – firms with larger union worker or permanent worker share are associated with workers with strong bargaining power in negotiating for wages. The inclusion of bargaining could control for selection – unions establish in firms with high profits.

To further characterise the segmentation, this chapter uses the RIF decomposition technique as proposed by Fortin, Lemieux & Firpo et al. (2011). The RIF is a quantile regression-based technique used to estimate and decompose the wage gap between two groups and it allows one to determine the part of the wage distribution where segmentation is high (see Appendix for Chapter 4, D1 for comprehensive specification**)**. Methods that estimate the wage gap at the mean may conceal important information in characterising segmentation, as its extent may vary along the wage distribution (Fortin et al., 2011).

In contrast to the OLS methods of estimating the wage gap, the RIF decomposition compares, for example, the informal sector wage distribution to the reweighted informal sector wage distribution that mimics the formal sector wage distribution, and this allows us to get the composition effects of the wage gap. Further, it compares the formal sector wage distribution to a reweighted informal sector wage distribution, and this allows us to obtain the wage structure effect of the wage gap. If the part of the wage gap explained by the wage structure (unexplained part) is more than half, then evidence of labour market segmentation holds.

One reason we may wish to implement the RIF and look at the wage distribution is that labour market regulations may be more binding for low-wage workers (Bazen, 2000; Squire & Suthiwart-Narueput, 1997).

This chapter report results are based on the 10th, 50th and 90th quantiles. The key advantage of the RIF approach, as mentioned by Firpo, Fortin and Lemieux (2018), is that the reweighting provides a consistent nonparametric estimate of the counterfactual distribution based on the ignorability assumption and overlapping support[33]. See Appendix for Chapter 4 for details of the RIF decomposition specifications.

In estimating equations 4.12, one needs to be cautious about the endogeneity of profits (and other covariates). Endogeneity may, for example, arise in cases where firms offer efficient wages to increase workers' productivity, which in turn increases firm profits. This implies that wages determine firm profits and not vice versa. Under such a scenario, the coefficient of profits-per-employee estimated using OLS will be biased downwards. Further, a product market shock may also affect labour productivity and firm profitability concurrently. Blanchflower et al (1996) proposed two ways to deal with the problem. The first is to regress wages on the lagged value of profit-per-worker measures (Matano & Naticchioni, 2017; Rusinek & Rycx, 2013). The second is to find a plausible instrumental variable that is correlated with profits-per-employee but not wages. In reality, it is difficult to find such an instrument. Thus, this study attempts to solve this problem by first proxying profit-per-worker with lagged values of the sales-per worker, then using the cost of electricity as instruments (Blanchflower et al., 1996). We have established that there is a strong correlation between lagged sales per worker and profits per worker, making lagged sales per worker a credible proxy (see Table D4.4 in the Appendix for Chapter 4 for the correlation results).

One of the major issues when decomposing the wage gap using non-experimental data between two groups is selection bias[34].

[33] The ignorability assumption specifies that the distribution of the unobserved variables is the wage model is the same across the informal and formal sectors after controlling for productivity observed characteristics. The overlapping support assumption requires that every independent variable should have values for every member group.

[34] In this study, the selection bias is a result of self-selection of workers into a particular sector (e.g. formal or informal) of employment. People with certain characteristics or attributes may systematically self-select themselves either the formal or informal sector, such that the choice of a sector is systematic. An example is when poorly educated people systematically choose to work in the informal sector. Controlling for selection bias may be necessary for identification of the composition and the wage structure effects. To account for possible selection bias, the conventional method in literature is to use the Heckman two-stage selection model. The procedure requires the inclusion of a valid instrument explaining formal-informal employment selection, but not wages. To be valid, the instrument should be correlated with participation decision in either the formal and informal sector and uncorrelated with the wages.
It is, however, acknowledged in the literature that finding such an instrument is difficult (Casale & Posel, 2011). The use of inappropriate exclusion instruments may generate identification problems such as collinearity and high standard errors. Further, the selection procedure may lead to measurement errors, given that the expected value

4.3.3 Data and Measuring of Key Variables

The empirical analysis draws on the matched employer-employee survey data of Zimbabwean formal and informal manufacturing firms and workers that was collected between 2015 and 2018. The details of the data are presented in the Appendix for Chapter 1. A key attribute of this dataset is that we can control for both firm and worker heterogeneity in accounting for labour market segmentation. One of the weaknesses of the data is the limited number of observation (as compared to other studies in literature) due to the nature of the survey data used. The sample size is constrained by the low number of manufacturing firms in Zimbabwe (see Tables A1.2 and A1.3 in the Appendix for desired and actual firms survey). We acknowledge that the low sample size may affect the precision of the results. However, our sample is representative of the manufacturing sector and the effects of low sample size may have a limited impact on the precision of our estimates.

For the specifications between the formal and informal sectors, we restrict the sample for the formal sector to cover only small firms (those with less than 20 workers) for comparability with the informal sector, since there are no large informal sector firms. Thus, we look at segmentation between formal and informal within similar firm size category, industry and region. The aim is to a find comparable sample of firms to test whether wages differ. Adjusting the sample provides us with a sample of 346 formal workers out of the initial sample of 1384, with the initial sample of the informal workers remain unchanged at 264. The same sample restrictions also apply for the contract workers vs informal workers specifications. In this case, we are left with 202 contract workers and 264 informal workers. For within-sector specifications, there is no need for sample restrictions as we need the full variation in firm size.

The dependent variable used in the analysis is the individual hourly wage. Using hourly wages (rather than monthly) offers plausible comparability of wages across workers who work different time units. This is particularly important for most informal workers who work on piece rates. The questionnaire has information on the wages a worker is supposed to earn according to position and grade of employment after taxes. In several instances, due to the

of the error term is used in the second stage of the procedure. Burger & Walters (2008) also argue that the selection methods are sensitive to heteroskedasticity and the validity of the distribution assumptions discussed in the above section. It is still a contentious issue in the literature on how best to tackle the issue of the exclusion variable problem (Casale & Posel, 2011; Pratap & Quintin, 2006).

Thus, given these shortfalls, our inability to find plausible exclusion variables and lack of alternative methods to deal with the exclusion variable in literature, we do not correct for the selection bias in this chapter. However, we acknowledge that this may bias our results, and that the direction of the bias is difficult to predict.

economic challenges affecting firms, workers are paid less than what they are supposed to be paid. Hence, in addition to contractual wages, the questionnaire includes questions on the actual wage that the worker received net of taxes. In the wage variable we also take into account non-monetary wages workers receive in the form of allowances such as food, transport, airtime and pension contributions among others. Thus, our wage variable is measured as net after-tax income and it includes non-monetary contributions, allowances and pension payments. The advantage of reporting wages net of taxes is that we do not have the problem of overestimation of the formal sector wages that are subject to taxes.

4.3.3.1 Measuring of Key Variables

Our dataset includes rich information on other variables associated with the level of wages. We group these variables into four categories: Human capital; Individual worker characteristics; Firm characteristics and Job characteristics.

Human capital includes education, experience and training. To account for a potential non-linear relationship between education and wages, which is common amongst developing countries (Keswell & Poswell, 2004; Card, 1999), education is categorised as 1. Primary education, 2. Secondary education and 3. Tertiary education. Experience is measured as the years of experience before starting to work at the current place of work.

Individual worker's characteristics include gender, marital status and age. Gender is a dummy variable that is coded 1 if a worker is a male and zero otherwise. Marital status is also a dummy variable coded 1 if a worker is married and zero otherwise. Marital status has also been included in the literature to control worker's productivity. The idea is that employers perceive married workers as motivated, stable and disciplined and hence more productive (Cohen & Haberfeld, 1991; Benham, 1974). Further, we control for individual age, including the square of age to account for non-linear effects.

Firm characteristics comprise firm size, firm age, firm industry and firm location. Firm size is a categorical variable that indicates if an employee works in a firm with between 1 and 4 employees, between 5 and 20, between 21 and 100 and at least 101.

Job characteristics include job allowance (1=yes and 0 otherwise), work type (1=permanent and zero otherwise) and union (1=yes and 0 otherwise).

Table 4.1 presents the summary statistics for the key variables used in our analysis for the earnings differentials within and between the formal and informal manufacturing sector. On average, formal sector workers (permanent and contract) earn higher wages compared to informal sector wage earners. The mean log wage for permanent workers is 0.49 log points and 0.19 log points for contract workers in the formal sector. In contrast, the mean log wage for informal works is -0.16 logs points.

In Table 4.1 we also see that, compared to informal sector workers, formal sector workers are more educated, have more experience, are older, are more likely to receive job allowances, and are paid their wages per time period. Workers in the manufacturing sector are disproportionately male, with no discernible difference across formal and informal sectors.

Table 4. 1. Pooled summary statistics on key variables for the period 2015 -2016 for the formal sector and 2015-2018 for the informal sector.

	Formal Sector						Informal sector	
	(1) Overall		(2) Permanent		(3) Contract		(4) Overall	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Hourly wages (log US dollars)	0.39	0.64	0.49	0.62	0.19	0.63	-0.16	0.78
Education Level								
1. Primary (share)	0.07	0.26	0.09	0.28	0.05	0.22	0.03	0.21
2. Secondary (share)	0.78	0.41	0.75	0.44	0.86	0.35	0.89	0.38
3. Tertiary (share)	0.15	0.35	0.17	0.37	0.09	0.29	0.07	0.33
Experience (years)	5.88	7.43	6.01	7.49	5.56	7.26	3.30	4.21
Age (years)	42.66	11.22	44.30	10.58	39.15	11.80	30.55	9.27
Gender (share male)	0.83	0.38	0.86	0.34	0.76	0.43	0.84	0.37
Married (share)	0.90	0.30	0.92	0.28	0.86	0.35	0.76	0.33
Weekly hours of work	44.08	5.11	44.05	5.27	44.07	4.88	48.08	12.10
Methods of Payment								
1. Per time period (share)	0.96	0.18	0.97	0.17	0.96	0.19	0.47	0.43
2. Piece rate (share)	0.01	0.09	0.01	0.08	0.01	0.11	0.32	0.31
3. % of firm sales (share)	0.02	0.13	0.01	0.12	0.02	0.14	0.16	0.48
4. Commission (share)	0.01	0.09	0.01	0.10	0.01	0.08	0.05	0.15
Job allowance (share)	0.59	0.49	0.63	0.48	0.49	0.50	0.22	0.41
Union membership (share)	0.43	0.50	0.48	0.50	0.32	0.47	0.00	0.00
Other jobs (share)	0.31	0.46	0.28	0.45	0.35	0.48	0.14	0.35
N	1054		711		343		323	

Notes: Computed from our pooled employer-employee dataset. Presents summary statistics for the key variables used as explanatory variables in the analysis after taking into account overlapping missing data.

Formal sector employees work fewer hours per week, but this difference is more than offset by the wage difference, implying higher weekly earnings for formal sector workers.

4.3.4 Stylized Facts Emerging from the Data

In this section, we present a descriptive analysis of the data highlighting some of the main facts related to labour market segmentation. The section establishes a criterion that would provide insights into the presence of segmentation by first, presenting stylised facts on the existence of the wage gap among different types of segments. Second, we look at other aspects that signify segmentation and these include employment and wage flexibility. Lastly, the section looks into the insights on rent-sharing.

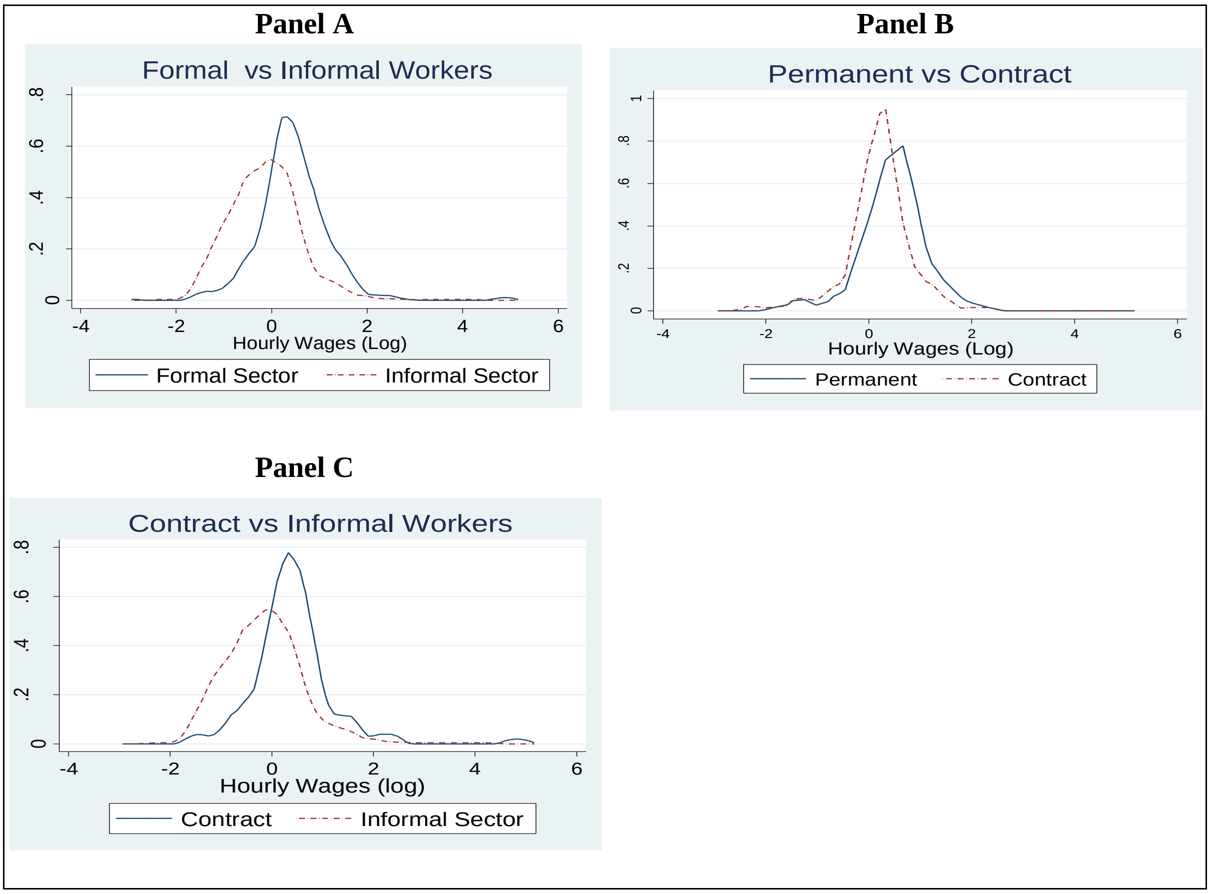
4.3.4.1 Identifying Heterogeneity of Labour Market Segmentation

While the summary statistics in Table 4.1 show average wage differentials across labour segments, some distributional comparisons provide some more insights. To present the facts on the existence of the wage gap among different types of segments, we first present kernel densities to check the wage overlaps between segments. Second, we construct the Pen's Parade quantile distributions of the wages within and between sector segments. This allows us to deepen our understanding of the wage distribution and determine at what quantiles the wage gap is large.

In Figure 4.1, we present the kernel densities for the comparisons of the wage distributions between various labour market segments. Panel A provides the wage distributions for the formal and informal sector workers. The distributions reveal that the informal sector wage distribution is to the left of the formal sector wage distribution, implying a higher probability that an informal sector worker has a lower wage than their formal counterpart. This indicates the possible presence of between-sector segmentation. However, we also note a wide distribution of wages in both sectors, with a substantial overlap in the density functions. The implication is heterogeneity among workers within and between the informal and formal sectors. To more tightly test the segmentation hypothesis, these characteristics need to be controlled for.

