A policy for the (jobless) youth: The Employment Tax Incentive

By

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Declaration

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

I declare that early versions of Chapters 4 and 5 have been published as working papers:

Ebrahim, A., Leibbrandt, M. & Ranchhod, V. 2017. The effects of the Employment Tax Incentive on South African employment. WIDER Working Paper 2017/5. Helsinki, Finland: UNU-WIDER.

Ebrahim, A. & Pirttilä, J. 2019. Can a wage subsidy system help reduce 50 per cent youth unemployment? WIDER Working Paper 2019/28. Helsinki, Finland: UNU-WIDER.

My contributions to each of these working papers are as follows. The first working paper, titled "The effects of the Employment Tax Incentive on South African employment", was co-authored with my supervisors, Murray Leibbrandt and Vimal Ranchhod. All data work and writing was conducted by myself apart from the normal guidance from my supervisors. The second working paper, titled "Can a wage subsidy system help reduce 50 per cent youth unemployment?" was co-authored with my supervisor, Jukka Pirttilä. All data work and writing was conducted by myself apart from the normal guidance from my supervisors.

I further declare that chapters 4 and 5 have been presented at several conferences and seminars. Papers and presentations may appear on conference websites:

Presentations and conferences	
2020	SALDRU Seminar Series, Cape Town, South Africa
2019	CSAE conference, Oxford, UK
	World Bank/IZA/NJD Jobs and Development conference, Washington, USA.
	UNU-WIDER Seminar Series, Helsinki, Finland
	Nordic Conference on Development Economics, Copenhagen, Denmark
	International Institute of Public Finance (IIPF) Annual Congress, Glasgow, Scotland
	UNU-WIDER Transformation Towards Better Jobs, Bangkok, Thailand
	Inclusive Growth in Mozambique: Transformation Towards Better Jobs, Maputo, Mozambique
2018	UNU-WIDER Think Development, Think WIDER conference, Helsinki, Finland.
	UNU-WIDER Seminar Series, Helsinki, Finland
2017	Tax, Customs and Excise Institute (SARS) Seminar, Pretoria, South Africa
	Tax Data Research workshop. DataFirst, Cape Town, South Africa
	Georgetown University in Qatar Seminar Series, Doha, Qatar
2016	UNU WIDER Growth and Development Policy Conference. Pretoria, South Africa.

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Declaration on the inclusion of working papers in PhD thesis

This declaration serves to confirm that chapters four and five of Amina Ebrahim's PhD thesis have appeared as working papers. It spells out the relationship between the chapters and the working papers and the levels of contribution of Amina and the supervisors to both the chapters and the working papers.

Chapter 4. Estimating firm-level impacts of the ETI. An early version of this chapter appeared as WIDER working paper 2017/5 with Murray Leibbrandt and Vimal Ranchhod listed as the co-authors. This working paper and this chapter were written by Amina Ebrahim. Murray Leibbrandt and Vimal Ranchhod made comments and provided guidance on the working paper and chapter in their role as PhD supervisor.

Chapter 5. Individual-level responses to a firm-side subsidy. An early version of this chapter appears as WIDER working paper 2019/28 with Jukka Pirttilä listed as the co-author. This working paper and this chapter were written by Amina Ebrahim. Jukka Pirttilä provided comments and guidance on the working paper and chapter in his role as PhD supervisor.

The co-author names appearing on both working papers reflect supervisory input and the intention is to submit these papers for journal publication in the future with further, substantive contributions from the supervisors.

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Abstract

The Employment Tax Incentive (ETI) is a first of its kind wage subsidy policy in South Africa. Designed to tackle the problem of youth unemployment, the ETI differs from previous policies as it aims to address unemployment through stimulating job creation. Youth unemployment has remained above 40 percent in the past ten years and is one of South Africa's key challenges. The policy was adopted in the face of this alarmingly high level of youth unemployment and at a time where the aggregate demand was low.

This thesis is an important contribution to the academic literature on the demand for young workers by providing insights into this large active labour market policy intervention.

The first substantive contribution is the preparation and development of a panel dataset based on payroll tax records. The tax data panel is then used to investigate the beneficiaries of the subsidy. Large firms in retail; manufacturing and financial services sectors are responsible for the highest number and largest value of subsidy claims. The subsidy is well targeted reaching younger workers in the eligible group. The subsidy is, however, only reaching half of all subsidy eligible workers.

The second contribution is the investigation of job creation at the firm level. Using a matched difference-in-differences approach, a subset of ETI firms is found to have increased their employment of youth and these results are robust to various measures of youth employment. No evidence of displacement of ineligible workers if found.

The third contribution explores the labour market outcomes of individuals eligible for the subsidy. Using both tax and survey data, I estimate the intention-to-treat impacts of the ETI using a triple differences method. There are very small positive effects on earnings and entry into employment and no evidence of change on overall employment and unemployment rates for young, low-wage workers.

The thesis concludes by assessing the aggregate implications from these results for understanding youth unemployment in the South African labour market and the role of active labour market policy in overcoming this problem.

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My daughter, Huda, who is almost as old as is this thesis. You have only known a mum who has been both studying and working while being a mum. I am putting my thesis to bed so we can spend the much-promised time together. You are the coolness of my eyes.

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List of Abbreviations

SARS – South African Revenue Service

COSATU - Congress of South African Trade Unions

ETI – Employment Tax Incentive

NT – National Treasury

DID – Difference-in-Differences

cDID – Conditional Difference-in-differences

UNU-WIDER – United Nations University World Institute for Development Economics Research

IRP5 - Employee's tax certificate

CIT – Company Income Tax

VAT – Value Added Tax

PSM – Propensity Score Matching

PAYE – Pay-As-You-Earn tax

CIA - Conditional Independence Assumption

ATT – Average Treatment Effect on the Treated

CVM – Covariate matching

DDD – difference-in-difference-in-differences or triple differences

Chapter 1. Introduction

1.1 Background and Motivation

The central question in this thesis is whether the South African youth wage subsidy has succeeded in creating jobs for young people. Also termed the Employment Tax Incentive (ETI), the subsidy policy is a large policy intervention aimed at increasing the employment of young, low wage workers. In the context of excessively high unemployment rates for young people and limited fiscal resources in South Africa, it is important to determine whether a policy such as the ETI is creating any jobs.

The ETI is one of several policy interventions in South Africa aimed at reducing high rates of unemployment. Despite these many policy interventions, these high rates of unemployment have persisted since the advent of democracy. Youth unemployment has been above 40 percent for most of the post-apartheid period. When using the expanded definition of unemployment (including those not economically active), the unemployment rate for youth is above 65 percent (Statistics South Africa, 2020). Prolonged periods of unemployment reduce future employment probabilities making it even harder for young people to access the labour market. Typically, governments facing high unemployment rates, also face high resource constraints emphasising the need for cost-effective and successful implementation of labour market policies.

Active labour market policies (ALMPs) are one way to deal with increasing and persistent unemployment rates. From a microeconomic point of view, ALMPs are evaluated by how well they benefit the target group. From a social cost and benefit point of view, it may be necessary to determine whether the ALMP is a cost-effective way of creating jobs relative to other interventions. Measuring the direct effect of employment policies requires an evaluation of the policy effects on the extensive margin, through employment and unemployment rates, as well as the intensive margin, through earnings. Thus, the second question in this thesis is how the subsidy has affected the wages of young workers.

The drivers of youth unemployment are many, ranging from challenges in educational attainment, lack of credit, challenges in the search for employment and the lack of available jobs. The ETI lies within this combination of policies that the government has implemented to specifically alleviate the high youth unemployment rate by aiming to increase the number of available jobs for youth. The policy was introduced in 2014 and is a tax credit targeted to the employers of young (below 30 years of age), low-wage (earning below R6,000 a month) workers.

The motivation behind the policy lies in the context of both large numbers of low-skilled youth and rigidities in the labour market. This has led to a situation where the employment of youth is

undesirable to firms. The stated aim of the subsidy is to address the low demand for young workers by reducing the costs and risks associated with employing youth (National Treasury, 2011).

A wage subsidy is a type of subsidy whereby private employers are given a temporary financial incentive that reduces the cost of employment a particular set of workers. The reduction in labour costs could result in higher labour demand for the target group. This increase in labour demand could translate into an increase in employment for the target group, however, it also has the potential to affect wages. Increasing the labour demand for the target group may lead to a decrease in the labour demand for the non-targeted group who, in this case are, older workers or workers above the wage threshold. There is a large body of evidence international showing that hiring subsidies have been effective in increasing the employment of the targeted group, but the success of these policies is dependent on the design (Martin & Grubb, 2001).

Evaluating wage subsidy programmes requires access to detailed information about subsidies claims and the international literature point to administrative data as the ideal source. In the case of the ETI, employers are the claimers of the subsidy and employees may not be aware of the subsidy being claimed for their employment. The ETI is claimed through the tax system as a reduction in taxes firms owe to the tax revenue authority. For this reason, evaluating the ETI requires access to tax administrative data (henceforth, tax data). This is the subject of Chapter 3. These tax data have recently been made available for research presenting an opportunity for study of the policy at the firm and individual level. Understanding the data, and how it affects the subsequent analysis, is key to answering the questions of this thesis and demands our attention early on. Once the data is found to be suitable, some descriptive evidence of the take up and use of the subsidy is presented.

From a budgetary perspective, the cost of the policy is non-negligible and is being borne by a government with limited fiscal resources. In this context it is imperative to clearly understand whether the money is well spent. This requires an examination of the firms that take up the ETI and evaluation of any new jobs created. This is the subject of Chapter 4. Subsidising jobs that would already have existed in the absence of the subsidy implies a deadweight loss and limited, or no, impact on the labour demand for youth.

The theory tells us that when labour demand is more elastic than labour supply, employment subsidies lead to higher wages and hence no or limited employment increases. An increase in wages is not necessarily a negative outcome for workers in South Africa, as this can be seen as an indirect transfer to young, low paid workers. However, this is not the desired outcome of the policy considering there are more than 3 million unemployed youth. Examining the incidence of the

subsidy, that is, the earnings response, is appropriate in completing our understanding of how the policy affects the target group. This is examined in Chapter 5.

1.2 Contribution

This is the first of its kind study of the ETI at both the firm and individual level in South Africa. The thesis contributes to the literature by examining the efficiency of wage subsidies in an emerging market context, where the capacity to administer the system (both in firms and within the administration) may be less perfect than in high-income countries. The sheer size of the unemployment crisis also makes pressing the evaluation of the efficiency of the policy.

The study of the ETI at the firm and individual level allows for a nuanced interrogation of the policy in which the whole is greater than the sum of the parts. The thesis contributes to the literature on the demand for young workers by providing insights into this large active labour market policy intervention in the context of a developing country.

The first contribution is the preparation and development of payroll tax records into firm and individual panel datasets. These two panels are then used to investigate the firms and individuals who benefit from the subsidy relative those who are eligible but do not. The second contribution is the study of employment behaviour at firms claiming the subsidy. The third contribution is the examination of subsidy eligible individuals; the employment, earnings, entry, exit and job duration effects on young, low-wage workers.

As a whole, this thesis is an examination of a policy tool used to combat youth unemployment. It considers and adds to three facets of examining the policy: the data, the firms, and the individuals affected by the subsidy.

1.3 Thesis structure

The thesis is structured as follows. Chapter 2 reviews the literature to contextualise the ETI among similar policies internationally. The chapter gives us a clear picture of the evidence of wage subsidies in other countries and the methods used to evaluate them. The chapter also situates the ETI in the context of various active labour market policies in South Africa then goes on the discuss the origins of the ETI, its design, implementation, and subsequent extension. The chapter includes a review of the small body of literature on the ETI within South Africa. Covered in the chapter are the expected outcomes of the ETI and outline the opposition towards the policy. The chapter develops our expectations of how subsidies perform against other ALMPs and draw lessons on how subsidies are typically evaluated.

Chapter 3 examines the tax data which has been accessed at the National Treasury Secure Data Facility in Pretoria. Evaluation of the ETI needs to be grounded in how it is designed and how the

policy works in practice. This thesis is one of the first in South Africa to use tax data and it is necessary to show that these data are up to the task of the evaluation. While the tax data includes the universe of firms (claiming and non-claiming), there are challenges in the data that relate directly to the subsidy claims and this chapter describes how these, and other, challenges are overcome. A job-level and firm-level dataset is built from the tax data and the chapter presents stylized facts on the firms claiming the ETI and the individuals employed in subsidized jobs. The chapter describes how much of the subsidy has been claimed as well as which firms, sectors and individuals are claiming the subsidy to set the scene for who could be benefitting from the policy.

Chapter 4 then uses these data to test whether firms claiming the subsidy are hiring more youth in absolute and relative terms. Using a conditional difference-in-difference approach, ETI firms are matched with non-ETI firms in the pre-policy period before comparing employment outcomes between the firms before and after the policy. The chapter checks for any changes in the employment of older workers or non-targeted workers and ensures that identification of any changes in employment are not as a result of pre-policy trends of firm growth or contraction.

Chapter 5 uses both the tax data and survey data to study subsidy eligible individuals. The chapter examines the intention-to-treat (ITT) estimates to identify the programme impacts. This chapter examines the incidence and employment impacts of the ETI using a triple differences method comparing subsidy workers to those just above the wage and age criteria. The chapter considers the policy design and take up, and examines the policy different gender, age, and wage groups.

Finally, Chapter 6 summarises key results from the thesis and outlines the implications of these results as a whole. The conclusion brings together our understanding of the role of the ETI in shaping the labour market for South African youth.

Chapter 2. Institutional background and literature review

2.1 Introduction

The post-apartheid period in South Africa is marked by low, but rising, labour force participation, high unemployment, and slow growth in labour demand (Casale & Posel, 2002; Leibbrandt et al., 2010b). Youth participation increases in the labour force since 1994. There are two possible explanations for this: previously discouraged youth may be more actively seeking employment; and there may be an increase in the number of new youth entrants to the labour market (Leibbrandt et al., 2010b). Normally, when labour supply increases faster than labour demand, the result is a decline in wages. In South Africa, there has been an increase in unemployment (Abel et al., 2014; Leibbrandt et al., 2010b) and wages have been static (Wittenberg, 2014).

In contemporary South Africa, 48 percent of people between the age of 18 and 29 are unemployed[1] in comparison to 29 percent for all working age adults (Statistics South Africa, 2020). The broad definition of unemployment (including those not economically active) paints an even worse picture for the youth with an unemployment rate of 59 percent. Table 2-1 below makes the comparison between the narrow and broad definitions of unemployment as well as distinguishes between the unemployment rates experienced by youth and all South Africans.

Table 2-1 Percentage of unemployed by narrow and broad definitions

	All	Youth
Narrow definition	29.1	48.4
Broad definition	38.7	59.3

Note: Youth is defined for those between the ages of 18 and 24 years old.
Source: Authors' estimated of unemployment rates from Statistics South Africa (2020)

Race is still a major factor in determining the likelihood of employment in the post-apartheid era. The unemployment rate for Blacks/Africans is approximately 30 percent, Coloureds 22 percent, Indians/Asian 11 percent, and Whites 7 percent. The overwhelming majority of unemployed youth are Black/African (85 percent) (Statistics South Africa, 2020).

When considering the youth unemployment (or employment) rate, one is looking at the number of youths in the labour market and the percentage of those who are unemployed (or employed). The labour force participation rate for youth is around 51 percent which means 49 percent, or 6 million youth are not part of the labour force. The remaining group are then defined as not

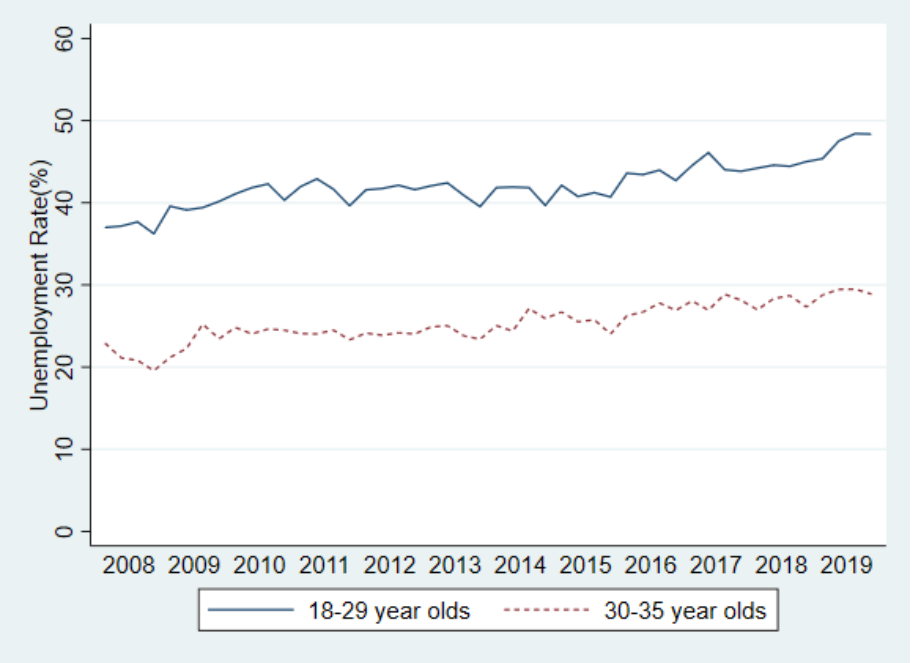
[1] Stats SA defines unemployed persons as those who are not employed in the survey week; and actively searched for employment or tried to start a business in the four weeks preceding the survey interview; and were available to work or had not actively looked for work in the past four weeks but had a job or was starting a business at a specific date in the foreseeable future.

economically active which does not account for any other activity a young person could be engaged in, such as education. It has become common practice to quote the youth NEET rate alongside youth unemployment statistics. The NEET rate refers to those Not in Employment, Education or Training and is used to highlight the percentage of unemployed youth or not involved in any education or training that would grow their human capital or make them more employable (Holte, Swart & Hiilamo, 2019). The NEET rate for youth is currently around 47 percent which is more than double the OECD average driven by both lower numbers in the labour market and by fewer young people in the training and education system (OECD, 2014).

In the post-apartheid period, the economy has not been able to engage new labour market entrants. Levinsohn (2014) argue that sectors demanding low skilled workers have declined while tertiary sectors such as the financial and services sector have grown, demanding high skilled workers. Bhorat and Khan (2018) show that the main sectors of the economy experienced an increase in skill intensity over the period 1995 to 2015 at the cost of low or unskilled labour. The authors argue that this has created a skill-biased labour demand trajectory, favouring high skilled workers, and making low and unskilled work seekers undesirable in the economy. The informal sector is very small and unable to engage low and unskilled work seekers. The majority of the unemployed are either low or unskilled.

The unemployment rate for young people is illustrated in Figure 2.1. In this thesis, youth is defined in the same way the policy defines youth: those aged 18-29. The graph shows that the youth unemployment rate has been persistently high, hovering above 40 percent, for the past 10 years. At the end of 2019, the unemployment rate for the policy target group was 48%. This means that 3 million youth, between the ages of 18 and 29 years old, are in the labour force without employment. The graph also illustrates the unemployment rate for a slightly older group, those between the ages of 30 and 35 years old. The unemployment rate for the older group is around 28 percent, which is lower in comparison to the youth unemployment but still incredibly high by international standards. These unemployment rates make it clear that the youth face extreme challenges in accessing the labour market in comparison to their older counterparts.

Figure 2.1 Unemployment rates by age group



Notes: The unemployment rate is calculated using the narrow definition of unemployment.
Source: Authors' calculations based on QLFS data from Statistics South Africa (2020)

Young workers are vulnerable to economic downturns as they have less experience and skills (National Treasury, 2016). Furthermore, unemployed youth in South Africa are unable to claim from the Unemployment Insurance Fund. This fund requires that a beneficiary should have had prior employment so as to contribute to the fund and thus stake a claim to it at a later stage. With most of the unemployed youth in South Africa lacking prior employment they are unable to access this passive labour market assistance.

No youth employment policy aimed at stimulating job creation has been implemented in South Africa before the Employment Tax Incentive. Several active labour market policies exist in South Africa but have typically been focused on improving the skill level of the target group rather than the demand for labour. This chapter covers the empirical literature on labour market policies and employment subsidies, describes the institutional background and theoretical framework of the ETI.

2.2 Labour market policies and employment subsidies: Empirical literature

This section starts with a broad overview of labour market policies and examine the literature on evaluating active labour market policies before diving into the empirical literature on wage subsidies nested in the active labour market setting.

Labour market policies grew in popularity in the 1920s after World War 1 (Martin, 1998). Unemployment was widespread, and governments designed public works programmes to combat

the problem. Policies such as unemployment insurance and benefits were popular as well. In the mid-1990s passive labour market policies were on the decline while active labour market policies (ALMPs) were gaining popularity.

ALMPs are programmes used by governments to intervene in the labour market to increase employment opportunities for the jobless and reduce the gap between available job opportunities and the unemployed. Policies can include assistance with job search, job matching, employment subsidies, public employment, and training programmes.

Public spending on ALMPs in OECD countries use a significant portion of GDP and has seen an increase between 1985 and 1996 (Martin, 1998). Spending on passive labour market programmes has, at the same time, been on the decline but remains a larger percentage of GDP when compared to ALMPs (Martin, 1998).

In 2001, 30 percent of the ALMP expenditure in the OECD countries was spent on job assistance programmes and training while approximately 20 percent was on worker and firm subsidies. Very little is known about the percentage of GDP spending on ALMPs in developing countries.

The National Treasury (2011) suggest that the largest ALMP expenditure is on direct employment through the EPWP, followed by skills development and the learnership programme. As a percentage of the gross domestic product (GDP), ALMPs are great than 1 per cent, while in developing countries the percentage is much lower (National Treasury, 2011).

Bördős, Csillag and Scharle (2015) conduct a meta-analysis on econometric evaluations of ALMPs. They examine 199 program estimates conducted between 1995 and 2007. The authors create a relative ranking of interventions by effectiveness of ALMPs and find that public sector employment programs have the least favourable estimates. In the short run, job search assistance programs appear to have insignificant or negative effects but are more successful in the medium term. On the other hand, they find job training programmes have relative positive results in the medium term.

In a more recent evaluation, Bördős, Csillag and Scharle (2015) analyse the impact estimates of ALMPs internationally whereby the authors group estimates by intervention type and target group and distinguish between three different post-program time horizons. The authors find the average impacts of ALMPs are close to zero in the short run, but results are positive 2-3 years after the policy. Policies that include a human capital accumulation (training) component see larger impacts. Greater impacts are also found for the long-term unemployed and for programs targeted at women. Lastly, the authors find that ALMPs are more likely to show positive impacts in a recession.

Most studies examined by Card, Kluve and Weber (2010) are from ALMPs in developed countries. Although few developing countries engage in ALMPs, far less has been written on the impact of ALMPs in developing countries where they do exist. Kluve et al. (2019) conduct a meta-analysis of 107 youth interventions worldwide. A large part of their contribution to the literature is their evaluation of programmes in middle- and low-income countries. The authors conclude that programmes in middle- and low-income countries are more successful and that the design of the programme is more important than the type of intervention. They present evidence that interventions targeted at low wage youth reported larger effect sizes lending to the argument that ALMPs should be targeted. Only modest impacts are seen for policy participants across evaluations of ALMPs. While this remains true, the effects of policies vary, where some have large impact and others have no impact.

Assessments of ALMPs often focus on the microeconomic perspective, examining the beneficiaries of ALMPs. Many ALMP evaluations do not examine the public economics outcomes of programs such as the social desirability and cost-effectiveness or the macroeconomic outcomes such as productivity or structural unemployment. The long-term effects, lack of estimates of deadweight loss, displacement and substitution effects, changes in the composition of the labour market, provide a very narrow view of a policy (Brown & Koettl, 2015). To consider the suitability of implementation of ALMPs in other contexts it would be useful to understand the reasons why some policies succeed, and others fail. In this regard, the literature provides conflicting accounts of what is required described later in this section.

2.2.1 Evaluating Active Labour Market Policies

There is a large literature seeking to evaluate specific ALMPs (Bertrand & Crépon, 2014; Martin, 1998). There are two main types of evaluations of ALMPs. The first type measures the impact of an ALMP on an individual once the program has ended. This is popular for ALMPs which seek to train, give experience or job-search assistance to the unemployed, also described as supply-side interventions. A suitable control group is constructed to be compared to those who received the intervention.

The second type of evaluation measures the effect of the ALMP on the overall prospect of employment or the unemployment rate. This is done by estimating the deadweight losses, substitution, and displacement effects. This method is popular when evaluating wage subsidies or methods that aim to stimulate demand for employment and is often referred to as demand-side interventions.

Some countries, for example the USA and Canada, have been evaluating ALMPs for a long period of time (Martin, 1998). Many countries have a mix of ALMPs running concurrently and the evaluation results are not always able to single out specific programs that cause the success (or failure) of the policy. The evidence showcases the short-run effects of programs and the long-run effects are largely ignored. Social outcomes, such as crime rates and mental health, are not often examined when evaluating ALMPs. When the evidence does indicate a positive result from the ALMP, it is unclear whether or not the program is scalable.

Heckman, Lalonde and Smith (1999) provide a review of the methods used to evaluate ALMPs. They suggest that there is no one method suitable to evaluate various policies. The authors raise the importance of the "quality of the underlying data" alongside the economic model and questions being posed (Heckman, Lalonde & Smith, 1999:1866). Difficulties in determining credible causal impacts have pushed contemporary research to consider using randomised control trials (RCT) to evaluate ALMPs. In the case of South Africa, one RCT was conducted before the implementation of the youth wage subsidy programme.[2] The RCT provides the subsidy to firms through the worker while in the case of the policy, the subsidy is provided to the firm through the tax system without the workers' knowledge (discussed in further detail in section 2.3.1). It is plausible that a supply side mechanism is in effect in the RCT. Firms may view workers with a subsidy voucher more favourably than workers without a subsidy voucher that would then lead to a hire. The mechanism of youth wage subsidy policy is, however, to influence the labour demand of works at firms. The lesson from the study, for South Africa, is the reluctance of firms take on the administration required to claim a subsidy. We show later in the thesis that take up of the policy is in fact very low (approximately 13%) and this reluctance may explain why firms would leave such monetary benefits untouched.

Meta-analysis, such as (McKenzie, 2017), have pointed out that impacts of ALMPs such as wage subsidies and vocational training programs have limited effects in developing countries. At best, the effects are modest while the policies are associated with high costs.

McKenzie (2017) argues that wage subsidies may be useful in contexts where temporary employment creation is required such as countries with large numbers of unemployed youth. This would suggest that a policy such as the ETI would be effective in creating temporary employment in South Africa where youth are inexperienced and less able to signal productivity. The next section reviews the set of labour market policies in South Africa to provide further context under which the ETI is established.

[2] See Levinsohn et al. (2014)

2.2.2 Labour Market Policies in South Africa

This subsection focuses on ALMPs in South Africa; taking stock of what has been implemented thus far and how these policies have affected the youth labour market starting with skill development and training programmes. The typical aim of a training programme is to reduce the skills shortage or skills mismatch in an economy. For participants, training programmes should increase their productivity and increase their chances of becoming employed. For employers, training programmes increase the pool of skilled workers. Oosthuizen and Bhorat (2005) carefully document the change in the labour demand for unskilled workers by sector over the period 1995 to 2002. The authors show a substitution effect between less skilled and skilled workers. The agriculture, manufacturing, community, social and personal services, and utilities sectors were replacing low and semi-skilled workers with skilled workers. The wholesale and retail trade and construction sectors were at the same time employing unskilled workers at a higher rate than they were employing skilled workers. The overall result was a decrease in the demand for unskilled labour and an increase in demand for semi- and skilled labour. Training programmes and policies can thus serve to fill this gap by helping to facilitate entry into the labour market.

One of the policies in South Africa includes the establishment of the Sector Education and Training Authorities (SETAs) and Technical and Vocational Education and Training (TVET) colleges to enhance the level of skill and education of the youth. Regrettably, SETAs and TVETs have fallen short of providing the necessary skill required in the market (Leibbrandt et al., 2010b). There is also a worry that bridging the skills divide, although important, is not enough and employers also require some level of work experience.

The National Youth Development Agency (NYDA) provides training to youth through The Graduate Development Programme, the Job Preparation Programme, and the National Youth Service (NYS). Training includes work related life skills, resume preparation, interview readiness, accredited technical skills and more. The NYS started in 2011 and is a one-year programme where young participants are placed in a structured programme with an emphasis on developing technical skills (Graham & Mlatsheni, 2015). No known evaluation of the NYS and other training programmes by the NYDA are available to date.

The learnership tax incentive (LTI) was implemented in 2009 to enhance the skill level of the work force. Learnerships are on-the-job training programmes paid for by employers. The learnerships provide young people with additional training as well as work experience in the hope that this will enhance their prospects of employment later (Graham & Mlatsheni, 2015). Firms can claim a tax incentive of up to R30,000 per year, per employee trained. An additional R30,000 allowance is available per employee on completion of the training. The training is formal and needs

to be aligned to the National Qualifications Framework (NQF) allowing for some standardisation and accreditation in the training. The LTI can also be regarded as an employment subsidy because it lowers the cost of hiring an individual. The administrative burden on firms to administer the training and claim the subsidy means that it tends to be the larger firms that are implementing the programme (Coetzee, du Preez & Smale, 2013). There is little formal evaluation of the LTI programme due to the paucity of data. The success of the programme is therefore unknown.

Public works programmes enlist the unemployed in short term work related to the public sector. Conceptually, public works programmes have the same aim as wage subsidy programmes; to provide the unemployed with experience that will improve their chances on employment. In the long term, a better public infrastructure can also mean more growth in the economy and therefore more jobs. Public works programmes can be seen as an alternative to government welfare assistance to the unemployed where instead of a cash transfer there is a skill transfer given to the more vulnerable unemployed (Leibbrandt et al., 2010a).

The Expanded Public Works Programme (EPWP) in South Africa was launched in 2004 and entered its second phase in 2009. The programme provided productive employment opportunities to unskilled unemployed individuals. The jobs are temporary and include training. The first phase of the programme provided workers with 51 days of employment in the infrastructure sector and 165 days of employment in the social sector (Hemson, 2007). This is considered too short a period of employment to improve the probability of future employment. McCord et al. (2007) provide a thorough review of the first phase of the programme. The second phase of the programme aimed to increase the job duration and include more training. There is little evidence that the EPWP improved the worker's probability of employment once the job ended (National Treasury, 2011). Public works programmes can rapidly increase the employment rates in the short-term and their appeal lies in the increase in the demand for jobs which is suitable in the South African context. Again, there is little evidence that the EPWP increased the demand for labour although it had the potential to do so in the second phase of the programme.

The Community Works Programme began in 2010 and was designed as a public works programme with a focus on community development. The programme similarly provided access to employment at the local level (Philip, 2013). Both the EPWP and the Community Works programmes have a large literature touched upon here in relation to the context of ALMPs in South Africa and in comparison, to the ETI. See McCord et al. (2007) and Philip (2013) for reviews of the EPWP and the Community Works Programmes, respectively.

Job search and job matching initiatives are provided by the Department of Labour. The Department of Labour maintains a register with vacancies and in conjunction with other

government departments, publishes an annual list of national scarce skills. Local labour offices provide placement services for job seekers. The NYDA offers job search and job match services specifically to young job seekers. This is done through the Jobs & Opportunity Seekers (Jobs) database and the Graduate Database (focusing on unemployed graduates) where both initiatives aim to match young job seekers with job opportunities through an online platform. Job seekers can upload their resumes and employers can search for young workers. National Treasury (2011) indicate that these databases are increasingly being used by employers to search for employees they could enrol in learnerships. The NYDA also established Youth Advisory Centres where young job seekers can find assistance with job search and matching activities as well as receive career counselling (National Treasury, 2011).

There are a few factors which affect the usefulness of job search and matching services. Firstly, informal networks are one of the most common ways to search for employment. Young job seekers with limited to no informal networks are disproportionately affected by unemployment. Secondly, the unemployed often live far from economic hubs which raises the costs of job search and limiting the ability of job seekers to find employment (Leibbrandt et al., 2010a). Lastly, while the database of jobs and scarce skills list helps bridge the information asymmetry between employers and jobs seekers, examining the scarce skills list shows that many of the jobs require skilled labour leaving the unskilled vulnerable.

South Africa has a relatively low level of entrepreneurial activity in comparison to other sub-Saharan countries (Turton & Herrington, 2013; Xavier et al., 2013). The support for entrepreneurship has been a policy area focus but this has not translated into increases in employment (National Treasury, 2011). The NYDA run entrepreneurship programmes targeted towards young people. The programmes include entrepreneurship education, business planning support and information about procurement opportunities. While some young people endeavour to start their own business, many are concerned about the sustainability (Mlatsheni, 2014). Since small, medium, and micro enterprises (SMMEs) are not big employment creators, investing in entrepreneurial activities and policies may not yield the necessary number of jobs to affect the unemployment rate in South Africa (Kerr, Wittenberg & Arrow, 2014).

While not an ALMP, South Africa does provide income support to the unemployed through the Unemployment Insurance Fund (UIF). The UIF supports individuals who have been fired or retrenched, become ill or went on maternity leave and provides income support for up to 8 months from the time the employment ended. Individuals are only eligible to receive the income if they have contributed to the UIF while working and as such, the UIF is targeted at the frictionally unemployed. This means that young workers, who have never worked, are not eligible to claim the

UIF and find themselves outside of this protection. The short coverage period of the UIF income also means that individuals go unsupported after 8 months. It is not expected that more experienced youth will crowd out access to the ETI for less experienced youth as experienced youth will seek higher wages rendering them ineligible for subsidised jobs.

The South African government has raised several policy options to alleviate the high levels of unemployment: education and training programmes, income support through the UIF, learnerships incentive to firms, entrepreneurial programmes, job matching and job search services and public employment initiatives. At the same time, the labour market is demanding more skilled workers, a dilemma that the government is trying to solve through labour supply side initiatives. However, the volume of low or unskilled workers simply cannot be absorbed by the labour market even if there were to be an increase in overall skill levels. It is in this context, high number of unskilled young workers with little prospect of employment, that sets the stage for an employment subsidy in South Africa. The next sub-section considers the literature on employment subsidy policies.

2.2.3 Literature on international employment subsidy programs

Wage subsidies can be offered either to the job seeker, or to the firm. A subsidy can be claimed by a job seeker once employment has been found. Also known as worker side subsidies, wage subsidies offered to job seekers aim at increasing labour supply in the market and are often seen in developed countries. Such policies include the Earned Income Tax Credit (EITC) in the United States, Working Families' Tax Credit (WFTC) in Britain, the Self-Sufficiency Project (SSP) in Canada and other programmes in Australia, New Zealand, Finland, Ireland and Belgium (Smith, 1993).

Firm-side subsidies are subsidies given to firms when the firm employs individuals eligible for the subsidy. The aim of a firm-side subsidy is to incentivise firms to hire eligible individuals they would otherwise not be interested in hiring. A wage subsidy decreases the cost of employing an individual without any change in the amount an individual is paid. This allows firms to increase employment of the subsidized group leaving the wages of the subsidized individual unchanged. The elasticity of labour demand and the amount of the subsidy determines the increase in employment at a firm.

Between the two types of subsidies, the firm side subsidy fits the South African context as the aim is to increase the demand for youth labour where the youth labour supply is already high. Furthermore, firm side wage subsidies do not affect (decrease) the wages being paid to workers.

There are several examples in the literature of targeted firm side wage subsidies in other countries; Crichton and Maré (2013) in New Zealand, Betcherman, Daysal and Pagés (2010) in Turkey, Rotger and Arendt (2010) and Kaiser and Kuhn (2016) in Denmark , Bruhn (2016) in Mexico and Hujer, Caliendo and Radic (2002) in West Germany, Kangasharju (2007) in Finland and Webb, Sweetman and Warman (2016) in Canada. These examples evaluate the subsidy at the firm level. Matching and difference-in-difference (DID) are popular methods in the literature to compare similar firms across the pre and post policy periods.

Crichton and Maré (2013), for example, use propensity score matching to analyse a wage subsidy programme in New Zealand. The authors use tax administrative data covering a 10-year period from 2000 to 2010. The wage subsidy was targeted at disadvantaged jobseekers, lasted for up to one year, and represented approximately 50 percent of the weekly wage. Firms employing a subsidized worker were matched to a subset of firms that had a similar likelihood of hiring a subsidized worker but that had not yet hired one. They restricted their sample to firms continuously hiring in the three months prior to hiring a subsidized worker to ensure that firms with similar employment trends were matched. The probability of hiring a subsidized worker is modelled as a function of past employment trends, workforce composition, industry, and region. The authors run separate logistic regressions in firm size categories. Each treated firm is matched to a minimum of five control firms. The authors find that firms increase the hiring of subsidized workers and see an increase in their total employment relative to the matched comparison firm. The authors cannot, however, establish whether the growth in total employment is due to the subsidy, as firms are increasing their employment at the same time and they were unable to control for this.

In Turkey, two employment subsidy policies introduced were expanded in a progressive manner across neighbouring provinces, a fact that Betcherman, Daysal and Pagés (2010) use to identify appropriate treatment and control groups for estimation. The authors use monthly administrative panel data for the period 2002–2005 implementing a difference-in-differences (DID) method. The two policies varied in their incentives, which included a subsidy on social security contributions, an income tax subsidy, an energy consumption subsidy, and a five-year land subsidy. The authors find that the employment subsidy schemes led to significant net increases in registered jobs in provinces where the policy was implemented, despite deadweight loss (considerable in the case of the first policy). Furthermore, they find that the employment subsidy policies led to an increase in the number of registered firms; in other words, informal or unregistered firms were incentivized to register to benefit from the policy.

Rotger and Arendt (2010) use a DID matching estimator to calculate the employment effects of a wage subsidy on small private firms in Denmark. The wage subsidy amounted to approximately 50 percent of the monthly wage and was available for up to one year. The authors use monthly administrative data including individual and firm-level data for 10 months in 2006. The authors use a logit model to estimate the propensity score for treatment before conducting the DID estimation. They find little evidence of deadweight loss or substitution effects and they show that the wage subsidy has a net employment effect of 0.26 employees, that is, an additional 0.26 employees are hired as a result of the subsidy.

Measuring the effects of another Danish wage subsidy programme, Kaiser and Kuhn (2016) find a positive significant effect on the number of employees per firm in the year of the programme. The subsidy aimed to increase the employment of highly skilled workers, lasted between 6 and 12 months and subsidized up to half of the eligible employees' wages. The authors examine the performance of the firms that hired subsidized workers, using a sample of 316 firms. They match treatment and potential control groups on observed characteristics in the year before the wage subsidy programme was introduced.

Hujer, Caliendo and Radic (2002) estimate the effects of wage subsidy programmes on labour demand in West Germany. The subsidies were targeted at individuals with poor labour market prospects, including the long-term unemployed and those over 50 years old. In terms of value, the subsidies ranged between 30 and 80 percent of the monthly wage, depending on the programme, and lasted around 24 months. The authors make use of annual firm survey data to calculate the effect of the subsidy using a conditional DID approach. They measure the change in labour demand by examining the change in actual employment at the firm. No significant effect of the subsidy on employment was found. The authors suggest that this is due to displacement or substitution effects.

Kangasharju (2007) examines the effect of a wage subsidy on employment in subsidized firms in Finland. The subsidy was available to the long-term unemployed, unemployed youth under 25 years old, was equivalent to approximately one-third of their average monthly wages and lasted a maximum length of 10 months. The author uses a DID approach preceded by regression and matching methods using annual tax administrative data for the period 1995 to 2002. In the preceding studies, the authors examined changes in employment by measuring the number of employees. Kangasharju (2007) measures the change in employment by calculating the change in payroll and concludes that there is roughly a 9 percent increase in employment at the subsidized firm based on the change in payroll.

The Canadian Youth Hires program, evaluated by Webb, Sweetman and Warman (2016) is targeted to youth between the ages of 18 and 24 years. The authors use a DID approach and find a small reduction in the unemployment rate. They find no evidence of the displacement of older, non-subsidized workers, who are considered substitutes to younger workers.

In the context of Chapter 5, I also examine the literature on firm side subsidies evaluated at the individual level in developing countries. The consensus view in the earlier economic work on the impacts of wage subsidies (such as Gruber (1997) on Chile) suggests that since labour demand is typically more elastic than labour supply, the incidence of wage subsidies (or payroll tax reduction) falls on the employees. This means that earnings rise and the final gross wage cost to the employer is not affected. Hence, employment does not react either. However, recent work on Colombia (Kugler & Kugler, 2009), Greece (Saez, Matsaganis & Tsakloglou, 2012), France (Cahuc, Carcillo & Le Barbanchon, 2019), and Sweden (Saez, Schoefer & Seim, 2019) indicates the opposite; earnings are not affected and hence the incidence is (mostly) on employers, opening up a way to positive employment impacts.

In Greece, Saez, Matsaganis and Tsakloglou (2012) analyse the earnings response to an increase in payroll taxes for individuals employed from 2003 onwards. Using administrative data for the full population, the authors use a regression discontinuity design to estimate the effect on labour supply and earnings. The authors find that firms increase the gross wages for the new workers but the net wage for the old and new workers remain the same implying that firms bear all of the payroll tax difference. The authors find no change in labour supply.

In the case of a Finnish payroll tax subsidy scheme, Huttunen, Pirttilä and Uusitalo (2013) examine the effect on employment and wages. The subsidy was targeted at the older, full-time, low-wage workers and accounted for 16 percent of wages. The subsidy was available for 5 years and the target group was large. The eligibility criteria allow the authors to use a triple differences estimation strategy to measure the subsidy effects. The authors find that the subsidy does not change the employment rate or wages of eligible workers. The only effect was a small increase in working hours for pension workers with part time working arrangements. The authors conclude that the demand for older workers is relatively inelastic which means a subsidy would expectedly have limited impacts on employment.

More recent research finds no change in earnings where a subsidy was implemented, thereby allowing firms to absorb the wage subsidy and generate employment. One study in France by Cahuc, Carcillo and Le Barbanchon (2019) indicates that a hiring credit had a significant impact on employment and no effect on wages. The authors used administrative data to estimate a

structural search and matching model. Cahuc, Carcillo and Le Barbanchon (2019:1) conclude that the subsidy can generate employment due to the following reasons:

> Simulations of counterfactual policies show that the effectiveness of the hiring credit relied to a large extent on three features: it was unanticipated, temporary, and targeted at jobs with rigid wages.

Saez, Schoefer and Seim (2019) obtain similar finding for a Swedish subsidy programme. The authors also use administrative data and a DID method to estimate the effects of the subsidy. The subsidy was large and afforded to employers of young workers. The authors find no effect on wages of the subsidised young workers relative to slightly older unsubsidized workers. They also find an increase in youth employment of between 2 percent and 3 percent. Firms with a larger share of young workers before the policy started to also increase their capital, sales, and profits. The wages of both young and older workers are seen to increase in these firms as the tax credit is large and the firms engage in rent sharing. Saez, Schoefer and Seim (2019:39) make a different conclusion about the reasons for the policy success:

> Some features of the tax cut we study may have enhanced its effectiveness. It was employer borne, salient, administered in a way to ensure near-perfect, immediate and automatic take-up, it targeted young workers but was encompassing (i.e., applied not just to new hires out of unemployment or a subset), it was intended to be permanent, and it was large.

In the French wage subsidy Cahuc, Carcillo and Le Barbanchon (2019) tells us the three key design features of a wage subsidy: short term, targeted and unforeseen. Saez, Schoefer and Seim (2019), on the other hand, explains that the Swedish subsidy was effective as it was long term, applied to all young workers and had near perfect take up.

Less developed countries

The concentration of wage subsidy evaluations is found in developed countries. In general, developing countries have invested far less in ALMPs than developed countries and wage subsidies can be costly policies. I outline some cases in the developing countries to bring us closer to the South African context.

