WAGE DYNAMICS, TRADE-RELATED WAGE PREMIA AND PRODUCTIVITY SPILLOVERS: EVIDENCE FROM THE SOUTH AFRICAN MANUFACTURING SECTOR

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Declaration

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Abstract

South Africa continues to grapple with low economic growth, unemployment and inequality, making it crucial to gain further insights into wage inequality which is the largest component of income inequality. This thesis uses the South African Revenue Service and National Treasury tax administration linked employer–employee panel dataset to investigate wage dynamics, trade-related wage premia and productivity spillovers from foreign-connected firms in the South African manufacturing sector.

Firstly, this thesis is the first to look at wage growth, taking into account unobserved worker and firm heterogeneity in South Africa. Over time the manufacturing sector has become more productive, while shedding low-skilled, labour-intensive jobs, with increasing wage inequality. As such, this thesis conducts a variance decomposition of wage levels and growth and finds that worker fixed effects dominate both wage levels and growth. However, for low-income employees' wage levels, the firm fixed effect is relatively more important, showing that firm characteristics should not be neglected when analysing less-skilled workers' wage differentials. Turning to wage growth, worker fixed effects are found to explain a higher proportion of the change in the wage for low-income workers compared to wage levels. Further, the importance of firm fixed effects in explaining the variation in wage levels increases with firm size.

Secondly, this thesis extends the South African literature by estimating the wage premium for simultaneously being a foreign-connected firm and an exporter and/or importer (i.e. a hybrid). This thesis is also the first to empirically estimate the wage premium by differentiating between pure exporters/importers and firms that are both importers and exporters, as well as trading firms and domestically/foreign-owned foreign-connected firms. Given the increasing wage inequality in the sector, it is important to understand which types of firms pay the highest wage premia. There is evidence of hybrid firms paying the highest wage premium. As such, it is the combination of exposure to foreign markets through imported inputs, export sales and foreign direct investment that results in the highest wage premia.

Lastly, this thesis is also the first to explore productivity spillovers from foreign-connected firms to local firms using the South African Revenue Service and National Treasury tax administration linked employer–employee panel dataset. One of the ways in which local firms learn from foreign-connected firms is by hiring workers with experience gained in foreign-connected firms. Therefore, understanding the extent to which such spillovers occur in the manufacturing sector is important for

knowledge sharing between firms in the sector. There is strong evidence of productivity spillovers from foreign-connected firms to non-foreign-connected firms. These spillovers arise mainly from foreign-connected firms above the median firm size and are received mostly by small local firms. Further, the results suggest that spillovers mainly occur through high-wage foreign-connected firm workers, highlighting the importance of skills.

Opsomming

Suid-Afrika worstel steeds met lae ekonomiese groei, werkloosheid en ongelykheid, wat die belangrikheid onderstreep om nog insigte te bekom oor loonongelykheid; dié is die grootste komponent van inkomste-ongelykheid. Hierdie tesis maak van die Suid-Afrikaanse Inkomstediens en die Nasionale Tesourie se belastingadministrasie gekoppelde werkgewer-werknemer paneeldata gebruik om loondinamika, handelsverwante loonpremies en produktiwiteitsoorlope van ondernemings met buitelandse verbintenisse in die Suid-Afrikaanse vervaardigingsektor te ondersoek.

Eerstens – dié tesis is die eerste wat loongroei, met inagneming van onwaargeneemde werker- en firma-heterogeniteit in Suid–Afrika, onder die loep te plaas. Met verloop van tyd het die vervaardigingsektor meer produktief geword, terwyl daar van laag-geskoolde, arbeidsintensiewe werksgeleenthede ontslae geraak is, met toenemende loonongelykheid. As sulks onderneem hierdie tesis ’n wisselingsontleding van loonvlakke en -groei en word daar bevind dat werker-vasgestelde effekte loonvlakke, sowel as groei, oorheers. Vir die loonvlakke van lae-inkomste-werknemers, is die onderneming se vasgestelde effek egter relatief belangriker, wat toon dat onderneming-eienskappe nie verontagsaam moet word met die ontleding van minder geskoolde werknemers se loonverskille nie. Wat loongroei betref, is bevind dat werknemers se vasgestelde effekte ’n hoër deel van die verandering in die loon van werknemers met lae inkomste verklaar in vergelyking met loonvlakke. Voorts groei die belangrikheid van onderneming-vasgestelde effekte (wat die wisseling in loonvlakke toelig) algaande die onderneming uitbrei.

Tweedens – dié tesis verbreed die Suid-Afrikaanse literatuur deurdat dit ’n skatting lewer van die loonpremie om gelyktydig 'n buitelandse onderneming en 'n uitvoerder en/of invoerder (dit wil sê 'n hibried) te wees. Hierdie tesis is ook die eerste om die loonpremie empiries te skat deur tussen suiwer uitvoerders/invoerders en ondernemings te onderskei, wat sowel invoerders as uitvoerders is, sowel as handelsondernemings en plaaslike/buitelands beheerde en ondernemings met buitelandse verbintenisse. Gegewe die toenemende loonongelykheid in die sektor, is dit belangrik om te begryp watter soorte ondernemings die hoogste loonpremies betaal. Daar is bewyse dat hibriede ondernemings die hoogste loonpremie betaal. As sulks is dit die kombinasie van blootstelling aan buitelandse markte deur ingevoerde insette, uitvoerverkope en direkte buitelandse beleggings wat die hoogste loonpremie meebring.

Ten slotte, hierdie proefskrif is ook die eerste om produktiwiteitsoorlope van ondernemings met buitelandse verbintenisse na plaaslike ondernemings, wat gebruik maak van die Suid-Afrikaanse Inkomstediens en Nastionale Tesourie se belastingadministrasie-gekoppelde werkgewer–werknemer paneeldatastel, te ondersoek. Een van die wyses waarop plaaslike ondernemings by buitelandse ondernemings kennis opdoen, is deur werknemers in diens te neem met ondervinding wat opgedoen is in ondernemings met buitelandse verbintenisse. Daarom is dit belangrik om te begryp in watter mate sulke oorlope in die vervaardigingsektor voorkom, met die oog op die deel van kennis tussen ondernemings in dié sektor. Daar is stewige bewyse van produktiwiteitsoorlope van ondernemings met buitelandse verbintenisse, na ondernemings wat nie met die buiteland verbind is nie. Hierdie oorlope kom hoofsaaklik voor by ondernemings met buitelandse verbintenisse, wat bo die grootte van die gemiddelde onderneming is, en word meestal deur klein plaaslike ondernemings ontvang. Die resultate dui voorts daarop dat oorlope die belangrikheid van vaardighede benadruk en hoofsaaklik voorkom weens werkers wat hoë lone ontvang en wat buitelands verbind is.

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Abbreviations and Acronyms

AKM	Abowd, Kramarz, Margolis
BC	Bargaining council
CFC	Controlled foreign company
CIT	Company income tax
CPI	Consumer price index
DTA	Double-taxation agreement
ERRP	Economic Reconstruction and Recovery Plan
EXIM	Exporters and importers
FCF	Foreign-connected firm
FDI	Foreign direct investment
GDP	Gross domestic product
GHS	General Household Survey
HI	High income
ICT	Information and communication technology
IES	Income and Expenditure Survey
IPAP	Industrial Policy Action Plan
ISIC	International Standard Industrial Classification
JtJ	Job-to-job
JuJ	Job-unemployment-job
KIDS	KwaZulu-Natal Income Dynamics Study
KZN	KwaZulu-Natal
LEED	Linked employer–employee data
LFS	Labour force survey
LI	Low income
MNE	Multinational enterprise

NDP	National Development Plan
NIDS	National Income Dynamics Survey
NIPF	National Industrial Policy Framework
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary least squares
PAYE	Pay as you earn
PSLSD	Project for Statistics on Living Standards and Development
QLFS	Quarterly Labour Force Survey
RIS	Re-imagined industrial strategy
SARS	South African Revenue Service
SARS-NT	South African Revenue Service–National Treasury
TES	Temporary employment services
TFP	Total factor productivity
TWFE	Two-way fixed effects
UIF	Unemployment insurance fund
UJ	Unemployment-to-job
UK	United Kingdom
UNIDO	United Nations Industrial Development Organization
US	United States
VAT	Value-added tax

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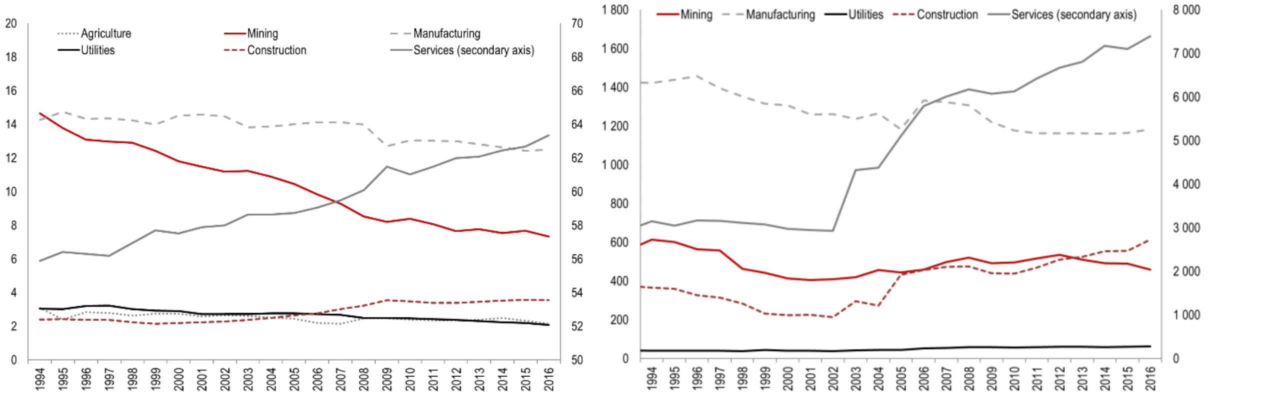
Chapter 1: Introduction

1.1 Background and context of the study

South Africa continues to grapple with high levels of unemployment, poverty and inequality, which are central to the government's economic policy. This is evidenced in the focus on the elimination of poverty, the reduction of inequality, and job creation in the National Development Plan (NDP). Given that South Africa has one of the highest levels of inequality globally, it is imperative that we understand all the factors that contribute to this inequality as well as its consequences. Inequality in the distribution of income is one of South Africa's core economic challenges. The high level of inequality is partly attributable to the historically entrenched wage inequality in the South African labour market (Van der Berg, 2011). Van der Berg (2011) decomposed inequality by income source and found that wage income is the dominant component in overall income inequality. Further, wage inequality derives largely from differences in both education levels and quality, which are an indication of skill levels.

Bhorat et al. (2014) highlighted the strongly skills-biased labour demand trajectory in the South African labour market, which has led to better-educated, skilled workers being the winners and less-skilled workers the losers in terms of employment opportunities. They indicated that this trend has been intensified by trade, global competition and technological spillovers. Further, the rising demand for skilled labour has a bearing on the evolving structure of wages and thus wage inequality. They ran quantile regressions and found an increase in the wage levels of high-skilled workers with face-to-face tasks, an information and communications technology (ICT) component and analytical tasks; and a decline in the wage levels of low- and medium-skilled workers with automated or routine tasks. This reflects the structural change in the South African economy, which is becoming more services-orientated and is shifting away from the primary and secondary sectors (see **Figure 1-1**). However, this change is not limited to South Africa; a reduction in barriers to trade and technology transfer has shifted sectoral structures globally (Wood, 2019). Wood (2019) found that between 1985 and 2015, manufacturing in skill-abundant developed countries became more skill-intensive and employment declined; labour-intensive manufacturing increased in land-scarce developing East Asia, while South Asia was constrained by low literacy rates and poor infrastructure; and manufacturing shares fell in land-abundant Africa, Latin America and the Middle East.

Figure 1-1: Share of GDP (%) and formal employment ('000) by economic activity



Source: Aterido et. al. (2019) using Statistics South Africa (1st panel) and Statistics South Africa historical QLFS series (2nd panel) between 1994 and 2016.
Note that long-term employment in agriculture is not provided in this long-term data series.

The South African manufacturing sector has undergone significant change over the last three decades. Despite the decline in employment in the sector, manufacturing remains a significant contributor to the South African economy. It also has an important policy focus in South Africa owing to its role in driving growth and employment. Kerr (2018) looked at job flows, worker flows and churning, using the South African Revenue Service–National Treasury (SARS–NT) tax administration panel dataset, and found that both worker flows and job flows vary substantially by industry. This indicates that the level of job mobility will also vary across industries, which will have an impact on the analysis in this thesis. As a result, the analysis in the thesis is restricted to the manufacturing sector.

It is important to understand the dynamics within the manufacturing sector, which provide context for this study. The sector's contribution to gross domestic product (GDP) gradually declined from 14.4% in 1994 to 12.5% in 2016 and employment decreased from 1.42 million jobs in 1994 to 1.18 million jobs in 2016. Despite its declining contribution to GDP and employment, the manufacturing sector is becoming more productive. Using the SARS–NT tax administration panel dataset, Kreuser and Newman (2018) found that productivity in the manufacturing sector grew on average between 2010 and 2013. However, there is significant heterogeneity in productivity within and between subsectors. Further, total factor productivity (TFP) increases with firm size and TFP growth is driven by larger firms in terms of number of employees. Aterido et al. (2019) corroborated this result, using the SARS–NT tax administration panel dataset, and showed that although firms in South Africa (including those in the manufacturing sector) have increased their productivity, this has not translated into employment growth. Even manufacturing value-added has increased at the expense of labour. Further, labour productivity in the manufacturing sector almost doubled between 1995 and 2014 (Rankin, 2016). This was mainly driven by within-industry growth as high-productivity firms are increasing their share of output, while smaller firms employing higher proportions of unskilled workers are exiting. Autor et al. (2020), in their attempt to explain the decline in labour's share of value-added in the US and other countries, found that globalisation and technological change direct sales and resources towards the most productive firms, creating 'superstar firms'. They also found evidence that sales are increasingly concentrated in a small number of firms, and that industries displaying the highest increase in concentration have the lowest labour shares and have also experienced higher growth in productivity.

Fedderke et al. (2018) used the SARS–NT tax administration panel dataset between 2010 and 2012 and found that the manufacturing firm exit rate exceeded the entry rate, consistent with the rising average concentration of the manufacturing sector. They also found significant rates of entry and exit among small firms, with exits dominating the flow. Kerr et al. (2014) found that net job creation in South Africa was driven by large firms and that net job creation rates were negative in manufacturing between 2005 and 2011. Aterido et al. (2019) also indicated that between 2010 and 2014, job creation was concentrated in incumbent firms, which are old and large; thus, job creation from entry and exit was negligible.

Rankin (2016) observed that there has been 'catch-up' by low-productivity manufacturing industries which have been growing faster than high-productivity industries. However, the growth in labour productivity has been coupled with higher real wages. Thus, firm attrition in the manufacturing sector is related to labour productivity and labour costs. As indicated earlier, lower-labour-productivity firms and lower average-wage firms, which tend to be small firms hiring higher proportions of unskilled workers, are more likely to exit. Rankin (2016) also found that there is a relationship between unskilled employment intensity, import competition and bargaining council (BC) coverage.[1] Smaller firms in BC industries are more likely to exit than larger ones; moreover, import competition is positively associated with exit in BC industries but negatively associated with exit in non-BC industries. Firms with higher proportions of unskilled workers are more likely to exit in BC industries.[2] Bassier (2021), using the SARS-NT panel, found that low-wage BC firms decreased in

[1] 'Bargaining Councils cover collective bargaining at a sectoral, rather than firm or plant, level and are formed by representatives of businesses and workers in a specific sector. If a Bargaining Council represents the majority of workers and employers within a sector, then agreements reached by that council can be extended to all participants in the sector, irrespective of whether they were party to such agreements, although a formal exemption can be applied for and granted by the Minister of Labour. In addition to these institutionalized processes, bargaining can happen at a plant or firm level' (Edwards et al., 2015, p. 21).

[2] One explanation for this is that 'smaller firms have lower bargaining power in the bargaining council structure even if they participate in the bargaining process – decisions taken by firms who employ the "majority" of workers in the sector and worker organisations, often representing only these workers, are binding for all firms in the sector. In this type of institutional set-up, small firms are likely to have to pay the types of wages larger firms pay. This is more likely to be binding for smaller firms and firms employing large numbers of unskilled workers. If capital is "lumpy" or smaller firms cannot substitute with other types of labour or inputs, then these firms may become unprofitable and exit.' (Rankin, 2016, p. 24).

size following a wage increase while medium- and higher-wage firms had neutral or positive firm size effects. Further, Rankin (2016) indicated that higher levels of import competition make smaller, low-skilled, labour-intensive and low-labour-productivity firms more sensitive to higher wages. This is unsurprising as earlier research on the impact of trade on domestic production, which led to strong growth in capital-intensive exports and import penetration in ultra-labour-intensive sectors, indicated the shift towards more capital-intensive production in South Africa, especially in manufacturing industries (Edwards, 2001).

Increased trade or export-led growth remains at the heart of South Africa's industrial and economic policies, including the NDP, the National Industrial Policy Framework (NIPF) and the Industrial Policy Action Plan (IPAP). However, the differences between exporting and non-exporting firms also result in increased inequality. In South Africa, it has been shown that exporting is concentrated and dominated by a group of large 'super-exporters' (Matthee et al., 2016). Bezuidenhout et al. (2020) looked at the distribution of wages within manufacturing exporting firms relative to non-exporting firms in South Africa and how wage differentials might contribute to wage inequality. They found that exporters pay higher wages; however, there is also a high degree of wage inequality within these firms. Thus, exporting firms' wage inequality may have a significant impact on overall wage inequality in South Africa.

1.2 The contribution of this study to our knowledge

This thesis uses the South African Revenue Service and National Treasury tax administration linked employer–employee panel dataset to investigate wage dynamics, trade-related wage premia and productivity spillovers from foreign-connected firms (FCFs)[3] in the South African manufacturing sector. Wage dynamics, trade-related wage premia and productivity spillovers from FCFs are important considerations in South African manufacturing, as the sector becomes more productive while shedding low-skilled, labour-intensive jobs, with increasing wage inequality and increased import competition. This thesis seeks to gain insights into the phenomenon of wage growth in the South African manufacturing sector (Chapter 2). Given the increasing wage inequality in the sector, it is important to understand which types of firms pay higher wages. In this regard, this thesis extends the analysis of the 'exporter wage premium' to include importers as well as FCFs (Chapter 3). One of the ways in which local firms learn from FCFs is by hiring workers with experience from these

[3] FCFs have at least 10% equity held in or by a foreign firm. FCFs can also be domestically owned firms with foreign connections. A detailed definition is given in Chapter 3.

firms. Thus, the extent to which such spillovers occur is estimated through worker mobility in the manufacturing sector (Chapter 4).

Chapter 2 in this thesis explores the relative contribution of observable and unobservable worker and firm characteristics in the determination of both wage levels and growth; this is also disaggregated by gender, wage quantiles and firm size. The literature mainly focuses on wage levels; however, there is also a high level of dispersion in wage growth. Most of the studies in the literature have found that worker fixed effects dominate firm fixed effects in explaining the variation in wage levels. Even in South Africa, Bhorat et al. (2017), using the SARS–NT tax administration panel dataset, found that worker fixed effects are more important than firm fixed effects in explaining the variation in wage levels. However, their analysis straddles all the sectors in the South African economy and does not look at wage growth. As such, this is the first study to look at wage growth, taking into account unobserved worker and firm heterogeneity in South Africa. As a robustness check and extension to Sørensen and Vejlin (2013), Chapter 2 also conducts a variance decomposition controlling for firm characteristics. In addition, it includes a variance decomposition which accounts for match effects. However, this is limited to the orthogonal match effects model.

Numerous studies in the South African literature have focused on the exporter wage premium (Matthee et al., 2018; Rankin, 2001; Rankin & Schoër, 2013). Edwards et al. (2018) further distinguished between the wages of firms that only export, that only import, and that are both exporters and importers. However, foreign-owned firms have been found to be the most productive firms globally (Girma et al., 2002 [for the UK]; Helpman et al., 2004 [for the US]; Temouri et al., 2008 [for Germany]; Engel & Procher, 2012 [for France]). As such, these firms are likely to have a higher wage premium relative to exporters. Both trade and foreign direct investment (FDI) are important for growth. However, they also make it challenging to achieve inclusive growth owing to the wage premia exhibited by firms that engage in these activities. Thus, Chapter 3 of this thesis jointly estimates the wage premium of firms that engage in trade and FDI, extending the South African literature by estimating the wage premium for simultaneously being an FCF and an exporter and/or importer (i.e. a hybrid). To my knowledge, the only papers that have revealed similar studies are those of Tanaka (2015) for Japan and Schröeder (2020) for Germany. However, they do not distinguish between firms that are simultaneously exporters and importers and pure exporters and importers. As such, this thesis is the first to empirically estimate the wage premium by differentiating between pure exporters/importers and firms that are both importers and exporters, as well as domestically owned and foreign-owned FCFs.

Given the differences in wages and productivity between FCFs and local firms, it is important to understand whether there are any spillovers that occur between these types of firms. In South Africa, productivity spillovers have only been estimated for exporters, R&D and training (Hlatshwayo et al., 2019) as well as horizontal, forward and backward spillovers (Sørensen, 2020). Thus, Chapter 4 of this thesis explores worker mobility as a channel for productivity spillovers from FCFs to domestic firms, making this the first study to conduct such an analysis in South Africa.

1.3 Data overview

The main challenge associated with analysing the distribution in income and wage inequality in South Africa has been the dearth of good-quality income data that links employees and employers. Among the datasets used to conduct research on wages and income inequality are the Census, the Income and Expenditure Survey (IES), the General Household Survey (GHS), the Quarterly Labour Force Survey (QLFS), the Project for Statistics on Living Standards and Development (PSLSD), the KwaZulu-Natal Income Dynamics Study (KIDS) and the National Income Dynamics Study (NIDS). The income and expenditure information used to create most of these datasets was collected through the recall method. However, the IES has used the diary method since the 2005/2006 version. The data in these surveys is either self-reported or proxy-reported (i.e. reported by another household member on behalf of the index person). Individuals often do not know what their gross earnings are and other members of their household are even less likely to know. One of the benefits of the SARS-NT data is that firms are reporting the wages they have paid to employees, and this provides more accurate wage data on tax forms than is available in survey data.

Further, some of these surveys (e.g. IES) do not occur annually and changes occur between various waves, making it difficult to analyse income over long periods of time. Yu (2013) explains that this is partly due to the measurement errors in surveys, which are intensified when two data points are compared a few years apart and each has its own errors and idiosyncrasies. Another limitation is that all the datasets mentioned above are samples, including the Census. In census and survey data, earnings are sometimes collected in brackets or a bracket option is provided for those who respond that they don’t know or refuse to respond. Researchers then have to decide how to treat these bracket responses. In particular, researchers have to decide what to do with the top bracket which is generally open-ended (e.g. greater than R30 000). This has several implications; however, the key issue is that they are likely to undercount the top end of the income distribution, which is important information when analysing income or wage inequality. This is another benefit of the SARS-NT panel – it provides the actual income received by employees as reported by their employers and the data is collected from all formally employed worker earning more the R2000 per year.

The analysis in this thesis is conducted using the linked employer–employee dataset from the National Treasury and SARS. This dataset is the first of its kind in South Africa, combining administrative tax information from individuals (employees) and balance sheet information from firms (employers). The dataset matches employers and employees to form a panel allowing for individuals to be tracked over time. The dataset covers the entire population of individuals who submit tax returns or have employers who submit IRP5 forms on their behalf. Thus, the data captured covers 'formal' employers and employees.

South Africa is not the first country to produce a linked employer–employee dataset of this nature. Countries like Germany, France, New Zealand and Denmark have similar datasets but the availability of this type of data in developing countries is limited. A growing body of research has been conducted using this type of data, with analyses ranging from the relationship between age and productivity to worker mobility. The use of linked employer–employee data has recently become popular as it permits a more in-depth analysis of economic relationships and the labour market.

The SARS and National Treasury tax administrative panel dataset (henceforth referred to as the SARS–NT panel) from 2011 to 2016 is used to conduct this research. The panel dataset consists of four data sources, namely:

- Company income tax (CIT) data – from CIT-registered firms who submit an IT14 and/or ITR14 form/s;
- Individual tax certificate (IRP5 and IT3a) data – from employee income tax certificates submitted by employers;
- Value-added tax (VAT) data – from VAT-registered firms; and
- Customs data (SAD 500–Customs declaration form) – transaction-level data from exporters and importers.