Panel B and C compare the wage distributions of permanent and contract workers within the formal sector, and formal contract workers and informal workers. The density functions reveal that contract workers tend to earn lower wages than their permanent counterparts, while informal workers earn lower wages than formal contract workers. These results are consistent with the presence of labour market segmentation within the formal sector and between the formal contract labour market and the informal sector. Once again, there is a wide distribution of wages within each category.

Figure 4. 1. Wage distributions within and between the formal and informal sector

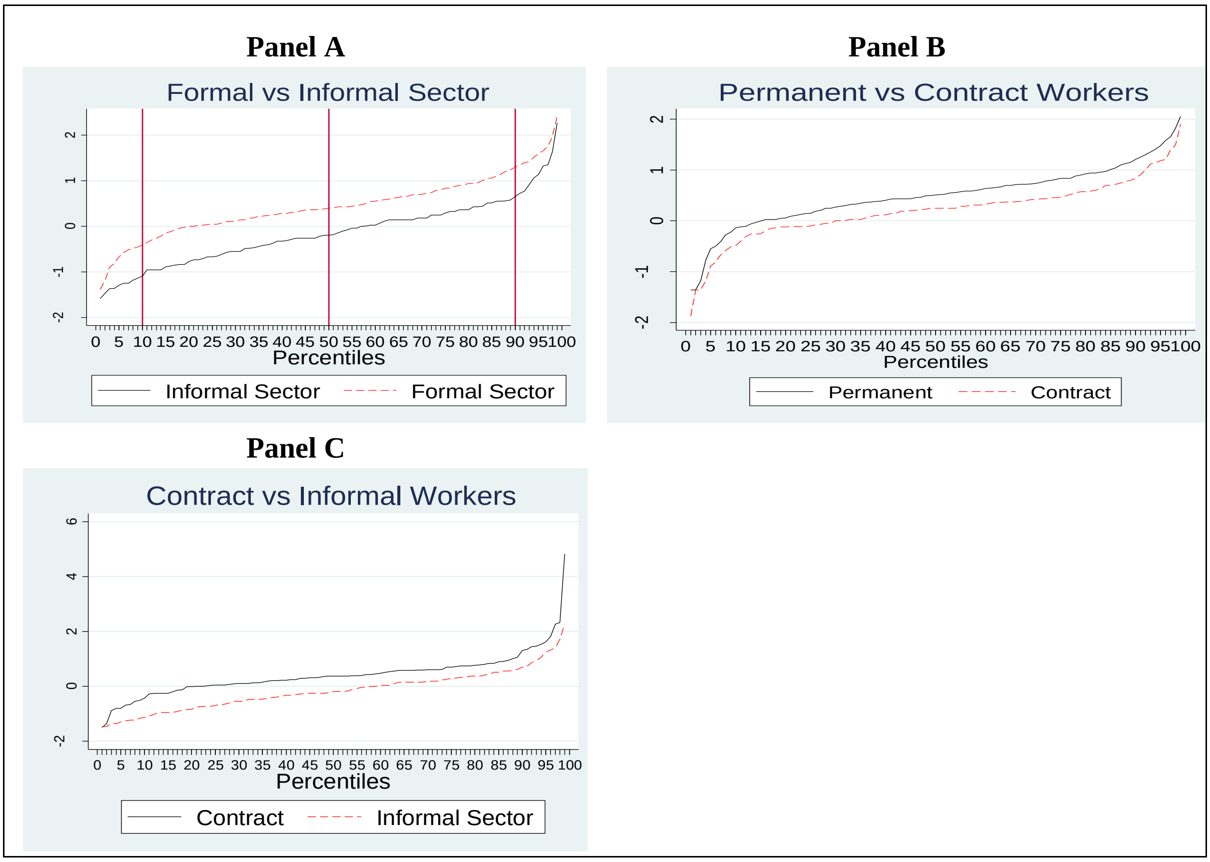


Notes: Differences in hourly wages between labour markets segments. Hourly wages are in logs. The dashed line represents informal wage, contract and tiers in Panels A, B, and C. Panel A and C shows wage differences between sectors, while Panel B shows the difference within sectors. In Panel A and C we have restricted the sample for formal firms to include only those with less than 20 workers for plausible comparability.

An alternative approach to assessing wage gaps across the distribution is Pen's Parade quantile wage distributions, as presented in Figure 4.2. The Pen's Parade distributions are just cumulative density functions, but with hourly wages on the vertical axis. They allow one to test whether wages stochastically dominate one another and to determine which quantiles show high segmentation or wage gaps. The argument is that the wage gap may not be constant along the wage distribution.

Figure 4.2 (Panel A) illustrates that the formal sector wages stochastically dominate informal wages (the informal distribution is below the formal for all wages). Workers would choose to be in the formal sector at any given percentile of the wage distribution. Panel B shows that permanent workers dominate contract ones (Panel B) and contract workers dominate informal workers (Panel C). It also shows that the wage gap is higher at the lower quantiles and decreases sustainably as we move to the upper quantiles in Panel A and C. This is useful as it tells us that it is not only the mean wage that is lower for informal, but that the entire cumulative distribution is to the left. One concern here is that the workers may differ in terms of characteristics. This lends itself to regression analysis, and then decomposition to identify the precise gap.

Figure 4. 2. Pen's Parade quantile functions for the between sector wage differentials



Notes: Pen's Parade quintile functions for the differences in hourly wages between and within the formal manufacturing sector labour markets. Hourly wages are in logs. In Panel A and C we have restricted the sample for formal firms to include only those with less than 20 workers for plausible comparability.

The illustrations in Figure 4.1 and 4.2 highlight the heterogeneity of the labour markets in Zimbabwe. Figure 4.2 shows that the wage gap is not constant across the wage distributions. These results provide a strong motivation for the use of the method that decomposes the wage gap along the quantiles rather than at the means. Such a technique includes the RIF that will be used later in the empirical analysis.

In addition to wage gaps, labour market segmentation is characterized by labour market inflexibility. We, therefore, use the 2015 and 2016 panel data from the worker surveys to assess labour market inflexibility, by looking at the mobility of workers across formal and informal sectors.

Table 4.2 presents an assessment of the change in labour market status (formal permanent, formal contract, informal worker, informal firm owner) of workers interviewed in 2015 and 2016. The results in Table 4.2 show low levels of mobility between formal and informal employment, and between contract and permanent positions within the formal sector. Looking at column (1), 81 percent of formal permanent workers in 2015 remained permanently employed in 2016. Of the remainder, none entered into informal wage employment, while 6 percent entered the informal sector as firm owners and 13 became unemployed (primarily as a result of firm closures and retirement). Similarly, as shown in column (2) no contract workers in 2015 shifted into the informal wage employment or obtained permanent contracts in 2016. 25 percent of contract workers in 2015 became unemployed over the period, reflecting the vulnerability of their employment positions.[35]

Table 4.2. Mobility of workers across different labour segments between 2015 and 2016

		2015			
		Formal Sector		Informal Sector	
	employment status	Permanent (1)	Contract (2)	Informal Workers (3)	Informal firm owners (4)
2016	Permanent	81.27	0.00	0.00	0.00
	Contract	0.00	63.99	9.21	0.00
	Informal Workers	0.00	0.00	35.53	0.00
	Informal firm owners	6.20	11.92	50.00	98.98
	Unemployed	12.53	24.09	5.26	1.02
	Total	100.00	100.00	100.00	100.00

Notes: Movement of workers across different labour markets segments between 2015 and 2016. Permanent and contract workers constitute the formal sector, while informal workers and informal firm owners constitute the informal sector.

[35] The main reasons provided were company closures and the termination or non-renewal of their employment contracts.

Looking at informal workers (column 3), we see much greater mobility of workers across labour market status, with 65% percent of 2015 workers changing labour market status. None of the 2015 informal workers transitioned into permanent contract positions in the formal sector over the period, although 9 percent obtained contract jobs in the formal sector. The bulk (50 percent) shifted to being informal firm owners, while a few (5 percent) became unemployed. Finally, informal firm owners' mobility rates are very low, with 99 percent not transitioning from being informal firm owners over the period.

The low transition into and out of permanent employment suggests a high degree of rigidity in the formal labour market. Table 4.3 draws on the survey responses from firm owners and managers on factors preventing firms from laying off permanent workers should they wish to do so.

Table 4.3. Main factors preventing firms from laying off workers in the formal sector and informal sector.

	Formal Sector Firms	Informal Sector firms
No difficulty	13.85	85.50
Difficulty redundancy procedure	30.72	0.00
High severance pay	37.35	0.00
Difficulties in rehiring workers	9.04	12.98
Other	9.04	1.52

Notes: Measures of employment flexibility in the formal and informal sector.

The contrast between the formal and informal sector firms is striking. 85.5 percent of informal sector firms find no difficulty in laying off workers, compared to 13.9 percent of formal sector firms. 31 to 37 percent of formal firms highlight the difficulty of redundancy procedures that includes the requirement that firms seek approval from the trade unions and the government to lay off workers, and high severance pay as factors preventing lay-offs.

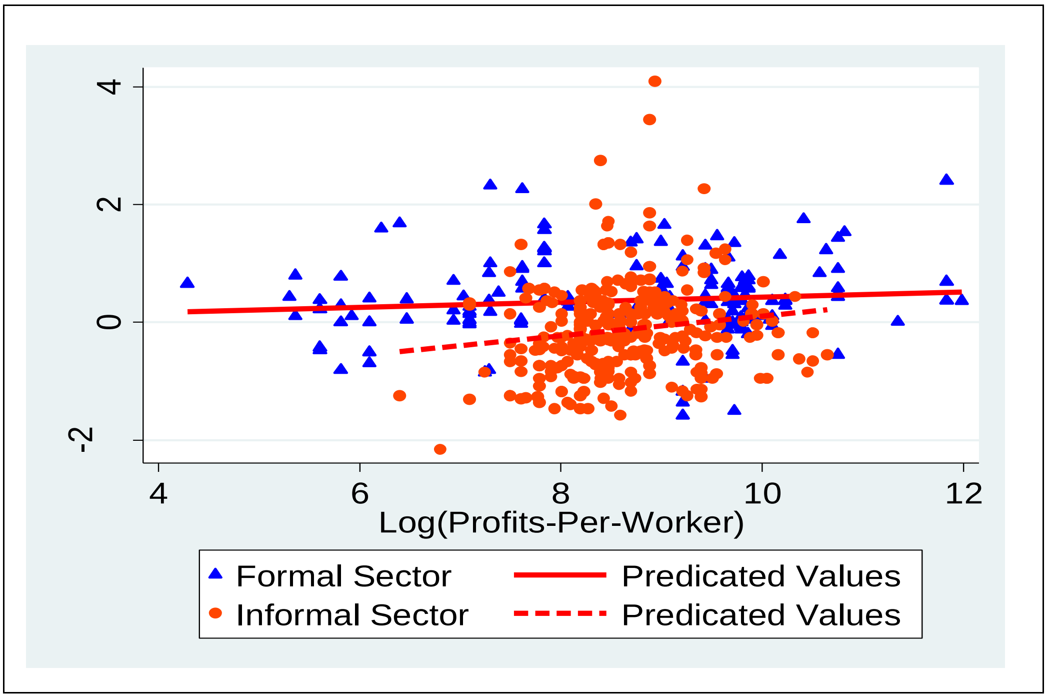
These labour market rigidities may explain the low transitions into and out of permanent worker status, and consequently the presence of labour market segmentation. Further, these rigidities provide permanent workers higher bargaining power that could result in above-market equilibrium returns, as predicted by rent-sharing models.

4.3.4.2 Relationship between Firm Profits and Wages

The rent-sharing model predicts that wages will be positively correlated with firm profits. To assess the consistency of the data with this hypothesis, Figure 3 plots individual wages against firm value-added per worker, a proxy for profit-per-worker.

Figure 4.3 reveals no significant relationship between firm profits-per-worker and individual wages in both the formal and informal sectors. If anything, the positive relationship appears to be weaker in the formal sector, contrary to expectations given the rigidities in laying-off workers in that sector. However, the scatter plot reveals substantial variation in wages and profits across firms. Other confounding factors may thus be present, obscuring the relationship between wages and firm profits. The next section, therefore, conducts more rigorous econometric testing of the wage segmentation hypothesis, while controlling for individual and firm characteristics.

Figure 4. 3. Relationship between value added-per-worker and wages



Notes: Scatter plot on the relationship between profits-per-worker and wages. Profits-per-worker is proxied by value-added per worker. All variables are in logs. The triangle scatters and solid fitted line represent the formal sector while the circle scatters and dotted fitted line represents the informal sector.

4.4. Empirical Results

This section uses the empirical methods discussed in the prior section to more rigorously test for the extent and sources of labour market segmentation in Zimbabwean manufacturing. First, we test for the significance of the wage gaps between and within the formal and informal sector segments. We then estimate the conditional relationship between wages and profit-per-worker.

4.4.1 Wage Gaps

Table 4.4 presents the results where we pool the formal and informal data and regress wages on a dummy variable for informal worker status. Column (1) presents the baseline results that exclude controls. The results reveal a significant (at 1 % level) wage gap of -51 log points (or 40 percent)[36].

To control for the human capital of the worker, column (2) includes controls for education, experience and training. The wage gap falls to -35.9 log points, reflecting the higher human capital endowment of workers in the formal sector, but it remains significant at the 1 percent level. In column (3) additional controls for job characteristics, industry and location are included. The coefficient remains significant but falls further to -24.8 log points, implying a 22 percent wage deficit for informal workers.

According to the competitive theories of labour markets, earning differentials should be exclusively explained by differences in human capital endowments. The fact that we observe a huge wage gap after controlling for human capital, individual, job firm industry and location dummies is the first indication that the labour markets in Zimbabwe are segmented and the extent of segmentation is quite high.

[36] Calculated as exp(beta)-1.

Table 4.4. The wage gap between the formal and informal manufacturing sector workers

VARIABLES	(1) Baseline	(2) +Human Capital	(4) +industry and location
1.Informality	-0.514***	-0.359***	-0.248**
	(0.0673)	(0.080)	(0.099)
1.Gender		0.035	-0.045
		(0.098)	(0.112)
Age		0.051**	0.059***
		(0.021)	(0.020)
Age square		-0.001**	-0.001***
		(0.000)	(0.000)
1.Married		0.117	0.068
		(0.097)	(0.096)
Education Level			
2.Secondary		0.152	0.026
		(0.125)	(0.124)
3.Tertiary		0.618***	0.329**
		(0.147)	(0.161)
1.Training		0.528	0.714***
		(0.330)	(0.270)
Years of Experience		0.006	0.004
		(0.014)	(0.012)
Years of Experience square		-0.000	-0.000
		(0.001)	(0.000)
Constant	0.384***	-1.056***	-1.069***
	(0.0511)	(0.404)	(0.411)
Observations	494	494	494
R-squared	0.098	0.178	0.244
Job Characteristics	NO	NO	YES
Firm Industry and Location	NO	NO	YES

Notes: The dependent variable is the log of hourly wages. Informality is a dummy variable coded 1 if one is an informal wage worker. Column (1) shows the raw wage with no controls in the model. Column (2) shows the wage gap after controlling for human capital and individual characteristics. In column (3) we add job characteristics, firm industry and location dummies. Job characteristics include job allowance and methods of wage payment. Asterisks denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Robust standard errors are in brackets

We now unpack the extent to which firms in the formal sector pay permanent and contract workers different wages after controlling for the same human capital endowments (using the model specified in equation (4.10). Temporal work contracts have traditionally been used by firms to seek some flexibility in employment and wages. We are thus testing the hypothesis that there exists a wage gap between contract and permanent workers.

Table 4.5 presents the results estimating the wage differential between the formal sector permanent and contract workers. The coefficient on the dummy variable *Contract* (equals 1 if contract worker, 0 if permanent worker) denotes the wage gap relative to permanent workers within the formal sector. The baseline results without controls presented in Column (1) show an estimated wage gap of 28.2 log points that is significant at the 1 percent level. Because characteristics of permanent and contract workers may differ, Column (2) includes human capital controls. The coefficient falls slightly to -0.213.