In the wake of an economic crisis, a wage subsidy was introduced in Mexico to incentivise firms to retain workers in the manufacturing industry. Subsidies were granted to firms that retained workers instead of letting them go during an economic crisis and the policy lasted eight months. Bruhn (2016) use monthly administrative data for the period 2004–2013 and matching DID to evaluate the policy. A positive but not statistically significant effect is found that ranges from a 5 percent to a 13 percent increase in employment. After the policy ends, the author finds that

employment at firms in eligible industries recovered from crises more quickly than in ineligible industries.

Gruber (1997) studies a policy change that led to a large reduction in the average payroll tax rate in Chilean firms. Examining all manufacturing firms in Chile, the author find evidence that the incidence of the drop in the payroll tax is entirely on wages, that is, there is an increase in wages. The author finds no evidence on an effect on employment.

Kugler and Kugler (2009) consider the effect of large payroll tax increase on manufacturing firms in Colombia. The authors show that the payroll tax increase leads to a limited increase in wages (between 1.4 percent and 2.3 percent) and that a 10 percent increase in payroll taxes decreases employment (between 4 percent and 5 percent).

In less developed countries, it is also important to consider the cost effectiveness of a wage subsidy policy. If the costs are high and the policy is not effective, then perhaps the government should be spending their resources on a different policy. Brown (2015) examines the characteristics of hiring subsidies in the context of ALMPs targeted at the unemployed. Brown (2015) points to four positive characteristics of hiring subsidies: one, less deadweight loss and other negative effects than wage subsidies; two, allows for employers to screen workers and give the unemployed some experience; three, targeting the long-term unemployed increases the positive effects found in the labour market, and four, cost-effective method of increasing employment probabilities in the future. Correspondingly, the author points out, there are four main disadvantages of hiring subsidies. One, impact can vary depending on the target group and policy design; two, vague targeting can create displacement and deadweight loss; three, narrow targeting increases administrative costs for employers and, four, the long-term effects of hiring subsidies on employment trajectory have not been well studied. The main take away from (Brown, 2015) is that cost-effectiveness of the policy lies in the design and the group being targeted.

In a separate publication, Brown and Koettl (2015) examine the cost effectiveness of hiring subsidies in the context of other ALMPs accounting for the policy objectives and the state of the economy when applied. They argue that hiring subsidies are more cost effective than wage subsidies as they support the unemployed with low labour market prospects such as the long-term unemployed or unemployed with low skills. Brown and Koettl (2015:11) point to studies that show that hiring subsidies are also more effective at getting the unemployed into work in comparison to training and public employment policies. Lastly, the authors suggest that the cost-effectiveness depends on whether the hiring subsidy has an impact on the long-run employment probabilities on the subsidised group.

There are key lessons from the international empirical literature. Administrative data is a common data choice due to its advantage of policy population coverage. The South African tax data are thus best suited for the evaluation of the ETI as it has detailed information on the subsidy claims and covers the entire population of firms and formally employed, private sector workers.

DID estimation methods are commonplace with variations depending on the context, design, and implementation of the subsidy scheme. These variations include matching before the DID and using location as a source of variation. This best practice methodology is contextualised and implemented in our analysis. At the firm-level, this thesis will use a matched DID approach and at the individual-level, a triple differences approach in line with the design of the subsidy.

There are no strong lessons from the literature whether to expect that the policy will be successful or not. In fact, the literature is at times conflicting on whether a more targeted or more permanent subsidy system works better. There are a handful of studies from less developed countries, thus requiring more intimate knowledge on the operation of employment subsidies in an emerging economy such as South Africa.

Lastly, in a country where there are fiscal constraints and policy-makers need to consider various options to create employment, it is important to examine whether the positive view on the cost effectiveness of hiring subsidies expressed in Brown (2015) and Brown and Koettl (2015) remains valid in the case of the ETI. This is not the focus of any particular chapter in this thesis however, the cost of the policy is covered in Chapter 4.

2.3 Institutional background

Proposals for a wage subsidy in South Africa were made early after the first democratic election in 1994. In 1995, parliament established the Presidential Labour Market Commission. Among other tasks, the commission was mandated to develop a framework for employment growth. The commission's report was published in June 1996 and included a description of an Employment Subsidy that had been proposed to boost employment. The report includes some statements that were made to the commission and interestingly concludes: "The listed disadvantages would seem to be much greater and more persuasive" (Standing, Sender & Weeks, 1996:482). Wage subsidies continued to be proposed as part of South Africa's post-apartheid growth strategy (Heintz & Bowles, 1996; Levinsohn, 2008; Lewis, 2001; Pollin et al., 2009). Proposals by Heintz and Bowles (1996), Levinsohn (2008), Burns, Edwards and Pauw (2010) and Schöer and Rankin (2011) considered the South African context, appropriateness of a wage subsidy and possible firm responses. The authors proposed details for the design of the policy that would enable employment growth.

The ETI, previously called the youth wage subsidy, was then conceptualised, and proposed by the National Treasury (NT) in 2011. In a discussion paper, the NT highlights the need to address the problem of youth unemployment in South Africa. They emphasise the necessity of a "multi-pronged strategy to raise employment and support inclusion and social cohesion" (National Treasury, 2011:5). The discussion paper names economic growth and progress in the education system as two important parts to solve the problem of youth unemployment.

The NT discussion paper also reviews ongoing active labour market policies aimed at youth in South Africa. Sector Education Training Authorities (SETA), Learnerships and Technical and Vocational Education and Training colleges[3] (TVET), were established to enhance the level of skill and education of the youth. SETA's and TVET colleges are criticised for being underfunded and for poor management and poor quality of lecturers (Bernstein, Altbeker & Johnston, 2016).

A host of programmes such as the Graduate Development Programme (GDP), Job Preparation Programme (JPP), the National Youth Service, Jobs & Opportunity Seekers (Jobs), the Graduate Database and Youth Advisory Centres were established by the National Youth Development Agency (NYDA) to provide job search and job matching assistance to young people. The NYDA also hosts many entrepreneurship programmes to provide youth with assistance from the inception to establishment of a small business.

These labour market policies that are aimed at increasing individuals' education or skill levels, are termed as labour supply interventions. This, however, has not always transferred into successful employment for youth (Altbeker, Schirmer & Bernstein, 2007). Even if one considers the scenario where youth have higher education and skill levels, the question remains as to whether there are enough jobs in the economy to absorb these youth. If too few jobs exist, then any increase in the skill level of youth will limit the extent to which youth are gainfully employed.

There have been two interventions, before the ETI, aimed at increasing the demand for labour. The Expanded Public Works Programme (EPWP) and the Learnership programme. The EPWP started in 2004 and continues to be implemented. The programme gives individuals an average of 80 days of work but has not been found to change the future employment probabilities of workers (Altbeker, Schirmer & Bernstein, 2007). As the ETI is aimed at private sector workers there is no contamination problem when evaluating the ETI. Later in the thesis, the learnership programme is accounted for in the empirical strategy.

The Learnership programme began in 2002 and continues to be implemented. The programme provides incentives to firms that train young employees. The majority of those entering the Learnership programme were previously unemployed indicating that the intervention is reaching

[3] previously Further Education and Training (FET) colleges

the required target group. Visser and Kruss (2009) find that 76 percent of those registered for high skill level learnerships are employed two years after first registration while only 46 percent of those in the low skills programme are employed two years later. The enrolment for the low skills programme was double that of the high skills programme. This means that there is a large group of youth going through the learnership programme but not finding suitable employment afterwards. Section 2.2.2 further details the EPWP and the Learnership programme.

In the Learnership programme, firms can claim a tax subsidy for training workers while employed. Among the previous unemployed on the learnership programme, 73 percent are in learnership programmes at large firms. Very few participants report being in learnership programmes at smaller firms. This is thought to be the result of the high costs associated with administering the learnership programme both in terms of claiming the subsidy as well as formally enrolling employees into an accredited programme.

Even after the implementation of the various programmes discussed above, youth unemployment remains stubbornly high in South Africa. The ETI was proposed in addition to many of the other policies and programmes aimed at youth. The defining difference is that the ETI is designed to stimulate the demand for youth labour by lowering the relative cost of hiring an inexperienced youth, a labour demand side initiative.

Proposals for a wage subsidy in South Africa were made by Heintz and Bowles (1996) soon after the first democratic election in 1994. Wage subsidies were proposed as part of South Africa's post-apartheid growth strategy (Lewis, 2001; Pollin et al., 2009). Reducing unemployment emerged as a policy priority on the agenda of the ANC-led government. The government's New Growth Path strategy aimed to create 5 million jobs by 2020 (Development, 2011) and is emphasised in the National Development Plan 2030 (Presidency, 2011). In 2011, President Jacob Zuma announced the governments' intention to spend 9 billion rand on job creation (Zuma, 2011). The same year, the National Treasury proposed the Youth Employment Subsidy as one of multiple policies to combat youth unemployment (National Treasury, 2011).

2.3.1 Between policy proposal and implementation

Several studies conducted after the wage subsidy was proposed by Heintz and Bowles (1996) in 1996 were of the opinion that it had the potential to change the employment prospects for youth (Burns, Edwards & Pauw, 2010; Levinsohn, 2008; Levinsohn, 2014; Levinsohn & Pugatch, 2014; Mtembu & Govender, 2015; National Treasury, 2011).

Earlier work by Pauw and Edwards (2006) using a computable general equilibrium (CGE) model of the South African economy, evaluate the general equilibrium effect of the prospective

wage subsidy. The authors find that employment of semi- and unskilled workers can be increased through a wage subsidy. They suggest the effects of the wage subsidy will vary by sector.

Levinsohn (2008) put forward the proposal for a targeted wage subsidy to deal with the unemployment problem. He makes recommendations on how the policy should be implemented in order to be effective, coupled with suggestions on how to deal with some of the negative consequences of a wage subsidy through good policy design.

Go et al. (2010) assess the employment effects and cost of the wage subsidy. The authors find that the employment impact is dependent on the elasticities of substitution of the factors of production. The authors highlight that the wage subsidy will be able to increase the employment of low- and semi-skilled workers if there is medium elasticity of substitution for the factors of production. They warn that the effect of the policy might be reduced by labour market rigidities.

Burns, Edwards and Pauw (2010) provide a general review of the wage subsidy literature and apply it to the South African context. They show that design, implementation, and the structure of the labour market in South Africa are key in determining the success of a wage subsidy policy. They argue that the wage subsidy might be successful in creating jobs in South Africa if it is associated with skills training, especially in industries that are sensitive to labour costs, and should have a focus on youth.

Schöer and Rankin (2011) find that firms recruit and hire few youths creating a disadvantage for youth seeking employment. Firms indicate their willingness to hire subsidised youth but not in addition to their workforce.

The Congress of South African Trade Unions (COSATU) responded to the NT discussion paper (National Treasury, 2011) and the draft Employment Tax Incentive Bill through a formal response to draft bill and an analysis of the proposed policy (COSATU, 2013). The union raised several issues it had with the policy including possible downward pressure on wages and the displacement of unsubsidised workers. The union was not optimistic and claimed the subsidy would not be of benefit to the targeted group of young workers.

Levinsohn and Pugatch (2014) use a structural search model to estimate the prospective impact of a wage subsidy on youth in Cape Town. The authors find that a R1,000 wage subsidy leads to an increase of R660 in mean accepted wages and a decrease in the share of youth experiencing long-term unemployment.

Levinsohn et al. (2014) conducted a randomized control trial in South Africa before the policy was enacted to examine how a wage subsidy might affect youth unemployment in the South African context. Participants in the trial were given a voucher for a wage subsidy that the firm could claim monthly for up to six months. The authors found that participants who were given a

wage subsidy voucher were more likely to be in waged employment both one year and two years after they were given the voucher. The wage subsidy voucher differs from the ETI as it provides a voucher to the employee which they use to find employment. The ETI is a tax credit provided to firms for all eligible youth hired after the 1st of October 2013.

Mtembu and Govender (2015) examined the perception of the wage subsidy among unemployed youth and employers in Kwazulu-Natal. The authors find that both parties were in support of the policy, hoping that it would decrease youth unemployment and ease the wage burden.

Between the policy proposal and implementation, the perception and outlook for the ETI was mostly positive. Firms seemed committed to use the incentive to create new jobs for youth and simulation models indicated that jobs could be created by the policy. Overall, in the literature, the criteria, structure, and implementation of the programme was thought to be an important determinant of whether or not the policy would be successful.

2.3.2 Mechanics of the policy

The ETI policy was enacted in December 2013, implemented on 1 January 2014, and retroactively applied to new hires from 1 October 2013. The ETI was available for a period of three years, ending on 31 December 2016. During 2016, the NT conducted an evaluation of the policy and decided to renew the policy for an additional two years ending 28 February 2019. No changes were made to the policy. In 2018, a second evaluation was done where the outcome was to extend the policy for an additional 10 years ending in 2029 (Ramaphosa, 2019). The 10-year extension also included a small increase to the monthly wage condition and subsidy value.

The ETI is similar in design to the Learnership programme. Firms hiring ETI eligible employees can claim the tax subsidy through reduction tax bill. However, the ETI also differs from the learnership programme because firms were not required to provide any training for the eligible workers in order to claim the subsidy.

The ETI is a hybrid of a hiring subsidy and a wage subsidy. Hiring subsidies typically cover new hires and are only valid for a short period of time while wage subsidies are targeted at specific worker groups, irrespective of when they were employed and typically long term or permanent. The ETI is available to employers of workers hired after a specific date, however the subsidy period is 24 months which far exceeds a typical hiring subsidy period. On the other hand, the ETI also targets a specific group of workers; young and low wage workers, making it more similar to a wage subsidy. Brown (2015) suggest that hiring subsidies tend to be more successful than wage

subsidies because of their targeted and temporary nature. A similar sentiment is expressed by (Cahuc, Carcillo & Le Barbanchon, 2019).

The subsidy is subject to a set of criteria for the firms wishing to claim the tax credit as well as for the individuals for whom firms can claim the subsidy. The criteria are outlined in Table 2-2.

Table 2-2 Criteria to claim the ETI.

Employer criteria	**Employee criteria**

- Employers in the Public sector are ineligible.
  o not in the national, provincial, or local sphere of government
  o not a public entity listed in Schedule 2 or 3 of the Public Finance Management Act (PMFA)[4]
  o not a municipal entity
- Employers need to be registered, or eligible to register, for Pay-As-You-Earn (PAYE)
- Employers cannot claim if any money is owed to SARS.
- Employers not disqualified for the displacement of an employee
	- Employees need to be between the ages of 18 and 29 years.
	- Employees are required to be hired after 1 October 2013.
	- Employee wages should be less than R6,000 per month but more than the minimum wage.
	- Employees need to be South African citizens.
	- Employees cannot be related to employer.

Note: PAYE refers to the direct payment of taxes from employers to the revenue collector.
Source: Author's own construction based on information from the SARS website.
https://www.sars.gov.za/TaxTypes/PAYE/ETI/Pages/default.aspx

The policy does not require any training for the employed youth and is available to all industries. No requirements are placed on length of unemployment for eligible youth as is sometimes seen in similar policies in other countries. Domestic workers and public sector employees are not eligible for their employer to claim the subsidy. Employers of domestic workers are not required to register as an employer and employers in the public sector are ineligible to claim.

To reduce the displacement of older workers that might result from the policy, a R30,000 penalty per employee displaced was included in the policy for offending firms. Penalties are also imposed on firms that claim the ETI for workers who are paid less than the minimum wage. No information is however available about the monitoring of displacement of older workers and whether any penalties were imposed on employers.

Firms can claim the subsidy for a 24-month period for an eligible employee. However, the amount of the subsidy is greater for the first 12 months of the employment contract than the second 12 months. The amount claimed per employee is based on the employee's monthly salary, as shown in Table 2-3. Firms can claim the subsidy for as many eligible workers they employ after 1 October 2013. This is unlike the case of the Turkish wage subsidy where firms were only able to

[4] List of public entities from the PMFA can be found here: PFMA Public Entity Schedules

claim the subsidy after a certain threshold number of eligible workers were hired (Betcherman, Daysal & Pagés, 2010).

Table 2-3 Monthly subsidy calculation per employee

	First 12 months	**Next 12 months**
R0-R2,000	50% of monthly income	25% of monthly income
R2,001 – R4,000	R1,000	R500
R4,001 – R6,000	R1,000-0.5x (monthly income-4000)	R500-0.25x (monthly income-4000)

Notes: Minimum wages occur in some sectors. The subsidy applies to part time employment.
Source: Author's computation based on the Employment Tax Incentive Act (2013)

The amount of the subsidy follows a sliding scale. In the phase-in region, between R0 and R2,000, the subsidy rate is 50 percent of monthly income. Between the R2,000 and R4,000, the plateau region, the subsidy is a constant amount equally R1,000. In the phase-out region, for wages above R4,000, the amount of the subsidy decreases as a rate of 50 percent until it reaches zero. The subsidy is phased out at this point where the monthly income is equal to R6,000. Figure 2.2 graphically depicts the monthly subsidy value in relation to the monthly income. The value of the subsidy is halved in the following 12 months of employment.

Figure 2.2 Monthly subsidy amount

Note: Graph depicts the subsidy value in relation to monthly income for the first and second years of employment.
Source: Authors' own estimates.

Where employees worked for less than 160 hours per month, part time, the subsidy value is calculated by calculating the monthly salary (hourly wage x 160 hours), matching this to the correct monthly subsidy value and then dividing the monthly subsidy value by 160 over the number of hours worked. For example, if someone works for 80 hours per month and earns R2000, the

associated monthly salary would be R4000 (multiply by 2) corresponding to an ETI value of R1000. The calculated subsidy value is therefore R500 (divide by 2).

The subsidy is not automatically applied to employers of eligible workers. In order to claim the subsidy firms are required to submit the Monthly Employment Declaration form (also known as EMP201 form) which includes an ETI field for the value of the subsidy they wish to claim in the month. This means that the wage received by the employee is not affected and employees may not be aware that employers are claiming the subsidy for their employment. The forms are submitted to SARS monthly, and the subsidy amount reduces the amount of PAYE tax that is owed to the revenue service.

A scenario of how the ETI works is useful in understanding the value and mechanics of the subsidy: Paula is hired on 1 January 2014 at ABC retail. Paula is 21 years old and earns R3,000 per month. ABC retail is a privately-owned company, is registered for PAYE and owes no debt to SARS. For the first twelve months of her contract, ABC retail can claim a tax incentive of R1,000 per month through a reduction in taxes owed to SARS. Paula's contract is renewed in December 2014 and she continues working for ABC retail. Her salary from January 2015 is R3,750 per month, however, ABC retail claims a reduced tax incentive of R500 per month from January to December 2015 after which no further ETI can be claimed for Paula.

2.3.3 Challenges facing the ETI

Disadvantages, warnings, and criticisms of the ETI have stemmed from both the research community and the trade unions. The criticisms relate to the design and implementation of the policy. This subsection discusses the challenges to the wage subsidy, what each challenge means and how the design or implementation of the policy have addressed, or not addressed, these problems. This also provides some framing for the empirical work in the subsequent chapters where some of these challenges are quantified.

The **cost** of the ETI is paid for by the government through revenue collection from taxpayers. The subsidy applies to youth earning less than R6,000 per month who pay no employment taxes[5]. Unsubsidised workers paying taxes are thus indirectly financing the policy. The National Treasury estimated that the policy would cost a total of R5 billion over the first three years and create 178,000 jobs at a cost of R28,000 per job created (5 billion ÷ 178,000). This is similar to cost-per-job estimates from The Jobs Fund, a business funding initiative also aimed at creating jobs (National Treasury, 2014). The expanded public works programme, also a job creation initiative

[5] The SARS rates of tax for individuals can be seen at the following link: http://www.sars.gov.za/Tax-Rates/Income-Tax/Pages/Rates%20of%20Tax%20for%20Individuals.aspx

by the South African government, is said to have had a cost of R100,000 per job[6]. In this context, R28,000 does not appear to be as high if the targeted number of jobs are created. The actual costs and number of jobs created are examined in Section 4.6 in Chapter 4.

The ETI is to be claimed for newly hired youth employees. These criteria were stipulated in order to stimulate the creation of jobs but could be hampered if firms are hiring youth with past work experience. Thus, ETI workers may not necessarily be new entrants to the labour market. The employment history of ETI participants is examined in Section 3.4.7 in Chapter 3.

The wage subsidy decreases the relative cost between a subsidised and unsubsidised worker. This has the potential to place **downward wage pressure** on unsubsidised workers. Downward pressure can also be experienced by subsidised workers. Firms could hire two people with a monthly subsidy of R2,000 each and claim a total subsidy of R2,000 but at the same cost of hiring one person with a monthly remuneration of R4,000 per month and only claiming a R1,000 subsidy. The subsidy also tapers off at a higher rate for those earning between R4,000 and R6,000, making wage increases for this group more expensive to employers exerting a downward pressure on wages for earners within this group. The flipside of this argument is that firms employing part time workers for R1,000 per month would earn a subsidy of R500. If they increase the number of hours so that the monthly remuneration is R2,000 per month, the firm will receive a R1,000 monthly subsidy. This would result in no net cost effect to the firm. The point here is that the cost-minimizing nature of firms will determine how they respond to the subsidy and how wages will be affected. This is examined in Section 5.6 in Chapter 5.

Where eligible and ineligible youth workers are substitutes, the ETI will create an incentive to hire eligible workers instead of ineligible workers known as a **substitution effect**. For example, one could consider that the scenario where a worker earning R6,200 and may be substituted for a worker earning R5,900. The eligible worker, earning R5,900 will be hired as they attract a tax credit for the firm. This is due to the change in the relative labour-cost that the policy creates. Another way to think about this is to consider the scenario where firms may substitute medium-ability workers with low ability workers. This is however unlikely in the case of the ETI due to the value of the subsidy close to the threshold. Going back to the example of a worker earning R5,900, the associated subsidy value is R50. The cost of firing the worker earning R6,200 and rehiring a new worker earning R5,900 is likely to cost more than the tax benefit the firm will receive decreasing the likelihood of this kind of substitution to take place.

[6] The source of this information is from an article written by Carol Paton quoting this information from Andrew Donaldson the https://www.businesslive.co.za/bd/national/labour/2013-11-25-startling-cost-effectiveness-in-creation-of-150000-new-positions/

Substitution is not always seen as unfavourable. Fay (1996) points out that targeted wage subsidies aim to 'shuffle-the-queue' of the unemployed. Subsidies targeted at the youth with low employment probabilities may induce firms to hire them instead of those youth with good employment probabilities who would have been hired anyway. Arguably this is one of the aims of the policy, to give some work experience to youth with low employment prospects.

Displacement can also occur between subsidised youth workers and unsubsidised older workers. This has been one of the biggest concerns voiced by COSATU (COSATU, 2013). Firms could hire subsidized workers instead of hiring unsubsidised workers or fire unsubsidised workers in order to replace them with subsidised workers. **Displacement effects** can also occur when the subsidy expires after 24 months and the subsidised worker is fired. The policy, however, has a penalty in place for firms who are found to displace workers in order to employ subsidised workers. Enforcement and monitoring of displacement in firms might be hard and it is not clear if any firms have been fined for displacing any worker. Levinsohn (2008) argues that the dismissal of unsubsidised workers will be limited because of South African regulations around layoffs. Brown, Merkl and Snower (2011) also highlight that some level of displacement may be tolerated where it is expected that the employment experience gained by the target group is more valuable as it enables the long-term unemployed to enter the labour market, gain some experience and improve their overall employability. Displacement effects can be mitigated when subsidies only apply to additional workers (Hujer, Caliendo & Radic, 2002). This, however, is not the case for the ETI. Chapter 4 examines the effects of the subsidy on older and ineligible workers and calculates any deadweight loss.

The policy is at risk of creating a large **deadweight loss**. A deadweight loss occurs when the aid of the policy accrues to beneficiaries who, in the absence of the policy, would meet the aim of the policy. This can occur with the ETI when firms would have hired eligible workers in the absence of the policy. There is some expectation of deadweight loss since firms are expected to hire several eligible workers over the duration of the policy irrespective of the subsidy and again, firms are not required to hire any additional workers.

Another indirect effect of the ETI may be a **churning effect**. Churning occurs when the subsidy beneficiary only participates to claim the benefits. One way in which a firm can continuously benefit from the ETI is to layoff subsidised workers once their subsidy ends and hire a new eligible worker. The high unemployment rate for low-income youth in South Africa means there are enough eligible youth who could be used as replacements by firms. Levinsohn (2008) argues that firms are unlikely to get rid of good workers in order to claim the subsidy but that some level of churn can be expected as an outcome of the policy. Additionally, firms may incur

some costs related to hiring and training which they will need to pay again if they hire a new worker. The counterargument, also made by Levinsohn (2008), is that it is the job experience that is valuable to the worker, with the ETI contributing to a change in their employment probabilities where they would have still been unemployed. As with the displacement effect, some level of churning may be tolerated.

In other wage subsidy programmes, the targeted population are sometimes **stigmatised** and perceived to be deficient (Kluve, Lehmann & Schmidt, 1999). This has been found in developed countries where subsidy vouchers were given to the unemployed. This was tested in the South African context through the randomised control trial conducted by Levinsohn et al. (2014). The authors find an increase in employment of those with a wage subsidy voucher and thus no evidence of stigmatisation. In the case of the ETI, the subsidy is claimed by the employer and stigmatisation could take place if a subsequent employer finds out that a potential employee was in a subsidised position previously signalling low productivity of the worker. There is little chance of this happening as there is no easy way for an employer to know whether a worker was previously subsidised.

The target population of ETI includes recent school-leavers and thus can induce students to leave school early in order to find a subsidised job also termed a negative **skill-acquisition effect**. Levinsohn (2008) suggests that the design of the policy only allows for subsidy claims for workers aged 18 and above. This means that those who remain in school can be employed in subsidised jobs once they finish school. In practice, youth do not have enough knowledge of the policy or were led to believe they were easily able to get a job should they drop out of school. The target audience for promoting the policy, by the NT, is firms.

Lastly, there are two potential ways in which fraud can manifest in the ETI. One, a person could set up a dummy firm, hire young unemployed relatives and claim the subsidy. This will be hard to monitor if persons are easily able to set up dummy firms. Two, firms can claim the subsidy for employees not eligible for the subsidy. The potential of fraud is explored in Chapter 3 and some of the other criticisms of the ETI in the subsequent chapters.

In some ways the design of the policy has tried to mitigate some of the challenges that arise in a wage subsidy setting. Challenges such as churning, displacement and substitution effects, deadweight loss need to be calculated and weighed up against any benefit the policy brings.

2.3.4 Policy evaluation

Within the first 5 months of the policy period, President Zuma announced that 133,000 employees had benefitted from the policy in 11,000 firms (Zuma, 2014). In his state of the nation address in

February 2015, President Zuma indicated that the subsidy had been claimed for 270,000 youth in 29,000 firms at a cost of R2 billion in the first year of the policy period (Zuma, 2015).

Few studies have been published with the aim of evaluating the policy. De Jongh, Meyer and Meyer (2016) studied perceptions of the ETI among 13 local businesses in the Vaal triangle in Gauteng. The authors find that firms were in support of the policy, but that 8 of the 10 businesses claiming subsidies had admitted to not creating any new jobs. Singizi Consulting (2016) produced a qualitative report on the ETI for the National Economic Development and Labour Council (NEDLAC). The report details interviews and focus groups conducted with 42 firms across certain industries and of varying sizes. The report suggests firms are using the ETI to create or retain jobs and that the subsidy was being used to increase overall employment at firms.

Ranchhod and Finn (2014) examine the policy six months after its inception. They measured the effects of the ETI using nationally representative survey data. The authors implement an individual-level difference-in-differences model to estimate the effects of the ETI on the employment probabilities of youth. The method examines the employment probabilities of youth before and after policy implementation accounting for any changes in the economic climate at the time of the policy. The authors find no change in youth employment probabilities in the first six months after the policy was implemented. Extending their analysis to the first 12 months of the policy period, they do not find a statistically significant change in the probability of youth employment (Ranchhod & Finn, 2015).

In 2016, the treasury released a descriptive report on the ETI, formalising the information provided by the president Zuma. The report also indicates that the number of jobs supported are greater than what was previously projected in the 2011 discussion paper (National Treasury, 2016). The report does not make any claims about the success or failure of the policy.

In a conference presentation, Makgetla (2016) used a comparative interrupted time series method to evaluate the ETI. The author finds no sustained impact on employment of young people at firms on aggregate. She did find positive employment effects amongst small firms and finds a decrease in the youth employment at large firms but notes that there is a problem of adequate controls for larger firms. The study is limited by the period of data available with only one full policy year included in the sample.[7]

The limited results from the quantitative and qualitative literature leaves fertile ground for further evaluation of the policy. The little evidence is in part due to the difficulty that survey data may not capture the effect of the subsidy since employees might be unaware of the subsidy claims

[7] At the same conference Neil Rankin also presented analysis of the ETI using tax data in conjunction with the National Treasury. The presentation and paper are not available and therefore their contribution has not been added here.

made by their employers. A limitation of studies on wage subsidies, presented in (McKenzie, 2017), is the but something As the subsidy is claimed through the tax system the only way to examine subsidy claims is through examining tax data.

2.4 Theoretical framework

Having established that firms are the beneficiaries of the ETI, this section begins by showing the effects of a wage subsidy on firms, then looks at the effect on labour demand considering two labour supply scenarios.

Drawing from both Hujer, Caliendo and Radic (2002) and Burns, Edwards and Pauw (2010), the theoretical effects of a wage subsidy on labour demand at the firm are illustrated. Figure 2.3 illustrates a simple static model where a firm produces output y using two inputs L_{Youth} and $L_{NonYouth}$ and describe this equation (2.1).[8]

$$y = F(L_{Youth}, L_{NonYouth}) \tag{2.1}$$

The model assumes $F_i > 0$, $F_j < 0$ and $F_{ij} > 0$ where $i, j = L_{Youth}, L_{NonYouth}$. It also assumes the two input factors are separable from capital and the labour supply is infinitely elastic.

Firms maximise their profit $\pi = F(L_{Youth}, L_{NonYouth}) - wL_{Youth} - rL_{NonYouth}$ by choosing how much of each factor (youth or non-youth labour) to use. w is the cost of youth labour and r is the cost of non-youth labour. The first order conditions are:

$$F_{L_{Youth}} - \lambda w = 0$$
$$F_{L_{NonYouth}} - \lambda r = 0'$$

where λ is the Lagrangean multiplier. The optimal demand for youth and non-youth workers is set according to the ratio of the two conditions:

$$\frac{F_{L_{Youth}}}{F_{L_{NonYouth}}} = \frac{w_{L_{Youth}}}{r_{L_{NonYouth}}}$$

That is, the marginal rate of technical substitution, where $\frac{F_{L_{Youth}}}{F_{L_{NonYouth}}}$ equals the factor-price ratio, $\frac{w_{L_{Youth}}}{r_{L_{NonYouth}}}$, for a profit maximizing firm. This optimal demand for youth and non-youth lies at point A on isocost curve IC_1 in Figure 2.3. The wage subsidy will rotate the isocost curve from IC_1 to IC_2.

[8] The typical approach considers labour, L, and capital, K, as factors. The analysis can also be applied to high versus low skilled, local versus foreign workers and young versus old as is done here.

Crucial to the analysis of a wage subsidy is the elasticity of substitution between the two input factors L_{Youth} and $L_{NonYouth}$, holding output constant. This is the rate of change in the use of $L_{NonYouth}$ to L_{Youth} from a change in the relative price of w to r, holding output constant. The definition of this elasticity is described in equation (2.2) :

$$\sigma = \frac{\%\ in\ \frac{L_{NonYouth}}{L_{Youth}}}{\%\ in\ \frac{w}{r}} = \frac{F_{L_{Youth}} F_{L_{NonYouth}}}{YF_{L_{Youth}L_{NonYouth}}} \tag{2.2}$$

Intuitively, this elasticity measures the ease of substituting non youth labour for the youth labour in response to a change in the price on youth labour without changing output. A larger elasticity of substitution means youth and non-youth labour become closer to perfect substitutes. The closer the elasticity of substitution is to zero, the youth and non-youth labour cannot be substitutes. Equation (2.2) cannot be negative.

The main aim of a subsidy is the change in labour demand as a result of the change in the wage or the constant output labour demand elasticity described in equation (2.3) below:

$$\Delta L_{Youth} = \frac{\%\ change\ in\ Labour\ Demand}{\%\ change\ in\ wages} = (1 - s)\sigma \tag{2.3}$$

where ΔL_{Youth} reflects the increasing demand for youth labour, s is the share of labour costs for young workers in total revenue ($s = \frac{wL_{Youth}}{Y}$) and σ is the elasticity of substitution between youth and non-youth labour.

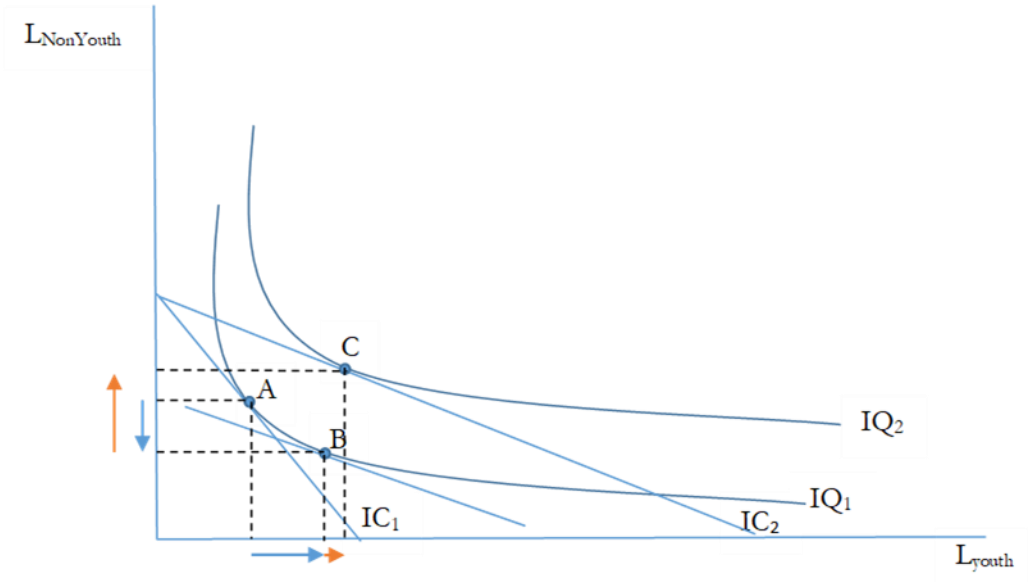
The relative price of non-youth labour increases thereby reducing the demand for non-youth labour presented in equation (2.4) below:

$$\Delta L_{NonYouth} = -(1 - s)\sigma \tag{2.4}$$

Together equations (2.3) and (2.4) describe the substitution effect or the move from point A to point B on isocost curve IC_1.

Finally, the model needs to account for the lower production costs in subsidised firms brought about by the decrease in costs of youth labour. Lower production costs mean a decrease in prices and an increase in demand for the produced good y in subsidised firms. This is termed the scale or output effect and is seen as the shift from point B on IC_1 to point C on IC_2. The output effect is the youth labour factor's share times the product demand elasticity, given as η in equation (2.5).

Figure 2.3 Theoretical effects of a wage subsidy



Note: The figure depicts the rotation of the isocost curve from IC_1 to IC_2 as a result of a wage subsidy. Both substitution and output effects are depicted.
Source: Author's own illustration

The total demand effect for youth and non-youth labour can be described in the equations below:

$$\Delta L_{Youth} = (1-s)\sigma + s\eta \quad > 0$$
$$\Delta L_{NonYouth} = -(1-s)\sigma + s\eta \quad \begin{cases} > 0 \\ = 0 \\ < 0 \end{cases} \tag{2.5}$$

The change in youth labour demand is the summation of the substitution effect and the output effect, both of which are positive. The theory thus predicts that the effect on youth labour will be positive. The total demand effect for non-youth is negative for the substitution effect but positive for the output effect and the magnitude of these effects will determine effect on non-youth. Where the elasticity of substitution is high, the demand for non-youth workers will decrease, where the elasticity of substitution is low the demand for non-youth increases (Burns, Edwards & Pauw, 2010).

The implicit assumption in this model is that all youth are eligible for the subsidy. This assumption does not hold true for the ETI as only a subset of youth, within a low-income bracket, are eligible for the subsidy. The problem could arise if eligible youth are substitutes for non-eligible youth. Depending on the elasticity of substitution between these two groups, eligible and non-eligible youth, there may be substitution effects. The substitution between eligible and non-eligible

youth produces a net employment effect of zero as no new jobs would have been created, a desired outcome of the ETI. This is examined in Chapter 5.

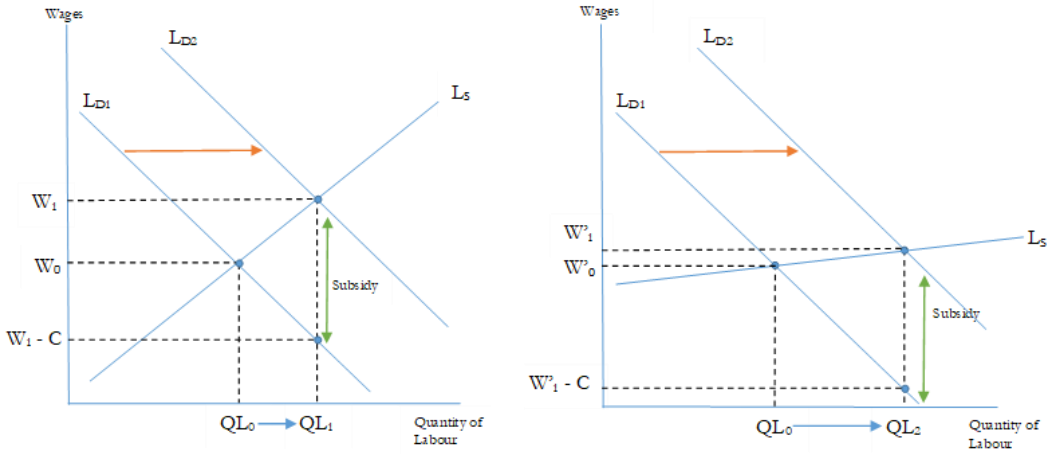
The static model does not show the effect of providing experience to unemployed youth who would have remained unemployed otherwise. This is important in the context of South Africa where past work experience is positively correlated with future employment prospects (Kingdon & Knight, 2004).

The aggregate demand for youth labour is the sum of the demand for youth labour in each firm at a point in time. The policy can therefore increase the number of youths employed through increasing the number of firms that employ youth or increasing the number of youths employed in existing firms, or both. The flip side of this that there are possibly no general equilibrium effects when only some firms take advantage of the subsidy. It is possible that ETI claiming firms poach eligible workers from non-ETI claiming firms. While this will increase youth employment in the ETI firm the non-ETI firm will see a decrease in youth employment and thus no aggregate effect. In the short run analysis covered in this thesis, it can be expected that any changes in youth employment are likely to happen in existing firms and given the high churn and high numbers of eligible workers is unlikely to see ETI-firms poaching workers from non-ETI firms.

Within each firm, a wage subsidy reduces the cost of employment and causes an increase in the demand for labour. This means that a shift to the right of the aggregate demand for labour in the economy from L_{D1} to L_{D2} illustrated in Figure 2.4.

Where the Labour Supply curve L_S is upward sloping the effect of the subsidy will be shared between the workers and the firms depending on the elasticity of labour demand and labour supply. This raises the wages of workers from W_0 to W_1 and decreases the cost of employment to firms from W_0 to $W_1 - C$. The amount of labour demanded moves from QL_0 to QL_1. I consider the case where labour supply is highly elastic as the unemployment rate in South Africa is high. In the second scenario, there is a small increase in wages to workers and a large reduction in the cost of employment to firms. The amount of labour demanded moves from QL_0 to QL_2 a larger increase than in the first scenario.

Figure 2.4 Shift in the labour demand curve



Notes: The graph on the left shows a shift to the right of the aggregate demand for labour in the economy from L_{D1} to L_{D2} where the Labour Supply curve (LS) is upward sloping leading to a rise in wages from W_0 to W_1 and decline in cost of employment to firms from W_0 to W_1–C. The graph on the right shows the case where labour supply is highly elastic. With the labour supply is highly elastic, there is a small increase in wages to workers from W'_0 to W'_1, decreases in the cost of employment to firms from W'_0 to W'_1 – C and a large increase in labour demanded from QL_0 to QL_2.
Source: Author's own illustration

From a theoretical standpoint, a wage subsidy targeted at youth can create jobs for them, in part alleviating the large youth unemployment problem as well as producing a positive impact on low wage youth. On the other hand, the theoretical framework does not indicate a clear positive or negative effect on non-youth. The prevailing view on wage subsidies in the 1990's proposed that the relative elasticity of labour demand in relation to labour supply meant that employees were mainly the beneficiaries of the subsidies and not employers (Gruber, 1997). This means that while earnings rise, the gross wage cost to employers is only slightly, or not, affected. This provided evidence to the view that subsidies were not affecting employment.

2.5 Conclusion

The South African ETI is a targeted, non-permanent subsidy that requires some administrative effort to claim. It is a mix between a wage subsidy and a hiring subsidy. In 2014, the first year of the subsidy, it likely functioned more as a hiring subsidy as the eligibility criteria meant that only new employees hired after 1 October 2013, were eligible for the subsidy claim.

Several ALMPs have been implemented in South Africa including skills development or training programmes, a public employment programme and job-search and job-matching initiatives. These policies have not, however, translated into decreases in the unemployment rate.

The skills shortage highlighted by the scarce skills database points to excess labour demand for skilled workers that is not being met by labour supply. It is agreed that increasing skill levels will assist in decreasing the unemployment rate and could lead to greater economic growth. It is not

believed that increasing skill levels alone will address the unemployment problem. Increasing skill level also takes time and is difficult to do given the systemic issues in South Africa's education system. The combination of the lack of policy success in creating employment and the nature of the South African labour market set the stage for a policy that can increase the demand for unskilled labour, a necessary tool to bring down the high levels of youth unemployment.

While discussions of the ETI started in the early democratic years, the policy was formally proposed in 2011 and came into effect in 2014. Several criticisms were levelled against the policy in the proposal phase some of which were considered in the design of the policy, such as the penalty for displacing unsubsidised workers. The mechanics of the policy are not straight forward as is the case in many other countries, thus presenting some challenges in terms of evaluating the policy and placing it in the literature.

The theoretical literature tells us that a decrease in the cost of hiring a young worker increased the likelihood of employment of young workers. The decrease in costs of employment of one group means an increase in the relative cost of employing another group and therefore a decrease in employment for the non-targeted group. The theoretical literature also suggests that the elasticity of labour demand and labour supply will determine the effectiveness of a subsidy in creating employment.

The empirical literature presents several examples of subsidy programmes applied in other countries, although dominated by the developed countries due to the high costs associated with implementing a subsidy programme. There are very few instances of a wage subsidy being implemented in developing countries and even fewer in Africa. Wage subsidy programmes are mostly targeted at the unemployed with low labour market prospects. This often includes youth, the long-term unemployed and in some cases, older workers.

The literature measuring the firm-level employment effects of a wage subsidy show that the observed effects are positive (Crichton & Maré, 2013; Kaiser & Kuhn, 2016; Rotger & Arendt, 2010). In many cases, the observed effects are modest, ranging from 0.17 to 1.09 additional jobs at the firm. Kangasharju (2007) and Betcherman, Daysal and Pagés (2010), on the other hand, see a 5 and 12 percent increase in employment in their respective studies. Many of these studies suggest that the long-term effects of the policies are either modest or short-lived. Only a few estimate deadweight loss and substitution effects, as these are often harder to measure.

When turning to individual-level studies, the literature is mixed. Older studies find that subsidy programmes lead to wage changes while the recent literature shows impacts on employment and limited effects on wages. The literature points to contradictory policy design features that could

lead to the successful creation of jobs making it difficult to conclude whether the ETI will be effective or not.