Chapter 2 of this thesis uses only the IRP5 component of the data between 2011 and 2016. Chapter 3 uses the IRP5, CIT data and customs data between 2013 and 2016.[4] Chapter 4 uses the IPR5 and CIT data between 2013 and 2016. For the observations dropped as part of the cleaning process for Chapter 2, see **Table *A-1*** and for Chapters 3 and 4, see **Table *A-2***. When merging the IRP5 and CIT data, only 63% of the observations are successfully matched for the manufacturing sector.

[4] The required customs variables are kept in the CIT in Chapter 3 and are dropped in Chapter 4.

Individuals are identified by their unique identity numbers. Firms are identified by a unique pay-as-you-earn (PAYE) number and CIT number. A firm can have multiple PAYE numbers which can be matched to a unique CIT number. However, the reverse is not possible. As such, the PAYE number represents multiple branches of the same organisation. Chapter 2 only uses the IRP5 data and the PAYE number is used as the firm identifier. This implies that workers switching jobs between branches in an organisation will be considered movers. It should also be noted that branches of the same firm can be in different locations. However, Chapters 3 and 4 use the CIT number as the firm identifier. As such, movement between branches is not considered movement.

The IRP5 form is submitted by employers and includes information on the total employee tax amount, taxable income, retirement fund income, gender, date of birth, employment start and end dates, and industry. An employer issues an IRP5 certificate to each employee if remuneration is paid and tax on that remuneration has been deducted. If no tax has been deducted and the employee remuneration is equal to or greater than R2000 per year, then an IT3a certificate is issued. More importantly, firms with workers who earn less than R2000 per year are not taxed and an IRP5 or an IT3a form is not issued. As such, these employees are not captured in the panel. Consequently, any analysis of wages does not cover the lower end of the wage distribution (Pieterse et al., 2018).

The data-cleaning process starts by dropping duplicate certificates which are likely to be revisions and labour brokers.[5] Total earnings per job are generated by summing gross non-retirement fund income (the salary paid to an employee from which contributions to medical aid and UIF are deducted), non-taxable income (including arbitration awards, purchased annuities, travel reimbursements, subsistence allowances and uniform allowances) and gross retirement income (or pension contributions). Earnings are converted to monthly figures and are deflated using the economy-wide consumer price index (CPI). The top percentile of wages is trimmed to drop outliers – these are individuals earning more than R395 143.30 per month, which is equivalent to R4.7 million per year. This translates into approximately 5 million observations.

All the manufacturing sector jobs held by an individual, i.e. those jobs confined to the manufacturing sector, are kept in the sample. Employment duration is calculated as the absolute value of the difference between the start and end dates for each job. The start and end dates for each job are used

[5] Also known as temporary employment services (TES). TES workers employed through labour brokers are employed by staffing agencies, which are ultimately responsible for the salary, taxes and benefits of the leased employee. Temporary employment services workers are different from seasonal, temporary or part-time workers, who are contracted directly by a firm and are usually let go when the work is complete. As such, these workers are not employees of the firm they assist. Further, these workers may be posted to different firms, which means they are changing jobs but in the data they would appear as 'stayers' because they will always appear as employed by a labour broker. Thus, they are excluded from the sample.

to clean for overlaps and drop all duplicates by keeping entries with higher wages and longer durations, with the duplicates accounting for 8.72% of all observations. Individuals with multiple short-term contracts with the same firm are dropped; these account for 0.99% of all observations. For example, if an individual had three job spells of a three-month duration each, with varying wages, all the observations for that job will be dropped. The idea is to have only one unique firm–worker combination in a year, regardless of the number of days worked.[6]

A mover/switcher is an individual employed in firm x in time t who moves to another firm in either time t or t+1. Individuals who enter the panel (i.e. do not move from another firm) are called entrants. Entrants could be coming from unemployment or another sector. The rationale for calling people coming from other sectors 'entrants' is that this thesis focuses on manufacturing-specific skills and experience when looking at movers relative to stayers. As such, only spillovers from moving within the manufacturing sector are captured. Workers who exit the sample could be moving from a job to unemployment or moving to another sector. It is not possible, using the SARS-NT, to identify unemployment between jobs. As such, the analysis is limited to job-to-job transitions. If a worker is seen in the panel in 2013 and is missing in 2014 and shows up again in 2015 in the same or a different firm, they are considered an entrant again – so a missing year of data means that all the accumulated human capital until that point is lost. However, if a worker has a job in consecutive years in the panel, regardless of tenure, they are considered to have been employed throughout the panel. As such, a job change is considered a switch so long as the gap between two job spells is less than a year. Jobs with a tenure of less than a year are kept in the sample.

Following Hlatshwayo et al. (2019), tenure[7] is set to 1 when a worker is first seen in the panel; tenure then increases by 1 for every year that the worker is seen at the same firm. Tenure falls back to 1 following a job switch. As such, tenure is the cumulative number of years that a worker is seen in a firm. The main difference between employment duration and tenure is that contracts that are less than a year are rounded up to a year in the tenure calculation. If a worker is seen in a firm, they get a 1, regardless of the days worked. As such, seasonal workers with three-month contracts at the same firm for consecutive years will be included as workers in that firm throughout the panel.

[6] There are 1,059,940 workers with contracts of less than 90 days across all the years of the IRP5 in the manufacturing sector. These workers are retained in the analysis as some firms use seasonal workers as part of their production process. As such, short and long contact jobs are not treated differently.

[7] Although the IRP5–CIT panel is used from 2013 to 2016 in the analysis, the IRP5 panel runs from 2011 to 2016. The IRP5 data is used to calculate tenure before it is merged with the CIT data which has a shorter timeframe.

The IRP5 form does not include firm size; thus, firm size is calculated as the number of employees reported as employed by a firm in a given year, weighted by the number of months employed. Gender and date of birth variables are also used in the analysis. Age is restricted to between 19 and 65 years.

The IT14 and ITR14 forms make up the CIT data and contain information on firm characteristics, financial information from firms' income statements and balance sheets, and tax information. The tax year starts on 1 March of the previous year and ends on the last day of February in the current year. Most firms submit their tax returns according to their financial year. That said, most firms' tax years coincide with the SARS tax year; only 15% of firms do not follow the SARS convention. To ensure that firms are reporting as close as possible to the same financial year, firms with financial years ending after 30 August are moved to the next financial year. For example, a firm with a financial year ending on 30 September 2012 will be moved from tax year 2012 to tax year 2013 (Pieterse et al., 2018).

Sales, cost of sales and capital are found in the CIT data. Capital is calculated as the sum of property, plant and equipment, and other fixed capital stock items available in the data. All monetary values are deflated using the industry-level deflators. The top percentile of output is trimmed and includes roughly 200 observations for each year between 2013 and 2016. Information captured in the CIT data is used to identify FCFs (see detailed definition in Chapter 3). Merged customs and CIT data is used to identify exporters and importers. These are firms that reported positive export or import activity between 2013 and 2016.[8] The IRP5 and CIT data are merged for the analysis conducted in chapters 3 and 4.

Lastly, the analysis in this thesis is restricted to the manufacturing sector which accounts for a 15% share of employment in the panel. The largest sector in the panel is the financial services sector which accounts for 28.37% of the formal jobs in South Africa, followed by government (16.32%) and then manufacturing.[9]

[8] When merging the IRP5 and CIT data, it is not possible to identify firms that do not trade directly and use a separate entity to trade. Thus, only direct exporters/importers can be identified in the sample.

[9] In 2014 the manufacturing sector accounted for 13% of employment, financial services accounted for 22% and government accounted for 22%, according to the QES data. Thus, the SARS-NT panel is comparable to other data sources like the QES.

Chapter 2: Job Mobility and Wage Growth in South African Manufacturing

ABSTRACT

The relative contribution of worker and firm fixed effects (i.e. the unobserved time-invariant worker and firm characteristics) to the dispersion in wage levels and wage growth are estimated in the manufacturing sector, using the SARS–NT tax administrative panel dataset between 2011 and 2016. The results show that worker fixed effects dominate. However, for low-income employees, the firm fixed effect is relatively more important, indicating that company characteristics should not be neglected when analysing less-skilled workers' wage differentials. Further, the importance of firm fixed effects in explaining the variation in wage levels increases with firm size. Moving away from a levels analysis to a consideration of wage growth characteristics, worker fixed effects are found to explain a similar proportion of the wage variation across low- and high-wage workers. Match effects explain a relatively small but important share of the variation in wages for both wage levels and growth. Overall, wage dynamics for low-wage workers differ substantially from the rest of the wage distribution, and for these workers, staying in the same job is very important for their wage growth.

2.1 Introduction

Wage growth has been studied for several decades (Lazear, 1976), as have job mobility and wages (Bartel & Borjas, 1978; Mincer, 1986). Previous studies have shown that workers experience higher wage growth when they change jobs (Bartel & Borjas, 1978; Topel & Ward, 1992). Topel and Ward (1992) showed that workers' propensity to leave a job may be due to different, unobservable characteristics, such as motivation and ability. The estimation of these unobservable characteristics has become possible with linked employer–employee data. The availability and use of linked employer–employee panel datasets has resulted in a growing interest in understanding the share of individual- and firm-level, unobserved, time-invariant characteristics that explain differences in wages. The main aim of this chapter is to estimate an empirical model of wage growth, allowing for both worker and firm fixed effects. This is the first study to analyse wage growth using both worker and firm fixed effects, applying the SARS–NT panel for the manufacturing sector between 2011 and 2016.

This chapter takes a closer look at wages in formal South African manufacturing firms, analysing both wage levels and wage growth. The focus is on the relative importance of observable characteristics and unobservable worker and firm characteristics estimated by worker and firm fixed effects, while also adding a match effect. This adds to the literature on unobserved worker and firm heterogeneity of both wage levels and wage growth. In South Africa, understanding wage growth is important because the wage gap between low- and high-wage workers remains wide. Some insight into how the share of individual- and firm-level, unobserved, time-invariant characteristics explains differences in wage growth could assist policymakers in their quest to think of interventions to reduce income/wage inequality.

Consistent with previous literature, the worker effect dominates for both wage levels and wage growth. However, there is a much larger error term for wage growth, indicating that we know less about what drives the variation in wage growth. In terms of wage levels, firm fixed effects are relatively more important for low-wage workers. This indicates that for less-skilled workers (low wage), the firm at which they are employed is more important relative to high-skilled workers (high wage). Further, the importance of firm fixed effects in explaining the variation in wage levels increases with firm size.

Turning to the wage growth analysis, the worker fixed effect explains a similar proportion of the wage variation across low- and high-wage workers. This could indicate that less-skilled workers are likely to accept the wage offered (resulting in a lower worker effect in the wage level estimation), but once they are in the firm, they gain more bargaining power to negotiate a higher wage, which is reflected in the higher worker effect in the wage growth estimation.

The match fixed effect is also included in the two-way fixed effect model and the results indicate that match effects explain a small but important proportion of the variation in wage levels and growth in South Africa. This could reflect the low bargaining power that workers have in negotiating wages with their employers (Card et al., 2013).

There is a negative correlation between the worker and firm fixed effects (consistent with previous studies), indicating negative assortative matching in the manufacturing sector in South Africa. However, the results indicate that the negative assortative matching is more prevalent among smaller firms than among larger firms.

Overall, the analysis shows that while there is a fair amount of movement in the sector, workers who stay in the same job tend to have higher wage levels. However, workers who change jobs experience higher wage growth. The only workers this does not apply to are low-wage workers, indicating that movement at the low end of the wage distribution is likely to be involuntary, while also reflecting the small wage difference across firm sizes at the lower end of the wage distribution. As such, low-wage movers are unlikely to see high-wage growth, even if they move to a large firm. More importantly, wage growth for low-wage workers is very different to the rest of the distribution; for these workers, staying in the same job is essential for their wage growth.

This chapter is structured as follows: section 2.2 provides a review of the literature, section 2.3 presents the descriptive statistics, section 2.4 outlines the methodology applied, section 2.5 details the empirical results and section 2.6 concludes.

2.2 Literature review

The Abowd et al. (1999) seminal paper on high-wage workers and high-wage firms was the first paper to introduce the analysis of both observed and unobserved heterogeneity, as well as the extent of sorting between workers and firms (henceforth referred to as AKM). They decomposed annual earnings per worker into observable characteristics, individual heterogeneity, firm heterogeneity and a residual. The AKM methodology has been adopted in a number of studies, using data from various countries, including Goux and Maurin (1999) using French data; Andrews et al. (2008) using German data; Gruetter and Lalive (2009) using Austrian data; Hyslop and Maré (2009) using New Zealand data; Sørensen and Vejlin (2011) using Danish data; Card et al. (2013) using German data; Barth et al. (2016) using US data; and Jinkins and Morin (2018) using Danish data. The model has also been extended to include match effects (Sørensen & Vejlin, 2013; Woodcock, 2015). Most of the studies in the literature found that worker fixed effects dominate firm fixed effects in explaining the variation in wage levels. Even in South Africa, Bhorat et al. (2017), using the SARS–NT panel, found that worker fixed effects are more important than firm fixed effects in explaining the variation in wage levels. Unlike this chapter, their analysis was conducted across all economic sectors in South Africa and did not look at wage growth.

Most of the literature focuses on wage levels. However, there is also a large degree of dispersion in wage growth. Nevertheless, initial wages have been shown to be important for wage growth, as Sørensen and Vejlin (2014) found a negative relationship between initial wages and wage growth. As such, looking at both wage levels and growth is important. Sørensen and Vejlin (2011) and Jinkins and Morin (2018) investigated Danish wage growth, using the two-way fixed effect model. Like Sørensen and Vejlin (2011), the current analysis has interesting policy implications because if there is no variation in wage growth across firms, then workers only need to find a new job to receive a higher wage. However, if most of the variation in wage growth is due to firm effects, then the firm the worker moves to matters for their wage growth. This will inform whether labour market policy should focus purely on providing each worker with a job or if finding the right job is more important. The more important firm effects are for wage growth, the more important it is for the worker to find the right job. The same holds for worker fixed effects. If all workers were identical, then placing them in any job would be optimal. In South Africa, understanding wage growth is important because the wage gap between low- and high-wage workers remains wide.

Sørensen and Vejlin (2011), using their full sample for wage levels, found that worker effects explained 58% of the variation in wages, firm fixed effects 14%, observable characteristics 9% and the residual 19% in Danish firms. The methodology for both wage levels and wage growth follows Sørensen and Vejlin (2011), the only difference being that the sample used in this chapter is restricted to the manufacturing sector. Bhorat et al. (2017), using the SARS–NT panel across all the sectors in the South African economy, estimated that approximately 61% of wage variance is due to worker effects, while at least 13% is due to firm effects.[10] Further, Bassier (2019) showed that South African firms have a larger role to play in determining wages relative to the international literature on firm wage premia and worker effects (also using the SARS–NT panel).

Sørensen and Vejlin (2011) found that much less of the variation in wage growth can be explained by observables and worker and firm effects compared to wage levels. They found that in their wage growth estimates for their full sample, worker fixed effects explained only 9% of the variation in wages, firm fixed effects 4%, observable characteristics 2% and the residual 85%. Jinkins and Morin (2018) used different samples to estimate their firm fixed effects, i.e. job-to-job (JtJ), unemployment-to-job (UJ), job-unemployment-job (JuJ) and full sample.[11] The current study focuses on JtJ transitions.[12]. Jinkins and Morin (2018) indicate that their approach is closely related to Gruetter and Lalive (2009) who identified different mobility patterns for JtJ movers compared to JuJ movers and estimated separate fixed effects for these two types of workers. However, in their paper, they use the firm fixed effects estimated from the UJ movers and apply these to the wage growth of JtJ movers.

[10] Bhorat et al. (2017) use the merged IRP5 and CIT panel. In this chapter, only the IRP5 panel is used, and thus observable firm characteristics are not controlled for, to replicate the standard AKM model as well as Sørensen and Vejlin (2011).

[11] Comparing the JtJ sample to the UJ sample, the relative contribution of worker effects to the variance of wages is considerably lower for the set of workers who were hired from unemployment, while time-varying observables and, to a certain extent, firm effects explain more of the dispersion in wages for this sub-sample of workers. These discrepancies suggest that wage determination might differ according to a worker's labour market status at the time of hiring.

[12] Jinkins and Morin (2018) also have unemployment benefit data which is equivalent to unemployment insurance fund (UIF) data in South Africa. As such, they are able to indicate when a worker was unemployed between jobs. It is not possible, using the SARS-NT, to identify unemployment between jobs. As such, the analysis is limited to job-to-job transitions.

Their studies indicate that only using the JtJ movers may underestimate the role of firms in explaining wage differences. For their full sample of wage levels, they found that worker fixed effects explain 78% of the variation in wages, firm fixed effects 12%, observable characteristics negligible and the residual 12%. These estimates also include workers hired directly from unemployment as well as workers who have a break in employment between jobs. The estimates in this chapter capture JtJ movers only. Further, their wage growth analysis differs from the current study as they take the first difference of the wage equation, thus eliminating worker fixed effects. Consequently, for their full-sample wage growth estimates, they find that firm fixed effects explain 24% of the variation in wages, observable characteristics 4% and the residual 72%.

The inclusion of a match effect has also been shown to be important in the literature (Sørensen & Vejlin, 2013; Woodcock, 2015, Jinkins & Morin, 2018; Mittag, 2019). Woodcock (2008) theoretically introduced the match effect into the AKM model. This branch of the literature indicates that it matters which workers match with which firms. A good-quality match would be a good worker matching with a good firm. As such, specifications that omit match effects attribute too much variation to personal heterogeneity (i.e. the worker effect) and underestimate the extent to which good workers sort into employment at good firms (Woodcock, 2015). Sørensen and Vejlin (2013) estimate the match effects model presented in Woodcock (2008), i.e. the standard AKM worker and firm fixed effects model, which includes an orthogonal match effect, and a hybrid mixed effect model, which also allows for a match effect that is correlated with the worker and firm effects. They found that match effects explain around 7% of the variation in wages in the orthogonal match effect model and 9% in the hybrid model. Woodcock (2015) finds that match effects explain 4% of the variation in wages using the orthogonal match effect model and 16% using the hybrid match effect model.

Jinkins and Morin (2018) extend Sørensen and Vejlin (2013) and Woodcock (2015) by adding a match effect to wage growth, while the previous studies only included match effects to wage levels. They indicate that including a match effect that is orthogonal to the worker and firm fixed effects is a strong assumption and that even the hybrid model requires a weaker identification assumption than a standard random effects model. Thus, they propose an alternative, two-step estimation strategy which assumes that endogenous mobility is satisfied for the employment spells of workers hired from unemployment. They find that match effects explain 66% of the variation in wage growth in their JtJ sample, using firm fixed effects calculated from the UJ sample and 56% using fixed effects estimated from the JtJ sample.

This chapter also extends Sørensen and Vejlin (2013) and Woodcock (2015) by adding a match effect to wage growth. However, the analysis is limited to their orthogonal match effects model estimated, using the two-way fixed effects (TWFE) command developed by Mittag (2019).

2.3 Descriptive statistics

2.3.1 Wages and firm size

In this chapter the IRP5 data is used for the analysis. The number of workers in the sample ranges from 1.4 million in 2011 to 1.8 million in 2016, with 75% males and 25% females employed in the sector (see **Table 2-1**). There were more jobs than workers as some workers held multiple jobs. Most workers held one job between 2011 and 2016.[13]

Table 2-1: Key summary statistics

	2011	2012	2013	2014	2015	2016
Number of workers	1,489,280	1,612,539	1,730,818	1,826,034	1,842,098	1,827,503
Number of firms	41,714	43,016	45,927	49,594	48,822	44,756
Number of jobs	1,537,289	1,670,940	1,796,050	1,910,703	1,937,138	1,896,391
Number of females	502,391	543,652	586,065	622,359	631,844	631,481
Number of males	986,898	1,068,901	1,144,770	1,203,691	1,210,271	1,196,041
Mean real monthly wage	14635.23	14615.21	14729.07	14494.37	14777.46	14881.71
Median real monthly wage	7121.04	7214.87	7245.57	7314.38	7428.92	7616.86
Mean worker age	37	37	37	37	37	38
Median worker age	35	35	35	35	35	35
Mean number of jobs per worker	1.07	1.08	1.08	1.1	1.1	1.1
Mean number of workers per firm	1466	1501	1472	1503	1508	1634
Median number of workers per firm	175	185	190	191	198	217

Source: SARS–NT panel (own calculations)

The number of firms in the sample gradually increased from 41,714 in 2011 to 44,756 in 2016.[14] The wages in this thesis are reported as monthly wages, and log monthly wages are used for most of the analysis. Wage inequality is high in South Africa, evidenced in the distribution of wages – even at the top end of the wage distribution. The average and median wage both increase over time; however, the mean wage is double the median wage (see **Table 2-1**).

There are very large firms that skew the distribution of firms, evidenced in the large difference between the median and the mean. Further, even the income of the 99th percentile workers is almost

[13] See **Table 2-16** for the number of firms a worker is employed in for the analysis.
[14] This is not an indication of pure firm entry; it also captures the expansion of branches within an organisation.

double that of the 95th percentile (see **Table 2-2**). Wages have increased marginally over time. However, what is interesting is that between 2011 and 2016, wages in the 25th and 50th percentiles increased by 7% and in the 75th by 6%, while in the 90th percentile wages increased by only 3% and in the p95 and p99 by 4%. Despite the higher growth in the lower percentiles, the wage distribution remained the same between 2011 and 2016. However, this is a relatively short period in which to see a significant shift in the wage distribution.

Table 2-2: Monthly real wage percentiles

Year	p25	p50	p75	p90	p95	p99
2011	R3 679.57	R7 120.73	R15 617.03	R33 693.56	R49 743.92	R98 581.65
2012	R3 689.73	R7 213.62	R15 864.68	R34 184.83	R50 710.52	R98 772.98
2013	R3 698.15	R7 245.57	R15 907.98	R34 055.68	R50 405.70	R99 014.59
2014	R3 758.52	R7 312.61	R16 021.33	R34 173.63	R50 691.48	R98 592.77
2015	R3 876.58	R7 427.48	R16 274.05	R34 554.77	R51 546.73	R101 718.00
2016	R3 943.56	R7 615.31	R16 584.02	R34 662.83	R51 521.32	R102 537.30

Source: SARS–NT panel (own calculations)

The median manufacturing firm in the sample has approximately 200 workers, while the mean firm has around 1500 workers (see **Table 2-1**). The firm size distribution shows that most manufacturing firms have between 100 and 499 employees (see **Table 2-3**). However, firms with between 1000 and 49,999 employees disproportionately have the largest share of employment.

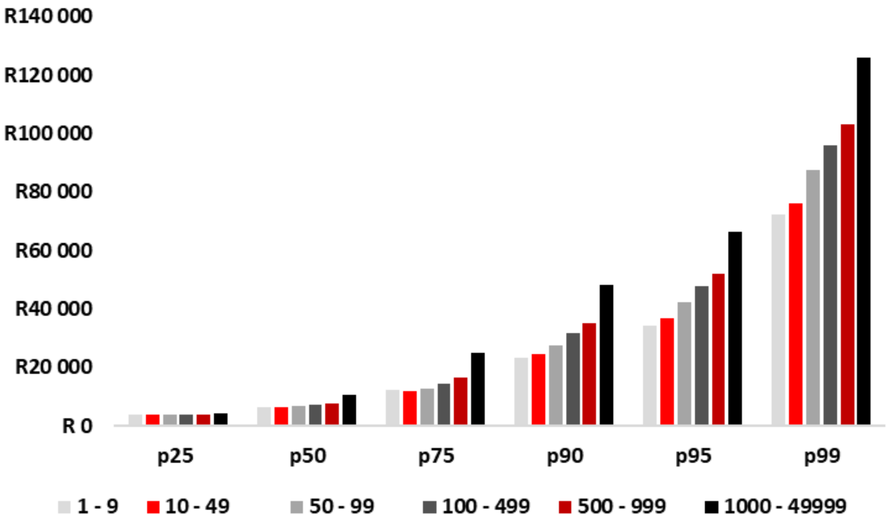
Table 2-3: Proportion of firm size categories and their employment share

Firm size	**Proportion**	**Employment share**					
	2011-2016	2011	2012	2013	2014	2015	2016
1 - 9	5.3	0.02	0.02	0.02	0.02	0.02	0.02
10 - 49	21.0	0.4	0.4	0.4	0.4	0.4	0.4
50 - 99	11.9	0.6	0.6	0.6	0.6	0.6	0.5
100 - 499	27.9	4.5	4.4	4.8	4.6	4.6	4.22
500 - 999	9.8	4.7	4.6	4.8	4.6	4.7	4.5
1000 - 49999	24.1	89.7	90	89.7	89.8	89.7	90.4
Total	100	100	100	100	100	100	100

Source: SARS–NT panel (own calculations)

Large firms also pay higher wages. **Figure 2-1** below shows the difference in wages paid by each firm size across the various percentiles. In terms of firm size, large firms (1000–49,999) pay workers in the 25th percentile approximately 12% more than other firm sizes. Large variations between firm sizes mainly arise with workers in the 75th percentile and higher, with some workers being paid up to 109% more in large firms. This indicates that 25th percentile or low-wage workers are paid low wages regardless of the size of firm at which they are employed. However, workers in the 75th percentile and higher can earn relatively higher wages from working in a larger firm. This is likely due to the wage determination structures in the manufacturing sector which mainly occur through bargaining councils.[15] Managers, professionals, associate professionals and technicians are generally excluded from bargaining council coverage (Flowerday et al., 2017). Thus, bargaining council agreements essentially set a minimum wage which should be paid by firms in a certain sector or region.[16] This gives firms more discretion when setting wages for higher-skilled workers. As such, small firms have to match wages paid by larger firms at the lower end of the distribution due to the minimum wage requirements that apply to low-skilled workers.