The inclusion of controls for job characteristics and firm fixed effects in Column (3), reduces the wage gap coefficient further to -0.149, although it remains highly significant. The inclusion of firm FE implies that the wage gap is estimated using the within-firm variation for wages among contract and permanent workers. The coefficient is thus an indicator of the segmentation of the permanent and contract labour markets 'within' firms. These results suggest the existence of segmented labour markets within firms in the formal sector. This adds another dimension of segmentation – within-firm segmentation.

Table 4.5. Within firms in the formal labour market wage gap: Permanent vs Contract workers

	Permanent vs Contract workers		
VARIABLES	(1) Baseline	(2) +Human Capital	(3) +Firm FE
Contract	-0.282***	-0.213***	-0.149***
	(0.0336)	(0.034)	(0.035)
Constant	0.538***	-0.350	3.726***
	(0.490)	(0.549)	(1.420)
Observations	1896	1896	1896
R-squared	0.039	0.172	0.466
Human Capital Characteristics.	NO	YES	YES
Individual Characteristics.	NO	YES	YES
Job Characteristics	NO	NO	YES
Firm FE	NO	NO	YES

Notes: The dependent variable is the log of hourly wages. Column 1-3 present results for within formal sector firms. *Contract* is dummy variable coded 1 if one is a contract worker. Column (1) shows the raw wage with no controls in the model. Controls include human capital (education, experience, training), individual characteristics (age, marital status, gender), job characteristics (job allowance, methods of payment) and firm FE. Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Robust standard errors are in brackets.

We may also think of short-term contract workers in the formal sector as some form of formal sector 'informalisation'. We, therefore, test for the existence of the wage gap between the contract workers and informal sector workers. Table 4.6 presents the results. While the contract employees work in the regulated formal sector firms, they are not governed by labour markets institutions and legislations such as unions.

The coefficient on the dummy variable *Informal_contract* (equals 1 if informal worker, 0 if contract worker) denotes the wage gap relative to contract workers. The baseline results in column (1) exclude controls. The results indicate a significant (at 1 percent level) wage gap of -27 log points. After controlling for human capital characteristics in column (2), the wage gap falls to -12 log points that are statistically insignificant. The fact that the wage gap became insignificant after controlling for human capital characterises suggests evidence against segmentation.

By adding the controls for job characterises, industry and location, the wage gap slightly increased to -16 log points and became weakly significant at 10 percent level. The results show that segmentation between contract and informal workers is not as profound as between formal and informal workers.

Table 4.6. Contract vs informal sector wage gap

	Contract vs Informal Sector Workers		
	(1)	(2)	(3)
VARIABLES	Baseline	+Human Capital	+industry and location
Informal_contract	-0.273***	-0.116	-0.167*
	(0.071)	(0.083)	(0.092)
Constant	0.391***	-0.785***	-0.731***
	(0.0799)	(0.441)	(0.461)
Observations	329	329	329
R-squared	0.035	0.117	0.145
Human Capital Charact.	NO	YES	YES
Individual Charact.	NO	YES	YES
Job Characteristics	NO	YES	YES
Industry and Location	NO	NO	YES

Notes: The dependent variable is the log of hourly wages. *Informal_Contract* is a dummy variable coded 1 if one is an informal wage worker and 0 if a contract in the formal sector. Columns 1-3 show regression results. Column (1) shows the raw wage with no controls in the model. Controls include human capital (education, experience, training), individual characteristics (age, marital status, gender), job characteristics (job allowance, methods of payment), industry and location. Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1).

The above results present estimates of the wage gap around the mean of the wage distribution. The weakness of estimating and basing our analysis on equations 4.9 - 4.11 is that it is practically difficult to control for all variables as some variables are not available in the data set or are unobserved. Drawing on the literature reviewed in the earlier section, we additionally apply the Oaxaca-Blinder decomposition technique to further characterise the wage gap. The technique is essentially used to explain the differences in the mean of the dependent variable (wages) between two groups by decomposing the gap into two part: the explained (observed) effect and the unexplained (unobserved) effect. The explained effect of the wage gap is the one that shows differences in observed individual productivity characteristics such as education, training and experience. The unexplained effect shows the differences in the structure of the labour markets, that is, unobserved characteristics. The extent to which the wage structure effect explains the wage gap determines the extent to which the labour market is segmented. Table 4.7 presents the Oaxaca-Blinder decomposition results for the following groups: formal vs informal workers (in column 1), permanent vs contract workers (in column 2), and informal vs contract workers (in column 3). The results in column 1 show that the unobserved (unexplained) characteristics are statistically significant (at 1 percent level), and accounts for 57% (0.294/0.514) of the wage gap. This indicates that formal and informal sector labour markets are segmented. Similarly, column 2 results illustrate that the unexplained part of the wage is statistically significant (at 1 percent level) and accounts for 63% (0.18/0.287) of the wage gap, thereby suggesting segmentation within the formal sector (permanent vs contract workers). Lastly, column 3 also shows that the unexplained wage gap accounts for 75% percent of the wage and is statistically significant at a 5 percent level.

Table 4. 7. Oaxaca-Blinder wage decomposition

	(1) Formal Vs Informal	(2) Permanent vs Contract	(3) Informal vs Contract
Group_1	0.384***	0.538***	0.294***
	(0.051)	(0.0188)	(0.0486)
Group_2	-0.130***	0.252***	0.0238
	(0.044)	(0.0303)	(0.0591)
Difference	0.514***	0.287***	0.270***
	(0.067)	(0.0357)	(0.0765)
Explained	0.220***	0.107***	0.0681
	(0.074)	(0.0189)	(0.0588)
Unexplained	0.294***	0.180***	0.202**
	(0.097)	(0.0361)	(0.0902)
Observations	494	1896	329

Notes: The table presents the Oaxaca-Blinder decomposition. *Group_1* represents averages wages for formal, permanent and informal workers in columns 1, 2 and 3 respectively, while *Group_2* represents average wages for informal, contract and contract in column 1, 2 and 3 respectively. We control for human capital, individual and job characteristics as well as industry location in all columns. Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Robust standard errors are in brackets.

The results in Table 4.7 provide evidence that traditional dualists models of segmentation do not apply in the Zimbabwean labour markets. Hence, labour markets in Zimbabwe are more integrated. These results are also consistent with Tansel and Kan (2012), who find the wage gap to be explained by observable individual and employment characteristics and they concluded that stylised facts of segmentation do not hold in Turkey labour markets.

Noting the strength of the Oaxaca-Blinder decomposition, its weakness is that it estimates the wage gap at the means, just like the OLS. The wage gap may differ across the wage distribution and the Mincerian regression and the Oaxaca-Blinder decomposition misses this. This is captured using the RIF.

Table 4.8 presents the results of RIF decomposition for the Formal vs Informal in columns 1-3, Permanent vs Contract in columns 4-6, and Contract vs Informal in columns 7-9 for the 10^{th}, 50^{th} and 90^{th} quantiles. In all the specifications, we control for human capital, individual, job characteristics and we also adjust the sample to include only a small firm category for comparability. The results in columns 1-3 show that the wage gap is higher 10^{th} and 90^{th} quantiles of the wage distribution. In columns 1-3 characteristics are also not significant in explaining the observed wage gap while the unexplained part of the wage is statistically significant at 1 percent level. We see that in columns 1-3 the unexplained part contributes entirely to the wage gap. These results reveal that the between formal and informal sector labour markets are highly segmented along the entire wage distribution.

Further, columns 4-6 presents decomposition results for within formal firm segmentation, that is, permanent vs contract workers. These results indicate that the wage gap is higher at the 10^{th} and 90^{th} percentiles. At the 10^{th} quantile, the unexplained part accounts significantly (at 1 percent level) for 70 percent (0.227/0.325) of the wage gap. At the 50^{th} quantile, the unexplained part accounts for a significant 66 percent (0.195/0.294) (at 1 percent level of significance) of the wage while it accounts insignificantly for only 19 percent (0.061/0.323) at the 90th percentile. The results suggest that segmentation within formal firms is higher at the lower part of the wage distribution.

Table 4. 8. The RIF decomposition results for the wage gap

	Formal vs Informal			Permanent Vs Contract			Contract vs Informal		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quantiles	10th	50th	90th	10th	50th	90th	10th	50th	90th
Formal	-0.431***	0.349***	1.330***						
	(0.0976)	(0.0374)	(0.0903)						
Informal	-1.059***	-0.179***	0.722***				-0.868***	0.005	1.035***
	(0.0618)	(0.0511)	(0.0850)				(0.073)	(0.064)	(0.155)
Permanent				-0.182***	0.556***	1.330***			
				(0.038)	(0.017)	(0.040)			
Contract				-0.507***	0.261***	1.007***	-0.396***	0.319***	1.084***
				(0.073)	(0.023)	(0.067)	(0.093)	(0.039)	(0.114)
Wage gap	0.628***	0.528***	0.608***	0.325***	0.294***	0.323***	0.472***	0.314***	0.049
	(0.116)	(0.0633)	(0.124)	(0.082)	(0.029)	(0.078)	(0.118)	(0.075)	(0.193)
explained	-0.283	0.00560	-0.329	0.098**	0.099***	0.262***	0.057	0.075	0.517***
	(0.376)	(0.140)	(0.339)	(0.039)	(0.020)	(0.048)	(0.117)	(0.050)	(0.149)
unexplained	0.911**	0.522***	0.937***	0.227***	0.195***	0.061	0.415**	0.239***	-0.468**
	(0.391)	(0.152)	(0.358)	(0.088)	(0.032)	(0.085)	(0.164)	(0.088)	(0.233)

Notes: The table presents the evolution of the earnings differentials for 10th, median (p50) and 90th (p90) quantiles using the RIF decomposition. We control for human capital, individual and job characteristics as well as industry location in all columns. Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Robust standard errors are in brackets.

Comparing columns 7-9 for contract vs informal sector workers, that segmentation is characterised at the bottom of the wage distribution, as indicated by the unexplained part that accounts significantly (at 1 percent level) for 88 percent (0.415/0.472) of the wage gap at the 10th quantile. At the 90th quantile, the wage gap is insignificant and is entirely accounted for by the explained part. It is, therefore, amongst the cohort of low wage that we see evidence of the greater impact of segmentation on wages. The RIF decomposition results are in line and comparable with the Oaxaca-Blinder decomposition results presented in Table 2.7.

Thus far, we tested for and identified the different types of labour market segmentation. We have been able to provide some empirical answers to our first research question on the extent and heterogeneity nature of labour market segmentation in Zimbabwe. In the remainder of this chapter, we test a specific source of labour market segmentation that is related to rent-sharing.

4.4.2 Rent-sharing as Explanation for Formal Sector Segmentation

4.4.2.1 Baseline Results

Given the extent of segmentation identified in the above sections, we now test the hypothesis that rent sharing is a source of labour market segmentation. Table 4.9 present the baseline results for the rent-sharing model.

The robust OLS serves as our baseline results for the analysis. In this model, we regress the logarithm of hourly wages on lagged values of sales per worker as presented in equation (4.12). As discussed in detail in the earlier section, we use lagged sales per worker as a proxy for profit-per-worker to reduce some bias associated with using level values of profits-per-worker.[37]

In column 1 we only include the key variable of interest, lagged sales per worker, without any controls. We find a positive significant association between wages and lagged sales per worker. A 1 percent rise in firm profitability is associated with a 0.14 percent rise in wages. In columns 2-7, we test for the importance of bargaining power in influencing wages through rent-sharing. We control for the influence of human capital, individual, job and firm characteristics (firm size, firm industry and industry dummies). For example, *firm size* is expected to be positively related to firm profitability, as bigger firms are likely to be more productive (Van Biesebroeck, 2005; Oi & Idson, 1999; Schmidt & Zimmermann, 1991). Hence to isolate the true unbiased coefficient on profits-per-worker we extended our model by adding some controls discussed above and clustering at the firm level. The inclusion of the controls leads to a drastic reduction in the coefficient on profits-per-worker in all columns, but it remains highly significant except in column 5.

In column 2 we measure bargaining power with the share of union workers in the firm. The positive significant association between wages and share of union workers suggests that firms with a higher proportion of union workers pay high wages; this is consistent with the rent-sharing theory. In column 3 we interact *union share* with the lagged values of the *sales-per worker*, as we are also interested in the marginal relationship that bargaining and rent-sharing have with influencing wages. We find an insignificant marginal difference between firms with higher union share and those with lower union share on the relationship between wages and

[37] A better option would have been to use lagged values of valued-added per-worker, but we are unable to construct this variable for this period given our data.

sales-per worker suggesting that effects of rent-sharing are the same for unionised and non-unionised firms. This result is consistent with the findings by Velenchik (1997b), who argues that employees are unlikely to have meaningful bargaining power in Zimbabwe due to widespread unemployment. One possible explanation for the correlation between profits-per-worker, bargaining and wages is that firms are coerced to pay higher wages out of rents due to stringent government policies and labour market regulations. Although we cannot infer this argument from our data, it is consistent with the intervention of government in wage-setting processes, and this particularly favours the permanent or unionised workers as shown by our results.

In column 4 we proxy bargaining power with the share of permanent workers in the firm. The results are consistent with the results in column 2, showing a positive but weakly significant association between wages and the share of permanent workers. The interaction between profit-per worker and share of permanent workers is insignificant, as shown by results in column 5. In column 6 we proxy bargaining power with a binary variable for individual worker status (1 if a worker is permanent). The results show a strong positive association between permanent worker status and wages. However, there are no marginal differences in rent-sharing between permanent and non-permanent workers as indicated by an insignificant interaction term in column 7.

Overall, the results in Table 4.9 suggest that more profitable firms pay more wages to their workers. Such a positive relationship between wages and sales-per-worker indicates that rent-sharing is a source of segmentation in the formal labour markets. The results also indicate that high bargaining power is associated with higher wages. However, we find no evidence indicating that bargaining power influences wages through rent-sharing.

Table 4. 9. Rent-sharing in the formal sector labour markets.

		Measures of Bargaining Power					
	Baseline	Union_share	Union_share × lagged sales per-worker	Permanent_ share	Permanent_ share × lagged sales per worker	Permanent- _worker status	Permanent_ Status × lagged sales per-worker
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales/worker (lagged)	0.140***	0.098***	0.098***	0.094***	0.051*	0.094***	0.080***
	(0.028)	(0.015)	(0.017)	(0.014)	(0.030)	(0.014)	(0.017)
Bargaining_power		0.019**	-0.037	0.101*	0.550*	0.161***	-0.065
		(0.009)	(0.073)	(0.053)	(0.316)	(0.031)	(0.189)
Bargaining_power × Sales/worker (lagged)			0.012		-0.060		0.031
			(0.015)		(0.043)		(0.025)
Constant	-0.559***	-1.077***	-0.992***	-0.982***	-0.574	-1.145***	-1.041***
	(0.214)	(0.342)	(0.285)	(0.325)	(0.392)	(0.281)	(0.283)
Observations	1,902	1,764	1,764	1,836	1,836	1,902	1,902
R-squared	0.076	0.234	0.200	0.232	0.236	0.244	0.244
Human Capital	NO	YES	YES	YES	YES	YES	YES
Individual Characteristics	NO	YES	YES	YES	YES	YES	YES
Job Characteristics	NO	YES	YES	YES	YES	YES	YES
Firm Controls	NO	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is the log of *hourly wages*. *Lagged sales per worker* are in logs and is a proxy for profit-per-worker. Controls include human capital (education, experience, training), individual characteristics (age, marital status, gender), job characteristics (job allowance, methods of payment), firm characteristics (firm age, firm size, industry dummies, and location dummies). Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Standard errors are in brackets. Bargaining power is proxied by *Union share* (share of union workers to total employment in the firm) in column 2 and 3, *Permanent share* (share of permanent workers to total employment in a firm) in column 4 and 6, and *Permanent worker status dummy* (1 if permanent and 0 otherwise) in column 6 to 7.

