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WIDER Working Paper 2017/25

Firm-level determinants of earnings in the formal sector of the South African labour market

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February 2017

Abstract: Labour market analysis in the South African context provides a relatively robust understanding of the individual characteristics that influence wage differentials across workers (i.e. supply-side characteristics), but provides relatively little insight into the firm-level characteristics influencing these differentials (i.e. demand-side characteristics). This is largely due to the relative paucity of firm-level data in South Africa. Therefore, the availability of micro firm-level data derived from anonymous corporate and individual tax data, presents an opportunity to explore this relatively uncharted and important territory in the South Africa labour market. Therefore, this paper examines the firm-level (demand-side) characteristics that explain wage differentials across formal private sector workers in South Africa. Using the FEiLSDVj method, we measure the relative contribution of firm (demand-side) and individual (supply-side) characteristics in explaining wage formulation in the South African formal sector labour market, which advances the existing literature by including a developing country case. Consistent with results for the French and Austrian labour markets, approximately 61 per cent of wage variance is due to individual effects, while at least 13 per cent is due to firm-level effects. Overall, our results suggest that firms that are profitable, older, more capital-intensive, more productive, and involved in international trade pay higher wages, on average. Interestingly, and contrary to the literature, our results indicate a negative relationship between firm size and wages.

Keywords: Administrative data, tax, firm level, wages
JEL classification: D24, J31

Acknowledgements: We would like to thank Friedrich Kreuser and Wayde Flowerday for assistance in the construction of this database. We would also like to thank Neil Rankin for his valuable input. Finally, thanks to UNU-WIDER, SARS, and the National Treasury.

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This study has been prepared within the UNU-WIDER project on 'Regional growth and development in Southern Africa'.

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ISSN 1798-7237 ISBN 978-92-9256-249-6

Typescript prepared by Lesley Ellen.

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UNU-WIDER acknowledges specific programme contribution from the National Treasury of South Africa to its project 'Regional Growth and Development in Southern Africa' and core financial support to its work programme from the governments of Denmark, Finland, Sweden, and the United Kingdom.

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1 Introduction

Much of the existing analytical work on the South African labour market provides a relatively robust understanding of the individual characteristics which shape wage levels and wage differentials across the sample of individual workers. Yet, such a standard supply-side approach can provide only a limited empirical insight into the firm-level, or demand-side, factors that predict earnings outcomes in the labour market. For example, the impact of supply-side factors such as education, experience, race, gender, and location on individual earnings, is fairly well known—and largely a function of the availability of household survey data, such as the Quarterly Labour Force Survey.[1] In contrast, very little is known about the role played by firm-level characteristics such as firm size, capital intensity, trade status, and product market power, in predicting formal private sector employee wages in South Africa.[2] This is largely due to the relative paucity of firm-level data in South Africa. Ultimately then, the availability of micro firm-level data presents a unique opportunity to explore this relatively uncharted and important territory in the South Africa labour market.

Using matched employer–employee data, we address the following research objectives in this paper. Firstly, specific focus is placed on understanding the relative importance of firm and individual characteristics in explaining wage formulation in the South African formal sector labour market. Secondly, we examine the role of various firm characteristics (conditional on data) in explaining wage levels and wage differentials across individual workers. Thirdly, and consistent with the literature, we focus on the firm size–wage relationship and test this relationship fairly rigorously.

This paper benefits from the use of matched employer–employee administrative panel data, derived from anonymized corporate and individual tax data made available by the South African Revenue Services (SARS) in collaboration with the National Treasury (NT).[3] The use of matched employer–employee data allows for two key contributions to the broader analysis of the South African labour market. Firstly, the data allows one to analyse the role of firm or demand-side factors in explaining wage formulation in the South African labour market. In the South African context, we are unaware of any other studies that have been able to examine the firm-side determinants of wages using data that is representative of the entire South African tax base.

Secondly, the availability of this matched employer–employee panel data and the methodological developments by Abowd et al. (1999), allow for the decomposition of wage differentials by observable firm and worker characteristics, firm heterogeneity, and worker heterogeneity. As such, this paper is one of the first to measure the relative importance of firm and worker characteristics in explaining wage formulation in South Africa. Furthermore, this analysis contributes to an existing literature focused on the relative importance of firm and worker characteristics in wage determination, and whether this varies across countries. Thus, we are able to compare our findings to other studies for

[1] See for example: Mwabu and Schultz (2000); Allanson et al. (2002); Hinks (2002); Keswell and Poswell (2004); Posel and Muller (2008); Casale and Posel (2011).

[2] It is important to note the following: firstly, the nature of the firm tax data on employees restricts the analysis to the formal sector (i.e. workers employed in registered firms); secondly, the analysis is restricted to the private sector since there is no firm level data for public sector workers.

[3] It is important to acknowledge the role of UNU-WIDER in supporting the research using this unique dataset.

France (Abowd et al. 1999) and Austria (Gruetter and Lalive 2009), and thus provide a developing country perspective.

In order to gain insight into the firm characteristics driving employee wage-differentials, we present a descriptive analysis showing how wages vary by firm characteristics. This is followed by multivariate analysis, which allows one to isolate the key drivers of wage differentials among private formal sector workers. We estimate a fixed-effects model that allows one to control for both unobserved firm and worker heterogeneity. In particular, we employ the FEiLSDVj method developed by Cornelissen (2008), which allows one to estimate the extent to which individual and firm characteristics explain variation in wages across workers. Finally, using the quantile regression estimator, we further interrogate the manner in which the various firm characteristics influence worker wages at different points of the earnings distribution

The paper is structured as follows. In Section 2 we provide a brief overview of the literature. In particular, we assess the firm-level characteristics driving earnings differentials across workers and the theoretical explanations for these observed relationships. Section 3 presents a description of this unique dataset and the methods employed to analyse it. In Section 4 we present the results of our analysis. We conclude and provide policy recommendations in Section 5.

2 Literature review

This paper examines the manner in which firm characteristics influence variation in the returns to employment in a developing economy, specifically South Africa. The analysis in this paper is informed by a broad theoretical and empirical literature on the subject. As such, in this section we consider each firm characteristic systematically. This aligns with the literature, where studies typically adopt a more focused position by examining one or two of these firm characteristics. However, it is worth noting that these firm characteristics tend to be closely related. For example, it is well established in the trade literature that trading firms are larger, more capital-intensive, more productive, more skill-intensive, and pay higher wages (Bernard et al. 2007).

A key firm characteristic that impacts on wage differentials across individuals is a firm's capital intensity of production. Arai (2003) states that there is a direct relationship between wages and capital intensity, and provides a number of explanations for this relationship. Firstly, the less important labour costs are to capital costs, the greater the possibility of workers extracting rents. When labour costs are minor, there is less resistance to higher wage demands than in the case where labour costs comprise a significant share of overall costs. Secondly, a high capital-to-labour ratio may be indicative of high fixed costs, which are associated with high barriers to entry and hence product market power. These product market rents may be shared with workers. Finally, higher capital-intensity and the associated technology intensity may increase the costs of turnover and poor performance. Efficiency wage theory predicts that firms pay wage premia that incentivize experienced workers to remain at firms and thereby reduce turnover costs.

Evidence for the positive relation between wages and capital-intensity are evident in Arai (2003). Using linked employer–employee panel data for Sweden, the author finds that an increase in the capital-to-labour ratio by one standard deviation is associated with wage differentials of around 2.4 per cent, after controlling for worker and job characteristics. Similarly, using linked employer–employee panel data for the US, Troske (1999) finds a positive relation between wages at the individual level and the capital-to-labour ratio.

Recent research shows a shift toward increasingly capital-intensive production techniques in South Africa, especially in manufacturing industries (Edwards 2001; Edwards and Lawrence 2008). As such, it is interesting to consider the likely impact of this increasing capital-intensity on wages. Therefore, we consider the role of capital-intensity on wages in our estimations.

It is also evident in the literature that there is a positive link between wages and productivity. Zhang and Liu (2013) state that in a well-functioning labour market, wage and productivity growth should move in tandem.[4] There are a number of factors that may influence labour productivity: Firstly, firm size may positively influence labour productivity if there is the existence of internal economies of scale in large firms. Secondly, higher levels of capital intensity, a possible proxy for technological prowess, requires more skilled workers, which is linked with higher wages. Thirdly, in the spirit of Melitz (2003), participation in international markets is associated with higher levels of productivity (in the next subsection we discuss how firms engaged in international trade, on average pay higher wages).

Dunne et al. (2004) investigate the link between technological change, wages, and productivity. The purpose of which is to provide an explanation for increasing wage inequality in the US since the 1970s. They posit that technological change has a skills bias that drives bot productivity and wage dispersion over time. In particular, they are interested in whether the increasing use of computing technology among US manufacturers drives demand for skilled labour, which in turn increases the skilled-to-unskilled wage ratio. Using plant-level data, firstly, they find that wage dispersion between plants is the largest and increasingly larger contributor to overall wage dispersion. Secondly, they find that much of this between-plant dispersion of wages is occurring within industries. Thirdly, they find that between-plant dispersion in wages and productivity has increased since the 1970s and that a significant share of this dispersion can be accounted for by changes in the distribution of computer investment across plants. Hence, Dunne et al. (2004) highlight the important link between technological advancement and productivity growth and how this translates into varying wage trends.

Bernard et al. (1995) examine the wage premium associated with exporting. Bernard et al. (1995), in the context of the NAFTA agreement, examine the impact of trade liberalization on US jobs. They argue that the opportunities afforded by liberalization to exporting firms are positive. Exporters are successful establishments that compete on the global market and provide better jobs that pay higher wages. They find that exporters, relative to non-exporters, pay wages that are 14 per cent higher. After controlling for plant, industry, and regional characteristics, the wage premium still holds—between 7 and 11 per cent. The export wage premium finding is corroborated by Bernard et al. (2007). In fact, they argue that exporters are fundamentally different to other firms and exhibit various other premia: they are larger, more productive, more capital-intensive, and employ more skilled workers.

However, one of the shortcomings of the Bernard et al. (1995) study is that the wage premium is estimated using average data at the plant or firm level. Schank et al. (2007) argue that the Bernard et al. (1995) study, and subsequent empirical papers applying the same methodology and unit of measure, do not take into account individual characteristics of workers that might influence their productivity,

[4] Zhang and Liu (2013) also mention that in instances where productivity growth outstrips wage growth, institutional intervention by unions and collective bargaining councils should correct this divergence.

and hence their wages. As such, Schank et al. (2007) test the existence of this premium using German linked employer–employee panel data that allows them to control for observable and unobservable worker and firm characteristics. They find evidence for the export premium in Germany and state that it is neither large nor negligible. Interestingly, they posit that the premium in the German context may be explained by efficiency wage theory where higher wages reduce turnover. The authors argue that German exporters compete on quality in the global market, and thus firms place high value in retaining, through higher wages, experienced workers that are able to maintain high levels of quality.

Using the same data employed in this paper, Matthee et al. (2016) provide evidence for the exporter wage premium in South Africa. Applying a similar approach on the same dataset, Edwards et al. (2016) show that this premium is stronger for firms that both export and import, followed by firms that only import, and then firms that only export. However, when estimating the premium, both of these recent studies follow Bernard et al. (1995) and regress aggregate wages by industry on an exporter status dummy variable and various controls. As such, the critique by Schank et al. (2007) applies. We extend these initial analyses by estimating wage equations that control for observed and unobserved worker and firm characteristics, thereby ensuring a more reliable estimate of the exporter wage premium.[5] In addition, we follow Edwards et al. (2016) and differentiate trading firms into two-way versus one-way traders.[6]

Another strand in the literature is concerned with whether workers are able to extract rents from profitable firms (or profitable firms share rents). A competitive model with friction allows for rents in the short run (i.e. a positive relationship between wages and firm profits). A change in demand that shifts profits upwards may be associated with higher wages, provided that worker reallocation is frictional. In the long run wages should adjust to the competitive level. However, this adjustment may be prevented in the presence of constraints, such as wage bargaining in the presence of product market rents.

Arai (2003) states that the positive relation between wages and profitability may be driven by efficiency wage model considerations. In such a case, firms are able to generate higher profits because they pay higher wages that induce increased productivity. There are also union bargaining explanations, where unions are able to capture rents for their members. However, in both instances, the rents can only persist in the long run in the presence of product market power.

Using linked employer–employee panel data for Sweden, Arai (2003) finds that profits per employee affect wages positively.[7] The size of the effect is reduced once human capital controls are included, which suggests a systematic sorting of workers with high levels of education and experience into high profit firms. This profit–wage relation is consistent across samples of blue versus white collar workers, union versus non-union workers, and manufacturing versus non-manufacturing workers. Arai and Heyman (2009) employ similar data and advance the methodology by controlling for both individual and firm heterogeneity in order to get more reliable estimates. Furthermore, they differentiate between

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[5] It is worth noting that the exporter wage premium was not the focal point of the analysis by Matthee et al. (2016).

[6] Edwards et al. (2016) find that two-way traders are larger, pay higher wages, are more productive, and more capital-intensive than one-way traders and non-traders.

[7] It is worth noting that linked employer–employee data allows the researcher to focus on whether otherwise identical individuals are paid higher wages in high profit firms. Industry or firm level data does not allow for differences in observed (i.e. education) and unobserved (i.e. ability) individual-level characteristics, which results in biased estimates.

firms that are experiencing increasing and decreasing profits. They find a positive relationship only in firms with increasing profits, and conclude that falling profits do not lead to falling wages due to wage stickiness, but that rising profits lead to wage increases.

Gürtzgen (2009) investigates the linkages between individual wages, firm profitability, and collective bargaining coverage using German linked employer–employee data. The key question addressed is whether wages respond differently to profits in firms given variation in bargaining coverage. They explore whether the link between wages and profits varies according to wage determination in the sector-specific bargaining coverage context, the firm-specific bargaining coverage context, and the absence-of-bargaining coverage context. They find a strong positive link between individual wages and firm profitability in the non-union context and the firm-specific bargaining coverage context. However, the responsiveness of individual wages to firm profits is weaker in the case of industry-specific bargaining.

The basic premise behind the link between wages and product market power is that market power allows for monopoly rents and that these rents may be captured by workers (Nickell 1999). Nickell et al. (1994) state that firms might share rents because it may make the life of managers more comfortable, it enables unions to be kept out, or it avoids drops in productivity due to worker disenchantment arising from perceptions of unfair pay. Long and Link (1983) state that higher wages resulting from market power may be driven by firms in concentrated markets being able to pass higher labour costs on to consumers. It may also be the case that with a small number of firms in an industry, it is easier for unions to organize and demand higher wages.

Nickell (1999) discusses how bargaining and efficiency wage models relate to the link between wages and product market power. A bargaining model posits that collective bargaining is able to capture monopoly rents. In the absence of collective bargaining, the efficiency wage model predicts that managers can raise wages by sharing rents, in order to ensure a quiet life.

Using a panel of 800 UK manufacturing firms with an aggregated wage measure, Nickell et al. (1994) find that product market power is positively associated with firm-level wages. The estimated effect is quite small, with a 13 per cent increase in market share being associated with a 1 per cent rise in wages in the long run. When interacting these effects with firm size and union status, they find that workers in larger firms are better able to extract rents, while the presence of unions has no impact of rent extraction. Long and Link (1983) broaden the measure of the dependent variable, and find a positive relationship between concentration and wages and fringe benefits, and a negative relationship with respect to worker turnover.

Evidence of a firm size–wage differential—a pattern whereby the wages of observationally similar workers vary by firm size—is ubiquitous in the literature on wage determination.[8] In particular, this differential refers to a wage premium associated with employment in larger firms. In general, this differential persists even after controlling for a variety of firm and employee characteristics in wage equations. It is thus argued that unobserved factors captured in the error term may explain this differential. As such, a number of studies provide theoretical explanations for the manner in which these unobserved factors relate to firm size and hence induce the firm size–wage differential.

[8] For example, see Brown and Medoff (1989), Morissette (1993), and Oi and Idson (1999).

The first of these theoretical explanations concerns employee working conditions (Belfield and Wei 2004; Pedace 2010). It is argued that workers are compensated for poor or less than desirable working conditions (e.g. high rates of injury). It is further argued that undesirable working conditions are typically associated with larger firms or factories.

Secondly, there is the capital–skill complementarity hypothesis where capital and skills are complements in production (Troske 1999). Larger firms use more capital and thus, in order to manage this capital, hire skilled workers who demand a higher wage. It is argued that the firm size– wage differential arises from not controlling for firm capital intensity.

A third explanation for the firm size–wage differential is derived from efficiency wage models (Oi and Idson 1999). Larger firms are faced with higher monitoring costs, and in order to reduce shirking and supervision costs they pay wages above competitive levels. These efficiency wages in turn attract workers who are more skilled and thus require less monitoring. Relatedly, there is the job screening explanation for the firm size–wage differential (Ferrer and Lluis 2008). Similarly, this explanation relies on the assumption that monitoring costs increase with firm size. In this case, large firms acquire less accurate information on the abilities of their workers than smaller firms, and thus place greater emphasis on observable indicators of skills, such as education and experience. Thus, larger firms tend to employ more highly skilled workers than smaller firms, which in turn drive the wage premium associated with larger firms

Fourthly, part of the firm size–wage differential may be explained by the sorting of high-ability workers into the largest firms. The main assumption of this explanation is that different skills are not equally productive across different size firms. Thus utility maximizing workers choose the size of employer in which their abilities are best suited. It is argued that high-ability workers are best suited to work in large firms and that this in turn influences the wage premium associated with larger firms.

Another explanation for the firm size–wage differential relates to the level of unionization across firms varying in size. There are two basic arguments: Firstly, Pedace (2010) states that larger firms may attempt to reduce the unionization of its labour force by offering wages above competitive levels. Secondly, Belfield and Wei (2004) argue that there is a greater prevalence of unions in larger firms because of economies of scale in bargaining and union formation. Unions bid up the wages of workers in larger firms and thus the firm size–wage differential can partly be explained by a union wage gap.

A final explanation for the firm size–wage differential relates to rent sharing and market power. Less competitive industries are characterized by fewer larger firms that are able to share higher rents (profits) with workers. Therefore, these larger firms pay higher wages. However, this explanation is clouded by the following: firstly, it is not clear what mechanism enables workers to capture higher wages; secondly, to the extent that product market power is linked to monopsonistic labour market power, it may be the case that industry dominance is reflected in lower wages.

Naturally, the formulation of theoretical explanations for the firm size–wage differential has been accompanied by the empirical testing of such theories. Brown and Medoff (1989) provide early evidence of this differential, describing it as sizeable and omnipresent, and lament their inability to provide an adequate explanation for what may be driving it. They find no evidence in favour of the working conditions explanation, or the union avoidance explanation. They do find evidence for part of the differential being explained by differences in labour quality. Nevertheless, a sizeable differential remains. Oi and Idson (1999) estimate a differential of 35 per cent in the US in the 1980s and early

1990s. They provide an in-depth discussion of various theories that may explain the differential but do not test these theories.