Figure 2-1: Real monthly wage percentiles by firm size



Source: SARS–NT panel (own calculations)

2.3.2 Movers and stayers

Roughly 60% of the workers stayed in the same job and 40% got a new job between 2012[17] and 2016. 'Same job' refers to a unique job held for two consecutive years. The number of jobs held for a minimum of two periods increased between 2012 and 2016. 'New job' refers to a job that is held by an individual in year t and was not held in year t-1. New jobs increased from 2012 until 2014 and then gradually declined in 2015 and 2016 (see **Table 2-4**). Job entry and exit[18] occur at the individual level, so it captures an individual who is entering the panel for the first time or leaving the panel.[19]

[15] 'Bargaining Councils cover collective bargaining at a sectoral, rather than firm or plant, level and are formed by representatives of businesses and workers in a specific sector. If a Bargaining Council represents the majority of workers and employers within a sector, then agreements reached by that can be extended to all participants in the sector, irrespective of whether they were party to such agreements, although a formal exemption can be applied for and granted by the Minister of Labour. In addition to these institutionalized processes, bargaining can happen at a plant or firm level' (Edwards et al., 2015, p. 21).
[16] This paper does not include bargaining councils in the analysis. However, where applicable, their potential impact is discussed.
[17] 2011 is the first year of the panel; as such, all the workers are entrants in that year with new jobs.
[18] There is no exit in 2016 because it is the last year of the panel.
[19] It is possible to leave a job but not the panel if one had multiple jobs.

The number of individuals entering the manufacturing sector has declined over time and the number of individuals exiting has increased. Notably, there was more exit than entry in the sample in 2014 and 2015. There are also workers who change jobs for two consecutive years; these workers are referred to as churners. This is a small subset of workers which has gradually increased since a sharp decline in 2013.

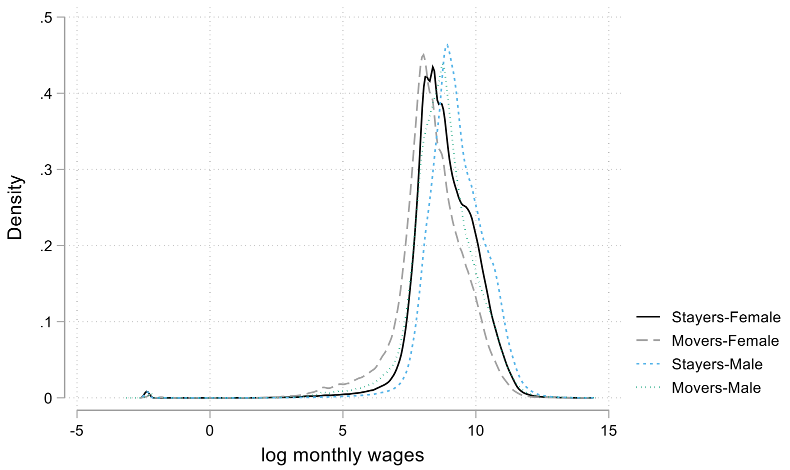
Table 2-4: Same jobs, new jobs, entry, exit and churners

	2012	2013	2014	2015	2016
Same jobs	1,149,200	1,248,166	1,349,666	1,383,775	1,402,343
New jobs	460,538	482,088	490,982	484,695	427,672
Entry	394,231	407,749	395,039	358,825	348,929
Exit	305,703	332,742	409,450	554,639	-
Churners	63,500	31,992	39,486	41,333	44,652

Source: SARS–NT panel (own calculations)

The k-density of monthly wages for males and females who have the same job (stayers) and those with new jobs (movers) are shown in **Figure 2-2** below. For both males and females, the movers' distribution is slightly to the left of the stayers, indicating higher wages of stayers. In addition, there is a higher density of females in the lower-wage segment who are movers. Further, the male movers' and stayers' distributions are slightly to the left of the female movers' and stayers' distributions, showing that male workers earn slightly more than females.

Figure 2-2: Individual monthly wage movers vs stayers by gender



Source: SARS–NT panel (own calculations)

2.3.3 Transitions

Most workers in the sample stay in the same job. The transition matrix for 2014 shows that 96.39% of the workers who were in the same job in 2013 were still in the same job in 2014 and only 3.61%

were in a new job in 2014 (see **Table 2-5**). Among those workers who had a new job in 2013, 83.21% were still in that job in 2014 and 16.79% were in another new job in 2014. These proportions are relatively similar across all the years in the panel.

Table 2-5: Job-level transitions

		2014	
		Same jobs	New jobs
2013	Same jobs	96.39	3.61
	New jobs	83.21	16.79

Source: SARS─NT panel (own calculations)

Firms with between 100 and 499 workers had the highest proportion of same jobs, new jobs, entry, exit and churners in 2014 (see **Table 2-6**). Firms with 10 to 49 workers followed closely, with the exception of the same job category where firms with between 1000 and 49,999 workers were higher. Firms with 1 to 9 workers had the smallest proportions in all categories. However, within firm size categories, firms with between 1000 and 49,999 workers have the highest proportion of workers who stayed in the same job. Churners account for less than 2% of each firm-size category.

Table 2-6: Firm size by new jobs, same jobs, entry, exit and churners in 2014

	1–9	10–49	50–99	100–499	500–999	1000–49,999
Same jobs	76,718	289,760	157,630	371,031	131,377	323,150
% row	*5.68*	*21.47*	*11.68*	*27.49*	*9.73*	*23.94*
% col	*49.66*	*49.38*	*48.28*	*48.33*	*50.28*	*54.98*
New jobs	27,546	107,911	61,754	147,665	49,524	96,582
% row	*5.61*	*21.98*	*12.58*	*30.08*	*10.09*	*19.67*
% col	*17.83*	*18.39*	*18.91*	*19.23*	*18.96*	*16.43*
Entrant	22,512	86,774	48,552	115,862	39,602	81,737
% row	*5.70*	*21.97*	*12.29*	*29.33*	*10.02*	*20.69*
% col	*14.57*	*14.79*	*14.87*	*15.09*	*15.16*	*13.91*
Exit	25,801	93,338	52,782	120,451	37,316	79,762
% row	*6.30*	*22.80*	*12.89*	*29.42*	*9.11*	*19.48*
% col	*16.70*	*15.91*	*16.16*	*15.69*	*14.28*	*13.57*
Churners	1,912	9,058	5,804	12,714	3,446	6,552
% row	*4.84*	*22.94*	*14.70*	*32.20*	*8.73*	*16.59*
% col	*1.24*	*1.54*	*1.78*	*1.66*	*1.32*	*1.11*

Source: SARS─NT panel (own calculations)

Analysing worker transitions (i.e. only movers) by firm size, reveals that most workers move to firms with the same firm size, with the exception of the 1–9 and 50–99 firms. Firms with between 1 and 9 workers have the lowest proportion of workers moving within the same firm-size category. Firms with between 100 and 499 workers have the most movers between the same size category (see **Table**

2-7). Workers are more likely to move to the firm-size category above their current firm size. However, most workers moving from 100–499 firms transition to 1000–49,999, and vice versa.

For proportions, see **Table 2-8.** In 2013, 52.73% of the workers in 100–499 firms moved to the same size category, 18.08% moved to 1000–49,999 firms, 10.41% moved to 500–999 firms, 7.91% moved to 50–99 firms, 9.36% moved to 10–49 firms and 1.52% moved to 1–9 firms.

Table 2-7: Firm size transitions for workers who changed jobs between 2013 and 2014

		2014					
		1-9	10-49	50-99	100-499	500-999	1000-49999
2013	1-9	**750**	1 241	481	664	181	256
	10-49	665	**6 217**	2 684	4 243	1 022	1 661
	50-99	275	1 475	**2 155**	3 494	676	1 320
	100-499	342	2 106	1 780	**11 870**	2 343	4 071
	500-999	77	452	341	1 772	**2 539**	2 431
	1000-49999	161	829	675	2 528	868	**4 144**

Source: SARS–NT panel (own calculations)

Table 2-8: Firm size transitions for workers who changed jobs between 2013 and 2014 (%)

		2014					
		1-9	10-49	50-99	100-499	500-999	1000-49999
2013	1-9	**20.99**	34.73	13.46	18.58	5.07	7.16
	10-49	4.03	**37.70**	16.27	25.73	6.20	10.07
	50-99	2.93	15.70	**22.94**	37.19	7.20	14.05
	100-499	1.52	9.36	7.91	**52.73**	10.41	18.08
	500-999	1.01	5.94	4.48	23.28	**33.36**	31.94
	1000-49999	1.75	9.01	7.33	27.46	9.43	**45.02**

Source: SARS–NT panel (own calculations)

The sample is divided into wage quantiles, creating four categories where the first quantile represents individuals with low wages and the fourth quantile individuals with high wages. In 2014, the highest proportion of new jobs, entry, exit and churners among the low-wage workers and most of the individuals staying in the same jobs were high medium and high-wage workers (see **Table 2-9**). This shows that most of the movement comes from low-wage workers.

Table 2-9: Wage quantiles by new jobs, same jobs, entry, exit and churners in 2014

	Low wage	Low–medium wage	High–medium wage	High wage
Same job	256,583	333,708	366,019	392,806
%	*19.02*	*24.74*	*27.13*	*29.12*
New job	205,602	125,659	93,348	66,342
%	*41.88*	*25.60*	*19.01*	*13.51*
Entry	181,676	103,593	68,370	41,374
%	*45.99*	*26.23*	*17.31*	*10.47*

Exit	172,280	93,829	74,465	68,443
%	*42.12*	*22.94*	*18.21*	*16.73*
Churner	11,729	9,745	9,637	8,374
%	*29.70*	*24.68*	*24.41*	*21.21*

Source: SARS–NT panel (own calculations)

Most workers stay in the same wage quantiles and move to a lower-wage quantile (see **Table 2-10**). High-wage workers have the highest number of workers staying in the same wage quantile.

Table 2-10: Wage quantile transitions

		2014			
		Low wage	Low medium wage	High medium wage	High wage
2013	Low wage	**14 556**	3 989	1 249	369
	Low medium wage	6 051	**13 184**	3 374	613
	High medium wage	2 366	4 145	**16 747**	2 770
	High wage	1 446	1 298	4 188	**21 827**

Source: SARS–NT panel (own calculations)

Of the workers with low wages in 2013, 72.19% stayed in the same quantile in 2014. Notably, among the low medium-wage workers, 26.02% moved to the low-wage quantile (see **Table 2-11**). This transition matrix indicates that workers are likely to stay in the same-wage quantile, which shows much less mobility compared to the findings of Vermaak (2010) and Finn et al. (2012) whose studies sampled mainly the extreme low end of the wage distribution and informal employment. These are discussed below.

Table 2-11: Wage quantile transitions (%)

		2014			
		Low wage	Low medium wage	High medium wage	High wage
2013	Low wage	**72.19**	19.78	6.19	1.83
	Low medium wage	26.02	**56.77**	14.53	2.64
	High medium wage	9.09	15.93	**64.34**	10.64
	High wage	5.03	4.51	14.56	**75.90**

Source: SARS–NT panel (own calculations)

Prior to the availability of the SARS–NT panel, the NIDS, KIDS and Labour Force Survey (LFS) panels were used for analysing income or wage mobility. Cichello et al. (2003) analysed earnings dynamics among Africans in KwaZulu-Natal (KZN) between 1993 and 1998, using the KIDS. They found that working-age Africans in KZN experienced large gains in earnings between 1993 and 1998. Further, they found that while obtaining formal employment was an important pathway to growth in earnings, most of those who ‘got ahead’ did so by remaining in the same sector.

Vermaak (2010) used six waves of the South African labour force panel (2001–2004) to assess low-wage mobility and found that low-wage workers who maintain their employment are more likely to experience upward, rather than downward, earnings mobility. The aggregate transition matrices in her paper show that the probability of an individual earning less than R800 remaining in the same earnings category is less than 50% and the probability of someone earning more than R800 remaining in that earnings category is 91.45% (see **Table 2-12**). This reflects a high level of mobility among low-wage groups (i.e. less than R800). The greater-than-R800 category has a very high range and does not adequately capture the earnings mobility of the workers in it.

Table 2-12: Aggregate transition patterns between earnings categories for all employed individuals

		t						
		<R150	R150-R299	R300-R499	R500-R799	R800+	Total	% of t-1
	<R150	**32.64**	28.56	17.28	10.48	11.05	100	2.78
	R150-R299	10.81	**43.33**	22.84	10.76	12.26	100	7.00
t-1	R300-R499	4.84	14.53	**42.70**	21.15	16.79	100	9.96
	R500-R799	2.30	5.93	15.41	**46.57**	29.80	100	11.56
	At least R800	0.38	1.16	2.28	4.73	**91.45**	100	68.70

Source: Vermaak (2010) using LFS panel, September 2001 to March 2004

Finn et al. (2012) also analysed income mobility in South Africa; however, they used the first two waves of the NIDS. They found that individuals earning less than R515 and those earning more than R1 898 displayed the least mobility and those in the middle had the most mobility (see **Table 2-13**).

Table 2-13: Transitions across earnings in the first two NIDS waves

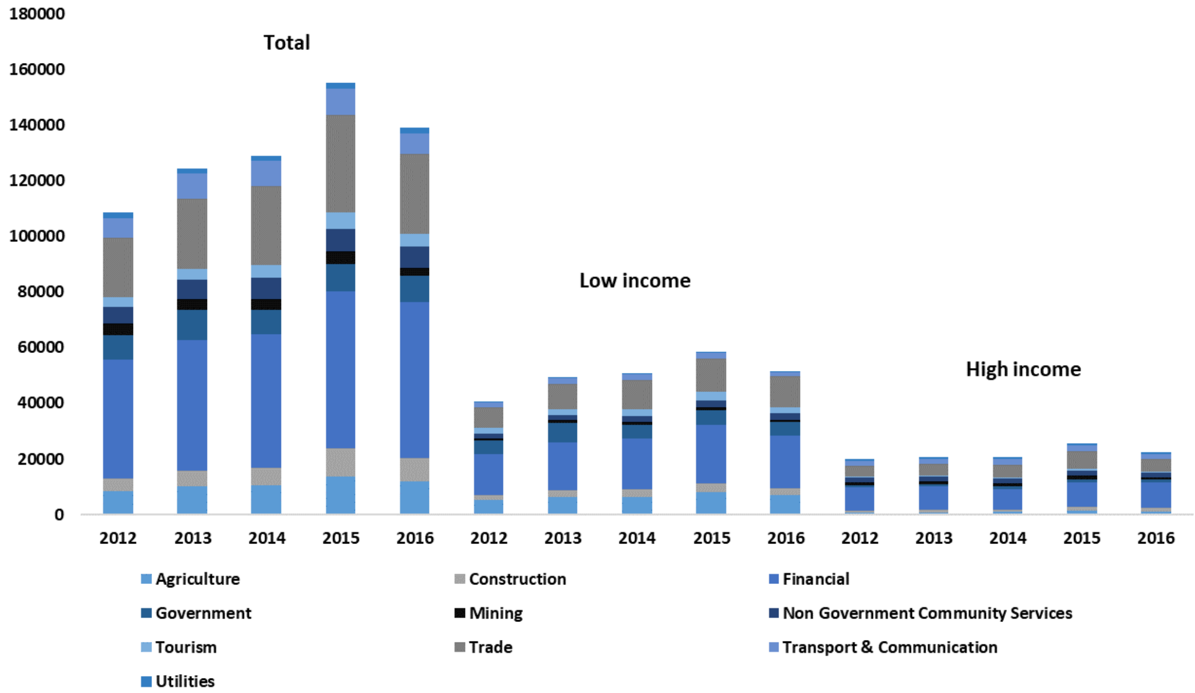
	Wave 2				
Wave 1					
	<515	515-948	949-1898	>1898	
<515	70%	20	7	3	100%
515-948	41	31%	21	7	100%
949-1898	20	22	35%	22	100%
>1898	5	5	14	76%	100%

Source: Finn et al. (2012) using NIDS waves 1 and 2

The South African studies above were conducted as individual-level surveys which oversampled the lower end of the wage distribution and the informal sector. However, this chapter covers the formal manufacturing sector for individuals earning more than R2000 per year.

It is also important to look at transitions across different industries, given that a number of workers change industries and move out of the manufacturing sector. Most of these individuals move to the financial services and trade sectors. **Figure 2-3** shows that most of the workers leaving the sector are low-wage workers (i.e. the bottom quantile). Thus, the manufacturing sector is mostly losing low-income workers to other sectors.

Figure 2-3: Individuals moving from the manufacturing sector to other sectors



Source: SARS–NT panel (own calculations)

2.3.4 Wage growth

It is also interesting to examine the average wage increase of movers and stayers. For this analysis, the sample is restricted to workers who receive less than a 100% increase in their wages and workers who take a maximum 50% wage cut. As such, 7% of the observations are dropped from the analysis. This is to reduce the noise in wage changes, especially the low wages, when calculating percentage changes, e.g. an increase from R300 a month to R750 a month is a 250% increase. Thus, it should be noted that this analysis potentially underestimates wage growth from low-wage workers as these workers are most likely to be affected by the restriction.[20]. The average wage change for all workers across the panel was 6.3% and average inflation between 2011 and 2016 was 5.6%. Thus, wages increased by more than inflation over the period. On average, movers have higher wage growth compared to stayers (see **Table 2-14**). This is the opposite of what **Figure 2-2** shows, where stayers generally have higher wage levels compared to movers. This indicates that staying in the same job is important for people's wage levels; however, they experience higher wage growth by changing jobs.

In terms of wage growth, there is not much difference by gender, as both male and female movers earn significantly more (2.6%) than stayers. Notably, low-wage workers have the lowest wage growth

[20] The assumption in this analysis is that workers are staying in similar types of jobs. As such, extreme wage increases are unlikely. Further, when there are no restrictions included in the analysis, low-wage workers on average have negative wage growth. Additional research is required to explore the volatility of low-wage work in South Africa.

compared to the other quantiles. What is also interesting is that the low-wage category is the only wage quantile where movers have lower wage increases compared to stayers. This could indicate that job changes at the lower end of the wage distribution are unlikely to be voluntary. Further, it could also reflect that bargaining council agreements are in place in the industry. It could also reflect what is shown in **Figure 2-1** above, i.e. given the small difference in wages across firm sizes at the lower end of the wage distribution, movers are unlikely to see high wage growth, whether they move within the same firm-size category or move to a larger firm.

All of this indicates that wage growth for low-wage workers is very different to the rest of the distribution, and for these workers, staying in the same job is very important for their wage growth – unlike higher-wage workers who get higher returns from moving.

Table 2-14: T-test on the mean difference in wage growth between movers and stayers

	Movers	Stayers	Difference
All	**8,8**	**6,1**	**2,7*** **
Gender			
Male	8,8	6,2	2,6***
Female	8,7	5,9	2,7***
Monthly wage quantiles			
Low wage (q1)	0,2	2,3	-2,1***
Low medium wage (q2)	8,4	5,9	2,5***
High medium wage (q3)	12,3	7,3	5,0***
High wage (q4)	12,8	7,2	5,5***

*** p<0.01, ** p<0.05, * p<0.1

Source: SARS–NT panel (own calculations)

The descriptive analysis shows that wage inequality in South Africa is strongly evidenced in the distribution of wages, even at the top end of the wage distribution. The average monthly wage is R14 729, while the median wage is almost half this number at R7 245. However, the difference between the wages of workers in the 95th percentile (R50 675) is almost half that of workers in the 99th percentile (R98 592).

The largest proportion of firms in South Africa have between 100 and 499 workers. However, firms with between 1000 and 49,999 workers account for the highest proportion of employment (90%). The distribution of firms is also skewed, with the average firm employing approximately 1500 workers and the median firm around 200 workers.

There is substantial movement in the sector and the highest proportion of new jobs, entry, exit and churners are the low-wage workers. Thus, the manufacturing sector is mostly losing low-income workers to other sectors. In examining workers who leave the manufacturing sector, most are found to move to the financial services and trade sectors.

The results indicate that staying in the same job leads to higher wage levels and changing jobs results in higher wage growth. However, this does not apply to low-wage workers where movers experience lower wage increases compared to stayers. This indicates that movement at the low end of the wage distribution is likely to be involuntary; it also reflects the small wage difference across firm sizes at the lower end of the wage distribution, which is due to the wage determination processes in the sector. Moreover, this shows that for low-wage workers, staying in the same job is important for their wage growth.

The following section focuses on the variance decomposition, which indicates the extent to which observed and unobserved worker characteristics and firm characteristics explain wage levels and wage growth.

2.4 Methodology

2.4.1 Two-way fixed effects

Chapters 2, 3 and 4 all follow the two-way fixed effects estimator of Abowd et al. (1999, 2002),[21] with wage levels decomposed into a linear relationship between observed covariates, an unobserved worker fixed effect, an unobserved firm fixed effect, and the residual/error term. The worker fixed effects capture unobservable characteristics, such as workers' ability and motivation. The firm fixed effects capture unobservable characteristics, such as management ability, skill and effectiveness. This study extends this to wage growth, following Sørensen and Vejlin (2011) who assume that a worker's wage growth from time t-1 to time t arises from the linear model, similar to equation 1 with a dependant variable $\Delta Y_{it} = \mathrm{y}_{\mathrm{it}} - \mathrm{y}_{\mathrm{it}-1}$. Further, the same specification is used for the estimation of wage levels and growth.

The following fixed effect model is estimated:

$$Y_{it} = \beta' x_{it} + \theta_i + \psi_{j(i,t)} + \varepsilon_{it} \quad (1)$$

Where:

[21] The main difference is that in Chapter 2, only worker characteristics are controlled for, like the original AKM model. In Chapters 3 and 4, the AKM model is extended to also control for firm characteristics, which has been done in other studies in the literature.

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- Y_{it} is the log wage/ ΔY_{it} log change in wage (wage growth);
- x_{it} is a vector with K observable characteristics of the worker, i.e. age, age squared, age cubed, gender and time effects (a full set of year dummy variables);[22]
- β is the coefficient that captures the effects of observed time-varying characteristics;
- θ_i is the worker fixed effects;
- $\psi_{j(i,t)}$ is the firm fixed effects, i.e. J(i,t); and
- ε_{it} is the idiosyncratic error term.

The underlying assumption is that the error term is orthogonal to all regressors and to the worker and fixed effects (Abowd et al., 1999). Thus, ε_{it} assumes following properties:

$$E[\varepsilon_{it}|x_{it}, i, t, J(i,t)] = 0 \qquad (2)$$

and

$$cov[\varepsilon_{it}, \varepsilon_{ns}|x_{it}, x_{ns}, i, t, n, s, J(i,t), J(n,s)] = \begin{cases} \sigma^2 & \text{for } i = n \text{ and } t = s \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

This implies strict exogeneity, which means that workers' mobility decisions are independent of ε_{it}. This rules out endogenous mobility.