Lastly, the literature suggests there could be high costs associated with a subsidy programme depending on the design. Abel et al. (2014) and Bertrand and Crépon (2014) suggest, more generally, that ALMPs need to be well designed and locally contextualised as the costs involved are high and the results varying or unknown. Betcherman, Daysal and Pagés (2010) warn that the cost of subsidized employment is especially high in cases where there is large deadweight loss. In the context of subsidy programmes, Brown (2015) suggests hiring subsidies can be more cost effective than wage subsidies.

The aim of the ETI is to increase the number of jobs for unskilled youth in the national economy. The literature review shows that the design features are very important to potential success and to appropriate methods of evaluating this success.

The low economic growth in South Africa suggests that firms will welcome that tax windfall however, this does not imply that the ETI will create jobs. With no previous subsidy policy of its kind in the country, firms may be slow or reluctant to take up the policy until they can understand the implications thereof. The theory suggests we should expect an increase in youth employment, but the empirical evidence leaves us questioning whether this will be possible in South Africa.

The next chapter begins with an examination of the policy by describing the administrative tax data used in our analysis and the beneficiaries of the subsidy.

Chapter 3. Wage subsidy beneficiaries

3.1 Introduction

Governments around the world record information in their administration of education, health, safety, social security, and tax programmes. The data are systematically collected and stored by the relevant authority and used to make decisions or report on the relevant programme. Administrative data can include sales transactions, medical records, car registrations and education records. Tax records are one kind of administrative data, more simply referred to as tax data.

Administrative data are seen as the "big data" in social science research. The buzz generated around big data stems from the rich set of opportunities that big data offers which cannot be matched by other sources. In economics, 'big data' has more frequently been used to describe tax data and is considered to be an authoritative source of information. The use of tax data for empirical research is gaining popularity internationally (Card et al., 2010). Research using tax records to evaluate public policy has become widespread in Europe and the USA. There is a substantial literature making use of tax data as well as literature on the advantages and disadvantages, access procedures and confidentiality of tax records.

Tax data are attractive as they can offer additional analysis into important issues beyond survey data. Firstly, tax data typically offers much larger sample sizes than survey data. In the case of formally employed individuals or registered firms, tax data can present a full census of the population. Larger sample sizes lend well to broader and more persuasive research designs.

Secondly, tax authorities regularly collect information from taxpayers allowing for the tracking of taxpayers over time. This enables policy evaluation as the data provides information before, during and after policy implementation enabling long-term follow up.

Thirdly, tax data can provide more dependable information. Survey data is vulnerable to high rates of non-response, attrition or under sampling. Tax records are often audited providing an added level of reliability. Technological advances also mean tax forms are sometimes prepopulated with information from employers or information previously provided to the revenue collector.

Fourth, the use of tax data can be less costly than designing surveys and collecting new data. Income information can be particularly difficult to collect via a survey due to respondents' desire not to disclose their personal information.

There are, however, disadvantages related to using all administrative data. Researchers do not collect the data and have no control over the method of collection and what information is collected, affecting the scope and depth of analysis that can be conducted. There is also a lack of theory and methods to guide the use of administrative data, for example, when considering that administrative data are the full population and not a sample (Wallgren & Wallgren, 2014).

Additionally, much of the information that is collected in surveys is not required by administrative forms and thus these data may be incomplete or incorrect. For example, not all fields are required to be completed on a tax form; some fields are optional, and many relevant fields are not on the form at all. Lastly, administrative data often does not have any metadata or accompanying information available and requires researchers to make their own assumptions about the data where the details cannot be verified.

The confidential nature of tax data means it is typically not publicly available. Several research projects using tax data indicate the examination of de-identified or anonymized data in a secure facility (Crichton & Maré, 2013). Secure facilities additionally require researchers and proposals to be passed through an approval process to maintain strict standards of confidentiality while still providing data access.

The South African Revenue Service (SARS) made anonymized tax data available, under secure conditions at the National Treasury offices in Pretoria, South Africa. Through a joint SARS, NT, and UNU-WIDER initiative, the data have been made available for use to researchers in the National Treasury Secure Data Facility. These data include, but are not limited to, Company Income Tax (CIT), Employee Tax Certificate (or IRP5), Value Added Tax and Customs data. These data can never be removed from the facility; only research results can be taken out.

This chapter describes in detail the South African administrative tax records that will be used to evaluate the ETI. The tax data is not publicly available, and access to the secure facility is limited to approved researchers. This means that there is little description of the data available and even less information available about the ETI which this chapter describes.

What follows is a description of the data, the inconsistencies and challenges encountered in the data and the way in which the data is cleaned and prepared for analysis. Using the tax data, the ETI is documented by presenting the characteristics of firms and individuals linked to the policy. This chapter puts forth a set of facts about ETI firms and ETI participants that provides the groundwork for our explanation of the effects of the ETI.

3.2 South African tax data

This thesis makes use of the payroll data (henceforth IRP5 data) for the period 2011 through 2018. The Company Income Tax data (henceforth CIT data) is available for the period 2008 through 2016. The data is only used from 2011 onwards due to data quality concerns in the earlier years. There is a lag in access to the full complement of the CIT data as companies have 12 months from their financial year-end in which to complete their tax returns. Additionally, if there are any

disputes with SARS about the taxes owed or paid, firms or individuals may not be reported in the version of data used within this research but may become available at a later stage.

The tax data administration act (2011) allows for the use of the tax data for research purposes at the NT. The anonymized data were accessed under a non-disclosure agreement that allows for research to be conducted where no individual or firm can be identified. Most of the data work contained in this thesis was conducted at the secure data facility at the NT. The results are not considered official statistics and have been created for this research.

The tax data initiative started around 2015 where the first extractions of data from SARS were conducted and analysed (Arndt, 2018). There have been various extractions and versions of the data with little or no documentation about these differences. The most recent extraction of the data is assumed to be the most accurate as resolution of disputes, resubmission of tax forms or errors made may have been corrected. It is therefore likely that research conducted at a different time to this analysis will reflect slightly different numbers.[9]

3.2.1 Data advantages with respect to the ETI

The use of administrative tax records is advantageous for the evaluation of the ETI as the subsidy claims are processed through the tax system. The ETI is claimed through a reduction in firm taxes owed to SARS. There are records of these claims for every firm that claimed the subsidy as well as the amount claimed. The subsidy is available to all firms registered for pay-as-you-earn (PAYE) taxes and the administrative data represents the entire population of PAYE-firms irrespective of their claim on the subsidy. PAYE is the withholding tax on compensation to employees which firms are liable to pay to SARS on behalf of employees. The data allows us to observe tax paying individuals and firms before the subsidy start and during implementation. In the context of the ETI, surveys would have been costly to administer and would be subject to response biases as firms may not be willing to discuss their tax claims or employee wage information. However, there are some challenges with the administrative tax data related to the ETI which is discussed in a subsequent section.

3.2.2 Description of IRP5 data

The IRP5 data is a collection of job-level administrative tax records. Firms are required to register with SARS within 21 days of becoming employers and furnish all employees with an IRP5 certificate each year where compensation was paid or is payable. The data also includes IT3(a) certificates which are issued where an employee received more than R2,000 per month but no tax

[9] Where possible we include in reference list details of the data used herein.

has been deducted. Henceforth, the data is referred to as IRP5 data acknowledging that it includes IT3(a) certificates as well.

Employees must submit their IRP5 certificates to SARS within 60 days of the end of the tax year. Public entities also issue IRP5 certificates to their employees; consequently, the data includes employees in both the formal private sector and the public sector. If an individual has multiple jobs in a year (within the same firm or in different firms), that individual will be seen multiple times in the data. Small firms such as sole proprietors with only one employee need not register for PAYE. The data excludes those who are self-employed but does include individuals collecting a pension income from a company. The individual identifier in the IRP5 data is an anonymized South African national identity (ID) number. Where no South African ID number exists but an anonymized passport number was present, it is assumed that the individual is a non-resident of South Africa.

The data includes some basic individual-level information—date of birth, gender, start and end of employment dates. The lack of further demographic information is often typical of administrative data. Details on the tax certificate also include total wages paid by the employer, total amount of tax paid by the employer, unemployment insurance fund contribution as well as ETI amounts claimed. The PAYE reference number (or payroll reference) serves as the firm identifier in the IRP5 data. Larger firms may have several payrolls and therefore several PAYE reference numbers but only one Company Income Tax (CIT) reference number.

The data is organised in two ways: one, by creating a panel of IRP5 data and two, by aggregating the IRP5 data by the CIT reference number to create a panel of firms. No CIT reference number exists for public entities thus our firm panel is restricted to data on formal private sector firms.

3.2.3 Description of the CIT-IRP5 panel

The CIT-IRP5 panel was created during the UNU-WIDER regional growth and development in Southern Africa programme[10]. The dataset is an unbalanced panel created by merging four tax administrative datasets: company income tax (CIT) data, employee income tax certificates IRP5, value-added tax (VAT) data, and customs records from trading firms. Variables in the panel are created from the fields of tax forms submitted to SARS. The CIT data includes firm-level information such as revenue amounts, tax paid, location and sector of the firm and is derived from the *Income Tax Returns for Company* forms. This is also known as the IT14 form which was replaced with ITR14 forms in the 2013 tax year. Variables relating to employees come from aggregated IRP5 data. This includes information about remuneration, tax paid, deductions and contributions

[10] For more information: https://www.wider.unu.edu/project/regional-growth-and-development-southern-africa

of the firm. The VAT data includes information about the VAT paid by the firm and the customs data contains records on the products imported and exported, value and volume of goods, and origin and destination information.

The CIT-IRP5 panel matches employer–employee variables from the IRP5 and CIT datasets. The panel includes tax information from 2008 to 2017 and makes use of the CIT reference number as the unique identifier for the firm. Pieterse, Kreuser and Gavin (2016) provide a more detailed description of the CIT-IRP5 panel. The authors discuss how the panel was constructed, any biases it might contain, and compare the panel with other data sources. The CIT-IRP5 panel also contains no public firms.

The overwhelming majority of firms in the CIT panel (96%) have only 1 payroll (also known as PAYE Reference). The largest firm, in terms of number of payrolls, has 396 payrolls (or PAYE References) making up the CIT firm. To complement our analysis, firm-level variables are used from the CIT-IRP5 panel with the IRP5 panel created. Firm-level variables from the CIT-IRP5 panel include firm sales, age of firm, firm assets, firm debt, and firm trade status.

3.3 Data structure and challenges

The IRP5 data is unaudited, presenting some challenges when conducting any analysis. Only a handful of researchers have accessed the administrative tax data and even fewer researchers have used the IRP5 data. The contribution of this section is the examination and discussion of the challenges in the IRP5 data. The data cleaning process described below creates two datasets; an IRP5 firm-level dataset to examine youth employment at the firm lever, and a job-level dataset to assess the impact of the ETI on individuals and jobs.

The IRP5 records, unlike the company income tax records, are organised within the South African tax year which begins on the 1st of March the previous year and ends on the 28/29th February of the tax year. Administrative data gives us information over time through the panel, but the data is drawn at a specific point in time. This means that late submissions and revisions after this cut off point will not be in the data. Any correction made to an IRP5 certificate and later resubmitted will not be available in this data.

The use of the tax year in the data also affects the examination of the ETI. The ETI was implemented from 1 January 2014, however, the 2014 tax year ends on 28 February 2014. This means that while there are claims for the ETI in the 2014 tax year, the claims only represent two months of the policy period. From the 2015 tax year, the ETI is captured for the full 12 months of the tax year.

This section starts off with a description of the cleaning of the IRP5 data. Once cleaned, the data is aggregated to the firm level which the later subsections discuss.

3.3.1 Nature of person

The first step in the cleaning the IRP5 data is recognising that the data includes certificates for clubs, partnerships, retirement funds, associations and other types of entities that are required to submit IRP5 tax forms. All non-individuals are removed from the data. Identifying and keeping individuals is a method used to overcome the issue of retirement income listed as individual income identified in the IRP5 data by Kerr (2016). Where the nature of person was missing, it is inferred from other years whether the observation was the tax form submission of an individual. For example, where the nature of person identified an observation as individual (coded "A" in the data) in 2012 and 2015 but was missing for the same person (identified by the ID number) in 2013 and 2014, the observations in 2013 and 2014 are classified as individuals. This reduces the number of observations that are dropped due to missing 'nature of person' information.

3.3.2 Hires and Separations

Due to the errors in the start and end dates of employment, the calculation of a new hire or a separation is not straightforward. One error is the large number of individuals who report the start of employment within one week of the beginning of the tax year.[11] This is dealt with in the following manner: where an employee was hired after 1 March in the tax year but was not previously seen in the data in the previous tax year, the employee is regarded as a true hire. Where employees were seen in a previous year, but they only report a start date one week after the beginning of the tax year, this is regarded as a continuation of the period employed from the previous year.

A similar occurrence is found for the end date of employment. Many individuals do not report employment in the last two weeks of the tax year which affect how separation are counted. To make sure our analysis is not affected by this error, employees are not counted as separated from a firm if the end date listed is after the 14th of February in a tax year. The end date is counted as a separate if the individual is not seen in the same job in the following tax year.

Lastly, if an employee has multiple jobs in the same firm in the same year, they are not counted as a new hire or repeated separations. This issue is discussed in a subsequent section.

[11] This is also described by Kerr (2016)

3.3.3 Age

An age variable is constructed from the reported date of birth on the IRP5 record. As the ID number is anonymized, the date of birth cannot be verified. There is a small percentage of observations with missing data on date of birth. The population of interest is those of working age. Approximately 0.18% of the data includes those below 15 years of age. This is regarded as a data entry error in the date of birth variable as it is illegal for children under the age of 15 to be employed. Approximately 7% of the individuals per tax year are over the age of 65. There is also a very small percentage of observations with ages over 99 years.

The ETI can only be claimed for employees over the age of 18 and under that age of 30. For this reason, the age at the start of the employment date is calculated to determine eligibility of the ETI. In the end, observations with ages below or beyond the working age range from 15 to 65 years old are dropped to maintain a dataset of those of working age.

3.3.4 Income

There are several income variables in the IRP5 data. The three prominent income variables: gross non-retirement fund income, gross retirement fund income and gross taxable income. In the 2017 tax year, the gross non-retirement fund income becomes gross remuneration amount. These variables are summed to give us the income variable for each observation in the data. For those with a reported annual income of more than 100 million rand the observations are dropped due to possible data entry error only affecting a handful of observations.

ETI eligibility is based on several factors including monthly income, that is, the subsidy is available to those who earn a monthly income of less than R6,000. The monthly income is therefore calculated by dividing the annual income by the number of days worked, and then multiplying it by $\frac{7}{5}$ and 21.75 as the average number of working days in calendar month[12]. This is described in equation (3.1) below:

$$Monthly\ income_{i,f,t} = \left(\frac{total\ income_{i,f,t}}{period\ employed_{i,f,t}}\right) \times \frac{7}{5} \times\ 21.75 \qquad (3.1)$$

where i relates to the individual, f represents the firm and t represents the tax year. For example, if the income is R10,000 and the period employed is 365 days then the monthly income is R834. In cases where the period of employment cannot be determined, the monthly income cannot be calculated.

[12] The average number of days in a month is 30.44 which is calculated by multiplying $\frac{7}{5}$ by 21.75.

Where individuals work overtime, or less hours than required in the month, the monthly income variable will be higher, or lower, respectively, than the true monthly income. The IRP5 data does not include any information on the number of hours worked thus the direction of the bias cannot be verified in monthly income.

3.3.5 Repeatedly identified in the same year

One of the biggest challenges in the IRP5 data is the repeated observation of the same individuals in the tax year. The IRP5 data allows for individuals to be seen multiple times in the same year. Individuals can be seen multiple times if they change jobs, move firms, resubmit an IRP5 certificate or perhaps held multiple jobs. This is both advantageous and challenging. An individual is identified in the data using the unique anonymized SA ID number while an individual within a firm is identified by a combination of the SA ID number and the PAYE reference number. This combined is also referred to as the 'Job ID'. There are many instances where the Job ID is repeated sometimes up to 14 times. Table 3-1 highlights 7 cases where individuals are repeatedly seen and describe them below. Table. 3.A.1 in the appendix mirrors this cleaning process with the number of observation and individuals dropped.

Case 1: The Job ID is repeated, and the start or end date of employment is missing. The job duration, monthly income, ETI amount and worker's weights cannot be verified without start and end dates of employment thus these observations are dropped. Approximately 0.6% of observation are dropped. These observations are labelled IRP5 1 in Table 3-1.

Case 2: No Job ID exists as the South African ID number is missing. There are approximately 600,000 observations per year (3 to 4 per cent of all observations) without a South African ID number. This does not represent the number of *individuals* without an ID number, there is a chance that many of these will be repeated observations which is unverifiable. It is assumed that those without a South African ID number are foreigners. Those with a missing ID are removed from the dataset as foreigners are not eligible for the ETI. These observations can be seen in "Case 2" in Table 3-1.

Case 3: In this case 3, individual identified as IRP5 3 claims they work at PAYE 3 for 1 day in April and again 1 day in May. A job is defined as a paid position of regular employment. As this does not represent regular employment, it is not considered a job and thus drop these observations. Approximately 5% of observations report only 1 day of employment.

Case 4: Repeated Job ID with the same start and end dates but different income amounts.

Scenario 1: IRP5 4 works in firm PAYE 4 for the full year (365 days). The entries are repeated four times where the start and end dates are the same and the income is the same for each entry except the last one.

Scenario 2: IRP5 6 works in firm PAYE 6 for 184 days. The entries are repeated twice. The start and end dates are the same, but the income is different.

Revisions of the IRP5 certificates may also result in Job ID repeats in the same tax year. Repeated records are dropped. It is assumed that the repetition is due to a revision of the IRP5 certificate. The entry with the highest income in kept. Again, this affects a very small sample of the dataset.

Case 5: Separate periods of employment can be identified when an individual works for different periods in the same tax year in the same firm. This could occur in sectors such as agriculture and manufacturing where there could be seasonal employment: Consider 2 scenarios:

Scenario 1: IRP5 7 claims they work at firm PAYE 7 from 1 March to 30 June (122 days) then works from 28 July to 1 September (36 days) then works 22 September to 3 October (12 days) and again works 30 October to 14 November (16 days). We consider this one job as a seasonal worker and do not count the separate start dates and end dates as a hire or a separation.

Scenario 2: IRP5 8 claims they work at firm PAYE 8 from 1 March to 31 December and again from 1 January to 28 February. In this scenario, the total work period ads up to 365 days, a full year. This can occur where a firm has a financial year end different from the tax year end such as December 31st as in this scenario. We count this as one job.

In Case 5 the period worked, the income, the ETI amount claimed, and the worker weight are summed to reflect only 1 job in the data. Only the summed-up observation is kept.

Case 6: Overlapping periods of employment: an individual works multiple jobs in the same firm in the same tax year. Consider the scenario:

The individual identified as IRP5 9 works at firm PAYE 9 from 1 March to 20 February (357 days) but also works at the same firm from 1 March to 27 June (119 days) in the same tax year. We consider this a case of multiple part time jobs in the same firms. However, we limit this to scenarios where an individual has at most 3 part-time jobs in the same firm.

In Case 6 the repeated entries are kept as they are considered as 3 separate part time jobs.

Case 7: Multiple overlapping periods with multiple income values. This is similar to Case 6 but here there are three or more repeated entries. This is considered as one job and an average of the job duration, income and ETI amount claimed is used. This is illustrated through individual IRP5 10 and firm PAYE 10 and individual IRP5 11 and firm PAYE 11 in Table 3-1. The number of

observations left with after cleaning represents the number of jobs in the data. As this method allows individuals to have multiple jobs within the tax year there are more jobs than there are unique individuals in the data.

Lastly, the cases listed above are not mutually exclusive. Observations with Missing ID numbers may also have missing information on their start or end dates of employment or only be employed for one day. Included in the appendix Table. 3.A.1 are the number of observations at the start and the number dropped at each stage of the cleaning process. After the cleaning processes is complete, an average of 16% of observations are removed per tax year but approximately 4% of individuals.

Table 3-1 Repeatedly identified individuals

Examples	ID Number	PAYE Ref No	Start Date	End Date	Job Duration	Income	ETI amount	Worker Weight	Comments
Case 1	IRP5 1	PAYE 1	-	07-Sep-14	-	117	1,000	-	Observations dropped
	IRP5 1	PAYE 1	22-Oct-14	-	-	1,002	5,000	-	
Case 2	-	PAYE 2	01-Mar-12	30-Jun-12	122	3,000	-	0.33	Observations dropped
	-	PAYE 2	01-Jul-12	30-Dec-12	183	4,000	-	0.50	
Case 3	IRP5 3	PAYE 3	07-Apr-14	07-Apr-14	1	10,000	12,000	0.00	Observations dropped
	IRP5 3	PAYE 3	22-May-14	22-May-14	1	6,000	6,000	0.00	
Case 4	IRP5 4	PAYE 4	01-Mar-14	28-Feb-15	365	246,408	10,000	1	Choose highest income and highest ETI amount. Keep job duration and worker weight.
	IRP5 4	PAYE 4	01-Mar-14	28-Feb-15	365	246,408	10,000	1	
	IRP5 4	PAYE 4	01-Mar-14	28-Feb-15	365	246,408	12,000	1	
	IRP5 4	PAYE 4	01-Mar-14	28-Feb-15	365	277,087	10,000	1	
	IRP5 4	PAYE 4	01-Mar-14	28-Feb-15	365	277,087	12,000	1	
	IRP5 6	PAYE 6	01-Mar-13	31-Aug-13	184	29500	-	0.5	
	IRP5 6	PAYE 6	01-Mar-13	31-Aug-13	184	6200	-	0.5	
	IRP5 6	PAYE 6	01-Mar-13	31-Aug-13	184	29500	-	0.5	
Case 5									
	IRP5 7	PAYE 7	01-Mar-14	30-Jun-14	122	66,825	4,000	0.33	Sums up period worked, income, ETI amount and worker weight. Repeats are dropped so that only one job observation remains
	IRP5 7	PAYE 7	28-Jul-14	01-Sep-14	36	14,447	1,000	0.1	
	IRP5 7	PAYE 7	22-Sep-14	03-Oct-14	12	4,895	300	0.03	
	IRP5 7	PAYE 7	30-Oct-14	14-Nov-14	16	8,942	400	0.04	
	IRP5 7	PAYE 7	01-Mar-14	30-Jun-14	186	95,109	5,700	0.5	
	IRP5 8	PAYE 8	01-Mar-10	31-Dec-10	306	108,980	-	0.84	Sometimes happens when firms' year-end is 31 Dec
	IRP5 8	PAYE 8	01-Jan-11	28-Feb-11	59	30,212	-	0.16	
	IRP5 8	PAYE 8	01-Mar-10	31-Dec-10	365	139,192	-	1	

Examples	ID Number	PAYE Ref No	Start Date	End Date	Job Duration	Income	ETI amount	Worker Weight	Comments
Case 6	IRP5 9	PAYE 9	01-Mar-14	20-Feb-15	357	24650	6,000	0.98	Count as two separate part time jobs
	IRP5 9	PAYE 9	01-Mar-14	27-Jun-14	119	12325	1,900	0.33	
	IRP5 10	PAYE 10	01-Mar-14	20-Feb-15	357	24650	1,000	0.98	Count as three separate part time jobs
	IRP5 10	PAYE 10	10-Mar-14	15-May-14	67	4520	500	0.18	
	IRP5 10	PAYE 10	01-Jul-14	30-Aug-14	61	4332	450	0.17	
Case 7	IRP5 11	PAYE 11	01-Mar-11	16-Dec-11	291	20457	-	0.80	There are more than 3 repeats, averages are taken for job duration, income, ETI amount and Worker weight
	IRP5 11	PAYE 11	01-Mar-11	01-Sep-11	185	58198	-	0.51	
	IRP5 11	PAYE 11	01-Mar-11	16-Aug-11	169	5160	-	0.46	
	IRP5 11	PAYE 11	11-Sep-11	15-Feb-12	158	9085	-	0.43	
	IRP5 11	PAYE 11	01-Mar-11	16-Dec-11	201	23225		0.55	*Average taken
	IRP5 12	PAYE 12	01-Mar-15	16-Dec-15	291	20457	9000	0.80	There are more than 3 repeats, averages are taken for job duration, income, ETI amount and Worker weight
	IRP5 12	PAYE 12	01-Aug-15	01-Sep-15	32	58198	1000	0.09	
	IRP5 12	PAYE 12	01-Apr-15	16-Aug-15	138	5160	1500	0.38	
	IRP5 12	PAYE 12	11-Sep-15	15-Feb-16	158	9085	2500	0.43	
	IRP5 12	PAYE 12	01-Mar-11	16-Dec-11	154.75	23225	3500	0.42	*Average taken

Note: The table highlights seven cases where individuals are repeatedly seen in the data and describes how these observations are dealt with.
Source: Author's own illustration of IRP5 data.

3.3.6 Job duration and worker weights

The IRP5 certificate contains information on the start of the period of employment and the end of the period of employment in each tax year. They correspond to the fields "Period Employed From" and "Period Employed To". Employers are instructed to fill in the date of the employee's start for the relevant tax year for the former field and fill in the last date which the employee's tax is being calculated for the latter field. This information can be used to determine the job duration of the individual and informs us on the hiring and separations of employees.

Job duration is calculated by taking the end date and subtracting it from the start date. The job duration is also used to create a weighted employment variable. The weighted employment variable accounts for the case where individuals are not employed for the full tax year. This becomes important later when firm labour is calculated. Weighted employment is calculated by job duration divided by the number of days in the tax year as described in equation (3.2).

$$weight_{i,f,t} = \frac{\left(end_{date\,i,f,t} - start_{date\,i,f,t}\right)}{number\ of\ days\ in\ the\ year_t} \tag{3.2}$$

where i relates to the individual, f represents the firm and t represents the tax year.

If the employee's start date is listed in the previous tax year, the start date is brought forward to the first day of the relevant tax year. Similarly, where an employee's end date is in the following tax year, the end date is brought back to the end of the relevant tax year. For example, if an employee's start date is listed as 1 January 2012 for the 2013 tax year, this date is brought forward to start their work period on 1 March 2012. If an employee's end date is 15 June 2013 for the 2013 tax year, this date taken back to 28 February 2013 to match the tax year. This gives a job duration for each tax year based on the period employed the relevant tax year.

There are, however, some errors in the start and end dates of employment. For example, there are cases where the employment start is after the employment end date and the correct dates cannot be verified. There are also cases where the start or end date of employment is missing. In both these cases, job duration is calculated using two alternative variables. The IRP5 form captures the number of pay periods in which the employer divides the tax year as well as the number of periods the employee works of the pay periods the employer lists. These are the variables "Total Periods in Year of Assessment" and "Total Periods Worked". This means that if an employee worked 22 weeks in the year, then we can still record their employment weight as described in equation (3.3).

$$weight_{i,f,t} = \frac{Total\ Periods\ Worked}{Total\ Periods\ in\ Year\ of\ Assessment} \tag{3.3}$$

Where both employment dates and periods worked are missing, observations are dropped.

3.3.7 ETI in the data

Each IRP5 certificate after 2013 contains two variables related to the ETI; an indicator whether the form includes an ETI claim and a variable with the amount of ETI claimed. There are many errors in the data related to the eligibility criteria of the ETI claims as well as the amount claimed.

The ETI is targeted at a specific group of youths: individuals between the ages of 18 and 29, starting work after 1 October 2013, earning less than R6,000 per month and working in the private sector. However, the data includes many claims for the ETI from people who do not meet these eligibility criteria. Five types of errors in claims in the data are identified:

1. Over age: those older than 30 years old at the start of their work period
2. Underage: those younger than 18 years at the start of their work period
3. Before the policy claims in the 2014 tax year from individuals hired before 1 October 2013.
4. Public sector: claims from those employed in the public sector.
5. Over-claimed: claims that are more than is possible. The maximum possible claim amount for an individual per month is R1,000. The ETI came into effect on 1 January 2014; thus, for the 2014 tax year the maximum claim per individual is R2,000. The ETI was in effect for the full tax years (2015-2018); thus, the maximum claim for each tax year is R12,000 per eligible employee.

Table 3-2 Types of incorrect claims, by tax year

	2014	2015	2016	2017	2018
Over-claimed	1.08	0.24	0.14	0.04	0.04
Over age	16.90	0.92	0.35	0.20	0.38
Underage	0.48	0.42	0.33	0.26	0.23
Before policy	34.49	-	-	-	-
Public sector	0.09	0.03	0.05	0.01	0.04
Total number of incorrect claims	120,794	14,694	9,732	6,490	8,934
Percentage of incorrect claims	53.0	1.6	0.9	0.5	0.7
Total number of claims	227,735	906,013	1,127,005	1,267,929	1,300,843

Note: The table describes the percentage and total number of incorrect claims seen in the tax data.
Source: Authors' estimates based on IRP5 data.

The figures in Table 3-2 present the percentages of incorrect ETI claims per tax year. However, they may be understated in two categories: over age and over-claimed. First, it cannot be established that claims ended when an employee turned 30, as the data is annual. Second, employees earning between R2,000 and R4,000 have a maximum claim of R1,000 per month. For employees earning R1,500 per month the maximum claim in the first 12 months is R750 per month. By setting the maximum claims to R2,000 for 2014 and R12,000 for subsequent years, the

cleaning process may be missing employees over-claiming in the R0–2,000 and R4,000–6,000 categories of monthly income.

Alarmingly, 53 per cent of the claims made in 2014 had some error. This is mainly due to the large number of claims made for individuals who started work before 1 October 2013. The number of incorrect claims drop to 1.8 per cent in 2015 and 1 per cent or lower in the subsequent years, indicating that firms better understood the eligibility criteria for the ETI in the later years. The incorrect claims cases are not mutually exclusive; for example, there are very few cases where multiple criteria are violated on the same claim. In the data, it can be identified where firms have made errors in their claims for the subsidy. Given that firms need to register for PAYE in order to claim the subsidy, the likelihood of fraudulent cases (such as a dummy firm hiring unemployed relatives to claim the subsidy) is low.

In cases where the ETI claims are incorrect due to their age, start date before 1 October 2013 or are in the public sector, their claim amount is set to zero. Where ETI claims are more than the maximum annual claim value, the claim amount is set to the maximum amount per tax year. This is what is assumed happens during the auditing process at SARS the claims that are not eligible are rejected or the claim values are recalculated in the reconciliation process between SARS and firms.

3.3.8 Data cleaning summary

Thus far, we have described at length the characteristics of the tax data and how we choose to clean the data. This short section can be viewed as an interim summary of this process. Table 3-3 reports the number of observations before and after the data cleaning process. There are between 16 million and 19 million observations each year and around 4% of these observations do not have ID numbers. There appears to be a lower number of observations in 2018 which is expected as there is some delay in reporting tax records to SARS. As advised early in this chapter, this is dependent on the version of data used. Later versions of the data may reflect slightly different (increased) numbers of observations.

What results from the cleaning process is an unbalanced job-level panel from 2011 to 2018 from the IRP5 data. The panel is limited to the working-age population (15 to 65-year-olds) and includes more than 12 million individuals.

Table 3-3 Data description by tax year

	2011	2012	2013	2014	2015	2016	2017	2018
Before cleaning								
All IPR5 certificates	16,304,393	17,085,352	17,229,167	17,791,554	19,773,138	18,316,154	19,537,156	17,366,496
No. of observations with missing ID numbers	775,865	716,343	734,608	726,011	767,398	745,049	877,804	702,572
Missing (%)	4.8%	4.2%	4.3%	4.1%	3.9%	4.1%	4.5%	4.0%
After cleaning								
No. of IRP5 jobs	12,681,797	12,822,654	12,962,240	12,966,110	13,266,810	13,221,745	13,377,984	12,640,044
No. of ETI eligible jobs	-	-	-	540,088	2,692,550	2,594,056	2,468,684	2,241,741
No. of ETI jobs	-	-	-	137,596	810,834	1,002,556	1,101,897	1,110,552
ETI claims as percentage of all jobs	-	-	-	1.1%	6.1%	7.6%	8.2%	8.8%
ETI claims as percentage of ETI eligible jobs	-	-	-	25.5%	30.1%	38.6%	44.6%	49.5%

Note: The table describes the IRP5 data by tax year before and after cleaning including the ETI characteristics.
Source: Authors' estimates based on IRP5 data.

3.3.9 Defining the firm

Using the job-level panel, a firm-level panel is created. There are two ways in which to aggregate the data at the firm-level; using the PAYE reference number or the CIT reference number. Original to the IRP5 data is the PAYE reference number of the business entity completing the tax certificate. The PAYE reference number is pre-populated on the form. Company income tax information is reported at the level of the CIT tax reference number. The overwhelming majority of firms have only one PAYE reference number related to a single CIT reference number. The CIT reference number is not native to the IRP5 data and SARS provides a concordance file that allows us to link the CIT reference numbers to PAYE reference numbers.

The IRP5 data is aggregated at the CIT-level and thus the firm is defined as the CIT reporting entity. This allows the merging of firm level variables from the CIT-IRP5 panel into the aggregated IRP5 panel. The downside of aggregating the IRP5 data at the CIT-level is that some IRP5 observations are not linked to the CIT reference number. This happens because some firms, for example in the public sector, are not required to submit company income taxes and therefore cannot be matched. For an evaluation of the ETI this is not a concern as firms in the public sector are not allowed to claim for the ETI. Henceforth, these aggregated observations are referred to as IRP5 firms.

In Table 3-4, the total number of firms are shown for each tax year. This is the number of firms found in the IRP5 data. There is a year-on-year increase in the number of firms reported. The second row in Table 3-4 shows the number of firms with matched CIT information merged from the CIT-IRP5 V3.3 panel. Approximately 70% of IRP5 firms have corresponding CIT data. It is not clear why the remaining 30% of IRP5 firms do not have corresponding CIT information. At the time of writing this was being queried at SARS.

As described in the paper by Pieterse, Kreuser and Gavin (2016), several firms in the CIT-IRP5 panel do not have any corresponding values for some important variables such as sales and cost of sales. This does not seem to have a big impact on our data as shown in row 3 of Table 3-4. In the years 2011, 2012 and 2013 there are fewer firms with corresponding CIT information. The reason for this may be the change over from the IT14 form to the ITR14 form in this period. As the CIT-IRP5 panel covers the years 2008 – 2017 there are no firms reported for the 2018 tax year. All 2018 IRP5 firms are therefore dropped.

Table 3-4 Total number of firms by tax year

	2011	2012	2013	2014	2015	2016	2017
Number of CIT Firms	231,297	235,309	237,115	240,391	245,331	248,426	251,392
Matched number of firms	164,339	167,619	167,098	166,462	168,526	167,063	156,147
Matched with CIT info	159,366	163,711	164,499	166,462	168,526	167,063	156,147

Note: The table describes the number of CIT firms matched with the firm-level IRP5 data.
Source: Author's own estimates based on firm-level IRP5 and CIT-IRP5 version 3.3 panel data

CIT and IRP5 data do not perfectly align, and this is perhaps a subtle, but important, point about the data. Not all the firms in the IRP5 data have corresponding company tax information. And vice versa, all the firms in the CIT data do not have corresponding employee information. From the population of firms in the IRP5 data, approximately 69% have matched company tax information that is non-missing. Part of the matching problem is related to delays in firms filing their company income tax with SARS and the remainder is an unresolved anomaly in the data which SARS have been unable to provide any reasons for this occurrence. Pieterse, Kreuser and Gavin (2016:21) provide detail on the CIT firms with missing information. These firms are sometimes dormant companies, share block companies or body corporates. Implications for the analysis are discussed in section 3.4.1.

3.3.10 Tax year versus financial year

The IRP5 data are reported by tax year where the tax year for individuals in South Africa runs from 1 March to 28/29 February the following year. The tax year for firms is calculated from the firm's financial year end. Approximately 85 per cent of firms have their financial year end at the end of February (Pieterse, Kreuser & Gavin, 2016). Firms in the CIT-IRP5 panel with a financial year end different to the tax year end are dealt with in the following way: Firms that have a financial year end in calendar year 2013 are added to the 2013 tax year even though the tax year ends on 28 February 2013. Table 3-5 below illustrates this.

Table 3-5 Tax year versus company financial year end

Tax reference number	Tax year	Company Financial Year end
CIT 1	2013	1 January 2013
CIT 2	2013	30 September 2013
CIT 3	2013	31 December 2013
CIT 4	2014	28 February 2014
CIT 5	2014	31 August 2014

Note: The table depicts five examples of differences between tax year and company financial year.
Source: Authors' illustration based on the Pieterse, Kreuser and Gavin (2016) merging of the CIT-IRP5 version 3.3 panel data.

There are two further important points about timing in the CIT-IRP5 panel; companies are required to submit their tax returns to SARS within 12 months of the end of their financial year.

A firm with a financial year end of 31 December 2017 may only submit their tax return in December 2018 after which it takes some time before SARS releases the data. The second point is when the CIT-IRP5 panel was updated. This thesis uses the CIT-IRP5 panel version 3.3. The delay in submission to SARS, the lag in SARS reporting the data and the actual date of update of the panel means that the CIT-IRP5 is mostly complete for the 2016 tax year but does not contains all the firms for the 2017 tax year. This is perhaps why there is a slight drop off in the number of firms matched in 2017 in comparison to 2016.

This concludes all the pertinent information on the cleaning of job-level IRP5 data and the creation of the firm-level IRP5 data. Having created a new dataset that allows for the analysis of the ETI, our attention changes to the description of the firms claiming the ETI thereafter the individual participants of the ETI.

3.4 Who is claiming the ETI?

To assess whether the policy is indeed creating any jobs, a thorough investigation of the firms claiming the ETI will guide the evaluation of the policy. Furthermore, there are the questions about how much was spent on the ETI and who really benefitted from the subsidy funds.

This section describes the firms claiming the ETI; the take up rate, size, location, structure, industry, hiring and separations patterns. Interesting differences in the ETI-claiming firms versus those eligible but non ETI-claiming firms are highlighted. The main advantage of accessing the tax data is the ability to observe ETI claiming firms. The firm-level data allows us to examine the different types of firms employing youth. It gives us information on whether the ETI has changed the firm preference to youth over older workers and lastly, allows us to see which firms are benefitting financially from the policy. This section breaks down the firm characteristics that are related to the take up of the ETI.

3.4.1 The ETI claiming firm

More than thirty thousand firms are claiming the tax subsidy each year.[13] The statistics in Table 3-6 reflect the number of ETI claiming firms after the data has been cleaned and the incorrect claims have been accounted for. The 2014 tax year reflects only two months where firms could claim the subsidy. Claims in subsequent years reflect the full tax year. The total number of firms for each year ranges between 226,000 and 251,000 firms. The number of ETI claiming firms are divide by the total number of firms to get a take-up rate of approximately 12.7%[14]. This take-up

[13] In 2015, only 25,544 ETI firm have company income tax information available and matched into the data. This becomes important in Chapter 4 as we lose information on 6,261 ETI firms when we estimate the impact of the ETI at the firm level.

[14] This excludes the 2014 tax year where the take up rate appears low due to the duration of the subsidy validity in the 2014 tax year.

rate seems low when comparing to similar programmes in other countries. For example, take up was nearly 100 per cent for firms hiring eligible workers for a young workers tax cut in Sweden (Saez, Schoefer & Seim, 2019). In South Africa, the take up rate is viewed as high as the government anticipated that fewer firms would use the subsidy. Thus, an alternate take-up rate is considered; the number ETI claiming firms over the number of ETI-eligible firms where ETI-eligible firms are defined as firms that have at least one young, low wage (eligible) worker. The take up rate is on average 25%; still low in comparison to other countries but not as low as previously thought.

Table 3-6 Summary statistics for ETI firm claims by tax year

	2014	2015	2016	2017	2018
ETI duration (months)	2	12	12	12	12
No. of firms claiming ETI	12,157	31,786	30,108	30,660	30,785
No. of ETI eligible firms	50,776	130,321	126,010	120,627	104,486
No. of firms not claiming ETI	228,234	213,545	218,318	220,732	196,021
No. of firms claiming ETI with CIT information	10,093	25,544	23,801	2,282	-
Percentage of ETI-firms	5.1%	13.0%	12.1%	12.2%	13.6%
Total number of firms	240,391	245,331	248,426	251,392	226,806
Percentage of ETI eligible firms	23.9%	24.4%	23.9%	25.4%	29.5%

Note: ETI eligible firms refers to firms that hired at least 1 ETI eligible worker.
Source: Author's estimates based on IRP5 firm-level data.

The subsequent subsections compare firms claiming the subsidy to those not claiming, with consideration for firms who employ eligible workers but may not claim the subsidy.

3.4.2 Industries that claim the ETI

Employment of low or unskilled youth varies by industry. It would then follow that the ETI take up would vary across industries. The industries where take up of the ETI is possible is described, that is, industries with firms that employ young low-wage workers.

Wage subsidies are sometimes targeted to specific industries to reduce the cost of the policy or increase effectiveness. For example in Mexico, the wage subsidy program was targeted to the manufacturing industry as this is where the job losses were expected to be high in the wake of the 2008 economic crisis (Bruhn, 2016).

Burns, Edwards and Pauw (2010) recommends that the ETI be targeted to industries where employment is responsive to lower costs of labour. This is not the case in the design of the policy, the ETI is available to all private sector firms excluding only public-sector entities.

Industry codes are generated from the "main income source code" variable in the job-level IRP5 panel. These codes are converted to the ISIC4 codes for which there are 21 industry categories.[15]

The industry codes are aggregated to the firm level. In some cases, IRP5 records within the same firm report different industry codes. In such cases when aggregating at the firm level, the most repeated industry is taken as the firm industry. In cases where there is a 50-50 split between two industries, the industry is coded as missing. This is not a concern as it affects only 2% of firms. Lastly, firms are permitted to list different industries in consecutive years. This only affects approximately 1% of firms.

Within the data the sectoral affiliation of firms that hire low- or semi-skilled youth. The industries of firms with at least one eligible youth employed are examined. Eligible youth are defined by the policy as individuals employed at the firm between the ages of 18 and 29 and earning less than R6,000 per month. Firms do not necessarily claim the subsidy for all eligible youth. Some firms may not be claiming the ETI for any eligible youth. In the face of declining demand for young, low-wage workers, it may be challenging for the ETI to create any new employment or the ETI may just be what firms need to encourage them to employ young workers.

Table 3-7 documents the industries of firms with at least one young, low wage worker for the period 2011 to 2017. Firms with eligible workers are concentrated in manufacturing, wholesale and retail, financial services, professional, scientific, and technical, agriculture and construction. Firms in these sectors account for up to 75% of firms employing young, low wage workers. The table also shows us that there is a decline in the employment of young, low wage workers in the manufacturing sector over the period. Although excluded from the ETI, it is known that the public sector is not a large employer of young, low wage workers.

Another interesting feature about Table 3-7 is the overall decrease in the number of firms that employed young, low wage workers. In 2011, approximately 60%, or 138,350, of all firms, employ at least 1 young, low wage worker, while in 2017 this drops to 48% or 120,749 firms.