A key limitation faced by earlier studies in explaining the firm size–wage differential is that the firm and individual factors used to explain the differential in the theories were not easily controlled for in limited datasets. For instance, detailed employee-level data was accompanied by stark information on the firm side. Therefore, as linked employer–employee datasets became more widely available to researchers, so too did their ability to interrogate the theoretical explanations for the differential.

For instance, Troske (1999), aided by a dataset with detailed information on both firm and individual characteristics, tested a variety of theoretical claims regarding the differential.[9] Troske (1999) provides evidence that wages are higher in firms that: have higher capital-to-labour ratios, have more skilled workforces, operate in concentrated product markets, and have more skilled managers. He also finds evidence in favour of the capital–skill complementarity hypothesis and the notion that skilled managers match highly skilled workers with other highly skilled workers. Only the latter two explanations reduce the differential, while a substantial share of the differential remains unexplained. Troske (1999) concludes that one possible explanation for the unexplained differential may be due to bigger firms investing more in human capital.

Belfield and Wei (2004), using UK data, find an elasticity of pay with respect to firm size of 0.0602 when only worker characteristics are controlled for. They sequentially control for a variety of firm characteristics and find that the differential is reduced, but does not disappear. In particular, they find strong evidence in favour of internal labour markets, where larger firms are better able to successfully match employees to occupations according to their specific skill set, and thereby reduce turnover.

Evidence for job screening is provided by both Ferrer and LLuis (2008) and Cerejeira and Guimaraes (2012). In both studies, the authors find that unobserved ability is rewarded more highly in smaller firms whereas observed skills are rewarded more highly in larger firms. Monitoring costs are higher in larger firms and thus larger firms employ workers by screening their observable human capital characteristics.

A number of papers have also tested whether the firm size–wage differential varies across countries. For instance, Lallemand et al. (2007) examine the size and determinants of the differential across five European countries—Belgium, Denmark, Ireland, Italy, and Spain—using detailed linked employer–employee data. They find evidence for the firm size–wage differential after controlling for human capital variables, gender, and occupation. They find that the differential is driven by sectoral effects, differences in working conditions by firm size, regional effects, and size differences in levels of wage bargaining. However, the authors are unable to control for either firm or individual heterogeneity and thus the estimates do suffer from possible bias. Söderbom et al. (2005) provide one of the first tests of the size–wage differential in African countries by using match employer–employee panel data from Kenya and Ghana. They find evidence for a firm size premium, which remains substantial even after controlling for individual fixed effects.

[9] Troske (1999) links US manufacturing employee census data in 1990 to census data for manufacturing firms.

Related to firm size is the notion that firm age is positively linked to wages.[10] There are a variety of explanations for the positive relation between firm age and wages. Firstly, Brown and Medoff (2003) state that this relation may be driven by older firms paying higher wages to their workers who tend to be more experienced and have longer tenure. Secondly, it is possible that differences in survivability between old and new firms may impact on the firm age–wage relationship. The relationship may be negative due to workers demanding a higher wage to compensate for the instability associated with employment in a young firm. Alternatively, the relationship may be positive because older firms with secure employment prospects are more likely to invest in on-the-job training and offer opportunities for job advancement. These firm characteristics are likely to influence the mix of workers that firms employ, resulting in higher demand for high-skill and high-ability workers. As such, with this worker mix, older firms are likely to pay higher wages.

Thirdly, Heyman (2007) mentions that a firm's ability to pay, hence its profitability, influences this relationship. If it takes time for a firm to become profitable, then there will be differences in ability to pay between old and young firms. Furthermore, this relationship may be linked to the discussion on rent sharing. The positive link between profits and wages may be partly driven by the profitability of older firms. Younger firms may be less profitable and stable than older firms thus allowing managers to claim an inability to pay higher wages. Conversely, the credibility of such argument in older, stable, and more profitable firms has less strength.

Brown and Medoff (2003) find that older firms pay higher wages, but once they control for worker characteristics this relationship becomes insignificant, and in some cases negative. They also find that the relationship is non-monotonic, with wages initially declining in firm age and then increasing at higher age levels. Similarly, using matched employer–employee data from Sweden, Heyman (2007) finds a positive relationship between firm age and wages, but finds that this relationship is robust to the inclusion of various observed firm and individual characteristics. Furthermore, in questioning whether the firm size–wage premium is simply a firm age–wage premium, they find that the firm size estimates are robust to the inclusion of firm age controls.

The various strands of literature discussed above are concerned with whether specific firm characteristics influence wages differentials. However, there are a number of studies that decompose wage differentials into components due to observable firm and worker characteristics, firm heterogeneity, and worker heterogeneity. As such, this provides an indication of the relative importance of firms and workers in wage determination. The statistical methodology used to decompose wage differentials into these components was developed by Abowd et al. (1999).[11] Importantly, the analysis was enabled by the availability of a longitudinal matched employer–employee dataset covering French private sector firms. Abowd et al. (1999) show worker heterogeneity to be more important than firm heterogeneity in explaining wage variation across workers as well as wage variation across industries.

Decomposing wage differentials in Austria, Gruetter and Lalive (2009) show that firm heterogeneity is more important in explaining variation in industry wage structure than variation in individual worker wage structure. They find that firm heterogeneity accounts for 26.6 per cent of the variation in worker

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[10] In fact, the close link between firm size and firm age led Brown and Medoff (2003) to question whether the firm size–wage premium is not simply the firm age–wage premium.

[11] Formulation of the algorithm behind this methodology is explained in practical detail in Abowd et al. (2002).

wage rates. In comparison, firm heterogeneity accounts for 74.2 per cent of variation in average industry wages. They conclude that these results suggest that firm wage policies differ substantially across industries.

This paper benefits from the availability of longitudinal matched employer–employee data for South Africa. Using a methodology that draws on Abowd et al. (1999), we are able to measure the relative importance of firms and workers in wage determination in the South African labour market. Therefore, we are able to complement the existing literature on the South African labour market that details the worker or supply-side characteristics driving wage differentials, with insight into the relative importance of firm or demand-side characteristics.

Three key points emerge from this exploration of a broad literature on the firm-level determinants of wage differentials. Firstly, one can expect a positive link between wages and the size of the firm, the age of the firm, whether the firm is profitable, the level of productivity of the firm, whether the firm is involved in international trade, the capital intensity of production, and whether the firm has product market power. Secondly, there is a distinct trend toward increased use of longitudinal matched employer–employee data, which enables one to control for both worker and firm heterogeneity. Controlling for both these effects allows for unbiased estimates of the wage equation. Thirdly and relatedly, the use of this data in combination with a methodology drawing from Abowd et al. (1999), allows for the decomposition of wage differentials, thereby allowing this paper to determine the relative importance of supply-side and demand-side characteristics in explaining wage differentials in South Africa.

3 Methodology and data

This section discusses the data and methodology employed in this paper. The first sub-section provides an overview of the data used. In particular, we discuss how the panel dataset employed in the analysis is constructed. We also briefly describe how we defined and measured two key measures in the analysis: firm size and wages.[12] In the second sub-section, we describe the methodology that enables us to determine the firm characteristics that drive wage differentials.

3.1 Data

3.1.1 Panel creation

The data used is extracted from anonymized corporate income and individual tax returns made available by the South African Revenue Services (SARS) in collaboration with the National Treasury (NT). Firm-level data is in the form of Corporate Income Tax (CIT) data, sourced from the Income Tax Return for Companies (form IT14, replaced with form ITR14 in May of 2013). Individual-level data is from the employer-issued Employee Tax Certificate, which is an IRP5 that discloses the total employment remuneration and deductions earned for the year of assessment.

[12] For a detailed description of the data and variables used, please see Appendix A: Data.

We create an unbalanced individual-level panel for the years 2010 to 2013, including lagged firm-level data for the years 2008 and 2009. Table 1 below provides the number of individuals and firms in each year of our panel. The panel is made up of those individuals who have ID numbers and are aged 15 to 64 (i.e. of labour market age). Further restrictions to the panel are detailed in Appendix A: Data.

Table 1: Sample size—individual–firm panel

	2010	2011	2012	2013
Individuals	4 488 493	4 757 426	4 757 168	4 820 370
Firms	99 247	100 619	97 364	95 077

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

This panel encompasses the full population of private sector firms and their employees but excludes public sector employers and employees. There is individual wage data for public sector employees, but since there is no corresponding firm-level data we exclude them from the sample. The very nature of the dataset—administrative data—suggests that the sample does not capture informal sector firms and workers. Note also that this is the panel of individuals and firms. In reality, we examine the panel from a 'jobs' perspective. A 'job' is any individual–firm match within a given year. As an individual may work for more than one firm in a given year, neither individuals nor firms are unique within each year of the panel dataset. Rather, unique observations are 'jobs'—or unique individual–firm matches within the year. As some individuals appear working for the same firm more than once within a given year, we collapse the panel to unique jobs, or one observation per individual per firm per year. This is detailed in section 0, below.

3.1.2 Availability of individual and firm-level data

There is very little information available on the individual worker in the overall dataset. While the IRP5 does contain information on gender and marital status, this data was not available during the analysis phase of this paper.[13] Furthermore, the IRP5 does not contain any information on level of education or population group.[14] One can calculate the age of individuals in the dataset (calculated using year of birth), and generate a limited measure of tenure of an individual within the same firm. Tenure is calculated by looking at the number of years that an individual works for the same firm between 2008 and 2013.[15] Where an individual appeared to be working at the same firm multiple times but with gaps between periods of employment, tenure was calculated as the number of times that individual appeared in the firm.[16] Firm-level characteristics used include firm age, firm size, trade

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[13] It is expected that future access to the administrative dataset would include this data.

[14] However, this is not a major problem since time-invariant controls, such as race and gender, are perfectly correlated with individual fixed effects, and the within transformation wipes out these controls.

[15] For example, a tenure of one year in 2013 indicates that 2013 is the first year that the individual is observed working at that specific firm (i.e. the individual did not work at their current firm at any point before 2013). A tenure of six years in 2013 indicates that the individual has been working at the same firm between 2008 and 2013.

[16] For example, if an individual worked at a firm in 2010 and 2013 but not in the years in-between, tenure in that firm in 2013 was two years. Overall, almost a third of individuals were working for their current firm for the first time in 2013 (i.e. tenure was one year) and 8 per cent had been working in their current firm every year between 2008 and 2013 (tenure was six years). The small fraction of workers with consistent tenure over the full period of available data is consistent with Kerr (2016). Using the same data, he estimates worker flows to be 50 per cent per year (worker flows is defined as the number of persons whose place of employment differs between year 1 and year 2).

status, measures of profit, loss and turnover, capital-to-labour ratio, labour productivity, industry, and measures of market power. For detailed information of how these variables were created, please see Table A1 in Appendix A.

A key advantage of the data is the fact that employees are matched to employers over time and thus one is able to control for firm and worker heterogeneity in the regressions. The manner in which the worker and firm fixed effects are dealt with varies according to the methodology employed—this is discussed in Section 3.2.

3.1.3 Firm size and wages

The CIT data does not contain specific information on the number of workers employed in a firm in a given tax year. In order to generate this (our measure of firm size), one sums the IRP5 forms linked to each firm in the CIT dataset. However, the fact that individuals are not working for the full duration of the year needs to be taken into account when calculating firm size. Therefore, firm size should be weighted by the number of days worked by an individual in the firm in that year. This is done by using the start and end date variables, which give the date on which an individual started or ended their job at that firm. Firm size is then weighted by the number of days worked divided by the number of days in each year, as follows:[17]

$$Date\_Weight_{i,f,t} = \frac{Period\ Employed\ To_{i,f,t} - \ Period\ Employed\ From_{i,f,t}}{Days\ in\ Year_t}$$

However, there are a number of cases where the data on start date or end date is unreliable. We therefore dropped all jobs which we deemed to have invalid start or end dates.[18] The result is that 0.19 per cent of all jobs worked by individuals in the sample in 2013 were dropped. For a more detailed analysis of jobs excluded due to invalid start or end dates, see Appendix A: Data.

In addition, there were some cases where the start or end date of the job fell outside of the tax year in question. In these cases, the start or end date was updated to reflect the start or end date of the given tax year. This process mimics that of Pieterse et al. (2016) and is detailed in their paper. In summary, when an individual's job start date is before the corresponding tax year, it is brought forward to be in line with the start of that financial year. Similarly, when an individual's job end date is after the end of the corresponding tax year, it is brought backwards to be in line with the end of that financial year.[19]

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[17] Equation taken from: Pieterse et al. (2016).

[18] This was the case where:

1. The start date for employment was after 28 February of that year. For example, the 2010 tax year is 1 March 2009 to 28 Febryart 2010. If the 2010 job's start date was after 28 February 2010, this was deemed an invalid job period.
2. The job end date was before the start of the tax year. For example, the 2010 tax year is 1 March 2009 to 28 February 2010. If the 2010 job's end date was before 01 March 2009, this was deemed an invalid job period.

[19] For example, the 2010 financial year runs from 1 March 2009 to 28 February 2010. If an IRP5 indicates a start date of 12 February 2009, this date was brought forward to 1 March 2009 to reflect the start date of the 2009 financial year. Similarly, end dates which were after the end of the corresponding financial year were brought back to the last day of that financial year.

In addition, and as detailed in Appendix A: Data, many individuals have multiple IRP5s for the same firm in one financial year. This indicated multiple jobs worked by that individuals within the same firm in a given year. This data was collapsed into one job per individual per firm per year. Therefore, while our dataset may contain multiple jobs per individual per year, these are jobs worked in different firms within that year. Where an individual works for only one firm within a given year, this is reflected as only one job worked within that year in the data.

The wage measure used is defined as real gross remuneration,[20] which is the sum of gross taxable income, gross retirement funding income, and gross non-retirement funding income. It is important to note multiple manipulations were necessary in order to be able to analyse the individual-level wage data, which was calculated at a daily rate, detailed in Appendix A: Data.[21]

3.2 Methodology

The availability of matched employer–employee panel data allows one to evaluate the extent to which both firm and individual characteristics affect wages, in a way that has previously been impossible in South Africa. We make use of linked CIT-IRP5 data in order to evaluate the firm-level determinants of wages. Firm characteristics of interest include firm size, firm age, industry, product market power, degree of profit/loss, labour productivity, capital intensity, and trade status.

We begin by conducting a descriptive analysis of formal private sector employee wages (see Section 0). This is useful in providing an initial indication of what firm characteristics may be driving employee wage differentials. Following this, we estimate a range of econometric models in order to isolate the key drivers of wage differentials across individuals. There are four parts to the econometric analysis. Firstly, we estimate a pooled regression on the full sample of data. Secondly, we estimate a fixed-effects model, namely the spell fixed-effects method. Thirdly, we estimate another fixed-effect model, namely the FEiLSDVj method. Finally, we estimate quantile regressions on the 10th, 50th, and 90th percentiles of the wage distribution. In the latter three methods, we estimate the regression on samples of the overall dataset.

3.2.1 Pooled regressions

The first stage of our econometric analysis is to run a pooled regression on the full sample panel.[22] As mentioned above, the sample comprises private formal sector workers for the period 2010 to 2013. For the pooled regression we estimate the following semi-logarithmic wage function:

$$y_{ijt} = x_{ijt}\beta + \varepsilon_{ijt} \tag{1}$$

[20] We deflate wages to 2012 prices using the consumer price index.

[21] Note that we allow an individual to have multiple IRP5s across firms, but we restrict the data to one IRP5 per individual per firm per year.

[22] The full sample is made up of approximately 19 million observations. We are able to estimate the pooled regression using the full sample because the computation requirements of the OLS estimator is not as demanding as the fixed-effects estimations and the quantile regressions.

where y_{ijt} is the outcome of interest, in this case the log of real monthly[23] wages for worker (job) i in firm j in period t.[24] X_{it} are the observable individual- and firm-level characteristics affecting wages. As mentioned above, the only individual characteristics that we are able to measure are age and tenure. However, we include a number of firm covariates in our estimations, such as: firm size categories, firm age categories, trade status categories, a measure of capital intensity, a measure of labour productivity, a measure of product market power, and a measure of profit/loss. We also include industry and time dummies. ε_{ijt} is the error term.

However, we need to take into account the fact that workers are not randomly distributed across firms. For example, large firms may attract 'better-quality' workers, in terms of education level or productivity. This means that unobservable variables are correlated with observable firm-level data. Failing to account for this unobserved heterogeneity may introduce bias into the estimates. For this reason, we will also run two fixed-effects models that exploit the panel nature of the data. This will allow us to control for time-invariant unobservables that affect wages in the model, enabling us to obtain consistent estimates. The following section gives an overview of the fixed-effects methods that we undertake.

3.2.2 Fixed-effects specifications

In this paper we employ two fixed-effects estimation methods to estimate the wage function. Firstly, the spell fixed-effects method, and secondly, the FEiLSDVj method. The description of these methods is informed by Abowd et al. (2002), Andrews et al. (2004) and Cornelissen (2008).

The linear wage equation to be estimated has the form:

$$y_{it} = x_{it}\beta + w_{j(i,t)t}\gamma + \theta_i + \psi_{j(i,t)} + \epsilon_{it} \tag{2}$$

Workers (in our case jobs) are indexed by $i = 1, \ldots, N$. These workers (jobs) are observed once per period $t = 1, \ldots, T_i$ in firm $j = 1, \ldots, J$. Over time, workers can shift across firms and this is denoted by the function $j(i,t)$, which maps worker (job) i to firm j at time t. The dependent variable, denoted by y_{it}, is the log of the real monthly wage for worker (job) i at time t.[25] x_{it} denotes observed (measured) time-varying characteristics of worker (job) i at time t. $w_{j(i,t)t}$ denotes observed (measured) time-varying characteristics of firm j at time t. It must be noted that because the firm characteristics are also recorded at the (i,t) level, firm-level covariates also vary at that level. The individual fixed effect, denoted by θ_i, captures time-invariant unobserved worker (job) heterogeneity. Similarly, the firm fixed effect, denoted by $\psi_{j(i,t)}$, captures time-invariant unobserved firm heterogeneity. ϵ_{it} denotes the error term.

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[23] Monthly wages calculated by scaling daily wages up to their monthly equivalent.

[24] It is worth noting that each observation in the panel dataset refers to an individual in a job, in a firm, at a point in time. There are a number of individuals with multiple IRP5 forms across multiple firms in a given year. We do not collapse these employment spells by individual because each spell may be linked to a different firm with different characteristics. As such, our 'individual' or 'worker' is essentially a job.