We extend the analysis to the informal manufacturing sector. However, our analysis is limited as we only have concurrent sales per worker. Thus, the results may be affected by endogeneity bias. The results for the informal sector rent-sharing model are shown in Table D4.1 (in the Appendix for Chapter 4). The baseline results in column 1 show a significant positive association between profit-per-worker and wages. In column 2, after adding the controls for human capital, individual, job and firm characteristics the profit-per-worker coefficient falls slightly and becomes less significant (albeit still at a 5 percent level). It is difficult to justify that the correlation between wages and profits in the informal sector indicates rent-sharing since these workers are neither regulated nor unionised. Rather, such a relationship may be a result of the payment structure in the informal sector. It should be emphasised that most of the informal sector workers are paid piece rate. Consequently, if more profitable firms sell more, then they will pay workers more. Thus, what may be driving the informal sector results is the piece-rate system.

As already mentioned in the earlier sections, our benchmark specifications might suffer from the endogeneity of sales-per-worker. To test the robustness of the results, we adopt the instrumental variable regression approach. Following Blanchflower and Oswald 1996, we use the cost of electricity as our instrument. A good instrument should be able to sufficiently explain the variation in the potential endogenous variable (sales-per-worker) but not the variation in the dependent variable (hourly wages).

Using a two-stage least squares (2SLS) regression where, in the first step (see Table D4.2 in Appendix for Chapter 4), we regress the value of lagged sales-per-worker on the cost of electricity. The coefficient of our instrument in Table D4.2 is positive and significant at the 1 percent level of significance. These results, therefore, satisfy the requirement that the instrument should be highly correlated with the explanatory variable. Further, as argued by Blanchflower et al. (1996), the cost of energy does not directly enter the wage equation as there is no theoretical link between the two. This suggests that the cost of energy is a valid instrument and that our IV models are well specified.

Table 4.10 presents results for the second stage of the instrumental variable regression for formal sector workers. The results generally corroborate with our earlier findings that rent-sharing is significant in determining wage setting processes.

Table 4. 10. 2SLS results for the formal sector sales-per-worker and the wage relation.

		Measures of Bargaining Power					
	Baseline	Union_share	Union_share × lagged sales per-worker	Permanent_ share	Permanent_ share × lagged sales per worker	Permanent- _worker status	Permanent_ Status × lagged sales per-worker
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales/worker (lagged)	0.117***	0.114***	0.106**	0.085***	0.107	0.092***	0.078*
	(0.024)	(0.030)	(0.041)	(0.030)	(0.113)	(0.029)	(0.044)
Bargaining_power		0.024**	-0.028	0.096*	0.039	0.161***	-0.071
		(0.011)	(0.134)	(0.055)	(0.982)	(0.030)	(0.319)
Bargaining_power × Sales/worker (lagged)			0.010		0.006		0.032
			(0.026)		(0.138)		(0.043)
Constant	-0.392**	-1.177***	-1.009***	-0.916**	-1.071	-1.130***	-1.028**
	(0.179)	(0.379)	(0.372)	(0.373)	(0.962)	(0.333)	(0.407)
Observations	1,902	1,764	1,764	1,836	1,836	1,902	1,902
R-squared	0.066	0.228	0.231	0.232	0.236	0.244	0.246
Human Capital	NO	YES	YES	YES	YES	YES	YES
Individual Characteristics	NO	YES	YES	YES	YES	YES	YES
Job Characteristics	NO	YES	YES	YES	YES	YES	YES
Firm Controls	NO	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is the log of *hourly wages*. *Lagged sales per worker* are instrumented by the cost of power. Controls include human capital (education, experience, training), individual characteristics (age, marital status, gender), job characteristics (job allowance, methods of payment), firm characteristics (firm age, firm size, industry dummies, and location dummies). Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Standard errors are in brackets. Bargaining power is proxied by *Union share* (share of union workers to total employment in the firm) in column 2 and 3, *Permanent share* (share of permanent workers to total employment in a firm) in column 4 and 6, and *Permanent worker status dummy* (1 if permanent and 0 otherwise) in column 6 to 7.

The coefficients for sales-per-worker in all the specifications, except for column 5, are positive and significant at 1, 5, or 10 percent.

Compared to the non-instrumented results in Table 4.9, the 2SLS estimated coefficients are larger indicating a downward bias associated with failure to account for endogeneity.
We are only able to conduct robustness for the formal sector as we do not have plausible instruments for the informal sector. For example, we do not have a stand-alone measure for the cost of electricity as it is pooled together in rentals and water costs.

In summary, the extent that firms' profits are associated with individual wages confirms that the labour markets in Zimbabwe are segmented and that firm's ability to pay plays a critical role in explaining wage differentials. Our findings are in line with other results in literature from developing economies (Bigsten et al., 2003; Söderbom & Teal, 2001; Velenchik, 1997b; Teal, 1995). These studies have established that rent-sharing plays a key role in explaining labour segmentation. Although the nature of our data could not allow us to do a complete exploration of the sources of rent-sharing, our results provide a plausible link between profits-per-worker and the wage determination process in Zimbabwe.

4.5. Conclusion

This study investigated the extent and source of labour market segmentation between and within the formal and informal manufacturing sectors in Zimbabwe. First, we used the wage between different labour market segments to identify the extent of labour segmentation. Second, we tested a specific source of segmentation associated with the association between profit-per-worker and wages. The chapter draws on the recent employee-employer matched dataset we collected in the manufacturing sector in Zimbabwe between 2015 and 2018. The advantage of our dataset is that we were able to control for firm characteristics.

We found evidence suggesting the following stylised facts. First, we found that the nature of labour market segmentation is heterogeneous across labour market segments. Second, we found that the mobility of workers is unidirectional towards the informal sector, while the movement to the formal sector (especially on permanent jobs) is highly restricted. Firms in the formal sector face high rigidities in laying off workers should they wish to do so. These stylised facts imply the immobility of workers to the primary sector, and this is consistent with labour market segmentation theories.

The empirical results have provided some key insights. First, we have found evidence suggesting that labour markets in Zimbabwe are segmented between the regulated formal sector and the unregulated informal sector. The results show a raw wage gap of about 52 percent and a conditional wage gap of about 25 percent. We then used the RIF decomposition technique to characterise segmentation. The RIF results show that the unexplained part accounts for relatively more of the wage, thus indicating evidence of labour market segmentation. Second, we have found evidence indicating labour market segmentation within formal sector firms, that is between permanent and contract workers. The RIF decomposition illustrates that the segmentation is higher at the top tail of the wage distribution. Thirdly, the results show insignificant wage differentials between contract workers in the formal sector and informal sector workers after controlling for human capital characteristics.

Concerning rent-sharing as a source of segmentation, the study found a positive and significant association between firm sales-per-worker and individual wages in the formal sector. We also found a positive but weak significant association between sales-per-worker and wages in the informal sector. To the extent that firm sales-per-worker significantly explain wages, these results confirm that competitive labour models do not apply in the formal labour markets. The results imply that rent-sharing is an important source of labour market segmentation in Zimbabwe, thus indicating that labour markets are inefficient.

Given the potential contribution of this study, we conclude with a word of caution when interpreting the results. The major issues concerning our results are the selection bias associated with estimating sectoral earnings differentials, and the potential endogeneity problem associated with estimating the relationship between wages and profits-per-worker.

Regarding the endogeneity of profits-per-worker, we first proxy profits-per-worker with the lagged values of sales-per-worker to account for endogeneity associated with using level values of profits per worker. We then used the instrumental variable strategy to try to minimise endogeneity. However, it is also always a challenge to find plausible instruments. Thus, future studies could focus on securing panel data on formal sector firms that can allow one to utilise a wide range of methods such as fixed effects that can deal with some endogeneity and selection bias issues more comprehensively.

Chapter 5

5. General Conclusion and Policy Implications

5.1. Summary of Key Findings

This thesis examines the effects of market frictions and distortions on allocative inefficiency and aggregate TFP in the Zimbabwean formal and informal manufacturing sectors. The thesis contributes to the growing literature on identifying and measuring misallocation and its implication for aggregate TFP in emerging economies.

The empirical analysis in this thesis makes use of a matched employer-employee dataset of Zimbabwean formal and informal manufacturing firms and workers that was collected between 2015 and 2018. The survey design and implementation of some aspects of the informal sector survey were conducted specifically as part of this thesis. The data contains detailed information for both firms and workers that allows a comprehensive analysis of the thesis objectives.

The thesis constitutes of three main empirical chapters. The first main chapter (Chapter 2) investigates the extent of allocative inefficiency within and between the formal and informal sector firms. The objective is to assess the importance of factor market distortions in contributing to misallocation and the associated consequences on aggregate TFP losses. Using the firm-level dataset for formal and informal sector firms we collected in 2015 and then applying the HK methodology, the study finds the following evidence: first, the results show firm productivity heterogeneity for both the formal and informal sectors. The TFPQ distribution for the small formal firms shows a large thick left tail, suggesting that low-productivity small formal firms do not exit production, thereby creating zombie firms. The existence of zombie firms is an indication of allocative inefficiency. The distribution of the aggregate measure of allocative efficiency, TFPR, show large dispersion, highlighting the existence of misallocation of resources within and between the formal and informal sector.

Second, the results show a positive correlation between the indicator of misallocation (TFPR) and productivity. This indicates that misallocation is considerably higher for higher-productivity firms in both the formal and informal sectors. To understand the sources and nature of distortions, the aggregate measure of misallocation (TFPR) is decomposed into capital and output distortions. The results show that there is a positive correlation between firm productivity and measures of capital and output distortions in the formal and informal sectors. The results suggest that relatively more productive firms face high output and capital distortions, which induce them to produce lower than optimal output. A comparison between the formal and informal sector firms indicate that informal sector firms suffer relatively more from both the capital and output distortions. While there is a slight difference in the extent of output distortions between these two sectors, capitals distortions are strikingly larger for the informal sector firms. These results stipulate that distortions act as a tax to comparatively more productive firms, causing more productive firms to become inefficiently small while less productive firms become inefficiently large, thereby suppressing aggregate TFP.

Third, the results show that by removing misallocation of resources, aggregate TFP gains of 153.6 percent can be realized. The results further indicate that the elimination of misallocation in the formal sector leads to 156.6 percent improvement in formal sector TFP, while in the informal sector the TFP gains increases by 151.2 percent. The results point out the importance of efficient allocation of resources to improve aggregate TFP.

The chapter concludes by presenting the robustness of the results through the use of WBES as an alternative dataset to our primary dataset. It also uses the OP covariance approach as an alternative to HK methods. The robustness check results corroborate our baseline findings indicating the existence of large misallocation in the Zimbabwean manufacturing sector.

Chapter 3 examines how financial access constraints contribute to misallocation and hinder productivity-enhanced firm performance for the informal manufacturing sector firms. The chapter draws from the panel dataset of informal sector firms that we collected between 2015 and 2018. The chapter first examines the association between financial access constraints and indicators of misallocation and determine if financial constraints amplify aggregate TFP losses via the misallocation channel. It then looks at how financial access constraints impede productivity-enhanced firm performance. Firm performance is measure by employment growth and change in the capital (investment), while measures of financial access constraints are constructed directly from the information on firm financing activities available on the questionnaire.

The results show heterogeneity in access to finance by informal sector firms. Evidence indicates that young and relatively small firms are more financially constrained. Further, results reveal that more productive firms are financially constrained relative to less productive firms. Empirically, the chapter first shows evidence indicating a significant and positive association between firm TFP and the measures of misallocation, suggesting that aggregate TFP losses due to misallocation are amplified (a result that is consistent with findings in Chapter 2). Second, we find a positive association between financial constraints and indictors of misallocation. This indicates that financial constraints impose an additional source of misallocation. Third, we find a positive association between indicators of misallocation and the interaction between financial constraints and firm TFP. This result signifies that financial constraints further compound aggregate TFP losses through misallocation. Fourth, we find that financial constraints magnify aggregate TFP losses through MRKP, capital distortions and output distortions. Thus, financial constraints act as a tax, leading to firms using less capital relative to labour than is optimal.

With regard to the link between financial access constraints and productivity-enhanced reallocation of employment growth and investment, the results reveal a negative and significant association between financial constraints and firm investment. Financial constraints thus reduce a firm's investment capacity, leading to shrinking firm performance and, eventually, aggregate TFP. The results further indicate an insignificant relationship between firm productivity and investment. There is also evidence suggesting an insignificant relationship between firm investment and the interaction between financial constraints and productivity. This indicates that productivity-enhanced capital reallocations are not realised in the informal manufacturing sector. Moreover, the results show an insignificant relationship between financial constraints and employment growth. Evidence also reveals that productivity-enhanced allocation of labour is not achieved in the informal sector. This implies that financial access constraints do not have a direct link to employment growth. Thus, the negative effects of financial access constraints on misallocation run through the investment channel and not squarely through employment growth.

Lastly, chapter 4 examines the efficiency of labour markets in allocating labour in the manufacturing sector. In particular, chapter 4 addresses the question of the extent and sources of labour market segmentation within and between the formal and informal sector employees. Labour market segmentation theoretical models have traditionally been used to test the efficiency of labour markets by analysing the source of the wage differential between labour market sub-groups. The study is inspired by the rent-sharing models that theoretically explains the channels through which bargaining can lead to private but social sub-optimal allocations of labour. The empirical questions in this chapter are addressed using the matched employer-employee dataset that includes the panel dimension for employees and informal sector firms.

The chapter considers the labour market divide between the regulated formal and unregulated informal labour market segments, and the divide between permanent and contract (part-time) employees within the formal sector. We also consider the divide between the contract workers in the formal sector and workers in the informal sector. The comparison between formal and informal sector workers shows a significant raw wage gap of 52 percent and a conditional wage gap of 25 percent. These results indicate that the labour markets between the formal and informal sector firms are highly segmented. Likewise, a comparison between permanent and contract workers in the formal sector labour markets reveals a wage gap of between 16 and 28 percent, thus highlighting that within the formal sector, labour markets are also segmented. The RIF decomposition results show that the unexplained part accounts for relatively more of the wage, thus indicating evidence of labour market segmentation across the entire wage distribution. We also find evidence of segmentation between permanent and contract workers within firms in the formal sector (a raw wage gap of 28 percent and conditional wage gap of 15 percent). The RIF decomposition illustrates that the segmentation is higher at the top tail of the wage distribution.

Concerning rent-sharing as a source of wage differentials, the study finds a positive and significant association between firm profit-per-worker and employee wages in both the formal and informal sector. We also find evidence suggesting that more bargaining power is associated with higher wages. The results suggest evidence of rent-sharing as a source of segmentation within the formal sector, thus confirming that competitive labour models do not apply in the Zimbabwe labour markets. Thus, labour markets are inefficiently allocating labour resources.

5.2. Policy Implications of Findings

The findings of this thesis contribute to the understanding of how factor market inefficiencies affect allocative efficiency and aggregate TFP. Studying allocative efficiency using the newly available matched employer-employee data that includes both the formal and informal sector firms for an emerging economy provides an important policy perspective on the effects of idiosyncratic distortions and firm dynamics. Several policy implications can be drawn from the thesis.