[15] See https://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=27 for a detailed list of the International Standard Industrial Classification of All Economic Activities, Rev.4

Table 3-7 Industry affiliation of firms employing at least one young, low wage worker (%)

	2011	2012	2013	2014	2015	2016	2017
Agriculture, forestry & fishing	7.5	7.9	8.3	8.4	8.7	8.9	9.3
Mining & quarrying	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Manufacturing	24.8	24.6	24.1	23.6	22.9	22.3	21.8
Electricity, gas, steam, & AC supply	0.5	0.5	0.5	0.5	0.5	0.5	0.4
Water supply & waste management	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Construction	7.3	7.1	7.0	7.0	6.9	6.9	6.9
Wholesale & retail	16.4	16.3	16.2	16.1	15.8	15.6	15.4
Transportation & storage	3.1	3.1	3.0	3.0	2.9	2.8	2.6
Accommodation & food services	4.7	4.8	5.0	5.1	5.2	5.5	5.7
Information & communication	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Financial & insurance services	11.2	11.2	11.2	11.0	10.7	10.5	10.2
Real estate activities	1.5	1.5	1.5	1.5	1.5	1.6	1.6
Professional, scientific, & technical	8.2	8.2	8.1	8.0	7.8	7.7	7.7
Administrative & support services	1.2	1.2	1.2	1.2	1.3	1.3	1.3
Public administration	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Education	2.5	2.6	2.7	2.8	2.9	3.0	3.2
Human health & social work	3.5	3.5	3.6	3.5	3.5	3.5	3.4
Arts, entertainment, & recreation	0.9	0.9	0.9	1.0	1.0	1.0	1.0
Other service activities	3.2	3.3	3.3	3.3	3.2	3.2	3.2
Missing	1.5	1.5	1.6	2.3	3.5	3.9	4.4
Number of firms with at least 1 eligible worker	138,350	137,738	135,681	132,835	130,440	126,139	120,749
Total number of firms	231,297	235,309	237,115	240,391	245,331	248,426	251,392
% of firms with at least 1 eligible worker	59.8%	58.5%	57.2%	55.3%	53.2%	50.8%	48.0%

Note: Industry codes are based on the International Standard Industrial Classification of All Economic Activities Revision 4 (ISIC4), available at: http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=27.
Source: Authors' estimates based on IRP5 data.

Table 3-8 summarizes the percentage of ETI firms, non-ETI firms and all firms in the respective industries. In the subsidy period, tax years 2014 to 2017, the industry mostly likely to claim the ETI was manufacturing. Almost a quarter, 22.3%, of firm ETI claims in 2017 were from firms in the manufacturing sector. Following manufacturing, the wholesale and retail sector accounts for around 17.4% of firm ETI claims. This is followed by the financial and insurance services and agricultural sectors with 10.5% and 10.5% of claims from these sectors, respectively. These four sectors account for more than 60% of all firm ETI claims. Claims for the subsidy are lowest in the information and communication industry. It seems surprising that the financial and insurance services sector is one of the main sectors claiming from the ETI as the sector is expected to be a higher-paying and higher-skill sector. However, Table 3.7 suggest that many firms in the financial and insurance sector employ young, low-wage worker even before the policy period. The jobs that are subsidised by firms in this sector are unknown as the tax data do not include the occupation of workers.

Using input-output tables from Statistics South Africa, Edwards (2001) show that there has been a declining demand for low skilled labour across sectors in the late 1990s. Banerjee et al. (2008) use survey data to show the increase in supply and decrease in demand for low skilled labour in the years after the apartheid period. Low-wage employment is most evident in the agriculture, wholesale and retail, construction, and manufacturing sectors (Valodia et al., 2006). The manufacturing and retailing sectors are the industries with the largest ETI take-up as they typically require low-waged labour. These findings are similar to Hamersma (2008), where the industries with a large low-skilled workforce are more likely to claim wage subsidies.

Pauw and Edwards (2006) suggest the effects of the wage subsidy will vary by sector. In Chapter 4 accounts for these important differences when analysing the firm-level effect of the policy.

Table 3-8 ETI firms versus all firms, by tax year and industry

	2014			2015			2016			2017		
	ETI	Non-ETI	All	ETI	Non-ETI	All	ETI	Non-ETI	All	ETI	Non-ETI	All
Agriculture, forestry & fishing	8.4	6.7	6.8	9.7	6.4	6.9	10.4	6.5	7.0	10.5	6.6	7.1
Mining & quarrying	1.3	0.9	0.9	1.2	0.9	0.9	1.1	0.9	0.9	1.1	0.9	0.9
Manufacturing	24.2	20.5	20.7	23.1	19.5	20.0	22.5	19.2	19.6	22.3	18.7	19.2
Electricity, gas, steam, & AC supply	0.4	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Water supply & waste management	0.5	0.8	0.8	0.6	0.8	0.8	0.6	0.8	0.8	0.5	0.9	0.8
Construction	5.2	6.3	6.3	5.5	6.2	6.1	5.9	6.0	6.0	5.7	6.0	5.9
Wholesale & retail	17.8	13.4	13.6	17.3	12.6	13.2	17.5	12.3	12.9	17.4	12.0	12.6
Transportation & storage	3.1	3.1	3.1	2.9	3.0	3.0	2.7	3.0	3.0	2.6	3.0	2.9
Accommodation & food services	7.6	3.4	3.6	6.9	3.1	3.6	7.3	3.2	3.7	7.5	3.2	3.7
Information & communication	0.3	0.3	0.3	0.2	0.3	0.3	0.2	0.4	0.3	0.1	0.4	0.3
Financial & insurance services	12.0	13.7	13.7	10.9	13.6	13.3	10.5	13.5	13.2	10.5	13.3	13.0
Real estate activities	0.6	2.7	2.6	1.0	2.8	2.5	1.0	2.8	2.6	1.0	2.8	2.6
Professional, scientific, & technical	8.6	10.0	9.9	8.8	9.9	9.7	8.6	9.9	9.7	8.4	10.0	9.8
Administrative & support services	1.6	1.0	1.0	1.5	1.0	1.0	1.6	1.0	1.1	1.6	1.0	1.1
Public administration	-	0.1	0.1	-	0.1	0.1	-	0.1	0.1	-	0.1	0.1
Education	2.6	2.3	2.3	2.8	2.2	2.3	2.7	2.3	2.3	2.9	2.3	2.4
Human health & social work	2.0	5.7	5.5	2.4	5.9	5.5	2.1	6.0	5.5	2.0	6.0	5.5
Arts, entertainment, & recreation	1.1	0.9	0.9	1.1	0.9	0.9	1.2	0.9	0.9	1.3	0.9	0.9
Other service activities	2.4	3.7	3.6	2.6	3.6	3.5	2.7	3.6	3.5	2.8	3.5	3.4
Missing	0.4	4.2	4.0	1.2	6.8	6.1	1.4	7.5	6.7	1.3	8.3	7.4
Total number of firms	12,157	228,234	240,391	31,786	213,545	245,331	30,108	218,318	248,426	30,660	220,732	251,392

Note: Industry codes are based on the International Standard Industrial Classification of All Economic Activities Revision 4 (ISIC4), available at: http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=27. Source: Authors' estimates based on IRP5 data.

3.4.3 Firm location

Firms benefit from access to labour, suppliers, and infrastructure in a location. The tax data provides only broad location of the firms in the data. The ETI is not restricted to any location in the country however, it is expected that the presence of location economies will affect where ETI claiming firms are seen. In the case of the Turkish wage subsidy programme, examined by Betcherman, Daysal and Pagés (2010), the subsidy was restricted to provinces below a certain income per capita threshold.

At the provincial level, most claims are from provinces with large economic centres such as Gauteng, the Western Cape and KwaZulu-Natal. This is shown in Table 3-9. Gauteng has almost double the number of ETI-firms than the next province, the Western Cape. This means heterogeneous impacts of the policy across different provinces can be expected. The take up rate by province is reported in Table. 3.D.1 in the Chapter appendix. Take up of the subsidy is highest in the Northern Cape province.

Table 3-9 ETI firms, by province

	2014		2015		2016		2017	
	ETI	All	ETI	All	ETI	All	ETI	All
Western Cape	19.4%	14.9%	18.9%	14.9%	19.3%	14.7%	18.1%	13.8%
Eastern Cape	4.9%	3.8%	5.1%	3.7%	5.4%	3.7%	5.3%	3.4%
Northern Cape	1.7%	1.1%	1.8%	1.1%	1.8%	1.1%	1.8%	1.0%
Free State	2.8%	2.4%	2.8%	2.3%	2.8%	2.2%	2.8%	2.1%
KwaZulu-Natal	11.4%	9.4%	12.6%	9.3%	12.7%	9.0%	11.9%	8.4%
North West	2.7%	2.1%	2.4%	2.1%	2.4%	2.1%	2.2%	2.0%
Gauteng	33.8%	30.2%	30.4%	29.9%	28.8%	29.2%	26.8%	26.6%
Mpumalanga	3.4%	2.8%	3.5%	2.7%	3.2%	2.7%	3.0%	2.6%
Limpopo	2.0%	1.8%	2.1%	1.8%	1.9%	1.8%	2.0%	1.7%
Missing	17.9%	31.7%	20.4%	32.2%	21.7%	33.6%	26.1%	38.6%
Number of ETI firms	12,157	240,391	31,786	245,331	30,108	248,426	30,660	251,392

Note: The table shows the percentage of ETI firms and all firms by province and tax year.
Source: Authors' own estimates using IRP5 data.

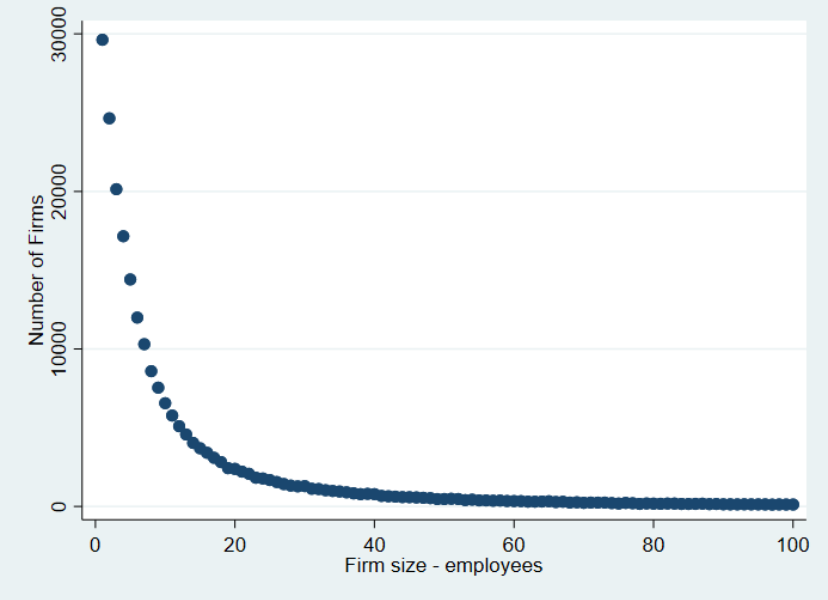
3.4.4 Firm size

Firm size is likely to be an important determinant of the change in the labour composition at the firm. The effect of hiring one additional young employee at a firm with 10 employees is very different from a firm with 500 employees. The subsidy may mean more to a small firm, allowing them to hire

additional youth, while larger firms, already hiring eligible workers, might be claiming the subsidy for youth they were already planning to hire, creating a deadweight loss.

There are many ways in which firm size can be defined. Firms can be classified in terms of number of employees, the revenue of a firm or the assets of a firm. The number of employees in a firm per year is used to measure the firm size. As observations with missing ID are dropped, what remains is a firm size variable that reflects only the number of employees with a South African ID. Figure 3.1 illustrates the firm size distribution for the 2015 tax year for firms with less than 100 employees. Approximately 95% of firms have fewer than 100 employees.

Figure 3.1 Firm size distribution, 2015



Note: Unweighted number of employees are used to calculate the firm size.
Source: Author's own illustration based on the 2015 IRP5 data.

De Mel, Mckenzie and Woodruff (2016) test whether hiring additional labour can benefit small firms in Sri Lanka. The authors run an experiment where they provide a temporary wage subsidy to small enterprises that covers half the wage of an unskilled worker for a six-month period. The authors argue that there are firms who would benefit from employing more workers but do not increase their workforce due to hiring constraints. Hiring and firing frictions may prevent a firm from employing additional workers and a wage subsidy lowers the cost of employment thereby temporarily increasing employment. The long-term effect happens if firms recruit employees that are good matches and will therefore retain once the subsidy ends.

Table 3-10 interrogates firm size, examining the take-up rate by firm size in terms of weighted number of employees per firm. As before, two definitions of the take-up rate are considered, first as the percentage of firms claiming the ETI divided by the total number of firms in the category, and second, the percentage of firms claiming the ETI divided by the number of firms eligible for the ETI (employing at least 1 eligible worker). Take up rates are low for firms with less than 10 employees even when only considering eligible firms. The take up rates are higher for firms with more than 10 employees when considering only eligible firms. For example, the take up rate is around 10% for small firms when measured against all firms but more than 30% when considering eligible firms. This means that more than 30% of small firms hiring at least one eligible youth are making use of the subsidy. Take up rates are high for very large firms, and only higher when considering take up by eligible firms.

The take up rates in Table 3-10 are similar to Hujer, Caliendo and Radic (2002), the take-up for firms with less than 50 employees is low and the take-up for large firms, more than 50 employees, is high. One explanation for the low take-up rate in small firms is that they may find it difficult to administer the subsidy or that the cost of administering the subsidy outweighs the benefits of claiming for very few employees. For large firms, the opposite is true, it might be easier to administer the ETI for all eligible employees as larger firms have an accountant, tax practitioner or finance department who are able to administer the ETI successfully. This could be one reason for the high take up rates at larger firms.

Given these findings, the later analysis controls for the firm size by examining the effects within firm size subgroups and more carefully try to consider the evaluation of larger firms where the take up rate is higher.

Table 3-10 Subsidy take-up rate by firm size

	2014		2015		2016		2017		2018	
	All	Eligible	All	Eligible	All	Eligible	All	Eligible	All	Eligible
Micro: 0 – 5	0.9%	14.4%	3.1%	11.6%	3.1%	12.7%	3.1%	13.8%	3%	15%
Small: 6 – 10	2.7%	15.6%	9.5%	15.3%	9.4%	16.0%	9.8%	17.6%	10%	20%
Medium: 11 – 50	7.4%	20.4%	21.5%	25.7%	20.2%	25.0%	20.6%	26.4%	23%	31%
Large: 51 - 100	20.7%	31.8%	45.9%	48.6%	40.5%	43.7%	40.0%	44.1%	49%	54%
Very Large: 100+	37.6%	46.2%	63.7%	65.7%	56.3%	58.8%	56.4%	59.6%	66%	70%
Overall take-up	5.1%	23.9%	13.0%	24.4%	12.1%	23.9%	12.2%	25.4%	14%	29%
Total no. of firms	240,391	50,777	245,331	130,322	248,426	126,013	251,392	120,625	226,806	104,484

Note: Number of jobs per firm are weighted by the period worked. The take up rate is calculated as the number of firms claiming the ETI over the total number of firms in the same size category.
Source: Authors' own estimates based on IRP5 data.

3.4.5 Employment, hiring and separation rates

Anchoring the ETI analysis in the general hiring process of the firm is crucial to assessing the impact. The ETI functions as a hiring subsidy therefore it is expected that firms with a higher employment growth rate are more likely to take up the ETI. The ETI has the potential to be claimed by all firms but only some firms claim the subsidy. Table 3-11 displays the mean firm employment growth for the years 2012 to 2017. The table reports the employment growth by firm size categories. The employment growth rate is calculated as the difference in the number of employees between two years divided by the number of employees in the previous year.

Table 3-11 Employment growth by firm size, 2012-2017

Firm size: Number of employees	2012	2013	2014	2015	2016	2017
Micro: 0 – 5	-0.034	-0.076	-0.056	-0.050	-0.053	-0.048
Small: 6 – 10	0.105	0.068	0.077	0.077	0.077	0.085
Medium: 11 – 50	0.122	0.092	0.093	0.091	0.088	0.091
Large: 51 – 100	0.134	0.136	0.108	0.114	0.109	0.108
Very Large: 100+	0.164	0.166	0.133	0.131	0.119	0.127

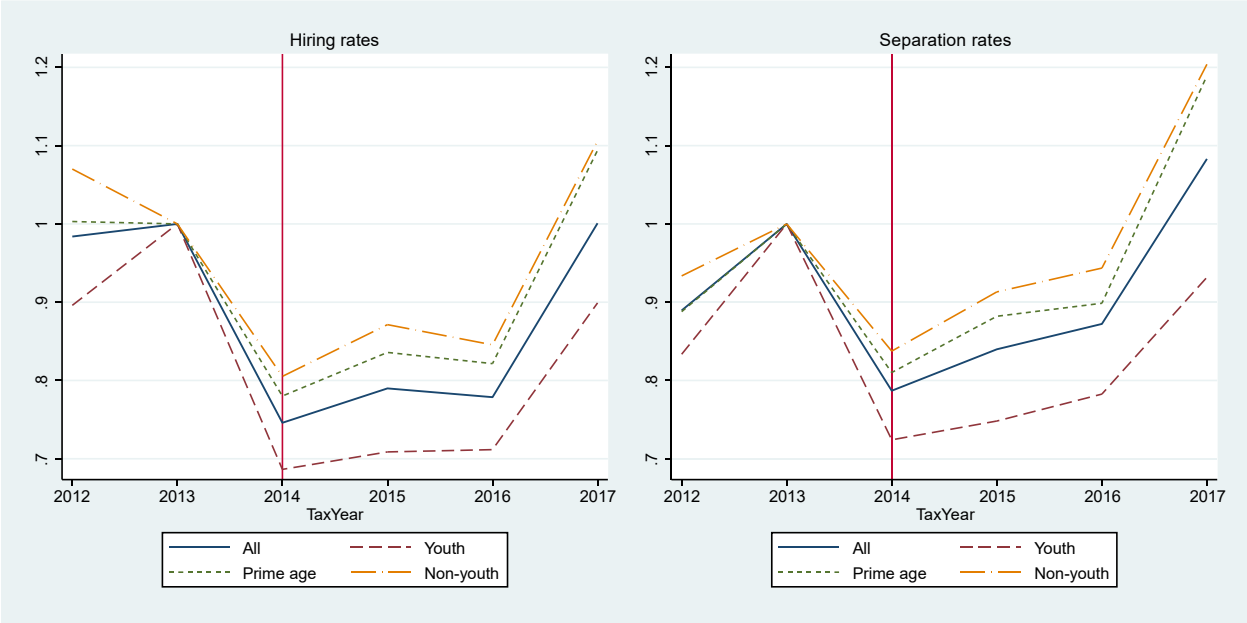
Note: Weighted number of employees is used
Source: Authors' own estimates based on IRP5 data.

Employment growth at micro, small, medium firms seem consistent across the years except for 2012 where the growth rate for all size groups appears higher. Large and very large firms do see a difference in their employment growth in 2013 and 2017 indicating a decline in employment growth at large and very large firms.

The ETI imposes some restrictions designed to hinder the substitution of young workers for older employees. The next step is to look at the hiring and separations of employees to establish whether hiring a subsidized worker is associated with the substitution of older workers.

Two categories of older workers are defined: non-youth are workers older than 30 years but younger than the retirement age of 65, prime age workers are between the ages of 30 and 40 years old. The rate of hiring (separation) is calculated as the number of new hires (separations) divided by the number of employees in the previous period.

Figure 3.2 Rates of hiring and separation of workers, by age group



Note: The graphs show the hiring and separation rate for all ages, youth (18-29 years), prime age (30-40 years) and non-youth (30-65 years). The rate of hiring (separation) is calculated as the number of new hires (separations) divided by the number of employees in the previous period.
Source: Authors' own estimates based on IRP5 data.

In the left panel of Figure 3.2, there is a decline in hiring rates between 2013 and 2014 across groups. The hiring rates increase across all groups in 2015 but the rate of increase appears less pronounced for youth. The hiring rate decreased in 2016 across group but increase 2017. The increase in the 2017 tax year corresponds with the 2016 calendar year when the subsidy was initially set to expire. It is possible that firms may have realised that this was the final year to make use of the wage subsidy and increased their hiring of young people before the policy was confirmed to be extended. The announcement was made late in the year so it is less likely that firms may have reacted to the extension announcement. The graphs do not suggest displacement of prime age or non-youth workers.

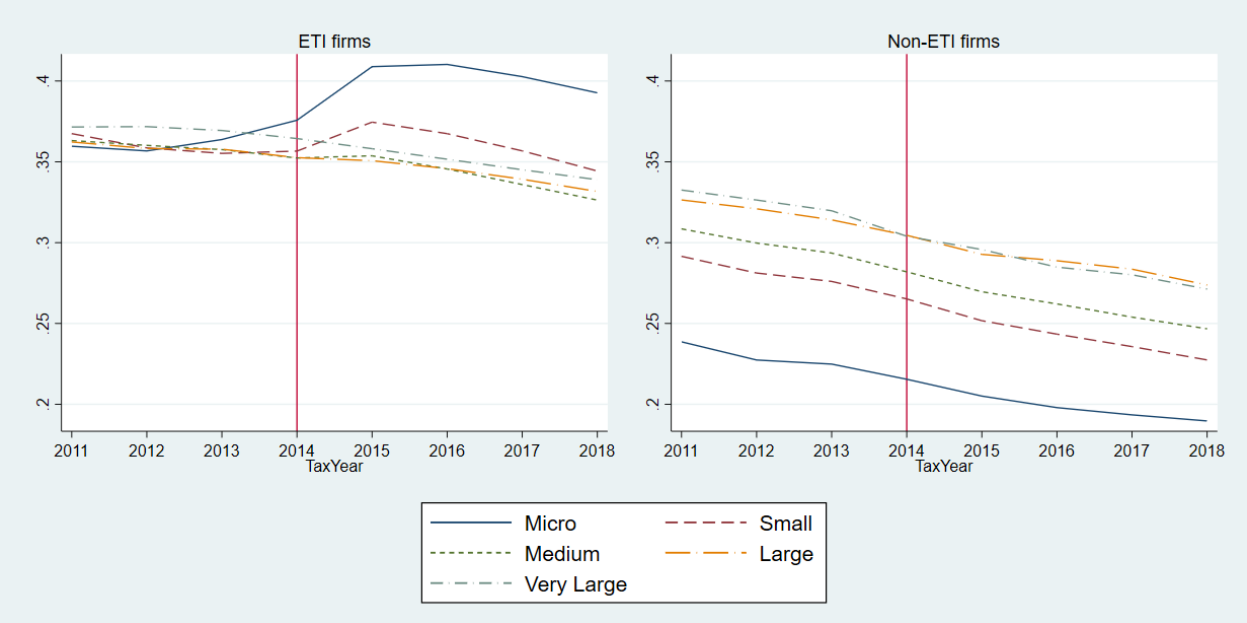
In the right panel of Figure 3.2, the separation rates for youth, prime age, non-youth, and all employees are presented. The separation rates decrease across all groups in the year preceding the start of the policy. The separation rates increase across all groups after the 2014 tax year but the rates of increase in separation differ between some groups.

Chapter 5 tests whether the differences in the employment of youth and non-youth is significant. Firms with a higher youth hiring rate can derive greater benefit from the ETI than firms that are not hiring youth or are downsizing. The hiring rate may thus be an important determinant for ETI take-up.

3.4.6 Youth concentration

The policy has the potential to shift the focus of employment towards youth and away from non-youth. Another way to look at this is to examine the youthfulness of firms. To do so, the youth concentration at the firm level is calculated by taking the ratio of youth to total employees at the firm. This is done within firm size groups as the take up rates vary between small and larger firms. This is separately considered for ETI firms and non-ETI firms in order to examine the differences between the two groups in the Figure 3.3 below.

Figure 3.3 Youth Concentration at ETI and non-ETI firms, by size



Note: The graphs show the youth concentration at firms of different sizes for ETI claiming (on left) and non-ETI claiming firms (on right).
Source: Authors' own estimates using IRP5 firm-level data.

The concentration of youth is higher at ETI firms. There is a steep decline in the concentration of youth from 2011 to 2018 in non-ETI firms. The pattern for small and medium ETI firms is somewhat different; small and medium ETI firms become more youthful with the advent of the policy. For medium and larger firms, the youth concentration faces a steep decline in the youth concentration over the same period.

3.4.7 How much has been claimed?

Since the take up of the policy has been higher than the government expected[16] and is borne by the government, it is important to examine what the cost of the policy has been and weigh this against the benefit. In this section, some detail on the cost of the policy is provided. The details on subsidy claim values for the policy period provides a framework for the later discussion.

For the period 1 January 2014 to 31 December 2014, the first calendar year of the policy, President Jacob Zuma declared in the 2015 State of the Nation address that "R2 billion has been claimed to date by some 29 000 employers, who have claimed for at least 270 000 young people." (Zuma, 2015). This would amount to a cost of R7,407 per job. It is important to keep in mind that while the subsidy may have been claimed for 270,000 young workers, these claims may have been for workers for whom firms already planned to employ and do not necessarily imply that these are new jobs that had been created in response to the policy.

Using the tax data, the total amount claimed per tax year is found in Table 3-12. The total ETI claimed for the first two months of the policy is R151 million. The claimed amount peaks in 2017 at R3.9 billion and is only slightly lower in 2018. This means a total of R14.7 billion was claimed for 50 months of the policy presented in the table. While the National Treasury budgeted R5 billion for the first 3 years of the policy, the claims for the period were closer to R8 billion.[17] This is attributed to the higher than expected take-up rate of the policy by firms.

[16] The National Treasury did not release information or calculations to support their estimates for the number of jobs created and take-up of the policy.

[17] This is not the same at the totals in the Table 3.13 since the government reported values were for calendar years not tax years.

Table 3-12 Total ETI amount claimed

	2014	2015	2016	2017	2018
Claimed total (in millions)	151	2,911	3,781	3,943	3,921
Top 20 total claimed (in millions)	44	823	973	965	852
% of ETI claimed by Top 20	29%	28%	26%	24%	22%
% of ETI claimed by Top firm	10%	8%	6%	7%	7%
Number of firms claiming >R10 million	1	22	32	38	42
Total number of firms	12,157	31,786	30,108	30,660	30,785

Notes: 2014 duration is 2 months, while all other years are 12 months.
Source: Authors' estimates based on IRP5 firm-level data.

Furthermore, the twenty highest claiming firms account for approximately a quarter of the total ETI claimed per year. This is an astonishing development as it means that only 20 firms are claiming a subsidy value of R852 million in the 2018 tax year alone. Perhaps more troubling, is the firm claiming the highest amount of the ETI, claims between 6% and 10% of the total ETI each year. The top 20 claiming firms are very large firms with more than 200 employees.

The take up rate by firm size described earlier suggests there may be heterogeneous effects of the subsidy by firms of different sizes. This is examined in the next chapter, but the value of claims by firm size groups may be important to think through the efficiency of the policy should the cost and effect vary. Table 3-13 breaks down the value of the claims by firm size and confirms, as one would expect from the previous table, that the very large firms claim a large portion of the ETI.

Table 3-13 Value of ETI claims by firm size (in millions)

	2014	2015	2016	2017	2018
Micro: 0 – 5	1.9	23.4	25.4	24.7	21.9
Small: 6 – 10	2.5	41.5	46.9	46.9	42.7
Medium: 11 – 50	12.9	269.5	331.4	344.0	334.1
Large: 51 – 100	10.4	211.2	277.0	294.4	309.1
Very Large: 100+	123.2	2,365.2	3,100.0	3,233.5	3,212.9
Total	151.0	2,910.7	3,780.6	3,943.5	3,920.6

Note: Number of jobs per firm are weighted by the period worked.
Source: Authors' estimates based on IRP5 firm-level data.

Examining the value of ETI claims is important because the ETI is being funded through tax revenue that could be used for other policies or interventions. It is also important to measure the total amount claimed in relation to the number of jobs created to give us the cost of additional jobs created in South

Africa. Lastly, where no jobs were created, the incentive claimed by firms amounts to a deadweight loss. Imperfect market conditions jeopardize the employment-generating potential of a wage subsidy scheme. Firms with some market power may be able to capture some of the subsidy as rent (Go et al., 2010). The higher the degree of non-competitiveness, the lower the incentive for firms to raise employment or reduce output prices (Burns, Edwards & Pauw, 2010).

In summary, ETI claiming firms are concentrated in a handful of industries and in provinces with large economic hubs. ETI claiming firms are large with an average of 135 employees. Take up rates vary substantially by firm size with the value of claims following a similar pattern. While firm size is not necessarily important to the overall employment impact of the subsidy, heterogeneous effects within firm size subgroups may be important in determining where job creation is possible and how the policy can be better implemented. Lastly, employment growth and hiring and separation rates suggest there are no large changes in the employment of youth during the policy. Before delving into the discussion on the firm-level effects of the subsidy in the following chapter, the last part of this chapter is dedicated to presenting some facts about the participants of the ETI.

3.5 Participants of the ETI

Little is known about the employees for whom firms are claiming the ETI mainly due to a paucity of data available. While a survey of young workers is possible, youth might not be aware of their firm claiming the ETI once they were employed, therefore a survey of youth employed after the policy inception will not provide us with the relevant information. The tax data indicates which employees the ETI was claimed for and provides some details on the participants of the ETI. The tax data falls short in terms of ETI participant demographic information such as educational attainment, occupation, or race; factors which affects labour market outcomes. In this section the IRP5 job level panel described in section 3.3 is used.

3.5.1 Eligibility, jobs, and participants

In this section, ETI-participants are individuals for whom their employer claimed a wage subsidy for employing them. ETI-jobs refers to the job at the firm for which there is a corresponding ETI claim. ETI participants can have multiple jobs some of which will be ETI-jobs. For example, an individual can change jobs during the year and both jobs can be ETI-jobs. This is counted as two ETI-jobs but only one ETI-participant.

While the subsidy was made available to all private sector firms, not all firms claimed the subsidy for eligible employees. There are many reasons why firms do not claim the subsidy: Firms may not have been aware of the subsidy, or the administrative costs outweighed the benefit, or firms may have been nervous that claiming the subsidy would attract a financial audit by SARS. This means that there are an excess number of eligible workers who are not ETI participants as described in Table 3-14.

Table 3-14 Numbers of eligible workers, ETI participants, eligible jobs and ETI jobs

	2014	2015	2016	2017	2018
Number of eligible workers	514,503	2,274,549	2,183,675	2,091,622	1,922,229
Number of ETI participants	136,726	749,784	910,004	994,892	1,006,954
Number of eligible jobs	540,088	2,692,527	2,594,080	2,468,650	2,241,755
Number of ETI jobs	137,597	810,847	1,002,569	1,101,868	1,110,591

Note: The table shows the number of ETI eligible workers and jobs and ETI participants and jobs for tax years 2014 to 2018.
Source: Authors' estimates based on IRP5 data.

There are around 2 million eligible workers in each tax year (excluding 2014 tax year given the two-month subsidy claim period). The number of participants increases each year. The take-up rate, the number of participants divided by the number of eligible workers, is around 50 percent in 2018, the highest take-up rate of the policy thus far. There are slightly higher numbers of eligible jobs and ETI jobs compared to eligible worker and ETI participants, but the pattern remains the same, there is an increase in take-up of the policy in each successive year.

3.5.2 Industries hiring low wage youth

Table 3-15 documents the industries where low-wage youth are working. The industries with the greatest number of low-wage youth are the finance and insurance sector, followed by the wholesale and retail sector, followed by the manufacturing sector and then the agricultural sector. The same trend is maintained over the period in the data. The table also points out that the public sector employs approximately 5 percent of young, low-wage workers.

Table 3-15 Eligible youth, industry affiliation, 2014-2018

	2014	2015	2016	2017	2018
Agriculture	346,557	366,070	413,905	407,508	364,463
Mining and quarrying	30,139	26,178	20,871	21,947	18,718
Manufacturing	392,775	373,346	380,364	327,188	324,410
Electricity, gas, steam, & AC supply	7,631	5,648	4,441	4,631	4,074
Water supply & waste management	5,410	5,178	4,743	4,847	5,639
Construction	107,398	101,404	90,510	83,249	67,046
Wholesale & retail	529,103	541,999	507,675	517,429	455,686
Transportation & storage	51,142	47,663	44,278	32,686	32,016
Accommodation & food service	117,527	131,552	130,251	134,489	104,924
Information & communication	12,668	12,341	14,623	14,496	12,384
Financial & insurance services	611,324	581,266	553,709	492,887	451,254
Real estate activities	9,684	9,629	7,906	8,848	6,621
Professional, scientific, & technical	222,050	214,513	171,504	157,589	157,692
Administrative & support service	82,543	82,255	59,956	68,189	58,378
Public administration	140,628	151,395	150,306	130,617	117,556
Education	83,927	88,706	89,352	93,194	89,372
Health & welfare	29,432	30,438	28,474	27,736	23,703
Arts, entertainment, & recreation	22,130	23,037	23,428	24,353	24,664
Other service activities	43,506	41,368	37,618	35,843	31,347
Missing	6,675	9,941	10,475	11,545	9,367
Number of eligible youths	2,852,249	2,843,927	2,744,389	2,599,271	2,359,314

Note: Industry codes are based on the International Standard Industrial Classification of All Economic Activities Revision 4 (ISIC4), available at: http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=27.
Source: Authors' estimates based on IRP5 data.

Table 3-16 documents the number of ETI jobs per industry. The distribution closely follows what is seen at the firm level. The majority of claims arise in the manufacturing sector, followed by the financial and insurance sector, wholesale and retail and the agricultural sector. There is a notable increase in ETI jobs in agriculture.

Table 3-16 ETI jobs, industry affiliation, 2014-2018

	2014	2015	2016	2017	2018
Agriculture	19,226	129,250	200,588	216,801	206,175
Mining and quarrying	1,240	5,542	5,384	8,314	8,123
Manufacturing	17,271	94,720	113,215	122,424	142,113
Electricity, gas, steam, & AC supply	212	833	762	819	1,036
Water supply & waste management	195	1,830	1,697	1,648	3,205
Construction	3,744	20,919	23,484	22,260	21,398
Wholesale & retail	35,945	200,939	238,551	277,554	280,147
Transportation & storage	1,886	10,955	13,844	13,829	14,454
Accommodation & food service	5,702	42,220	56,853	65,481	49,765
Information & communication	252	937	1,105	1,466	1,455
Financial & insurance services	30,299	179,708	225,295	235,534	238,276
Real estate activities	182	1,956	1,233	3,563	2,497
Professional, scientific, & technical	10,337	67,544	69,601	68,946	74,041
Administrative & support service	5,036	24,759	19,199	30,481	28,614
Education	1,364	8,692	9,362	9,219	12,968
Health & welfare	1,267	6,541	6,987	5,358	7,608
Arts, entertainment, & recreation	1,413	5,959	8,563	10,573	10,628
Other service activities	1,946	6,793	5,949	6,627	7,053
Missing	80	750	897	971	1,035
Number of ETI jobs	137,597	810,847	1,002,569	1,101,868	1,110,591

Note: Industry codes are based on the International Standard Industrial Classification of All Economic Activities Revision 4 (ISIC4), available at: http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=27.
Source: Authors' estimates based on IRP5 data.

There emerges a clear set of industries in which low-skilled, low-wage young workers are in demand. Levinsohn (2014) argue that sectors demanding low skilled workers have declined while tertiary sectors, such as the financial and services sector, have grown, demanding high skilled workers. Bhorat and Khan (2018) show that the main sectors of the economy experienced an increase in skill intensity over the period 1995 to 2015 at the cost of low or unskilled labour. The authors argue that this has created a skills-biased labour demand trajectory favouring high skilled workers and disadvantaging low and unskilled work seekers. The informal sector is also very small and unable to engage low and unskilled work seekers. The majority of the unemployed are either low or unskilled. Burns, Edwards and Pauw (2010) suggest that the policy should be targeted to industries that can grow the demand for low-skilled youth. Horn (2018) provides an industry list ranking employment intensity suggesting the subsidy could be better targeted should it be more narrowly applied in the higher-ranking industries.

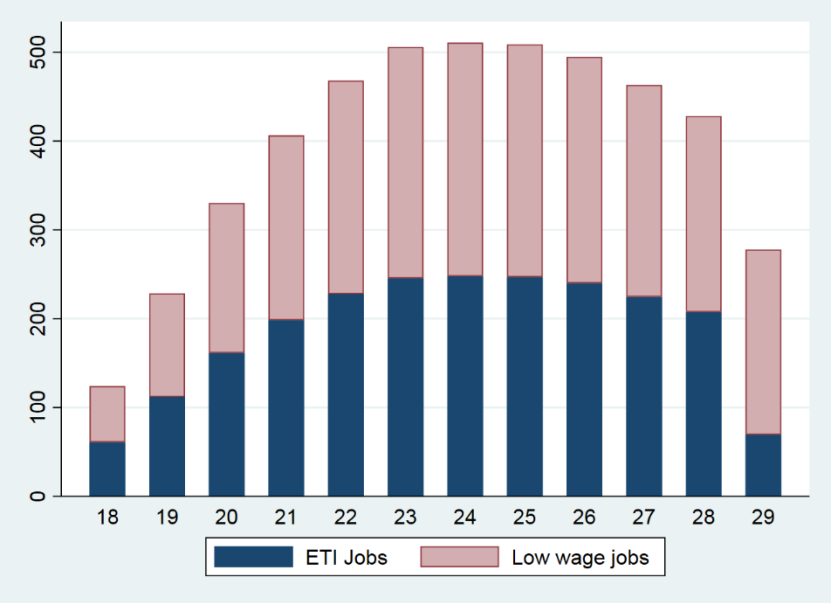
It does not appear that any of the industries have shifted their employment to favour youth in order to claim the subsidy. However, this is unlikely as certain industries require higher skill levels from young workers and the ETI will not affect them in the same way as, for example, the wholesale and retail sector where high numbers of low-skilled (low-wage) young workers are employed. A further example to highlight this, the mining sector employs large numbers of unskilled labour but the minimum wage in the mining sector is greater than R6,000 with only few eligible workers.

3.5.3 Age of ETI job claims

The unemployment rates for those aged 15-24 was 55.2% while the unemployment rate for those aged 25-35 was 36.1% at the end of 2019 (Statistics South Africa, 2020). Older youth are more likely to be employed than younger youth highlighting the desperate need for jobs for younger youth.

The earlier a young person gets a job, the greater the likelihood of being employed in later years. In South Africa, the longer one is unemployed, the harder it becomes to find a job. A problem that is sometimes referred to as chronic unemployment. The ETI is a wage subsidy that targets this most vulnerable group in two ways. One, the subsidy is restricted to youth between the ages of 18 and 29 years old and two, the subsidy is structured such that it can only be claimed for a new employee.

Figure 3.4 Age distribution of ETI jobs, 2018



Note: The graphs present the number of ETI jobs in 2018 against the total number of ETI eligible jobs by age.
Source: Author's own estimate based on IRP5 data

Figure 3.4 presents the age distribution of those holding ETI jobs in 2018. The previous years have a similar pattern shown in the appendix in Figure. 3.E.1. The majority of ETI jobs are occupied by youth between the ages of 21 and 25 years old. This points to successful targeting of the policy and fits the general trend of youth employment, that is, the older individuals are more likely to be employed. There are fewer workers in low-wage jobs from the age of 25 and up. This is likely due to higher reservation wages for the older cohort in the target group. Older workers may also have more years of work experience and firms may offer higher paying jobs to employees with some work experience who are not eligible for the subsidy. The fact that the ETI is claimed for workers above the age of 25 could also point to good targeting of the policy if the older workers have less experience and are vulnerable to long-term unemployment.

3.5.4 ETI characteristics

The tax data allows us to measure the effect of the ETI on the intensive margin, through earnings. A shortcoming of the tax data is that it does not include information on the number of hours worked. The design of the policy permits claims for full time and part time employees as discussed in the previous chapter. Firms could increase the number of hours they employ eligible workers. The duration of the ETI job is especially important to those who are employed for the first time, as it provides them with some work experience should they change jobs.

The average employment duration for an ETI job ranges from 189 to 212 days in the period 2015 to 2018. This falls short of a full year of employment. Kerr (2016), using the same administrative data, indicated that job churn is high. On the other hand, it is expected that firms would try to retain ETI workers for up to one year to maintain their ETI claims. The job duration in 2016 is possibly lower as some ETI-participants may be in their second year of employment where the subsidy is reduced leaving room for firms to remove these workers in favour or new eligible workers, but this is not obviously seen in the data.

Table 3-17 Job duration and wages

	2014	2015	2016	2017	2018
Average ETI job duration (days)	78	189	206	212	209
Average ETI eligible non-claimer job duration (days)	67	229	221	217	213
Average ETI job wages (Rands)	2,884	2,763	2,862	3,058	3,165
Average ETI eligible non-claimer wages (Rands)	2,302	2,678	2,731	2,755	2,809

Note: The table includes the average job duration and average wages in Rands for ETI jobs and ETI eligible jobs where there are no ETI claims,
Source Author's own estimates based on IRP5 data

The average wage for an ETI job is R2,763 in 2015. The maximum claim amount is R1,000 for those earning between R2,000 and R4,000 per month. At R2,000 this means a 50% wage subsidy but at R4,000 this means a 25% wage subsidy. The wage subsidy means the most to employers paying a wage of something closer to R2,000 than R4,000.

3.6 Conclusion

The tax data available at the National Treasury Secure Data Facility is possibly one of the richest and most useful administrative datasets that South Africa has to offer researchers at present. The tax data are collected to calculate the tax lability of the relevant taxpayer and as such has several opportunities and constraints for research analysis. Some of these constraints include the lack of demographic information of individual taxpayers that is considered key to labour market analysis in South Africa, for example, years of education or race group.[18] The other constraint with the data lies within the variables themselves. This is related to how the data is collected, stored, and transferred to the secure lab. This chapter carefully documents these issues and suggest ways in which they can be resolved. Once cleaned, the data has an average of 11 million individuals for each year available in the data. What remains from the cleaning process is a dataset that is still the best available to examine the effects of the ETI, given that the subsidy is claimed through the tax system.

Take up of the policy has been concentrated at large firms in the manufacturing and wholesale and retail sectors. Further the take up is expectedly higher in Gauteng, the Western Cape, and Kwa-Zulu Natal where South Africa's large economic centres are. There is no graphical evidence that the ETI has changed the hiring or separation rates of eligible or older workers. Micro and small firms claiming the ETI do appear to be more youthful once the policy starts. Considering how much has been claimed

[18] At the time of writing there is little that can be done to solve the lack of information, in the future, it is possible that the tax data could be merged with other data sources, such as the Department of Higher Education data.

for the policy, it is alarming that the twenty highest claiming firms account for 26% of the total value of the subsidy claimed each year. These firms are large with more than 200 employees.

The final section of the chapter looks at those eligible for the subsidy and examine the individuals for whom the subsidy was claimed. For each year that the subsidy has been available, there have been around 2 million eligible workers and between 700,000 and 1 million ETI participants. The subsidy is not being claimed for every possible worker. The sectoral analysis suggests that there are clear sets of industries in which low-skilled, low-wage young workers are in demand. The subsidy does, however, appear to be targeting a younger cohort of eligible workers which is a good sign as younger workers are more vulnerable to long-term unemployment. The average wage of ETI participants appear to be higher than eligible non-claiming workers, but the average job duration appears to be lower for ETI participants. This is something investigated in Chapter 5; the earnings and job duration response to the ETI, alongside the response to entry and exit of workers.

In summary, there are differences between firms claiming the subsidy and those not claiming. These differences need to be accounted for as selection into the programme will affect our evaluation of any change in employment.

In the subsequent chapters of this thesis, the cleaning process is taken as given. Lastly, there may be additional errors not identified here and may be identified by future tax data users.

3.7 Appendix

Appendix 3.A Data Cleaning summary

Table. 3.A.1 Results of duplicate and invalid job cleaning

	2011	2012	2013	2014	2015	2016	2017	2018
Raw number of observations	15,710,843	15,494,214	15,240,497	14,754,992	16,881,841	15,821,825	15,882,581	15,551,416
Raw number of individuals	11,459,724	11,506,856	11,640,467	11,370,019	11,717,110	11,662,905	11,831,318	11,891,982
Missing job duration	44	9721	56	24	56	145	78	44
Missing ID numbers	565,710	470,113	455,492	436,226	482,627	469,403	487,315	496,716
Missing income information	6	2	7	23	12	13	23	63
1-day contracts	633,718	735,636	538,930	447,271	863,484	405,103	513,706	556,318
Repeated job contracts	521,635	409,334	371,182	275,265	2,391,135	1,379,399	998,296	564,940
Total number of observations	13,778,572	13,542,556	13,565,808	13,162,767	13,507,484	13,573,274	13,667,933	13,668,806
% observations dropped	12.3%	12.6%	11.0%	10.8%	20.0%	14.2%	13.9%	12.1%
Total number of individuals	10,609,890	10,828,667	11,051,480	11,123,102	11,374,061	11,387,158	11,502,375	11,566,138
% of individuals dropped	7.4%	5.9%	5.1%	2.2%	2.9%	2.4%	2.8%	2.7%

Note: The number of observations lost at each step of the cleaning process by tax year.
Source: Authors' estimates based on IRP5 data.