[25] Please refer to discussion on data, specifically regarding the various measures of earnings in Appendix A: Data.

The spell fixed-effects method involves time-demeaning within each unique worker–firm combination (or spell). This method suffices if one is not interested in the individual estimates of the worker (job) and firm fixed effects, since for each worker–firm combination (spell) neither θ_i nor $\psi_{j(i,t)}$ vary. Spell-level heterogeneity (defined as $\lambda_s \equiv \theta_i + \psi_{j(i,t)}$) is swept out by subtracting means at the spell level. This is shown in the following equation:

$$y_{it} - \overline{y_s} = (x_{it} - \overline{x_s})\beta + (w_{j(i,t)t} - \overline{w_s})\gamma + (\epsilon_{it} - \overline{\epsilon_s}) \tag{3}$$

As such, the spell fixed-effects method does not allow the researcher to obtain estimates for the firm, $\psi_{j(i,t)}$, and worker fixed effects, θ_i.

Alternatively, the FEiLSDVj method allows the researcher to obtain estimates for both $\psi_{j(i,t)}$ and θ_i. An alternative to the within transformation applied for worker–firm spells in the spell fixed-effects method, is to use the least-squares dummy variable estimator (LSDV). However, given the sheer size of employer–employee datasets, such as the data employed in this paper, using the LSDV estimator is not feasible. Drawing on Abowd et al. (1999), the FEiLSDVj method uses a combination of the LSDV approach and within transformation. This is done by including dummy variables for firm heterogeneity and sweeping out the worker heterogeneity algebraically using the within transformation. As such, the method generates a dummy variable for each firm,

$$F_{it}^{j} = 1\{j(i,t) = j\}, j = 1, \dots, j$$

where $1\{\quad\}$ is the dummy variable indicator function and the function $j(i,t) = j$ maps worker i at time t to firm j. Substitute

$$\psi_{j(i,t)} = \sum_{j=1}^{J} \psi_j \, F_{it}^{j}$$

into (3). The worker fixed effects are removed by time-demeaning over i:

$$y_{it} - \overline{y_s} = (x_{it} - \overline{x_s})\beta + (w_{j(i,t)t} - \overline{w_s})\gamma + \sum_{j=1}^{J} \psi_j \, (F_{it}^{j} - \overline{F_i^{J}}) + (\epsilon_{it} - \overline{\epsilon_s}) \tag{4}$$

Equation (4) indicates that demeaned firm dummies also need to be created. It is important to note that effects are identified by the number of movers in each firm.[26] The effects cannot be identified for firms with no worker turnover because every $F_{it}^{j} - \overline{F_i^{J}} = 0$. The importance of movers is increasingly evident in the case where one needs to use a sample of the population. In a sample, a mover can only be identified if that worker moved from one firm in the sample to another firm in the sample. As

[26] The term 'movers' refers to workers that move between firms over the period of analysis.

such, in the generation of the samples used in the analysis to follow, we generated samples where all moments of a worker are maintained.[27]

With large datasets, such an estimation procedure results in computational problems.[28] The Stata command *felsdvreg* skips the step of creating dummy variables. Rather it exploits information provided by group identifiers to directly create cross-product matrices needed for the least-squares equations.[29] These cross-product matrices are of a much lower dimension and thus space saving. The *felsdvreg* procedure incorporates the grouping algorithm proposed by Abowd et al. (2002).

A useful aspect of the *felsdvreg* procedure is that it decomposes variation in wage differentials into components due to observable firm and worker characteristics, firm heterogeneity, and worker heterogeneity, as well as the residual. As such, this provides an indication of the relative importance of firms and workers in wage determination in South Africa. This constitutes a key contribution made by the paper.

3.2.3 Data limitations: high computing requirements

Due to the high computational requirements associated with running these estimations on this size of sample, we run the fixed-effects and quantile regressions using a number of random samples of the overall population sample.[30]

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[27] In each of the FEiLSDVj estimations, approximately 23 per cent of the sample are 'movers' thus suggesting a substantial amount of worker turnover need to identify firm and worker effects.

[28] Andrews et al. (2004) specify two computational problems. Firstly, the number of firms J, which is typically high when using administrative datasets such as those used in this paper. The software needs to invert the matrix of dimension $(K + J)\times(K + J)$. Secondly, one must create and store the J mean deviations for N^* observations, resulting in the prohibitively large data matrix $N^*\times(K + J)$. For more on this see Andrews et al. (2004) and Cornelissen (2008).

[29] Abowd et al. (2002) state that a connected group of workers and firms occurs when the group contains all the workers who ever worked for any of the firms in the group and all the firms at which any of the workers were ever employed.

[30] For the spell fixed-effects and quantile regression estimations we use nine 10 per cent samples. Using the random sample generation tool in Stata, we set three seeds and created three random samples within each seed, thus totalling nine. For the FEiLSDVj estimation we use five 10 per cent samples and two 20 per cent samples (running the FEiLSDVj estimation on the 10 and 20 per cent samples takes approximately three and three and a half hours to run, respectively. In light of time constraints, we were only able to run seven of these regressions). When creating the samples, we created them in such manner that we would capture all the moments relating to an individual worker. In other words, if the sample generator selected an individual, the generated sample would contain all the data points over time and across firms pertaining to that individual. The 10 and 20 per cent sub-samples consist of approximately two and four million observations, respectively.

4 Results

In this section, we begin by providing initial evidence of the relationship between wages and a variety of firm characteristics. The econometric results reported in Section 4.2 allow us to examine the role of each of these firm characteristics in explaining wage differentials across individual workers, while controlling for individual and firm characteristics. The decomposition of wage differentials across individuals allows us to determine the relative importance of firm and individual characteristics in explaining wage formulation in the South African formal sector labour market.[31]

4.1 Descriptive analysis—link between firm characteristics and wages

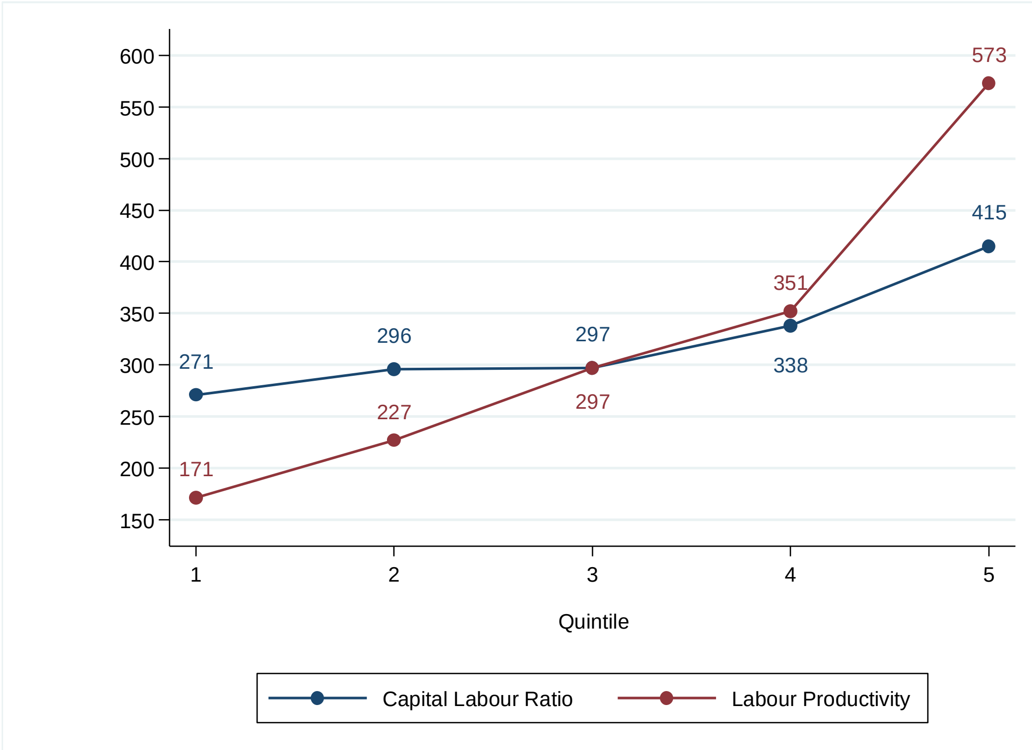
4.1.1 Technology and productivity

In this sub-section, we consider the link between firm characteristics capturing technology and productivity, and the wages paid by firms. The capital-to-labour ratio is used as a proxy for technological intensity, based on the assumption that physical capital tends to be technology-intensive. Drawing on the literature discussed in Section 2, we would expect a positive relationship between capital intensity and wages. The link between productivity and wages is also considered. This is by, firstly, considering the link between wages and a measure of labour productivity. Secondly, given that firms involved in international trade tend to be more productive than firms that only serve the domestic economy (see Melitz 2003), we consider the link between trade status and wages. It is expected that both labour productivity and trade status are positively associated with wages.

Figure 1 shows the average wage by quintile for the capital–labour ratio and labour productivity. The capital–labour ratio is calculated by dividing total fixed assets by firm size. This measure indicates that average wages increase consistently with each quintile of the capital–labour ratio, with those firms in quintile 1 paying wages that are on average R144 lower than those firms in quintile 5. Average wages also increase consistently with labour productivity (calculated by dividing gross sales by firm size), with those firms in labour productivity quintile 1 paying wages that are on average only 30 per cent of the wages paid by firms in productivity quintile 5. It is clear that, based on these descriptive statistics, the relationship between wages and both capital–labour ratio and labour productivity is non-linear, with wages increasing by the largest amount between quintiles 4 and 5.

[31] For more detailed descriptive analysis of firm characteristics, including firm distribution, median wage, and standard deviation, please see Appendix B, Table B1.

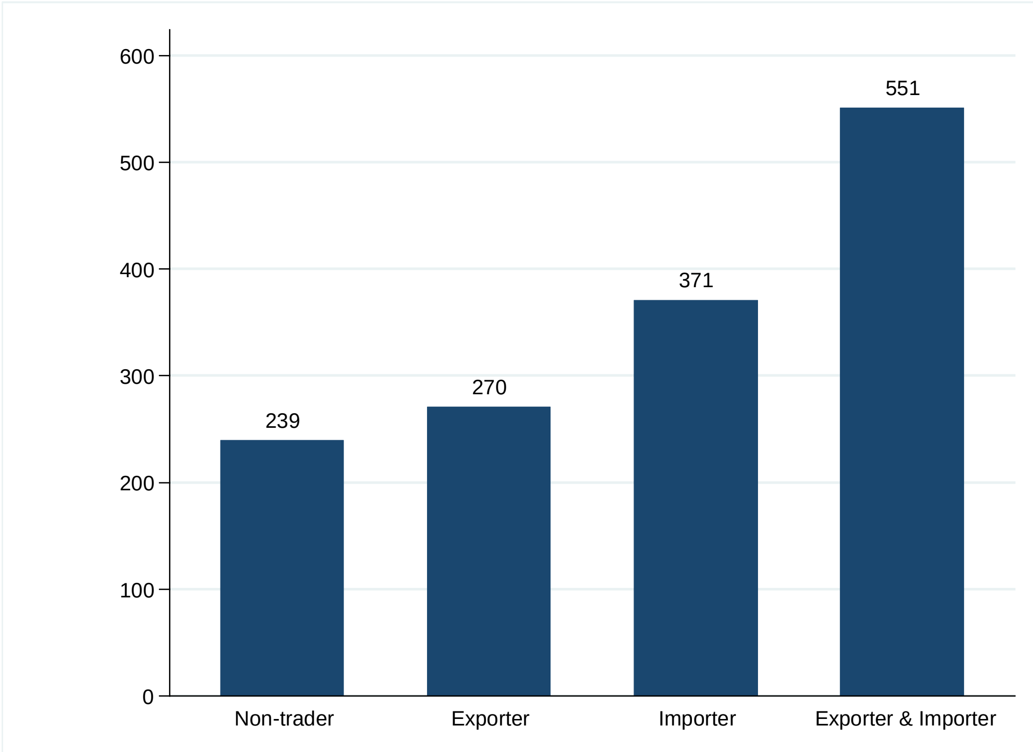
Figure 1: Technology, productivity, and wages



Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

With respect to trade status, Figure 2 indicates that non-trading firms pay the lowest average wages, with average wages increasing marginally for exporting and importing firms and substantially for those firms involved in two-way trade. This is consistent with Edwards et al. (2016) who, using the same data, find the same ordering of wage premia by trade status. Furthermore, it is also evident that a relatively small share of firms is involved in international trade (22.9 per cent). This is consistent with the heterogeneous firm literature, which finds that exporting firms are scarce since only the most productive firms are able to successfully enter the international market (Bernard et al. 2007).

Figure 2: Trade status and wages



Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

4.1.2 Profitability and market power

In this section, we consider the link between lagged measures of profit, loss, and turnover, and average wages in 2013. Lagged measures are used in order to take into account the adjustment period between firm performance and subsequent wage changes. In the case of profit and loss, a weighted average of profits or losses over the period 2010 to 2012 is used.[32] This is done in order to (at least partially) smooth the large profits and losses which firms can make from one year to the next. We expect profits to be positively related to wages in cases where workers are (at least to some extent) able to extract rents from these firms. We also look at the relationship between wages and market power. We assume that market power allows for monopoly rents which may be shared with the workers. On the other hand, firms with a high degree of market power are price setters in the market for labour. They may therefore choose to bargain wages down where labour is in excess supply and pay higher wages where labour is in excess demand.

In terms of profitability, Figure 3 indicates a relatively similar wage pattern with respect to firm profit and loss. In both cases, average wages rise with profits and losses (the exception is the second loss category). Those firms which are making the largest profits and losses—or R1 million or more—pay substantially higher wages on average than firms that are making smaller amounts of profit or loss.

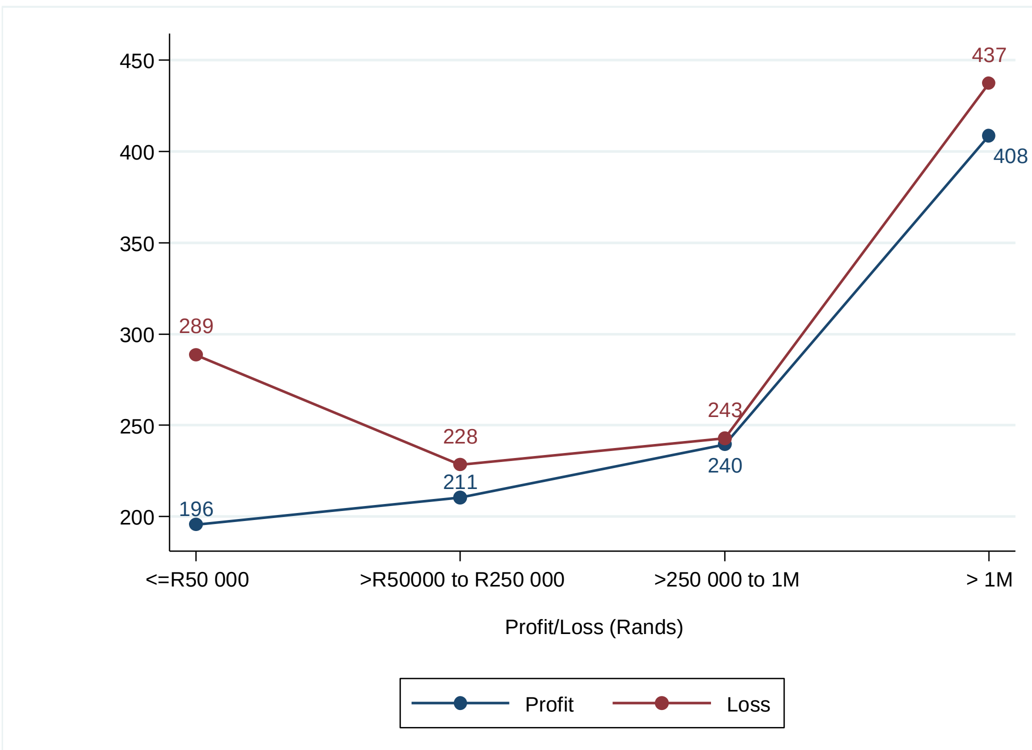
[32] More recent years are weighted twice as heavily as the year previous to it. This results in the following formula: 2012*0.5714 + 2011*0.2857 + 2010*0.1429. If the result is negative, that firm is described as having made a loss, and vice versa.

This indicates that the distinction between profit and loss may not be important in evaluating average wages paid in a firm. Rather, those firms making very large profits or very large losses are associated with a substantial wage premium.

This result may be because of the variability of profit and loss, which can change considerably from one year to the next. This means that these measures may not be good indicators of financial sustainability, although we attempted to mitigate this by using weighted profit or loss from the last three years. Secondly, very large profits and losses may be associated with other firm characteristics, such as firm age and firm size, which may explain the high wage-premium associated with firms generating large profits or losses.

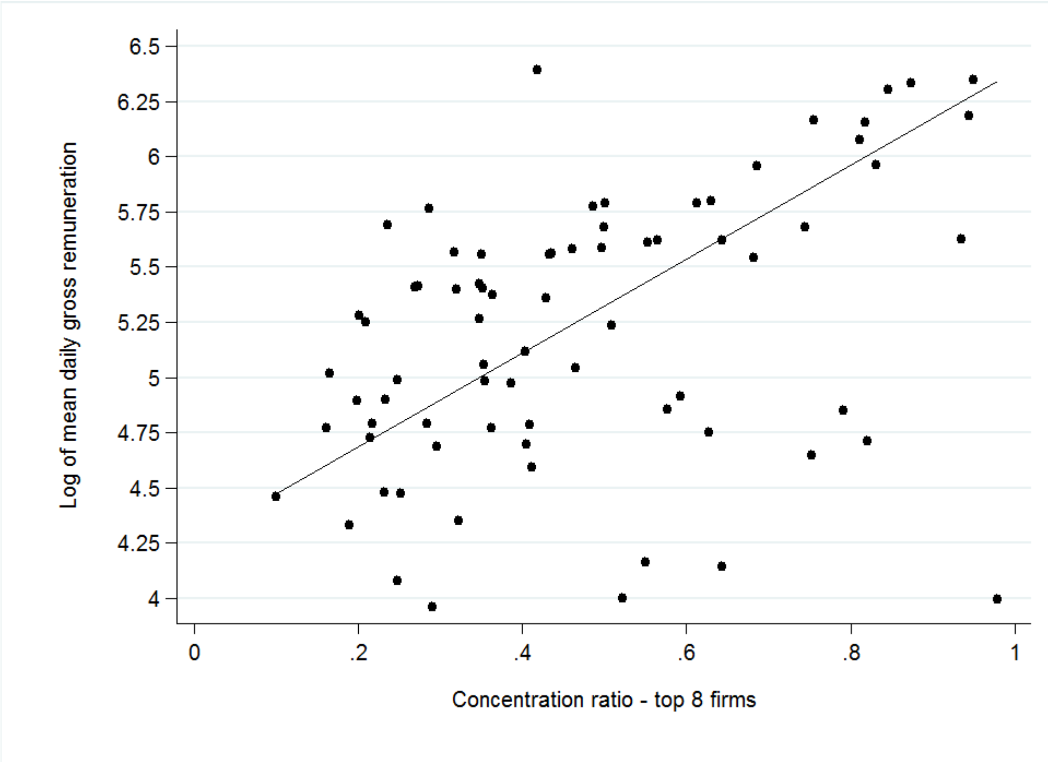
Regarding market power, Figure 4 provides a scatter plot of mean wages by industry concentration ratio. The industry concentration ratio is calculated by summing the market share of the top eight firms within each industry, where industry is based on the ISIC 2-digit codes. This figure indicates that mean wages increase with an increase in industry concentration ratio. Therefore, market power may be segmenting the labour market by reinforcing high wages in firms with substantial market power.