In matrix notation:

$$Y = \boldsymbol{X}\beta + \mathbf{D}\theta + \boldsymbol{F}\psi + \varepsilon \qquad (4)$$

where X is an N* x K matrix of observable covariates, D is an N* x N matrix of worker dummy variables for the worker effect, F is an N* x J matrix of firm dummy variables for the firm effect, Y (log wages) and ε (residual/error) are N* x 1 vectors, where N*=NT.

The main variables of interest are the estimated unobservable worker θ_i and firm ψ_j fixed effects. To estimate equation 4, N worker effects and J firm effects need to be computed. N is usually in millions and J in thousands, making the estimation unfeasible with standard estimation methods (Sørensen & Vejlin, 2011). As such, the grouping algorithm developed by Abowd et al. (2002) – which is applied by Conelissen (2008) – is used, based on the fixed effects model and least squares dummy variable model. The grouping algorithm uses movers to connect workers and firms such that certain movers link all the firms and workers in a group. The analysis is thus restricted to the largest connected group of firms (see section 2.4.4 for the descriptive statistics).

[22] Note that firm characteristics are not included following the initial AKM specification.

As indicated earlier in the literature review, there are some methodological differences between the estimation in this chapter and Jinkins and Morin (2018). The wage growth specifications used in this thesis differ due to Jinkins and Morin (2018) using a first difference of the wage growth equation, which eliminates the worker fixed effect. They indicate that wage growth can only be explained by time-varying, observable characteristics, the change in firm characteristics from moving between the sending and receiving firm, and the residual. Sørensen and Vejlin (2011) follow Kramarz et al. (2008) who used a value-added model in which they decompose the change in educational outcomes into a student fixed effect (i.e. worker fixed effect), a school-grade year effect (i.e. firm fixed effect) and an error term. This allows for the time-varying, unobservable characteristics to have long-term consequences for wage growth. As a result, the specification in this chapter retains the worker fixed effect in the wage growth specification, allowing for the estimation of both firm and worker fixed effects and their relative contribution to the change in wage growth – something that has not been done in South Africa. Although worker fixed effects do not change over time, it is still important to see how they affect workers' wage growth after they change jobs. It is assumed that the workers' unobservable characteristics, such as motivation and ability, play a role in the determination of wage growth. Most value-added models also control for characteristics from the previous year of study as they play a role in current educational outcomes. As such, as a robustness check, firm size and lagged firm size are included to control for some characteristics of the sending firm as well as the current firm.

2.4.2 Variance decomposition

The aim of this analysis is to estimate the worker and firm fixed effects and to determine the relative importance of each component's contribution to the explanation of the variance in the dependent variables. This is done for both wage growth and wage levels in order to compare the models. Following Sørensen and Vejlin (2011), the variance decomposition is given as follows:

$$Var(Y_{it}) = Cov\left(Y_{it}, \beta' x_{it} + \theta_i + \psi_{j(i,t)} + \varepsilon_{it}\right) = Cov(Y_{it}, \beta' x_{it}) + Cov(Y_{it}, \theta_i) + Cov(Y_{it}, \psi_{j(i,t)}) + Cov(Y_{it}, \varepsilon_{it}) \quad (5)$$

Dividing through by the variance of the wages or the change in wages:

$$\frac{Cov(Y_{it}, \beta' x_{it})}{Var(Y_{it})} + \frac{Cov(Y_{it}, \theta_i)}{Var(Y_{it})} + \frac{Cov(Y_{it}, \psi_{j(i,t)})}{Var(Y_{it})} + \frac{Cov(Y_{it}, \varepsilon_{it})}{Var(Y_{it})} = 1 \quad (6)$$

2.4.3 Variance decomposition, including a match effect

As a robustness check, the two-way fixed effect model from equation 1 is also run with match effects. Woodcock (2008, 2015) extends the two-way fixed effect model by adding a match effect, which is an interaction between the firm and worker effects. The following fixed effect model is estimated:

$$Y_{it} = \beta' x_{it} + \theta_i + \psi_{j(i,t)} + \Omega_{ij} + \varepsilon_{it} \tag{7}$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- Y_{it} is the log wage/ ΔY_{it} log change in wage (wage growth);
- x_{it} is a vector with K observable characteristics of the worker, i.e. age, age squared, age cubed, gender and time effects (a full set of year dummy variables);
- β is the coefficient that captures the effects of an observed, time-varying worker;
- θ_i is the worker fixed effects;
- $\psi_{j(i,t)}$ is the firm fixed effects;
- Ω_{ij} is the match fixed effect; and
- ε_{it} is the idiosyncratic error term.

The main variables of interest are the estimated unobservable worker θ_i, firm ψ_j, and match Ω_{ij} fixed effects. To estimate the model, Mittag (2019), who developed an algorithm that simplifies the estimation of the match effect model, is used. An explanation of the model is outlined in Mittag (2019).

A central assumption in this analysis is that fixed effects are calculated for the largest connected group of workers and firms. Thus, the level of one set of fixed effects is only identified relative to the other set of fixed effects in each group. In addition, the match effects model includes the interactions between firm and individual fixed effects. Thus, the match effect is dependent on both the firm and worker fixed effects; it is also time invariant. This means that a specific match differs from other matches of the same firm and from other matches of the individual (Mittag, 2019). As such, the match effect is assumed to be orthogonal to the worker and firm fixed effects by construction, but they are not necessarily orthogonal to the observable characteristics (Woodcock, 2008). This method is applied to both wage levels and wage growth.

The current estimation differs from Jinkins and Morin (2018) as they indicate that including a match effect that is orthogonal to the worker and firm fixed effects is a strong assumption and that even the hybrid model requires a weaker identification assumption than a standard random effects model. They propose an alternative two-step estimation strategy which assumes that endogenous mobility is satisfied for the employment spells of workers hired from unemployment. Thus, they estimate the two-way fixed effect wage model on only the workers hired from unemployment, and then decompose the observed wage growth of job-to-job movers using the fixed effects – estimated from the firms hired from unemployment. Thus, the same fixed effects are used for both unemployment-to-job as well as the job-to-job samples. Further, their analysis of wage growth includes match effects but eliminates the worker fixed effect.

2.4.4 Worker mobility and firms connected by worker mobility

The largest share of workers only appear once in the panel, approximately 20% are seen six times in the sample and 4% are seen seven times or more (see **Table 2-15**). Workers who appear less than three times in the sample account for 46.58%.

Table 2-15: Number of observations per worker

	1	2	3	4	5	6	7 or more
Frequency	912,095	591,946	386,956	306,175	272,059	632,728	127,104
%	28.25	18.33	11.98	9.48	8.43	19.59	3.94

Source: SARS–NT panel (own calculations)

Only 15.8% of the workers in the sample have more than two employers (see **Table 2-16**). This is lower than the movement in Sørensen and Vejlin (2011) for Danish firms (66%). However, the SARS–NT panel only has six years of observations, while Sørensen and Vejlin (2011) had 26 years.

Table 2-16: Number of firms in which a worker is employed

	1	2	3	4 or more
Frequency	2,720,030	412,725	73,973	22,335
%	84.24	12.78	2.29	0.69

Source: SARS–NT panel (own calculations)

Only firms connected by worker mobility will have an estimate, i.e. only connected groups of firms that have had workers move to another firm can have fixed effects estimated. For example, there are many firms across the country that will never be connected because workers in certain areas will never move to jobs in other parts of the country. As such, the analysis is restricted to the largest connected group of workers and firms (see **Table 2-17**). For the analysis, the sample is divided into male and female; then males and females are further divided into the first and fourth quantiles (as a proxy for low-income and high-income workers) and, lastly, into firm size.

The largest connected group in the wage level analysis in the sample contains approximately 3.2 million workers in 44,162 firms, which are connected by 508,449 movers. The sample for wage growth is smaller, with around 2.1 million workers in 32,975 firms connected by 203,109 movers. When all the groups of firms are combined (i.e. all manufacturing firms over all the years in the panel), there are 56,693 unique firms and 3,229,064 individuals. A summary of the total number of workers, firms, fixed effects estimated, and groups is provided in **Table B-1** and **Table B-2** in Appendix A for every sub sample. For the remainder of this chapter, the sample is restricted to only the largest connected group, which is the full sample used for the analysis.

Table 2-17: Sample sizes using the largest connected group

	Wage levels			Wage growth		
	Number of workers	Number of firms	Number of movers	Number of workers	Number of firms	Number of movers
Total	3,175,896	44,162	508,449	2,090,977	32,975	203,109
Female	1,076,228	27,821	160,017	636,424	15,938	58,844
High income (q4)	215,646	9,832	32,336	161,648	5,646	16,224
Low income (q1)	422,862	6,539	31,935	135,468	1,781	4,705
Male	2,035,063	40,029	346,632	1,350,526	28,547	141,063
High income (q4)	431,883	14,729	65,979	346,001	9,293	35,940
Low income (q1)	825,341	20,248	79,508	282,956	6,413	13,378
Firm size						
10–49	729,904	21,326	54,524	225,414	8,460	12,557
50–99	550,890	5,714	26,146	200,898	2,875	5,981
100–499	1,149,271	3,921	90,753	709,513	3,568	32,265
500–999	451,057	474	18,313	273,314	417	6,977
1000–49,999	882,214	248	46,354	583,511	239	20,902

Source: SARS─NT panel (own calculations)

Note 1: Firms employing 1–9 employees did not have a large group of firms connected by mobility; instead, there were numerous small groups of connected firms.

2.5 Results

2.5.1 Variance decomposition

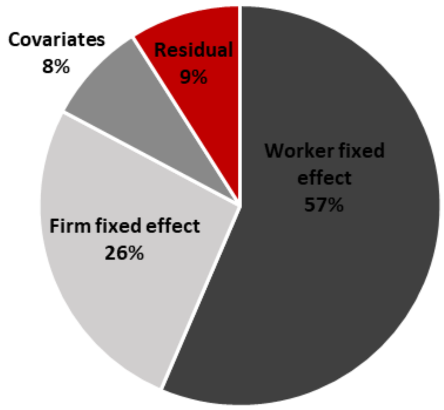
2.5.1.1 Wage levels

The estimation results and variance decomposition are shown in **Table B-3** and **Table B-4** in Appendix A. Starting with the full sample on the wage levels regressions, which is the standard AKM model, the results show that worker fixed effects dominate the firm fixed effects and explain 57% of the variance in wages, while firm fixed effects explain 26% of the variation in wages, the observable characteristics/covariates explain 8% and the residual 9%[23] (see **Figure 2-4**). The worker effect

[23] Generally, the relative shares of the worker fixed effects, firm fixed effects, observable characteristics and residual sum to 1; however, the covariances can become negative, making it difficult to interpret the numbers as shares (Cornelissen, 2008).

estimates are similar to Sørensen and Vejlin (2011) who found 58%. However, firm effects only explained 14% of the variation in Danish wages and 26% of South African manufacturing firms' fixed effects. Although the worker fixed effects dominate the firm fixed effects, which is similar to the findings in the literature, the firm fixed effects in manufacturing companies in South Africa are higher than in the literature, indicating that these firms play a larger role in explaining the variation in wage levels. It should be noted that the studies in the literature estimate these effects across all sectors, whereas this thesis looks at manufacturing only.

Figure 2-4: Wage level variance decomposition for the full sample



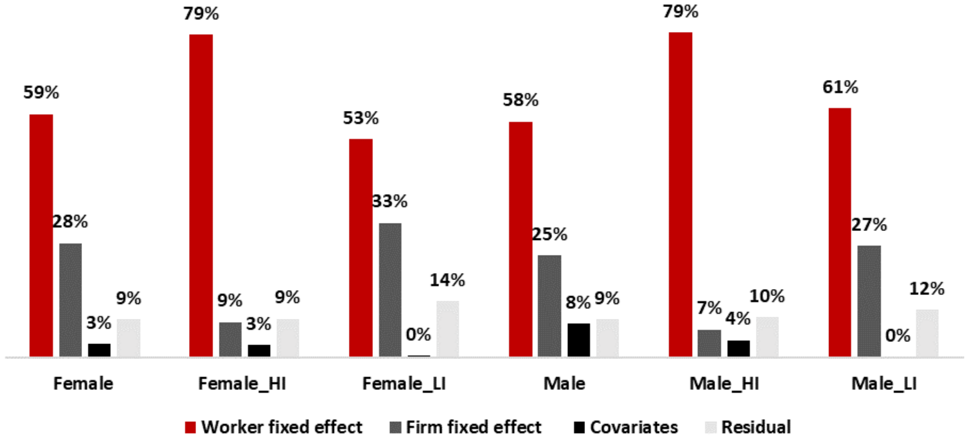
Source: SARS–NT panel (own calculations)

The results for the full sample are very similar to those for males and females, which reflects that gender is not the main source of heterogeneity. However, both worker and firm effects explain slightly more of the variation in female wages. Dividing the sample by gender as well as wage/income quantiles (restricted to the first and last quantiles, i.e. low income (LI) and high income (HI) respectively) shows that there is much more heterogeneity. Education level would have been a more appropriate indicator to use; however, education is not reported in the data. Thus, the income quantile that a worker falls under is used to compare workers in the absence of education levels. Many individual-level characteristics are not available in the data, and characteristics like education, which are unlikely to change once an individual enters the labour market, will fall into the fixed effect estimates along with race, worker ability and motivation. Education also gives an indication of the skill level of a worker. However, a worker's skills can still change over time, even if their education does not change. One of the limitations of the SARS-NT data is that a worker's skills cannot be identified in the data. Skills can change over time, which means that they are not controlled for by the unobserved worker fixed effects. The implication of this is that we might be overestimating the unobservable worker fixed effect.

Low-income employees' worker fixed effects are found to have a lower explanatory power than high-income workers' effects and their firm fixed effects have a higher explanatory power than high-income employees' effects. This essentially means that a larger proportion of the low-income employees' wages are explained by the firm at which they are employed and their personal attributes determine less of their wages compared to high-income employees. Among low-income females, worker effects explain 53% of the variation in their wages, while among high-income females, they explain 79%. Among low-income males, firm effects explain 27% of the variation in their wages, while they explain only 7% per cent among high-income males. These trends are similar for both males and females and are presented in **Figure 2-5** below.

This finding makes sense intuitively and is what is expected. Low-income workers are likely to be covered by collective bargaining agreements, and the analysis in this thesis does not include or control for the wage determination process. Thus, the impact of bargaining councils (BCs) is not accounted for. As such, the results indicate that low-income workers have lower bargaining power and are more likely to take the wage offered to them by a firm. However, high-income workers are likely to have a higher skill level, giving them more leverage to negotiate a higher wage, irrespective of the firm. Further, higher-income workers are not covered by BCs. As a result, firms have discretion when setting wages for these workers. This reinforces the trend found in the descriptive analysis where workers in the 25th percentile earned low wages, regardless of the firm at which they worked. Further, there was not as much variation in the wages across firm size for these workers compared to 50th-, 75th- and 90th-percentile workers. As such, the results highlight the important role firms play in determining wages, particularly for low-wage workers.

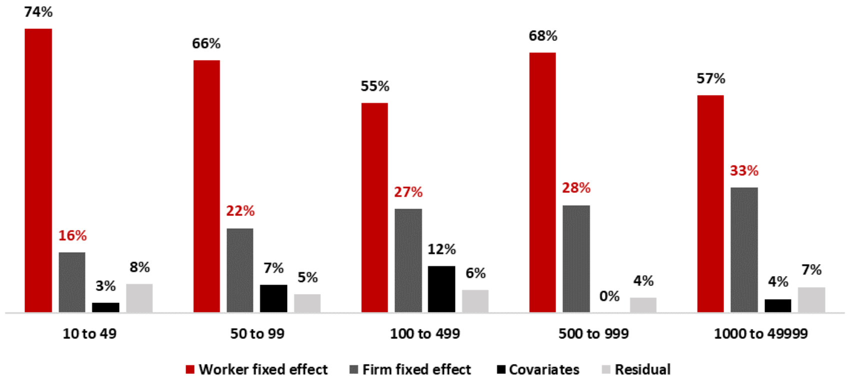
Figure 2-5: Wage level variance decomposition across gender and income quantiles



Source: SARS–NT panel (own calculations)

The sample is also divided by firm size, using the number of employees in the firm (see **Table B-4** in Appendix A).[24] Worker fixed effects dominate firm fixed effects across firm size. However, the firm fixed effects reveal an interesting pattern, where they increase with firm size (see **Figure 2-6**). Thus, the larger the firm, the more important the firm fixed effect becomes in explaining the variation in wages. This further reinforces the role that large firms play in determining wages.

Figure 2-6: Wage level variance decomposition across firm size



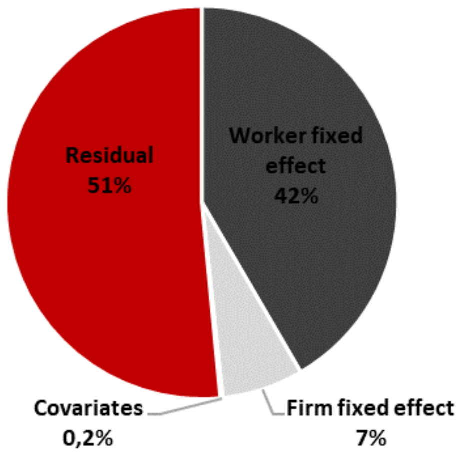
Source: SARS–NT panel (own calculations)

2.5.1.2 Wage growth

The variance decomposition is now performed on the wage growth estimations. Notably, the error term explains much more of the variation in wage growth, indicating that we know less about what explains the variation in wage growth. Sørensen and Vejlin (2011) found that the residual explains 85% of the variation in wage growth. This study finds that the residual explains only 51% of the variation in wages, which is lower than previous studies (see **Figure 2-7**). What is interesting is that the worker effects explain 42% of the variation in wages, which is much higher than the Sørensen and Vejlin (2011) estimate of 9%. The firm fixed effects explain 7% of the variation in wages compared to 4% by Sørensen and Vejlin (2011). This indicates that in the manufacturing sector, the worker effect explains a much higher proportion of wage growth, resulting in a lower residual.

[24] Firms with 1–9 employees are not included in the analysis.

Figure 2-7: Wage growth variance decomposition for the full sample



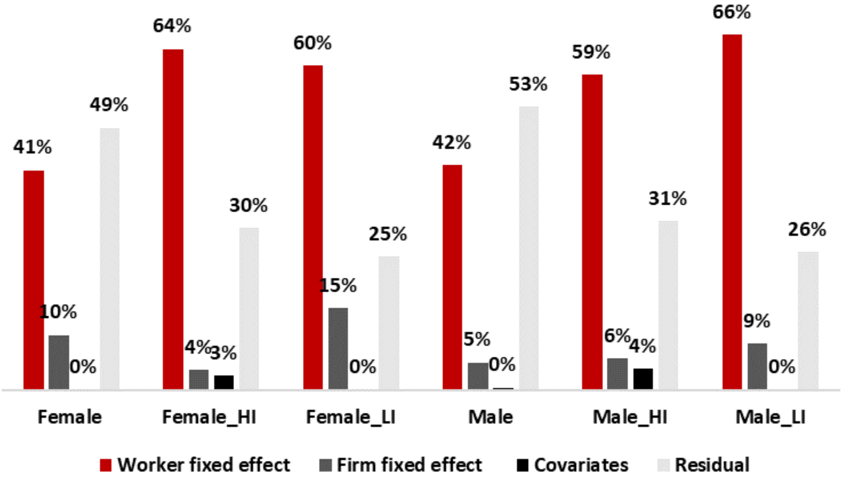
Source: SARS–NT panel (own calculations)

The results for the full sample are similar to those for the male and female sub samples. However, when examining the gender sub samples by income quantiles, worker fixed effects increase and explain around 60% of wage growth and the residual falls to around 30% (see **Figure 2-8**). What is interesting is that the worker effect explains a similar amount of variation in wages, irrespective of whether someone is a high- or low-income male or female. Notably, among low-income males and females, their worker effect explains a higher proportion of the variation in wage growth compared to the wage level. This could indicate that low-income workers are likely to accept the wage offered (resulting in a lower worker effect in the wage level estimation), but once they are in the firm, they gain more bargaining power to negotiate a higher wage (this includes the effect of being covered by BC agreements), which is reflected in the higher worker effect in the wage growth estimation.

Malindi (2016), using nationally representative household panel data from Statistics South Africa, found that black workers experienced much larger wage growth from an additional year of firm tenure than from an additional year of labour market experience. The opposite was true for white workers. These results provide evidence in favour of greater ex ante uncertainty around the expected productivity of black workers as the key mechanism behind the relatively larger wage returns from tenure for black workers because black workers face a greater penalty in wage returns as a result of the wedge between potential and actual experience. This corroborates the finding that low-wage workers accept the wage offered by a firm when they enter the firm but have increased ability to earn more when they have experience working in the firm. This is assuming that black workers are a proxy for the low-wage quantile in the absence of race in the SARS–NT panel.

In terms of firm fixed effects, low-income females have the highest proportion of variation explained by firm effects at 15%, while all the sub samples are less than 8%. The observable characteristics/covariates are generally low across the sample.

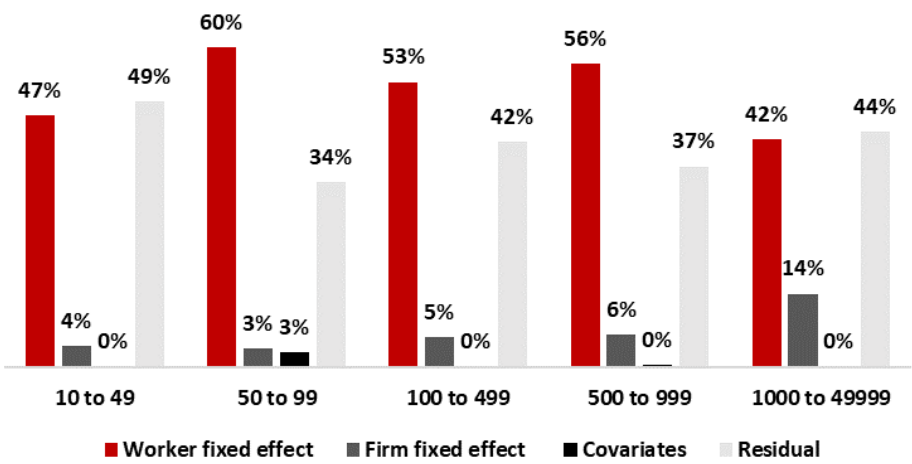
Figure 2-8: Wage growth variance decomposition across gender and income quantiles



Source: SARS–NT panel (own calculations)

The worker fixed effect for wage growth explains less of the variation in wages compared to wage levels using firm size. Firm fixed effects explain very little of the variation in wage growth, ranging from 3% to 6% for all firm sizes, with the exception of firms employing 1000 to 49,999 workers where they explain 14% – these firms having the largest share of employment (see **Figure 2-9**). Again, the residual is much higher in the wage growth estimation compared to the wage levels estimation. However, the residuals in this chapter are lower than Sørensen and Vejlin (2011).

Figure 2-9: Wage growth variance decomposition across firm size



Source: SARS–NT panel (own calculations)

One possible explanation for these findings is that low-wage workers have less bargaining power when they enter a firm and have an increased ability to bargain for higher wages when they have experience working in the firm. As such, low-wage workers benefit from longer tenure at firms. This is corroborated by the descriptive analysis on wage growth where the low-wage category was the only category where movers had lower wage increases than stayers. This could indicate that job changes at the lower end of the wage distribution are likely to be involuntary. It could also reflect the small wage difference across firm sizes at the lower end of the wage distribution (see **Figure 2-1**), which also reflects the wage determination structures in the manufacturing sector. As such, low-wage movers are unlikely to experience high wage growth, whether they move within the same firm-size category or move to a larger firm.

2.5.2 Robustness checks

2.5.2.1 Variance decomposition with firm fixed effects

The first robustness check involves running the AKM specification with controls for firm size and lagged firm size to control for firm characteristics. As indicated earlier, Sørensen and Vejlin (2011) follow Kramarz et al. (2008) who use a value-added model where they decompose the change in educational outcomes into a student fixed effect (i.e. worker fixed effect), a school-grade year effect (i.e. firm fixed effect) and an error term. Although value-added models keep the same variables for levels and growths in student performance, they also control for the previous grade and teacher effects. Thus, as a robustness check, lagged firm size is also included as a control to capture the firm size of the worker's current and previous firm (for job changers).

For wage levels, using the full sample, worker fixed effects are found to explain 68% of the variation in wages – an increase of 11% from the specification without firm characteristics (see **Table B-5** in Appendix A). Firm fixed effects explain 23% of the variation in wages, which is only 3% lower than the specification without firm fixed effects. Observable characteristics and the residual also decline. When disaggregating by gender as well as gender wage quantiles (high and low income), worker fixed effects increase by between 4% and 11%, and firm fixed effects decrease by between 1% and 4%.