Appendix 3.B Variable list

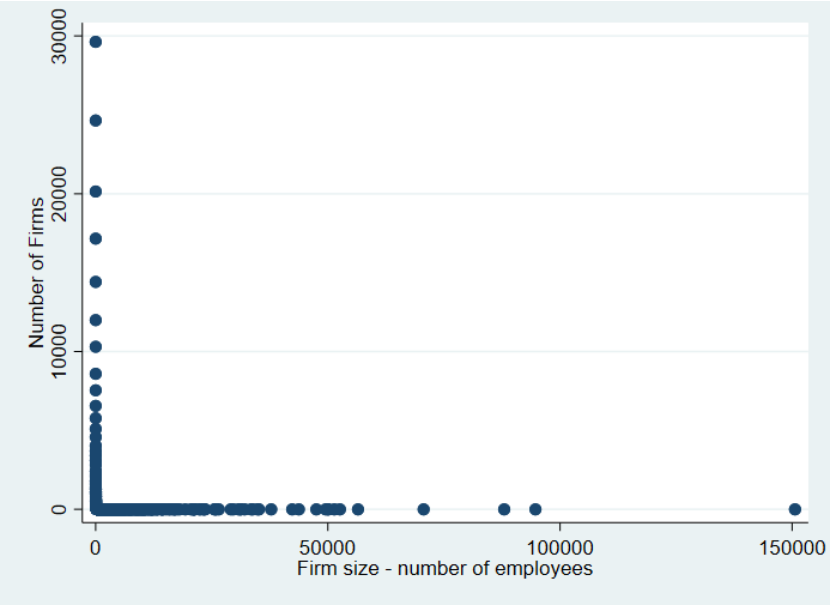
Table. 3.B.1. List of variables used and created

Variable name	Description
Employment Panel	
tax_year	The tax year starts 1 Mar and ends the following year 28/29 Feb
id_number	Anonymized South African identity number
date_of_birth	Date of birth as completed on IRP5 form
certificate_number	The number on the IRP5 certificate
paye_ref_no	Anonymized PAYE reference number for firm
amtgrossnontaxableinc	Gross non-taxable income amount
amtgrossretfundinc	Gross retirement fund income amount
amtgrossnretfundinc	Gross non-retirement fund income amount
employment_start	Date of the start of employment
employment_end	Date of the end of employment
eti_amount	Amount of ETI claimed
main_income_source_code	Main income source code for the individual
natureofperson	Nature of Person includes individuals, pensioners, clubs, associations
gender	Gender where ID number is non-missing
totalperiodinyearofassessment	The periods recorded in the tax year of assessment
totalperiodsworked	The periods worked in the year of assessment
- variables created	
income	Summation of income variables in the data.
month_inc	Income divided by the period worked converted to a monthly amount
work period	End date of employment minus the start date of employment
age_start	Start of employment date minus date of birth
eti	Indicator for ETI claim, excluding incorrect ETI claims
industry	Main income source code converted to the ISIC4 codes
hire	Indicator for newly hired
exit	Indicator for separation from job
firm_size	Weighted number of employees per CIT firm
firm_eti	Weighted number of ETI employees per CIT firm
firm_eti_amt	Amount of ETI claimed per CIT firm
CIT-IRP5 panel	
taxrefno	Unique ID for CIT firm
tax_year	The tax year starts 1 Mar and ends the following year 28/29 Feb
ITR14_c_taamt	Total assets owned by the firm
ITR14_l_totliabilities	Total debts owed by the firm
g_sales	Firm profit item - Total sales amount per firm
g_cos1	Firm profit item - Total cost of sales
y_np	Firm income - Net profit
x_wages	Firm Expense - Total payroll
x_labcost	Firm Expense - Labour cost
cust_impexpind	Customs Item - Categorical variable for trade status
c_province	Firm characteristic - Firm location variable
- created	
lticlaim	Learnership tax incentive claim indicator
tot_var_cost	Total Variable Cost
PAYE_1col_1	
taxrefno	Company Income Tax reference number
paye_ref_no	PAYE reference number

Source: Authors' own list of variables used from the tax data.

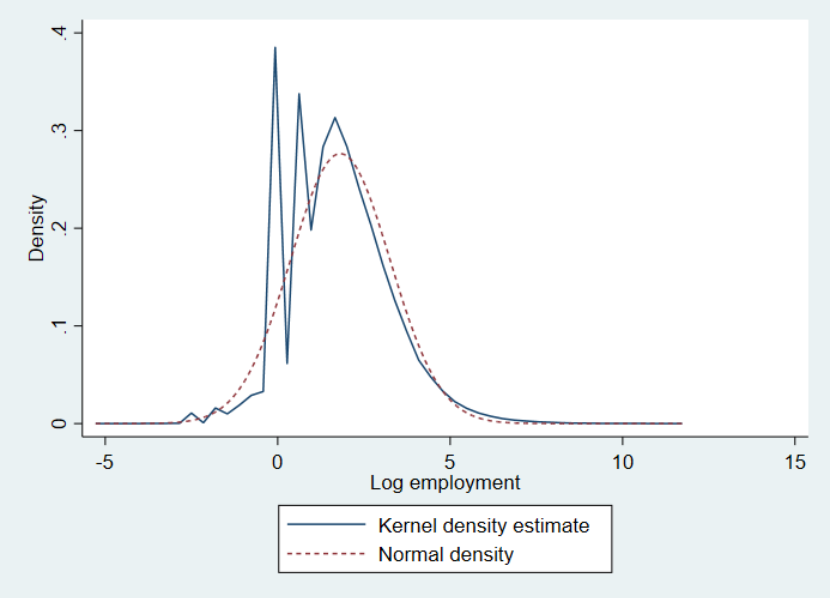
Appendix 3.C Firm size graphs

Figure. 3.C.1 Firm size



Note: The graph shows the number of firms by firm size calculated by the number of employees.
Source: Author's own estimates using IRP5 data.

Figure. 3.C.2 Firm size distribution against normal distribution



Source: Author's own estimates using IRP5 data.

Appendix 3.D Firm location take-up

Table. 3.D.1 Take up rate by province

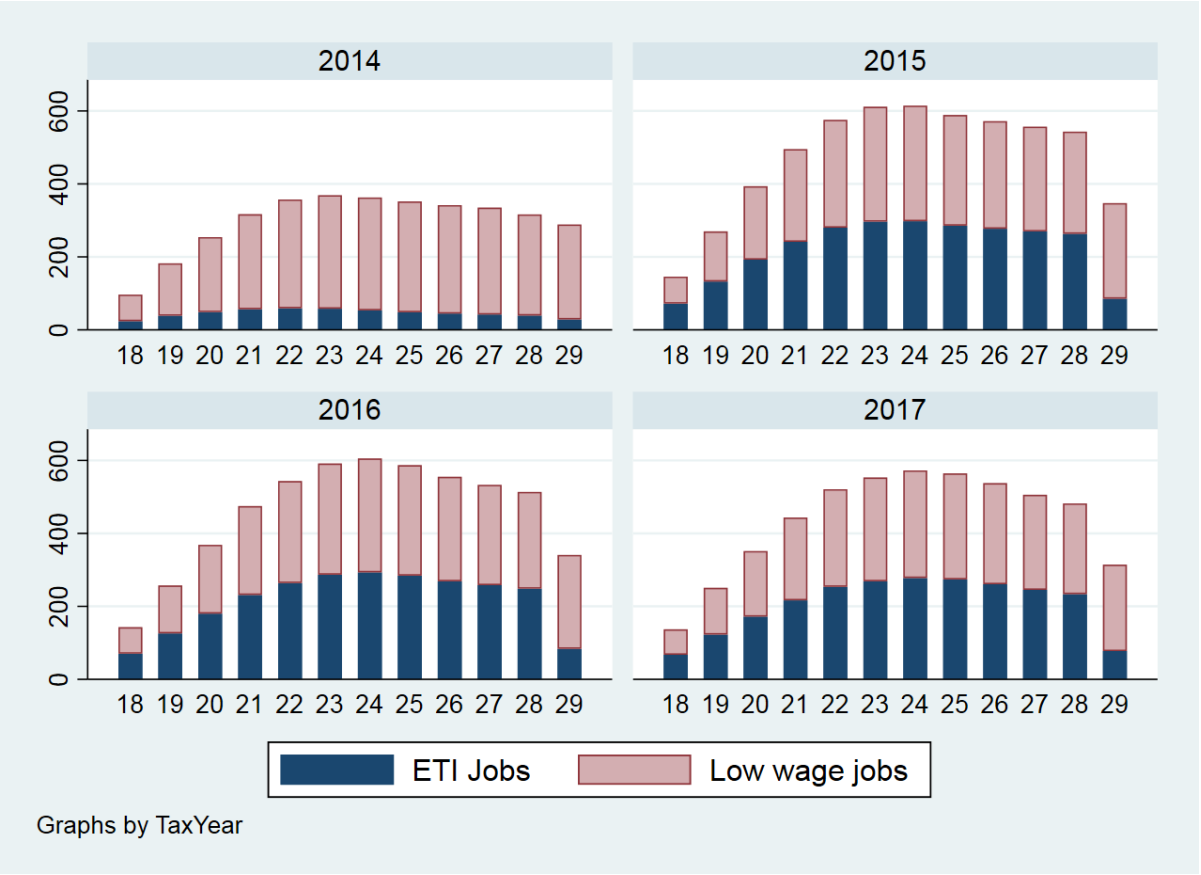
	2014	2015	2016	2017
Western Cape	7%	16%	16%	16%
Eastern Cape	7%	18%	18%	19%
Northern Cape	8%	22%	21%	21%
Free State	6%	15%	15%	16%
KwaZulu-Natal	6%	17%	17%	17%
North West	7%	14%	13%	13%
Gauteng	6%	13%	12%	12%
Mpumalanga	6%	16%	14%	14%
Limpopo	6%	15%	13%	14%

Notes: Take up rate is calculated as the number of ETI claiming firms in each province divided by the number of firms in the province.

Source: Author's own estimates using IRP5 data.

Appendix 3.E Age distribution

Figure. 3.E.1 ETI age distribution, 2014-2017



Note: The graphs present the number of ETI jobs against the total number of ETI eligible jobs by age for the 2014 to 2017 tax years.
Source: Author's own estimates using IRP5 data.

Chapter 4. Estimating firm-level impacts of the ETI

4.1 Introduction

The main contribution of the present chapter is the analysis of the ETI at the firm level. This is done by examining the impact of the ETI at firms. This chapter utilizes a matched difference-in-difference approach to isolate the causal effect of the ETI on the number of youth employed at the firm.

Early analysis of the ETI made use of survey data to analyse the effect of the ETI on youth employment probabilities (Ranchhod & Finn, 2014; Ranchhod & Finn, 2015). The key conclusion of the analysis is that the ETI has had no positive significant impact on the employment probabilities of young workers in the first policy year. Linking back to the very early discussion in Chapter 2, the stated objective of the ETI was to create 178,000 jobs in the first three years of the programme. Assuming the aim was to create approximately 60,000 jobs per year, or 30,000 jobs in the first six months, due to the survey sample size and design it may not have been possible to observe these changes.

A more recent analysis by the National Treasury (2016) provides a descriptive overview of the policy using the same tax data used in this thesis. The limitation of the report is that it does not qualify whether the policy is meeting its objective through creating any jobs.

While only a few studies of the ETI exist, a more extensive review of these studies, their methodologies and findings are presented in Section 2.3.4. Different from previous work on the ETI, this chapter presents an analysis of the ETI at the firm-level allowing us to measure the change in youth employment against the backdrop of stated policy objectives.

With detailed information on the take-up of the subsidy from the tax data, the types of firms where the subsidy has been most effective in creating jobs can be examined. Propensity score matching is used to construct a group of ETI and non-ETI firms that are statistically similar in terms of pre-policy firm characteristics. Then a difference-in-differences estimation strategy is used and a positive statistically significant effect on youth employment is found. Other outcome variables such as non-youth employment is used to examine any substitution effects and additionally examine the effect on payroll and youth ratio at the firm to check the sensitivity of the results. It matters little whether small or large firms create unemployment in South Africa since the unemployment problem, described in Chapter 2, is so large. However, small, and large firms react differently to the policy and any difference in effect at small or large firms could point to deadweight losses or opportunities to improve the implementation of the policy. For this reason, different firm sizes are evaluated separately by separately matching and estimating difference-in-differences for firm size subgroups established in Chapter 3.

The theoretical framework in section 2.4 describes how a targeted subsidy can have both a positive and negative employment effect on non-target groups. Indeed, there is a major policy concern that the ETI would decrease the demand for or increase the churn for older workers in the non-target group. Examining the non-target group as a whole could hide the effect of the subsidy on non-target workers who are substitutes for the target group. For example, it is more likely that a 32-year-old is substitute for a subsidy eligible 29-year-old than a 45-year-old. Also, a worker earning R6,200 per month may be a closer substitute for a worker earning R5,800 per month. To examine the possible displacement effects of the subsidy, two non-target groups are considered: older workers, between the ages of 30 and 40 years old, as well as 'higher wage' young workers earning between R6,000 and R7,500.

The last section of this chapter does a basic cost and benefit analysis of the policy. Thus far, the cost of this policy has been non-negligible and begs the question as to whether scarce government funding should continue to be spent on this policy or if it could be better spent on a different policy. The resulting number of jobs created, and cost of these jobs, are measured against the intention of the policy.

This chapter is organized in the following manner: the next section lays out the evaluation process; defining the outcomes to be assessed and outlining our identification strategy. Section 4.3 describes the study sample of firms, Section 4.4 details the matching process including estimating propensity scores, assessing the matching algorithm, and evaluating the matched treatment and control groups. Section 4.5 presents the results of conditional difference-in-differences methods and finally, Section 4.6, concludes.

4.2 Evaluation process

4.2.1 Outcome Measure

The evaluation process is started by choosing suitable outcome measures. This is to clarify how the policy works and what is defined as a policy success. The ETI was aimed at addressing the youth unemployment problem through stimulating the demand for youth labour. The aggregate demand for youth labour is the sum of the demand for youth labour in each firm. The number of youth employed at a firm is used as proxy for labour demand for youth.

This chapter aims to test whether there is an aggregate increase in youth employment in firms due to the implementation of the ETI. Wage subsidies decrease the relative cost of employing youth, thereby in theory increasing the demand for youth workers. However, holding all other things constant, if youth workers are substitutes for non-youth workers, the decrease in the relative cost of employing youth will result in substitution (of employment) away from non-youth workers.

At the same time, all other things are not constant and a decrease in the wage bill lowers production costs, resulting in lower prices and an increase in demand for produced goods - termed the output effect.[19] The effect on youth and non-youth therefore also depends on whether the substitution effect or the output effect is larger. A change in non-youth employment as a result of the ETI will be evidence of an output effect.

Many wage subsidy policies see an increase in total employment, greater than the change in employment for the subsidised group (Crichton & Maré, 2013; Kaiser & Kuhn, 2016; Rotger & Arendt, 2010). This is viewed as a positive externality; the increase of unsubsidised employment can amplify the effect of the policy through enabling firms to grow. Total employment and payroll are examined as additional outcomes of the policy.

Over time, wage subsidies can increase the number of formal firms through incentivising informal firms to register with the government, as was the case in the Turkey (Betcherman, Daysal & Pagés, 2010). Existing firms could also increase the number of youth employed in established firms. These outcomes are not mutually exclusive and can occur simultaneously. The sample is restricted to established firms to measure the change in the number of youth employed, not allowing for any firm entry or exit.

The subsequent sections outline the evaluation problem and the solution to assessing the above-mentioned outcomes.

4.2.2 The Microeconometric Evaluation problem

The impact of the wage subsidy policy on the outcome of the ETI claiming firm requires us to consider how the ETI firm would have behaved in the absence of the policy. It is impossible for us to observe the ETI firm not claiming the subsidy. The pre-policy behaviour is used to anchor how it is expected that the ETI firm would behave in the absence of the policy. A simple before-after analysis would be susceptible to any possible confounding such as changes in economic growth. Any change in employment at the ETI firm would erroneously be interpreted as a change due to the policy where the response may be a result of the change in economic growth.

The difference-in-difference (DID) method allows us to examine the policy impact by comparing the pre- and post-policy change in employment for the ETI firm relative to a comparison group. The comparison group should mimic the behaviour of the ETI firms in the absence of the policy. The difficulty in policy evaluation is finding a credible comparison. The key assumption in a DID analysis is a parallel trend between the ETI firms and the comparison group.

[19] Assuming firms are price-takers, this would invalidate the Stable Unit Treatment Values Assumption (SUTVA) assumption.

A parallel trend would suggest that the average change in the comparison group characterizes the counterfactual change in the ETI firms without the policy. The descriptive statistics in Chapter 3 point to several differences between ETI firms and non-ETI firms. Notably, ETI firms are large by number of employees, concentrated in the agriculture and manufacturing sectors and have higher concentrations of youth. These observable differences mean the assumption of unconditional parallel trends, between ETI and non-ETI firms, is unlikely to hold. The next subsection discusses how ETI take-up is modelled so that the parallel trends assumption holds conditional on covariates. The randomisation of the policy implementation at firms means that with a large enough sample, the many dimensions on which firms differ from each other is accommodated and the average difference is truly due to the policy. This is not the case for the ETI as the policy was available to all firms at the same time. Instead to construct our comparison group matching is done on some of the key observables identified in the previous chapter. This problem is described mathematically and applied to our evaluation of the ETI.

Consider two outcomes: Y^T, where the firm claims the ETI and Y^C, where the firm does not claim the ETI. Borrowing language from the evaluation literature, Y^T refers to the "treated firm" and Y^C the "control firm". Let ETI be an indicator for whether a firm claimed ETI or did not claim the ETI.

The treatment effect is the difference between the treated and control firm:

$$\Delta = Y^T - Y^C \tag{4.1}$$

However, the ETI firm not claiming the subsidy, Y^C, cannot be observed if the firm has claimed the subsidy, a challenge in casual inference research (Angrist & Pischke, 2008; Holland, 1986). The observed outcome for each firm is:

$$Y = ETI.Y^T + (1 - ETI)Y^C \tag{4.2}$$

This means Y_f^T and Y_f^C cannot be observed at the same time. When $ETI = 1$, that is the firm is treated, Y_f is Y_f^T and Y_f^C is the counterfactual. When $ETI = 0$, that is the firm is not treated, Y_f is Y_f^C and Y_f^T is the counterfactual. The average treatment effect on the treated is thus:

$$E(\Delta|ETI = 1) = E\left(Y_f^T \middle| ETI = 1\right) - E\left(Y_f^C \middle| ETI = 1\right) \tag{4.3}$$

This equation calculates whether there is difference in outcome between the firm who claimed the ETI compared to the hypothetical situation where the same firm did not claim the ETI. However, the hypothetical firm not claiming the ETI represented by $E\left(Y_f^C \middle| ETI = 1\right)$ cannot simultaneously be observed.

In cases where a randomised experiment is conducted, the control group is constructed such that it is a valid counterfactual because the following condition holds true:

$$E(Y_f^c|ETI = 1) = E(Y_f^c|ETI = 0) \quad (4.4)$$

That is, on average, the control firm is a comparable to the hypothetical firm.

Firms claiming the ETI were not randomly assigned thus the condition is not true:

$$E(Y_f^c|ETI = 1) \neq E(Y_f^c|ETI = 0) \quad (4.5)$$

Using the mean outcome of the non-claiming firms to approximate the outcomes for the hypothetical firm that did not claim the ETI is not ideal as ETI and non-ETI firms may differ without the policy. Using the non-ETI firms as a control group will thus lead to selection bias on observable and unobservable characteristics (Hujer, Caliendo & Radic, 2002). The next subsection tries to address the selection bias problem.

4.2.3 Selection on observable characteristics

One way to deal with selection bias on observables is through matching. Matching is done to construct a credible counterfactual group for the DID analysis.[20] The idea behind matching is to search for a similar and comparable non-ETI firm from a large group of non-ETI firms. Similarity is based on firm pre-treatment covariates and matching can be conducted by covariates (Rubin, 2006) or by propensity scores (Rosenbaum & Rubin, 1983).

The difference in outcomes computed between the treated and matched control groups can then be attributed to the policy (Rosenbaum & Rubin, 1983).

Matches are made based on the identifying assumption that, conditional on all relevant pre-treatment covariates (X), the potential outcomes (Y^T, Y^C) are independent of participation (conditional independence assumption or CIA)(Angrist & Pischke, 2008).

$$Y^T, Y^C \perp\!\!\!\perp ETI|X \quad (4.6)$$

If the CIA holds, then the treatment and control groups are balanced, thus the control group is a valid counterfactual for the treatment group. This means the observed outcome of the non-ETI firm can be used to estimate the counterfactual outcome of the hypothetical ETI firm if it did not claim the ETI. This is described in the equation below:

$$E(Y_f^c|X, ETI = 1) = E(Y_f^c|X, ETI = 0) = E(Y_f^c|X) \quad (4.7)$$

[20] As discussed in the previous section, the parallel trends assumption is unlikely to hold given the many differences between ETI and non-ETI firms.

The role of matching is to ensure balance between the treatment and control groups based on pre-treatment covariates. This confirms independence between the potential outcome and treatment and gives an unbiased estimator assuming that the expected value of the two error terms is both equal to zero. That is, there is no difference between the two error structures.

The most intuitive way to match firms is to match directly using firm characteristics. However, the number of covariates that determine selection is large and it becomes impossible to match directly; also known as the curse of dimensionality. There are two ways to proceed; through mapping covariates into a metric measuring the closeness of two observations (Rubin, 2006) or matching by propensity score (Rosenbaum & Rubin, 1983). Both methods make the distribution of covariates in the treatment group and in the control group the same. Rosenbaum and Rubin (1983) recommend the use of a balancing score, that is a function of the covariates. The propensity score is an example of a balancing score summarising information of covariates (X) into a single index function that gives us the probability of claiming the ETI based on the observed characteristics of the firm.

$$Y_f^T, Y_f^c \perp\!\!\!\perp ETI \mid P(X) \tag{4.8}$$

The CIA then extends to propensity scores, that is, conditional on propensity scores $P(X)$, the potential outcomes Y^T and Y^C are independent of treatment (in the pre-policy phase) as described in equation (4.8).

Equation (4.7) is amended to include the conditioning from X to $P(X)$ to get the following equation:

$$E\left(Y_f^c \middle| P(X), ETI = 1\right) = E\left(Y_f^c \middle| P(X), ETI = 0\right) = E\left(Y_f^c \middle| P(X)\right) \tag{4.9}$$

The curse of dimensionality is avoided with the use of $P(X)$ and if the unobservable characteristics are the same. This means our counterfactual can be represented as follows:

$$E\left(Y_f^c \middle| ETI = 1\right) = E_{P(X)}\left[E\left(Y_f^c \middle| P(X), ETI = 0\right) \middle| ETI = 1\right] \tag{4.10}$$

Equation (4.10), the average treatment effect on the treated (ATT), is updated with the new counterfactual:

$$E(\Delta | ETI = 1) = E\left(Y_f^T \middle| ETI = 1\right) - E_{P(X)}\left[E\left(Y_f^c \middle| P(X), ETI = 0\right) \middle| ETI = 1\right] \tag{4.11}$$

This means that ETI firms can be matched with non-ETI firms where they have the same propensity score. The propensity score can be estimated using a standard probability model such as a logit or probit model and the quality of matching depends on how well the propensity score

is estimated and the ability to find comparison firms. An examination of the firms not matched will give us confidence whether any incomplete matching will bias our results.

4.2.4 Conditional Difference-in-Difference approach

Thus far, we have argued that matching allows us to deal with selection bias on observables, what remains is for us to deal with the selection bias from unobservable factors. Assuming the matching is successful, we assume that both treated and untreated firms face the same economic milieu allowing us to assess the effect of the policy. The DID measures the difference between the treatment and control group before the policy and subtracts from it the difference between the treatment and control after policy implementation. This is represented in equation (4.12).

$$DID = E(Y_1^T - Y_0^T | ETI_1 = 1) - E(Y_1^C - Y_0^C | ETI_1 = 0) \quad (4.12)$$

The DID approach requires a parallel time trend assumption and allows for time invariant selection bias.

Heckman et al. (1998) introduced the conditional DID (cDID) estimator extending the usual DID through conditioning the outcomes on the propensity score.[21] The identifying assumption is thus:

$$E(Y_1^T - Y_0^T | P(X), ETI_1 = 1) = E(Y_1^C - Y_0^C | P(X), ETI_1 = 0) \quad (4.13)$$

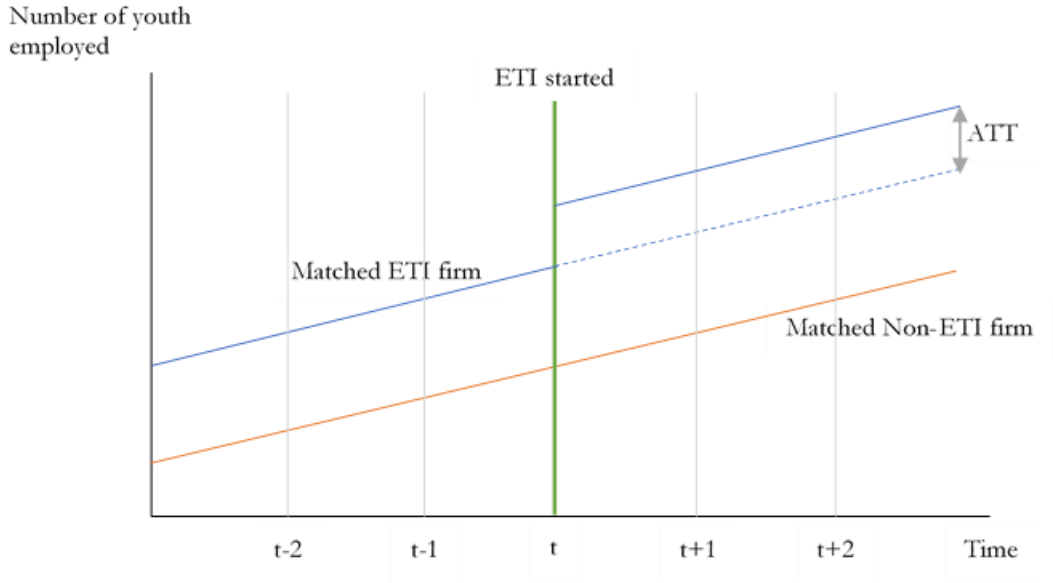
Equation (4.13) demonstrates that conditional on propensity score matching, the average treatment effect on the treated is estimated by examining the differences between the matched treated-control firms before and after the policy.

This is similar to the approaches of Bruhn (2016), Crichton and Maré (2013), Hujer, Caliendo and Radic (2002), Kaiser and Kuhn (2016), Kangasharju (2007) and Rotger and Arendt (2010) for the evaluation of wage subsidy programmes, using administrative data in other countries.

This cDID approach accounts for selection on observables through the matching and unobservable characteristics through the difference-in-differences. This idea is illustrated in Figure 4.1 below.

[21] Conditional DID means combining matching with the DID.

Figure 4.1 Conditional Difference-in-differences approach



Note: Matching does not eliminate the differences between firms thus it is expected that matched ETI and non-ETI firms are different in pre-treatment years.
Source: Author's own illustration

ETI and non-ETI firms are matched at time $t-1$. Matching does not eliminate the differences in employment of youth between ETI and non-ETI firms, rather, it provides us with a statistically comparable non-ETI firm with which to compare ETI firms. This means it is possible for firms to have substantial differences on some of the firm characteristics. It is also possible for there to be different between matched treatment and untreated groups when there are thin densities in at least one group of firms who are untreated. This is when the difference-in-differences approach is required. Differences in employment of youth at $t-1$ are compared and subtracted from the difference between the ETI and non-ETI firms at $t+1$. This provides the average treatment on the treated as indicated in Figure 4.1. The estimation equation for the ATT is thus:

$$\Delta_{t+1} = \left[Y_{t+1}^{T'} - Y_{t-1}^{T'}\right] - \left[Y_{t+1}^{C'} - Y_{t-1}^{C'}\right] \tag{4.14}$$

where:

Y	Refers to the outcome measured
T'	Refers to the matched ETI firm
C'	Refers to the matched non-ETI firm
$t-1$	Refers to the pre-policy period
$t+1$	Refers to the period after policy implementation at time t.

The ATT estimates the change in employment beyond the number that would have been employed in the absence of the subsidy. This means that the interpretation of the ATT estimate is the number

of jobs created due to the wage subsidy policy. The estimation method assumes non-interference across firms. This assumption would break down if the increase in employment at one firm is due to the loss of employment at another firm. Given the large number of unemployed youth in South Africa this is unlikely. Young workers are unaware of the wage subsidy and there would be no incentive for them to switch jobs.

As a scenario, Firm A and Firm B are both expanding their firms and hiring more workers. Both firms are in industries that have a need for semi or low-skilled youth. In the absence of the subsidy, these firms will continue to hire and expand. The subsidy is introduced in 2014 but only Firm A claims the subsidy. Firm B does not claim the subsidy as they are unaware of the policy. Firms A and B are matched on their pre-policy characteristics, including industrial classification, firm size, and employment growth rate. During the policy years, it is assumed that a recession takes place that affects both firms' hiring patterns. Firm A sees an increase in youth employment beyond the recession compared with the period before. A before–after comparison will be limited, as it does not account for any change in the economic environment. A DID approach, on the other hand, takes the economic environment into account and reflects the true effect of claiming the ETI. This means that a cDID approach will distinguish any increase in youth employment at Firm A and allow us to attribute it to the policy.

Lastly, Kahn-Lang and Lang (2020) argue that DID will be more plausible if the treatment and control groups are similar in levels. In this case, this means that youth employment levels are similar between matched treatment and control groups. DID with matching makes youth employment levels more similar, however, both treatment and control groups contain very small and very large firms. This forms part of the motivation for the further analysis done by matching firms within firm size groups.

4.3 Study sample

Firms in the final empirical equation are a subset of firms in the data. First, the group of control firms needs to be selected. Firms in the public sector are removed as they are ineligible for the subsidy. There are 328,111 firms in the unbalanced panel from 2011 to 2015, of which 175 public sector firms are dropped. Public sector firms are assumed to be so different and to operate in such a different "market" that they hold no relevant information for tracking even the impact of time varying circumstances and are thus not a good comparison group.

Second, the panel data is supplemented with firm characteristics from the Company Income Tax panel (CIT-IRP5). This gives more information on firms that enables a more suitable match between firms to be found. The downside of this, however, is that not all firms in the IRP5 have

corresponding CIT data. This can be a result of the lag in submitting a firm tax return to SARS. Since matching is done in 2013, firms with no CIT information in 2013 are dropped.

Third, 'pre' and 'post' intervention data is required to conduct the DID. For example, a firm that registered for the first time in the 2014 tax year will not be included in our analysis as the data does not include sufficient pre-intervention information with which to match a firm not claiming the ETI. The sample is further restricted to firms that were operating in 2011 and 2012 to include lagged employment information in our estimation. Thus, no firm that registered after 2011 is included in the model giving a balanced panel of 115,053 firms.

The balanced panel includes 18,719 firms claiming the ETI in 2015. This is less than the total number of firms claiming the ETI in 2015 presented in Table 3-4 as the restrictions applied reduces the sample. The remainder of non-claiming firms are used to form the control group of firms.

Lastly, firms with more than 1,200 employees are dropped. This is because the take-up rate for these very large firms is approximately 72% and the credibility of our matching may be compromised. There are 367 firms with more than 1,200 employees claiming the subsidy, which represents 2% of all ETI firms. However, the value of ETI claimed is large. In terms of the value of ETI claims, the study sample of ETI firms claim R2.37 billion in subsidy and the 367 very large firms claim 56% of this. Dropping these firms has an implication on the external validity of the results. The estimation will therefore be limited to formal sector private firms; operating from 2011 onwards; with company tax information in 2013 and with less than 1,200 employees representing 57% of all ETI claiming firms in 2015.

4.4 Estimating the propensity score, matching, and achieving balance

4.4.1 Determinants of ETI take-up

Crucial to the assessment of the employment impacts of the ETI at firm level, are the determinants of policy take up. It has been shown, in the previous Chapter, that there are many factors that may affect the firm's choice to hire an eligible worker and claim a subsidy. All firms in the private sector are eligible to claim the subsidy when they employ a young, low-wage worker. However, not all firms with eligible employees are making use of the subsidy. A simple comparison of firms claiming the subsidy with firms not claiming the subsidy runs the risk of selection effects.

Caliendo and Kopeinig (2008) advise the use of a logit or probit model for the binary treatment case as the two models have similar results and thus, decision is not critical. In this analysis the logit model is used to estimate the probability of ETI take up:

$$y_i^* = \beta' x_i + u_i \tag{4.15}$$

where y_i is equal to 1 if firm i claims the ETI in 2015 and 0 if firm i does not claim the ETI. The drivers of participation in the ETI are given by the vector x_i. The variables used to predict the probability of subsidy take up are from the pre-policy period, 2013. Explanatory variables in the pre-policy period include firm location, 1-digit industry and firm size by number of employees. In addition to these factors, we include firm turnover, assets, firm learnership claims indicator, average wages and average age as these are standard determinants of labour demand (Kangasharju, 2007).

The results of the logit estimation are presented in Table 4-1. The dependent variable gets the value of 1 if the firm claimed the subsidy in 2015.

The estimation results indicate that firm size and learnership claim status have a positive significant impact on the likelihood of firms taking up the policy.[22] Unsurprisingly, the higher the mean age and mean wage at the firm, the less likely a firm is to take up the subsidy given the wage and age criteria linked to the subsidy claims.

The set of factors identified here are taken into the matching process using the study sample outlined.

[22] Firm size bins are used as this results in a larger number of matched firms.

Table 4-1 Determinants of Firm ETI take-up

	Coefficient	Standard Error
Firm sales turnover	-1.01e-11	(5.65e-12)
Firm assets	-1.15e-11	(1.04e-11)
Firm learnership claim (dummy)	0.754***	(0.0599)
Average age	-0.0852***	(0.00228)
Average wage	-1.28e-05***	(1.22e-06)
Employment growth rate (%)	-0.0127	(0.0407)
Lagged employment growth rate (%)	-0.0114	(0.0345)
Youth employment growth rate (%)	-0.0133	(0.0272)
Lagged youth employment growth rate (%)	0.00170	(0.0260)
Firm province (reference Western Cape)		
- Eastern Cape	0.0211	(0.0427)
- Northern Cape	0.132*	(0.0716)
- KwaZulu-Natal	-0.238***	(0.0552)
- Gauteng	-0.128***	(0.0319)
- North West	-0.299***	(0.0574)
- Mpumalanga	-0.315***	(0.0259)
- Free State	-0.335***	(0.0503)
- Limpopo	-0.412***	(0.0626)
Firm industry (reference Agriculture)		
- Mining	-0.229**	(0.0968)
- Manufacturing	-0.0391	(0.0390)
- Electricity supply	0.00478	(0.140)
- Water management	-0.311**	(0.128)
- Construction	-0.224***	(0.0513)
- Wholesale & retail	0.137***	(0.0408)
- Transportation & storage	0.0274	(0.0625)
- Accommodation & service activities	0.318***	(0.0535)
- Information & communication	-0.937***	(0.203)
- Financial & insurance services	-0.113**	(0.0462)
- Real Estate Activities	-0.208**	(0.105)
- Professional, scientific, & technical	-0.0372	(0.0494)
- Administrative & support service activities	-0.131	(0.0904)
- Education	0.146*	(0.0857)
- Health & social work activities	-0.188**	(0.0827)
- Arts & entertainment	-0.0934	(0.114)
- Other service activities	-0.116	(0.0950)
Firm size (reference: Micro firms 0-5 workers)		
- Small: 6 – 10	0.780***	(0.0439)
- Medium: 11 – 50	1.750***	(0.0389)
- Large: 51 - 100	2.826***	(0.0455)
- Very Large: 100+	3.540***	(0.0472)
Constant	0.406***	(0.0889)
Observations	79,476	

Note: The full population of firms are used in this estimation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' own estimates based on IRP5 data

4.4.2 Propensity score matching

Each ETI firm is matched in the year prior to the policy to a "counterfactual" non-ETI firm based on the firms' propensity scores. To calculate the propensity scores, the probability of take-up is estimated on firm characteristics in 2013 conducted in the previous section.

Caliendo and Kopeinig (2008) provides some guidance regarding the variables to include in the propensity score model. Variables that affect the choice to claim the ETI and influence the number

of employees should be included in the model. However, variables should be unaffected by the ETI and thus the propensity score model is estimated based on the 2013 (pre-ETI) firm characteristics. Where firms cannot claim the ETI, the probability of take-up cannot be explained by any of the covariates and matching cannot be used. This is the case for firms in the public sector who are ineligible for the ETI and the common support condition required for matching fails. This was established when the study sample was constructed.

Matching on firm size, industry and previous employment finds firms that would plausibly exhibit common trends in the absence of the subsidy policy. Matching allows the comparison to ETI firms with non-ETI firms if done correctly. The mechanics of this are as follows: each ETI firm is matched to one or more comparable non-ETI firm based on their propensity score to minimise the differences between the firms where all key controls are in the take-up equation. The results from the estimation of the probability of ETI take-up (from equation 4.15) are then used to generate matches between ETI and non-ETI firms.

There are various ways in which to use propensity scores to conduct matching. (described in detail by Caliendo and Kopeinig (2008)). Matching methods trade bias against precision where bias relates to the differences between the treated and control groups while precision relates to the size of the control group. Both nearest neighbour and kernel matching methods are used in this chapter.

Nearest neighbour matching identifies the 'most similar' non-ETI firm to be compared with an ETI firm. The downside of this matching method arises if the nearest neighbour is "far away". In this case, some ETI firms have many close neighbours and others have few neighbours that may be far away. Kernel matching is favoured over nearest neighbour matching in such a situation as nearest neighbour matching could result in poor matches when compared to kernel matching (Bryson, Dorsett & Purdon, 2002).

Kernel matching is a non-parametric method using all firms in the control group to build a weighted composite according to the distance between propensity scores. Observations closer in absolute propensity score distance, $\left|P(X_i) - P(X_j)\right|$, are assigned a greater weight. Kernel matching produces smaller standard errors as more information is used to build the weighted counterfactual. In the matching process the Gaussian kernel function is used with a bandwidth of 0.06. We later show the results for both nearest neighbour and kernel matching to show that our estimates are not sensitive to the choice of matching method.

Another way of improving the matching method may be to conduct matching within groups. An example of this can be seen in the study by Hujer, Caliendo and Radic (2002) where matches are made within firm size and industry groups. This method requires enough treatment and control

units in each of these sub-categories within which to match. Given the large differences in take up rates between firms of different sizes, matching is also conducted within firm size groups and present the results.

The matching strategy finds counterfactual firms in about 92 percent of all cases. Matching itself does not identify the treatment effect in our model, matching provides us with a treatment and control group for the DID estimation. Before the cDID estimation takes place, the matching success needs to be confirmed.[23]

4.4.3 Common support and achieving balance

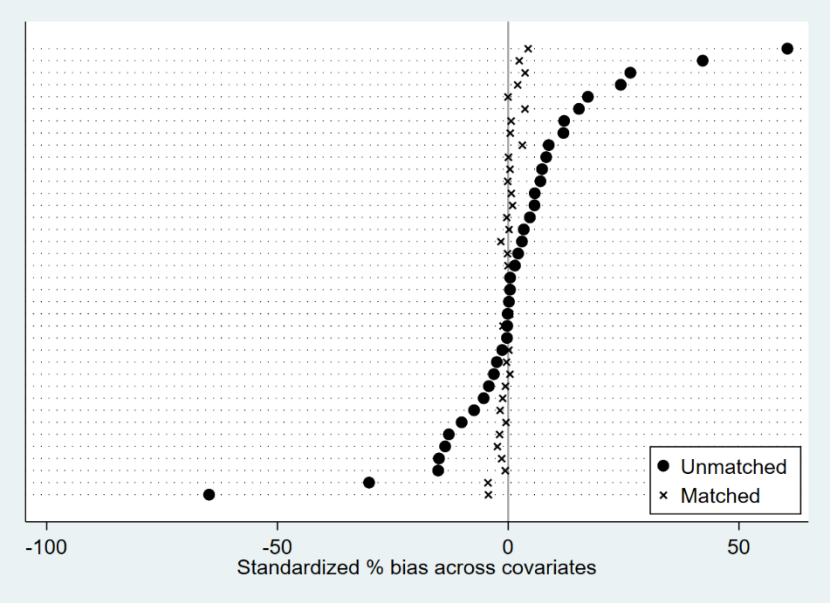
Checking whether the matching process has reduced the difference between the ETI, and non-ETI firms renders them comparable giving confidence in estimating the average treatment effect on the treated in the cDID. The matching process is incomplete if insufficient matches are found for all the treated firms in 2015. However, firms with a propensity score equal to zero cannot be matched. There are 1,489 ETI firms with a propensity score of zero that cannot be matched. Examination of these zero propensity score firms reveals no potential bias created by dropping them. This gives us confidence in proceeding with the cDID estimation to estimate the ATT. Overall, there are 18,352 ETI firms in our study sample, of which matched are found for 16,863 ETI firms representing 92% of study sample of ETI firms.

Examining the covariate means before and after matching ensures that any differences before matching have been reduced by the matching process. Figure 4.2 presents the standardised percentage bias across the covariates used in the matching process. This offers a graphical depiction of the covariate balance between the matched and unmatched groups using the kernel matching method. The standardised percentage bias is the percentage difference of the sample means in the treated and control (matched and unmatched) groups of firms.[24] A measure further away from zero suggests a large difference while a measure closer to zero represents a small or no difference. Visible from the graph are the large differences in some covariates between the treated and control groups before matching. These differences are reduced for the matched treated and control groups indicated by the bias close to zero for all the covariates. The same graph using the nearest neighbour matching method is presented in the chapter appendix section 4.7. The nearest neighbour matching also appears to reduce all the differences in covariates between the two groups.

[23] Our estimations are conducted using Stata 16 along with the "psmatch2" user-written module by Leuven and Sianesi (2003)

[24] The standardised percentage bias is a balancing score used to compare treatment and control groups. The standardised percentage bias is the percentage difference of means, in the two groups, as a percentage of the square root of the average of the sample variances in the treated and control groups (Rosenbaum & Rubin, 1983).

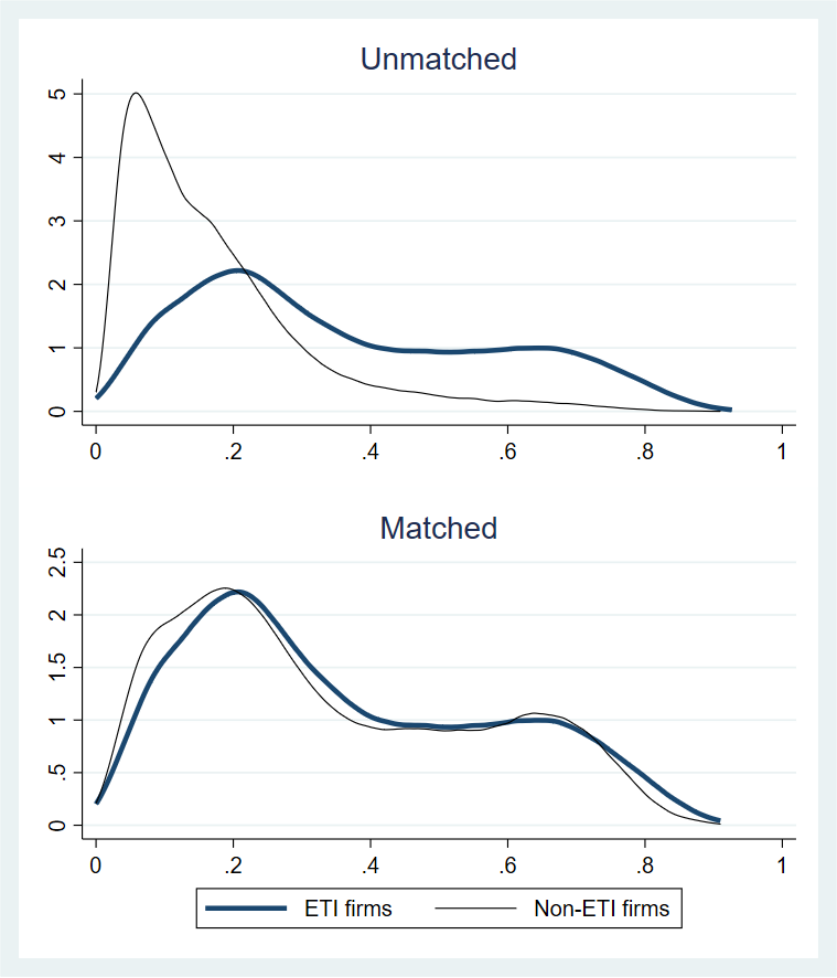
Figure 4.2 Covariate comparison using kernel matching



Notes: All covariates in the matching process are included. The full list covariates are included in Table 4-1.
Source: Author's own estimates using IRP5 and CIT data.