Figure 3: Profit, loss, and wages



Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Figure 4: Concentration ratio and wages



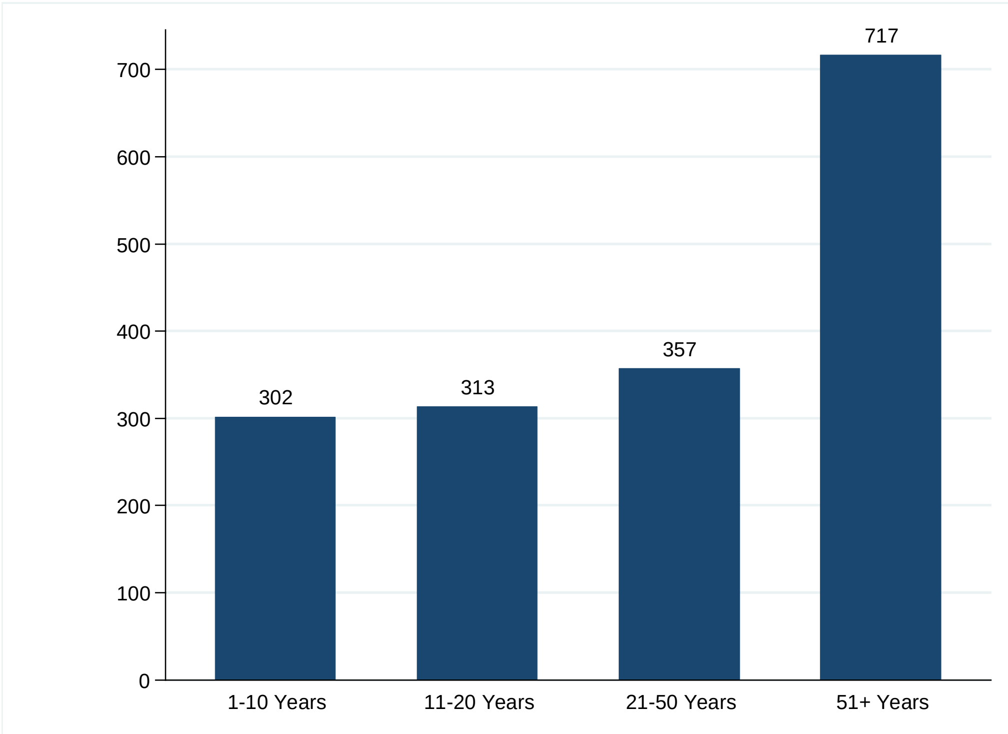
Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

4.1.3 Firm age and size

The following section looks at the relationship between firm age, firm size, and wages. As discussed in Section 2, a positive link between these two firm characteristics and wages is expected.

Figure 5 presents the mean wage and distribution of firms by firm age categories. The figure indicates that the mean wage increases consistently with firm age, with average wages amongst firms that are 1 to 10 years old being less than half of those in firms that are 51 years or older. As such, there is initial confirmation that the relationship between firm age and wages is broadly consistent with the literature.

Figure 5: Firm age and wages



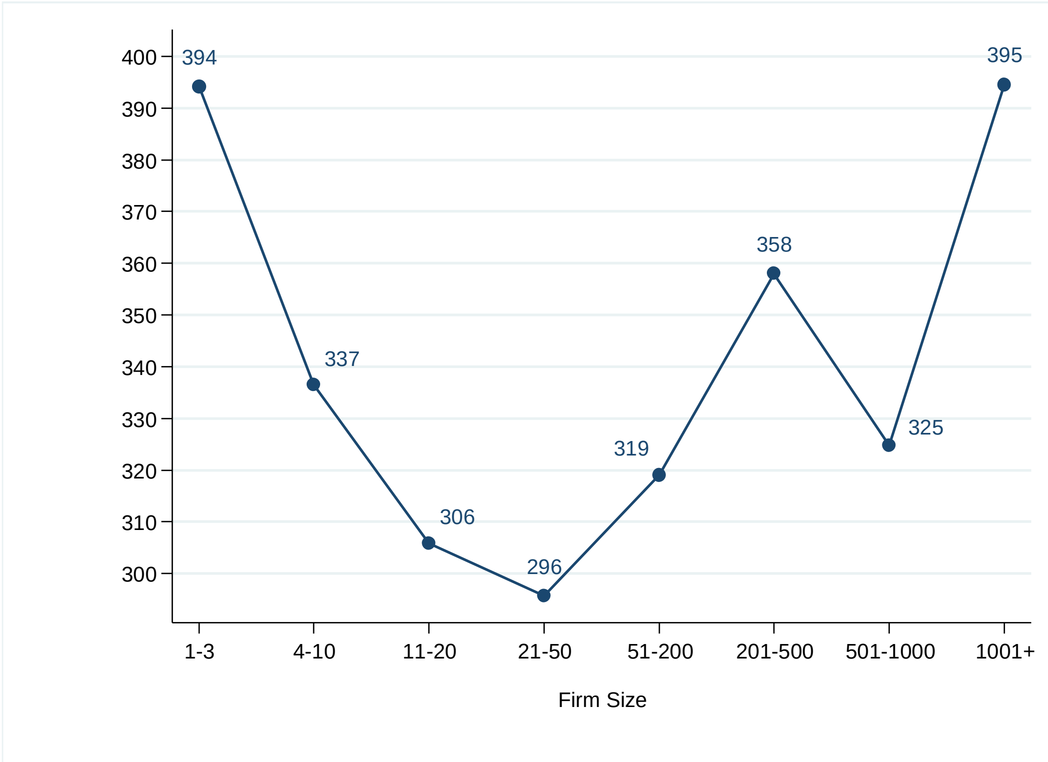
Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

However, the initial descriptive results showing the relationship between firm size and wages run contrary to the existing literature. Figure 6 shows the linkage between firm size and wages,[33] indicating a U-shaped relationship, with employees working in the smallest firms and largest firms earning the highest average wages. The lowest average daily wage is earned by those individuals working in firms with 21 to 50 employees, who earn an average of R296 per day. This is just under R100 less than those working in firms with 1 to 3 and with 1000 and more employees.

In order to investigate whether the firm size–wage relation is being driven by industry differences, the average daily wage by firm size for each industry is reported in Table 2. It is worth noting that firms within various industries are likely to have an inherent structure and thus firm size is unlikely to vary randomly across industries. For example, firms involved in mining and commercial agriculture are likely to be large since profitability is closely linked to scale. Mining firms may pay higher wages due to a high degree of unionization and required skill level. Furthermore, they are likely to pay a compensating differential due to the nature of mining work, which involves unpleasant and often dangerous working conditions. However, it may also be the case that there are a large number of low-wage workers in the mining and commercial agriculture firms, which lowers the mean firm wage.

[33] It is worth noting that all descriptive statistics as well as subsequent regression analysis was performed using three different firm size measures, please see Appendix A: Data for details. Results are relatively consistent across all three measures.

Figure 6: Firm size and wages



Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Table 2: Mean wages by firm size and industry

	1–3	4–10	11–20	21–50	51–200	201–500	501–1000	1001+
Agriculture	288.2	187.1	179.5	131.7	110.2	107.9	103.6	244.4
Mining	561.6	418.0	410.6	400.2	1028.5	707.3	970.0	622.3
Manufacturing	533.5	299.9	290.7	308.0	358.5	471.6	423.9	611.4
Utilities	385.4	344.8	300.3	371.8	412.4	601.9	589.1	1112.4
Construction	264.5	247.7	226.4	227.3	230.0	310.9	264.6	292.7
Wholesale & retail	314.2	375.4	279.8	274.1	286.8	345.6	308.0	435.4
Transport	356.3	363.1	426.9	494.0	444.5	560.8	449.0	684.0
Finance	426.8	375.0	332.2	314.6	329.1	287.2	290.8	262.9
CSP	371.5	404.2	649.1	376.5	382.2	388.0	296.8	502.2
Other	362.1	328.6	332.4	353.3	329.6	271.9	223.1	139.1

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

It is evident from Table 2 that the U-shaped relationship is present in both the agriculture and manufacturing industries. Regarding agriculture, the small-firm wage premium may relate to small-scale, high-value, and capital-intensive agriculture firms, such as those involved in plant propagation. The relatively low minimum wage paid to farm workers may also be driving the average wage in larger firms down. There is a small-firm wage premium in the financial sector, with average daily wages of R427 in firms with 1 to 3 employees—substantially higher than the average daily wage in any other firm size group. Firms in the financial sector indicate a downward sloping relationship between firm size and average wages, with firms employing 1 to 3 individuals paying higher wages than firms in any other size category. Financial firms in the smallest size category pay an average daily wage of R427, compared with just R263 in the largest financial firms (or those with 1,001 or more employees). However, there appears to be a large firm wage premium in both utilities and mining. Mining firms in the largest four size categories pay substantially higher average wages than those in the smallest four size categories. Furthermore, average wages for firms employing 1000+ workers in the utility industry are almost three times higher than wages in the smallest firms. These results indicate that there is heterogeneity in the relationship between firm size and wages across industry. Therefore, it is important to control for industry in the regression analysis to follow.

Transition matrices allow us to assess the dynamic relationship between firm size and wages. Table 3 shows transitions of firms between firm size categories over the period 2010 to 2013. Rows in these tables sum to 100 per cent. The shaded cells running diagonally from top left to bottom right correspond to the proportion of firms that did not change in size over the period. The two columns on the far right indicate the summed proportion of firms that either contracted or expanded in size.

A number of points emerge from the analysis of Table 3. Firstly, the shaded diagonal cells indicate that larger firms are more likely to remain in their size category. For instance, 77 per cent of firms with 1,001 plus employees in 2010 remain in this size category in 2013. However, this may simply be a data construct issue, since larger firm size categories have larger ranges from which to change. Secondly, the higher probabilities in cells adjacent to the shaded cells indicate that shifts in firm size are typically small shifts. Thirdly, small firms are least likely to remain small, and most likely to be missing (or exit) from the data in 2013. Of those firms with 1 to 3 employees in 2010, 30 per cent had exited (or, were no longer in the data) in 2013. This may indicate that the relatively high average wage in smaller firms is contributing to their high likelihood of firm exit. Fourthly and relatedly, small firms are the most likely to be missing from the data in 2010. Tentatively, this may be indicating that the probability of entry is highest among smaller firms. This coupled with the high probability of exit of small firms is consistent with the notion that there is a greater deal of churn among small firms.

The transition matrix in Table 4 shows the percentage change in average wages by change in firm size. For example, of those firms that had 1 to 3 employees in 2010 and still had 1 to 3 employees in 2013, average real wages increased by 30 per cent. The cells to the left of the shaded cells indicate the percentage change in average wages for firms whose size contracted. Conversely, the cells to the right of the shaded cells indicate the percentage change in average wages for those whose size expanded. The last two columns average out the percentage change in average wages for all instances of contraction and expansion by firm size category. Three clear patters emerge from Table 4. Firstly, when one considers the cells to the right of the shaded cells, it is evident that in many instances where firms grew (i.e. shifted to larger firm size categories), the average percentage changes in wages was negative. Secondly, when one considers the cells to the left of the shaded cells, it is evident that in all cases where firms contracted in size, the average percentage change in wages was positive. Thirdly, when these expansions and contractions are aggregated by firm size category (see final two columns), one observes that the average percentage change in wages for expanding firms is either negative or small and positive. Conversely, in the case of contracting firms, the average percentage change in wages is positive and substantially larger than in the case of expanding firms.

Table 3: Transition matrix of change in firm size, 2010 to 2013

		Firm size 2013										
		1–3	4–10	11–20	21–50	51–200	201–500	501–1000	1001+	Exit	Contracted	Expanded
Firm size 2010	1–3	41.3	21.4	4.7	2.3	0.7	0	0	0	29.5	-	29.1
	4–10	10.1	51.6	13.8	3.8	0.9	0.1	0	0	19.8	10.1	18.6
	11–20	2.0	14.6	47.9	17.3	2.0	0.2	0	0	16.0	16.6	19.5
	21–50	0.8	3.0	11.4	58.5	12.2	0.3	0	0	13.7	15.2	12.6
	51–200	0.4	1.4	1.8	10.7	67.0	5.6	0.2	0.2	12.7	14.3	6.0
	201–500	0.3	0.5	0.8	1.8	13.3	60.0	8.9	1.5	12.8	16.8	10.5
	501–1000	0.3	0	0	0.5	2.3	12.0	55.0	15.3	14.6	15.1	15.3
	1001+	0.3	0	0.6	0	0.6	1.7	8.3	76.6	12.0	11.4	-
	Missing	38.9	32.7	13.4	9.3	4.5	0.8	0.2	0.2	-	-	-

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Table 4: Transition matrix of % change in average wages by change in firm size, 2010 to 2013

		Firm size 2013									
		1–3	4–10	11–20	21–50	51–200	201–500	501–1000	1001+	Contracted	Expanded
Firm size 2010	1–3	30.0	10.9	-19.3	-22.0	42.3	-	-	-	-	9.0
	4–10	65.6	17.3	4.6	-14.2	13.7	-62.3	-	-	65.6	0.9
	11–20	144.9	24.3	12.7	10.1	-23.0	-29.1	-	-	38.6	6.2
	21–50	673.9	174.6	25.0	12.9	1.5	-47.6	-	-	90.0	0.0
	51–200	242.4	344.0	178.4	39.8	12.0	-0.4	7.6	-46.0	92.1	-1.3
	201–500	1273.3	358.6	553.2	190.2	36.1	23.6	-2.4	2.9	110.8	-1.6
	501–1000	159.7	-	-	509.5	160.1	20.9	14.3	1.7	61.1	1.7
	1000+	6.2	-	0.0	-	47.1	163.8	42.4	27.5	61.3	-

Note: This table gives change in average wage only for those individuals earning R1 or more per day. Inflation adjusted using average CPI.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

The key question concerns what is driving this pattern? Are firms that are contracting becoming more capital-intensive?[34] In such a case, wages may rise because more skilled workers are needed to operate the machinery and firms pay an efficiency wage. Alternatively, the declining relative importance of labour costs may allow insiders to capture more of the rents. Are firms that are contracting adopting more skill-intensive production technologies, thereby resulting in higher wages paid to workers needed to operate these technologies? The high average wages are present in firms in the manufacturing and financial services industries. Both these industries have the potential to shift to skill-intensive production techniques. Are firms contracting as a result of a stagnant post-'great recession' macro environment, and does this impact on wage patterns? For instance, in a declining economic environment, it is possible that the first workers to lose their jobs are low-wage workers, while most highly skilled high-wage workers remain, thereby translating into a higher average wage. What exactly is driving this wage pattern is beyond the scope of this paper. However, it may provide insight into the regression results to follow.

In summary, the descriptive statistics reveal fairly standard results. Higher average wage levels are associated with firms that are more capital-intensive, more productive, involved in international trade, and older. However, the data reveals a U-shaped pattern between wages and firm size. The firm size–wage pattern found here may be due to observable differences between small and large firms in South Africa. While an OLS regression controlling for these variables will indicate if this is the case, the regression does not control for any unobservable differences between small and large firms that we are unable to account for in the data. For example, it may be the case that small South African firms are attracting workers of a higher ability and that this influences the wage paid in these firms. Therefore, we use a fixed-effect regression to control for both firm and individual-level time-invariant unobservables that may affect the relationship between firm size and wages. Therefore, unobservable worker characteristics such as work ethic and other intangible attributes which may influence wages will be controlled for, on the assumption that these attributes will not change substantially during the three-year period. However, the fixed-effects regression will not control for time-varying unobservables, for example individuals who increase their level of education or training between time periods.

4.2 Firm-level characteristics of wage differentials

The econometric analysis is comprised of four sections. Firstly, we report estimates for the pooled OLS regression. This provides a baseline for developing an understanding of what firm characteristics are driving wage differentials. Secondly, we present the estimates of the FEiLSDVj model, which deals with unobserved firm and individual heterogeneity, and thus provides unbiased estimates. Thirdly, we discuss the decomposition results in order to determine the relative importance of firm and individual characteristics in explaining wage differentials in the South African formal sector labour market. Finally, we present quantile regression estimates, which provide insight on how firm characteristics affect wage differentials at different points along the wage distribution.

Two points are worth mentioning with regard to the presentation of the econometric results. Firstly, although we do control for individual characteristics, we limit our reporting of regression estimates to those pertaining to the various firm characteristics. Secondly, we reconcile the large number of

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[34] Edwards and Lawrence (2008) provide evidence that manufacturers in South Africa are becoming increasingly capital-intensive.

estimates across the fixed-effects and quantile regressions into summary tables. In the summary table, we indicate the predominant sign of the estimated coefficient for each firm characteristic, and how many times that sign prevailed. We specify how many times the estimated coefficient was statistically significant. We also provide the minimum and maximum value of the statistically significant coefficients, in order to provide insight into the magnitude of the effect on wages. Full regression results for each sample can be obtained from the authors.

4.2.1 Pooled regression estimates

The pooled regression estimations use the entire sample of firms and workers over the period 2010 to 2013. Results are reported according to the firm characteristic groupings specified in Section 4.1.

Technology and productivity

The estimates in Table 5 indicate that firms that adopt more capital-intensive production techniques pay, on average, higher wages. A 1 per cent increase in capital per worker is associated with a 1.4 per cent increase in wages.[35] This finding is consistent with the literature where higher levels of capital intensity are associated with higher wages.