Turning to wage growth, using the full sample, worker fixed effects are found to explain 44% of the variation in wage growth and firm fixed effects 7%. This is an increase for both fixed effects relative to the specification without firm fixed effects, while the residual declines. Disaggregating by gender and gender wage quantiles has mixed results relative to the base specification, where worker fixed effects increase for female workers and remain the same or decline for all the other categories. Firm fixed effects increase for all the categories, with the exception of females.

Although the relative contribution of worker and firm fixed effects changes when firm characteristics are included, the overall trend of worker fixed effects dominating firm fixed effects remains. Further, worker fixed effects for low-income female and male workers remain higher in the wage growth specification compared to wage levels.

2.5.2.2 Variance decomposition with match effect

The AKM model is also run, including the match effect as a robustness check. However, this also extends Sørensen and Vejlin (2013) and Woodcock (2015) by adding a match effect to their wage growth specification. However, the analysis in this chapter is limited to their orthogonal match effects model estimated using the TWFE command developed by Mittag (2019).

For wage levels, using the full sample, match effects are found to explain 3.2% of the variance in wages and the worker effect dominates.[25] In terms of wage growth, the match effect explains 4.2% of the variance in wage growth and the residual is higher than the worker effect (see **Table B-6** in Appendix A). Sørensen and Vejlin (2013) found that match effects explain around 7% of the variation in wages in the orthogonal match effect model and 9% in the hybrid model. Woodcock (2015) showed that match effects explain 4% of the variation in wages using the orthogonal match effect model and 16% using the hybrid match effect model. These estimates are in line with their orthogonal match effects model.

The main difference with the match effect model and the standard AKM model comes from the low-income females' sub sample where firm fixed effects are higher for wage growth compared to wage levels – this is the opposite of what was found using the normal two-way fixed effect model. However, high-wage females and males as well as low-wage male results are in line with the normal two-way fixed effects model.

The hybrid model is not estimated; but it should be noted that the estimates using this model would likely explain a slightly higher proportion of the variation in wages. However, it is unlikely to change the overall finding that worker fixed effects dominate firm fixed effects. Previous comparable

[25] In the regressions using the TWFE, there are large negative values for some of the covariances, making it challenging to interpret the shares as contributions. In the results, the observable characteristics are negative. It should be noted that all the observable characteristics are worker characteristics. As such, for ease of interpretation, the observable characteristics are grouped with the worker fixed effects. This term can be taken as both the observable and worker fixed effect contribution to the variation in wages.

literature has shown that even when the match effect is included, it has not been larger than the firm fixed effect. Thus, as expected, the match effects explain a relatively small but important share of the variation in wages across all the decompositions with the match effect explaining less than 5% of the variation in wages. Card et al. (2013) provide a potential explanation, indicating that small match effects in wages could reflect the low bargaining power of workers negotiating with their employers.

2.5.3 Correlation of the worker and firm fixed effects

The correlation between the worker and firm fixed effects on both wage levels and growth is analysed (see **Table 2-18**), the expected result being that high-wage workers sort into high-wage firms, i.e. positive assortative matching (Abowd et al., 1999). However, numerous studies (including Goux & Maurin, 1999; Barth et al., 2016; Andrews et al., 2008) have found evidence of a small negative correlation between firm and worker effects, implying that high-wage workers tend to sort into low-wage firms. The analysis in this chapter reveals a negative correlation between the firm and work effects across the full sample and all the gender wage level sub samples. Thus, on an aggregate level, there is negative assortative matching in the manufacturing sector. There is a stronger negative correlation in the wage growth estimations, and the correlation is negative across the full sample and all sub samples of wage growth.

Table 2-18: Worker and firm effects' correlation across gender and income quantiles

		Firm effects	
		Wage levels	Wage growth
Worker effects	Total	-0.0165	-0.6056
	Female	-0.0809	-0.6869
	Male	-0.0518	-0.6587
	Female_LI	-0.2603	-0.5712
	Female_HI	-0.2439	-0.7480
	Male_LI	-0.2563	-0.5566
	Male_HI	-0.3025	-0.7127

Note 1: Worker fixed effects - θ_i, Firm fixed effects - $\psi_{j(i,t)}$

Note 2: The correlations are estimated from equation 3.

Andrews et al. (2008) suggest that the estimation of the worker and firm fixed effects are carried out with error; thus, it is possible that the estimated correlation is biased downward because an overestimation of worker effects can lead to an underestimation of firm effects. As such, the bias is bigger when the data has fewer movers, termed 'limited mobility bias'. However, Andrews et al. (2008) also found that while the bias can be considerable, it is not large enough to remove the negative correlation entirely.

The sample was then divided by firm size; however, firms with less than 10 employees were excluded.[26] Focusing on the wage level correlations, there is evidence of a negative correlation between firm and worker fixed effects in firms with less than 500 employees. However, firms with 500 to 999 and 1000 to 49,999 employees display positive assortative matching (see **Table 2-19**). For simplicity, firms employing less than 500 employees are referred to as small, firms employing between 500 and 999 employees as medium and firms with more than 1000 employees as large. Thus, among medium and large South African manufacturing firms, high-wage workers sort into high-wage firms. There is evidence of a negative correlation across all firm sizes for wage growth. Thus, on aggregate, there is a negative correlation, which is consistent with the literature. However, this hides the differences by firm size, which shows that firms employing more than 500 workers in South Africa have positive assortative matching.

Table 2-19: Worker and firm effects' correlation across firm size

		Firm effects	
		Wage levels	**Wage growth**
Worker effects	10 to 49	-0.4367	-0.3513
	50 to 99	-0.3549	-0.8090
	100 to 499	-0.0014	-0.5516
	500 to 999	0.1714	-0.7706
	1000 to 49999	0.0932	-0.2577

Note 1: Worker fixed effects - θ_i, Firm fixed effects - $\psi_{j(i,t)}$

Note 2: The correlations are estimated from equation 3.

Corneließen and Hübler (2011) found that among large German firms (more than 1000 employees), low-wage firms tend to be stable firms and high-wage workers are more stable workers, which increases their incentive to choose stable, low-wage firms. However, this does not hold for small firms where low-wage firms are unstable and high-wage firms are stable. Given the aggregate trends in the South African manufacturing sector, where productivity is increasing at the cost of labour (particularly low-wage workers), this result could be picking up highly paid owners/managers working in small firms.

Another explanation could be trade. Davidson et al. (2014) and Bombardini et al. (2019) found that access to international markets improves matching between firms and workers. Thus, firms that are exporters exhibit positive assortative matching. In South Africa, exports are highly concentrated. Edwards and Hlatshwayo (2020) found that the top 1 percentile of firms by export size make up 73–78% of the total value of exports, while the share of the top 0.1 percentile ranged from 39–46%

[26] This is due to the low number of firms connected by worker mobility for this firm size.

between 2010 and 2014, using the SARS–NT panel. Naughtin and Rankin (2014) investigated super-exporters which can be regarded as very large manufacturing firms that occupy a dominant position in the export market. They found that these firms display superior productivity and the top 1% of these exporters employ around 500 employees, while the top 5% of firms employ around 100 employees. Given that exporting is concentrated in large firms in South Africa, trade could explain the positive assortative matching in firms with 500 or more employees.

This could be explored in depth in further research. However, the focus of this thesis is to understand the variance decomposition of wage levels and wage growth in the South African manufacturing sector.

2.6 Conclusion

Wage inequality in South Africa is high, evidenced in the distribution of wages, even at the top end of the wage distribution. The average monthly wage is R14 729, while the mean wage is almost half this number at R7 245. Even the difference between the wages of workers in the 95th percentile (R50 675) is almost half that of workers in the 99th percentile (R98 592). The distribution of firms is also skewed, with the average firm employing approximately 1500 workers and the median firm around 200 workers. The largest proportion of firms in South Africa have between 100 and 499 workers. However, firms with between 1000 and 49,999 workers account for the highest proportion of employment (90%).

The manufacturing sector has been gradually evolving over time, with a shift towards services. As indicated in the literature, employment is declining, particularly among low-skilled workers (Aterido et al., 2019; Rankin, 2016; Bhorat et al., 2014). This analysis finds that there has been more job exit than entry activity in the sector from 2014 and that the sector is mostly shedding the low-wage quantile, with the highest proportion of new jobs, entry, exit and churners being low-wage workers.

This chapter finds that staying in the same job results in higher wage levels and changing jobs results in higher wage growth. The only workers whom this does not apply to are low-wage workers, indicating that movement at the low end of the wage distribution is likely to be involuntary. It could also reflect the small wage difference across firm sizes at the lower end of the wage distribution. As such, low-wage movers are unlikely to experience high wage growth, even if they move to a large firm. More importantly, wage growth for low-wage workers is very different to the rest of the distribution, and for these workers, staying in the same job is very important for their wage growth.

The results from the variance decomposition of wage levels and wage growth reveal that a worker's individual, unobserved characteristics are consistently more important than firm fixed effects in explaining the variation in wages. Low-income workers have lower worker fixed effects and higher firm fixed effects compared to high-income workers, which could indicate that they have lower bargaining power and are more likely to take the wage offered to them by a firm. High-income workers are likely to have a higher skill level, giving them more leverage to negotiate a higher wage, irrespective of the size of the firm they are joining. This highlights the important role that firms play in determining wages of low-wage workers, which is reinforced by the wage determination process in the sector.

Turning to wage growth, worker effects are found to explain a similar proportion of the change in the wage, regardless of the income level. Thus, initially, low-income workers are likely to accept the wage offered (resulting in a lower worker effect in the wage level estimation), but once they are in the firm, they gain more bargaining power to negotiate a higher wage, which is reflected in the higher worker effect in the wage growth estimation. Disaggregating by firm size also shows an interesting dynamic at the wage level where the firm effect increases with firm size. As such, the larger the firm at which an individual works, the more important the firm fixed effect becomes in explaining the variation in wage levels. This further emphasises the impact of large firms in determining wages, particularly for low-wage workers.

As a robustness check, firm characteristics are added to the AKM specification. The results indicate that the firm fixed effect declines marginally and the worker fixed effect increases, while the residual and observable characteristics decline. Lastly, the AKM is also run with match effects. The findings reflect that match effects explain a relatively small but important share of the variation in wages across all the decompositions (i.e. gender and wage quantiles), with the match effect explaining less than 5% of the variation in wages.

Further, there is evidence of a negative correlation between firm and worker fixed effects across the full sample. This indicates that there is negative assortative matching on an aggregate level; so, high-wage workers sort into low-wage firms, which is a similar finding to the rest of the literature. However, when disaggregating by firm size, only small firms with less than 500 employees have negative assortative matching, whereas medium firms (500–999 employees) and large firms (1000–49,999 employees) have positive assortative matching. As such, on aggregate, there is negative assortative matching, which is consistent with the literature; but this hides the differences by firm size, which shows that firms employing more than 500 workers in South Africa have positive assortative matching.

It is important to further understand the role that large firms play in determining wages, given that they are the largest employers in the manufacturing sector. More research needs to go into exploring the reasons for job changes among low-wage workers as well as the sorting of workers and firms. From a policy perspective, there is an urgent need for policymakers to find ways to upgrade the skill level of low-wage workers as this will contribute to large firms paying low-wage workers more over time. Further, improved screening of (i.e. more information on) low-wage workers could improve their initial wage level, given their low bargaining power. Carranza et al. (2020) showed that assessing job seekers' skills and communicating the assessment results to both job seekers and firms increases employment by 17%, income by 34%, and hourly wages by 20% for the assessed job seekers. Thus, policymakers as well as the private sector need to explore ways to improve worker screening and assessment.

This chapter focused on understanding wage levels and growth in the South African manufacturing sector and estimating the extent to which observed and unobserved worker characteristics and firm characteristics explain variations in wage levels and wage growth. In the next chapter, the focus shifts to the wage premia paid by different types of firms in the manufacturing sector. This is done by extending the analysis of the 'exporter wage premium' to also include importers, firms that simultaneously export and import, and firms that trade and engage in FDI. The analysis will start to unpack the firm fixed effect discussed in this thesis.

Chapter 3: Wage Premia for Foreign-Connected Firms, Exporters and Importers: Evidence from South African Linked Employer–Employee Data

ABSTRACT

Using South African linked employer–employee data, this chapter estimates the wage premium for simultaneously being an FCF and an exporter and/or importer (i.e. a hybrid) and further distinguishes between pure exporters and importers and firms that are both exporters and importers (EXIM) as well as domestically owned and foreign-owned FCFs. There is evidence of hybrid firms paying the highest wage premium. Further, workers moving to hybrid firms receive the highest wage gains. Thus, it is the combination of exposure to foreign markets through imported inputs, export sales and FDI that results in the highest wage premia.

3.1 Introduction

This chapter examines the wage premia paid by different types of firms, including exporters, importers and firms with foreign ownership. Given the increasing wage inequality in the manufacturing sector, it is important to understand which types of firms pay higher wages. Further, this chapter helps to unpack some aspects around the firm fixed effect discussed in Chapter 2.

The phenomenon of an exporter wage premium has been explored extensively in the literature.[27] There are also studies that have shown that multinational enterprises (MNEs)/FDI firms pay higher wages[28] (referred to as foreign-connected firms [FCFs][29]). However, very few studies have

[27] Bernard and Jensen (1999), Bernard et al. (2003), Schank et al. (2007), Munch and Skaksen (2008), Verhoogen (2008) and Helpman et al. (2017).

[28] Heyman et al. (2007), Balsvik (2011), Martins (2011), Pesola (2011) and Poole (2013).

[29] See data section for the definition used in this thesis. FCFs have at least 10% equity held in or by a foreign firm. FCFs can be domestically or foreign owned.

simultaneously looked at both the exporter and the FCF wage premia.[30] The SARS–NT panel is restricted to the manufacturing sector between 2013 and 2016 to estimate the wage premium for exporters, importers and FCFs. Thus, this chapter extends the literature on the exporter wage premium to include importers and FCFs.

Exporting is relatively rare and there is much heterogeneity among exporters (Bernard et al., 1995; Bernard & Jensen, 1999; Matthee et al., 2018). As such, it is important to take a closer look at the various types of trading firms in the sector. In this chapter firms are classified under seven categories: local, pure exporters, pure importers, EXIM (simultaneous exporters–importers), domestically owned FCFs, foreign-owned FCFs and hybrid firms (exporters, importers and FCFs).

The findings in this chapter indicate that hybrid firms are a niche subset of all trading firms and FCFs. They have the highest mean and median monthly wage, output per worker and firm size. After controlling for unobserved worker and firm characteristics, there is still evidence of hybrid firms paying the highest wage premium, followed by domestic FCFs and EXIM firms. Workers moving to hybrid firms have the highest wage premia, followed by workers moving to EXIM firms. This indicates that the level and type of exposure that firms have to foreign markets have implications for the wage premia that firms pay. Consequently, the combination of exposure through imported inputs, export sales and FDI results in the highest wage premia.

The chapter is structured as follows: section 3.2 provides a review of the literature, section 3.3 provides the descriptive statistics, section 3.4 presents the methodology applied, section 3.5 details the empirical results and section 3.6 concludes.

3.2 Literature review

3.2.1 Theoretical framework

The theory on international trade and FDI explores alternative reasons for multinational activity and the ways in which it occurs. The literature makes a distinction between vertical FDI, on the one hand, and horizontal FDI, on the other. Vertical FDI occurs when firms have different stages of production across various countries, usually driven by cost considerations. This branch of the literature stems from Helpman (1984) where a distinction is made between the headquarters and the manufacturing plant. Thus, companies entering new markets need to be able to cover the cost of setting up a firm in another country as well as headquarter-related costs, which include R&D, technology and financing.

[30] To my knowledge, only Tanaka (2015) and Schröeder (2020).

Another branch of the literature explores horizontal FDI, which occurs when a firm replicates the same production process across multiple locations. Helpman et al. (2004) assume that firms locate in different countries to secure market access and focus on the firm's choice between exporting and horizontal FDI by introducing differential firm-level productivity, as established in Melitz (2003).

The theory on horizontal and vertical FDI is a simplified version of how FDI occurs in reality. Firms can undertake a combination of horizontal and vertical FDI. It is possible for firms to have headquarters in their home country and set up a branch in another country which is used solely for exporting to a third country. Ekholm et al. (2007) call this export platform FDI. Further, firms can have intermediate stages of production in different countries, which Yeaple (2003) refers to as a complex integration strategy. Grossman et al. (2006) extended Yeaple (2003) by including varying productivity levels across firms, allowing for a variety of complex integration strategies. All these models are based on a three-country model to allow for more complex strategies.

The theoretical framework for this thesis starts with the Grossman et al. (2006) model, which – following Melitz (2003) and Helpman et al. (2004) – allows for firm heterogeneity. The Melitz (2003) model shows that operating in foreign markets through trade induces only the most productive firms to enter the export market; less-productive firms continue to serve domestic markets and the least-productive firms are forced to exit. An underlying assumption is that there are trade costs associated with moving and marketing goods across different countries and only firms that can afford to pay these costs will engage in trade-related activities. Helpman et al. (2004) found the same sorting pattern as Melitz (2003) but went on to include FDI. Their model indicates that among the firms serving export markets, only the extremely productive firms go on to invest in foreign markets, while less-productive firms choose to serve foreign markets through exports. This is owing to the higher fixed costs of setting up operations in a foreign country while maintaining headquarters in the home country.

Grossman et al. (2006) present a three-country model, which includes two identical countries in the North and one low-wage country in the South. Firms with differentiated products have a headquarters, produce intermediate inputs and then assemble these inputs into a final product. Production of intermediate goods or assembly, or both, can take place outside the home country where the headquarters are located. Further, a firm can perform these activities in one or a range of locations. They assume that the cost of producing intermediate inputs and assembly is lower in the South. However, a firm incurs a fixed cost of opening each plant it operates in a foreign country to produce either intermediate inputs and/or assembly, and the setup costs of the plants might differ. Intermediate inputs and final goods have trade costs associated with them and the cost of transporting them might differ. Thus, the relative cost of setting up different plants, the cost of transporting different goods/inputs and the size of the market in the South are the key indicators used to describe an industry. Grossman et al. (2006) use the model to predict a firm's outcomes under three scenarios: (i) zero transport costs, (ii) transport costs for the final product, and (iii) transport costs of intermediate inputs. The simplest case is the no-transport-cost scenario. Lower-productivity firms will produce both intermediate and final goods in the home country and export the final goods to the other country in the North as well as the South. Intermediate-productivity firms will separate the production of intermediate inputs and final goods. As such, these firms will engage in intra-firm trade and either use the South as an export platform to serve the other country in the North or export from their home country. High-productivity firms produce intermediate inputs as well as assembly of final goods in the South. One limitation of this model is the assumption that a firm produces its own intermediate inputs. In reality, firms might import intermediate inputs from a different country/company.

Kasahara and Lapham (2013) extend the Melitz (2003) model to include firms that are EXIM (simultaneous exporters–importers). Thus, they incorporate imported intermediate inputs into their model. In their model, using imported intermediate inputs increases a firm's productivity. However, owing to the fixed costs associated with importing only, firms that have high productivity are able to import intermediate inputs. We already know that there are costs related to exporting. However, importing also requires high start-up costs, as firms need to establish a network with foreign suppliers, learn about various regulations, and adapt production processes to use new input materials, among other things. Thus, this model indicates that firms that are either exporters or importers have higher productivity compared to firms that do not engage in trade-related activities, while EXIM firms have the highest productivity. Kasahara and Lapham (2013) note that a substantial number of exporters are also importers. One explanation they offer for this is that export- and import-related, fixed and sunk costs have complementarities, which induce firms to both export and import. One of the limitations of their model is that it does not consider how multi-plant and multinational firms arrive at collective export- and import-related decisions for their different plants.

Bernard et al. (2018) conducted the first study to allow for simultaneously exporting, importing and FDI. They call these firms 'global firms'. They provide a theoretical framework whereby a firm can simultaneously decide on production locations (i.e. FDI) in which to operate plants, export markets and associated export products for each plant, countries from which to source inputs for each plant, and intermediate inputs to import for each plant. Their model predicts that all these choices are correlated and, further, that the greater a firm's participation along one of these margins, the more likely they are to actively engage along another. There are two mechanisms through which these correlations arise in their model: (1) higher productivity leads to greater international participation along all margins simultaneously, and (2) there is complementarity in the decision to participate along any one of these margins. Firms that are able to meet the fixed costs of exporting are generally more productive firms. Exporting increases their production; this makes the choice to incur fixed importing costs feasible because of the potential lower cost of production associated with importing cheaper inputs. Further, it boosts profitability, allowing the firm to incur fixed exporting costs for additional markets and for operating in different locations.

This chapter ranks the seven types of firms (local, exporter, importer, EXIM, foreign FCF, domestic FCF and hybrid) according to the models detailed above, i.e. Melitz (2003), Helpman et al. (2004), Grossman et al. (2006), Kasahara and Lapham (2013) and Bernard et al. (2018). Melitz (2003) indicates that the lowest-productivity firms will be local firms, followed by firms that engage in trade, i.e. exporters. Kasahara and Lapham (2013) show that firms that are both exporters and importers (EXIM) have higher productivity compared to local firms and, further, that EXIM firms have the highest productivity of all the trading firms. Helpman et al. (2004) extended the Melitz (2003) model to include FDI firms and found that FDI firms have higher productivity than firms that trade in goods only, regardless of whether they are pure exporters or importers or EXIM. Grossman et al. (2006) indicate that FDI firms, which use imported intermediate inputs from their headquarters and assemble the final products in another country, have intermediate productivity. However, firms that produce intermediate goods and final goods in a foreign country have the highest productivity. Lastly, Bernard et al. (2018) indicate that high-productivity firms are more likely to simultaneously engage in exporting and importing intermediate inputs, and FDI.

This chapter focuses on the wage premia paid by these firms and uses their expected productivity to provide an indication of which types of firms are expected to pay the highest wages. The theoretical framework indicates that local firms are likely to pay low wages, followed by exporters/importers, EXIM, foreign FCFs and domestic FCFs, with the highest-paying firms likely to be hybrid FCFs (i.e. exporters, importers and FDI firms).

3.2.2 Empirical evidence

Numerous studies have presented robust evidence indicating that exporters are superior to non-exporters, pay higher wages, are more productive, are larger firms, and are more capital- and skills-intensive (see Bernard & Jensen, 1999; Bernard et al., 2003; Schank et al., 2007; Munch & Skaksen, 2008; Verhoogen, 2008; Helpman et al., 2017). In South Africa and sub-Saharan Africa, Rankin (2001), Bigsten et al. (2004) and Rankin et al. (2006) found that, on average, exporters pay higher wages, have higher levels of capital and output per worker, and have a larger firm size. The quality of intermediate inputs, the destination and distance have also been shown to be important for the exporter wage premium (see Verhoogen, 2008; Brambilla et al., 2012; Schmillen, 2016). In South Africa, Rankin and Schöer (2013) found that workers employed in firms that export to the region were paid less than workers in firms that produce for the domestic market. However, workers in firms that export outside the region were paid higher wages relative to domestic producers. Matthee et al. (2018), using the SARS–NT panel, found that South African manufacturing exporters differed from other firms in terms of the number of products and destinations. Further, multi-product and multi-destination exporters contributed the most to total export value and were bigger and more productive than other types of exporters. They also found that most of South Africa's export growth comes from expansion on the intensive margin (i.e. existing exporters exporting more of their existing products to existing destinations).

The exporter wage premium has been explored extensively in the literature. In their seminal paper on exporters, jobs and wages, Bernard et al. (1995) found evidence of exporters paying higher wages. However, their premium was lower when controlling for capital intensity, industry, plant scale and location. They indicated that had they been able to control for worker characteristics, their estimates would have been even lower. 'Thus, the wage benefits that are attributable solely to exporting appear to be rather small.' (Bernard et al., 1995, p. 113f).

Using German-linked employer–employee data to control for observable and unobservable individual and plant characteristics, Schank et al. (2007) found that the exporter wage premium was neither large nor negligible compared to identical plants that do not export. However, they observed that wages increased with the share of production that firms sold to foreign markets. Irarrazabal et al. (2013) used Norwegian manufacturing-linked employer–employee data and found that the wage premium fell by roughly 50% after controlling for observed and unobserved worker characteristics, while the TFP premium fell by 25%.