The requirement for the successful implementation of matching is sufficient overlap between the distributions of propensity scores for the treated and control groups. Figure 4.3 contains the distribution of the propensity scores for the unmatched and matched groups. The top panel indicates that there is sufficient common support suggesting matching on propensity score may be successful in removing any observable differences between ETI and non-ETI firms. In the lower panel, the matched group is displayed and the propensity score distribution of the ETI and non-ETI groups closely overlap. The same graph is prepared for the nearest neighbour matching and presented in Figure. 4.A.1 in the appendix. The comparison between ETI and non-ETI firms in the matched group is indistinguishable. Kernel matching is strengthened by the large group of non-ETI firms, but the nearest neighbour matching appears to further reduce any differences in comparison to the kernel matching. For this reason, both matching methods are presented in the next section.

Figure 4.3 Distribution of propensity scores for unmatched and matched groups



Notes: Matching is done in 2013, before the policy start.
Source: Author's own estimates using IRP5 and CIT data.

Finally, having confirmed the matching process has sufficient common support the next step is to conduction the cDID. The matched ETI and non-ETI firms feature in the main results regression which takes the following form:

$$Y_i = \alpha + \beta ETI_i^* + \gamma after_i + \boldsymbol{\delta}(\boldsymbol{ETI_i^* \cdot after_i}) + \varepsilon_{i,t} \qquad (4.16)$$

where Y_i is the outcome variable (employment) for firm *i*, ETI_i^* is an indicator variable with value equal to one where the matched firm is claiming the ETI and zero where the matched firms is not claiming the ETI. $after_t$ is an indicator set to one for the post policy period, 2015. The coefficient $\boldsymbol{\delta}$ of the DID interaction term, $\boldsymbol{ETI_i^* \cdot after_i}$ is the coefficient of interest which measures the impact of policy or the treatment effect.

4.5 Results

4.5.1 Conditional difference-in-differences estimation

This section estimates the effect of subsidy usage using the conditional difference-in-differences method and propensity scores calculated in the previous section. Table 4-2 displays the results from the conditional DID estimation for the matched sample and five firm size group subsamples. The coefficients represent the effect of claiming the ETI for youth employment, non-youth employment and total employment. The results represented the average treatment effect on the treated.

Table 4-2 Results of the cDID estimators from matched firms

	Youth		**Non-youth**		**Total employment**	
	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel
Matched sample (<1200 employees)	2.904*** (0.760)	2.897*** (0.759)	5.776*** (1.156)	5.772*** (1.157)	8.675*** (1.808)	8.663*** (1.807)
Micro firms (0-5 employees)	1.709*** (0.145)	1.647*** (0.138)	1.301*** (0.206)	1.236*** (0.194)	3.031*** (0.328)	2.899*** (0.311)
Small firms (6-10 employees)	2.353*** (0.301)	2.232*** (0.300)	2.048*** (0.439)	2.076*** (0.441)	4.411*** (0.708)	4.317*** (0.712)
Medium firms (11-50 employees)	2.656*** (0.182)	2.544*** (0.175)	2.581*** (0.260)	2.725*** (0.251)	5.253*** (0.396)	5.280*** (0.382)
Large firms (51-100 employees)	6.147*** (1.095)	5.977*** (1.081)	7.597*** (1.763)	7.672*** (1.748)	13.77*** (2.669)	13.67*** (2.648)
Very large firms (101-1200 employees)	12.22*** (3.638)	11.90*** (3.594)	19.80*** (6.017)	19.55*** (5.950)	32.13*** (8.777)	31.56*** (8.671)

Note: The 2014 tax year is excluded from the specification because the policy began at the end of the tax year. For the kernel estimates use the Gaussian kernel with a bandwidth of 0.06. Alternate bandwidths and kernel functions were checked with no significant difference on the estimates presented. The firm sample considered is indicated for each row. The coefficients of the dependent variables are the differences between the outcomes in 2013 and the differences in outcomes in 2015. The independent variables used in the cDID are the same variables used to estimate the propensity score in the matching stage. For the matched sample in Row (1), the explanatory variables are reported in Table 4-1. The common support restriction is imposed for both nearest neighbour and kernel matching estimates. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' own estimates based on IRP5 data.

The two columns present the estimated effects using nearest neighbour and kernel matching estimators. The results for the matched sample indicate a positive significant increase in youth employment under both matching specifications. This means that ETI-firms have between 2.897 and 2.904 additional youth employed in 2015 when compared with non-ETI firms. At the same

time, positive and significant increases for non-youth employees and total employees are seen at the firm.

The estimated effect on non-youth employment is larger than for youth employment. There are two possible ways non-youth can be affected by the policy. One, non-youth employment can decrease if youth are substitutes for non-youth workers and two, an increase in the demand for non-youth labour can be seen should the firm use the savings from the tax incentive to employ additional older workers with more experience (the technical details of the effect on non-youth is discussed in Section 2.4). The output effect would need to be larger than the substitution effect to enable an overall positive effect on the employment of non-youth. The elasticity of substitution must be low to see this large increase in the demand for non-youth. The larger, positive, significant result implies that the ETI enables firms to grow both youth and non-youth employment. It is possible that firms hire additional older worker they believe to be more reliable and less risky. Firms may choose to hire some eligible workers in order to the claim the tax windfall but fewer additional eligible workers if they believe eligible workers are riskier that older, ineligible workers.

The positive significant results for total employment that is greater than the result of the target group is similar to results found in other studies (Kaiser & Kuhn, 2016; Rotger & Arendt, 2010).

The assumption in the model above is that of a "constant effect" at the firm level, that the ETI affects our sample of firms in the same way (Holland, 1986). This assumption is checked by estimating the average treatment effect on firm size subgroups as the subsidy take-up rates differ by firm size. This can also be seen as a way of improving the matching method. In order to do so, firms are matched within firm size groups. If the estimated effects vary, then the constant effect of the policy is violated, and the size of the firms driving the effect of the overall result will becomes apparent. Additionally, Table 4-2 contains the results of the cDID estimation within firm size subgroups on youth, non-youth, and total employment estimates.

The results suggest significant increases in employment at each of the firm size groups examined. The effect on youth is larger than the effect on non-youth for the small and medium sized firms. Comparing the results to the literature, Crichton and Maré (2013) find an increase of 1.1 subsidised workers in firms with less than 50 employees in New Zealand and Rotger and Arendt (2010) find an increase of 0.26 additional workers in small subsidised firms. The estimates are larger which may be related the broad application of the subsidy (all except the public sector) and the nature of the target groups where the supply of young, low-wage workers is in abundance.

In the case of micro, large firms and very large firms, the coefficients for non-youth workers is larger than for youth employees. Crichton and Maré (2013) see a similar trend where the increase in unsubsidised workers is greater than the increase in subsidised workers.

Often the literature does not test the outcomes for the non-subsidised group, instead measuring the impact on the subsidised group and total employment at the firm. However, when tested, it is frequently the case, where an increase in employment of the subsidised group is found, there is an increase in total employment greater than the increase of the subsidised group (Hujer, Caliendo & Radic, 2002; Kaiser & Kuhn, 2016).

In summary, the constant effect assumption is violated. This means that for the sample of firms examined, the ETI does not affect firms in the same way. This matters if it is believed that job creation is important for certain firm size subgroups. Birch (1979) argues that job creation happens at small firms and not at large corporations when he analyses employment generation in the USA. In a later work, Birch, Medoff and Medoff (1994) claim that it is not all small firms that create jobs but a subset of small firms growing rapidly, which the authors term 'gazelles'. Henrekson and Johansson (2010) conduct a meta-analysis of the literature and find that the Birch, Medoff and Medoff (1994) assertion can also be found in 20 studies in developed countries. Henrekson and Johansson (2010) find that Gazelles create all or a large share of net new jobs and they are, on average, younger and smaller firms. The findings in Table 4-2 support the argument that small firms are part of the groups of firms creating jobs.

4.5.2 Alternate outcomes and displacement

Next, three further outcomes are examined to check the sensitivity of the results to the choice of dependent variables as well as any displacement that could have resulted from the policy. Bruhn (2016) estimates the log of total employment for a wage subsidy programme in manufacturing firms in Mexico. The author uses a similar matching DID approach and finds positive but not statistically significant effects ranging from 5.7 to 13.2 percent in magnitude. Kangasharju (2007) uses payroll as a proxy for total employment at the firm and finds positive statistically significant effects of a wage subsidy on payroll.

These approaches are adapted to estimate the effect of the ETI on the log of number of youth and total payroll at the firm. In addition, the impact on the youth ratio at the firm is estimated, that is, the ratio of youth to total employment. The results presented Table 4-3 below are in line with the results found in Table 4-2; there is a positive significant impact on the employment of youth and total employment.[25]

In terms of displacement, concern was raised by COSATU regarding the replacement of older workers as a result of the policy (COSATU, 2013). The subsidy makes youth relatively cheaper to

[25] It is possible for the youth to total employment ratio to increase while the number of non-youth also increases provided the increase in the number of non-youth is less than double than the increase in the number of youth.

hire than non-youth, which may induce displacement of non-subsidised workers (see Section 2.3.3 for further discussion on displacement effects). Displacement effects have been found in other programmes and it may be reasonable to assume displacement could take place as result of the ETI (Crépon et al., 2013).

If non-youth workers are considered as a substitute for youth workers, there may be a decline in the employment of non-youth workers. The opposite is seen in Table 4-2; where instead there us an increase in the employment of non-youth. Older workers have more years of work experience and are less risky to employ given their experience. Firms may be employing older workers to compensate for the lower productivity in younger workers.

Table 4-3 Alternate employment outcome

	Log number of youth		Log payroll		Youth ratio		Non-youth (30-40)		Higher wage youth	
	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel
All firms	0.108***	0.0552***	0.146***	0.146***	0.0552***	0.0552***	3.213***	3.210***	0.356***	0.356***
	(0.0164)	(0.00224)	(0.0177)	(0.0177)	(0.00224)	(0.00224)	(0.614)	(0.613)	(0.0701)	(0.0701)
Constant	1.198***	0.352***	13.91***	13.91***	0.352***	0.352***	7.312***	7.312***	0.407***	0.407***
	(0.00458)	(0.000826)	(0.00545)	(0.00545)	(0.000826)	(0.000826)	(0.0743)	(0.0743)	(0.00682)	(0.00682)
Observations	311,026	317,904	317,896	317,880	317,904	317,888	317,904	317,888	317,904	317,888
R-squared	0.165	0.030	0.098	0.098	0.030	0.030	0.069	0.069	0.027	0.027

Note: The 2014 tax year is excluded from the specification because the policy began at the end of the tax year. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' own estimates based on IRP5 data.

To the extent that it is believed that not all non-youth workers are substitutes for young workers, two additional groups of ineligible workers are examined that are more likely to be substituted by eligible workers: first, workers between the ages of 30 and 40 years old and second, age-eligible workers earning between R6,000 and R7,000. Among 18 to 29-year-olds, the policy is making a subset of them cheaper to hire. If youth earning just below R6,000 are substitutes for youth earning just above R6,000 then the policy will likely displace higher wage youth.

The results indicate a positive statistically significant increase in the number of 30-40 year olds employed. In terms of magnitude this is larger than the effect on youth seen in Table 4-2. For the higher wage youth, the effect is positive and significant, but the magnitude is much lower than for the broad category of youth. These positive results, together with the positive results for non-youth employment in Table 4-2 indicate no displacement of workers was induced by the policy.

4.5.3 Robustness

Included in the matching process is a variable calculating firm employment growth. This variable is included to ensure that the estimation does not count intended firm employment growth as a result of the policy. To examine this point more explicitly, positive-growth firms and negative - growth firms are examined separately. Employment growth is defined as the difference in employment between 2012 and 2013. Positive employment growth refers to firms with a positive growth in 2013, negative employment growth refers to firm with zero or negative employment growth 2013. The results for the two groups are presented in Table 4-4.

Table 4-4 cDID estimation, by employment growth

	Youth		Non-youth		Total employment	
	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel	Nearest Neighbour	Kernel
Positive growth	3.951***	3.267***	6.696***	6.823***	10.65***	10.07***
	(1.020)	(0.969)	(1.554)	(1.445)	(2.435)	(2.283)
Negative growth	2.295**	1.341	3.788**	3.014**	6.096**	4.359*
	(0.980)	(0.942)	(1.618)	(1.517)	(2.447)	(2.318)
Alternate control	2.846***	2.349***	4.992***	4.800***	7.839***	7.145***
	(0.775)	(0.704)	(1.211)	(1.079)	(1.874)	(1.683)

Note: The 2014 tax year is excluded from the specification because the policy began at the end of the tax year. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column (1) restricts the sample to positive growth firms while column (2) includes on negative growth firms.
Source: Authors' own estimates based on IRP5 data.

Estimation results for the growing and shrinking ETI firms are positive and significant for youth employment. The effect is less pronounced for shrinking firms and the kernel matching

specification is not significant. This helps us understand that it is not only positive growth firms creating jobs but the ETI is allowing even the negative firms to create jobs.

Lastly, a narrower control group of firms is considered; firms with at least one eligible youth but have not taken up the subsidy. The results are robust to this change in control group. The results from this subsection give some confidence that the initial results are not driven by the assumptions made to ensure a well-constructed comparison group.

4.5.4 Discussion

The results from the cDID are nested in the distribution of all firms claiming the ETI and our econometric assumptions. When all firms claiming the ETI are observed versus firms not claiming the ETI there appears to be an increase in youth employment. It is known from the descriptive statistics that small firms are reacting differently to the ETI than very big firms. Taking away the very big firms, a trend break emerges but this is at the cost of removing firms that claim about half of the ETI and represent the employment of half of the youth in the ETI firms in the study sample. Since credible matches for these firms are challenging to find, it is not possible to confirm or deny whether these firms are creating any jobs or not. The cDID estimation for very large firms shows a positive significant result for the employment of youth suggesting that it may be possible for firms with more than 1,200 employees to be creating jobs. This leaves behind a group of firms that are large in number but do not represent the bulk of the ETI claim.

In the slightly broader context of youth employment, it does not matter whether small firms or large firms are creating jobs; what matters is that jobs for low-wage youth are being created. The policy could be better targeted to smaller and medium size firms that are creating more jobs.

To put the findings into context, the cost of the policy vis-à-vis the number of jobs created for youth is studied. Estimates from Table 4-2 are used to calculate the number of jobs created by multiplying the cDID estimate by the number of ETI firms in the category. This amounts to 50,370 new jobs created in the 16,863 firms that claimed the subsidy in 2015 and were matched for the analysis. Adding up the amount of ETI claimed by these firms then dividing the amount by the number of jobs created gives a cost of R11,704 per job created. The National Treasury, in its public discussion paper, predicted that 423,000 jobs would be subsidized and 178,000 jobs would be created over three years (National Treasury, 2011). If it is considered that for each year of the policy, 59,333 jobs were supposed to be created annually ($178{,}000 \div 3 = 59{,}333$) then according to the firm matching analysis, the number of jobs created is below the target.

4.6 Conclusion

There is a small body of literature evaluating the effect of wage subsidy policies on labour demand using administrative data. This chapters adds to this literature through the examination of the ETI as a policy intervention on labour demand in a developing country. This chapter makes use of administrative tax data, with the population of firms, to estimate the effects of the ETI on employment at firms in South Africa. Changes in the youth labour market are examined using a conditional difference-in-differences approach where firms are matched in terms of pre-policy firm characteristics.

Considering the effect of the ETI in all firm in the study sample a positive significant change in the number of youth employed is seen in the 2015 tax year. ETI firms have 2.897 additional youth compared to non-ETI firms as a result of the policy.

The findings are difficult to take up by firms of different sizes was different and it is understood that firms of different sizes reacted differently to the ETI. For example, it is possible that the reasons for not taking up the subsidy for a micro or small firm differs from, the reasons of a large firm. The positive ATT is limited to the firms that were matched in the analysis (firms that existed from 2011 with fewer than 1,200 employees).

The estimated impact of the ETI on firm employment is larger than estimates for similar programmes in other countries. Crichton and Maré (2013) estimate the impact of a wage subsidy programme in New Zealand and show that firms with less than 50 employees increase employment by 1.09 additional persons. The largest impact is 1.57 for firms with more than 250 employees. Kaiser and Kuhn (2016) estimate an impact of 0.458 additional workers for the highly skilled group that were subsidised in Danish firms.

When broken down into different firm size categories, firms employing up to 1,200 workers have a positive significant effect on youth employment. The methods used do not enable credible matches for firms with more than 1200 employees as the take-up rate for these very large firms is very high, leaving few very large non-ETI firms with which to match.

The increase in total employment is greater than the estimation of the increase in youth employment for the overall and subgroup estimations. This is in line with other international studies implying that wage subsidies enable firms to grow their total employment.

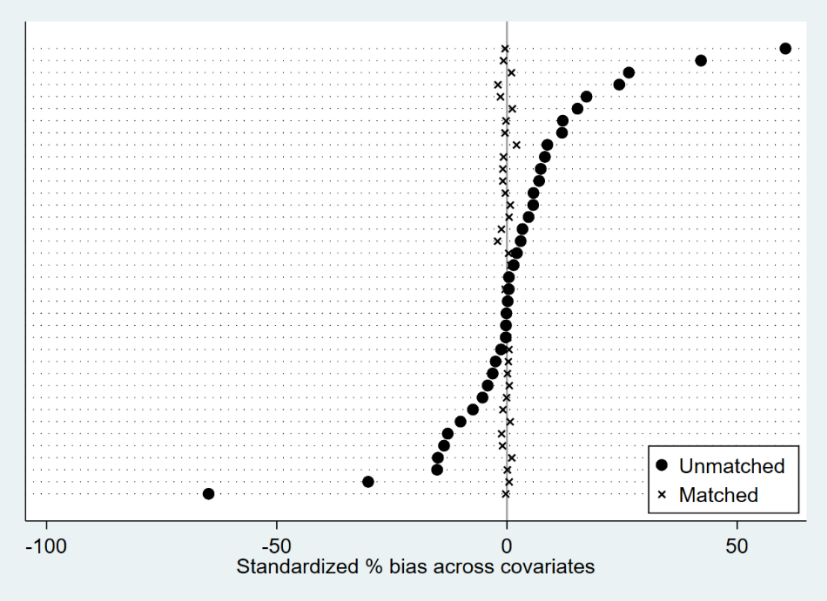
Other outcomes of the policy, log of youth employment, log payroll and youth ratio, all indicate positive significant results suggesting that among the firms matched there is an increase in youth employment. No evidence of displacement of older workers is found as a result of the policy. Lastly, the chapter considers the growing and shrinking firms. Estimates remain positive indicating that the main estimates are not being driven by firm employment growth.

These findings suggest that the youth wage subsidy may be an effective tool for increasing the demand for youth at small to medium size firms. The positive, statistically significant results for non-youth indicate that firms are not laying off workers in order to employ youth and benefit from the subsidy. The number of jobs created relative to the cost of policy in 2015 leaves questions about the efficiency of the policy. Future work on estimating the impact of the ETI at the firm level should check if there is a trend in the effects over time and consider the timing of the firm take up of the subsidy.

4.7 Appendix

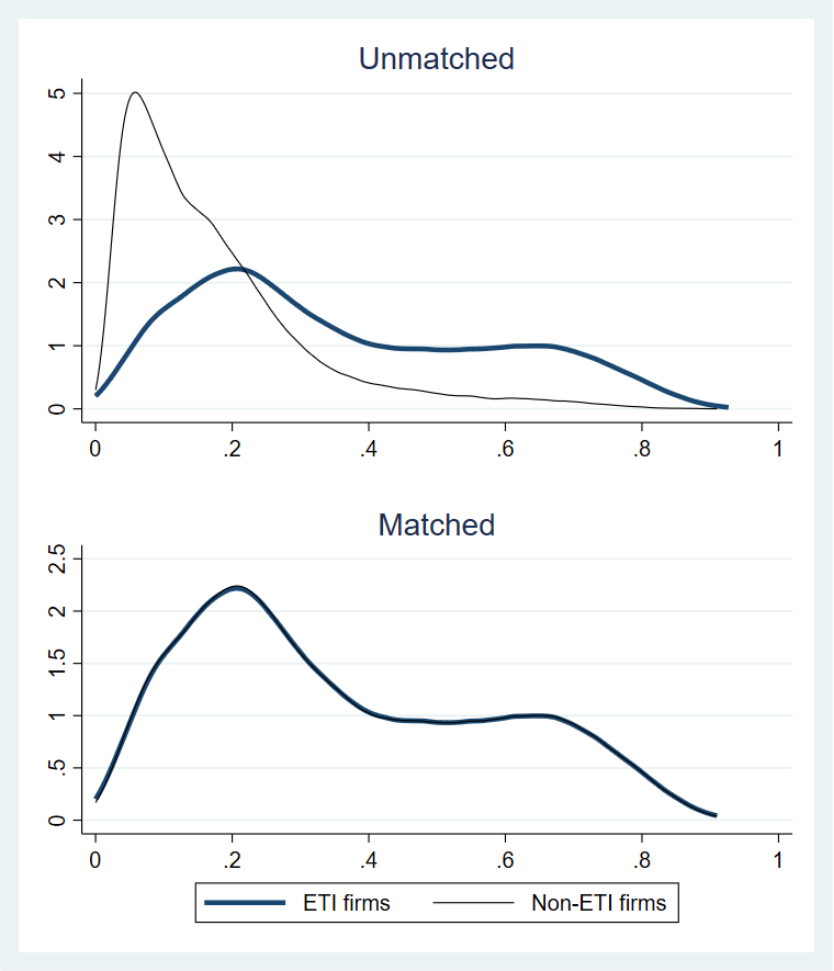
Appendix 4.A Nearest neighbour matching balance

Figure. 4.A.1 Covariate comparison using nearest neighbour matching



Notes: The graph shows the standardized percentage bias for each covariate used in the nearest neighbour matching process, before and after matching.
Source: Author's own estimates using IRP5 and CIT data.

Figure. 4.A.2 Propensity score for matched and unmatched groups.



Notes: The graph shows the distribution of propensity score for ETI and non-ETI firms. The top panel compares the propensity scores between unmatched firms while the bottom panel compares the propensity scores for matched firms.
Source: Author's own estimates using IRP5 and CIT data.

Chapter 5. Individual-level responses to a firm-side subsidy

5.1 Introduction

The consensus view in the earlier economic work on the impacts of wage subsidies (such as Gruber (1997)) suggests that since labour demand is typically more elastic than labour supply, the incidence of wage subsidies (or payroll tax reduction) falls on the employees. This means that earnings rise and the final gross wage cost to the employer is not affected. Hence, employment does not react either. However, recent work in Colombia (Kugler & Kugler, 2009), Greece (Saez, Matsaganis & Tsakloglou, 2012), France (Cahuc, Carcillo & Le Barbanchon, 2019), and Sweden (Saez, Schoefer & Seim, 2019) indicate the opposite effect: earnings are not affected and hence the incidence is (mostly) on employers, opening up a way to positive employment impacts.

One would need to know how employment subsidies work in an emerging economy such as South Africa. It is also important to examine whether the positive view on the cost effectiveness of hiring subsidies expressed in Brown (2015) and Brown and Koettl (2015) remains valid in the present case.

This chapter contributes to the literature by examining the efficiency of wage subsidies in an emerging market context, where the capacity to administer the system (both in firms and within the administration) may be less perfect than in high-income countries. The sheer size of the unemployment crisis also makes evaluating the efficiency of the policy pressing. The maximum duration of the subsidy is 24 months, which means that the system is a hybrid between a (short-term) hiring subsidy and a more permanent system. The policy was originally planned to last for three years, was subsequently extended for another two years, and has been extended for ten more years. This chapter uses labour market survey data and the universe of payroll tax data from the South African Revenue Service (SARS) to examine the impacts of the system.

Since the system has been targeted at both low-wage and young workers, any differential trends that have affected either young workers or low-wage workers can be separated out in a triple differences identification strategy. There are some earlier studies evaluating the South African ETI policy which is covered in Section 2.3.4. Relevant to this chapter is the study by Ranchhod and Finn (2015). The authors compare the development of youth and non-youth employment over time in a difference-in-differences (DID) fashion, but only for the first year after the reform.

One dimension not yet examined by previous ETI studies is the labour market outcomes of individuals eligible for ETI jobs. Little is known about the youth who entered jobs supported by the ETI system due to the paucity of data available. This chapter seeks to answer how a young person gets a job, where the employer is eligible for ETI and compare to the employment and earnings of youth in the absence of the policy. However, potential earnings cannot be observed

for the unemployed or those not entering ETI jobs, to make the comparison between the two groups. To get around this problem, predicted earnings are used instead of actual earnings from the PALMS data.

This chapter utilizes a triple differences approach (DDD), which uses exogenous or predicted characteristics of individuals to isolate the causal effect of the tax change on employment outcomes such as earnings, entry into employment, separations and number of days worked. The strength of a DDD over a difference-in-difference approach is that trends that may differently affect the treatment and control groups in a DID estimator are differenced out in a DDD estimator. The ETI was implemented when the South African economy was facing severe challenges in the labour market. It is possible that if employment downturns disproportionally affect young workers, a DID estimator would pick up this development. This would lead to a downwards biased estimate. The DDD estimate is robust to such trends since confounding impacts that only affect low-paid young workers would bias the estimate.

The key assumption in a DID estimator is the common trend assumption; that the treated and control groups evolve in the same way in the absence of the policy. The key assumption in the DDD estimator is that there is no additional shock during the treatment period that affects the demand for the treated and control groups.

The identification in this chapter is based on the eligibility of workers, that is, I am mainly interested in the intention-to-treat (ITT) estimates, which identify the programme impacts, including the part that stems from partial take-up. This is also the first study to examine the earnings incidence of the policy.

The chapter proceeds as follows. Section 5.2 presents the theoretical framework, Section 5.3 presents the data used and some descriptive statistics and Section 5.4 shows the empirical strategy. The results from the survey data are presented in Section 5.5, and the results based on administrative data are available in Section 5.6 with Section 5.7 concluding.

5.2 Theoretical framework

Wage subsidies can be offered either to the job seeker or to the firm. A subsidy can be claimed by a job seeker once employment has been found. Also known as worker-side subsidies, wage subsidies offered to job seekers aim to increase labour supply in the market and are often seen in developed countries. Such policies include the Earned Income Tax Credit in the United States, Working Families' Tax Credit in Britain, the Self-Sufficiency Project in Canada, and other programmes in Australia, New Zealand, Finland, Ireland, and Belgium (Smith, 1993).

Firm-side subsidies are subsidies given to firms when the firm employs individuals eligible for the subsidy. The aim of a firm-side subsidy is to incentivise firms to hire eligible individuals they would otherwise not be interested in hiring. A wage subsidy decreases the cost of employing an individual without altering the amount that the individual is paid. This allows firms to increase employment of the subsidized group and output, leaving the wages of the subsidized individual unchanged. The elasticity of labour demand and the amount of the subsidy determines the increase in employment at a firm. Of the two types of subsidies, the firm-side subsidy fits the South African context as it deals with the demand for youth labour where the youth labour supply is already high.

In recent years, tax credits have been discussed as a policy tool for reducing the cost of hiring groups with high unemployment rates. The policy discussion in South Africa is simple; targeted tax credits can boost employment of youth. Although firms could potentially pocket the tax credit as economic rent or release older workers in order to hire younger workers, the policy includes a penalty levied to firms found engaging in these practices.

5.3 Data

Two different datasets are used to investigate the impacts of the reform: the tax data complimented with the Post-Apartheid Labour Market Series (PALMS) data. PALMS 3.3 is a publicly available dataset from DataFirst at the University of Cape Town (Kerr, Lam & Wittenberg, 2019). The PALMS dataset provides consistent and harmonized survey information about employment and wages and is representative of the population. The survey data is used to estimate the effect of the subsidy on employment and unemployment rates and number of hours worked. The strength of the survey data lies in the richness of the many demographic variables available.

This chapter also makes use of the panel of individual level tax data derived from the IRP5 records described in Chapter 3. The panel is based on the PAYE reports (IRP5 forms) submitted by employers to SARS. The data are population wide with detailed information about earnings, as well as the actual ETI use status. However, the administrative data only have information about gender and age and possess no other demographic characteristics such as race or education level that would be useful in labour market analysis in South Africa. These data cover the tax years 2011 to 2018 and is used to measure earnings, labour market transitions and number of days worked. Both datasets are used to examine the extensive and intensive margins.

The use of tax data is advantageous for the examination of the earnings incidence as a results of the ETI. The subsidy is claimed through a reduction in taxes owed to SARS, which means there are records of these claims for every firm that claimed the subsidy. The subsidy is available to all firms registered for PAYE and the tax data represents the entire population of PAYE firms

irrespective of their claim on the subsidy. The data are panel in nature, which allows us to observe formally employed individuals before the start of the subsidy and during implementation.

The primary disadvantage of using tax data is its lack of demographic information and for this reason the survey data is used to compliment the tax data analysis. The remainder of this section provides descriptive statistics for the survey and tax data.

5.3.1 PALMS data

As a first step, all public sector and informal workers are removed from the data. As the subsidy is claimed through the tax system, it is not possible for firms to claim for informal workers. The subsidy was designed to stimulate job growth in the formal sector making public sector workers ineligible. The period of data used is from 2010 to 2018.[26] A low wage indicator is created for those earning less than R6,000 per month and the sample is restricted to those between the ages of 18 and 35 years old to identify the target population and a comparison group.

Table 5-1 Descriptive statistics for estimation sample

Variable	N	Mean	Standard deviation	Min	Max
Age	687,266	25.65	5.139	18	35
Hours worked	161,364	44.23	11.23	0	140
Years of education	682,737	10.68	2.385	0	17
Real Earnings	131,325	10,714	247,922	0	1.236e+08
Predicted earnings	682,737	3,145	2,522	874.3	37,908
Employed	687,266	0.255	0.436	0	1
Unemployed	687,266	0.358	0.479	0	1
Female	687,266	0.511	0.500	0	1
Married	687,266	0.212	0.408	0	1
Urban	687,266	0.647	0.478	0	1
Black	687,266	0.827	0.378	0	1
Coloured	687,266	0.0829	0.276	0	1
White	687,266	0.0650	0.247	0	1
Indian	687,266	0.0252	0.157	0	1

Note: The table displays number of observations, the mean, the standard deviation, minimum and maximum for a set of variables in survey dataset.
Source: Author's own estimates using PALMS v3.3.

In the survey data, there are three main variables of interest: *employed*, *unemployed* and *hours worked*. Table 5-1 provides summary statistics for these and other variables used in the analysis. The variable *Employed* takes the value one if the individual is classified as employed irrespective of the sector of employment. The variable is created from the employment status question in the

[26] While the first year of tax data examined is 2011, this covers the period 1 March – 31 December 2010 making the 2010 survey year comparable to the 2011 tax year.

Quarterly Labour Force Survey (QLFS). Similarly, the *unemployed* variable takes on the value of one if the individual is unemployed defined using the broad definition of unemployment, also from the employment status question in the QLFS. *Hours worked* refers to the number of hours worked in the last week. The age variable allows us to determine whether an individual is eligible for the subsidy or not and allows us to construct a control group from those just above the eligibility age. Race, gender, urban or rural location, marital status and years of education are also used in the analysis.

5.3.2 Tax data descriptive statistics

The take-up behaviour provides a backdrop for the analysis, as it indicates among which population groups the intention-to-treat impacts may be the greatest. Table 5-2 provides a breakdown of ETI take-up by year, gender, and age. It also displays those sectors where the take-up rate has been the highest. The mean take-up rate is somewhat higher among women. It is also much greater among younger workers in the eligible age group and among typical low-wage sectors, such as agriculture and retail. Perhaps the most pertinent feature which emerges from the table is that the take-up rate has been steadily increasing over the years. Based on this information, it is expected that the impacts could be greatest among the younger age groups during the latest years. This is taken this into account in the empirical approach by using year fixed effects and consider analysing subgroups separately. The treatment impact varying over the years is captured when including the year fixed effects.

Table 5-2 ETI take-up characteristics

	ETI eligible	ETI claimed	Take-up
By tax year			
2015	2,692,550	810,834	30 %
2016	2,594,056	1,002,556	38 %
2017	2,468,684	1,101,897	44 %
2018	2,241,741	1,110,552	49 %
By industry			
Wholesale and retail	2,129,276	1,033,152	48 %
Agriculture	1,640,091	772,088	47 %
Catering and Accommodation	524,519	220,028	41 %
Finance and Insurance	2,185,919	909,073	41 %
Water services	21,397	8,571	40 %
By gender			
Female	4,810,189	1,938,743	40 %
Male	5,726,930	2,224,692	38 %
By age			
18	103,443	44,609	43%
19	368,572	169,196	46%
20	591,857	271,793	46%
21	796,736	356,985	45%
22	967,798	421,122	44%
23	1,087,015	461,971	42%
24	1,145,347	471,593	41%
25	1,144,478	453,438	40%
26	1,115,514	422,390	38%
27	1,070,455	385,531	36%
28	1,022,823	349,216	34%
29	972,197	308,681	32%

Notes: The table displays the number of ETI eligible workers, the number of ETI claims and the take up rate (ETI claimed divided by ETI eligible) by tax year, industry, gender, and age group.
Source: Author's calculations using IRP5 data.

The years in the survey data relate to the calendar years. Since the 2014 year in the survey data relates to a full policy year this year of data is kept in the survey data analysis. The 2014 calendar year overlaps by 10 months with the 2015 tax year.

5.4 Empirical approach

The ETI is likely to affect employment at the extensive margin (i.e., whether an individual works or not) and the intensive margin (the wages and working hours of workers already employed).

The main approach is to estimate the intention to treat (ITT) or the impact of being eligible on the subsidy, using a triple differences (DDD) strategy. The approach is similar to Huttunen, Pirttilä and Uusitalo (2013) and is described as follows:

$$Y_{i,t} = \beta_0 + \beta_1 youth_i + \beta_2 low_i + \beta_3 after_t + \beta_4 youth_i low_i + \beta_5 youth_i after_t + \beta_6 low_i after_t + \boldsymbol{\beta_7 youth_i low_i after_t} + \epsilon_{i,t} \quad (5.1)$$

where $Y_{i,t}$ is the outcome variable (such as earnings or employment) for individual *i* in year *t*, $youth_i$ is an indicator variable with value equal to one if the individual is at most 29 years old, low_i is an indicator of whether the individual belongs to the low-wage group, and $after_t$ is an indicator set to one for the years after the reform. The coefficient β_7 of the triple interaction term, $youth_i low_i after_t$, is the coefficient of interest which measures the impact of being eligible for the youth wage subsidy system. A simpler DID strategy, where the interest is about the term $youth_i after_t$ would limit the analysis to the impact on all young workers.

The DDD uses both a different state and control group within the treatment state, a more robust analysis than the DID estimation where there are possible changes in the environment that could affect the treatment group differently to the control group. A DDD is suitable to the evaluation of the ETI as the subsidy is available to a subset of workers: defined both by age and wage.

The OLS estimate β_7 can also be expressed as follows:

$$\beta_7 = \left(\bar{Y}_{youth,low,after} - \bar{Y}_{youth,low,before}\right) - \left(\bar{Y}_{non-youth,low,after} - \bar{Y}_{non-youth,low,before}\right) - \left(\bar{Y}_{youth,non-low,after} - \bar{Y}_{youth,non-low,before}\right)$$

where

$\bar{Y}_{youth,low,after} - \bar{Y}_{youth,low,before}$	denotes the difference in outcome between low-wage, youth before and after the policy
$\bar{Y}_{non-youth,low,after} - \bar{Y}_{non-youth,low,before}$	denotes the difference in outcome between low-wage, non-youth before and after the policy
$\bar{Y}_{youth,non-low,after} - \bar{Y}_{youth,non-low,before}$	denotes the difference in outcome between non low-wage, youth before and after the policy.

The identifying assumption is that there are no differential trends that would have affected young low-wage workers differently than older low-wage workers or higher-wage young workers. The difference-in-difference-in-difference (DDD) approach can control for simultaneous changes that affect *all* young or *all* low-wage workers. The first control group is constructed by defining non-youth as those just above the age eligibility criteria, that is, 30 to 35 years old. The second control group is defined as youth as those with earnings just above the eligibility criteria, that is, earning between R6,000 and R9,000 per month.

The challenge in this analysis is that the earnings level is only observed if the individual is working. As a solution to this, in the PALMS analysis, predicted income is used based on pre-

reform data, using a model with age, race, gender, and years of education as regressors. This approach provides a good predictor of individuals' earnings, since the income levels differ markedly between socioeconomic groups (see Table 5-3). The *low* dummy takes a value of one if the predicted income is less than R6,000, in line with the policy wage eligibility criteria.

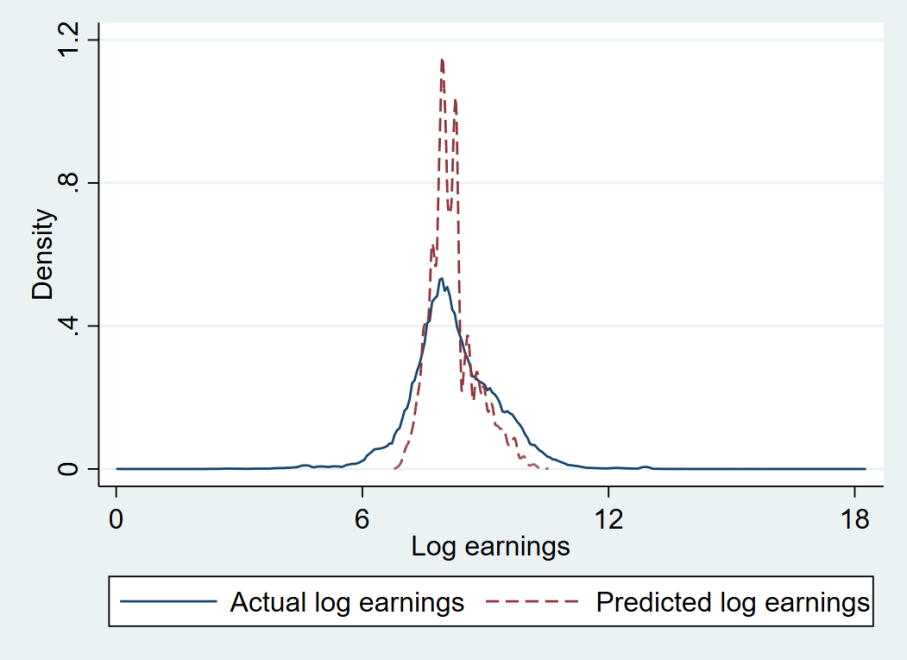
Table 5-3 Pre-reform shares of youths

	Africans		Non-Africans	
	Men	**Women**	**Men**	**Women**
Low education	0.82	0.93	0.64	0.80
High education	0.55	0.63	0.24	0.31

Note: The table shows the pre-reform share of youth within race, education, and gender groups. The sample is restricted to those with wage less than R6,000.
Source: Authors' own estimates based on the PALMS 3.3 data.

Figure 5.1 checks the predicted earnings against actual earnings. Around 75% predictions are correct, that is, for those who have income, they are low wage if they are predicted to be and not low wage if they are not predicted to be low wage.

Figure 5.1 Predicted versus actual log earnings.



Notes: The graph compares the actual log earnings to the predicted log earnings.
Source: Author's own illustration using PALMS 3.3 data.

The model overpredicts the prevalence of low wage. The predicted earnings distribution is narrower than the actual earnings distribution. We check the means of the background characteristics used to calculate the predicted earnings. The examination is done by quartile and reported below.

Table 5-4 Means characteristics by predicted earnings quartiles.

Quartile	Female	Black	Low education
1	0.64	0.95	0.96
2	0.58	0.92	0.42
3	0.54	0.92	0.11
4	0.32	0.57	0.03
Total	0.51	0.83	0.36

Note: The table displays the mean for gender, race group and education level by predicted earnings quartiles.
Source: Authors' own estimates based on the PALMS 3.3 data.

From the table we can see that those in the first quartile of the predicted earnings distribution capture the disadvantaged youth for which the ETI is aimed at. In the analysis using tax data the lack of demographic variables does not permit predicted earnings to be used. However, the missing earnings problem does not arise as the data is made up of everyone formally employed in the country. While it is recognized that the earnings can be endogenous, the actual wage rates are used to divide workers into low-wage and higher-wage categories.

Where possible, an instrumental variable (IV) strategy is implemented by using eligibility as an instrument for the subsidy claim. This is a Wald estimate, where the intention-to-treat (our DDD estimate) is multiplied by the inverse of the take-up rate. Hence, the IV can only be statistically significant when the intention-to-treat is significant.

Finally, we include a specification using year fixed effects in equation (5.2), a modification of equation (5.1). This is to account for the increase in take up of the policy each year. The estimation equation is as follows:

$$Y_{i,t} = \beta_0 + \beta_1 youth_i + \beta_2 low_i + \beta_4 youth_i low_i + \sum_{\tau=-4}^{4} \delta_\tau year_t + \sum_{\tau=-4}^{4} \eta_\tau youth_i year_t + \sum_{\tau=-4}^{4} \theta_\tau low_i year_t + \sum_{\tau=-4}^{4} \boldsymbol{\lambda_\tau youth_i low_i year_t} + \epsilon_{i,t} \quad (5.2)$$

No statistical significance for $\boldsymbol{\lambda_\tau}$ for the period $\tau \in [-4, -1]$ provides support to the assumption of no pre policy trends.

Identification in the analysis comes solely from the difference between treated (eligible) and untreated (ineligible) individuals over time and not from individuals going between treatment and control groups. This means this research does not suffer from the identification issues in typical event-study estimation using only the treated unit nor the issues from DiD with staggered treatment (Borusyak & Jaravel, 2017; Goodman-Bacon, 2018). The estimation results, λ_τ, from equation (5.2), are plotted to illustrate the effect of the policy on the outcomes of interest over time.

We include a specification using clustered standard errors in for equations (5.1) and **Error! Reference source not found.**. The motivation for clustering is that there may be unobserved parts of the outcomes for individuals within clusters which are correlated (Bertrand, Duflo & Mullainathan, 2004; Moulton, 1990). This may be a problem in our analysis and there is no single accepted way to address this challenge (Cameron & Miller, 2015). In an attempt to address the issue that eligibility for the ETI may be clustered, estimates with clustered standard errors are presented. Clustering at the level of treatment would, however, provide too few clusters. Since the extent of the treatment, the actual ETI amount, depends on the income level, clustering is done at the level of R500 income groups and age (younger and older workers). Results for regressions with clustered standard errors are reported in all tables.