First, evidence from chapter 2 shows that huge aggregate TFP gains can be realised if output and input distortions are removed. Resource misallocation usually arises due to poor economic policies, market frictions, and institutional and legislative rigidities that prevent the expansion of productive firms and promote the survival of less efficient firms. Zimbabwe is characterised by factor market distortions that reduce aggregate TFP. These distortions are particularly pronounced for capital markets with large effects on informal firms. Substantial gains in aggregate productivity can be achieved by reducing distortions, allowing factor markets to operate efficiently. A policy prescription that focuses on reducing these rigidities may go a long way in eliminating misallocation and bolster aggregate TFP in Zimbabwe. Eliminating misallocation is a difficult task that needs all policy levers. Structural policies that allow competitive access to the available resources by firms may play a critical role in reducing misallocation. A 'one size fits all' policy may exacerbate misallocation if less productive firms also benefit from such policy incentives. Thus, access to resources such as banks loans and government tax rebates should be conditional on firm productivity.

Second, the finding in chapter 3 that more productive firms are relatively financially constrained, and that there is a positive association between financial access constraints and indictors of misallocation, implies the need for policies to improve financial access for informal sector firms. Such a policy should be designed in a way that benefits more productive firms, as easy access to finance by every firm may create inefficiencies that reduce aggregate TFP. One intervention to improve supply-side financial access barriers is to better inform firms in the informal sector on the procedure and process needed to successfully apply for external sources of finance. Further, banking penetration can be enhanced by simplifying the required documentation, offering lower fees, and improving competition in financial institutions targeting small and micro firms. The negative association between financial constraints firm investments highlights that removal of financial access frictions may increase the much-needed capital investment in the informal sector, thereby increasing the productivity of this sector. However, access to finance may fail to improve the impact of employment growth, as the results show that there is no direct relationship between financial access and employment growth in the informal manufacturing sector.

Third, chapter 4 also provides some key policy insights. The evidence points out that the labour markets are highly segmented, and thus inefficient, as shown by the existence of wage gaps even after controlling for human capital endowments. In addressing the concerns of the labour market segmentation, care should be taken in designing policies that promote competitive labour markets and inclusive growth. One way to improve the competitiveness and efficiency of labour markets is to improve their flexibility by reducing the length and expenses of firing workers – these are exceptionally high in the context of Zimbabwe. This would bolster firm performance, productivity and prepare firms to increase employment in the long run. The inflexibility of labour markets is thought to discourage firms from employing permanent workers.

5.3. Suggestions for Future Research

This thesis offers an important contribution upon which further research can be built. In chapter 2, we use the firm-level dataset for both the formal and informal sector firms to analyse static allocative efficiency, there is a need for future research to put more attention into investigating the dynamics of the extent and source of misallocation. This can be made possible by increasing the availability and accessibility of firm-level panel datasets. Availability of such datasets will allow expansion of the analysis across a wider dimension and offer new insights into the analysis of the role of misallocation on aggregate TFP. Moreover, it will allow the use of other robust methods that cannot be used with cross-section datasets. Further, there is a need to carry out cross country comparisons to determine the extent of misallocation in Zimbabwe by benchmarking it to other SSA countries with similar economic structures.

While chapter 3 has extended the literature on misallocation by looking at the effects of financial access constraints on misallocation and productivity-enhanced firm performance using the panel data for the informal sector, we could not include the formal sector in the analysis. Such an analysis has been constrained by the unavailability of formal sector firm-level panel data. It is therefore suggested that the formal sector is included in the analysis of the effects of financial constraints on misallocation in future when such a dataset becomes available. Likewise, it would be informative to compare our results to other informal sectors in developing economies should such data be available. Further, it would be also interesting if, in future, we extend our sample time dimension to give robust dynamics analysis of the informal sector and assess how the exit and entry of firms affect misallocation and aggregate TFP.

Lastly, the major issues that might be weakening our analysis in chapter 4 are selection bias and the potential endogeneity of the profit-per-worker. While we have attempted to solve the endogeneity problem by using the instrumental variable methods, it will be helpful for future research to secure a panel data on formal sector firms and workers that will allow one to utilise a wide range of methods, such as fixed effects and generalised methods of moments (GMM) systems, that can deal with some endogeneity and selection bias issues in a more enunciated way. A panel dataset will also allow more robust and explicit analysis of the rent-sharing models and their labour markets efficient consequences.

References

Abel, A.B. & Eberly, J.C. 2011. How q and cash flow affect investment without frictions: An analytic explanation. *The Review of Economic Studies.* 78(4):1179-1200.

Ackerberg, D.A., Caves, K. & Frazer, G. 2015. Identification properties of recent production function estimators. *Econometrica.* 83(6):2411-2451.

Alti, A. 2003. How sensitive is investment to cash flow when financing is frictionless? *The Journal of Finance.* 58(2):707-722.

Amaral, P.S. & Quintin, E. 2006. A competitive model of the informal sector. *Journal of Monetary Economics.* 53(7):1541-1553.

Angrist, J.D. & Kuersteiner, G.M. 2011. Causal effects of monetary shocks: Semiparametric conditional independence tests with a multinomial propensity score. *Review of Economics and Statistics.* 93(3):725-747.

Arai, M. 2003. Wages, profits, and capital intensity: Evidence from matched worker-firm data. *Journal of Labor Economics.* 21(3):593-618.

Asker, J., Collard-Wexler, A. & De Loecker, J. 2014. Dynamic Inputs and Resource (Mis)Allocation. *Journal of Political Economy.* 122(5):1013-1063. DOI:10.1086/677072 Available: https://www.jstor.org/stable/10.1086/677072.

Aterido, R., Hallward-Driemeier, M. & Pagés, C. 2011. Big Constraints to Small Firms' Growth? Business Environment and Employment Growth across Firms. *Economic Development and Cultural Change.* 59(3):609-647. DOI:10.1086/658349.

Ayyagari, M., Demirguc-Kunt, A. & Maksimovic, V. 2008. How important are financing constraints? The role of finance in the business environment. *The World Bank Economic Review.* 22(3):483-516.

Baez-Morales, A. 2015. Differences in efficiency between Formal and Informal Micro Firms in Mexico. *AQR–Working Papers, 2015, AQR15/10.*

Banerjee, A.V. & Duflo, E. 2005. Growth theory through the lens of development economics. *Handbook of Economic Growth.* 1:473-552.

Banerjee, A.V. & Moll, B. 2010. Why does misallocation persist? *American Economic Journal: Macroeconomics.* 2(1):189-206.

Bargain, O. & Kwenda, P. 2014. The informal sector wage gap: New evidence using quantile estimations on panel data. *Economic Development and Cultural Change.* 63(1):117-153.

Bartelsman, E., Lopez-Garcia, P. & Presidente, G. 2017. Factor reallocation in Europe. *Forthcoming as ECB WP.*

Bartelsman, E., Haltiwanger, J. & Scarpetta, S. 2013. Cross-Country Differences in Productivity: The Role of Allocation and Selection. *The American Economic Review.* 103(1):305-334. DOI:10.1257/aer.103.1.305 Available: https://www.jstor.org/stable/23469644.

Bazen, S. 2000. The impact of the regulation of low wages on inequality and labour-market adjustment: A comparative analysis. *Oxford Review of Economic Policy.* 16(1):57-69.

Beck, T., Demirgüç-Kunt, A. & Maksimovic, V. 2005. Financial and legal constraints to growth: does firm size matter? *The Journal of Finance.* 60(1):137-177.

Beck, T. & Demirguc-Kunt, A. 2006. Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance.* 30(11):2931-2943.

Benham, L. 1974. Benefits of women's education within marriage. *Journal of Political Economy.* 82(2, Part 2):S57-S71.

Benjamin, N.C. & Mbaye, A.A. 2012. The Informal Sector, Productivity, and Enforcement in West Africa: A Firm-level Analysis. *Review of Development Economics.* 16(4):664-680.

Bento, P. & Restuccia, D. 2017. Misallocation, establishment size, and productivity. *American Economic Journal: Macroeconomics.* 9(3):267-303.

Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J.W., Oduro, A., Oostendorp, R. et al. 2003. Risk sharing in labor markets. *The World Bank Economic Review.* 17(3):349-366.

Bigsten, A. & Söderbom, M. 2011. Industrial Strategies for Economic Recovery and Long-term Growth in Africa. *African Development Review.* 23(2):161-171.

Bils, M., Klenow, P.J. and Ruane, C., 2020. Misallocation or mismeasurement? *National Bureau of Economic Research*, No. w26711.

Blanchflower, D.G., Oswald, A.J. & Sanfey, P. 1996. Wages, profits, and rent-sharing. *The Quarterly Journal of Economics.* 111(1):227-251.

Botelho, F. & Ponczek, V. 2011. Segmentation in the Brazilian labor market. *Economic Development and Cultural Change.* 59(2):437-463.

Buera, F.J., Kaboski, J.P. & Shin, Y. 2011. Finance and development: A tale of two sectors. *American Economic Review.* 101(5):1964-2002.

Buera, F.J. & Moll, B. 2015. Aggregate implications of a credit crunch: The importance of heterogeneity. *American Economic Journal: Macroeconomics.* 7(3):1-42.

Burger, J.D. & Walters, S.J. 2008. Testing fair wage theory. *Journal of Labor Research.* 29(4):318-332.

Busso, M., Fazio, M. & Algazi, S. 2012. (In) formal and (un) productive: the productivity costs of excessive informality in Mexico. *Inter-American Development Bank.*

Busso, M., Madrigal, L. & Pagés, C. 2013. Productivity and resource misallocation in Latin America1. *The BE Journal of Macroeconomics.* 13(1):903-932.

Caballero, R.J., Hoshi, T. & Kashyap, A.K. 2008. Zombie lending and depressed restructuring in Japan. *American Economic Review.* 98(5):1943-1977.

Calligaris, S. 2015. Misallocation and Total Factor Productivity in Italy: Evidence from Firm-Level Data. *Labour.* 29(4):367-393.

Campello, M., Graham, J.R. & Harvey, C.R. 2010a. The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics.* 97(3):470-487.

Card, D. 1999. The causal effect of education on earnings. In *Handbook of labor economics.* Elsevier. 1801-1863.

Card, D., Cardoso, A.R., Heining, J. & Kline, P. 2018. Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics.* 36(S1):S13-S70.

Card, D., Devicienti, F. & Maida, A. 2013. Rent-sharing, holdup, and wages: Evidence from matched panel data. *Review of Economic Studies.* 81(1):84-111.

Carneiro, F. & Henley, A. 2001. Modelling formal vs. informal employment and earnings: micro-econometric evidence for Brazil. *U of Wales at Aberystwyth Management & Business Working Paper.* (2001-15).

Casale, D. & Posel, D. 2011. Unions and the gender wage gap in South Africa. *Journal of African Economies.* 20(1):27-59.

Cazes, S. & de Laiglesia, J.R. 2015. Temporary contracts and wage inequality. In *Labour markets, institutions and inequality.* Edward Elgar Publishing.

Chang, P. & Lee, M. 2011. The WTO trade effect. *Journal of International Economics.* 85(1):53-71.

Chen, K. & Song, Z. 2013. Financial frictions on capital allocation: A transmission mechanism of tfp fluctuations. *Journal of Monetary Economics.* 60(6):683-703.

Chen, M.A. 2005. Rethinking the informal economy: linkages with the formal economy and the formal regulatory environment. *Research Paper, UNU-WIDER, United Nations University (UNU).* 2005/10 Available: https://www.econstor.eu/handle/10419/63329.

Chen, M.A. 2012. The informal economy: Definitions, theories and policies. *WIEGO Working Paper no 1.*

Chiburis, R.C., Das, J. & Lokshin, M. 2011. *A practical comparison of the bivariate probit and linear IV estimators.* The World Bank.

Cirera, X., Fattal Jaef, R.N. & Maemir, H.B. 2017. Taxing the good? distortions, misallocation, and productivity in Sub-Saharan Africa. *The World Bank.*

Clementi, G.L. & Hopenhayn, H.A. 2006. A theory of financing constraints and firm dynamics. *The Quarterly Journal of Economics.* 121(1):229-265.

Cochran, W.G. 2007. *Sampling techniques.* John Wiley & Sons.

Cohen, Y. & Haberfeld, Y. 1991. Why do married men earn more than unmarried men? *Social Science Research.* 20(1):29-44.

Collard-Wexler, A., Asker, J. & De Loecker, J. 2011. Productivity volatility and the misallocation of resources in developing economies. *National Bureau of Economic Research.*

Confederation of Zimbabwe Industries. 2012. Manufacturing Sector Survey Report. *CZI Report.* Available: http://www.czi.co.zw.

Cooper, R. & Ejarque, J. 2003. Financial frictions and investment: requiem in q. *Review of Economic Dynamics.* 6(4):710-728.

David, J.M., Hopenhayn, H.A. & Venkateswaran, V. 2016. Information, misallocation, and aggregate productivity. *The Quarterly Journal of Economics.* 131(2):943-1005.

David, J.M. & Venkateswaran, V. 2019. The sources of capital misallocation. *American Economic Review.* 109(7):2531-2567.

Davies, R., Kumar, P. & Shah, M.K. 2012. Re-manufacturing Zimbabwe: constraints and opportunities in a dollarized economy. *Background Paper for Zimbabwe: From Economic Rebound to Sustained Growth.Washington DC: World Bank.*

Davis, S.J. & Haltiwanger, J. 1992. Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics.* 107(3):819-863.

Davis, S.J., Haltiwanger, J. & Schuh, S. 1996. Small business and job creation: Dissecting the myth and reassessing the facts. *Small Business Economics.* 8(4):297-315.

De Vries, G., Timmer, M. & De Vries, K. 2015. Structural transformation in Africa: Static gains, dynamic losses. *The Journal of Development Studies.* 51(6):674-688.

Deakin, S. 2013. *Addressing labour market segmentation: The role of labour law.* Centre for Business Research, University of Cambridge Cambridge.

Deaton, A. 1997. *The analysis of household surveys: A microeconometric approach to development policy.* The World Bank.

D'Erasmo, P.N. & Boedo, H.J.M. 2012. Financial structure, informality and development. *Journal of Monetary Economics.* 59(3):286-302.

Dias, D.A., Marques, C.R. & Richmond, C. 2016. Misallocation and productivity in the lead up to the Eurozone crisis. *Journal of Macroeconomics.* 49:46-70.

Dias, D., Marques, C.R. & Richmond, C. 2016. Comparing misallocation between sectors in Portugal. *Banco De Portugal, Economics Research Department Economic Bulletin and Financial Stability Report Article.* 201602.

Doeringer, P. & Piore, M. 1971. Internal Labor Markets and Manpower Analysis, Lexington, Mass. *Health.*

Duchin, R., Ozbas, O. & Sensoy, B.A. 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics.* 97(3):418-435.

DuMouchel, W.H. & Duncan, G.J. 1983. Using sample survey weights in multiple regression analyses of stratified samples. *Journal of the American Statistical Association.* 78(383):535-543.

El Badaoui, E., Strobl, E. & Walsh, F. 2008. Is there an informal employment wage penalty? Evidence from South Africa. *Economic Development and Cultural Change.* 56(3):683-710.

El Badaoui, E., Strobl, E. & Walsh, F. 2010. The formal sector wage premium and firm size. *Journal of Development Economics.* 91(1):37-47.

Fafchamps, M. 1997. Trade credit in Zimbabwean manufacturing. *World Development.* 25(5):795-815.

Fafchamps, M., Pender, J. & Robinson, E. 1995. Enterprise finance in Zimbabwe.

Fajnzylber, P., Maloney, W.F. & Montes-Rojas, G.V. 2011. Does formality improve micro-firm performance? Evidence from the Brazilian SIMPLES program. *Journal of Development Economics.* 94(2):262-276.

Ferrando, A. & Ruggieri, A. 2018. Financial constraints and productivity: evidence from euro area companies. *International Journal of Finance & Economics.* 23(3):257-282.

Fields, G.S. 1990. Labour market modelling and the urban informal sector: Theory and evidence. In D. Turnham, B. Salomé, and A. Schwarz (Eds.), The informal sector revisited (pp. 49-69). *Organisation for Economic Co-Operation and Development.*

Fields, G.S. 2002. Accounting for income inequality and its change: A new method, with application to the distribution of earnings in the United States.