Through an extensive literature review, Brambilla et al. (2017) identified four major drivers of wage premia: exporting firms hire more skilled workers, use more sophisticated machines, purchase higher-quality input materials and are more productive than non-exporters. They also indicate that in many developing countries, exporting firms are owned by foreign companies and this may affect wages and employment. Further, they found that the exporter premia across different regions were lower when controlling for foreign ownership. This is unsurprising given that there is a plethora of evidence that foreign-owned firms or firms serving foreign markets through exports are more productive and pay higher wages than local firms.

Heyman et al. (2007), Balsvik (2011), Martins (2011), Pesola (2011) and Poole (2013), using linked employer–employee data, showed the existence of a foreign ownership wage premium. These studies found evidence of a wage spillover through worker mobility from FCFs to domestic firms. These studies do not look at the exporter premium and FCF premium simultaneously. To my knowledge, the only studies in the literature that have done this are Tanaka (2015) for Japan and Schröeder (2020) for Germany. This chapter uses linked employer–employee data for South Africa to conduct a similar analysis. Tanaka (2015) used quantile regressions and found the existence of a wage premium for foreign firms, with the foreign wage premium being larger in the higher quantiles of the wage distribution. However, the wage premia for exporters and domestically owned FCFs are smaller and even negative in higher quantiles. Schröeder (2020) also found evidence of FCFs paying the highest wage premium and developed a theoretical model that provides an explanation for positive exporter and FCF premia. She highlights that differences in screening efficiencies across various firms play a key role in explaining wage premia.

This thesis extends the empirical literature by also differentiating between firms that are simultaneously exporters and importers and pure exporters and importers. Using the SARS-NT panel, Edwards et al. (2018) found that most South African exporters are also importers and that these firms demonstrate premia in terms of productivity, employment, wages and capital intensity in production compared to both local firms and pure exporters or importers. Further, they found that importing boosts exports, especially when inputs are sourced from advanced economies. Bezuidenhout et al. (2019) explored the role of trading firms in gender inequality using the SARS-NT panel and found that trading firms have an 8 percentage-point higher gender wage gap relative to domestic firms. After controlling for fixed worker and firm effects, trading firms have a 1.5 percentage-point higher gender wage gap compared to domestic firms. The study also differentiated between pure importers, exporters and exporter–importer firms (which they used as a crude proxy for foreign ownership). They found that exporter–importer firms have a more equal pay structure than other groups. Thus, this is an indication that while trade liberalisation might widen the gender wage gap, allowing foreign investment from more equal countries could counteract this and contribute to a reduction in the gender wage gap in trading firms. This chapter does not look at the gender wage gap but it does explore the wage premium for exporter–importer firms and firms that import, export and have foreign ownership.

3.3 Descriptive statistics

3.3.1 Defining foreign-connected firms

In this chapter the merged IRP5 and CIT datasets, which also include customs information, are used, thus allowing for the identification of exporters and importers as well as FCFs.[31] This chapter and the next use the information outlined below to identify FCFs. The Organisation for Economic Cooperation and Development (OECD) (2008) benchmark definition distinguishes between an FDI enterprise and an MNE. MNEs are a sub category of FDI enterprises. FDI enterprises have at least 10% ownership by a foreign investor, whereas MNEs require at least 50% ownership by a foreign investor. Thus, in this thesis, a threshold of at least 10% foreign ownership is used and refer to these enterprises as FCFs. Thus, the FCFs in this thesis are equivalent to the OECD's FDI firms. FCFs include both foreign (**Table 3-1**) and domestic FCFs (**Table 3-2**). Using information available in the CIT data, foreign-owned FCFs are defined as firms that:

- are non-resident[32] in South Africa for tax purposes due to foreign incorporation or by virtue of a double taxation agreement (DTA). Most companies indicate that they are non-resident for tax purposes but do not give the reason for their non-residency. As such, the questions relating to non-residency due to foreign incorporation and by virtue of a DTA are poorly populated. ITR14 questions:
    - Is the company resident in South Africa for income tax purposes?
    - Is the company resident outside South Africa due to foreign incorporation (and not being effectively managed in SA)?
    - Is the company resident outside South Africa by virtue of a treaty to avoid double taxation?

[31] When merging the IRP5 and CIT data, it is not possible to identify firms that do not export directly and use a separate entity to export. Thus, the local firm variable may still have firms that are actually exporters. This will likely reduce the estimated premium as local firms might include more productive exporting firms.

[32] SARS interpretation note no. 6 (2002) indicates that a company is non-resident if it is not incorporated, established or formed in South Africa and does not have its place of effective management in South Africa. The place of effective management in the case of a company is the place where it is managed on a regular or day-to-day basis by the directors or senior managers of the company, irrespective of where the overriding control is exercised, or where the board of directors meets. Management by these directors or senior managers refers to the execution and implementation of policy and strategy decisions made by the board of directors. It can also be referred to as the place of implementation of the entity's overall group vision and objectives, https://www.sars.gov.za/wp-content/uploads/Legal/Notes/LAPD-IntR-IN-2018-12-Arc-12-IN6-Resident-Place-Effective-Management.pdf

- are a subsidiary or associate[33] of a foreign company that: has a foreign ultimate holding company;[34] has dividends exempt from taxation due to a DTA;[35] and is part of an MNE. ITR14 questions:
  - Is the ultimate holding company resident outside South Africa?
  - Total dividends subject to double taxation relief (amount).
  - Is the company part of a multinational enterprise? (This question was only introduced in 2016.)
- are a branch of a foreign firm. ITR14 question:
  - Is this return in respect of a branch/permanent establishment/agency of a foreign company?

Table 3-1: Foreign-owned foreign-connected firms

	Non-resident			Subsidiary/Associate			Branch
	Non-resident for tax purposes	Non-resident due to foreign incorporation	Non-resident by virtue of a DTA	Foreign holding company	Foreign dividends paid exemption	Part of an MNE	Branch/permanent establishment/agency
2013	4467	15	25	413	62	-	322
2014	4526	17	12	469	78	-	339
2015	4165	14	*	521	70	-	249
2016	4107	27	25	483	83	103	219

Source: SARS–NT panel (own calculations)
Note: full sample
* less than 10 observations
- no data

Domestic firms include non-FCFs as well as FCFs that can compete with foreign-owned firms in terms of productivity. Therefore, foreign-connected South African-owned firms are also identified. These are firms that:

[33] An associate is an enterprise in which foreign investors' ownership is between 10% and 50%. A subsidiary is an enterprise in which foreign-owned assets constitute more than 50% of total assets. Branches are also included under the OECD definition of FDI, https://www.oecd.org/daf/inv/investment-policy/2487495.pdf

[34] A company in which 50% or more of its operating assets are owned by a foreign firm.

[35] In terms of dividends tax, dividend payments to foreign residents may be subject to a reduced rate where the relevant DTA between South Africa and their country of residence provides for such. This normally requires the foreign beneficial owner to be a company and to hold between 10% and 25% of the share capital of the South African company paying the dividend, https://www.sars.gov.za/wp-content/uploads/Ops/Guides/DT-GEN-01-G03-A-Quick-Guide-to-Dividends-Tax-External-Guide.pdf

- have foreign income and expenditure in terms of s31(1)(a) of the Income Tax Act, 1962.[36] Transfer pricing (s31) is applicable when connected persons[37] engage in cross-border transactions. This allows one, for example, to capture South African-owned companies transacting with their subsidiaries in other countries. ITR14 questions:
    - For years of assessment commencing on or after 1 April 2012, did the company enter into any transaction, operation, scheme, agreement or understanding as set out in s31(1)(a)?
    - Did the company receive/accrue income?
    - Did the company incur expenditure?
- are headquarter companies where at least 80% or more of the cost of total assets are attributable to a qualifying foreign company.[38] ITR14 question:
    - Does the company comply with the requirement that at least 80% of the cost of its total assets (excluding cash and bank deposits payable on demand) is attributable to assets as listed in s9I(2)(b)?
- have foreign dividends exempt in terms of s10B(2)(a)[39] as well as foreign dividends subject to the participation exemption. ITR14 question:
    - Has the company claimed an exemption for any foreign dividends as referred to in s10(1)(k)(ii)(dd) or s10B (2)(a) ?
- have participation or voting rights in a controlled foreign company (CFC). ITR14 questions:
    - Were any of the foreign dividends subject to participation exemption?
    - Does the company directly or indirectly hold more than 10% of the total participation rights or voting rights in a controlled foreign company (s9D)?

[36] SARS Practice Note No.7 (1999) states that section 31 was introduced into the Act with effect from 19 July 1995 to counter transfer pricing practices that may have adverse tax implications for the South African fiscus. Section 31 enables the Commissioner to adjust the consideration in respect of the supply or acquisition of goods or services in terms of an international agreement between connected persons, https://www.sars.gov.za/wp-content/uploads/Legal/Notes/LAPD-IntR-PrN-2012-11-Income-Tax-Practice-Note-7-of-1999.pdf

[37] A connected person can be a resident company with a holding company, a subsidiary, subsidiaries of the same holding company, a natural person, a trust, a close corporation or a company holding at least 20% ownership, https://www.sars.gov.za/wp-content/uploads/Legal/Notes/LAPD-IntR-IN-2012-67-IN67-Connected-Persons.pdf

[38] The headquarter company is resident in South Africa and its asset cost base must comprise at least 80% in foreign companies in which it holds at least 10% equity shares and voting rights (for assets with a market value of more than R50 000), https://www.sars.gov.za/wp-content/uploads/Legal/Notes/LAPD-IntR-IN-2016-01-IN87-Headquarter-companies.pdf

[39] s10B(2)(a), which applies to any foreign dividend or a dividend paid by a headquarter company. This section provides that dividends received by a shareholder holding more than 10% of the equity shares and voting rights in the company declaring the foreign dividend, will be exempt from tax, https://www.sars.gov.za/wp-content/uploads/Legal/Notes/LAPD-IntR-IN-2016-07-IN93-The-taxation-of-foreign-dividends.pdf

Table 3-2: Domestically owned foreign-connected firms

	Foreign transactions (transfer pricing)		Foreign ownership		Foreign dividends	
	Foreign income	Foreign expenditure	Headquarter company with minimal asset rules	CFC	Dividends exempt from tax	Dividends subject to the participation exemption
2013	157	200	22	38	*	*
2014	219	293	23	46	14	11
2015	259	321	20	46	*	*
2016	248	305	23	45	*	*

Source: SARS–NT panel (own calculations)
Note: full sample
* less than 10 observations

It should be noted that in this chapter, domestically owned and foreign-owned FCFs are kept as separate categories. However, in Chapter 4, domestic and foreign FCFs are grouped to form FCFs, which other studies in the literature have done (Temouri et al., 2008; Balsvik, 2011; Hakkala & Sembenelli, 2018).

The firms in this chapter are classified into seven distinct groups:

1. Local: firms that are domestically owned and have no connection to foreign markets;
2. Exporters: firms that are domestically owned and serve foreign markets through exporting, i.e. pure exporters;
3. Importers: firms that are domestically owned and import from foreign markets; however, these firms do not export, i.e. pure importers;
4. Exporter–importers: firms that are domestically owned and are both importers and exporters, i.e. EXIM;
5. Domestic FCF: firms that are domestically owned which report outward FDI but do not import or export, i.e. FCF (dom);
6. Foreign FCF: firms that are foreign owned but do not import or export, i.e. FCF (for); and
7. Hybrid FCF: firms that are exporters, importers, domestically or foreign owned.

3.3.2 Summary statistics

Most of the firms in the sample are local firms (43%), followed by EXIM firms (18%) and foreign FCFs (15%). Hybrid firms account for 10% of the sample, exporters (7%), importers (6%) and domestic FCFs constitute the smallest group (0.1%). Only firms that are pure exporters and importers increased in number in the sample between 2013 and 2016. The number of all the other types of firms declined (see **Table 3-3**). Local firms are the largest category of firm in the sample, making up 43%

of manufacturing firms. Domestic FCFs are the smallest category, followed by pure exporters and importers. EXIM firms are the largest group among the FCFs and trading firms. Edwards et al. (2018) showed that of the firms that trade, half engage in both exporting and importing. Together, FCFs and EXIM make up half the trading firms and FCFs – with EXIM contributing 32% and hybrid firms 18%. This indicates that hybrid firms are a much smaller or niche subset of trading firms, which are simultaneously importers, exporters and FCFs.

Table 3-3: Number of firms by firm type

	FCF(for)	FCF(dom)	Hybrid	EXIM	Exporters	Importers	Local
2013	2 809	19	1 851	3 319	1 219	1 065	7 682
2014	2 839	15	1 961	3 313	1 314	1 133	8 023
2015	2 648	16	1 886	3 345	1 282	1 170	7 776
2016	2 497	16	1 727	3 223	1 310	1 138	7 342
*Proportion**	*15%*	*0,1%*	*10%*	*18%*	*7%*	*6%*	*43%*

Source: SARS–NT panel (own calculations)
Note: full sample
*Average between 2013 and 2016

The highest share of employment is accounted for by EXIM (34%), local (27%) and hybrid (18%) firms. Only hybrid, exporter and importer firms increased the number of workers who they employed over the period. However, hybrid firms were the only firms that consistently or incrementally increased employment for each year in the panel. The largest increase in employment came from hybrid firms, which increased employment from 121,324 in 2013 to 155,177 in 2016, followed by exporters and then importers (see **Table 3-4**). Although the highest job creation came from hybrid firms, EXIM and local firms employed more workers than hybrid firms.

Table 3-4: Number of workers by firm type

	FCF(for)	FCF(dom)	Hybrid	EXIM	Exporters	Importers	Local
2013	59 875	3 006	121 324	249 956	43 233	40 164	193 560
2014	57 930	2 259	130 728	246 410	51 985	42 812	209 433
2015	55 216	2 944	134 457	277 327	47 858	44 186	205 474
2016	57 805	1 024	155 177	241 351	49 950	41 024	189 050
*Proportion**	*8%*	*0,3%*	*18%*	*34%*	*7%*	*6%*	*27%*

Source: SARS–NT panel (own calculations)
Note: full sample
*Average between 2013 and 2016

Looking at the number of workers and firms across subsectors reveals that most subsectors do not have domestic FCFs and where they do, they total less than 10. Only the fabricated metals products and machinery & equipment subsectors have more than 100 hybrid firms in their subsectors (see **Table C-1** in Appendix B).

Hybrid firms have the highest mean and median monthly wage, output per worker and firm size (see **Table 3-5**). Notably, domestic FCFs have a higher mean and median wage compared to EXIM firms. Hybrid and EXIM firms have a mean firm size higher than 1000 workers. However, domestic FCFs have the highest median firm size, with 310 workers. Foreign FCFs also perform better than exporters, importers and local firms, but these firms have the lowest median firm size.

Table 3-5: Mean and median values for firm and worker characteristics

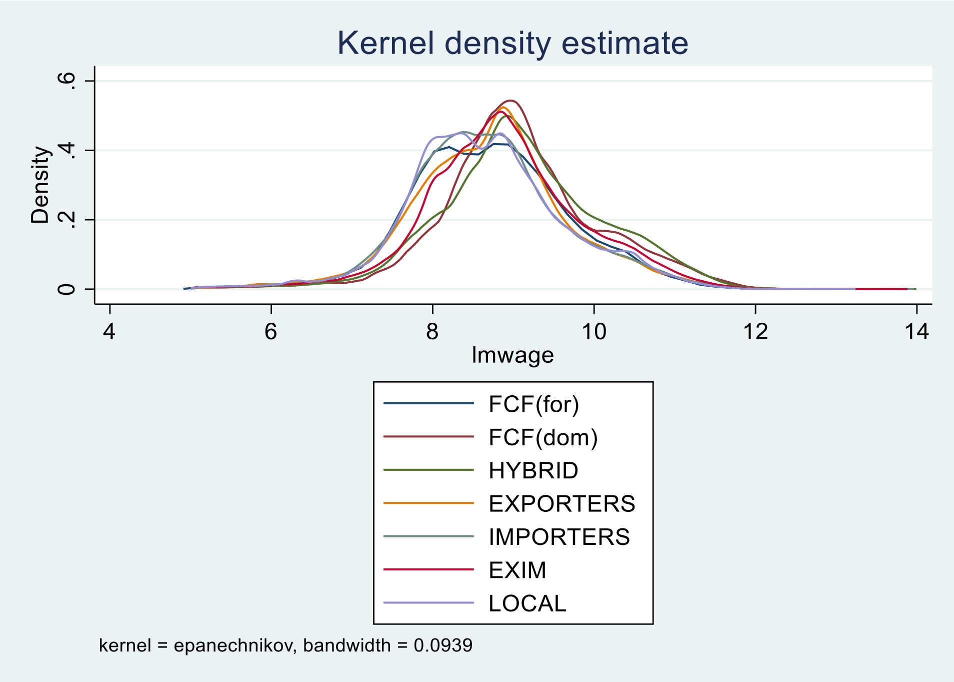
	FCF(for)	FCF(dom)	Hybrid	EXIM	Exporter	Importer	Local
				Mean			
Monthly wage	10280	14166	16449	12395	9701	9416	9425
Age	37	37	38	37	37	36	37
Tenure	3	3	3	3	3	3	3
Gender (female)	0,30	0,24	0,33	0,36	0,31	0,40	0,32
Output per worker	744 344	1 312 468	1 331 016	994 616	806 151	819 756	704 013
Firm size	299	498	1667	1041	174	215	268
				Median			
Monthly wage	5915	7958	8476	6869	6234	5513	5422
Age	35	37	36	36	36	34	35
Tenure	3	2	3	3	3	3	3
Output per worker	404 471	624 713	816 662	651 587	497 258	495 476	398 536
Firm size	43	310	211	192	88	112	72

Source: SARS–NT panel (own calculations)
Note: full sample

The k-density of log monthly wages for the different types of firms is given in **Figure 3-1**,[40] reflecting what was indicated above. Hybrid firms are to the right of all the other types of firms. This indicates that hybrid firms pay higher wages, particularly at the top end of the distribution. Domestic FCFs intersect with hybrid firms at the bottom of the distribution, reflecting that domestic FCFs pay higher wages relative to hybrid firms at the very bottom of the distribution.

[40] This figure is trimmed from 5 to 15. The full distribution is shown in **Figure C-1**.

Figure 3-1: Wage distribution by firm type



Source: SARS–NT panel (own calculations)

The extent of mobility between the different types of firms is shown in **Table 3-6**. There is a sizeable amount of movement between the various firm types. Almost 35% of the workers move between the same firm category, e.g. local to local. Movement of workers is highest between local firms, closely followed by movement between EXIM. Workers moving between local and EXIM firms as well as FCFs and EXIM firms all record more than 1000 movers between the period. Movers in this chapter capture job-to-job transitions. As such, the movement captured in **Table 3-6** does not include workers hired from unemployment and workers who leave the manufacturing sector. Most workers stay in the same firm – making the stayers the largest group of workers.

Table 3-6: Number of workers moving between firm categories

	loc	exp	imp	exim	fcf(dom)	fcf(for)	hybrid
loc	3267	598	366	2241	28	546	729
exp	814	188	81	461	*	140	166
imp	376	63	254	471	*	260	162
exim	2341	511	463	3139	27	456	1247
fcf(dom)	20	*	*	31	0	*	32
fcf(for)	682	106	99	520	*	292	311
hybrid	883	199	291	1149	12	376	1041
stayers	78032	14456	13269	1119324	360	17205	59518

*Less than 10 observations

3.4 Methodology

3.4.1 Baseline regression

This section outlines the methodology undertaken in this chapter. For the baseline regression, an ordinary least squares (OLS) estimation on a Mincer wage regression is performed. Worker and firm fixed effects are then added to the baseline regression to account for unobserved firm and worker characteristics. Having panel data makes it possible to also explore the different wage premia of workers moving to different firm types.

An OLS regression on individual wages is run to determine the existence and magnitude of the FCF and exporter wage premium. The following Mincer wage equation is estimated:

$$W_{it} = \beta_0 + \beta_1{}'\mathrm{FIRM}_{j(i,t)} + \beta_2{}'I_{it} + \beta_3{}'X_{j(i,t)} + \mathrm{v}_t + \mathrm{v}_{ind} + \varepsilon_{it} \qquad (1)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the log monthly wage;
- $\mathrm{FIRM}_{j(i,t)}$ is a dummy variable indicating firm categories, i.e. local, exporter, importer, EXIM, FCF_{for}, FCF_{dom} and hybrid;
- I_{it} is a vector with K observable individual characteristics, i.e. age, age squared, age cubed, gender and tenure;
- $X_{j(i,t)}$ is a vector firm characteristic, i.e. firm size and output per worker;
- v_{ind} industry dummy;
- v_t year dummies; and
- ε_{it} is the idiosyncratic error term.

The coefficient of interest is captured by β_1 which reflects the wage premia paid by the different types of firms relative to local firms.

3.4.2 Fixed effect regression

The baseline regression does not account for time-invariant, unobservable worker and firm characteristics. Controlling for unobserved firm and worker fixed effects captures the unobservable characteristics that may explain the wage premia from different types of firms. The unobserved worker and firm fixed effects are estimated following the same methodology as Abowd et al. (1999, 2002), with the inclusion of observable firm characteristics. The following fixed effect model is estimated:

$$W_{it} = \beta_0 + \beta_1{}'\mathrm{FIRM}_{j(i,t)} + \beta_2{}'I_{it} + \beta_3{}'X_{j(i,t)} + \mathrm{v}_i + \mathrm{v}_j + \mathrm{v}_{ind} + \mathrm{v}_t + \varepsilon_{it} \qquad (2)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the log monthly wage;
- $\mathrm{FIRM}_{j(i,t)}$ is a dummy variable indicating firm categories, i.e. local, exporter, importer, EXIM, FCF_{for}, FCF_{dom} and hybrid;
- I_{it} is a vector with K observable individual characteristics, i.e. age, age squared, age cubed, gender and tenure;
- $X_{j(i,t)}$ is a vector firm characteristic, i.e. firm size and output per worker;
- v_i worker fixed effects;
- v_j firm fixed effects;
- v_{ind} industry dummy;
- v_t year dummies; and
- ε_{it} is the idiosyncratic error term.

The coefficient of interest is captured by β_1, which reflects the wage premia paid by different firm types after controlling for unobservable worker and firm characteristics. Not controlling for these could lead to an overestimation of the wage premia in the baseline regressions. The underlying assumption is that the error term is orthogonal to all regressors and to the worker and fixed effects (Abowd et al., 1999). This implies strict exogeneity, which means that workers' mobility decisions are independent of ε_{it}.

To estimate equation 2, the grouping algorithm (conjugate gradient) from Abowd et al. (2002) is used, based on the fixed effects model and least squares dummy variable model by Conelissen (2008). Only the largest connected group of firms and workers connected by worker mobility is retained. The largest group connected by worker mobility has 16,887 firms and 1,208,132 individuals connected by 100,401 movers.[41] Movers account for less than 10% of the sample, with only 1% of movers being recorded in more than two firms. Most of the workers in the panel appear once (40.67%) and only

[41] The full sample had 25,416 firms and 1,274,199 workers.

20% appear in all four years of the panel. This is expected, given the short time period for this analysis.

3.4.3 Firm-switching regressions

This section examines the existence and magnitude of the wage premia experienced by workers moving between different firms in the panel. This is done to determine whether there is a wage level and wage growth difference when workers move between local, exporter, importer and FCFs. A wage equation, including non-FCF workers and new hires from FCFs as well as other non-FCFs, is estimated. Thus, the wage equation compares all the switchers from the different firm types relative to all workers who stay in the same local firm. The following equation is estimated:

$$W_{it} = \beta_0 + \beta_1{}'\mathrm{SWITCH}_{j(i,t)} + \beta_3' I_{it} + \beta_4' X_{j(i,t)} + \mathrm{v}_j + \mathrm{v}_t + \mathrm{v}_t * \mathrm{v}_{ind} + \varepsilon_{it} \quad (3)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the log monthly wage;
- $\mathrm{SWITCH}_{j(i,t)}$ is a dummy indicating a new worker in firm j from a local, exporter, importer, EXIM, FCF_{for}, FCF_{dom} and hybrid firm compared to workers who stay in a local firm;
- I_{it} is a vector with K observable characteristics, i.e. age, age squared, age cubed, gender;
- $X_{j(i,t)}$ is a vector firm characteristic, i.e. firm size and output per worker;
- v_j firm fixed effects;
- v_t year dummies;
- $\mathrm{v}_t * \mathrm{v}_{ind}$ industry and year interaction terms; and
- ε_{it} is the idiosyncratic error term.