One possible explanation for this, mentioned by Arai (2003), is that the possibility for rent extraction by workers is decreasing with the relative importance of labour costs to capital costs. As such, when labour costs constitute a minor share of firm costs, there is less resistance to high wage demands. In fact, the positive and statistically significant coefficient for the variable controlling for profitability provides evidence that workers are able to extract rents. Alternatively, capital-intensive production techniques are typically technology- and skill-intensive, and as a result the associated turnover costs are high. Efficiency wage theory predicts that in order to attract and keep the most skilled and able workers, firms pay a premium. Both explanations have a degree of credibility in the South African context, which is characterized by an increasing shift to more capital-intensive production, and a labour market shortage with respect to skilled workers.[36]

Higher levels of labour productivity are associated with higher average wages. The positive and statistically significant coefficient for the labour productivity variable indicates that a 1 per cent increase in the labour productivity of a firm is associated with a 30 per cent increase in wages. Higher labour productivity may be related to increased capital intensity in production (i.e. more can be produced with an extra unit of labour). Capital-intensive production may be technology-intensive, and thus require skilled labour that is associated with higher wages.

Since more productive firms enter international markets, we also investigate the link between trade status and wages. In the literature, researchers typically focus on the exporter wage premium (for example, see Bernard et al. 1995; Bernard et al. 2007). However, in this paper we also look at trade status more generally and include dummies for whether a firm is involved in one-way (exporter or importer) or two-way trade (exporter or importer). This is motivated by recent findings by Edwards et al. (2016) who show that South African firms that both import and export are different from firms that just export or import. These firms are larger, more productive, pay higher wages, and are more

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[35] Percentage calculated by using the following formula: $100\times(e^{\beta}-1)$.

[36] For example, see Bhorat and Hodge (1999) and Edwards (2001).

capital-intensive. The statistically significant estimates for the trade status variables in Table 5 indicate that relative to workers in firms only serving the domestic market, workers in firms involved in international trade earn higher wages, on average. Consistent with Edwards et al. (2016), the wage premium is highest for firms that are involved in two-way trade. As such, this provides initial evidence of a trade status wage premium that is consistent with the literature.

Profitability

The estimate for the lagged net profit/loss dummy variable provides an indication of whether workers are able to extract rents from firms or share in the total revenue pool.[37] The positive and statistically significant coefficient for the variable measuring firm profit indicates a degree of rent extraction. The coefficient estimate suggests that workers in firms that generated a net profit in the previous period are paid 6 per cent more than workers in firms that made a net loss in the previous period. This result is consistent with findings in Arai (2003) and Arai and Heyman (2009).

[37] We use a lagged measure of profit/loss in order to deal with concerns of endogeneity.

Table 5: Earnings function estimates for pooled regression

	Pooled OLS
Firm Size and Age:	
Firm size: 4–10	0.039***
	[0.003]
Firm size: 11–20	0.036***
	[0.003]
Firm size: 21–50	0.020***
	[0.003]
Firm size: 51–200	0.017***
	[0.003]
Firm size: 201–500	0.042***
	[0.003]
Firm size: 501–1000	0.045***
	[0.003]
Firm size: >1000	-0.117***
	[0.003]
Firm Age: 11–20	-0.058***
	[0.001]
Firm Age: 21–50	-0.058***
	[0.001]
Firm Age: >50	-0.053***
	[0.001]
Technology and Productivity:	
Ln Capital: Labour	0.014***
	[0.000]
Ln Labour Productivity	0.299***
	[0.000]
Exporter	0.016***
	[0.001]
Importer	0.043***
	[0.001]
Exporter and Importer	0.155***
	[0.001]
Profitability and Market Power:	
Lagged Net Profit/Loss	0.058***
	[0.000]
Concentration Ratio	-1.913***
	[0.150]
Constant	1.001***
	[0.005]
R-squared	0.333
Observations	19 902 914

Notes: 1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$ 2. Robust standard errors in brackets for pooled OLS and standard errors clustered at the individual for FE (1), FE (2), and FE (3). 3. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 4. Dependent variable is measured as real gross monthly remuneration per job. 5. Time and industry dummies included but not reported in the pooled regression. 6. Time dummies included but not reported in the fixed-effects regressions. 7. Fixed-effects estimations use a 10 per cent sample of the data (Seed 1 Sample 4). 8. The lagged net profit/loss variable is a dummy variable equal to 1 if net profit in previous period, 0 if loss.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

The profit–wage relation is important because an inequality-inducing growth path assumes that profit is only shared amongst the very rich (i.e. the shareholders). At this point the results suggest that this is not the case. However, in order to provide more nuance to this analysis, in Section 4.2.4 we use the quantile regression technique to examine whether the profit–wage relation varies at different points along the wage distribution. This enables one to tell whether workers at the top or the bottom of the earnings distribution are able to extract rents and thus provides some insight into the dynamics driving inequality.

It is well accepted that product markets in South Africa are characterized by high degrees of concentration. Using the same data employed in this paper, Fedderke et al. (2016) examine markups and concentration in South Africa's manufacturing sector. They find that markups are on average higher in South Africa than in Finland, and that levels of market concentration are higher than in the US. This motivates for the inclusion of a control for product market power in the specification.

Strangely, the results in Table 5 show a negative and statistically significant estimate for the measure of product market concentration. This result runs contrary to the literature, which predicts and finds a positive correlation between wages and product market power. Nickell (1999) states that market power generates rents and that these rents may be extracted by employees. He argues that in the presence of collective bargaining, rents can be shared with workers. However, in the absence of collective bargaining, managers would have to raise wages and share rents, and thus would need to find reason for doing so (e.g. shares rents in return for a quiet life). The relationship between product market power and wages is explored further in Section 4.2.4 below. In particular, using the quantile regression technique we examine whether the relationship varies at different points of the earnings distribution.

Firm age and size

The estimates for the firm age categories run contrary to the literature where firm age is positively correlated with wages. In Table 5 it is evident that relative to the base firm age category (1 to 10 years), the negative and statistically significant coefficients for older firm age categories suggest that workers in older firms were paid less on average. It is worth noting that this pattern changes when we control for unobserved firm and individual heterogeneity in the fixed-effects regressions.

At first sight, the estimates for the firm size categorical variables in the pooled regression presented in Table 5 align with the literature. Relative to the base category (1 to 3 employees), the positive and statistically significant coefficients for the larger firm size categories point to a firm size–wage premium. However, it is worth noting that the magnitude of the estimated coefficients for the first six firm size categories, follow a U-shape pattern, instead of an upward sloping pattern.[38] In addition, the largest firm size category, greater than 1000 employees, has a negative and statistically significant estimate. This suggests that, on average, workers in firms that employ more than 1000 workers were paid 1.69 per cent less than the mean wage paid to workers in the base group (1 to 3 employees). In light of these results, the firm size category estimates warrant further investigation.

It is worth noting that the results evident in the pooled regression estimates provide a benchmark from which to compare the subsequent estimates from the fixed-effects estimations. The pooled estimates are likely to be biased due to the potential for the unobserved firm and individual characteristics being correlated (contained in the residual) with the covariates of interest. For example, we know from the literature that exporting firms tend to employ relatively more skilled workers than non-exporters. Given that we are unable to control for the skill or education level of workers, it is

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[38] For example, in Ferrer and Lluis (2008) the size of the estimated coefficient for each firm size category increases in line with firm size, with the highest firm size–wage differential being associated with firms in the largest firm size category.

likely that a portion of the export premium is explained by this unobserved characteristic. Therefore, in order to take into account time-constant unobserved heterogeneity that may be correlated with observed characteristics, we estimate fixed-effects models.

4.2.2 Linear model with two high-dimensional fixed effects (FEiLSDVj method)

We now examine the estimates derived from the FEiLSDVj method regressions.[39]

Technology and productivity

The estimated coefficients for the capital-to-labour ratio are qualitatively consistent with those obtained using OLS in the pooled regression. The positive coefficient estimates are statistically significant across all seven estimations. Both the highest and lowest coefficient estimates are greater in magnitude than the estimate obtained in the pooled OLS estimation. The results indicate that, on average, workers in firms that are 1 per cent more capital-intensive earn between 1.8 and 2 per cent higher wages. This suggests that the extent to which a firm's capital intensity influences wage formation is slightly underestimated in the pooled OLS estimations.

Similarly, the estimates for labour productivity are positive and statistically significant across all seven estimations, and thus consistent with the pooled estimates. The results show that, on average, workers in firms that are 1 per cent more productive earn between 10.6 and 10.9 per cent higher wages. It is worth noting that the OLS coefficient estimates in the pooled regression overestimate the relative importance of labour productivity in firm wage formulation. This may be a result of the pooled regression not controlling for time-invariant individual characteristics, such as ability, which are associated with higher levels of worker productivity and higher wage returns.

The estimates for the trade status variables align with the notion of an exporter wage premium. The estimates for the 'exporter' and 'exporter and importer' dummies are qualitatively consistent with those obtained in the pooled OLS regression. Table 6 shows that relative to workers in firms that only serve the domestic market, workers in firms that export and two-way traders earn, on average, higher wages (0.8 to 1.6 per cent and 2.4 to 3.7 per cent higher, respectively).

After controlling for time-invariant individual and firm characteristics, the magnitude of the coefficient estimates for the 'exporter' and 'exporter and importer' dummies are smaller than those generated in the pooled OLS regression. As mentioned in Bernard et al. (2007), exporting firms tend to be more skill-intensive than firms that only serve the domestic market. By not controlling for time-invariant individual characteristics, such as skill or ability, the pooled OLS regression overestimates the exporter wage premium.

However, the estimates indicate that workers in firms that only import earn relatively less, on average, than workers in firms that only serve the domestic market. The result with respect to firms that import only is contrary to that found in Edwards et al. (2016) who find a positive coefficient. The differences in result may be due to unobserved worker heterogeneity, since their specification does not account

[39] We also ran spell fixed-effects regressions and report the results in Table B2 (controlling for individual fixed effects), Table B3 (controlling for firm fixed effects), and Table B4 (controlling for individual and firm fixed effects).

for variation across individuals (wages are aggregated by firm). What is driving the negative coefficient on import only firms is unclear and beyond the scope of this paper.

Profitability

With respect to the estimates for the lagged profit/loss variable, the signs of the estimated coefficients across all seven samples are all positive and statistically significant and thus consistent with those obtained in the pooled OLS regression. It is worth noting that the magnitude of the estimated coefficients is substantially smaller, suggesting that part of the strong positive relationship between wages and profits in the pooled regression estimates may be due to unobserved firm and/or worker characteristics. For example, the efficiency wage hypothesis posits that firms share rents, particularly with skilled workers, in order to reduce turnover costs. By controlling for unobserved time-invariant characteristics—e.g. skills—the fixed-effects estimates are thus lower.[40] [41]

[40] However, it is worth noting that we are not able to identify the nature of these unobserved characteristics

[41] When running fixed-effects estimations for each industry, the lagged profit/loss coefficient was positive and statistically significant in manufacturing and finance, while negative and statistically significant in construction and CSP. In the South African context, manufacturing and finance are generally semi-skilled and skill-intensive industries. The fixed-effects model may control unobserved skill levels, and this may provide some explanation for the drop in magnitude of the estimated coefficient in the fixed-effects model.

Table 6: Summary of earnings function estimates using the FEiLSDVj method

Firm Characteristic	Sign of Coefficient	Statistical Significance of Estimate[42]	Coefficient Estimates	
			Min	Max
Firm Size and Age:				
Firm size: 4–10	+VE (6 of 7)	Significant (3 of 7)	0.017	0.022
Firm size: 11–20	+VE (7 of 7)	Significant (3 of 7)	0.015	0.028
Firm size: 21–50	+VE (7 of 7)	Significant (4 of 7)	0.010	0.028
Firm size: 51–200	-VE (5 of 7)	Significant (2 of 7)	-0.015	0.012
Firm size: 201–500	-VE (7 of 7)	Significant (7 of 7)	-0.047	-0.017
Firm size: 501–1000	-VE (7 of 7)	Significant (7 of 7)	-0.079	-0.051
Firm size: >1000	-VE (7 of 7)	Significant (7 of 7)	-0.104	-0.080
Firm Age: 11–20	-VE (7 of 7)	Significant (7 of 7)	-0.020	-0.009
Firm Age: 21–50	+VE (7 of 7)	Significant (7 of 7)	0.015	0.028
Firm Age: >50	+VE (7 of 7)	Significant (7 of 7)	0.066	0.094
Technology and Productivity:				
Ln Capital: Labour	+VE (7 of 7)	Significant (7 of 7)	0.018	0.020
Ln Labour Productivity	+VE (7 of 7)	Significant (7 of 7)	0.106	0.109
Exporter	+VE (7 of 7)	Significant (7 of 7)	0.008	0.016
Importer	-VE (7 of 7)	Significant (7 of 7)	-0.027	-0.009
Exporter & Importer	+VE (7 of 7)	Significant (7 of 7)	0.024	0.036
Profitability:				
Lagged Net Profit/Loss	+VE (7 of 7)	Significant (7 of 7)	0.008	0.009
Concentration Ratio	-VE (7 of 7)	Significant (5 of 7)	-1.447	-1.191

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the seven samples that the sign prevailed. 5. Column 3 reports the number of times across the seven samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the seven samples. 7. In all instances, except for one, the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2. In the case of the two statistically significant estimates across the seven samples for the variable 'Firm size: 51–200', one is negative and the other is positive.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

The estimated relationship between employee wages and firm product market power is consistent with that found in the pooled OLS estimates. However, the magnitude of the negative coefficients is smaller and statistically significant in only five of the seven regressions, once we control for firm and worker heterogeneity.[43]

[42] In all instances, except for one, the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2. In the case of the two statistically significant estimates across the seven samples for the variable 'Firm size: 51–200', one is negative and the other is positive.

[43] Similarly, in the case of the spell fixed-effects regressions reported in Table B4, where the coefficient estimates for the measure of product market power is negative and statistically significant in only two of the nine estimations.

Firm age and size

The fixed-effects estimates for the firm age categories align better with the firm age–wage relation observed in the literature. In particular, it is evident in Table 6 that a U-shaped pattern emerges, which is consistent to that found by Brown and Medoff (2003). On average, relative to the base category (1 to 10 years), workers in firms aged between 11 and 20 years earn less (between 0.9 and 2.3 per cent less). The estimates for the firm age category 21 to 50 years are all positive and statistically significant, suggesting higher wages for workers in these firms (between 1.5 and 2.8 per cent higher). The positive and statistically significant estimates (across all seven estimations) for the 50 years plus firm age category, indicate that, on average, relative to the base category, workers in these firms earn more (between 6.8 and 9.9 per cent more).

There are two possible explanations for the difference in estimates across the pooled and fixed-effects regressions. Firstly, Brown and Medoff (2003) state that older firms pay higher wages because, on average, their employees tend to be more experienced and have longer periods of tenure. This explanation is not satisfactory since the regressions control for experience (using age and the square of age as a proxy) and tenure.[44] Secondly, Brown and Medoff (2003) mention that older firms pay higher wages because they are more likely to invest in on-the-job training and offer opportunities for advancement. As a result, older firms demand workers with high skill levels and thus pay higher wages, on average. To the extent that this is true, the pooled regression would not have picked up on unobserved skill and ability, thereby biasing the estimates with respect to firm age.

The firm size–wage relation no longer follows a U-shaped pattern, as observed in the OLS estimates above, but rather a downward sloping relation. This pattern is evident through positive, yet declining in magnitude, coefficient estimates for the initial firm size categories (4 to 10, 11 to 20, and 21 to 50). Thereafter, the coefficient estimates for the larger firm size categories (51 to 200, 201 to 500, 501 to 1000, and greater than 1000) are negative and increasing in magnitude as firm size increases.[45] This puzzling result suggests that relative to the base category firm size (1 to 3), employees in firms that employ more than 1000 workers earn less on average (between 7.7 and 9.8 per cent less). The firm size result runs contrary to the literature and the discussion in this sub-section and that to follow attempts to provide clarity on this.

One possible factor that may be influencing these results is the inherent nature of industries and how this relates to firm size and wages.[46] Firms operating in industries such as mining are by nature large firms, since profitability is derived from the scale of operations. A similar argument could be made for commercial agriculture.[47] Furthermore, in these industries it is likely that there are a large number of low-paid workers that bring down the mean wage in these large firms (and hence in the large firm

[44] The estimates for the observed individual characteristics are reported in Appendix A.

[45] In order to check the robustness of the firm size estimates to inclusion of other firm characteristics, we ran the spell fixed-effects estimation iteratively. Starting with the firm size variables we iteratively added the remaining controls in order to check whether the firm size estimates changed in any way. They were robust to this approach.

[46] Although we control for industry effects, it is possible that these dummies do not adequately capture the heterogeneity across firms within industries. As such, future research looking at the firm size–wage relation should focus on individual industries.

[47] Given that the dataset is derived from tax data, it is more likely to pick up various commercial agricultural activities. Small-scale informal (i.e. not registered for tax purposes) agricultural activities are not measured in the data.

size categories). This may affect the firm size results. In contrast, the distribution of firms within the retail and finance industries is likely to be more variable. For example, the financial industry is comprised of very large banking, insurance, and investment firms (e.g. Standard Bank), while also comprising small firms with highly skilled and well-paid workers (e.g. financial consultant). These small financial firms may be characterized by higher mean firm wages, and this may be driving the firm size–wage pattern to some extent.[48]

It is worth referring back to the transition matrices in Table 4, which indicated that the average wage in firms that contracted increased substantially, while the average wage in firms that expanded either increased slightly in the case of smaller firms or declined in the case of larger firms. The identification of the firm size coefficients in the fixed-effects regressions arises from firms that shift across firm size categories. Thus, if a large number of firms are contracting, and a large share of them are smaller firms, then the higher wage growth for these contracting firms may be influencing the firm size coefficients estimates. However, further analysis is required in order to unpack this dynamic further.

4.2.3 Relative importance of firm and individual effects in wage determination

The FEiLSDVj method allows one to measure the relative importance of firm and individual characteristics in explaining wage formulation. Cornelissen (2008) shows that the FEiLSDVj method allows one to decompose the variation in the dependent variable, real monthly wages, into each of the following four components: observed time-varying individual (x_{it}) and worker ($w_{j(i,t)t}$) characteristics, individual effects (θ_i), firm effects ($\psi_{j(i,t)}$), and the residual (ϵ_{it}). Table 7 shows the results for the variance decomposition across the seven estimations.[49]

It is evident in Table 7 that the main driver of the variation in worker wages is derived from time-invariant unobserved individual characteristics. On average, 61 per cent of the variation in formal sector wages in South Africa is accounted for by person effects. This result is unsurprising since various labour market studies for South Africa show the explanatory power of individual supply-side characteristics, such as education.[50] On average, approximately 13 per cent of the variation in wages is a result of unobserved firm characteristics. The importance of firm characteristics can be considered larger since much of the explanatory power of the time-varying characteristics in the regressions is derived from these demand-side variables. As such, one could argue that the non-negligible role of firm characteristics on wage determination provides motivation for demand-side labour market policies.