Fields, G.S. 2011. Labor market analysis for developing countries. *Labour Economics.* 18:S16-S22.

Firpo, S., Fortin, N. & Lemieux, T. 2018. Decomposing wage distributions using recentered influence function regressions. *Econometrics.* 6(2):28.

Fortin, N., Lemieux, T. & Firpo, S. 2011. Decomposition methods in economics. In *Handbook of labor economics.* Elsevier. 1-102.

Fossati, R., Rachinger, H. and Stivali, M. 2020. Extent and potential determinants of resource misallocation: A cross-sectional study for developing countries. *The World Economy.*

Foster, L., Grim, C. & Haltiwanger, J. 2016. Reallocation in the great recession: cleansing or not? *Journal of Labor Economics.* 34(S1): S293-S331.

Foster, L., Haltiwanger, J. & Syverson, C. 2008. Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review.* 98(1):394-425.

Gerlach-Kristen, P., O'Connell, B. & O'Toole, C. 2015. Do credit constraints affect SME investment and employment? *The Economic and Social Review.* 46(1, Spring):51-86.

Gilchrist, S., Sim, J.W. & Zakrajšek, E. 2013. Misallocation and financial market frictions: Some direct evidence from the dispersion in borrowing costs. *Review of Economic Dynamics.* 16(1):159-176.

Gindling, T.H. 1991. Labor market segmentation and the determination of wages in the public, private-formal, and informal sectors in San Jose, Costa Rica. *Economic Development and Cultural Change.* 39(3):585-605.

Gong, X. & Van Soest, A. 2002. Wage differentials and mobility in the urban labour market: a panel data analysis for Mexico. *Labour Economics.* 9(4):513-529.

Gopinath, G., Kalemli-Ã–zcan, Å, Karabarbounis, L. & Villegas-Sanchez, C. 2017. Capital allocation and productivity in South Europe. *The Quarterly Journal of Economics.* 132(4):1915-1967.

Günther, I. & Launov, A. 2012. Informal employment in developing countries: Opportunity or last resort? *Journal of Development Economics.* 97(1):88-98.

Gürtzgen, N. 2009. Rent-sharing and collective bargaining coverage: Evidence from linked employer–employee data. *Scandinavian Journal of Economics.* 111(2):323-349.

Hall, R.E. and Jones, C.I., 1999. Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*. 114(1), pp.83-116.

Haltiwanger, J., Kulick, R. & Syverson, C. 2018. Misallocation Measures: The Distortion That Ate the Residual. *National Bureau of Economic Research.* DOI:10.2139/ssrn.3347179.

Heintz, J. & Posel, D. 2008. Revisiting informal employment and segmentation in the South African labour market. *South African Journal of Economics.* 76(1):26-44.

Hildreth, A.K. & Oswald, A.J. 1997. Rent-sharing and wages: evidence from company and establishment panels. *Journal of Labor Economics.* 15(2):318-337.

Hopenhayn, H.A. 1992. Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society.* :1127-1150.

Hopenhayn, H. & Rogerson, R. 1993. Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy.* 101(5):915-938.

Howitt, P. 2000. Endogenous growth and cross-country income differences. *American Economic Review.* 90(4):829-846.

Hsieh, C. & Klenow, P.J. 2009. Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics.* 124(4):1403-1448.

Hsieh, C.T., & Klenow, P. J. 2013. Misallocation and manufacturing TFP in China and India – Correction appendix. Technical report. http://klenow.com/MMTFPAppendix.pdf

Inklaar, R., Lashitew, A.A. & Timmer, M.P. 2017. The role of resource misallocation in cross-country differences in manufacturing productivity. *Macroeconomic Dynamics.* 21(3):733-756.

Kalemli-Ozcan, S. 2016. Misallocation, property rights, and access to finance. *Modernization and Development.* :183-211. Available: http://www.econis.eu/PPNSET?PPN=872896072.

Kalemli-Ozcan, S. & Sørensen, B.E. 2014. Misallocation, property rights, and access to finance: Evidence from within and across Africa. In *African Successes, Volume III: Modernization and Development.* University of Chicago Press. 183-211.

Kalleberg, A.L. 2003. Flexible firms and labor market segmentation: Effects of workplace restructuring on jobs and workers. *Work and Occupations.* 30(2):154-175.

Kaplan, S.N. & Zingales, L. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics.* 112(1):169-215.

Kathuria, V., Raj, S.R. & Sen, K. 2013. Efficiency Comparison between Formal and Informal Firms—Evidence from Indian Manufacturing. *The Journal of Industrial Statistics.* 2(1):1-23.

Keswell, M. & Poswell, L. 2004. Returns to education in South Africa: A retrospective sensitivity analysis of the available evidence. *South African Journal of Economics.* 72(4):834-860.

Kinghan, C., Newman, C. & O'Toole, C. 2018. Capital allocation, credit access, and firm growth in Viet Name. (WIDER Working Paper 2018/67).

La Porta, R. & Shleifer, A. 2008. The unofficial economy and economic development. *National Bureau of Economic Research.*

La Porta, R. & Shleifer, A. 2014. Informality and development. *Journal of Economic Perspectives.* 28(3):109-126.

León-Ledesma, M.A. 2016. Potential growth, misallocation, and institutional obstacles: Firm-level evidence. *Asian Development Bank Economics Working Paper Series.* (480).

León-Ledesma, M.A. & Christopoulos, D. 2016. Misallocation, access to finance, and public credit: firm-level evidence. *Asian Development Review.* 33(2):119-143.

Leontaridi, M. 1998. Segmented labour markets: theory and evidence. *Journal of Economic Surveys.* 12(1):103-109.

Levinsohn, J. & Petrin, A. 2003. Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies.* 70(2):317-341.

Lohr, S.L. 2019. *Sampling: Design and Analysis: Design and Analysis.* Chapman and Hall/CRC.

Lopez-Martin, B. 2019. Informal sector misallocation. *Macroeconomic Dynamics.* 23(8):3065-3098.

Loveridge, R. and Mok, A.L., 2012. Theories of labour market segmentation: a critique. *Springer Science & Business Media.*

Luebker, M. 2008. Employment, unemployment and informality in Zimbabwe: Concepts and data for coherent policy-making. *International Labour Organisation. Integration Working Paper no. 90.*

Maloney, W.F. 1999. Does informality imply segmentation in urban labor markets? Evidence from sectoral transitions in Mexico. *The World Bank Economic Review.* 13(2):275-302.

Marcouiller, D., de Castilla, V.R. & Woodruff, C. 1997. Formal measures of the informal-sector wage gap in Mexico, El Salvador, and Peru. *Economic Development and Cultural Change.* 45(2):367-392.

Margolis, D.N. & Salvanes, K.G. 2001. Do firms really share rents with their workers? *IZA Discussion Papers, no. 330, Institute for the Study of Labor (IZA), Bonn.*

Masiyandima, N. & Edwards, L. 2018. Shaking Out or Shaking In: The Impact of Zimbabwe's Economic Crisis on the Country's Manufacturing Sector Allocative Efficiency. *ERSA Working Paper.*

Matano, A. & Naticchioni, P. 2017. The extent of rent-sharing along the wage distribution. *British Journal of Industrial Relations.* 55(4):751-777.

Mazumdar, D. & Mazaheri, A. 1998. The structure of labor market and wages in African manufacturing. *University of Toronto, Mimeo.*

McMillan, M.S. & Rodrik, D. 2011. Globalization, structural change and productivity growth. *National Bureau of Economic Research.* (No. w17143).

McMillan, M., Rodrik, D. & Verduzco-Gallo, I. 2014. Globalization, Structural Change, and Productivity Growth, with an Update on Africa. *World Development.* 63(1):1.

McPherson, M.A. 1991. *Micro and small-scale enterprises in Zimbabwe: Results of a country-wide survey.* Gemini.

McPherson, M.A. 1996. Growth of micro and small enterprises in southern Africa. *Journal of Development Economics.* 48(2):253-277.

Medina, L. & Schneider, F. 2018. Shadow economies around the world: what did we learn over the last 20 years? *IMF Working Paper 18/17.*

Melitz, M.J. 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica.* 71(6):1695-1725.

Midrigan, V. & Xu, D.Y. 2014. Finance and misallocation: Evidence from plant-level data. *American Economic Review.* 104(2):422-458.

Moll, B. 2014. Productivity losses from financial frictions: Can self-financing undo capital misallocation? *American Economic Review.* 104(10):3186-3221.

Mortensen, D.T. & Pissarides, C.A. 1994. Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies.* 61(3):397-415.

Mujeyi, K., Siziba, S., Sadomba, W.Z. & Mutambara, J. 2016. Technical efficiency of informal manufacturing sector enterprises: Evidence from the informal metal industry of Zimbabwe. *African Journal of Science, Technology, Innovation and Development.* 8(1):12-17. DOI:10.1080/20421338.2015.1128040 Available: http://www.tandfonline.com/doi/abs/10.1080/20421338.2015.1128040.

Newman, C., Rand, J. and Tsebe, M.A., 2019. Resource misallocation and total factor productivity: Manufacturing firms in South Africa (No. 2019/46). *WIDER Working Paper.*

Nguyen, H., Taskin, T. & Yilmaz, A. 2016. *Resource Misallocation in Turkey.* (7780). Available: http://hdl.handle.net/10986/24861.

Nguyen, H.C., Nordman, C.J. & Roubaud, F. 2013. Who suffers the penalty?: A panel data analysis of earnings gaps in Vietnam. *Journal of Development Studies.* 49(12):1694-1710.

Nichols, A. 2011. Causal inference for binary regression. *Stata Conference Chicago (Version June 14, 2011).*

Nickell, S.J. & Andrews, M. 1983. Unions, real wages and employment in Britain 1951-79. *Oxford Economic Papers.* 35:183-206.

Nickell, S. & Wadhwani, S. 1990. Insider forces and wage determination. *The Economic Journal.* 100(401):496-509.

Oi, W.Y. & Idson, T.L. 1999. Firm size and wages. *Handbook of Labor Economics.* 3:2165-2214.

Olley, S. & Pakes, A. 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica.* 64(6).

Potts, D. 2008. The urban informal sector in sub-Saharan Africa: from bad to good (and back again?). *Development Southern Africa.* 25(2):151-167.

Pratap, S. & Quintin, E. 2006a. Are labor markets segmented in developing countries? A semiparametric approach. *European Economic Review.* 50(7):1817-1841.

Rand, J. & Torm, N. 2012. The informal sector wage gap among Vietnamese micro-firms. *Journal of the Asia Pacific Economy.* 17(4):560-577.

Restuccia, D. & Rogerson, R. 2008. Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics.* 11(4):707-720.

Restuccia, D. & Rogerson, R. 2013. Misallocation and Productivity: Editorial. *Review of Economic Dynamics.* 16(1):1-10. DOI:10.1016/j.red.2012.11.003.

Restuccia, D. & Rogerson, R. 2017. The causes and costs of misallocation. *Journal of Economic Perspectives.* 31(3):151-174.

Rubin, D.B. & Thomas, N. 2000. Combining propensity score matching with additional adjustments for prognostic covariates. *Journal of the American Statistical Association.* 95(450):573-585.

Rusinek, M. & Rycx, F. 2013. Rent-Sharing under Different Bargaining Regimes: Evidence from Linked Employer–Employee Data. *British Journal of Industrial Relations.* 51(1):28-58.

Rycx, F. & Tojerow, I. 2004. Rent-sharing and the gender wage gap in Belgium. *International Journal of Manpower.* 25(3/4):279-299.

Ryzhenkov, M., 2016. Resource misallocation and manufacturing productivity: The case of Ukraine. *Journal of Comparative Economics*, 44(1), pp.41-55.

Schmidt, C.M. & Zimmermann, K.F. 1991. Work characteristics, firm size and wages. *The Review of Economics and Statistics.* :705-710.

Söderbom, M. & Teal, F. 2001. *Firm size and human capital as determinants of productivity and earnings.* United Nations Industrial Development Organization Geneva.

Söderbom, M. & Teal, F. 2004. Size and efficiency in African manufacturing firms: evidence from firm-level panel data. *Journal of Development Economics.* 73(1):369-394.

Söderbom, M., Teal, F. & Harding, A. 2006. The determinants of survival among African manufacturing firms. *Economic Development and Cultural Change.* 54(3):533-555.

Squire, L. & Suthiwart-Narueput, S. 1997. The impact of labor market regulations. *The World Bank Economic Review.* 11(1):119-143.

Syverson, C. 2011. What determines productivity? *Journal of Economic Literature.* 49(2):326-365. Available: http://www.econis.eu/PPNSET?PPN=664382037.

Teal, F. 1995. Real wages and the demand for labour in Ghana's manufacturing sector. *Centre for the Study of African Economies, University of Oxford.Working Paper Series 95-7.*

Teal, F. 1996. The size and sources of economic rents in a developing country manufacturing labour market. *The Economic Journal.* 106(437):963-976.

Thomas, M. & Vallée, L. 1996. Labour market segmentation in Cameroonian manufacturing. *The Journal of Development Studies.* 32(6):876-898.

Timmer, M., de Vries, G.J. & De Vries, K. 2015. Patterns of structural change in developing countries. In *Routledge handbook of industry and development.* Routledge. 79-97.

Udry, C. 2012. Misallocation, Growth and Financial Market Imperfections: Microeconomic Evidence. *Society of Economic Dynamics Annual Meeting.*

Ulyssea, G. 2018. Firms, informality, and development: Theory and evidence from Brazil. *American Economic Review.* 108(8):2015-2047.

Van Biesebroeck, J. 2005. Firm size matters: Growth and productivity growth in African manufacturing. *Economic Development and Cultural Change.* 53(3):545-583.

Velenchik, A.D. 1997a. Government intervention, efficiency wages, and the employer size wage effect in Zimbabwe. *Journal of Development Economics.* 53(2):305-338.

Velenchik, A.D. 1997b. Market power, firm performance and real wage growth in Zimbabwean manufacturing. *World Development.* 25(5):749-762.

World Bank. 2012. Zimbabwe: From Economic Rebound to Sustained Growth, Overview. Zimbabwe Growth Recovery Notes Series. *World Bank Report, Harare.*

World Bank. 2016. WHAT BUSINESSES EXPERIENCE. ENTERPRISE SURVEYS Zimbabwe 2016 Country Profile. *World Bank, Washington DC 20433.* Available: https://www.enterprisesurveys.org/content/dam/enterprisesurveys/documents/country/Zimbabwe-2016.pdf.

World Economic Forum. 2017. The global competitiveness report 2016–2017.

Wu, G.L. 2018. Capital misallocation in China: Financial frictions or policy distortions? *Journal of Development Economics.* 130:203-223.

ZEPARU. 2014. Harnessing Resources from the Informal Sector for Economic Development. *ZEPARU Working Paper.* Available: http://www.zeparu.co.zw/sites/default/files/2018-09/Harnessing%20Resources%20From%20The%20Informal%20Sector%20for%20Economic%20Development%20%282%29.pdf.

Zimstats. 2014. 2014 Labour Force Survey. *Zimbabwe National Statistical Agency.* Available: http://www.zimstat.co.zw/employment-statistics-zimbabwe.

Appendices

Appendix for Chapter 1

A1. Data and Sampling Procedure

This thesis draws on the matched employer-employee dataset of Zimbabwean manufacturing firms that was collected between 2015 and 2018 under the "Matched Employee-Employer Data for Labour Market Analysis in Zimbabwe" project. The data was collected for the firms and workers in the formal and informal manufacturing sectors. Two separate questionnaires were administered: a firm questionnaire and a worker questionnaire.