The coefficient of interest is captured by β_1, which reflects the wage premia for workers who move or change firms in the panel compared to workers who stay in local firms.

3.5 Empirical results

3.5.1 Baseline results

The baseline analysis has OLS and pooled OLS regressions (see equation 1). The pooled OLS regression estimates in **Table 3-7** control for time and industry (see column 1). Firm characteristics are then included (see column 2) as well as worker characteristics (see column 3). The baseline results reveal that hybrid firms pay the highest premium at 37% compared to local firms, when all the controls are included in column 3. This is followed by domestic FCFs with a 27% wage premium and then EXIM firms with a 21% wage premium. Exporters and importers pay a similar premium of around 6%. Foreign FCFs pay significantly less than local firms.

The baseline results are broadly consistent with what is expected, with the exception of foreign FCFs. Further, these results indicate that hybrid firms pay the highest wage premium. The result for foreign FCFs is surprising and indicates the importance of exports and imports for foreign FCFs. When a firm is a foreign FCF but does not engage in trade, it does not have a wage premium compared to local firms. Although the domestic FCF sample is much smaller, even domestic FCFs that do not record exports or imports still pay higher wages compared to local firms and have a higher wage premium than EXIM. This supports the literature which indicates that only the most productive firms in a country engage in FDI and the next tier of firms engage through exports and imports (Helpman et al., 2004).

Table 3-7: Baseline – wage premium

Base cat: Local		Pooled OLS		2013	2014	2015	2016
Export	0.0695**	0.0932**	0.0651**	0.0483**	0.0974**	0.0736**	0.0337**
	(0.00249)	(0.00249)	(0.00230)	(0.00490)	(0.00448)	(0.00459)	(0.00445)
Import	0.0102**	0.0560**	0.0627**	0.0663**	0.101**	0.0517**	0.0251**
	(0.00264)	(0.00264)	(0.00245)	(0.00511)	(0.00485)	(0.00479)	(0.00481)
EXIM	0.209**	0.257**	0.211**	0.202**	0.216**	0.200**	0.206**
	(0.00149)	(0.00156)	(0.00145)	(0.00300)	(0.00289)	(0.00286)	(0.00285)
FCF(for)	0.0381**	-0.0267**	-0.0105**	-0.0156**	-0.0182**	-0.00187	0.00323
	(0.00231)	(0.00241)	(0.00223)	(0.00444)	(0.00440)	(0.00442)	(0.00459)
FCF(dom)	0.355**	0.326**	0.269**	0.374**	0.188**	0.209**	0.327**
	(0.0103)	(0.0115)	(0.0106)	(0.0180)	(0.0211)	(0.0221)	(0.0277)
Hybrid	0.368**	0.429**	0.372**	0.348**	0.403**	0.339**	0.378**
	(0.00177)	(0.00184)	(0.00171)	(0.00359)	(0.00338)	(0.00337)	(0.00335)
Worker characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Firm characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	No	No	No	No
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,974,709	2,806,680	2,806,680	688,639	715,856	717,517	684,668
R-squared	0.161	0.145	0.268	0.260	0.272	0.274	0.282

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

The OLS regressions are also run on a cross-section for each year of the panel with all the controls included. The results are similar to the pooled OLS regression, as expected. The only difference is that the foreign FCF coefficients are significantly lower than local firms in 2013 and 2014. However, in 2015 and 2016, they are not significantly different from local firms. Both the pooled OLS and cross-sectional analysis show that firms with foreign connections pay higher wages than local firms, with the exception of foreign FCFs which do not trade. Further, the hybrid premium is higher than the domestic FCF, EXIM and pure exporter and importer premium. Thus, in South African, hybrid firms that export, import and engage in FDI, pay the highest wage premium, followed by domestically owned FCFs. Schröeder (2020) did not include importing in her analysis but found that in Germany hybrid firms paid the highest wage premia followed by foreign-owned FCFs. However, this study finds a negative wage premium from foreign FCFs.

3.5.2 Fixed effect regression results

The fixed effect regressions are estimated using equation 2. The baseline regressions overestimate the wage premia because they do not account for unobservable firm and worker heterogeneity. Thus, in these regressions a worker and firm fixed effect are included. As a robustness check, the firm fixed effect of the sending firm is also added. **Table 3-8** column 1 has the same specification as the baseline regressions. However, it is restricted to the largest group of connected firms to allow for the estimation of worker and firm fixed effects. As such, the baseline results remain unchanged, with the wage premia for each firm category declining by about 1%. In column 2, worker fixed effects are included these capture unobserved worker characteristics, such as ability and motivation. The hybrid firm premium remains the highest; however, it declines from 36% to 24.5%. This is followed by EXIM with a 15% premium. Notably, the domestic FCF premium falls away, which could be driven by the low number of observations. It could also indicate a very strong correlation between unobservable worker characteristics and domestic FCFs because they could potentially attract certain types of workers, given how productive they are.

When firm fixed effects are controlled for (see column 3), the hybrid firm wage premium declines to 23% and EXIM to 12%, while pure exporters and importers have roughly a 3% premium relative to local firms. Surprisingly, the domestic FCF coefficient becomes higher than the hybrid firms. However, given the small number of firms, this coefficient should be interpreted cautiously.

As a robustness check the sending firm fixed effects are also included (column 4). This captures any unobservable variation in wages attributable to the firm from which a worker comes. The results have slightly higher wage premia; however, the ranking for the different firm categories remains unchanged. The overall finding that hybrid and domestic FCFs pay the highest wages also remains unchanged. As expected, the wage premia after controlling for unobservable characteristics are lower than the baseline estimates.

Table 3-8: Fixed effect – wage premium

Base cat: Local	No FE	Worker FE	Firm FE	Firm FE
Export	0.0572**	0.0527**	0.0284**	0.0361**
	(0.00237)	(0.00152)	(0.00219)	(0.00285)
Import	0.0552**	0.0484**	0.0283**	0.0317**
	(0.00250)	(0.00160)	(0.00232)	(0.00309)
EXIM	0.200**	0.148**	0.117**	0.129**
	(0.00148)	(0.000949)	(0.00138)	(0.00183)
FCF(for)	-0.00726**	-0.00347*	-0.00450*	0.00167
	(0.00236)	(0.00151)	(0.00219)	(0.00301)
FCF(dom)	0.258**	-0.00633	0.299**	0.283**
	(0.0107)	(0.00682)	(0.00987)	(0.0152)
Hybrid	0.362**	0.245**	0.231**	0.265**
	(0.00174)	(0.00112)	(0.00163)	(0.00214)
Firmfe (sending)				-0.171**
				(0.00336)
Firm FE	No	No	Yes	Yes
Worker FE	No	Yes	No	No
Firm characteristics	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Observations	2,669,840	2,669,840	2,669,840	1,461,708
R-squared	0.277	0.703	0.379	0.333

Standard errors in parentheses
** $p<0.01$, * $p<0.05$, + $p<0.1$

3.5.3 Firm-switching results

The wage premium from moving between various types of firms compared to staying in a local firm is estimated from equation 3 and the regression results are presented in **Table 3-9**. Any movement is expected to have a higher wage premium compared to staying in a local firm. The results indicate that this is broadly true, with the exception of domestic FCFs which have very few movers as well as the negative wage premium that workers experience when moving from an exporting firm to a local firm.

Workers moving to hybrid firms receive the highest wage premia. However, workers from other hybrid firms receive the highest premium of 54% relative to workers who stay in local firms. This is followed by workers from domestic FCFs (50%) and EXIM (41.5%). Workers moving from hybrid firms receive the highest wage gains when they move to domestic FCFs, with a premium of 82% – however, there are very few movers in the sample. They also receive the highest premia when moving to other hybrid firms, local firms, importers and foreign FCFs. EXIM firms pay the highest premium to workers from other EXIM firms (37.5%), followed by hybrid and foreign FCF s. Notably, pure exporters pay the highest premia to workers from domestic FCFs and EXIM.

Table 3-9: Firm switching

sending (from)	receiving (to)						
stay_loc	loc	exp	imp	exim	fcf(dom)	fcf(for)	hybrid
loc	0.116**	0.0943**	0.147**	0.214**	0.0733	0.110**	0.309**
exp	-0.0317*	0.0658*	0.126**	0.204**	0.219	0.0826*	0.308**
imp	0.108**	0.0943*	0.00478	0.246**	0.0711	0.00358	0.356**
exim	0.163**	0.276**	0.240**	0.375**	0.189*	0.146**	0.415**
fcf(dom)	0.0465	0.380+	0.271	0.127	-	0.362	0.497**
fcf(for)	0.166**	0.139**	0.138**	0.267**	-0.312	0.0971**	0.346**
hybrid	0.223**	0.157**	0.395**	0.353**	0.819**	0.321**	0.538**

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Domestic FCFs have very few observations, such that there is no estimate for a premium for workers moving between domestic FCFs. For the estimated coefficients it seems that most workers moving to domestic FCFs come from EXIM and hybrid firms and they receive a significant wage premium. Workers moving from domestic FCFs receive wage gains when they move to exporting and hybrid firms. What is interesting is that even though there is no evidence of a wage premium for foreign FCFs, workers moving to and from these firms receive a wage premium relative to staying in a local firm.

When controlling for the sending firm fixed effects (see **Table 3-10**), the coefficients change marginally; some are higher and others lower. However, the premium in either direction of movement remains the same. As such, there is robust evidence that workers receive the highest gains relative to staying in a local firm when they move to a hybrid firm.

Table 3-10: Firm switching, including sending firm fixed effects

sending (from)	receiving (to)						
stay_loc	loc	exp	imp	exim	fcf(dom)	fcf(for)	hybrid
loc	0.115**	0.0772**	0.138**	0.195**	0.107	0.106**	0.282**
exp	-0.0405**	0.0462	0.116*	0.183**	0.264	0.0788*	0.291**
imp	0.106**	0.0940*	-0.00335	0.243**	0.0702	0.00864	0.341**
exim	0.172**	0.272**	0.240**	0.377**	0.192*	0.162**	0.403**
fcf(dom)	0.0347	0.294	0.228	0.0956	-	0.271	0.437**
fcf(for)	0.160**	0.125**	0.123**	0.241**	-0.183	0.0996**	0.329**
hybrid	0.246**	0.174**	0.411**	0.363**	0.863**	0.332**	0.539**

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

3.6 Conclusion

Hybrid firms (which are firms that participate in international trade and are foreign-owned) are a niche subset of all trading firms and FCFs, which have the highest mean and median monthly wage, output per worker and firm size. Both the pooled OLS and cross-sectional analysis show that hybrid firms pay the highest wage premium, followed by domestic FCFs and EXIM firms. However, contrary to other studies in the literature, which found that foreign-owned FCFs without exports also had a wage premium, this study finds that foreign-owned FCFs that do not export or import, pay less than local firms. This highlights the importance of trading, even for foreign FCFs. One explanation for the poor performance could be the small size of the South African market. Without any exports, these FCFs produce purely for the domestic market which could limit their growth and competitiveness. Further research is required to understand why such firms would continue producing purely for the domestic market. Given the short time period of the data, the results could be capturing firms that have recently set up operations in South Africa and have not started exporting or importing. Notably, domestically owned FCFs still have a wage premium despite not reporting any exports or imports, which supports the theory that domestic FCFs are the most productive firms in a country. However, there are very few domestically owned FCFs in the sample as well as workers moving from them.

After controlling for worker fixed effects, the wage premia decline. However, the hybrid wage premium remains the highest. The domestic FCF premium falls away, which could be driven by the low number of observations. When controlling for firm fixed effects, the wage premia decline further. Surprisingly, the domestic FCF coefficient becomes marginally higher than the hybrid firms; however, this is likely due to the small number of observations.

The results indicate that workers moving to hybrid firms receive the highest wage gains, followed by workers moving to EXIM firms. Workers moving from hybrid firms receive the highest wage gains when they move to domestic FCFs, other hybrid firms, local firms, importers and foreign FCFs. EXIM pay a slightly higher premium to workers hired from other EXIM. This is followed by hybrid firm workers. Besides the wage premium outlier of workers moving from hybrid firms to domestically owned FCFs, workers moving between hybrid firms have the highest wage premium compared to staying in a local firm.

Thus, while there is an exporter wage premium, there is also a higher EXIM wage premium and an even higher hybrid wage premium. This indicates that firms’ level and type of foreign exposure have implications for the wage premia that firms pay. As a result, exposure through imported inputs, export sales and FDI all leads to higher wages. However, the combination of all these factors results in the highest wage premium.

These results indicate that it is this group of hybrid firms that pays the highest wage premia. These firms are most likely the group of firms that previous South African studies have referred to as 'super-exporters' and Bernard et al. (2018) have termed global firms. The impact of the wage inequality between the different types of firms in this chapter is likely to contribute further to overall wage inequality in South Africa. Brambilla et al. (2017) identify four major drivers of wage premia: exporting firms hire more skilled workers, use more sophisticated machines, purchase higher-quality input materials and are more productive than non-exporters. Further, the correlation and complementarities between different trade-related activities mean that once firms export, they are more likely to also import and engage in FDI (Bernard et al., 2018).

For a firm to engage in trade, it needs to be able to cover the sunk costs and the cost of acquiring adequate information to engage in exporting, importing and/or FDI. These costs include identifying potential buyers, complying with the standards and quality requirements for products in foreign markets, establishing a network of foreign suppliers, adapting production processes to incorporate new input materials, learning about various regulations for operating in different countries, and meeting the cost of building production plants in different countries. As such, it is important for policymakers to assist firms with information that will help them secure market access, thus enabling them to sell their products abroad, take up more export opportunities and select foreign suppliers so that they can source inputs from abroad cost-effectively. The more firms engage in exporting and importing, the more likely they are to also engage in FDI in the future.

Wage inequality is driven by the skills premia arising out of the differences in types of workers who are employed by these firms. This is due to different production functions for local firms relative to trading firms and FCFs. As such, these firms are able to pay a premium and acquire high-skilled workers who are able to perform more complicated tasks and operate technologically sophisticated machinery. Policymakers also need to focus on improving training and skills development in the country.

Further research is needed to understand whether hybrid firms have higher within-firm wage inequality relative to EXIM, exporters, importers and local firms. This analysis will help provide more insights into the types of interventions required for the various types of firms.

This chapter focused on estimating the wage premia for various types of firms in the manufacturing sector. The literature indicates that trading firms and FCFs have higher productivity relative to local firms. The next chapter explores whether there are any productivity and wage spillovers from workers moving from FCFs to local firms. This is one way for local firms to catch up to FCFs – i.e. by hiring workers with experience from these types of firms.

Chapter 4: Worker Mobility as a Channel for Spillovers from Foreign-Connected Firms in South African Manufacturing

ABSTRACT

This chapter uses linked employer–employee data from South Africa to explore the extent to which spillovers arise through worker mobility from FCFs to domestic firms (non-FCFs). There is evidence of productivity spillovers from FCFs to non-FCFs and robust productivity spillovers from FCFs to non-FCFs below the median firm size (i.e. small domestic firms). The spillovers mainly come from FCFs that are above the median. These results suggest that the spillovers to these firms occur mainly through high-wage FCF workers – highlighting the importance of skills. Lastly, there is also evidence of a wage premium paid to new entrants in non-FCFs coming from FCFs with more than a three-year tenure.

4.1 Introduction

In this chapter worker mobility is explored as a channel for spillovers between FCFs and local firms. One of the ways in which local firms learn from FCFs is by hiring workers with experience from these firms. The literature highlights the wage and productivity differences between FCFs and local firms. As such, it is important to establish whether local firms and workers benefit from the presence of FCFs in the domestic market.

Early studies of FDI spillovers treated spillover channels like a 'black box' (Görg & Strobl, 2005). However, several channels for spillovers have been identified, including competition, imitation and worker mobility. This chapter focuses on the worker mobility channel. Theoretically, Fosfuri et al. (2001) and Glass and Saggi (2002) provide similar frameworks which identify worker mobility as a channel through which spillovers can occur. Many empirical studies have found that MNEs (hereafter referred to as FCFs) are more productive than local firms (see Girma et al., 2002 [for the UK]; Helpman et al., 2004 [for the US]; Temouri et al., 2008 [for Germany]; and Engel & Procher, 2012 [for France]). The technology and productivity advantage that foreign firms have over domestic firms presents an opportunity for domestic firms to gain access to this knowledge by hiring workers with previous foreign firm experience. Further, workers with experience from foreign-owned firms are generally paid higher wages relative to workers without this experience (Poole, 2013).

This chapter analyses FDI spillovers, using the SARS–NT panel, for the manufacturing sector between 2013 and 2016. The chapter explores worker mobility as a channel for productivity spillovers from FCFs[42] to domestic firms (non-FCFs) in South Africa. In South African literature, productivity spillovers have only been explored for exporters, R&D and training, using the SARS–NT panel, as well as horizontal, forward and backward spillovers. This makes it the first study to explore potential productivity spillovers from FDI through the worker mobility channel.

This study finds evidence of productivity spillovers from workers moving from FCFs to non-FCFs and does not find evidence of spillovers in the opposite direction. However, the results indicate that spillovers are more likely to occur between FCFs and small domestic firms and when movers come from FCFs above the median. The results also suggest that the spillovers to domestic firms occur mainly through male workers and high-wage FCF workers. This could reflect the different types of jobs held by males and females in the manufacturing sector; it also highlights the importance of the skill level of the worker for FCF productivity spillovers to occur through worker mobility. Lastly, there is evidence of a wage premium paid to new entrants coming from FCFs with more than a three-year tenure.

The chapter is structured as follows: section 4.2 provides a literature review, section 4.3 presents the data overview, section 4.4 provides the descriptive statistics, section 4.5 presents the methodology and productivity spillover analysis, section 4.6 presents the wage analysis and section 4.7 concludes.

4.2 Literature review

4.2.1 Theoretical framework

Models by Helpman et al. (2004), Grossman et al. (2006) and Bernard et al. (2018) extend the Melitz (2003) model on firm heterogeneity and show that FDI firms are more productive than firms that only serve foreign markets through exports. This chapter explores whether the presence of FDI firms leads to any spillovers for local firms. Fosfuri et al. (2001) and Glass and Saggi (2002) provide similar

[42] See data section for the definition used in this paper. FCFs have at least 10% equity held in or by a foreign firm. FCFs also include domestically owned firms with foreign connections.

theoretical frameworks which identify worker mobility as a channel for spillovers between FDI and local firms. Further, they outline the conditions under which FDI spillovers through worker mobility are possible.

This chapter focuses on Fosfuri et al. (2001) who created a model where multinational firms need to train a local worker on their 'technology' so that they can start operations in a foreign country. A technology can be new machinery/equipment, a new production process, a new managerial technique or a new organisational structure. A firm can either serve the foreign market through exports or FDI, where FDI involves having a headquarters and a manufacturing plant in a foreign country. Further, FDI requires a transfer of technology from the headquarters to the manufacturing plant, with transfer only possible if a local worker knows how to use the technology. Thus, the technology can only be transferred through oral communication or on-the-job training.

In the foreign country, there is a local firm that would produce the product if it knew how to use the technology. After being trained, the local worker has enough know-how to produce the product. The local firm requires the skills acquired by the trained worker to produce the goods; however, the multinational firm would prefer to keep the worker in view of the cost of training a new worker. As such, the local firm and the multinational firm compete for the trained local worker. The firms simultaneously and independently make offers to the trained worker and the firm that offers the highest wage gets the worker. Fosfuri et al. (2001) indicate that the hiring process operates like a first-price auction. As such, if an identical wage offer is made, the firm whose valuation of the worker is highest gets the worker – assuming symmetric information on the value of the trained worker.

Spillovers do not occur if the multinational pays a wage that is high enough to enable it to keep the trained worker. As such, it is harder for spillovers to occur when the local firms compete directly with the multinational firm. Spillovers are likely to occur when the multinational and local firms are not in direct competition but are instead vertically related (i.e. upstream or downstream) or sell the product in different markets. However, Fosfuri et al. (2001) do not provide empirical evidence of this prediction. They also indicate that spillovers do not occur when the technology is difficult to transfer. Thus, spillovers depend on the absorptive capacity of the local firm, and so the more general the on-the-job training, the easier it is to transfer the technology. Their model predicts that the more technologically advanced a foreign country is and the more highly skilled its workers, the higher the country's worker mobility and technology spillovers will be.

4.2.2 Empirical evidence

Empirically, the first study to attempt to look at worker mobility as a channel for spillovers was Görg and Strobl (2005), using a firm-level sample of manufacturing plants in Ghana. They found that firms opened and run by entrepreneurs with FCF experience in the same industry immediately before opening their own businesses are more productive than other domestic firms. However, this study looked only at workers who had left the FCFs to start their own companies. Balsvik (2011), Martins (2011), Pesola (2011), Poole (2013) and Huang and Zhang (2017) have found evidence of spillovers from workers moving from FCFs to existing non-FCFs. Other channels for spillovers have been identified in the literature, such as competition and imitation/demonstration (Demena & Bergeijk, 2019). However, in Indonesia and the Philippines, worker mobility was found to be the most viable channel for spillovers (Olayinka & Loykulnanta, 2019).

Workers with FCF experience receive training in the use of new technologies or machinery, advanced processes, process innovations, high-quality intermediate inputs and management techniques. They may have contacts or relationships with FCF suppliers and clients, allowing non-FCFs to connect to global supply and value chains, as well as acquire knowledge of potential international and regional markets and relevant training programmes for new techniques and technologies. However, the extent of transfer of this knowledge depends on the seniority, skill and exposure that the worker enjoyed while in the FCF. In exporting firms, Mion and Opromolla (2014) found that spillovers are likely to be higher for managers.

Heyman et al. (2007) used linked employer–employee data (LEED) from Sweden for the entire private sector, combining propensity score matching and difference-in-differences techniques. They found that greenfield investment FCFs paid the highest wages and non-FCFs paid the lowest wages. Further, domestically owned FCFs paid higher wages than foreign-owned FCFs. Martins (2011) used LEED from Portugal for the manufacturing and services sectors, controlling for unobserved worker and firm characteristics. He found that workers moving from non-FCFs to FCFs receive an average increase of 10% in their wages. However, there is a selection effect that arises due to foreign firms hiring workers who are, on average, already better remunerated in their domestic firms. He also showed that movers from foreign to domestic firms take a large pay cut when they move. This is contrary to the findings of other studies in the literature. Using Finnish data from 1994 to 2002, Pesola (2011) showed that having previous FCF tenure has a positive effect on earnings. However, workers who are highly educated receive a higher premium when moving from an FCF to a non-FCF. Pesola (2011) also highlights that while both Martins (2011) and Balsvik (2011) found that workers with FCF experience earn higher wages than their co-workers, Martins (2011) concluded that workers moving from FCFs to non-FCFs take a pay cut, and Balsvik (2011) observed a pay increase following migration.

Blasvik (2011) used LEED from the manufacturing sector in Norway and found a positive correlation between the share of workers with FCF experience in non-FCFs and the productivity of these firms. Beyond finding a positive wage spillover, workers with FCF experience contribute 20% more to the productivity of their plant than workers without such experience, after controlling for differences in unobservable worker characteristics. Poole (2013) used LEED in the manufacturing and services sectors in Brazil and also found that workers in firms with a higher share of workers with FCF experience earn higher wages compared to identical workers in firms that either do not have FCF-experienced workers or have a low share of FCF-experienced workers.

Using firm-level panel data from Chinese manufacturing firms over the period 2004–2007, Huang and Zhang (2017) found that the size of the wage gap between local and foreign-owned firms had an impact on FDI spillovers in terms of TFP. They found that there is a low threshold below which FDI spillovers are significantly negative and a high threshold beyond which local firms receive positive FDI spillovers, thus indicating that both negative and positive spillovers are possible. Setzler and Tintelnot (2021) used linked employer–employee panel data from the US between 1999 to 2017 to analyse foreign multinationals. They found that these firms pay a 7% wage premium on average; however, they found a larger wage premium for high-skilled workers and no premium for the lowest decile of skilled worker. They also found that domestically owned and foreign-owned multinationals have similar premia.

In South Africa, Hlatshwayo et al. (2019) explored productivity spillovers for exporters, R&D tax incentives and expenditure, and training expenditure, using the SARS–NT panel. Their results show strong evidence of productivity spillovers through worker mobility in the South African labour market. They also found that, unlike more advanced economies, negative spillovers can occur. Further, South African workers are, on average, more likely to move from low-productivity to high-productivity firms, thus reducing the average productivity of the receiving firms. This could be attributable to significant skills shortages in the South African labour market. Sørensen (2020) found robust evidence that FDI boosts the top-line export complexity in South African manufacturing firms.