[48] The separate industry regressions in Table B5 in Appendix B seem to confirm this story—the coefficient estimates for all firm size categories are negative and statistically significant relative to the base category.

[49] The table shows the minimum, maximum, and mean measure of each component of the decomposition.

[50] See for example Mwabu and Schultz (2000), Allanson et al. (2002), Hinks (2002), Keswell and Poswell (2004), Posel and Muller (2008), and Casale and Posel (2011).

Table 7: Variance decomposition for regressions using the FEiLSDVj method

	South Africa			Austria
	Min	**Max**	**Mean**	
Observed Time-varying Characteristics	-0.14	0.21	0.13	0.09
Person Effects	0.53	0.88	0.61	0.60
Firm Effects	0.13	0.13	0.13	0.27
Residual	0.13	0.13	0.13	0.05

Notes: 1. Columns 1, 2, and 3 report the minimum, maximum, and mean values of the variance decomposition across the seven samples in which the FEiLSDVj method was estimated. 2. The estimates for Austria are taken from Gruetter and Lallive (2009).

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

The decomposition results indicate that wage determination patterns in the formal sector labour market of a developing country, namely South Africa, are comparable to those in Austria and France. The final column of Table 7 shows that approximately 60 per cent of wage variation in Austria is a result of variation in worker characteristics (see Gruetter and Lallive 2009). The comparable estimate for South Africa is 61 per cent. Analysing French labour market, Abowd et al. (1999) also show worker heterogeneity to be more important than firm heterogeneity in explaining wage variation across workers. Therefore, existing research and the analysis in this paper point to the importance of worker characteristics in wage formulation.

4.2.4 Quantile regression estimates

The fixed-effects and pooled OLS regressions explain variation in wages by firm characteristics at the mean of the wage distribution. Quantile regressions allow one to examine the relationship between wages and the firm characteristic of interest at different points of the wage distribution. In this sub-section, using the quantile regression estimation technique, we explore the extent to which there is heterogeneity in the manner in which wages vary by firm characteristics at different points along wage distribution. In particular, we focus on the 10th, 50th, and 90th percentiles of the wage distribution.[51] In the analysis of the quantile regression estimates, we focus our attention on firm size, profitability, and product market power.[52]

It is interesting to note that the relationship between wages and firm profitability is consistent along the three points of the wage distribution. The estimates for the lagged profit/loss variable in Tables 8–10 are consistently positive and statistically significant. This suggests that workers at the top, middle, and bottom of the wage distribution are able to extract rents from firms. This wage pattern in relation to profits is unlikely to be inequality inducing, at least within the population of individuals who are employed.

[51] However, one must examine the results with caution since we do not control for firm and individual fixed effects in the quantile regressions.

[52] For the most part the coefficient estimates for the remaining firm characteristics are similar across the quantile and fixed-effects regressions.

The estimates for the concentration ratio are consistently negative in the pooled and fixed-effects regressions, but behave differently in the quantile regressions. The negative relationship between wages and product market power is still evident in the quantile regression estimates for the 10th and 50th percentiles. However, at the top of the wage distribution (see Table 10) the estimated coefficients for the concentration ratio is consistently positive and statistically significant—the result one would expect based on the literature. It may be the case that firms with a higher degree of market power are price setters in the market for labour. These firms are able to pay a premium to labour that is in shortage (skilled workers in the 90th percentile) and bargain down wages for those in surplus (less skilled workers in the 10th and 50th percentile). It could be argued that in many ways this is the labour demand equivalent of the insider–outsider nature of the South African labour market.

Table 8: Summary of earnings function estimates for quantile regressions—10th percentile

Firm Characteristic	**Sign of Coefficient**	**Statistical Significance of Estimate**	**Coefficient Estimates**	
			Min	**Max**
Firm Size and Age:				
Firm size: 4–10	+VE (9 of 9)	Significant (8 of 9)	0.043	0.083
Firm size: 11–20	+VE (9 of 9)	Significant (9 of 9)	0.036	0.088
Firm size: 21–50	+VE (9 of 9)	Significant (9 of 9)	0.031	0.087
Firm size: 51–200	+VE (9 of 9)	Significant (5 of 9)	0.029	0.054
Firm size: 201–500	+VE (8 of 9)	Significant (5 of 9)	0.018	0.054
Firm size: 501–1000	-VE (7 of 9)	Significant (2 of 9)	-0.034	0.031
Firm size: >1000	-VE (9 of 9)	Significant (9 of 9)	-0.322	-0.043
Firm Age: 11–20	-VE (9 of 9)	Significant (9 of 9)	-0.076	-0.031
Firm Age: 21–50	-VE (9 of 9)	Significant (9 of 9)	-0.032	-0.017
Firm Age: >50	-VE (9 of 9)	Significant (9 of 9)	-0.044	-0.018
Technology and Productivity:				
Ln Capital: Labour	+VE (9 of 9)	Significant (9 of 9)	0.072	0.075
Ln Labour Productivity	+VE (9 of 9)	Significant (9 of 9)	0.292	0.296
Exporter	+VE (9 of 9)	Significant (9 of 9)	0.018	0.035
Importer	-VE (8 of 9)	Significant (3 of 9)	-0.024	-0.015
Exporter & Importer	+VE (9 of 9)	Significant (9 of 9)	0.193	0.199
Profitability:				
Lagged Net Profit/Loss	+VE (9 of 9)	Significant (9 of 9)	0.038	0.051
Concentration Ratio	-VE (9 of 9)	Significant (9 of 9)	-43.488	-2.108

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the nine samples that the sign prevailed. 5. Column 3 reports the number of times across the nine samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the nine samples. 7. In all instances, except for one, the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2. In the case of the two statistically significant estimates across the nine samples for the variable 'Firm size: 501–1000', one is negative and the other is positive.

Source: Authors calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

In Table 8 we present the quantile regression results for the 10th percentile or the lower end of the wage distribution. It is interesting to note that the estimates for the firm size variables align closely to what one would expect if they were to follow the firm size–wage premium evident in the literature. The coefficient estimates for the firm size categories, 4 to 10, 11 to 20, 21 to 50, 51 to 200, and 201 to 500 are all positive. The coefficient estimates for the first three firm size categories are for the most part statistically significant, while the next two are both statistically significant in five of the nine estimations. Furthermore, the estimates for the 501 to 1000 category are mixed in their outcome. Although seven of the nine estimates are negative, only two estimates are statistically significant, one of which is a positive estimate. However, it is evident that the largest firm size category is consistently negative and statistically significant, thus not aligning perfectly with the firm size–wage premium finding. Nevertheless, at the lower end of the earnings distribution one could argue that increasing firm size is associated with higher returns, but up to a point.

Table 9: Summary of earnings function estimates for quantile regressions—50th percentile

Firm Characteristic	**Sign of Coefficient**	**Statistical Significance of Estimate**	**Coefficient Estimates**	
			Min	**Max**
Firm Size and Age:				
Firm size: 4–10	-VE (9 of 9)	Significant (9 of 9)	-0.049	0.056
Firm size: 11–20	-VE (9 of 9)	Significant (9 of 9)	-0.090	0.091
Firm size: 21–50	-VE (9 of 9)	Significant (9 of 9)	-0.122	0.101
Firm size: 51–200	-VE (9 of 9)	Significant (9 of 9)	-0.112	0.123
Firm size: 201–500	-VE (9 of 9)	Significant (9 of 9)	-0.058	0.137
Firm size: 501–1000	-VE (4 of 9)	Significant (4 of 9)	-0.017	0.012
Firm size: >1000	-VE (9 of 9)	Significant (9 of 9)	-0.064	0.095
Firm Age: 11–20	-VE (9 of 9)	Significant (9 of 9)	-0.040	-0.031
Firm Age: 21–50	-VE (9 of 9)	Significant (9 of 9)	-0.037	-0.026
Firm Age: >50	-VE (9 of 9)	Significant (9 of 9)	-0.032	-0.015
Technology and Productivity:				
Ln Capital: Labour	+VE (9 of 9)	Significant (9 of 9)	0.003	0.005
Ln Labour Productivity	+VE (9 of 9)	Significant (9 of 9)	0.271	0.274
Exporter	+VE (9 of 9)	Significant (9 of 9)	0.007	0.014
Importer	+VE (9 of 9)	Significant (9 of 9)	0.066	0.081
Exporter & Importer	+VE (9 of 9)	Significant (9 of 9)	0.114	0.121
Profitability:				
Lagged Net Profit/Loss	+VE (9 of 9)	Significant (9 of 9)	0.051	0.052
Concentration Ratio	-VE (9 of 9)	Significant (9 of 9)	-3.359	-1.394

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the nine samples that the sign prevailed. 5. Column 3 reports the number of times across the nine samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the nine samples. 7. In all instances, except for one, the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2. In the case of the four statistically significant estimates across the nine samples for the variable 'Firm size: 501–1000', three are negative and one is positive.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

When one focuses on the median of the wage distribution, the firm size estimates behave in a similar manner to the estimates in the fixed-effects estimations—a downward sloping pattern. Table 9 shows that the coefficient estimates for the firm size categories are consistently negative and statistically significant across all nine estimations (other than for firm size category 501 to 1000). This is unsurprising since both the quantile estimates at the 50th percentile and the fixed-effects estimations measure variation at the centre of the wage distribution.

Interestingly, the firm size estimates at the 90th percentile align perfectly with the firm size–wage premium literature (see Table 10). Across all nine estimations, each of the firm size category coefficient estimates is positive and statistically significant. Furthermore, the magnitude of the coefficient estimates increases as firm size increases up until the largest firm size category.

Table 10: Summary of earnings function estimates for quantile regressions—90th percentile

Firm Characteristic	Sign of Coefficient	Statistical Significance of Estimate	Coefficient Estimates	
			Min	Max
Firm Size and Age:				
Firm size: 4–10	+VE (9 of 9)	Significant (9 of 9)	0.033	0.070
Firm size: 11–20	+VE (9 of 9)	Significant (9 of 9)	0.065	0.101
Firm size: 21–50	+VE (9 of 9)	Significant (9 of 9)	0.073	0.111
Firm size: 51–200	+VE (9 of 9)	Significant (9 of 9)	0.095	0.127
Firm size: 201–500	+VE (9 of 9)	Significant (9 of 9)	0.113	0.147
Firm size: 501–1000	+VE (9 of 9)	Significant (9 of 9)	0.133	0.175
Firm size: >1000	+VE (9 of 9)	Significant (9 of 9)	0.067	0.104
Firm Age: 11–20	-VE (9 of 9)	Significant (9 of 9)	-0.054	-0.045
Firm Age: 21–50	-VE (9 of 9)	Significant (9 of 9)	-0.096	-0.085
Firm Age: >50	-VE (9 of 9)	Significant (9 of 9)	-0.051	-0.026
Technology and Productivity:				
Ln Capital: Labour	-VE (9 of 9)	Significant (9 of 9)	-0.029	-0.025
Ln Labour Productivity	+VE (9 of 9)	Significant (9 of 9)	0.299	0.305
Exporter	-VE (9 of 9)	Significant (9 of 9)	-0.040	-0.011
Importer	+VE (9 of 9)	Significant (9 of 9)	0.116	0.136
Exporter & Importer	+VE (9 of 9)	Significant (9 of 9)	0.180	0.195
Profitability:				
Lagged Net Profit/Loss	+VE (9 of 9)	Significant (9 of 9)	0.075	0.080
Concentration Ratio	+VE (9 of 9)	Significant (9 of 9)	25.801	38.475

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the nine samples that the sign prevailed. 5. Column 3 reports the number of times across the nine samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the nine samples.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

The results from the quantile regressions point to a firm size–wage premium at both the bottom (weakly) and top (strongly) of the wage distribution. The wage premium at the top of the distribution may be explained by larger firms being more willing to pay higher wages for the relatively more skilled and able employees that are typically in short supply in South Africa. In fact, one could argue that the efficiency wage and capital–skill complementarity hypotheses may be at play. The wage premium at the bottom of the distribution could be explained by the union wage gap. In this instance, larger firms are more likely to be unionized and thus insiders are able to extract a rent.

5 Conclusions and policy considerations

The availability of matched employer–employee data has provided the opportunity to determine the relative importance of firm (demand-side) and individual (supply-side) characteristics in explaining wage formulation in the formal sector labour market of a developing country, namely South Africa. The results indicate that individual characteristics are relatively more important than firm characteristics in wage formulation. This result is consistent with those found in studies on the French (Abowd et al. 1999) and Austrian (Gruetter and Lallive 2009) labour markets. From a policy standpoint, this validates the various supply-side policies (e.g. skills development levy) focused on the South African labour market.

Nevertheless, firm characteristics explain at least 13 per cent of the variation in wages across workers. This share could be higher since a large share of the wage variation due to observable characteristics may also be due to observable firm characteristics. This does suggest that there is scope for demand-side policies aimed at improving the overall performance of the South African labour market.

The paper also examines the role of various firm characteristics in explaining wage levels across individual workers. A number of interesting patterns emerge:

Firms that are more capital-intensive and productive pay, on average, higher wages. Relatedly, firms involved in international trade, particularly exporters and two-way traders, pay higher wages. Consistent with Edwards et al. (2016), the wage premium to trading is highest for two-way traders, who they find to be larger, more productive, and more capital-intensive than other firms. Conversely to Edwards et al. (2016), we find that importers pay lower wages. These results are consistent with the notion that jobs in firms that are involved in international trade are ‘good jobs’. Therefore, greater policy effort should be directed toward facilitating the entry and survival of firms in the international market.

Firms that are profitable pay, on average, higher wages. This indicates that workers are able to share in the total revenue pool. The quantile regression estimates show that the pattern of rent extraction by workers is evident at the bottom, middle, and top of the wage distribution. An inequality-inducing growth path would entail a situation where profit is only shared among the very rich at the top of the distribution (e.g. shareholders and highly skilled employees). These results suggest that the growth of these firms (formal private sector firms) is unlikely to be inequality inducing. This suggests, tentatively, that growth of the formal private sector of the South African economy, and thereby absorbing a greater share of the labour force, a quarter of which is unemployed, is likely to have an inequality reducing impact.

Puzzlingly, the results in the fixed-effects estimations point to a negative relationship between product market power and wages. However, the quantile regression estimates indicate that the manner in which wages relate to firm product market power varies according to position along the wage distribution. At the bottom and middle of the wage distribution, product market power is associated with lower wages. However, at the top of the wage distribution, product market power is associated with higher wages. Given the highly-concentrated nature of South African product markets, this may be suggesting that firms with a high degree of market power are price setters in the market for labour. These firms pay a premium to labour that is in shortage—skilled workers at the top of the wage distribution—and bargain down wages for those in surplus—less skilled workers at the bottom of the wage distribution. However, this result must be viewed with caution since the quantile regressions do not control for firm and worker heterogeneity. Certainly, future research could explore the relationship between product market power and the returns to labour using more advanced econometric techniques that better capture these relationships.

Older firms pay, on average, higher wages. However, the relationship between firm age and wages is non-monotonic and exhibits a U-shape.

The most puzzling result in the analysis concerns the relationship between firm size and wages. Contrary to the literature, the results in the fixed-effects estimation point to a negative relationship between firm size and wages. The analysis above sought to unlock what may be behind this wage pattern. One possible explanation may be found in wage patterns among expanding and contracting firms. The growth in the average firm wage for firms that contract is large and positive, while it is small and sometimes positive for expanding firms. The identification of the firm size coefficients in the fixed-effects regressions arises from firms that shift across firm size categories. Thus, if a large number of firms are contracting, and a large share of them are smaller firms, then the higher wage growth for these contracting firms may be influencing the firm size coefficient estimates. What is driving wage growth in contracting firms is an interesting question that requires further research.

It is also important to note that the firm size–wage relation may be confounded by industry effects. The distribution of firms by firm size is not random across industries. Firms operating in industries such as mining and commercial agriculture are by nature large firms, since profitability is derived from the scale of operations. In these industries it is likely that there are a large number of low-paid workers that bring down the mean wage in these large firms. Conversely, the distribution of firms within the finance industry is likely to be more variable. For example, the financial industry is comprised of very large banking, insurance, and investment firms while also comprising small firms with highly skilled and well-paid workers. These small financial firms may be characterized by higher mean firm wages, and this may be driving the firm size–wage pattern to some extent. Therefore, to further unpack the firm size–wage relation, future analyses of this nature should focus on individual industries.

The results from the quantile regressions point to a firm size–wage premium at both the bottom (weakly) and top (strongly) of the wage distribution. The wage premium at the top of the distribution may be explained by larger firms being more willing to pay higher wages for the relatively more skilled and able employees that are typically in short supply in the South African labour market. In fact, one could argue that the efficiency wage and capital–skill complementarity hypotheses may be at play. The wage premium at the bottom of the distribution could possibly be explained by the union wage gap. In this instance, larger firms are more likely to be unionized and thus insiders are able to extract a rent. Nevertheless, the firm size–wage relation in the South African context certainly warrants further research.

References

Abowd, J.M., F. Kramarz, and D.N. Margolis (1999). 'High Wage Workers and High Wage Firms'. *Econometrica,* 67(2): 251–333.

Abowd, J.M., R.H. Creecy, and F. Kramarz (2002). 'Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data'. Technical Paper No. 2002–06. Suitland, MD: Center for Economic Studies, US Census Bureau.

Allanson, P., J.P. Atkins, and T. Hinks (2002). 'No End to the Racial Wage Hierarchy in South Africa?'. *Review of Development Economics,* 6(3): 442–59.

Andrews, M., T. Schank, and R. Upward (2004). 'Analysing Linked Employer-Employee Data with Stata'. 10th Annual Stata Users Group. Available at: http://www.stata-journal.com/article.html?article=st0112

Arai, M. (2003). 'Wages, Profits, and Capital Intensity: Evidence from Matched Worker-Firm Data'. *Journal of Labor Economics*, 21(3): 593–618.

Arai, M., and F. Heyman (2009). 'Microdata Evidence on Rent-sharing'. *Applied Economics,* 41(23): 2965–76.

Belfield, C.R., and X. Wei (2004). 'Employer Size–Wage Effects: Evidence from Matched Employer–Employee Survey Data in the UK'. *Applied Economics*, 36*(*3): 185–93.

Bernard, A.B., J.B. Jensen, and R.Z. Lawrence (1995). 'Exporters, Jobs, and Wages in US Manufacturing: 1976–1987'. *Brookings Papers on Economic Activity. Microeconomics 1995*, 67–119.

Bernard, A.B., J.B. Jensen, S.J. Redding, and P.K. Schott (2007). 'Firms in International Trade'. *The Journal of Economic Perspectives*, 21(3): 105–30.