The firm questionnaire includes information on entrepreneur background, firm status and ownership structure, production and sales, investments, suppliers and customers, labour information, financial markets, infrastructure, and constraints facing the firms. A worker questionnaire captures information on employee demography and background, education, parent education, wages and allowances, job characteristics, household information, and employment history, among other key information. The rich information in the dataset allows us to provide a credible analysis of the research questions of this thesis. Below we explain in detail how the sample was collected in the formal and informal sectors.

The Formal Sector Survey

The survey data collection for the formal manufacturing sector was carried out in 2015 and 2016. The sample was chosen from the following manufacturing industries: food, beverages and tobacco; wood and furniture; metal, machinery and equipment; textile and leather; chemical, and rubber. The survey was carried in four main cities in Zimbabwe: Harare, Bulawayo, Mutare and Gweru. 195 firms and 1385 employees within these firms were interviewed in the year 2015. The total population of formal firms in Zimbabwe (sample frame) that have greater than 5 workers were 973. From this sample frame, our target was 240 firms. This means that we finally interviewed about 20% of firms. This is a relatively large proportion given our sample frame. Table A1.1 presents the number of formal firms interviewed by their size and industry.

Round two of the surveys of the employees who were initially interviewed in 2015 was done in 2016 via telephone. The idea was to create a panel of workers that allowed us to study the labour market dynamics in the manufacturing sector. Out of 1385 formal sector employee initially interviewed in round one, 1065 workers were successfully re-interviewed in round two. This represents a success rate of 76.9 percent. Some of the reasons why we were not able to contact all workers are (1) refusal by respondents to be re-interviewed, (2) telephone calls failing to connect, (3) some could not answer their phone even after several follow-ups. Nevertheless, our response rate is high enough to allow a credible analysis. The overall sample for the formal manufacturing sector includes 195 firms and 2450 pooled workers (1385 in the first round + 1065 in round two).

Table A1.1. Number of formal firms by firm size and industry

	Firm size			
	<20	20-99	100+	Total
Food, beverages and tobacco	1	12	13	26
Textile, wearing apparel and leather	14	12	13	39
Wood products, including furniture	8	10	6	24
Chemical, petroleum, coal, rubber and plastics	6	11	6	23
Metal, machinery and equipment	22	19	3	44
Other	13	16	10	39
Total	64	80	51	195

Sampling Procedure for formal

A stratified sampling procedure was used in the formal sector to select the sample size with firm size, industry and location strata. The desired sample size for the survey was set at 240 manufacturing firms. However, due to some failures to respond, 195 firms were interviewed, as presented in Table 2.1. The sample oversampled firms outside the two location strata Harare and surrounds and Bulawayo, such that at least 20 firms were included in each of the location strata of Gweru and Mutare. The sample also was designed to have an equal distribution of 80 firms, each across the three size strata (5-19, 20-99, 100+ employees). This results in an oversampling of large firms and under-sampling of small firms. Table A1.2 aggregates the desired sample to the city/town and size categories.

Table A1.2 Desired sample aggregated to location – size level.

	5-19	20-99	100+	Total	Share sample frame
Bulawayo	17	18	24	59	27%
Harare & Surrounds	48	48	42	138	23%
Manicaland: (Mutare)	9	7	5	21	**29%**
Midlands: (Gweru, Kwekwe/Redcliff)	7	8	9	24	**32%**
Total	81	81	80	242	
Share sample frame	14%	27%	70%		

Selection of sample firms from the lists

Because our sampling frame consists of three different lists, and the RPED firms were prioritized in the sample (to have enough panel firms), the selection of firms was done with the following steps:

1) For each eligible RPED firm (i.e. RPED firm that was found, not closed, and still operating in the manufacturing sector) it was determined in which strata it falls. The number of RPED firms to be interviewed in each strata was set at a maximum of ¾ of firms to be sampled within each strata block (if the number of available RPED firms exceeded the maximum, a random sample of RPED firms was selected). This is to deal with problem where the number of surviving RPED firms exceeds the strata quota. This approach allows us to sample new firms that came into existence subsequent to the RPED survey in each strata.

2) Of the remaining required sample in each strata, 2/3 is randomly drawn from firms that are in the 2011 Business Register.

3) The final 1/3 of the remaining required sample in each strata is randomly drawn from firms in the 'alternative' list that are neither in the 2011 Business Register nor the RPED list. Including firms from the alternative list allows us to update the 2011 Enterprise Register in terms of firms that have registered since 2011.

Final sample of interviewed firms

The following table presents the final sample of interviewed firms by location and size strata. The actual location-size distribution differs from the intended sample distribution (as reported in Table A1.2) because the targeted number of firms within each location-industry-size strata could not always be interviewed because of non-response (refusal by firms to be interviewed). Also because of the problem of non-response, the number of interviewed firms was 195 instead of 242. We also note that the small size category (5-19 workers) also includes three firms with less than 5 employees.

Table A1.3: Actual sample aggregated to location – size level

	5-19	20-99	100+	Total
Bulawayo	17	23	11	51
Harare & surrounds	33	50	36	119
Manicaland (Mutare)	2	6	2	10
Midlands (Gweru/Kwekwe/Redcliff)	9	4	2	15
Total	61	83	51	195

Sampling weights for the formal sector

Weights were constructed for two reasons. First, the desired sample purposively oversampled the larger firms as well as firms in the locations outside Harare and surrounds and Bulawayo. Second, the actual sample differs from the desired sample because of non-response.

The sampling weights were constructed as follows.

Step 1 – corrections for attrition and size transitions

For each of the three lists (RPED, 2011 business register, alternative list), we estimated the number of firms in each strata after correcting for attrition and size transitions.

Step 2 – correction for a total number of firms

Next, adjustments were made to the estimated number of firms in the 2011 business register and alternative list such that the combined number of firms from all lists (RPED, 2011 business register, alternative list) was equal to the corresponding number from 2015 ZIMSTAT in each strata. For a few strata no firms were reported in both the 2011 business register and alternative list, while 2015 ZIMSTAT indicated a larger number of firms than estimated from the RPED list. In these cases, we further adjusted the estimated number of firms from the 2011 business register and alternative list within each location/sector strata (i.e. combining the size strata).

Note that we did not adjust the total number of RPED firms because their estimated number in step 1 is assumed to be relatively reliable, given that much time and effort was undertaken to track these firms in order to construct the largest possible panel.

The Informal sector Survey

Survey data collections were all done in the informal manufacturing sector. The broad objective of the informal sector survey was to collect panel data to enable a study on how firms and workers in the informal manufacturing sector operate and survive in an uncertain economic environment. The particular focus of the research is on the linkages and transitions of workers and firms between formal and informal manufacturing. Surveys were done for the metal, wood, furniture and textile industries. These are industries in which the bulk of informal manufacturing takes place. Data collection was done in Harare and Bulawayo, the largest urban cities in Zimbabwe. Table A1.2 shows the number of informal sector firms interviewed between 2015 and 2018 by industry.

Table A1.3 provides the summary for the sample and waves of the data for firms and workers in the formal and informal manufacturing sectors. Round one of the surveys, carried out in 2015, yielded a sample size of 131 informal sector firms and 174 informal workers within these firms. The informal sector firms and workers were telephonically re-interviewed in 2016. 99 out of 131 firms were successfully re-interviewed, resulting in attrition of 23.8 percent, while 76 informal sector workers out of 174 initially interviewed were also re-interviewed (attrition of 56.3%). In 2017, a new wave of informal firms and workers was collected in Harare. The idea was to expand and sustain our sample for the informal sector in future panels. Thus, we interviewed 74 new firms and 92 employees within these firms.

The last round of surveys was done in 2018. In this last, we re-interviewed firms and workers that were initially interviewed in 2015 and 2017. Of the 131 firms and 174 workers initially interviewed in 2015, we successfully re-interviewed 108 firms and 109 workers. Further, of those initially interviewed in 2017, 68 firms were successfully re-interviewed. See Table A1.3 for the summary of the data. Unfortunately, we were not able to re-interview the workers in these firms due to budget constraints.

Table A1.4 Number of informal firms by industry and year

	Year				
	2015	2016	2017	2018	Total
Metal fabrication	41	31	24	54	150
Textiles, clothing and Leather	42	35	22	58	157
Wood and Furniture	46	28	28	57	159
Others	3	4	0	4	11
Total	131	98	74	176	480

Table A1.5. Summary of the sample and waves for the firms and workers in the formal and informal manufacturing sectors.

	Year			
	2015	**2016**	**2017**	**2018**
Formal sector (2015): Firms	196	-	-	-
: Workers	1380	1065	-	-

Informal sector (2015): Firms	131	99	-	108
: Workers	174	76	-	109
Informal sector (2017): Firms			74	68
: Workers			92	-

Notes: The base survey years in brackets

Sampling procedure for the informal sector

One of the challenges when administering informal sector surveys is getting a representative sample. This issue arises as a result of the unavailability of a sampling frame of the informal firms, as they are not registered with the government. There is no Census of firms in the informal sector in Zimbabwe. Some insights can be obtained from the FinScope 2012 MSME survey, as well as the 2014/15 Business Register, which includes information on the number of small firms by industry (less than 5 workers). Neither of these provides reliable numbers on the current population of informal manufacturing firms by industry. There is, therefore, no sampling frame from which to randomly draw the sample of firms.

A two-stage sampling process was followed in selecting informal manufacturing firms. The sample was divided into the following set of industries: textiles, clothing and leather products; wood products, including furniture; metal fabrication; and others. This process was made easier by a number of characteristics of informal markets in Zimbabwe where manufacturing takes place. Firstly, informal manufacturing industries are largely clustered in distinct geographical areas (clusters). Secondly, in some areas (e.g. Mbare Magaba area in Harare), firms are clustered within specific complexes (e.g. a defined area such as a building, shed, etc.). Thirdly, firms within informal markets/areas tend to be clustered by industry and geographic location. For example, in Harare, the metal industry is clustered in Mbare Magaba complex, the wood industry in Glenview area 8 complex while the textile is clustered in the central business district (CBD) downtown area.

Our sampling approach was as follows: In the first stage, the two main (or main area where informal production is located in a single area) informal areas for each of the industry strata were selected. Where it is possible or sensible these areas were then divided into blocks (enumerating areas) with roughly equal numbers of firms based on spatial area or building complex. Blocks were then randomly selected. In the second stage, firms within each of these randomly selected blocks were listed. A random sample of firms was then selected for interviewing purposes from the listed firms in each randomly chosen block. In Harare, the interviews were conducted at Mbare Magaba and Gazaland complex for the metal industry, Glenview complex and Mbare Magaba for the wood industry, and Highfield and CBD for the textile industry. The following areas were selected for sampling in Bulawayo: Renkin and Kelvin North for wood and metal, CBD for textile and Nguboyenja for wood. See Table A2a and A2b for actual samples. Sampling Weights Construction for informal sector firms.

Weights for the informal sector

Survey imperfections such as the selection of units with unequal probabilities cause bias and departure of the sample from the reference population. Thus, sampling weights were constructed to make the survey data representative of our targeted population. Because we followed a two-stage sampling design, base weights were constructed to reflect the selection probabilities at each stage. The overall probability of a firm being selected for an interview is given as the product of the selection probabilities at each stage. Hence, the overall weight is constructed as the reciprocal of the product of the selection probabilities. See Appendix A2c for more detail.

Table A2a. The sample frame constructed.

		Textile	Wood	Metal
Location	Cluster Location	no of firms	no of firms	no of firms
Harare	1.Vision Complex (metal)	0	0	88
Harare	2.Mukuvisi Complex (metal)	0	0	212
Harare	3.Mbare Home industry (metal)	0	0	103
Harare	4.Coffman Complex (wood)	0	46	0
Harare	5.Magaba Complex (wood)	0	28	0
Harare	6.Glenview Complex (wood)	0	157	0
Harare	7.Gazaland (metal)	0	0	120
Harare	8.Chinhoyi Bldng (textile)	48	0	0
Harare	9.Highfield (textile)	150	0	0
Harare	10.Mandela Bldng (textile)	45	0	0
Harare	11. Cameroon Bldng (leather)	10	0	0
Bulawayo	12.Kelvin North (textile)	3	0	0
Bulawayo	13.Kelvin North (wood)	0	48	0
Bulawayo	14.Kelvin North (metal)	0	0	10
Bulawayo	15. Renkin (wood)	0	3	0
Bulawayo	16. Renkin (metal)	0	0	25
Bulawayo	17.CBD (textile)	81	0	0

Bulawayo	18.Nguboyenja (wood)	0	5	0
Bulawayo	19.Others	0	0	0
	Total	337	287	558

Table A2b. The number of firms by cluster

Location	Cluster Location	Strata	Sampled Strata	total number of firms in a cluster	number of firms in a selected cluster (s)	Number of firms interviewed
Harare	1.Vision Complex (metal)	2	1	88	44	6
Harare	2.Mukuvisi Complex (metal)	6	1	212	37	6
Harare	3.Mbare Home industry (metal)	3	1	103	33	4
Harare	4.Coffman Complex (wood)	1	1	46	46	8
Harare	5.Magaba Complex (wood)	3	3	28	28	8
Harare	6.Glenview Complex (wood)	3	3	157	157	13
Harare	7.Gazaland (metal)	3	3	120	120	14
Harare	8.Chinhoyi Bldng (textile)	8	8	48	48	9
Harare	9.Highfield (textile)	30	6	150	30	8
Harare	10.Mandela Bldng (textile)	15	6	45	18	6
Harare	11. Cameroon Bldng (leather)	1	1	10	10	8
Bulawayo	12.Kelvin North (textile)	1	1	3	3	2
Bulawayo	13.Kelvin North (wood)	2	2	48	48	12
Bulawayo	14.Kelvin North (metal)	2	2	10	10	5
Bulawayo	15. Renkin (wood)	1	1	3	3	1
Bulawayo	16. Renkin (metal)	1	1	25	25	6
Bulawayo	17.CBD (textile)	3	3	81	81	9
Bulawayo	18.Nguboyenja (wood)	1	1	5	5	3
Bulawayo	19.Others	1	1	3	3	3
	Total			1185	749	131

A2c. Overall Weight Calculations

1st stage: Probability of strata selected for sampling: strata weight

$$Pi1 = \frac{\text{number of strata selected for sampling}}{\text{total number of strata in a location}}$$

Weight in stage 1

$$Wi1 = \frac{1}{Pi1}$$

2nd stage: Probability of selecting a firm in each selected strata: firm weight

$$Pi2 = \frac{number\ of\ firms\ sampled\ in\ a\ strata}{total\ number\ of\ firms\ in\ strata}$$

$$Wi2 = \frac{1}{Pi2}$$

Overall weight: weight

$$weight = Wi1 * Wi2$$

Appendix for Chapter 2

Figure B2.1. Unweighted distributions: Correlation between TFPR and firm productivity

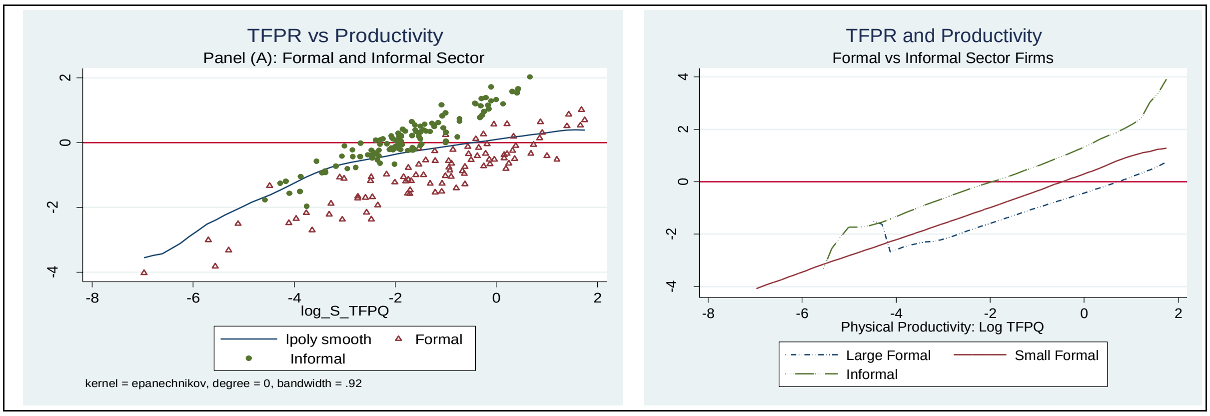


Figure B2.1. Unweighted distributions: Correlation between Capital distortions and firm productivity