The analysis is conducted for all eligible workers as well as for various sub-groups: men and women to examine whether there are any gendered effects of the policy, younger (18-24 year olds) and older cohorts (25-29 year olds) given the difference in unemployment rates of these two groups described in Figure 2.1, and by earnings level (below 2,000; 2,000-4,000, 4000-6000) in line with the ETI claim value structure outlined in Figure 2.2.

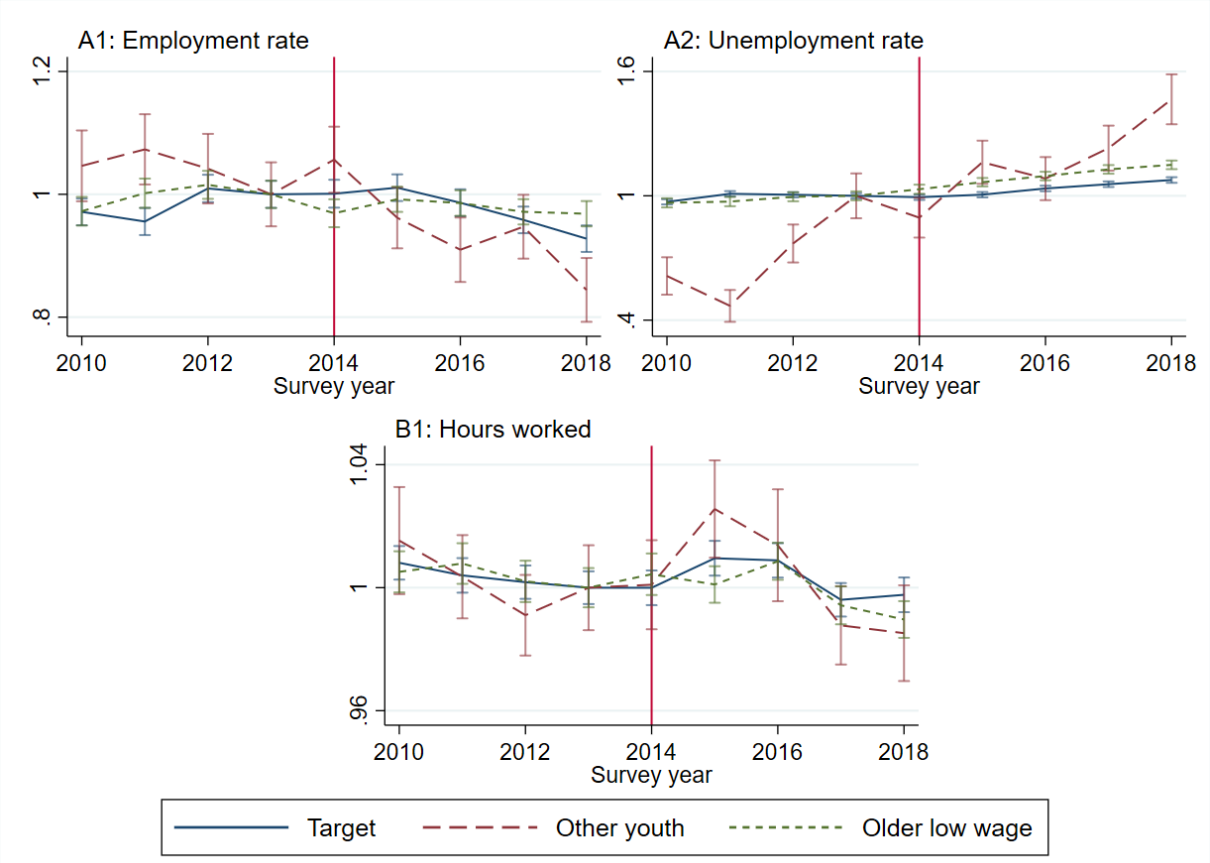
The next section examines employment, unemployment and number of hours worked as outcomes in the survey data.

5.5 Results using survey data

The intention-to-treat impacts of the policy on employment, unemployment and number of hours worked are examined in this section. Figure 5.2 provides graphical information about the trends in our outcomes of interest in the survey data. The graphs are normalised in 2013, before the policy start and make comparisons between the eligible group of workers and the two control groups, namely the higher wage youth and older low wage workers.

Figure 5.2 Panel A1, which describes the employment rate, suggests no trend break for the employment rates of the target group of low-wage young workers. There appears to be a small increase in employment rates in 2015 in comparison to control groups, but it decreases thereafter.

Figure 5.2 Normalized outcomes for target group and control groups.



Notes: The figures display the mean outcomes for employment, unemployment and hours worked. Mean outcomes are normalized to one for 2013 to adjust for the level differences across the three groups: target, other youth, and older low wage Only the private, formal sector is examined as the subsidy is limited to the private sector only. Low-wage status is based on predicted earnings. Older low wage is defined as workers between the ages of 30 and 35 years old with wages less than R6,000. Other youth is defined as workers earning between R6,000 and R9,000 between the ages of 18 and 29 years old. Corresponding regression estimates are provided in Table 5-5.
Source: Authors' own estimates based on PALMS v3.3.

Panel A2, describing the unemployment rate, suggests that there has been no trend break in the unemployment rate for low wage young workers when compared to both control groups. While

the unemployment rate is increasing in the treatment years, the rate of increase appears to be slower than both control groups.

As discussed in Section 2.3, the subsidy is offered to both part-time and full-time workers. Since firms can respond to the ETI by employing young workers for more hours than they were previously able to, the number of hours worked can be used to examine the effect of the policy along the intensive margin. The results are captured in Panel B1 of Figure 5.2. The graph does not suggest any trend break for the target group. Next, the DDD estimation results from Figure 5.2 are presented in Table 5-5.

Column (1) and (2) present results on employment, columns (3) and (4) on unemployment and columns (5) and (6) on hours worked. For each outcome, the results are presented for the ETI indicator corresponding to equation (5.1) in Panels 1 to 3 and year-specific treatment effect corresponding to equation **Error! Reference source not found.** in Panel 4. We further analyse a subgroup of individuals where the predicted income does not perform as well. That is, we drop quartiles 2 and 3 from the predicted earnings distribution where the predicted earning is greater than actual earnings even though the percentage of incorrect predictions is only 25 per cent. The results for this specification are presented in columns (2), (4) and (6).

The basic DDD estimated in Panel 1 shows that there is no significant change in employment rates. There is a small negative significant effect on unemployment rates and no change in number of hours worked. The subsequent panels consider other specifications as robustness checks. In Panel 2, differential pre-existing trends between the treatment and control groups are controlled. Potential differences in pre-trends are removed by estimating the trend from pre-reform data, predicting it for the post-reform years and subtracting this prediction from actual outcomes. The estimates are slightly greater for the effect on unemployment. Panel 3 uses clustered standard errors where the clustering is done by income level and age. The standard errors are large with the clustering and any significant results from Panel 2 are lost in Panel 3. Panel 4 displays the year-specific treatment effects for each outcome. There appears to be a positive significant increase in employment for the eligible group in 2016 and a negative significant impact on unemployment in the same year. This also corresponds to an increase in take up of the policy shown in Table 5-2.[27] There are two possible reasons why this may be the case. The first phase of the policy was set to end in 2016 and firms may have increased their take up of the policy to ensure they were able to benefit from it. Late in 2016, the government announced the extension of the ETI which may also have spurred a change in behaviour as firms would be able to benefit from the subsidy for a longer period.

[27] The 2016 calendar year in the survey data is captured in the 2017 tax year.

The second specification in columns (2), (4) and (6), limiting results to the first and fourth quartile of the predicted income distribution, are very similar to the main results in columns (1), (3) and (5) which suggest that there have been no significant employment gains for low-wage youth, small decreases in unemployment and no overall increase in the number of hours worked by the target group.

The switching of signs and changes in significance across the panels may also be a result of heterogeneous effects within the target group due to the design of the policy. The next subsection covers these possible heterogeneous effects.

Table 5-5 DDD estimation on employment, unemployment and hours worked.

	Employment rate		Unemployment rate		Hours worked	
	(1)	(2)	(3)	(4)	(5)	(6)
1: **Basic DDD**						
	0.0037	0.0043	-0.0495***	-0.0428***	0.3123	0.3764
	(0.0124)	(0.0128)	(0.0105)	(0.0110)	(0.3078)	(0.3262)
2: **control for pre-existing trends**						
	0.0045	0.0054	-0.0499***	-0.0430***	0.3146	0.3607
	(0.0124)	(0.0128)	(0.0105)	(0.0110)	(0.3077)	(0.3261)
3: **clustered standard errors**						
	0.0045	0.0054	-0.0499	-0.0430	0.3146	0.3607
	(0.0277)	(0.0309)	(0.0304)	(0.0308)	(0.4652)	(0.4917)
4: **year-specific treatment effects**						
x 2014	-0.0259	-0.0336	0.0253	0.0330	-0.5636	-0.5546
	(0.0247)	(0.0255)	(0.0215)	(0.0225)	(0.6199)	(0.6581)
x 2015	0.0228	0.0219	-0.0377*	-0.0164	-0.7023	-0.5220
	(0.0255)	(0.0263)	(0.0226)	(0.0235)	(0.6654)	(0.7040)
x 2016	0.0697***	0.0699***	-0.0603***	-0.0438*	-1.0916	-0.6748
	(0.0257)	(0.0265)	(0.0226)	(0.0236)	(0.6705)	(0.7090)
x 2017	-0.0019	-0.0032	-0.0387*	-0.0326	0.1125	0.2716
	(0.0261)	(0.0269)	(0.0232)	(0.0243)	(0.6554)	(0.6969)
x 2018	-0.0158	-0.0210	-0.0470*	-0.0314	0.5578	0.8451
	(0.0266)	(0.0274)	(0.0241)	(0.0251)	(0.6859)	(0.7220)
Observations	663,985	323,416	663,985	323,416	143,311	79,493

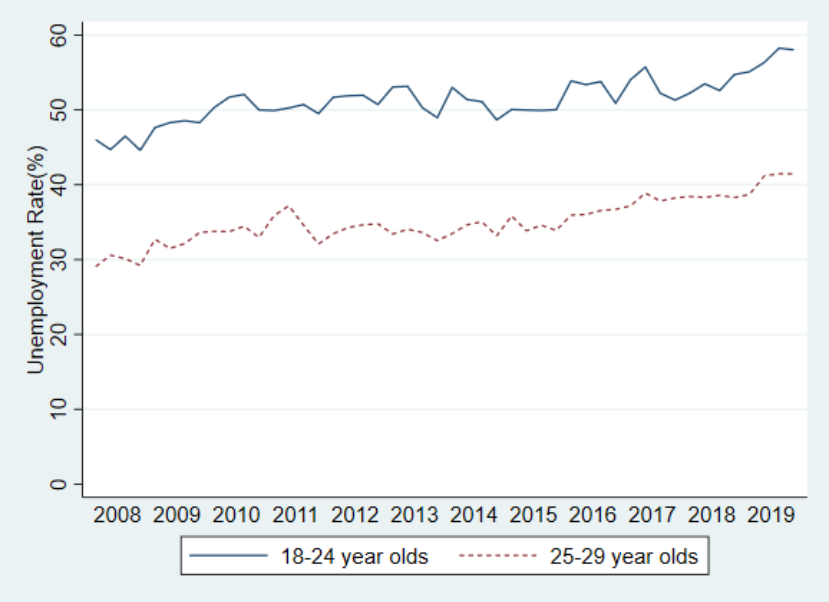
Notes: The table presents DDD estimation results for the employment rate, unemployment rate and number of hours worked. Estimates are based on equation (5.1) in Panels 1-3 and equation (5.2) in Panel 4. ETI dummy is an indicator for an ETI eligible worker. Panel 1 is the basic DDD estimate. Panel 2 controls for differential pre-existing trends for the treatment and control groups. Panel 3 uses clustered standard errors where clustering takes place at the level of R500 income groups and age (younger and older workers). Panel 4 presents the year-specific treatment effects estimations. Robust standard errors in parentheses for Panels 1, 2 and 4. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' own estimates using PALMS v3.3.

5.5.1 Gender and age cohort analysis

The analysis of subgroups is motivated by the ETI take up characteristics presented in Table 5-2. First, any differences in outcomes between men and women in the target group are considered. Next, younger, and older cohorts are considered within the target group. This is motivated by the

differences in unemployment rates for these two groups displayed in Figure 5.3. As a reminder, the unemployment rates for those between the ages of 18-24 is 58 percent at the end of 2019. In contrast the unemployment rate for those aged 25-30 is 42 percent.

Figure 5.3 Unemployment rates for younger and older cohort



Notes: Graph displays the unemployment rates for 18-24 year olds and 25-29 year olds for the period 2008 to 2019.
Source: Authors' own estimates using QLFS data (Statistics South Africa, 2020)

The DDD regression results for the impact of being eligible for the subsidy measured in subgroups are presented in Table 5-6. Columns (1) to (3) present the impact of ETI eligibility on the employment rates, columns (4) to (6) the impact on the unemployment rates and columns (7) to (9) the impact on number of hours worked. Estimates for all individuals, women, and men for the full target group and then separately for two age groups (18 to 24 and 25 to 29 year olds) are reported.[28]

The results highlight that the negative effect on employment has been concentrated among men with a larger negative impact on younger men. The employment results for women suggest small employment increases. Younger men appear to have the largest decrease in unemployment. No significant impacts are seen on the number of hours worked across the subgroups.

The general conclusion from the PALMS data analysis is that the ETI has had little effect on hours worked and employment but small decreases in the unemployment rate of youth.

[28] The estimates for the in columns (1), (4) and (7) for the full target group correspond to the estimates in Panel 2 of Table 5-5.

Table 5-6 The effect on employment, unemployment and hours worked, by subgroups.

	Employment			Unemployment			Hours worked		
	All	Women	Men	All	Women	Men	All	Women	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
All target group	0.00451	0.0440**	-0.0373**	0.00371	0.0376**	-0.0269	0.318	0.0542	0.446
	(0.0124)	(0.0184)	(0.0166)	(0.0125)	(0.0186)	(0.0168)	(0.308)	(0.408)	(0.464)
Age 18-24	-0.0450***	0.0263	-0.0873***	-0.0440***	0.00990	-0.0745***	0.0860	-0.0604	0.313
	(0.0152)	(0.0276)	(0.0190)	(0.0153)	(0.0281)	(0.0192)	(0.452)	(0.783)	(0.592)
Age 25-29	0.0512***	0.0389*	0.0462**	0.0494***	0.0355*	0.0516**	0.452	0.209	0.548
	(0.0142)	(0.0201)	(0.0198)	(0.0143)	(0.0202)	(0.0201)	(0.334)	(0.433)	(0.514)

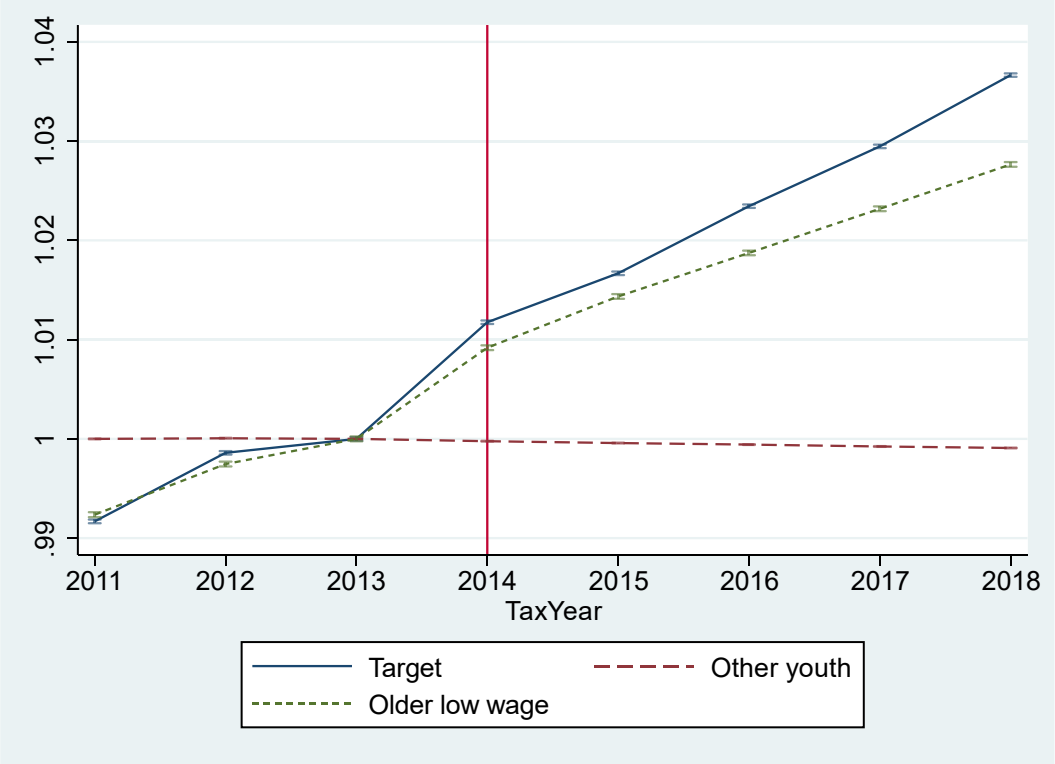
Notes: The table reports the DDD estimates for the effect of the ETI on employment, unemployment and hours worked for subgroup estimations. The estimates reported are in relation to equation (5.1) where the coefficient measures the impact of being eligible for the subsidy. All DDD estimates adjusted to account for existing pre-trend differences between the groups. There are 687,266 observation in the full target group, including those between the ages of 18 and 29 years old earning and both men and women. The first row in the table reports the triple difference coefficient of the full target age group (18-29 years old). The next row reports the triple difference coefficient where the sample is restricted to the younger individuals in the target group (18-24 years old). The last row reports the triple difference coefficient where the sample is restricted to the older individuals in the target group (25-29 years old). The first column in the table includes both men and women, the second column is restricted to women only and the third column includes only men. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' own estimates using PALMS 3.3.

5.6 Results using the tax data

This subsection turns the focus to the tax data where there are four outcomes of interest: earnings, entry into employment, exit from employment and job duration. As above, the development of key outcomes is examined using graphical evidence then followed with regression results. The regression results are also based on equations (5.1) and (5.2) as the previous section. The treatment group remains those who are eligible for the subsidy, that is workers between the age of 18 and 29, earnings less than R6,000 per month. The control groups are made up of non-youth (between the age of 30 to 35) and youth earning between R6,000 and R9,000 per month.

The investigation begins with the response to earnings level to detect the incidence of the subsidy. **Error! Reference source not found.** uses the normalised mean log earnings for the target and control groups. The figure suggests the target group experience a faster increase in earnings after the reform.

Figure 5.4 Normalised log earnings by group.

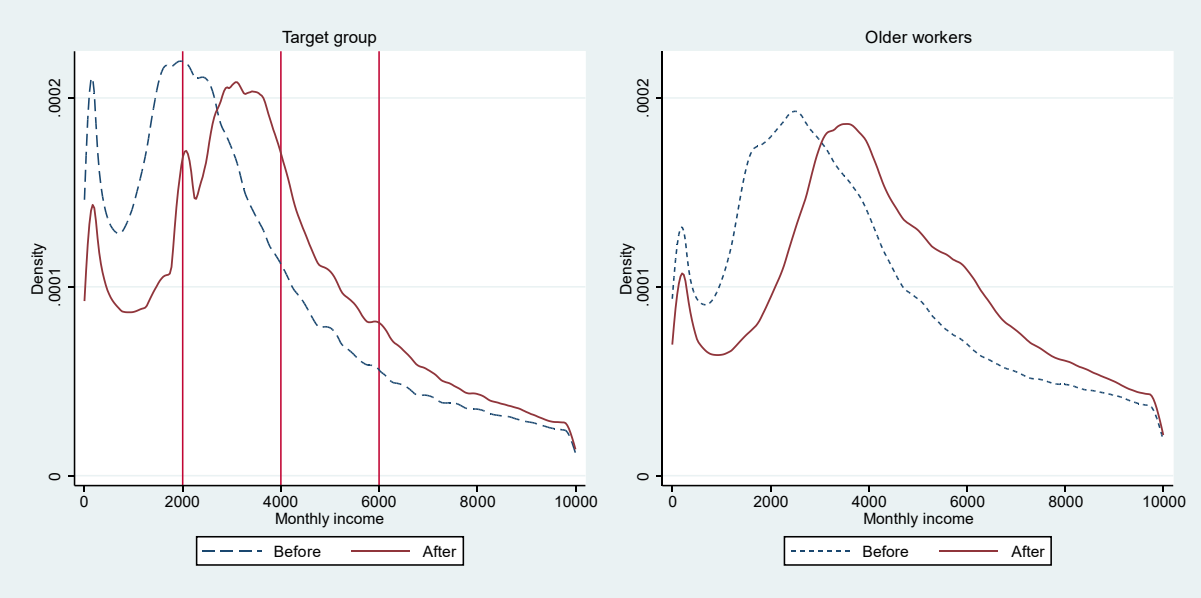


Notes: The figure displays the mean outcomes for log earnings. Log earnings are normalized to one for 2013 to adjust for the level differences across the groups: target, other youth, older low wage. Other youth is defined as workers earning between R6,000 and R9,000. Older low wage is defined as workers between the ages of 30 and 35 years old earning less than R6,000. Corresponding estimates are provided in Table 5-7.
Source: Authors' own estimates using IRP5 data.

To investigate this further, Figure 5.5 depicts the developments in the earnings distribution for young workers between 2013 and 2018. Because of the nominal earnings growth, the distribution

has shifted to the right. Early in the system, the general shift was the only marked change whereas five years into the system, in 2018, a spike in the distribution is visible at the R2,000 level, that is, where the subsidy rate is the greatest (See Appendix Figure A1 for 2015 comparison). It is likely that the employers have gradually learnt more about the system and have been able to adjust to offering jobs according to the incentives created by the system.

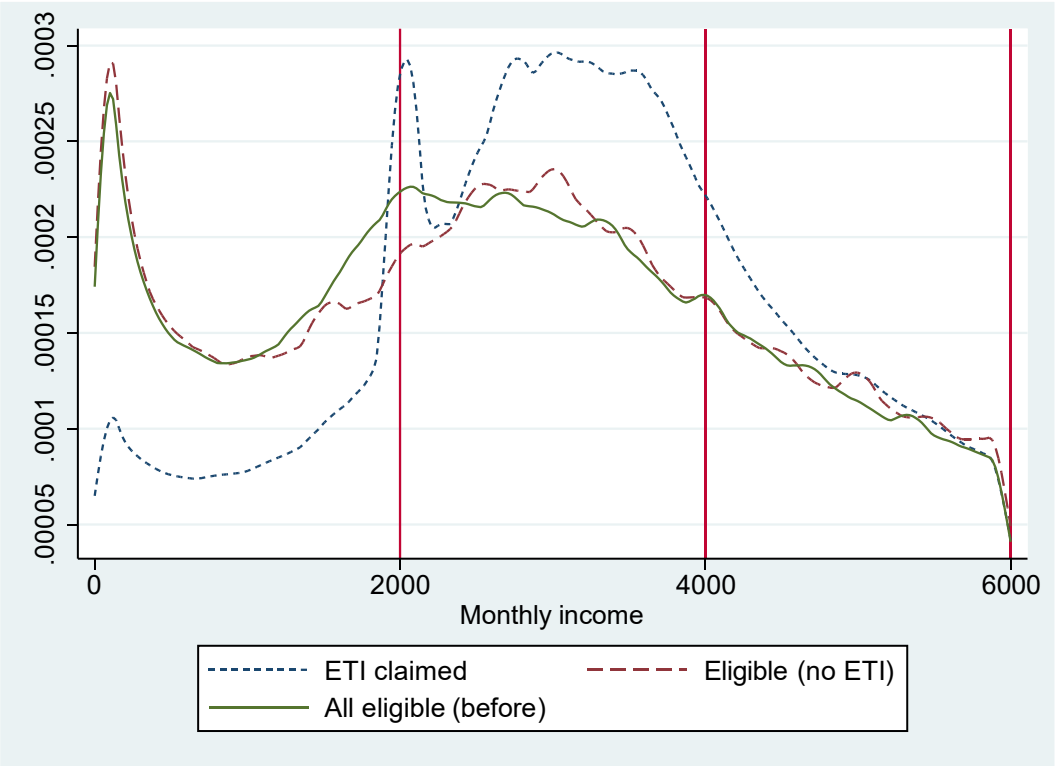
Figure 5.5 Distribution of earnings for young versus older workers



Notes: The figure illustrate the earnings distribution. The left panel compares the distribution of earnings in 2013 (before) versus 2018 (after) for the target groups of workers, whereas the right panel presents the same before-after comparison for older workers aged 30 to 35 years old.
Source: Authors' own estimates using IRP5 data.

Since it can be established whose employers have used the ETI, the wage distribution by ETI-claiming status is captured in Figure 5.6. The results confirm that there is now more mass in the wage distribution for ETI-supported jobs, whereas the distribution of workers has not changed for ETI eligible non-claimers.

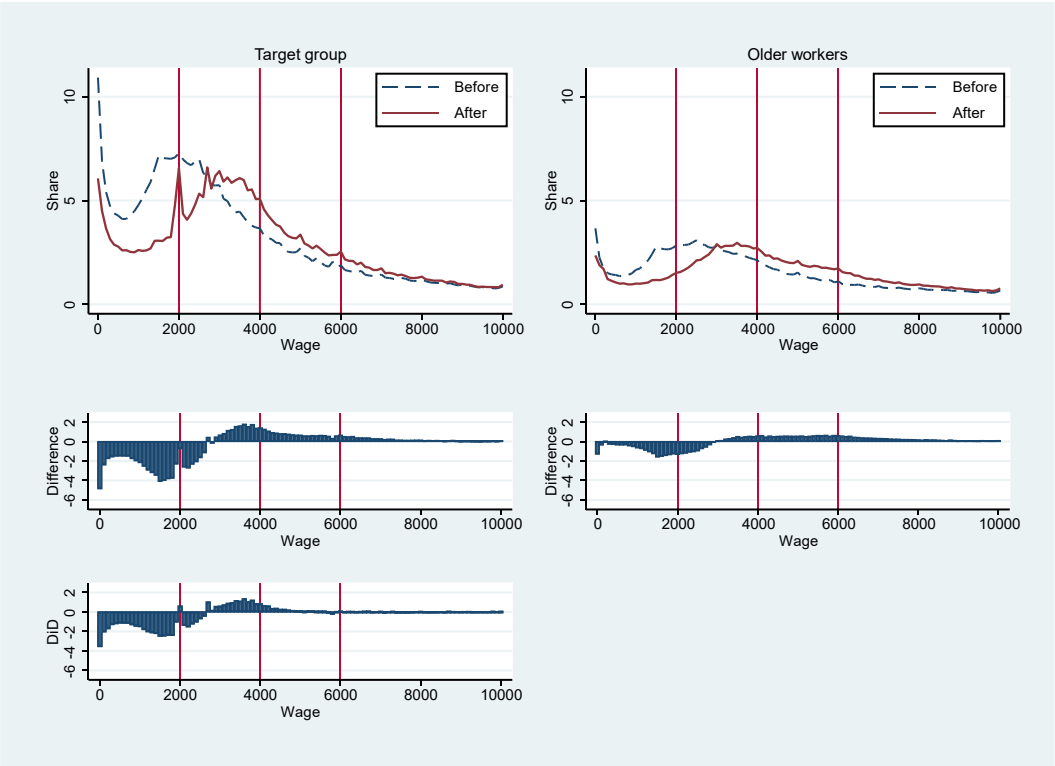
Figure 5.6 Earnings eligible vs ETI-claimers



Notes: The figure compares the wage distribution by ETI claiming status comparing the uprated wages of all those eligible (before the reform, 2013 and before) to those who are eligible but did not claim the subsidy (for 2016 and later) and those who were eligible and for whom the subsidy was claimed (for 2016 and later).
Source: Authors' own estimates using IRP5 data.

Figure 5.7 captures the changes in wage distribution in a DID manner. The figure depicts the distribution of wages and changes over time for young and older workers, respectively. There is wage growth for both younger and older workers and both an increase and a decrease in wages in the R2,000–R4,000 range. As a reminder, the subsidy to wage percentage is highest (50%) for those who earn R2,000 and less, a flat R1,000 in the R2,000-R4,000 range with a subsidy to wage percentage from 50% to 25%. The bottom panel, displaying the DID, suggests that there has been, in parts, both a negative and positive response in the wages.

Figure 5.7 Wage distribution for 18–29-year-olds, 2013 and 2018



Notes: The figure displays the wage distribution before and after the reform and the calculated differences. The top panel displays the wage distribution before (2013) and after (2018) for the target group and older, low wage workers. The second panel shows the before and after differences for the two groups. The sample of older workers is restricted to those between the ages 30 and 35, younger workers are restricted to the target group between the ages of 18 and 29. Only wages below R10,000 are included. The bottom left panel is the difference in the number of workers in earnings bins between young and older workers, that is, the difference between the middle panel left and right graphs. Source: Authors' own estimates using IRP5 data.

Following the graphical evidence, Table 5-7 estimates log earnings to check for any statistically significant change in earnings for the target group. The estimation considers the impact of being eligible for the subsidy (or the ITT) and corresponds to equation (5.1). The 2014 tax year is excluded from all the regressions using the tax data because the policy was implemented in the final 2 months of the tax year making it both a 'treated' and 'untreated' year.

The basic DDD estimated in Panel 1 of Table 5-7 shows that there is a small positive significant effect on log earnings. The effect of eligibility on earnings is around 2.5% $(exp(0.0248) \approx 1.025)$. For example, there is a R75 increase in wages for those with a monthly wage of R3,000. The subsequent panels consider other specifications as robustness checks. In Panel 2, differential pre-existing trends between the treatment and control groups are controlled by regressing the pre-existing trend against the pre-reform data (See example in Kleven et al. (2013)) The outcome is first regressed for all years prior to 2014 on group fixed effects and two group specific time trends. The residuals are then used as the outcome in the regression specifications (5.1). The estimates are almost unchanged when controlling for possible pre-existing trends. Panel 3 uses clustered

standard errors where the clustering is done by income level and age. The standard errors are larger in these estimations and the significance from the previous panels is lost. Panel 4 controls for imperfect take-up by instrumenting the ETI indicator (given actual take-up) by the intention-to-treat average ETI eligibility. This is the Wald Estimator which is calculated to control for the imperfect take up described in Table 5-2. The intention-to-treat estimate (DDD estimate from Panel 2) is multiplied by the inverse of the take-up rate. The Wald estimator has a coefficient of 0.0655 which is statistically significant at the 1% level and is larger than the effect reported in Panels 1 and 2. Panel 5 displays the year-specific treatment effect. The effect on log earnings is larger for later years of the policy which is in line with the increases in take up and change in behaviour by firms in the later years of the policy. The largest effect on wages is seen in 2018, that is, an increase of 5.87% or R176 for those with a monthly wage of R3,000.

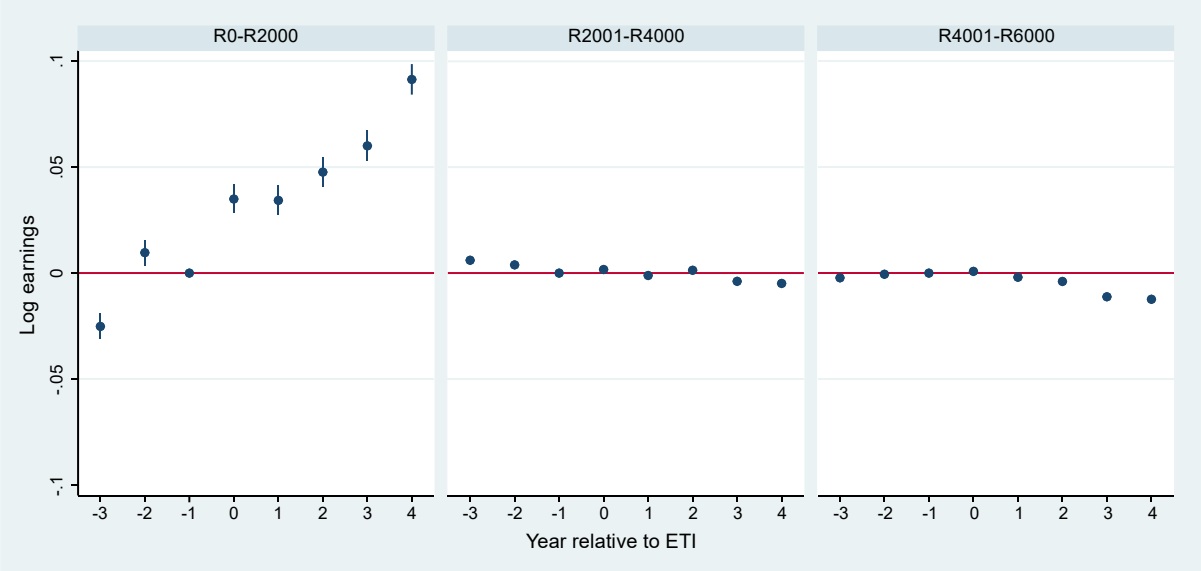
Table 5-7 DDD estimation on log earnings

	ETI dummy
1: **Basic DDD**	
	0.0248***
	(0.000857)
2: **control for pre-existing trends**	
	0.0247***
	(0.000856)
3: **clustered standard errors**	
	0.0247
	(0.0627)
4: **control for imperfect take-up (IV)**	
	0.0655***
	(0.0023)
5: **year-specific treatment effects**	
x 2015	0.0101***
	(0.00172)
x 2016	0.0262***
	(0.00170)
x 2017	0.0348***
	(0.00172)
x 2018	0.0570***
	(0.00171)

Note: The table presents DDD estimation results where the dependent variable is log earnings. Number of observations 36,098,402. Estimates are based on equation (5.1) in Panels 1-4 and equation (5.2) in Panel 5. ETI dummy is an indicator for ETI eligible worker. ETI amount is the potential subsidy value. The 2014 tax year is excluded from the specifications, because the policy was enacted in 2014 at the end of the tax year. Panel 1 is the basic DDD estimate. Panel 2 controls for differential pre-existing trends for the treatment and control groups. Panel 3 use clustered standard errors where clustering takes place at the level of R500 income groups and age (younger and older workers). Panel 4 controls for imperfect take-up, instrumenting the ETI indicator (given actual take-up) by the intention-to-treat average ETI eligibility. Panel 5 presents the year-specific treatment effects estimations. Robust standard errors in parentheses in Panels 1, 2, 4 and 5. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' own estimates using IRP5 data.

The estimation results on log earnings are positive and significant for all except for the specification using the clustered standard errors. Given the design of the policy, we examine the kink points in the value of the subsidy and the sharp bunching seen in Figure 5.7 which are suggestive of heterogeneous effects. Figure 5.8 presents the estimation results from equation (5.2) for income subgroups to establish whether there may be any differences. The graphs suggest that the ETI lead to a 10% increase in earnings for those that earn less than R2,000 per month shown in the first panel. The second panel shows the results for the R2,001-R4,000 wage group and the third panel show results in the R4,001-R6000 wage group. Large negative effects in the last subgroups could be driving the limited results for the estimates in Table 5-7.

Figure 5.8 Impact of the ETI on log earnings by subgroups

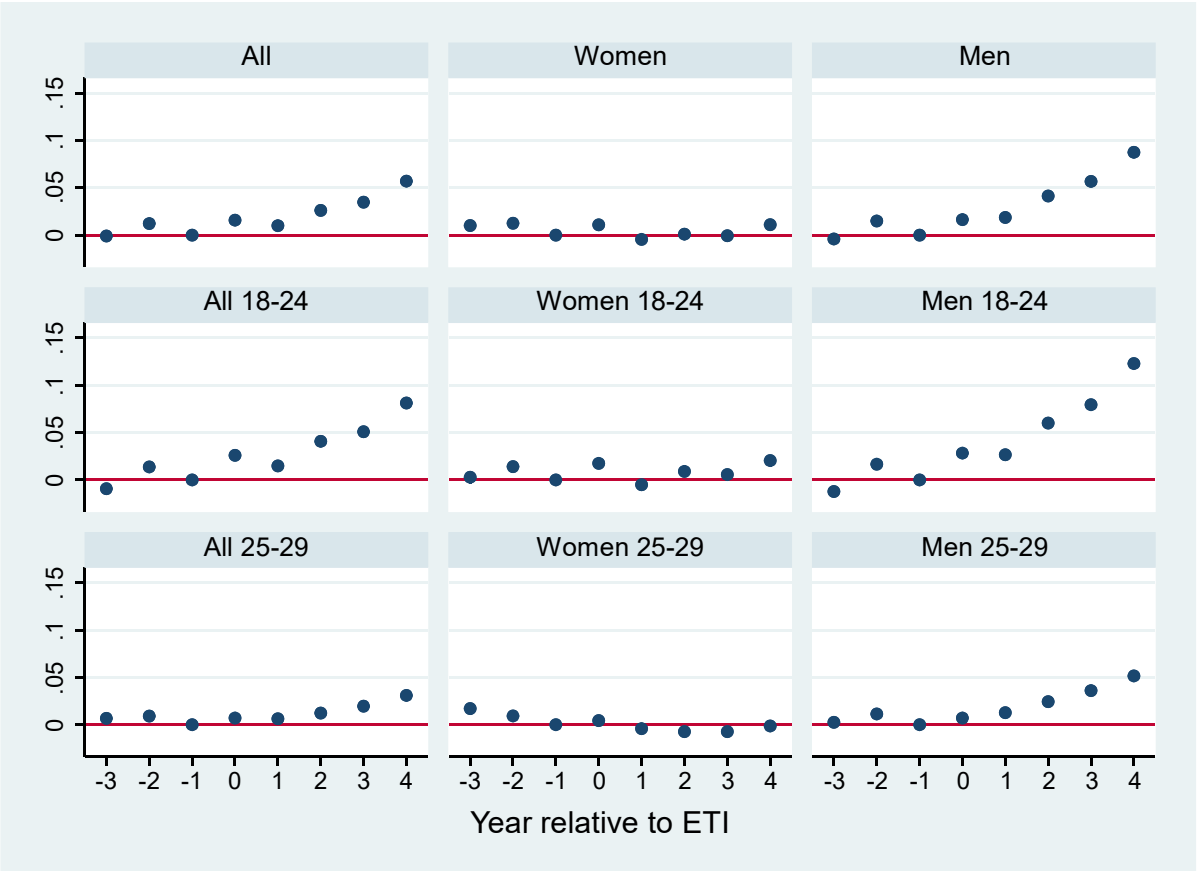


Notes: These figures report the DDD year-specific treatment estimates of the effect of the ETI on log earnings as described in equation (5.2)The first panel reports the impact for those with wages between 0 and R2,000, the second panel reports for the R2,001 to R4,000 group and the last panel for the R4,001 to R6,000 subgroup. 95 percent confidence intervals are displayed using robust standard errors.
Source: Authors' own estimates based on IRP5 data

It is recognised that the way in which the subgroups are divided would limit any earnings increased beyond the upper bound for each group. The takeaway point, however, is that the overall increase in earnings result may be driven by the increases for the very low earners.

Further heterogeneity effects are estimated as was done with the survey data. The results on earnings are presented in Figure 5.9. Column 1 presents estimates for both men and women, column 2 for women and column 3 for men. Row 1 presents estimates for the full target group, row 2 for 18 to 24 year olds and row 3 for 25 to 29 year olds. The largest positive impact on earnings is experience by younger men with almost no effect on earnings for women.

Figure 5.9. Impact of the ETI on log earnings by subgroups



Notes: These figures report the DDD year-specific treatment estimates of the effect of the ETI on log earnings, as described in equation (5.2), for age and gender subgroups. The first column includes both men and women, the second column only women and the third column only men. The top row includes everyone age 18 to 29, the second row includes those 18 to 24 years old, and the bottom row includes those 25 to 29 years old. 95 percent confidence intervals are displayed using robust standard errors.
Source: Author's own estimates based on IRP5 data.

The evidence on earnings suggests that, somewhat surprisingly and in contrast to the latest international literature, the incidence on the subsidy is (partly) on workers. This would limit the impact on employment and make sense in light of the results from the survey data.

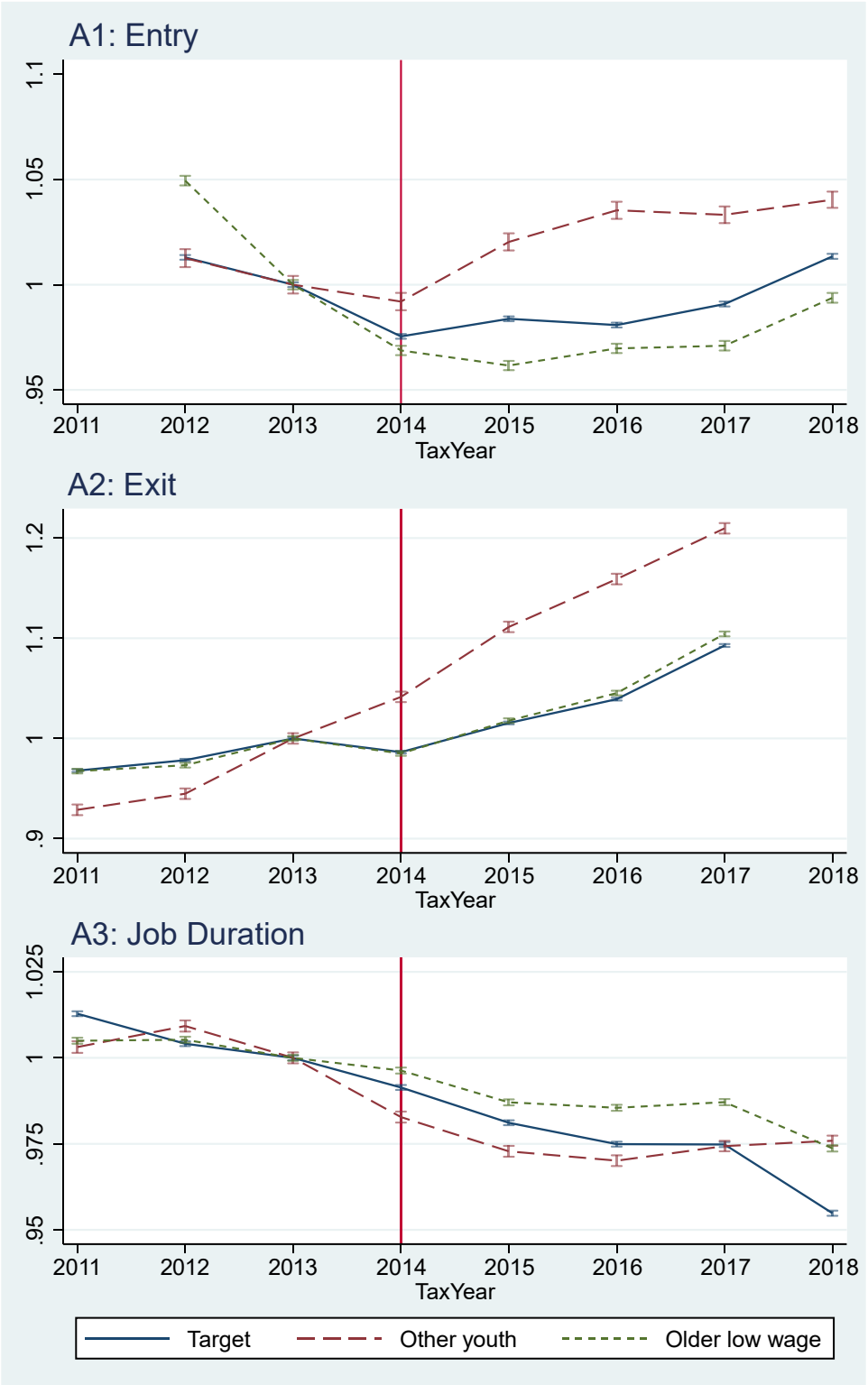
Next, additional outcomes in the tax data are examined. Different from the survey data, the tax data permit examination of entry into employment as the ETI is very similar to a hiring subsidy and could have the greatest impact through increased entry into employment. Earlier in Chapter 3, it was noted that, year on year, there are fewer firms hiring subsidy eligible youth so it would be interesting to see whether the subsidy stimulated entry.