Bhorat, H., and J. Hodge (1999). 'Decomposing Shifts in Labour Demand in South Africa'. *South African Journal of Economics*, 67(3): 155–68.

Brown, C.C., and J.L. Medoff (1989). 'The Employer Size-Wage Effect'. *Journal of Political Economy*, 97(5): 1027–59.

Brown, C.C., and J.L. Medoff (2003). 'Firm Age and Wages'. *Journal of Labor Economics*, 21(3): 677–97.

Casale, D., and D. Posel (2011). 'English Language Proficiency and Earnings in a Developing Country: The Case of South Africa'. *The Journal of Socio-Economics*, 40(4): 385–93.

Cerejeira, J., and P. Guimaraes (2012). 'The Price of Unobservables and the Employer-Size Wage Premium'. *Economics Letters*, 117(3): 878–80.

Cornelissen, T. (2008). 'The Stata Command Felsdvreg to Fit a Linear Model with Two High-dimensional Fixed Effects'. *Stata Journal*, 8(2): 170.

CIT (Corporate Income Tax) (n.d.). Unpublished data.

Dunne, T., L. Foster, J. Haltiwanger, and K.R. Troske (2004). 'Wage and Productivity Dispersion in United Sates Manufacturing: The Role of Computer Investment'. *Journal of Labour Economics*, 22(2): 397–429.

Edwards, L. (2001). 'Trade and the Structure of South African Production, 1984–97'. *Development Southern Africa*, 18(4): 471–91.

Edwards, L., and R. Lawrence (2008). 'South African Trade Policy Matters: Trade Performance and Trade Policy'. *Economics of Transition*, 16(4): 585–608.

Edwards, L., M. Sanfilippo, and A. Sundaram (2016). 'Importing and Firm Performance: New Evidence from South Africa'. WIDER Working Paper 2016/39. Helsinki: UNU-WIDER.

Fedderke, J., N. Obikili, and N. Viegi (2016). 'Markups and Concentration in South African Manufacturing Sectors: An Analysis with Administrative Data'. WIDER Working Paper 2016/40. Helsinki: UNU-WIDER.

Ferrer, A., and S. Lluis (2008). 'Should Workers Care About Firm Size?'. *Industrial and Labor Relations Review*, 62(1): 104–25.

Gruetter, M., and R. Lalive (2009). 'The Importance of Firms in Wage Determination'. *Labour Economics*, 16(2): 149–60.

Gürtzgen, N. (2009). 'Rent-Sharing and Collective Bargaining Coverage: Evidence from Linked Employer–Employee Data'. *The Scandinavian Journal of Economics*, 111(2): 323–49.

Heyman, F. (2007). 'Firm Size or Firm Age? The Effect on Wages Using Matched Employer–Employee Data'. *Labour*, 21(2): 237–63.

Hinks, T. (2002). 'Gender Wage Differentials and Discrimination in the New South Africa'. *Applied Economics*, 34(16): 2043–2052.

IRP5 (n.d.). Unpublished data.

Kerr, A. (2016). 'Job Flows, Worker Flows, and Churning in South Africa'. WIDER Working Paper 2016/37. Helsinki: UNU-WIDER.

Keswell, M., and L. Poswell (2004). 'Returns to Education in South Africa: A Retrospective Sensitivity Analysis of the Available Evidence'. *South African Journal of Economics*, 72(4): 834–60.

Lallemand, T., R. Plasman, and F. Rycx (2007). 'The Establishment-Size Wage Premium: Evidence from European Countries'. *Empirica*, 34(5): 427–51.

Long, J.E., and A.N. Link (1983). 'The Impact of Market Structure on Wages, Fringe Benefits, and Turnover'. *Industrial and Labor Relations Review*, 36(2): 239–50.

Matthee, M., N. Rankin, T. Naughtin, and C. Bezuidenhout (2016). 'The South African Manufacturing Exporter Story'. WIDER Working Paper 2016/038. Helsinki: UNU-WIDER.

Melitz, M.J. (2003). 'The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity'. *Econometrica*, 71(6): 1695–725.

Morissette, R. (1993). 'Canadian Jobs and Firm Size: Do Smaller Firms Pay Less?'. *Canadian Journal of Economics*, 159–74.

Mwabu, G., and T.P. Schultz (2000). 'Wage Premiums for Education and Location of South African Workers, by Gender and Race'. *Economic Development and Cultural Change*, 48(2): 307–34.

Nickell, S. (1999). 'Product Markets and Labour Markets'. *Labour Economics*, 6(1): 1–20.

Nickell, S., J. Vainiomaki, and S. Wadhwani (1994). 'Wages and Product Market Power'. *Economica*, 457–73.

Oi, W.Y., and T.L. Idson (1999). 'Firm Size and Wages'. *Handbook of Labor Economics*, 3: 2165–214.

Pedace, R. (2010). 'Firm Size-Wage Premiums: Using Employer Data to Unravel the Mystery'. *Journal of Economic Issues*, 44(1): 163–82.

Pieterse, D., F. Kreuser, and E. Gavin (2016). 'Introduction to the South African Revenue Service and National Treasury Firm-level Panel'. WIDER Working Paper 2016/042. Helsinki: UNU-WIDER.

Posel, D., and C. Muller (2008). 'Is There Evidence of a Wage Penalty to Female Part-time Employment in South Africa?'. *South African Journal of Economics*, 76(3): 466–79.

SARS (South African Revenue Service) (n.d.). Unpublished data.

Schank, T., C. Schnabel, and J. Wagner. (2007). 'Do Exporters Really Pay Higher Wages? First Evidence from German Linked Employer–Employee Data'. *Journal of International Economics*, 72(1): 52–74.

Söderbom, M., F. Teal, and A. Wambugu (2005). 'Unobserved Heterogeneity and the Relation between Earnings and Firm Size: Evidence from Two Developing Countries'. *Economics Letters*, 87(2): 153–59.

Troske, K.R. (1999). 'Evidence on the Employer Size-Wage Premium from Worker-Establishment Matched Data'. *The Review of Economics and Statistics*, 81(1): 15–26.

Zhang, J., and X. Liu (2013). 'The Evolving Pattern of the Wage-Labor Productivity Nexus in China: Evidence from Manufacturing Firm-level Data'. *Economic Systems*, 37: 354–68.

APPENDIX A: Data

1 SARS data utilized

Data used is from the firm- and individual-level tax returns made available by the South African Revenue Services (SARS) in collaboration with the National Treasury (NT). Firm-level data is in the form of Corporate Income Tax (CIT) data, sourced from the Income Tax Return for Companies (form IT14, replaced with form ITR14 in May of 2013). Individual-level data is from employer-issued Employee Tax Certificates, in the form of an IRP5 which discloses the total employment remuneration and deductions earned for the year of assessment.

Our unit of analysis is individual-level wages. We use South African Revenue Services (SARS) and National Treasury (NT) Firm Level Panel (SARS-NT Panel)[53] to collect the firm-level data for the analysis. The version we are using is from 29 April 2016.

Although this dataset contains some IRP5 data, it does not have individual wages, which we need for our analysis. We therefore went back to the IRP5 data (2010–13) in order to create all the necessary variables and merge them into the SARS-NT Panel. The variables we used to merge are IdNo (individual identifier) and taxrefno (firm-level identifier) as well as taxyear (time period identifier). This created an individual-level panel which included firm data for the years 2010 to 2013. Included in this were some lagged variables from the 2008 and 2009 Firm Level Panel (SARS-NT Panel).

2 Firm-level variables used

In this sub-section, we provide information detailing the exact names of datasets and variables used from the administrative data available at designated terminals at the National Treasury. We include the original names (in italics) of datasets and variables for the purposes of replication and modification by future researchers.

2.1 Dataset used

CITIRP5_panel_29042016 (SARS-NT Panel)

[53] The SARS-NT Panel is an unbalanced panel dataset created by merging several sources of South African administrative tax data (see Pieterse et al. (2016)).

2.2 Variables created

Table A1, below, lists variables created form the CIT-IRP5 made available to us by the Treasury. Note that variables are seperated as follows:

Variables in *Italics* are the raw variables available in the data.

Variables in **Bold** are variables created by other researchers in the data.

Variables in ***Italics and bold*** are variables we created in the dataset.

Table A1: Variables Created Using Existing CIT-firm Panel

Variable Created	Variables in Dataset Used	Method
Industry	*c_profcode*	We use the mode of industry over the years that the firm is in the data. If there are two modes, we use the most recent industry data. *c_profcode* is condensed to ISIC 4 codes, using Stata code from the National Treasury.
Total Assets	*k_ppe k_faother k_goodwill k_investsub k_ltloan_ifree k_ltloan_ibear k_ltloan k_deftax k_othernca k_inventory k_trade k_prepayment k_gccurracc k_stinvest k_sars k_cash k_otherca*	Summation of all asset variables.
Total Fixed Assets	*k_ppe*, *k_faother*	Created by summing fixed assets from property, plant and equipment, as well as other fixed assets: *k_ppe* (assets from plant, property and equipment) and *k_faother* (other fixed assets).
Turnover	*g_sales*	N/A
Cost of Sales	*g_cos*	N/A
Trade Status	*CUST_totalex, CUST_totalim*	A firm was coded as an exporter if their exports were positive and non-zero, and an importer if their imports were positive and non-zero.
Net Profit/Net Loss	*y_np, y_nl*	Firms appearing to make both a net profit and net loss were excluded.
Firm Age	*age*	N/A
Firm Size	**irp5_empl_daysweight**	Three firm size variables used, see section 4.2 of this Appendix. *irp5_empl_daysweight* was created in the Firm Level Panel (SARS-NT Panel) based on weighted number of days worked. An overview of how this variable was created is available in the Working Paper by Pieterse et al. (2016). In addition, we create our own firm size variable, as detailed in section 4.2 of this Appendix.
Capital–Labour Ratio	***Total Fixed Assets Firm size***	Created by dividing total fixed assets by the number of employees (jobs) in the firm (see Firm size).
Market Share	***Turnover Industry***	Created by dividing firm turnover by total firm turnover (the sum of every firm's turnover) for that year, by industry (based on ISIC 2-digit codes).

Concentration Ratio	***Market Share*** ***Industry***	Created by summing the market share of the firms with the highest market share. This is done for the top 5 per cent of firms, the top 4 firms and the top 8 firms by industry. Industry is based on ISIC 2-digit codes.
Herfindahl Index	***Market Share*** ***Industry***	Created by summing the square of market share of the firms with the highest squared market share. This is done for the top 8 firms by industry. Industry is based on ISIC 2-digit codes.

Source: Authors' illustration.

3 Individual-level variables used

3.1 Datasets used:

IRP5_2010_clean (version 2)
IRP5_2011_clean (version 2)
IRP5_2012_clean (version 2)
IRP5_2013_clean (version 2)

3.2 Variables created

Table A2 lists variables created form the CIT-IRP5 made available to us by the Treasury. Note that variables are seperated as follows:

Variables in *Italics* are the raw variables available in the data.

Variables in **Bold** are variables created by other researchers in the data.

Variables in ***Italics and bold*** are variables we created in the dataset.

Table A2: Variables Created Using Existing CIT-firm Panel

Variable Created	Variables in Dataset Used	Method
Gross Remuneration	*grossntaxableincomeamnt* *grossretfundincomeamnt* *grossnretfundincomeamnt*	Summing all relevant wage variables.
Year of Birth	*DateOfBirth*	Individual's year of birth (*DateOfBirth)* is subtracted from the year of data in use.
Tenure	N/A	Length of stay within the same firm between 2008 and 2013. In the case where an individual is seen in a firm (for example, in 2010), then is not seen the following year (for example, in 2011) then is seen again (for example, in 2012), this is coded as a tenure of two years within the same firm.

Source: Authors' illustration.

4 Methodology

4.1 CIT-IRP5 panel created

The following individuals were excluded from our panel:

- Those who were not employed. This was estimated using income source code data, in order to attempt to remove any individuals receiving income from a company who were not in reality employed. Individuals receiving income from the following source codes were coded as 'employed': 3601 3605 3606 3607 3615 3616 3617 3651 3655 3656 3701 3703 3707 3717 3718 3801 3802 3804 3805 3806 3807 3808 3809 3810 3813 3814 3815 3816 3820 3821.[54]
- All those who were not coded as individuals under the 'Nature of Person' variable were excluded. This excludes clubs, estates, partnerships, and welfare organizations, etc. from the sample.
- Individuals without ID numbers were dropped. This is because of difficulty tracking those individuals without ID numbers over time.
- Individuals not of labour market age. This excludes those aged below 15 and above 64 from the sample.

The following firms were excluded from our panel:

- Firms with no data on profit/loss, turnover, cost of sales, and assets. These variables were integral to this analysis, and these firms would have dropped out of the regression if any of this data was missing. In addition, this attempts to exclude firms which are not in reality producing anything/employing anyone.

Table A3 shows the results of the decisions on which firms and individuals to include in the panel. The final two rows give the numbers of matched individuals and firms—i.e. those individuals who were linked to a firm, and those firms who were linked to at least one employee. This is the sample size we are using for the years 2010 to 2013. We will not be using 2014 data as there was systematic attrition of large firm data at the time in which this analysis commenced.

[54] For a list of definitions, see the SARS website, available at: http://www.sars.gov.za/TaxTypes/PIT/Tax-Season/Pages/Find-a-Source-Code.aspx

Table A3: Creating Individual–Firm Panel

	2010	2011	2012	2013
All individuals	9 393 893	9 839 478	10 006 799	10 532 714
'Employed' individuals	9 043 990	9 513 509	9662761	9 575 012
Nature of Person	8 100 525	8 632 990	8 720 315	9 215 041
Has ID number	8 646 981	9 228 865	9 420 938	9 925 426
Labour Market Age	8 696 378	9 124 028	9 277 919	9 767 620
Total Individuals Kept	**7 557 803**	**8 061 841**	**8 204 490**	**8 639 014**
All Firms	218 382	226 991	226 141	234 245
Total Firms Kept	**103 574**	**105 645**	**102 281**	**100 185**
Panel: Matched Individuals	4 488 493	4 757 426	4 757 168	4 820 370
Panel: Matched Firms	99 247	100 619	97 364	95 077

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

4.2 Firm size

In order to calculate firm size, unique IRP5 forms linked to each firm in each year are summed. However, firm size needs to be weighted by the number of days worked by each individual in that firm for that year. This is done by using the start and end date variables, which give the date that an individual started or ended their job at a firm. Firm size is then weighted by the number of days worked divided by the number of days in each year, as follows.[55]

$$Date\_Weight_{i,f,t} = \frac{Period\ Employed\ To_{i,f,t} - Period\ Employed\ From_{i,f,t}}{Days\ in\ Year_t}$$

However, there are a number of cases where the data on work start or end date was unreliable. This included dropping all jobs which we deemed to have invalid job spells. This was the case where:

- The start date for employment was after 28 February of that year. For example, the 2010 tax year is 1 March 2009 to 28 February 2010. If the 2010 job's start date was after 28 February 2010, this was deemed an invalid job period.
- The job end date was before the start of the tax year. For example, the 2010 tax year is 1 March 2009 to 28 February 2010. If the 2010 job's end date was before 01 March 2009, this was deemed an invalid job period.
- The end date of the job was before the start date.
- The start or end date for the job was missing.

Table A4 shows the result of dropping all jobs with invalid start or end dates. It is evident that a marginal fraction of jobs were dropped from the overall dataset employed in the analysis.

[55] Equation taken from: Pieterse et al. (2016).

Table A4: Result of Dropping Invalid Job Spell Periods

Year	Jobs of All Individuals in Dataset			Jobs of Individuals in Sample		
	Total # Jobs	# Dropped Jobs	% Dropped Jobs	Total # Jobs	# Dropped Jobs	% Dropped Jobs
2010	11 746 816	37 367	0.32	9 222 750	19 844	0.22
2011	12 509 862	31 011	0.25	9 927 469	13 150	0.13
2012	12 768 486	30 836	0.24	10 143 016	12 350	0.12
2013	13 498 891	28 062	0.21	10 740 912	20 827	0.19

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

In addition, there were some cases where the start or end date of the job fell outside of the tax year in question. In these cases, the start or end date was updated to reflect the start or end date of the tax year. This process mimics that of Pieterse et al. (2016) and is detailed in their paper. In summary, when an individual's job start date is before the corresponding tax year, it is brought forward to be in line with the start of that financial year. For example, the 2010 financial year runs from 1 March 2009 to 28 February 2010. If an IRP5 form indicates a start date of 12 February 2009, this date was brought forward to 1 March 2009 to reflect the start date of the 2009 financial year. Similarly, end dates which were after the end of the corresponding financial year were brought back to the last day of that financial year.

In addition, and as detailed below, many individuals have multiple IRP5s for the same firm in one financial year. In order to get a single measure of days worked by an individual for a particular firm in each year, we restrict analysis to the three highest paying jobs in that time period (as analysing overlaps between time periods of more than three jobs is practically impossible).

In cases where the periods worked did not overlap between these multiple IRP5s, we summed the days worked across these forms. For example, if an individual worked for the same firm from 12 May to 22 May and from 12 June to 22 June, the individual worked for a total of 20 days for that firm. In cases where the periods worked overlapped, we took the earliest start date and the latest end date and used these to calculate days worked. For example, if an individual worked for the same firm from 12 May to 22 May and from 20 June to 22 June, the individual worked for a total of 41 days for that firm (or the number of days between 12 May and 22 June).

This way of calculating days worked was also used to calculate the daily wage rate, detailed in the section below. In addition to weighting by days worked, we attempted to isolate those individuals who were employed by the firm, rather than receiving income that was unrelated to employment activities. Individuals with positive employment income were included when calculating firm size and more generally in our individual–firm panel. Details of which variables were deemed 'employment income' are available in Section 3.2 of Appendix A: Data.

However, it should be noted that in 2010, 2011, and 2012 the source code for taxable income (income source code 3601) also included income associated with pensions and retirement annuities. This means that employment in these tax years may be overestimated.

4.3 Collapsing wage data

In the wage analysis below, the wage measure is defined as real gross remuneration.[56] Gross remuneration is the sum of gross taxable income, gross retirement funding income, and gross non-retirement funding income. It is important to note multiple manipulations were necessary in order to be able to analyse the individual-level wage data, which was calculated at a daily rate. A number of individuals had multiple IRP5 entries for the same company in the same year. This could be in the hundreds, with these IRP5s containing the same (i.e. same salary and time period worked) or different information from each other. A number of decisions were made in order to collapse this data into one observation per individual per firm per year.[57]

In order to collapse the data into one observation per individual per firm per year (i.e. an individual does not appear in the same firm more than once in a year), as with the calculation of firm size we restricted analysis to the three highest paying jobs in that time period (as analysing overlaps between time periods of more than three jobs is practically impossible).