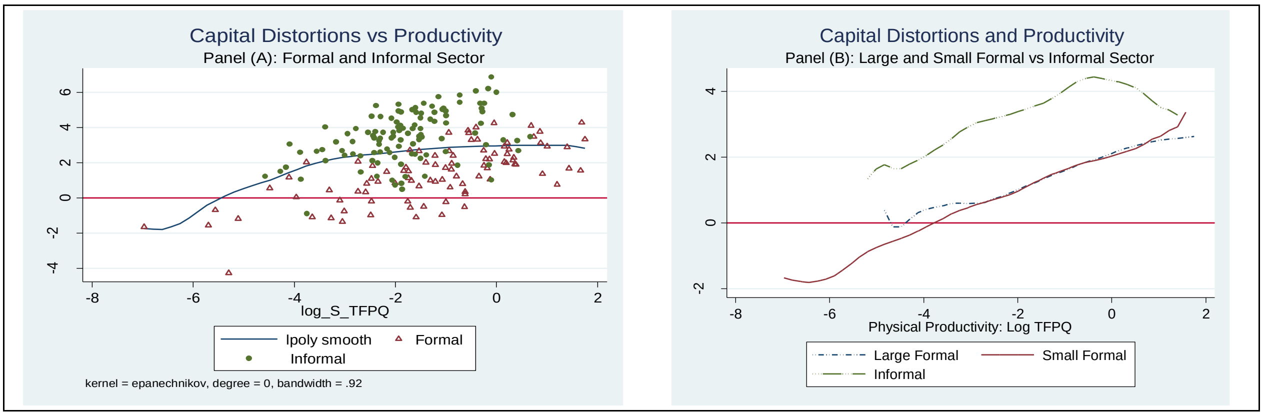


Figure B2.3. Unweighted distributions: Correlation between Output distortions and firm productivity

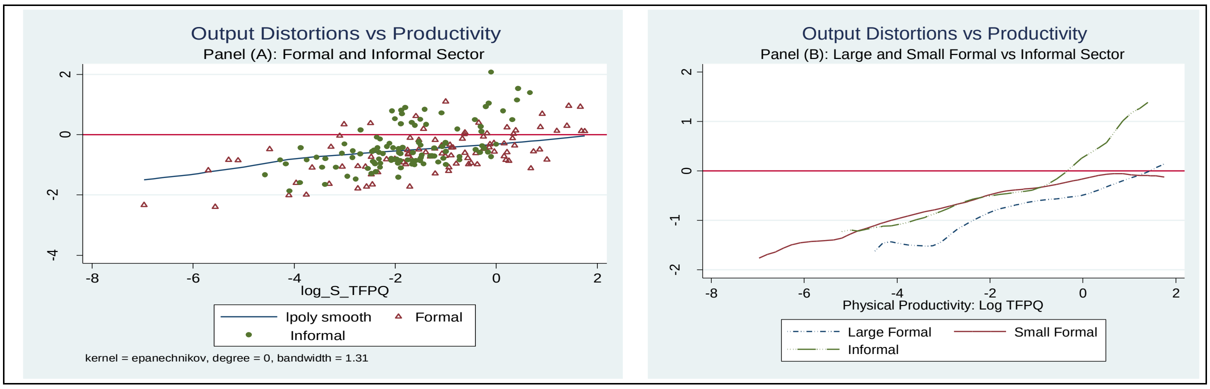


Table B2. 1. TFP gains from the Reallocation of resources.

	Total TFP Gains	
	(1)	**(2)**
	σ=4	**σ=5**
Panel A: Weighted		
Aggregate	223.6	302.8
Formal	228.4	311.3
Informal	219.6	295.6
Panel B: Unweighted		
Aggregate	170.2	232.7
Formal	176.7	237.5
Informal	171.2	228.9

Notes: Entries are $\left(\frac{\mathrm{TFP_s}^{\mathrm{efficient}}}{\mathrm{TFP_s}^{\mathrm{actual}}} - 1\right) * 100$, where $\frac{\mathrm{TFP_s}^{\mathrm{actual}}}{\mathrm{TFP_s}^{\mathrm{efficient}}} = \prod_{s=1}^{s}\left[\sum_{i=1}^{Ms}\left(\frac{A_{si}\overline{\mathrm{TFPR}_s}}{\bar{A}_s \mathrm{TFPR}_{si}}\right)^{\sigma-1}\right]^{\frac{\theta s}{\sigma-1}}$ and $\mathrm{TFPR}_{si} = \frac{P_{si}Y_{si}}{K_{si}^{a_s}(wL_{si}^{1-\alpha_s})}$. For weighted results, we have used sampling weights to account for representativeness.

Appendix for Chapter 3

Measuring Misallocation: Wu (2018) Approach

We also derive the measure of capital misallocation from the Wu (2018) model. Song and Wu (2015) and Wu (2018) constructed a measure of capital misallocation ($MRPK_{i,t}$) based on firm $ARPK_{i,t}$. They constructed the measure based on the linear relationship between ARPK and MRPK as presented in equation (c3.1) below;

$$MRPK_{i,t} \equiv \frac{\partial R_{i,t}}{\partial K_{i,t}} = \alpha_i(1-\eta_i)\frac{R_{i,t}}{K_{i,t}} \equiv \alpha_i(1-\eta_i)ARPK_{i,t} \qquad \text{(c3.1)}$$

They argued that although ARPK has been used to infer misallocation in the literature, it is a biased measure in the presence of unobserved heterogeneity, and argued that MRPK is a sufficient measure of capital misallocation. Wu (2018) attested that ARPK can only be a valid proxy for MRPK if $\alpha_i(1-\eta_i)$ in equation (c3.1) is similar across firms and this may not hold in cases where other firms have market power due to product distortions or frictions or where firms differ in terms of capital intensiveness due to frictions or distortions in technology adoption. Using the first-order Taylor expansion, Wu derived the approximation of for log $MRPK_{i,t}$ as;

$$logMRPK_{i,t} \backsimeq logARPK_{i,t} + log\frac{\pi_{i,t}}{R_{i,t}} - \eta_i\frac{R_{i,t}}{\pi_{i,t}} \qquad \text{(c3.2)}$$

Compared to ARPK, this measure of MRPK is not contaminated with frictions or distortions highlighted earlier. They then obtain the estimate of log $MRPK_{i,t}$ as the residuals from the regression model in equation (c3.3).

$$logARPK_{i,t} = \beta_0 + \beta_1 log\frac{\pi_{i,t}}{R_{i,t}} + \beta_2\frac{R_{i,t}}{\pi_{i,t}} + \beta_3 industry_{i,t} + \beta_4 location_{i,t} + \zeta_{i,t} \qquad \text{(c3.3)}$$

Where $logARPK_{i,t}$, is the log of revenue-capital ratio, $log\frac{\pi_{i,t}}{R_{i,t}}$ is the log of profit-to-revenue ratio, $\frac{R_{i,t}}{\pi_{i,t}}$ is a revenue-to-profit ratio, and $industry_{i,t}$ and $location_{i,t}$ are dummies for firm industry and location respectively.

Table C3.0. Attrition: Differences in characteristics between non-response and response firms. A probit model, with dependent variable capturing response vs non-response firms.

	(1)
VARIABLES	Firm (owner) characteristics
TFP	-0.003
	(0.085)
Firm size	-0.371
	(0.292)
Firm Location	-0.384
	(0.351)
Firm age	0.019
	(0.018)
Years of education (owner)	-0.014
	(0.063)
Gender	0.160
	(0.332)
Experience	0.044*
	(0.025)
Constant	1.155
	(0.883)
Observations	188

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C3.1. Correlation between various measures of financial access constraints

	Fin_Access1	Fin_Access2	Fin_Access1	Fin_Access1
Fin_Access1	1.0000			
Fin_Access2	0.1214	1.0000		
Fin_Access3	0.1137	0.0192	1.0000	
Fin_Access4	0.0727	-0.0838	0.0317	1.0000

Table C3.2. Robustness check using an alternative measure of financial constraints based send alternative objective measure.

	MRPK			ARPK		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fin Constraint		0.065	0.277**		0.394***	0.600***
		(0.110)	(0.124)		(0.111)	(0.134)
TFP_{t0}	0.447***	0.444***	0.320***	0.608***	0.593***	0.472***
	(0.045)	(0.045)	(0.074)	(0.042)	(0.041)	(0.070)
Fin Constraint×TFP_{t0}			0.237***			0.231***
			(0.086)			(0.076)
Constant	0.565***	0.525***	0.430***	3.619***	3.376***	3.283***
	(0.130)	(0.148)	(0.149)	(0.125)	(0.155)	(0.160)
Observations	276	276	276	276	276	276
R-squared	0.363	0.364	0.392	0.583	0.604	0.622
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The measures of misallocation are based on the Wu (2018) approach. We have used an objective measure (Fin_Acess1) as our main measure of financial access constraint. Firm Controls include industry and location dummies, firm size and firm age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05 and * p<0.1 represents 1%, 5% and 10% levels of statistical significance.

Table C3.3. Robustness check using an alternative measure of firm TFP based Levinson and Petrin (2003)

	MRPK			ARPK		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fin Constraint		0.189	0.256*		0.510***	0.546***
		(0.139)	(0.152)		(0.153)	(0.164)
TFP_{t0}	0.236**	0.208**	0.057	0.539***	0.461***	0.382**
	(0.104)	(0.104)	(0.160)	(0.121)	(0.114)	(0.173)
Fin Constraint×TFP_{t0}			0.265			0.140
			(0.205)			(0.222)
Constant	0.268*	0.151	0.111	3.264***	2.947***	2.926***
	(0.155)	(0.180)	(0.185)	(0.168)	(0.201)	(0.202)
Observations	273	273	273	273	273	273
R-squared	0.029	0.036	0.041	0.198	0.232	0.233
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The measures of misallocation are based on the Wu (2018) approach. We have used an objective measure (Fin_Acess1) as our main measure of financial access constraint. Firm Controls include industry and location dummies, firm size and firm age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05 and * p<0.1 represents 1%, 5% and 10% levels of statistical significance.

Table C3.4. Robustness check using alternative measures of firm productivity: Firm investment, Employment Growth and Financial Access Constraints

	Firm Investment				Employment Growth			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.Fin_Access1_b		-0.192***	-0.192***	-0.208***		-0.020	-0.020	-0.015
		(0.071)	(0.071)	(0.076)		(0.067)	(0.067)	(0.070)
TFP_base	0.016		0.018	0.033	0.035		0.035	0.029
	(0.038)		(0.037)	(0.046)	(0.043)		(0.043)	(0.046)
FA1_TFP				-0.016				0.005
				(0.028)				(0.033)
Observations	246	246	246	246	246	246	246	246
R-squared					0.049	0.046	0.049	0.050
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Results are from equation (3.7). *Firm investment* is a binary variable. Columns 1-4 presents the *Marginal Effects* for the investment model equation. Columns 5-8 presents results from the employment growth model. Columns 1 and 3 shows the baseline model. In Columns 2 and 5 and we control for initial firm productivity (TFP_{t0}). In columns 3 and 6 we control for the interaction between initial Fin_Constraint and initial TFP. Firm controls include industry and location dummies, firm size and firm age. Robust standard errors in parentheses. *** p<0.01, ** p<0.05 and * p<0.1 represents 1%, 5% and 10% levels of statistical significance.

Appendix for Chapter 4

D1. Re-centred Influence Function (RIF) Approach

Fortin et al. (2011) suggested a comprehensive methodology (very similar to the Oaxaca-Blinder) that include both re-weighting and RIF-regressions. One of the key advantages of the RIF approach over other approaches is that the RIF approach does not suffer from path dependence[38]. The RIF approach expresses the composition and the wage structure parts of the wage gap in terms of the regression coefficient and the mean of the independent variables. For other distributional parameters besides the mean, Firpo et al. (2011) methodology involve estimating a regression model where the outcome of interest (w in our case) is replaced by the re-centered influence function of the statistic of interest. In our case, we consider quantiles (q_τ) as our statistic of importance. Thus, our re-centred influence function is given by RIF(w, q_τ). The RIF of the r^{th} quantile is given by the aggregate of the statistics of interest (q_τ) and the influence function as expressed below;

$$RIF(w; q_\tau) = q_\tau + IF(w;\ q_\tau) \quad \text{(D1)}$$

The RIF in equation (D1) has some important properties: if the mean is used as a statistic of interest, then the RIF becomes the standard wage regression, and additionally, the results can be used to perform the Oaxaca-Blinder decomposition. The τ^{th} quantile influence function for the distribution is given by;

$$IF(w; q_\tau) = \frac{\tau - II\{w \leq q_\tau\}}{f_W(q_\tau)} \quad (D2)$$

Where $f_W(\cdot)$ is the marginal density function of W and $II\{\cdot\}$ is an indicator function for whether the outcome variable (w) is smaller than or equal to the quantile q_τ. In essence, the τ^{th} quantile RIF-regression sum the unconditional quantile of interest and it allows us to capture both the within and between effects of the covariates. Fortin et al. (2011) show how to compute the RIF. First the RIF is estimated by computing quantile q_τ and estimating the density using the kernel method at that point. Then an estimate of the RIF, $\widehat{RIF}(w; q_\tau)$, is obtained for each observation by inputting the estimates of the quantile, $\widehat{q_\tau}$, and the density, $\widehat{f_W}(\widehat{q_\tau})$, into equation (D2). In this study, we report results based on the 10th, 50th and 90th percentiles. The RIF decomposition compares the informal sector wage distribution to the reweighted informal

[38] A decomposition procedure is path dependent if the order in which different components of the decomposition are computed does affect the results of the decomposition (Fortin et al., 2011)

sector wage distribution that mimics the formal sector wage distribution. This allows us to get the composition effects of the wage gap. Further, it compares the formal sector wage distribution to reweighted informal sector wage distribution. This allows us to obtain the wage structure effect of the wage gap.

Table D4.1 Profits-per-worker and wages in the informal sector labour markets

VARIABLES	Baseline (1)	+Controls (2)
Profits-per-worker	0.185***	0.170**
	(0.059)	(0.069)
Firm size		0.217**
		(0.107)
Constant	-1.156***	-2.560***
	(0.374)	(0.894)
Observations	312	312
R-squared	0.035	0.200
Human Capital	NO	YES
Individual Characteristics	NO	YES
Job Characteristics	NO	YES
Firm Characteristics	NO	YES

Notes: The dependent variable is the log of hourly wages. The proxy for profit-per-worker is sales per worker in logs. Asterisk denotes level of significance (*** p<0.01, ** p<0.05, * p<0.1). Standard errors are in brackets

Table D4.3 First-stage Regression: The Relationship between the Profit-per-worker and the instruments-cost of electricity and value-added per capital.

VARIABLES	(1) **Dependent variable:** Profit-per- worker
log_in	0.330***
	(0.013)
Constant	3.389***
	(0.166)
Observations	1,902
R-squared	0.317
Human capital	NO
Job Characteristics	NO
Firm Characteristics	NO

Table D4.4. Correlation between lagged sales per worker and profits per worker

	Lagged Sales Per worker	Profits
Lagged Sales Per worker	1.0000	
Profits	0.4126	1.0000