The subsidy could also work by decreasing the exit from employment of youth. This would not be the desired outcome of the policy, but wage subsidies have been used in other countries during a recession to prevent the further job losses. Lastly, it is expected that the subsidy would keep youth in employment for a longer period, so job duration is studied.

Figure 5.10 displays the normalized entry into employment (Panel A1), exit from employment (Panel A2) and job duration (Panel A3) for the target and control groups. The graphs are all normalised to one in 2013, before the policy start.

In Panel A1 there appears to be an increase in entry relative to older low wage workers suggesting a substitution away from hiring older, low wage workers who are ineligible for the subsidy.

Figure 5.10 Normalized outcomes for target group and control groups



Notes: Mean outcomes are normalised to one for 2013 to adjust for the level differences across the three groups: target, other youth, and older low wage. Other youth is defined as workers earning between R6,000 and R9,000. Older low wage is defined as workers between the ages of 30 and 35 years old earning less than R6,000. The 2018 tax year is excluded from the analysis on exit from employment and the 2011 tax year is excluded from the entry to employment analysis due to data limitations (See Section 3.3.2 for full details). Corresponding estimates are provided in Table 5-8.
Source: Authors' own estimates using IRP5 data.

Panel A2 suggests decreased exit for the target group in comparison to other youth but no change relative to the older low-wage workers. Lastly Panel A3 depicts the job duration of the target group in comparison to the control groups. The policy gives firms an incentive to retain workers for longer, or at least for the first 12 months where the subsidy claims are higher. There is no visible trend break for the target group that would lead us to believe there is any change in job duration.

Table 5-8 presents the regression results on the outcomes examined in Figure 5.10. The 2018 tax year is excluded from the exit from employment regression and the 2011 tax year is excluded from the entry to employment as an entry and exit in these years cannot be confirmed (See Section 3.3.2 for full details).

The basic DDD estimation results are in Panel 1 of Table 5-8. In Panel 2, any differential pre-existing trends between the target and control groups are controlled, Panel 3 uses clustered standard errors where the clustering is done by income level and age, Panel 4 account for the imperfect take-up and Panel 5 displays the year-specific treatment effect.

There are very small positive significant increases for entry into employment and even smaller decreases in exit from employment. A decrease in exit can be seen as a positive spillover effect as retention could provide young workers with much needed work experience. While the effects on entry and exit are statistically significant, these effects are perhaps too small to see any effect on employment rates when using the palms data or derive any meaningful economic effect. Lastly, there are small positive significant increases in job duration.

As done with the earnings outcome, the intention-to-treat take up rates are instrumented by the actual take up rates to calculate the Wald estimator. The ITT estimates for entry, exit and job duration are statistically significant therefore the IV estimate can be statistically significant and, in this case, is more than double the estimates in Panel 2 for these outcomes.

Considering the way in which the subsidy is designed some of the switching between positive and negative results, or significant and non-significance in different specifications, could be driven by heterogeneous effects within the target group based on the value of the subsidy received (or monthly income on which the subsidy is based). This is the subject of the next subsection.

Table 5-8 DDD estimation on jobs, entry, exit and job duration.

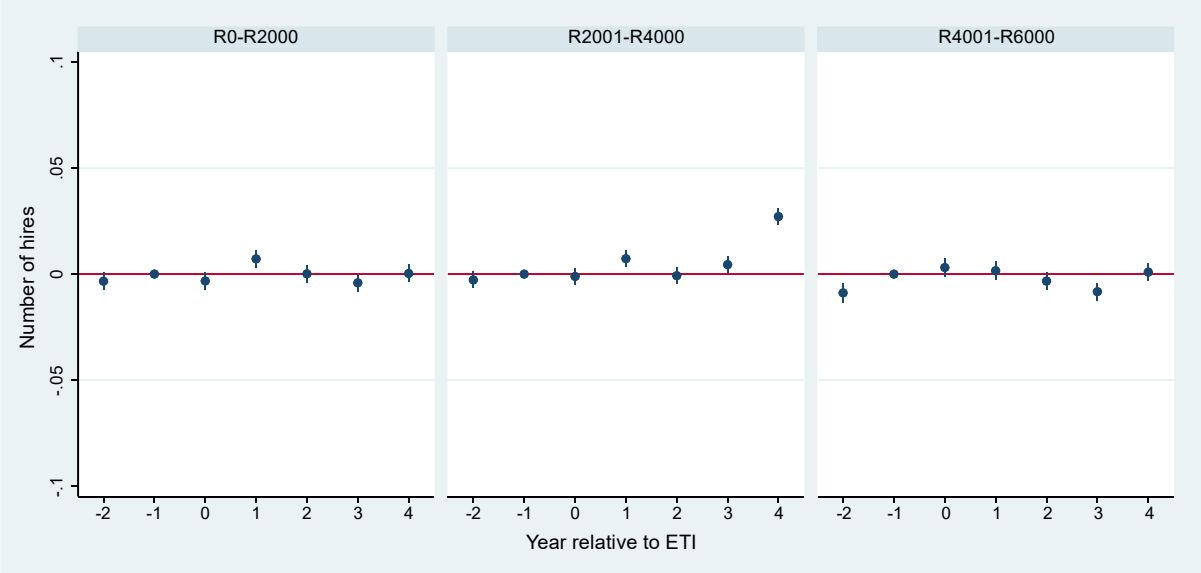
	(1)	(2)	(3)
	Entry into employment	Exit from employment	Job duration
1: **basic DDD**			
	0.0094***	-0.0020**	1.1907***
	(0.0010)	(0.0009)	(0.2399)
2: **control for pre-existing trends**			
	0.0095***	-0.0019**	1.1483***
	(0.0010)	(0.0009)	(0.2399)
3: **clustered standard errors**			
	0.0095	-0.0019	1.1483
	(0.0171)	(0.0152)	(5.4166)
4: **control for imperfect take-up (IV)**			
	0.0251***	-0.0053**	3.1278***
	(0.0025)	(0.0026)	(0.6350)
5: **year-specific treatment effects**			
x 2015	0.0105***	-0.0041**	-0.2801
	(0.0018)	(0.0017)	(0.4791)
x 2016	0.0025	-0.0054***	-0.5615
	(0.0018)	(0.0017)	(0.4756)
x 2017	0.0038**	0.0007	-0.1976
	(0.0018)	(0.0017)	(0.4711)
x 2018	0.0169***		-1.7161***
	(0.0017)		(0.4658)

Note: The table presents DDD estimation results. Estimates are based on equation (5.1) in Panels 1-4 and equation (5.2) in Panel 5. The table presents estimation results for the entry into employment, exit from employment and job duration. ETI dummy is an indicator for an ETI eligible worker. The 2014 tax year is excluded from the specifications, because the policy was enacted in 2014 at the end of the tax year. Panel 1 is the basic DDD estimate. Panel 2 controls for differential pre-existing trends for the treatment and control groups. Panel 3 uses clustered standard errors where clustering takes place at the level of R500 income groups and age (younger and older workers). Panel 4 controls for imperfect take-up, instrumenting the ETI indicator (given actual take-up) by the intention-to-treat average ETI eligibility. Panel 5 presents the year-specific treatment effects estimations. Robust standard errors in parentheses in Panels 1, 2, 4 and 5. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' own estimates using IRP5 data.

5.6.1 Heterogeneity by income, gender, and age group

We examine heterogeneity by income groups, gender, and age groups. Figure 5.11 captures the impact of the ETI on entry within wage groups by plotting the year-specific treatment effects. The first panel examines the wage group for those earning less than R2,000, the second panel the R2,001-R4,000 wage group and the third panel the R4,001-R6000 wage group. There are more clear positive significant increases in the number of entrants in the second wage group and negative but insignificant effects on the number of entrants in the first and third wage groups.

Figure 5.11 DDD year specific treatment estimation results on entry



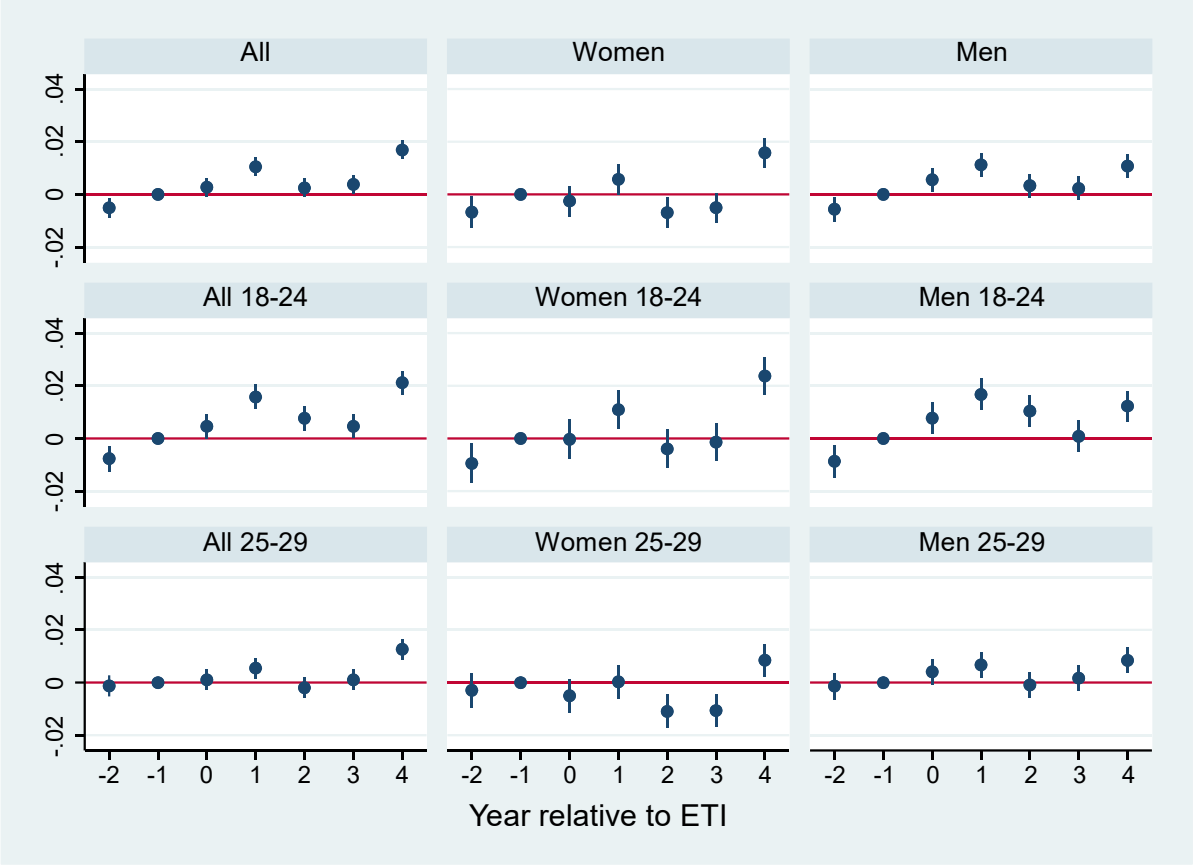
Notes: The graphs present the coefficients of the DDD year-specific treatment estimation results as described in equation (5.2). The dependent variable is the number new job entrants. The x-axis is the tax year relative to the ETI, that is, tax year zero is 2014 and the y-axis the coefficients of the number of hires. 95 percent confidence intervals are displayed using robust standard errors.
Source: Authors' own estimates using IRP5 data.

Given the way in which the policy was designed, there is an incentive for the increased job entry around the maximum subsidy which is seen in the results from Figure 5.11. The large number of workers in the R2,001-R4,000 category is likely driving overall positive impact found in Table 5-8. The same analysis is run within wage groups for exit and job duration and reported in the chapter appendix. The decrease in exit from employment from Table 5-8 appears to be driven by R0-R2,000 group. There appear to be positive increases in job duration in the first and second wage groups but trends in the pre-policy period give some rise for concern about our estimates on job duration.

Figure 5.12 displays the impact on age and wage groups for entry into employment. The graphs display the coefficient plots for the year-specific treatment effects.[29] The impact on entry appears to be stronger for the younger group, more pronounced for women in 2018 and more pronounced for men in 2015. Younger workers may be more attractive to firms as they would be eligible for the subsidy for longer which could explain the larger increase in entry for the younger groups.

The year-specific treatment effect graphs for exits and job duration within these same subgroups are available in the chapter appendix. No heterogeneous effects are observed for exit and job duration.

Figure 5.12 Impact of ETI on Entry by subgroups



Notes: The graphs present the coefficients of the DDD year-specific treatment estimation results, as described in equation (5.2), where the dependent variable is the number of job entries. The x-axis is the tax year relative to the ETI, that is, tax year 0 is the 2014 tax year. The y-axis represents the coefficients of the estimation results. The first column includes both men and women, the second column only women and the third column only men. The top row includes everyone age 18 to 29, the second row includes those 18 to 24 years old, and the bottom row includes those 25 to 29 years old. 95 percent confidence intervals are displayed using robust standard errors.
Source: Author's own estimates using IRP5 data.

5.6.2 Industries with high take up

Chapter 3 examined the distribution of take up among industries and find higher take up in some industries which is also described in Table 5-2. Towards the end of Chapter 3, it is established that

[29] The first graph, All, is the coefficient plot for column (3) of Panel 4 in Table 5-8.

there is a clear set of industries employing young, low wage workers. In the international literature, discussed in Section 2.2.3, it is found that some countries have limited their wage subsidy policies to certain industries where it is believed that a wage subsidy will have the largest impact. There were similar recommendations in South Africa to target the ETI policy to labour intensive industries where job creation is more likely. The motivation behind this is also to limit any possible deadweight losses arising from firms claiming the subsidy without creating any new jobs. In this final section, our analysis is limited to those industries with greater than average take-up of the ETI. The results for all outcomes examined in the tax data are displayed in Table 5-9. Comparisons are made to Table 5-7 and Table 5-8 reflecting the full population. For industries with higher than average take up rate, results are only slightly larger for earnings. The effect on entry is smaller but still significant. All significance is lost for the effect on exits and the effect on job duration is much stronger in the industries with above average policy take-up. The Wald estimate (accounting for imperfect take-up) in Panel 4 instruments the actual ETI claim for the intention-to-treat ETI eligibility. This correction has a larger impact on the estimate of job duration suggesting an increase of 13 days for ETI participants. This would point to intensive margin effects and, contrary to any expectations, suggest that job growth is not likely at industries with high subsidy take up.

Table 5-9 DDD estimation for industries with high take up

	(1)	(2)	(3)	(4)
	Log earnings	Entry into employment	Exit from employment	Job duration
1: **Basic DDD**				
	0.0278***	0.0077***	0.0006	5.874***
	(0.0012)	(0.0015)	(0.0015)	(0.389)
2: **control for pre-existing trends**				
	0.0286***	0.0082***	0.0007	5.673***
	(0.0012)	(0.0015)	(0.0015)	(0.390)
3: **clustered standard errors**				
	0.0286	0.0082	0.0007	5.874
	(0.0878)	(0.0214)	(0.0221)	(7.235)
4: **control for imperfect take-up (IV)**				
	0.0667***	0.0186***	0.0029	13.573***
	(0.0027)	(0.0035)	(0.0037)	(0.900)
5: **year-specific treatment effects**				
x 2015	-0.0099***	0.0103***	-0.0033	1.945**
	(0.0024)	(0.0029)	(0.0028)	(0.783)
x 2016	0.0264***	0.0001	0.0021	1.810**
	(0.0023)	(0.0028)	(0.0028)	(0.764)
x 2017	0.0211***	0.0013	0.0103***	2.638***
	(0.0023)	(0.0027)	(0.0027)	(0.746)
x 2018	0.0554***	0.0189***	-	-0.195
	(0.0023)	(0.0027)		(0.737)

Note: Estimates are based on equation (5.1) in Panels 1-4 and equation (5.2) in Panel 5. The table presents estimation results for log earnings, entry into employment, exit from employment and job duration. ETI dummy is an indicator for an ETI eligible worker. ETI amount is the potential subsidy value. The 2014 tax year is excluded from the specifications, because the policy was enacted in 2014 at the end of the tax year. Panel 1 is the basic DDD estimate. Panel 2 controls for differential pre-existing trends for the treatment and control groups. Panel 3 uses clustered standard errors where clustering takes place at the level of R500 income groups and age (younger and older workers). Panel 4 controls for imperfect take-up, instrumenting the ETI indicator (given actual take-up) by the intention-to-treat average ETI eligibility. Panel 5 presents the year-specific treatment effects estimations. Robust standard errors in parentheses in Panels 1, 2, 4 and 5. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' own estimates using IRP5 data.

5.7 Conclusion

This chapter set out to examine the individual-level effects of the ETI. In particular, the earnings and entry into employment impacts of the ETI. The subsidy has been available for the employers of workers below 30 years earning at most R6,000 a month. The targeted nature of the policy allowed for a triple difference estimation strategy to be utilised with both older workers, in the same earnings range and young workers, slightly above the wage criteria, as the two control groups. The analysis relied on two data sets: the publicly available harmonized survey data (PALMS) and the population-wide administrative payroll records from the South African Revenue Service (SARS) available at the National Treasury Secure Data Facility in Pretoria.

The analysis reveals that the policy has not increased the employment rate or led to large reductions in the unemployment rate for the eligible group. These results are in line with the findings of Ranchhod and Finn (2014) who examine a broader eligible and comparison group in the first year of the policy.

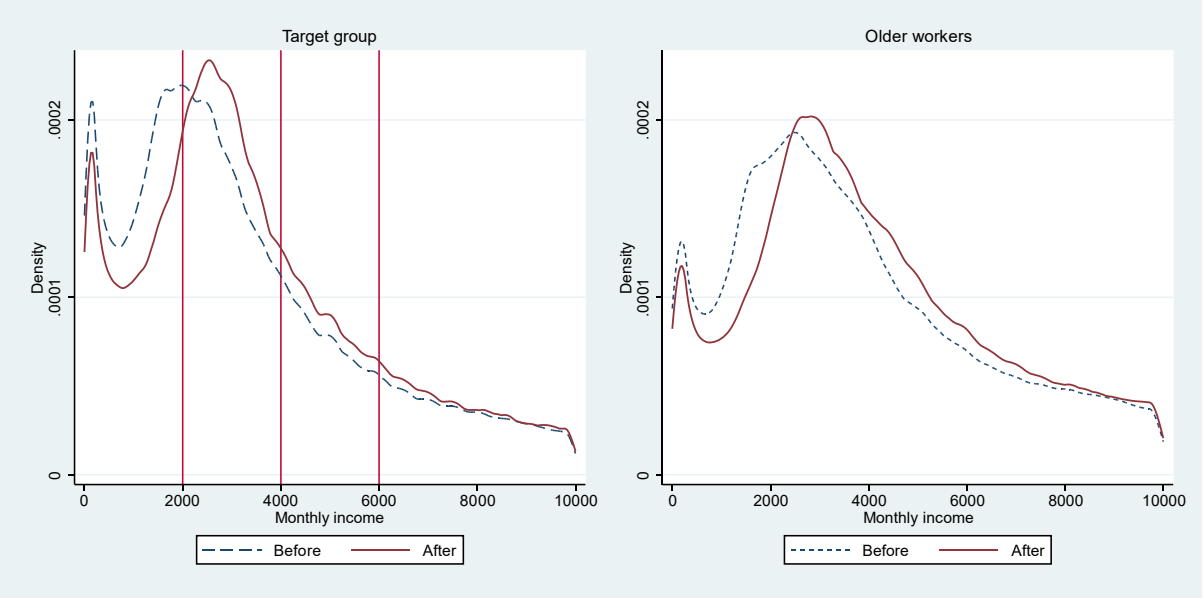
Despite this negative result, it is found that the policy led to a small, statistically significant increase in the earnings for the target group. On the one hand, this may be due to the fact that more new jobs were created in the range where the subsidy is the greatest (when earnings are between R2,000 and R4,000), but on the other hand, mean earnings even within this subsample increased. Increases in entry to employment and decreases in exit from employment are also found, but these effects are perhaps too small to see any change in the number of jobs. Lastly, while no increase in the number of hours worked are found in the survey data, there are statistically significant increases in the job duration for the eligible group with a larger impact seen in high take up industries.

The results in this chapter are at odds with the most recent influential work on the employment impacts of wage subsidies, including (Cahuc, Carcillo & Le Barbanchon, 2019) and Saez, Schoefer and Seim (2019). Very limited overall employment impacts are found, and the results also indicate that the incidence of the system was partly on workers.

5.8 Appendix

Appendix 5.A Earnings changes

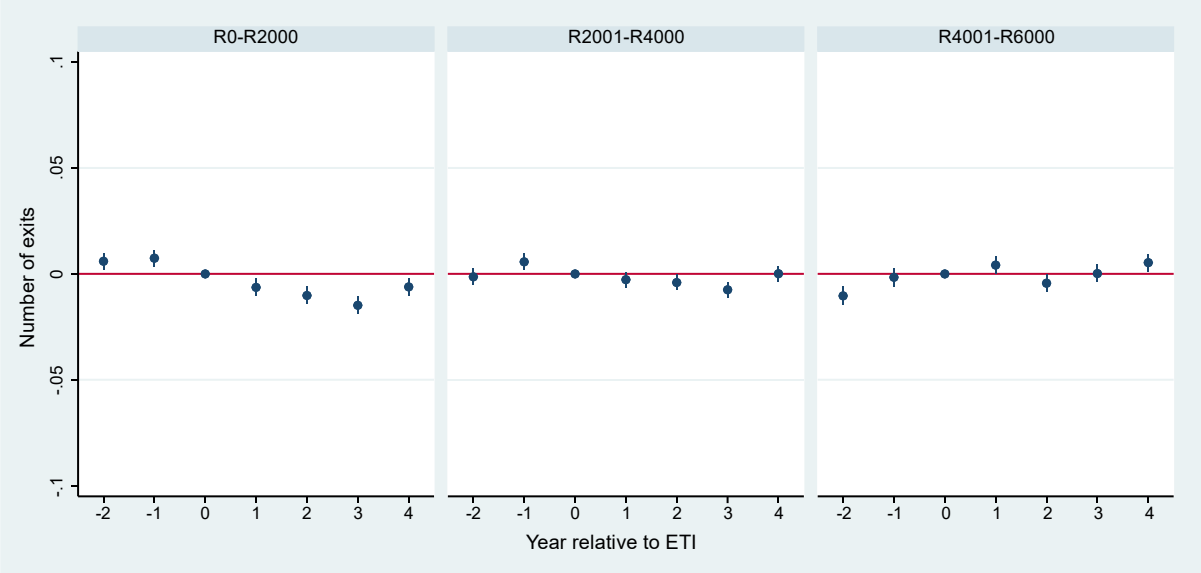
Figure. 5.A.1 Distribution of earnings for workers for young versus older workers



Notes: The left panel compares the distribution of earnings in 2015 versus 2013 for the target groups of worker, whereas the right panel presents the same comparison between 2015 and 2013 for low-wage workers aged 30 to 35 years old.
Source: Authors' own estimates using IRP5 data.

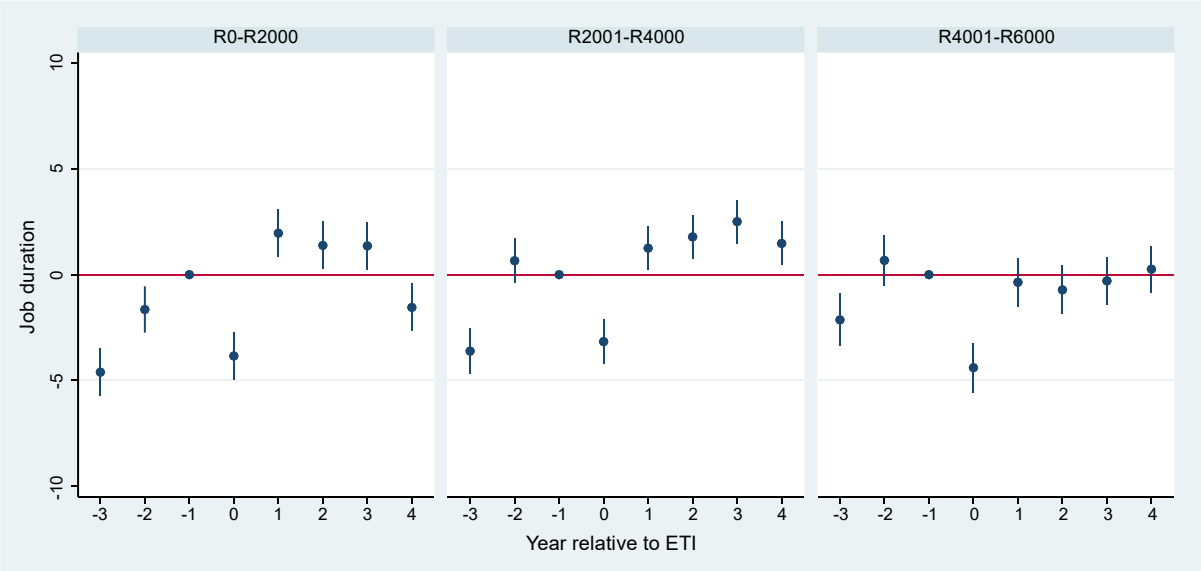
Appendix 5.B Heterogenous impacts on exit and job duration

Figure. 5.B.1 Estimated impact of ETI on exit, within wage subgroups



Notes: The graphs present the coefficients of the DDD year-specific treatment estimation results, as described in equation (5.2), where the dependent variable is the number of exits. The x-axis is the tax year relative to the ETI, that is, tax year 0 is the 2014 tax year. The y-axis represents the coefficients of the estimation results. 95 percent confidence intervals are displayed using robust standard errors.
Source: Authors' own estimates using IRP5 data.

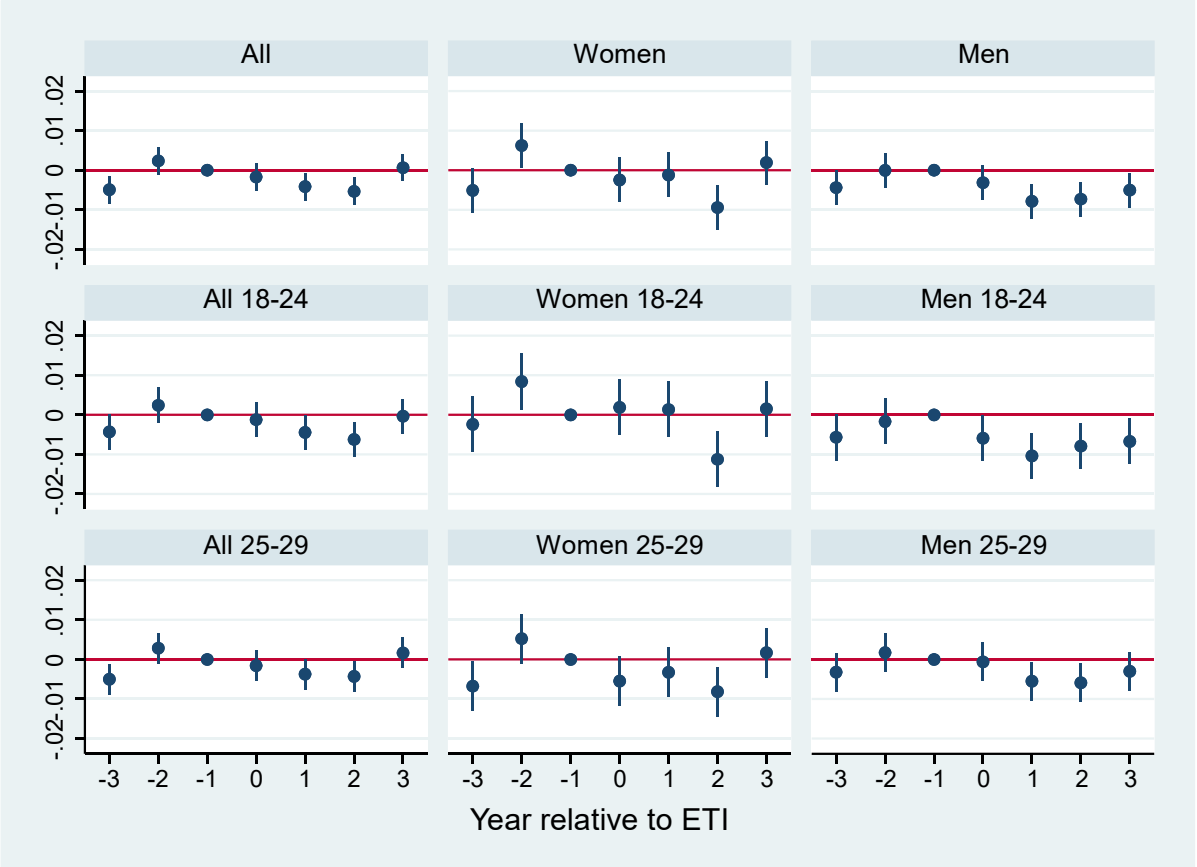
Figure. 5.B.2 Estimated impact of ETI on job duration, within wage subgroups



Notes: The graphs present the coefficients of the DDD year-specific treatment estimation results, as described in equation (5.2), where the dependent variable is job duration. The x-axis is the tax year relative to the ETI, that is, tax year 0 is the 2014 tax year. The y-axis represents the coefficients of the estimation results. 95 percent confidence intervals are displayed using robust standard errors.
Source: Authors' own estimates using IRP5 data.

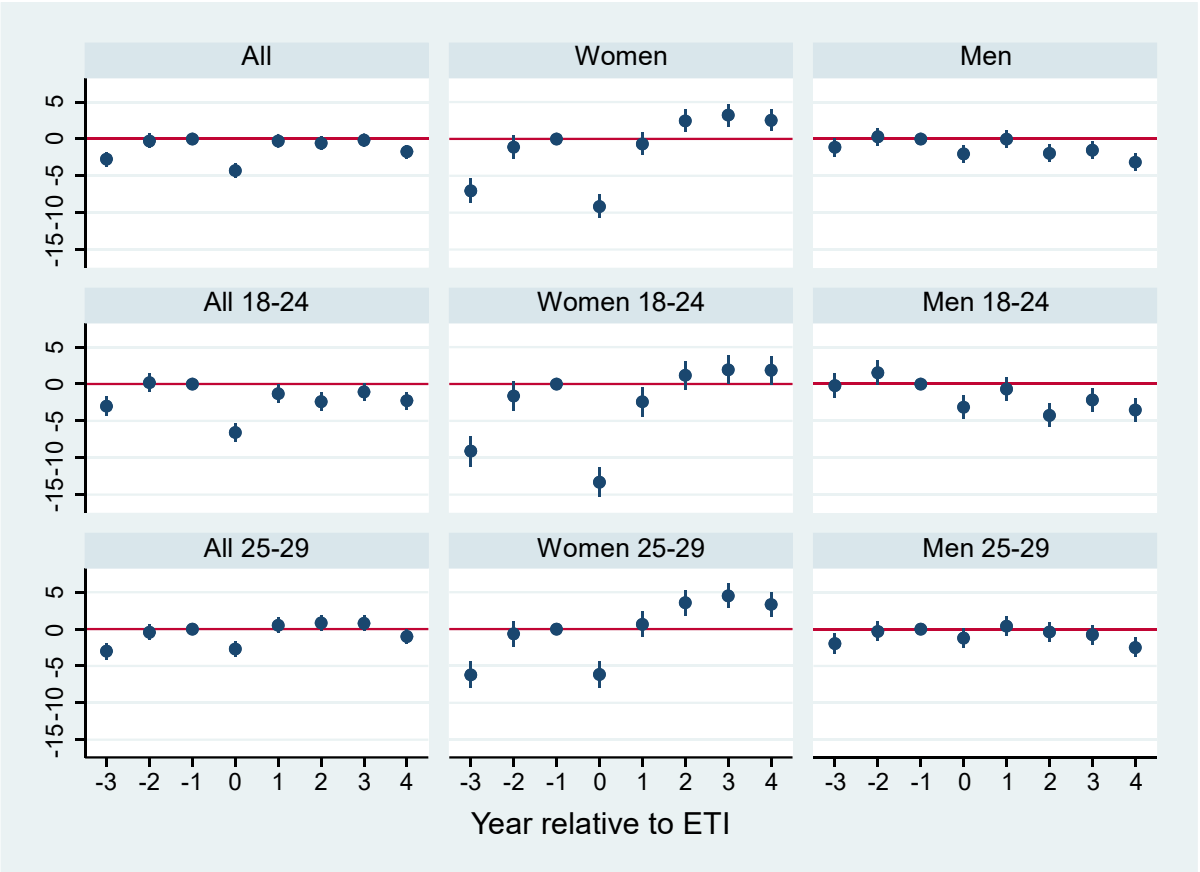
Appendix 5.C Subgroup analysis on exit from employment and job duration

Figure. 5.C.1 Impact of ETI on exit, by subgroup



Notes: The graphs present the coefficients of the DDD year-specific treatment estimation results, as described in equation (5.2), where the dependent variable is the number of exits. The x-axis is the tax year relative to the ETI, that is, tax year 0 is the 2014 tax year. The y-axis represents the coefficients of the estimation results. The first column includes both men and women, the second column only women and the third column only men. The top row includes everyone age 18 to 29, the second row includes those 18 to 24 years old, and the bottom row includes those 25 to 29 years old. 95 percent confidence intervals are displayed using robust standard errors.
Source: Author's own estimates using IRP5 data.

Figure. 5.C.2 Impact of ETI on job duration, by subgroup



Notes: The graphs present the coefficients of the event study estimation results where the dependent variable is job duration. The x-axis is the tax year relative to the ETI, that is, tax year 0 is the 2014 tax year. The y-axis represents the coefficients of the estimation results. The first column includes both men and women, the second column only women and the third column only men. The top row includes everyone age 18 to 29, the second row includes those 18 to 24 years old, and the bottom row includes those 25 to 29 years old. 95 percent confidence intervals are displayed using robust standard errors.
Source: Author's own estimates using IRP5 data.

Chapter 6 Conclusion

This aim of this thesis was to examine the Employment Tax Incentive in the context of stubbornly high levels of youth unemployment in South Africa. Thinking about the demand-side, instead of the supply-side challenges of youth unemployment, allowed for new questions to be posed and further discussions to be held about the labour market.

Active labour market policies such as the ETI are rare in developing country settings given the high cost and the uncertain outcomes of these policies. The main contributions of this thesis are relevant both within a South African and international context. The first main contribution is the development and description of the tax data used within this thesis as the best source of information on the implementation of the policy. This includes useful insights into both the benefits and the challenges for researchers interested in policy analysis using tax data in South Africa and other developing countries. A profile and set of characteristics, of the beneficiaries, firms, and individuals, of the ETI is also presented where only limited information was available before.

The second main contribution is a rigorous evaluation of the ETI at the firm level with the aim of understanding the wage subsidy as a mechanism for increasing labour demand for young, low-wage workers. This includes insights into the relationship between youth and non-youth labour pointing to no displacement or substitution between the two at low wage levels.

The third main contribution is the analysis of the individual-level impacts of the policy on the intensive and extensive margin using the strengths of both survey and tax data. Where the survey data provides a better picture of the employed versus the unemployed the tax data allows for a deep dive into the workers benefitting from the subsidy.

Chapter 2 situates the ETI policy in the international and local context of active labour market policies. Evaluations of ALMPs suggest that the effects of policies vary, though some have large impacts and others have no impact. An employment subsidy is one such ALMP that has seen varied impacts internationally which does not instil confidence that a subsidy policy in South Africa is likely to work. The chapter also provides us with a theoretical framework within which to examine the ETI in this thesis. The chapter covers the institutional background of the policy to ensure that this evaluation of the policy is rooted in the South African context. The ETI comes off the back of a collection of policies aimed at improving employment levels, however, it is the first large policy with very specific targeting of low-wage youth. The mechanics of the policy are documented and shows how the policy design allows for variation in the resulting outcomes. However, employment subsidy policies are not without potential disadvantages, many of which are acknowledged and apply to the South African job market.

Chapter 3 prepares for the analysis by providing all the necessary information on the tax data relevant to this thesis. It tells us about the firms claiming the subsidy and the subsidised workers. The tax dataset used in this thesis is constructed from the anonymized payroll and company income tax data available in the National Treasury secure data facility. The tax data comes with many advantages such as a large sample size and detailed information on subsidy claims and claimants. As the data has only been available in recent years and is not publicly accessible, the chapter covers, in some detail, the structure and challenges of the tax data. This is done to justify the use of the dataset for this thesis. There are also disadvantages to using tax data and the chapter brings to light the pitfalls of working with tax data for future analysis of the ETI and any other.

It is found that around 15% of all firms and, 25% of firms with one subsidy eligible worker are claiming the ETI in the first four years of the policy. These ETI firms are typically large, concentrated in provinces with large economic centres and with high take up rates in the manufacturing, wholesale and retail, and financial and insurance services sectors. Descriptively, there are no changes in the hiring or firing of young workers in these early policy years. Alarmingly, it is found that the top twenty claiming firms account for almost 30% of the total value of subsidies claimed. Chapter 3 also looks at the characteristics of eligible and participating workers. There are around 2 million workers eligible for the subsidy, but subsidy claims for only half of these individuals. The policy seems to be well targeted and reaching the younger workers in the target group with higher levels of unemployment.

Chapter 4 uses the firm-level dataset constructed in Chapter 3 to estimate the effects of the ETI on employment at firms in South Africa. Changes in the labour demand are estimated using a conditional difference-in-differences approach. Firms matched in terms of firm characteristics and results are estimated over a period that spans the start of the policy. In order to conduct the DID analysis information is needed about the two groups of firms, claiming and non-claiming, before and after policy implementation. The sample is restricted to ETI firms employing fewer than 1,200 worker as larger firms cannot be matched as take up of the policy is high and thus the comparison group too different and small. The matched ETI firms examined represent almost 60 percent of all ETI claiming firms in 2015. This limits the external validity of our results.

For the ETI firms examined a statistically significant increase in number of youth and all workers is seen. The effect varies by firm size, is robust to other measures of youth employment and is not driven by firms already growing their employment in the pre-policy period. No evidence of displacement of non-subsidized workers is found in the analysis.

Chapter 5 is focused on the subsidy eligible group of workers. It calculates the intention-to-treat (ITT) estimates, which identifies the impact of the policy on eligible workers. Using a triple

difference approach, comparing eligible workers to older, low-wage workers and young, higher wage workers, the individual level employment outcomes are studied. Different from Chapters 3 and 4, the individual worker perspective is considered making use of survey data in addition to the tax data. Earnings are predicted based on the pre-policy period using the several regressors from the survey data. This is done because earnings can only be observed where an individual is working. No evidence is found of the policy leading to increases in employment or decreases in unemployment from the estimations using the survey data and no change in the number of jobs in the tax data. There is evidence of the policy leading to small increases in entry and decreases in exit which, however, have not translated into impacts on the number of jobs. There is no evidence that the number of hours worked changed but positive significant impact on job duration or the number of days worked. Lastly, there is evidence of positive, significant impacts on earnings for eligible workers as a result of the subsidy policy.

The results from Chapters 4 and 5 appear to be contradictory in terms of changes in employment of youth. The results from Chapter 4 highlight that the ETI has been successful in creating jobs for youth at a subset of ETI firms while Chapter 5 suggests that there is no statistically significant effect on employment or the number of jobs for the eligible group of young, low-wage workers. This is plausible as it highlights the difference between an evaluation focussed on the actual employed versus those eligible to be employed. Only half of the population of eligible young, low-wage workers are being subsidized through the ETI and this is being driven by large firms. It is likely the case that the jobs created at ETI firms examined have not been sufficient to move the needle on youth unemployment in South Africa.

There are a few reasons why the ETI might not be having any effect on youth unemployment. Firstly, the ETI is claimed through the tax system, thereby excluding small firms not registered for PAYE or firms in the informal sector. In practice, the ETI has been used by medium and large sized firms. Given that small firms are more labour intensive than large firms, small firms could better facilitate job creation, however, the incentive is not accruing to these small firms. Secondly, the subsidy value may not be sufficient for firms to change their employment patterns. The ETI is challenging to calculate and paying for tax advice to claim the incentive may cost more than the benefit to the firm. Simplification of the policy design and implementation could quickly see increases in take up rates. Thirdly, the administrative burden and lack of information available to small firms means take up is incredibly low. Targeted information to small firms may go a long way to increase take-up and in turn, create jobs.

There are several policy insights that stem from this thesis. First, the scale of the programme in its original form was modest. Creating 178,000 jobs in light of 3 million unemployed youth is a

modest target and the policy was perhaps never adequately designed to deal with the youth unemployment crisis. The notion that the ETI is the silver bullet to solving South Africa's youth unemployment crisis is false. The policy was perhaps unfairly located relative to its size against other ALMPs. It has set the policy up for unrealistic expectations in terms of solving the scale of the problem and government could have worked harder to ensure that the policy was not the only hope for the country. The take up rate has been larger than the government estimated but a further increase in take up, even at small firms, may not yield sufficient jobs to curb unemployment.

Second, it is challenging to justify the deadweight loss in a country with constrained fiscal resources and many other challenges to address. A firm planning to employ 10 youth can simply claim a tax incentive for these employees and forgo any obligation to hire any additional ETI eligible employees. This is precisely what has been tested in Chapter 4. It has been demonstrated in Chapter 4 that these firms may be employing additional non-youth workers which is thought to be due to the low productivity of young workers. There is a view in government that it may be necessary to subsidise all youth employment as long as the youth are retained. This thesis finds some evidence to support this view, that is, there is evidence of a reduction in the exit rate of eligible workers. An analysis on the long-term impact on subsidised youth may be able to answer the question whether retention was a key part of the policy. In any case, leakages, such as increases in non-youth employment, can be seen as a simple cash transfers to firms. Against the policy's own merits, the policy might be working to create some jobs for youth, but the social cost may be high against the tsunami of the youth unemployment problem in the country.

Third, while the positive impacts on employment are seen, the policy can be better targeted, for example, to smaller firms in certain industries. The most concerning part of this thesis is the high value in claims by the top twenty claiming firms. Large firms dominate the formal sector employment which is a problem the ETI inherited and did not set out to fix. Should take up be increased at smaller firms, government will need to be honest about the scope to impact the extensive margin. There are several ways to deal with large firms claiming the bulk of the subsidy. One, create an upper limit on the value of claims thereby freeing up subsidy resources for smaller firms and reduce any possible deadweight loss at large firms. Two, introduce a condition for large firms to demonstrate job creation in order to claim the subsidy such as the case in Turkey (Betcherman, Daysal & Pagés, 2010). Three, make it a requirement for large firms to provide training to subsidised workers.

In terms of future research, one aspect of the policy that warrants attention is the long-term impact the period of subsidised employment has on subsidised workers. Within the international literature on wage subsidies this is an under examined topic. The tax data provide an opportunity

to see young workers enter into employment and then follow those who get a subsidy versus those who do not. You can then track which group of workers fare better in the labour market once their jobs end. Early in the thesis it was mentioned that the first job, and first work experience, are crucial for young people to find their next job.

At the time of ETI inception, the government was seeking, from the policy community, ideas for ALMP options to resolve South Africa's unemployment crisis. The government was seeking a policy to fund that would have a serious and lasting impact. The first phase of the ETI was short and the policy very narrowly targeted. One could consider the first phase as a pilot programme to see how a wage subsidy would perform in South Africa given particular characteristics of the formal private sector labour market characteristics highlighted in this thesis. While the policy was implemented in a low growth economy, there is also the question of whether the demand and supply sides of the labour market over the policy period were too daunting for any ALMP to work other than direct public sector employment policies. Although extensions have been made to the policy in terms of policy duration, little has changed in the structure of the policy since inception.

In summary, the results of this thesis are somewhat disappointing but not necessarily surprising. The necessity for the policy has not diminished since the policy was first conceived. The effects of the ETI are small and, in its current form, may never reach the desired outcome to change the trajectory of youth employment in South Africa.

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