Table A5 shows the number of individuals who had multiple job spells in the same firm collapsed into one observation.

Table A5: Number of Individuals with Multiple Job Spells in the Same Firm in Each Year

	All Individuals in Dataset		Individuals in Sample	
Year	# Individuals	% Individuals	# Individuals	% Individuals
2010	580 689	5.9	448 678	5.9
2011	625 423	6.4	477 939	5.9
2012	632 630	6.3	472 199	5.8
2013	672 409	6.4	516 041	6.0

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

We decided to sum the data if the time period was not overlapping. For example, if the time period worked in the company was January–May and August–December, the salary earned and days worked was summed, and the data collapsed into one observation. For multiple IRP5s where there were overlapping time periods worked, the manipulation is more in-depth. This is because we do not know why there have been multiple overlapping IRP5 entries for an individual for the same firm in one year. It could be the case that the individual legitimately earned all amounts on the multiple IRP5s. Alternatively, the IRP5 entries could be either repeated or updated entries of the same amount earned. In this case, only one of the multiple entries is a legitimate income source.

If time periods overlapped, we had to decide whether data should be summed (i.e. assume the individual earned all salaries in that time period) or averaged (i.e. assume the individual earned only one salary from that company in that time period, and thus take the average salary earned). An alternative to this is to take the highest salary earned, which we chose not to do.

Table A6 provides details of the average wage in 2013 using these methods, as well as the unmanipulated average wage rate. The mean method takes the average wage earned in the overlapping

[56] We deflate wages to 2012 prices using the consumer price index.

[57] Note that we allow an individual to have multiple IRP5s across firms, but we restrict the data to one IRP5 per individual per firm per year.

IRP5 entries. For example, if there are two IRP5s with the same start and end date, the mean method takes the average daily wage earned during that period, where the calculation of days worked accounts for the fact that the wages were earned within overlapping time periods (as explained in the section above). Therefore, if an individual earned a total of R1000 and R5000 respectively over an overlapping 10-day period, the average daily wage is R300 (or the average of the R100 and R500 daily wage rate earned over the period). The sum method adds all wages earned across the overlapping period. For example, if an individual earned a total of R1000 and R5000 respectively over an overlapping 10-day period, the summed daily wage is R600 (or R6000 in total earned over 10 days, averaged to R600 per day in that period). Finally, the unmanipulated wage does not collapse data into a single entry, and gives the average wage earned per day per individual regardless of whether they are multiple or single IRP5 entries.

Overall, these methods employed resulted in very similar wage statistics in 2013, detailed in Table A6. These figures are average daily wage rates, where days worked are calculated using the method used to calculate firm size, detailed above. After discussing these methods with various researchers and tax practitioners, we decided to use the mean method in our subsequent analysis. This is because we believe that it is most likely that IRP5s containing overlapping days worked do not reflect actual, separate amounts earned by the individual and are more likely a result of system error or recapturing of forms, etc.

Table A6: Wages: Unmanipulated, Mean, and Sum Method, 2013

Wage Type	Method	Mean	Median	SD
	Unmanipulated	R 382.58	R 143.22	R 18 568.00
Gross Remuneration	Mean method	R 372.19	R 144.62	R 17 758.20
	Sum method	R 376.83	R 145.28	R 17 770.37

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

4.4 Firm size and wages

Our analysis of mean wages by firm size indicates an unexpected relationship between these variables. For this reason, we ran all descriptive statistics and regressions using three different firm size measures.

Table A7 shows the linkage between firm size and wages using three different measures of firm size. Both Method 1 and 2 use employee weightings to augment the unweighted firm size measure (Method 3). These methods weight employment by the number of days worked by the employee in each year. Method 1 utilizes our own weighting method, detailed in Section 4.2 of this data Appendix. Method 2 uses an alternative weighting method created by Pieterse et al. (2016), which is denoted by equation (7) in their paper. In addition, we include the unweighted firm size for comparison (Method 3). We use three measures of firm size in order to provide robustness checks of our firm size result.

The U-shaped relationship is evident for all three methods of determining firm size. However, the extent to which there is a wage premium in small firms (i.e. firms with 1 to 3 employees) differs across these methods. Average daily wages amongst small firms are lowest using the unweighted Method 3, with firms in the three largest size categories all paying higher average daily wages than firms in the smallest size category. Using weighting Method 1 to calculate firm size (the authors' own), results in a larger wage premium amongst small firms, with firms with 1 to 3 employees paying higher daily wages on average than firms in all categories except the largest firm size category. Finally, using weighting Method 2 to calculate firm size, results in the largest wage premium in firms with 1 to 3 employees, with these firms paying substantially higher daily wages than firms in any other size category. The relative consistency of the firm size result using the three methods provides motivation for the use of our firm size method. In addition, it indicates that the U-shaped relationship between firm size and wages is not a construct of the firm size measure.

It is worth noting that all subsequent regression analysis was performed using all three size measures. As the results are relatively consistent across all three measures, we only report the results pertaining to our firm size measure, Method 1.

Table A7: Firm size and Wages, 2013

		1 to 3	4 to 10	11 to 20	21 to 50	51 to 200	201 to 500	501 to 1000	1001+
Method 1: Authors' Own	Distribution	24.4	31.7	17.7	15.4	8.7	1.6	0.5	0.4
	Mean wage	394.2	336.5	305.9	295.7	319.1	358.0	324.8	394.6
Method 2: Pieterse et al. (2016)	Distribution	26.5	31.9	17.5	14.8	7.6	1.2	0.3	0.3
	Mean wage	459.1	373.6	327.9	344.2	336.5	361.6	345.7	358.9
Method 3: Unweighted	Distribution	20.3	29.7	18.6	17.4	10.9	2.3	0.7	0.6
	Mean wage	341.3	318.2	310.6	302.1	324.8	364.6	353.3	377.7

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

APPENDIX B: Supplementary tables

Table B1: Wages by Firm Characteristics, 2013

Firm Age	**1 to 10**	**11 to 20**	**21 to 50**	**51+**	
Number of firms	45 871	35 948	12 710	925	
Firm distribution	48.1	37.7	13.3	1.0	
Mean wage	301.6	313.1	356.9	716.5	
Median wage	123.7	121.5	164.4	230.7	
Standard deviation	6 494.6	4 503.6	5 824.1	57 617.2	
Profit	**<=R50 000**	**>R50000 to R250 000**	**>250 000 to 1M**	**>1M**	
Number of firms	13 327	23 109	20 614	17 485	
Firm distribution	17.9	31.0	27.7	23.5	
Mean wage	195.7	210.6	239.6	408.4	
Median wage	113.5	114.5	119.8	153.6	
Standard deviation	590.1	575.0	883.7	20 828.5	
Loss	**<=R50 000**	**>R50000 to R250 000**	**>250 000 to 1M**	**>1M**	
Number of firms	24 953	7 629	4 719	2 481	
Firm distribution	62.7	19.2	11.9	6.2	
Mean wage	288.6	228.4	242.8	437.2	
Median wage	116.0	127.5	127.8	181.2	
Standard deviation	3 475.0	512.1	602.3	11 560.3	
Turnover	**<=R1M**	**>R1M to R2.5M**	**>2.5M to 10M**	**>10M**	
Number of firms	11 923	17 187	31 396	31 156	
Firm distribution	13.0	18.8	34.3	34.0	
Mean wage	195.5	195.6	218.4	377.2	
Median wage	107.7	107.9	112.8	143.2	
Standard deviation	728.9	2 506.3	769.2	18 294.8	
Capital–Labour Ratio	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Quantile cut-offs	< 5 623	5 623 - 18 761	18 761 – 44 859	44 859 - 122 205	> 1 22 205
Number of firms	18 887	19 084	19 139	19 150	19 098
Firm distribution	19.8	20.0	20.1	20.1	20.0
Mean wage	270.7	295.7	296.9	337.8	415.1
Median wage	143.6	153.7	157.4	167.6	202.5
Standard deviation	809.4	681.4	715.6	2 704.7	6 873.5
Productivity	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Quantile Cut-offs	< 227 404	227 404 – 413 704	413 704 – 712 935	712 935 – 1 440 446	> 1 440 446
Number of firms	19 179	19 140	19 080	18 986	18 973
Firm distribution	20.1	20.1	20.0	19.9	19.9
Mean wage	171.1	226.7	296.9	351.7	573.0
Median wage	95.6	143.4	171.0	201.6	279.2
Standard deviation	752.1	349.9	645.0	488.3	7 424.9
Trade Status	**Non-trader**	**Exporter**	**Importer**	**Exporter & Importer**	
Number of firms	73 654	4305	6184	11 341	
Firm distribution	77.1	4.5	6.5	11.9	
Mean wage	239.4	270.4	370.7	550.7	
Median wage	108.0	112.3	153.1	227.5	
Standard deviation	2 911.5	5 220.8	2 266.4	28 930.0	

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Table B2: Summary of Earnings Function Estimates for Fixed-effects Regression Controlling for Individual Fixed Effects

Firm Characteristic	Sign of Coefficient	Statistical Significance of Estimate	Coefficient Estimates Min	Coefficient Estimates Max
Firm size: 4-10	+VE (9 of 9)	Significant (3 of 9)	0.021	0.035
Firm size: 11-20	+VE (9 of 9)	Significant (2 of 9)	0.027	0.029
Firm size: 21-50	-VE (9 of 9)	Significant (2 of 9)	-0.026	-0.024
Firm size: 51-200	-VE (9 of 9)	Significant (9 of 9)	-0.068	-0.041
Firm size: 201-500	-VE (9 of 9)	Significant (9 of 9)	-0.119	-0.088
Firm size: 501-1000	-VE (9 of 9)	Significant (9 of 9)	-0.194	-0.155
Firm size: >1000	-VE (9 of 9)	Significant (9 of 9)	-0.362	-0.337
Firm Age: 11-20	-VE (9 of 9)	Significant (9 of 9)	-0.055	-0.045
Firm Age: 21-50	+VE (9 of 9)	Significant (3 of 9)	0.011	0.015
Firm Age: >50	-VE (9 of 9)	Significant (6 of 9)	-0.039	-0.017
Ln Capital: Labour	+VE (9 of 9)	Significant (9 of 9)	0.034	0.038
Lagged Net Profit/Loss	+VE (9 of 9)	Significant (9 of 9)	0.018	0.018
Concentration Ratio	-VE (9 of 9)	Significant (9 of 9)	-4.844	-1.695
Exporter	+VE (9 of 9)	Significant (9 of 9)	0.045	0.057
Importer	+VE (9 of 9)	Significant (9 of 9)	0.021	0.041
Exporter & Importer	+VE (9 of 9)	Significant (9 of 9)	0.094	0.100
Ln Labour Productivity	+VE (9 of 9)	Significant (9 of 9)	0.145	0.152

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the nine samples that the sign prevailed. 5. Column 3 reports the number of times across the nine samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the nine samples. 7. In all instances the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Table B3: Summary of Earnings Function Estimates for Fixed-effects Regression Controlling for Firm Fixed Effects

Firm Characteristic	Sign of Coefficient	Statistical Significance of Estimate	Coefficient Estimates	
			Min	Max
Firm size: 4-10	+VE (9 of 9)	Significant (5 of 9)	0.034	0.054
Firm size: 11-20	+VE (9 of 9)	Significant (5 of 9)	0.027	0.040
Firm size: 21-50	+VE (7 of 9)	Significant (0 of 9)	-0.004	0.028
Firm size: 51-200	+VE (6 of 9)	Significant (0 of 9)	-0.016	0.025
Firm size: 201-500	+VE (6 of 9)	Significant (0 of 9)	-0.013	0.031
Firm size: 501-1000	+VE (6 of 9)	Significant (0 of 9)	-0.021	0.022
Firm size: >1000	-VE (9 of 9)	Significant (0 of 9)	-0.069	-0.032
Firm Age: 11-20	-VE (9 of 9)	Significant (0 of 9)	-0.017	-0.007
Firm Age: 21-50	-VE (9 of 9)	Significant (0 of 9)	-0.018	-0.005
Firm Age: >50	+VE (9 of 9)	Significant (0 of 9)	0.026	0.044
Ln Capital: Labour	+VE (9 of 9)	Significant (9 of 9)	0.013	0.014
Lagged Net Profit/Loss	+VE (9 of 9)	Significant (9 of 9)	0.046	0.048
Concentration Ratio	+VE (8 of 9)	Significant (0 of 9)	-0.626	1.879
Exporter	+VE (9 of 9)	Significant (9 of 9)	0.041	0.055
Importer	+VE (9 of 9)	Significant (0 of 9)	0.047	0.069
Exporter & Importer	+VE (9 of 9)	Significant (9 of 9)	0.154	0.161
Ln Labour Productivity	+VE (9 of 9)	Significant (9 of 9)	0.259	0.263

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the nine samples that the sign prevailed. 5. Column 3 reports the number of times across the nine samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the nine samples. 7. In all instances the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Table B4: Summary of Earnings Function Estimates for Spell Fixed Effects: Controlling for Individual and Firm Fixed Effects

Firm Characteristic	Sign of Coefficient	Statistical Significance of Estimate	Coefficient Estimates	
			Min	Max
Firm size and Age:				
Firm size: 4-10	-VE (9 of 9)	Significant (9 of 9)	-0.072	-0.045
Firm size: 11-20	-VE (9 of 9)	Significant (9 of 9)	-0.105	-0.070
Firm size: 21-50	-VE (9 of 9)	Significant (9 of 9)	-0.135	-0.102
Firm size: 51-200	-VE (9 of 9)	Significant (9 of 9)	-0.183	-0.141
Firm size: 201-500	-VE (9 of 9)	Significant (9 of 9)	-0.216	-0.175
Firm size: 501-1000	-VE (9 of 9)	Significant (9 of 9)	-0.251	-0.204
Firm size: >1000	-VE (9 of 9)	Significant (9 of 9)	-0.297	-0.232
Firm Age: 11-20	-VE (9 of 9)	Significant (9 of 9)	-0.023	-0.017
Firm Age: 21-50	+VE (9 of 9)	Significant (2 of 9)	0.011	0.013
Firm Age: >50	+VE (9 of 9)	Significant (9 of 9)	0.045	0.083
Technology and Productivity:				
Ln Capital: Labour	+VE (9 of 9)	Significant (9 of 9)	0.004	0.005
Ln Labour Productivity	+VE (9 of 9)	Significant (9 of 9)	0.013	0.019
Exporter	-VE (9 of 9)	Significant (9 of 9)	-0.037	-0.024
Importer	-VE (9 of 9)	Significant (9 of 9)	-0.047	-0.033
Exporter & Importer	-VE (9 of 9)	Significant (9 of 9)	-0.038	-0.019
Profitability:				
Lagged Net Profit/Loss	+VE (9 of 9)	Significant (9 of 9)	0.001	0.002
Concentration Ratio	-VE (9 of 9)	Significant (2 of 9)	-0.996	-0.451

Notes: 1. Reference dummies refer to an individual working in a firm that employs between 1 and 3 employees in the agricultural industry, does not trade, and is no older than 10 years old. 2. Dependent variable is measured as real gross monthly remuneration per job. 3. Time and industry dummies as well as individual time-varying controls not reported. 4. Column 2 reports the sign of the estimated coefficient for the variable in question and the number of instances in the nine samples that the sign prevailed. 5. Column 3 reports the number of times across the nine samples that the estimated coefficient for the variable in question was statistically significant. 6. Columns 4 and 5 report the minimum and maximum statistically significant coefficient estimate across the nine samples. 7. In all instances the statistically significant coefficient estimates in column 3 are the same sign as that reported in column 2.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.

Table B5: Spell Fixed-effects Estimates for Firm size by Industry—Summary Across Samples

	Firm size: 4-10	Firm size: 11-20	Firm size: 21-50	Firm size: 51-200	Firm size: 201-500	Firm size: 501-1000	Firm size: >1000	Overall
Agriculture	Generally negative and not significant (6/9)	Generally negative and not significant (6/9)	Generally negative and not significant (5/9)	Always negative, generally significant (6/9)	Always negative, generally significant (6/9)	Always negative and highly significant	Always negative and highly significant	**Negative and significant (largest 4 size categories)**
Mining	Mixed sign (5 +), generally not significant (8/9)	Generally negative and not significant (7/9)	Mixed sign (5 -), generally not significant (8/9)	Generally positive and not significant (6/9)	Generally positive and not significant (6/9)	Always positive, generally not significant (6/9)	Always positive, generally not significant (5/9)	**No significant firm size effect**
Manufacturing	Generally negative and not significant (5/9)	Always negative, generally significant (5/9)	Always negative, generally significant (7/9)	Always negative and significant	Always negative and significant	Always negative and significant	Always negative and significant	**Negative and significant (largest 6 size categories)**
Utilities	Generally positive and not significant (6/9)	Generally negative and not significant (5/9)	Generally negative and not significant (5/9)	Generally negative and not significant (6/9)	Generally negative and not significant (7/9)	Generally negative and not significant (6/9)	-	**No significant firm size effect**
Construction	Mixed sign (5 +), generally not significant (8/9)	Generally positive and not significant (5/9)	Mixed sign (5 -), generally not significant (8/9)	Generally negative and not significant (5/9)	Generally negative and significant (6/9)	Generally negative and not significant (6/9)	Always negative and significant	**Negative and significant (largest size category only)**
Trade	Generally negative and significant (6/9)	Always negative and generally significant (8/9)	Always negative and significant	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	**Negative and significant or highly significant (all size categories)**
Transport	Generally positive and not significant (5/9)	Always negative and generally not significant (8/9)	Generally negative and not significant (6/9)	Generally negative and not significant (7/9)	Always negative and generally significant (6/9)	Always negative and generally significant (7/9)	Always negative and generally significant (6/9)	**Negative and significant (largest 3 size categories)**
Finance	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	Always negative and highly significant	**Negative and highly significant (all size categories)**
CSP	Always negative and generally significant (6/9)	Always negative and significant	Always negative and generally significant (7/9)	Always negative and significant	Always negative and generally significant (6/9)	Always negative and generally significant (6/9)	Generally negative and not significant (6/9)	**Negative and significant (all except largest size category)**
Other Services	Mixed sign (5 -), never significant	Mixed sign (6 -), generally not significant (7/9)	Mixed sign (5 -), generally not significant (7/9)	Generally negative and not significant (6/9)	Mixed sign (5 +), generally not significant (8/9)	Generally positive and not significant (5/9)	Always positive and generally not significant (5/9)	**No significant firm size effect**

Notes: 1. 'Significant' denotes significance at the 10% or 5% level. 'Highly significant' denotes significance at the 1% level.

Source: Authors' calculations using SARS (n.d.), IRP5 (n.d.), and CIT (n.d.) data.