His study estimated horizontal,[43] forward[44] and backward[45] spillovers and only found evidence of positive and significant forward spillovers for top-line exports. However, it did not explore potential productivity spillovers from FDI, which is what this chapter explores through the worker mobility channel.

4.3 Descriptive statistics

This chapter uses the merged IRP5 and CIT data as well as the FCF definition outlined in Chapter 3. However, in this chapter both domestic and foreign FCFs are defined as FCFs, as is the case in other studies in the literature (Temouri et al., 2008; Balsvik, 2011; Hakkala & Sembenelli, 2017).

The number of FCFs in the sample declined from 4679 in 2013 to 4237 in 2016, while the number of workers in these firms increased from 184,570 in 2013 to 214,955 in 2016. The number of non-FCFs and the number of workers in non-FCFs decreased over the period. The median and mean firm sizes for FCFs are higher than for non-FCFs; however, both increased between 2013 and 2016 (see **Table 4-1**).

Table 4-1: Number of workers and firms and firm size in FCFs and non-FCFs

	Number of firms		Number of individuals		Median firm size		Mean firm size	
	FCF	**Non-FCF**	**FCF**	**Non-FCF**	**FCF**	**Non-FCF**	**FCF**	**Non-FCF**
2013	4679	13,284	184,570	525,590	144	128	311	268
2014	4810	13,769	191,269	549,695	146	131	317	246
2015	4548	13,568	192,913	573,335	156	132	348	245
2016	4237	13,015	214,955	520,152	169	131	317	284

Source: SARS–NT panel (own calculations)
Note: full sample

Over the period 2013–2016, food products, fabricated metals, and rubber & plastic products had the highest number of firms, output and employment (see **Table 4-2**).

On average, a quarter of the companies in each subsector are FCFs. In the tobacco products, coke & refined petroleum, motor vehicles, and other transport equipment subsectors, FCFs account for more than 40% of employment. In the tobacco products, motor vehicles, other transport equipment,

[43] Horizontal spillovers occur within an industry. Estimated as the share of output accounted for by foreign firms in industry j in province p in year t.

[44] Forward spillovers occur when the FCF is an upstream player and spillovers flow to the downstream. Weighted share of foreign firms in all sectors supplying inputs to industry j in province p at time t.

[45] Backward spillovers occur when the FCF is a downstream player and spillovers flow to the upstream. Weighted share of foreign firms in all sectors sourcing inputs from industry j in province p at time t.

machinery & equipment, chemicals & chemical products and pharmaceuticals & medical products subsectors, FCFs account for more than 40% of output.

Notably, although FCFs are fewer in number, they actually contribute a substantial proportion to output and employment across sectors. As such, there is much scope for mobility from FCFs to non-FCFs and even within sectors.

Table 4-2: Output by subsector, 2013–2016

	Average number of firms	Proportion FCFs	Average number of workers	Proportion FCF workers	Average total output (R'bn)	Proportion FCF output
Manufacturing of food products	1 235	23%	80 240	17%	85,4	21%
Manufacturing of beverages	354	16%	19 438	21%	18,7	24%
Manufacturing of tobacco products	26	33%	343	43%	0,7	58%
Manufacturing of textiles	803	25%	37 369	27%	23,0	33%
Manufacturing of wearing apparel	653	23%	36 478	23%	16,8	34%
Manufacturing of leather and related products	217	21%	11 106	25%	8,0	38%
Manufacturing of wood and wood of product	1 083	26%	32 718	29%	16,8	29%
Manufacturing of paper and paper product	456	27%	20 357	22%	18,4	29%
Printing and reproduction of recorded media	671	24%	15 086	17%	11,1	16%
Manufacture of coke and refined petroleum	123	23%	16 062	47%	9,5	14%
Manufacture of chemicals and chemical products	950	25%	29 345	32%	45,8	45%
Manufacture of pharmaceuticals, medicinal products	331	24%	11 859	25%	14,7	42%
Manufacture of rubber and plastic products	1 413	26%	46 894	26%	50,0	32%
Manufacture of other non-metallic minerals	443	22%	19 969	18%	14,7	26%
Manufacture of basic metals	1 024	25%	33 214	28%	34,7	21%
Manufacture of fabricated metal products	2 560	24%	73 316	28%	62,9	33%
Manufacture of computer, electronic and optical products	297	23%	6 807	36%	7,6	36%
Manufacture of electrical equipment	774	24%	25 426	28%	26,7	36%
Manufacture of machinery and equipment	1 418	25%	36 485	31%	42,2	41%
Manufacture of motor vehicles, trailers and semi-trailers	361	28%	23 657	44%	22,3	54%
Manufacture of other transport equipment	231	28%	10 884	42%	12,4	55%
Manufacture of furniture	753	24%	23 161	21%	11,1	26%
Other manufacturing	3 935	23%	116 335	26%	96,4	31%
Repair and installation of machinery and equipment	1 053	25%	15 427	24%	11,0	29%

Source: SARS–NT panel (own calculations)
Note: full sample

Table 4-3 presents the mean values of the main variables in the chapter. The mean values for FCFs and non-FCFs are compared through a t-test of the mean differences reported in column 3. Mean worker and firm characteristics show that FCFs pay higher wages, employ older workers, and have a longer tenure, a larger firm size, higher output, and higher capital and cost of sales. Further, FCFs have higher firm and worker fixed effects as well as a higher share of workers with FCF experience.[46] Non-FCFs have a higher share of workers with non-FCF experience.

[46] The share of workers with FCF experience is discussed in section 4.5. It is calculated as the number of workers in a non-FCF with FCF experience divided by the total number of employees in the firm. The same is done for the share of workers with non-FCF experience. Thus, the share of FCF and non-FCF workers does not come to 1.

Table 4-3: T-test of mean differences between key variables for non-FCFs and FCFs

Mean	Non-FCF	FCF	Difference
Log monthly wage	8.730728	8.966659	-0.2359311***
Log output	17.74117	18.1547	-0.4135337***
Log capital	15.37821	15.89372	-0.5155098***
Log cost of sales	17.26127	17.66743	-0.4061601***
Log labour	4.593581	4.715488	-0.1219069***
Firm fixed effects	0.2295125	0.3200297	-0.0905172***
Worker fixed effects	5.888068	6.017432	-0.1293639***
Share FCF	0.033725	0.2876774	-0.2539523***
Share non-FCF	0.0566888	0.0354177	0.0212711***
Firm size	260.93	324.03	-63.09441***
Tenure	3.104019	3.124454	-0.0204346***
Age	36.77904	37.23454	-0.4554985***

*** p<0.01, ** p<0.05, * p<0.1

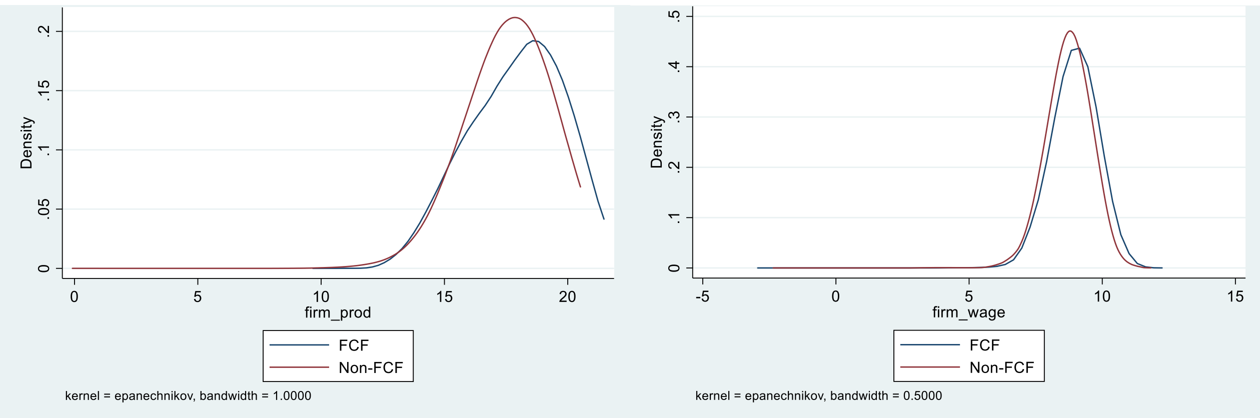
Source: SARS–NT panel (own calculations)
Note: full sample

4.4 Wage premium

4.4.1 Do FCFs pay a wage premium compared to non-FCFs?

The k-density of log monthly wages for non-FCFs and FCFs are used to understand the distribution of wages at both the individual and firm levels. At the firm level, k-densities for firm level output and wages are presented in **Figure 4-1**. These graphs indicate that FCFs have higher productivity measured as log output and they pay higher average wages.

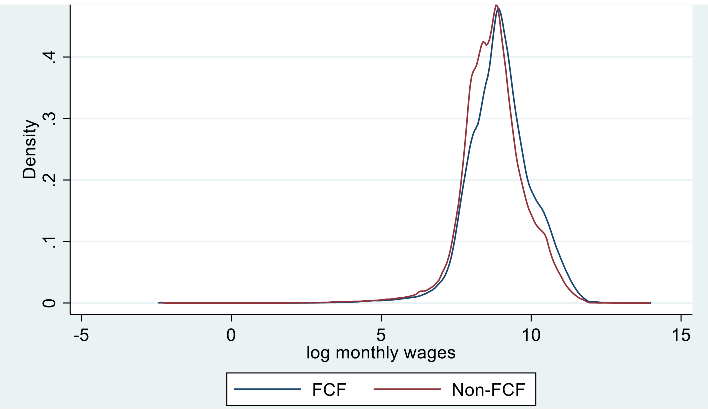
Figure 4-1: (a) Firm-level productivity (log output) and (b) Firm-level wages (log monthly wage)



Source: SARS–NT panel (own calculations)
Note: full sample

At the individual level, the k-density for wages indicates that non-FCF wages are slightly to the left of those of FCFs, which means that non-FCFs pay lower wages at the top and bottom of the distribution. **Figure 4-2** below uses data from 2014; however, this trend is the same across all the years in the panel. This k-density and the t-test for wages (see **Table 4-3** above) show that, on average, FCFs pay higher wages than non-FCFs.

Figure 4-2: Individual monthly wages, 2014



Source: SARS–NT panel (own calculations)
Note: full sample

OLS and quantile regressions on individual wages are used to estimate the wage premium with the following wage equation:

$$W_{it} = \beta_0 + \beta_1 \mathrm{FCF}_{j(i,t)} + \beta_2{}' X_{it} + \beta_3{}' F_{j(i,t)} + \mathrm{v}_t + \mathrm{v}_{ind} + \varepsilon_{it} \quad (1)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the log monthly wage;
- $\mathrm{FCF}_{j(i,t)}$ is a dummy variable indicating FCFs;
- X_{it} is a vector with K-observable characteristics, i.e. age, age squared, age cubed, gender and tenure;
- $F_{j(i,t)}$ is a vector firm characteristic, i.e. firm size and output per worker;
- v_{ind} industry dummy;
- v_t year dummies; and
- ε_{it} is the idiosyncratic error term.

The results from estimating equation 1 are shown in **Table 4-4** below. When controlling for year and industry dummies, the FCF wage premium is 16.1%, which declines to 15.7% when controlling for firm characteristics and 14.7% when controlling for both worker and firm characteristics.

The quantile wage regressions estimate a higher wage premium as one moves up the distribution from 7.42% in the 25th quantile to 14.4% in the 75th quantile, when controlling for worker and firm characteristics (see columns 3 to 6 in **Table 4-4**). This shows that the wage premia are highest at the top end of the wage distribution, which could indicate that the premium is greatest among high-skilled workers or management. This finding is similar to that of Mion and Opromolla (2014) who found that spillovers are likely to be higher for managers in exporting firms.

Table 4-4: Wage premium and quantile wage regression in FCFs

Log real monthly wages	No characteristics	Firm characteristics	Firm and worker characteristics	25th	50th	75th
FCF	0.161**	0.157**	0.147**	0.0742**	0.101**	0.144**
	(0.00131)	(0.00134)	(0.00124)	(0.00120)	(0.00116)	(0.00168)
Firm characteristics	No	Yes	Yes	Yes	Yes	Yes
Worker characteristics	No	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,991,079	2,821,595	2,821,595	2,821,595	2,821,595	2,821,595
R-squared	0.151	0.129	0.258			

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Within-firm standard deviations of wages are estimated using an OLS regression on the following wage equation:

$$W_{it} = \beta_0 + \beta_1 \mathrm{FCF}_{j(i,t)} + \beta_2' F_{j(i,t)} + \mathrm{v}_t + \mathrm{v}_{ind} + \varepsilon_{it} \qquad (2)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the std. dev of log monthly wage/mean log monthly firm wage;
- $\mathrm{FCF}_{j(i,t)}$ is a dummy variable indicating FCFs;
- $F_{j(i,t)}$ is a vector firm characteristic, i.e. firm size and output;
- v_{ind} industry dummy;
- v_t year dummies; and
- ε_{it} is the idiosyncratic error term.

The within-firm wage dispersion of FCFs relative to non-FCFs is 0.6%, which suggests that FCFs are slightly higher than non-FCFs on the wage distribution (see **Table 4-5**). However, the dispersion is slightly lower than one would expect.

Table 4-5: Within-firm standard deviation of wages

Std. dev (log monthly wage)	No characteristics	Firm size	Firm size and output
FCF	0.00845**	0.00731**	0.00674**
	(0.000352)	(0.000352)	(0.000368)
firmsize 10-49		0.0245**	0.00612**
		(0.000834)	(0.000871)
firmsize 50-99		0.0402**	0.00656**
		(0.000863)	(0.000948)
firmsize 100-499		0.0663**	0.0157**
		(0.000814)	(0.000976)
firmsize 500-999		0.0873**	0.0270**
		(0.000909)	(0.00113)
firmsize 1000-49999		0.0608**	0.00281*
		(0.00101)	(0.00130)
lnoutput			0.0148**
			(0.000148)
Year dummies	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes
Observations	2,988,077	2,988,077	2,829,244
R-squared	0.057	0.063	0.066

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

The wage premia estimated up to this point do not control for unobservable worker and firm characteristics or worker and firm fixed effects. As such, in the next section, unobservable worker and firm fixed effects are estimated and included in all estimations for the rest of the chapter.

4.4.2 Controlling for unobserved worker and firm fixed effects

The OLS regressions in the previous section do not control for unobserved worker and firm fixed effects, which is likely to overestimate the wage premia. Controlling for unobserved firm and worker fixed effects captures the unobservable characteristics that may explain the wage premium by FCFs if, for example, they have a selection bias towards more productive, skilled[47] and motivated employees. It also captures unobservable differences between non-FCFs and FCFs (such as the management structure or ability), which allow FCFs to pay higher wages.

[47] One of the limitations of the SARS-NT data is that a worker's skills cannot be identified in the data. Skills are likely to change over time, which means they are not controlled for by the unobserved worker fixed effects. The implication of this is that we might be overestimating the wage premium for certain individuals.

The unobserved worker and firm fixed effects are estimated using the AKM methodology, with the inclusion of observable firm characteristics. The following fixed effect model is estimated:

$$W_{it} = \beta_0 + \beta_1 \mathrm{FCF}_{j(i,t)} + \beta_2{}' X_{it} + \beta_3{}' F_{j(i,t)} + \mathrm{v}_i + \mathrm{v}_{j(i,t)} + \mathrm{v}_t + \varepsilon_{it} \qquad (3)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the log monthly wage;
- $\mathrm{FCF}_{j(i,t)}$ is the variable indicating both foreign and domestically owned FCFs;
- X_{it} is a vector with K-observable characteristics, i.e. age, age squared, age cubed, gender and tenure;
- $F_{j(i,t)}$ is a vector firm characteristic, i.e. firm size and output per worker;
- v_i is the worker fixed effect;
- $\mathrm{v}_{j(i,t)}$ is the firm fixed effect;
- v_t year dummies; and
- ε_{it} is the idiosyncratic error term.

The underlying assumption is that the error term is orthogonal to all regressors and to the worker and firm fixed effects (Abowd et al., 1999). This implies strict exogeneity, which means that workers' mobility decisions are independent of ε_{it}.

To estimate equation 3, the grouping algorithm (conjugate gradient) from Abowd et al. (2002) is used, based on the fixed effects model and least squares dummy variable model by Cornelissen (2008). When estimating individual and firm fixed effects, it should be noted that only firms connected by worker mobility will have an estimate, i.e. only connected groups of firms that have had workers move to another firm can have fixed effects estimated. There are 25,407 unique firms and 1,291,724 individuals[48] (i.e. all manufacturing firms over all the years in the panel). Most of the workers in the panel appear only once, i.e. they are only in the panel for one year. Approximately 20% are seen four times in the sample, while only 0.23% are seen six times or more (see **Table 4-6**).

Table 4-6: Number of observations per worker

	1	2	3	4	5	6 or more
Frequency	529,514	287,691	201,532	257,051	13,040	2896
%	40.99	22.27	15.60	19.90	1.01	0.23

Source: SARS–NT panel (own calculations)
Note: full sample

[48] These figures differ from Chapter 2 because they only capture firms that can be linked to the CIT data. This results in a smaller sample.

There is very little movement in the sample, with only 7.28% of the workers having more than two employers (see **Table 4-7**). However, the panel only has four years of observations, and the results apply to the manufacturing sector.

Table 4-7: Number of firms in which a worker is employed

	1	2	3	4 or more
Frequency	1,197,686	85,908	7,097	1,033
%	92.72	6.65	0.55	0.08

Source: SARS–NT panel (own calculations)
Note: full sample

The largest connected group of firms (i.e. connected by worker mobility) is used in the analysis, which has 1,205,284 workers and 15,870 firms which are connected by 93,291 movers (see **Table 4-8**).

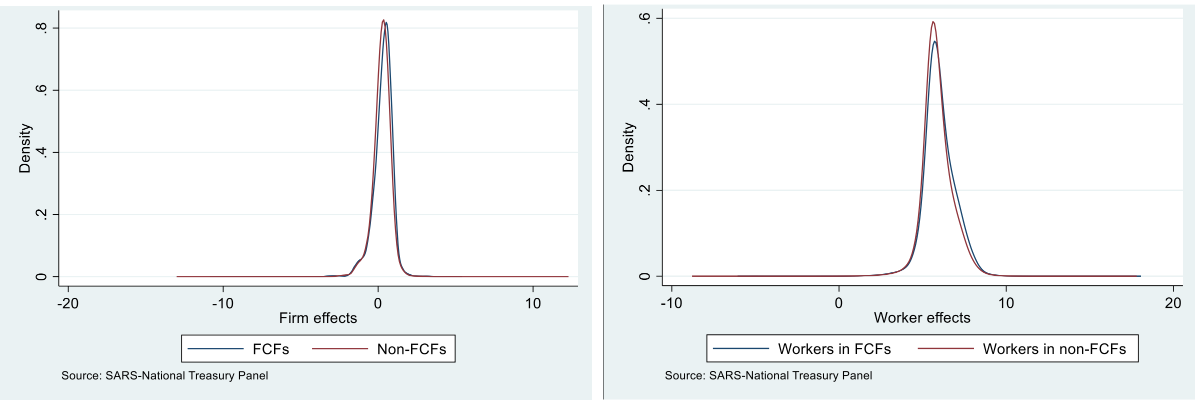
Table 4-8: Sample sizes of all groups and the largest connected group

	Number of workers	Number of firms	Number of movers	Number of groups	Number of estimable effects
All groups	1,291,724	25,407	94,038	312	16,228
Largest connected group (our sample for the rest of the chapter)	1,205,284	15,870	93,291	-	-

Source: SARS–NT panel (own calculations)

The distribution of the estimated worker and firm fixed effects across FCFs and non-FCFs is shown in **Figure 4-3**, using k-density graphs. The worker and firm fixed effects for non-FCFs are slightly to the left of the FCFs, which is consistent with the wage premium for FCFs and positive worker selection into FCFs.

Figure 4-3: (a) Firm fixed effects and (b) Worker fixed effects



Source: SARS–NT panel
Note: sample–largest connected group

Following Balsvik (2011), the estimated worker and firm fixed effects are regressed on the FCF dummy and two-digit industry dummies instead of the five-digit used in the Balsvik study. This fixed effect regression indicates that FCFs pay higher wages compared to non-FCFs when unobserved heterogeneity is also accounted for. There is a significant firm wage premium of 5.3% (see **Table 4-9**) and a significant 10.1% (see **Table 4-10**) worker wage premium. The FCF premium of 5.3% in South Africa is slightly higher than foreign firms in Norway at 3.5% (Balsvik, 2011) and Sweden at 2% (Heyman et al., 2007).

When the sample is divided into above and below the median firm size, the median firm size across all years of the panel is 137. As such, firms below the median are also referred to as small firms. There is a positive and significant FCF wage premium (10.9%) for firms above the median and a negative FCF wage premium for firms below the median (–1.61%). This indicates the heterogeneity across firm size.

Table 4-9: Unobserved firm fixed effects

	All	Above median firm size	Below median firm size
FCF	0.0530**	0.109**	-0.0161**
	(0.000758)	(0.000951)	(0.00119)
Industry dummies	Yes	Yes	Yes
Observations	2,642,113	1,320,523	1,321,590
R-squared	0.111	0.190	0.070

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

There is a significant positive FCF worker wage premium in firms above and below the median. However, there is a lower FCF premium in small firms (i.e. below the median).

Table 4-10: Unobserved worker fixed effects

	All	Above median firm size	Below median firm size
FCF	0.101**	0.163**	0.0302**
	(0.00124)	(0.00164)	(0.00176)
Industry dummies	Yes	Yes	Yes
Observations	2,642,113	1,351,304	1,470,291
R-squared	0.047	0.068	0.028

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

The existence of an FCF wage premium indicates that there is potential for spillovers between workers moving from FCFs to non-FCFs. The rest of the chapter seeks to establish whether having workers move from FCFs to non-FCFs generates any productivity spillovers for the non-FCFs in terms of productivity.

4.5 Productivity spillovers

4.5.1 Worker mobility between FCFs and non-FCFs

This section examines whether workers with FCF experience have an impact on the productivity of their plants. Balsvik (2011) found a positive correlation between the share of workers with FCF experience in non-FCFs and the productivity of these plants, as well as a higher wage premium with the length of tenure from the FCF. In this chapter, both the existence of productivity spillovers and the existence of a wage premium when workers from FCFs move to non-FCFs are explored.

Table 4-11: Worker mobility between FCFs and non-FCFs

	FCF to FCF	Non-FCF to non-FCF	Non-FCF to FCF	**FCF to non-FCF**
2013	952	7416	1713	**1818**
2014	1934	14,521	3365	**3581**
2015	3144	19,930	5880	**4957**
2016	3579	23,230	5324	**5996**

Source: SARS–NT panel (own calculations)
Note: sample–largest connected group

The extent of mobility between FCFs and non-FCFs needs to be quantified. The main interest is in workers moving from FCFs to non-FCFs because these are the workers who will be able to transfer spillovers from what they have learnt in the FCFs to the non-FCFs. There is a fair amount of movement from FCFs to non-FCFs and the level of movement is increasing over time (see **Table 4-11**). There is also a great deal of movement within FCFs and non-FCFs.

The next step is to find out what share of workers in non-FCFs have FCF experience. FCF experience is defined as having worked for an FCF for one or more of the last two years. Balsvik (2011) used the last three years, but the last two years are used in this study owing to the length of the panel, which is only four years compared to their 11-year panel. The number of workers in a non-FCF with FCF experience are counted and then divided by the total number of employees in the firm. The same is done with the share of workers with non-FCF experience.

In 2014, 4% of the workers, on average, employed in non-FCFs had FCF experience (see column 1 in **Table 4-12**). This fell to 3.4% in 2016. This is higher than the share of non-FCFs with FCF-experienced workers in the Balsvik (2011) study, which found 1% in 1993 and a subsequent increase to 2.7% in 2000. The proportion of non-FCFs employing workers with FCF experience increased from 59.3% 61.3% between 2014 and 2016. This is relatively high compared to Balsvik (2011) who saw an increase from 11.4% in 1993 to 28.1% in 2000. Notably, the time periods being compared are different.

Table 4-12: Share of workers in non-FCFs with FCF experience and proportion of non-FCFs employing workers with FCF experience

	Share of workers in non-FCFs with FCF experience	**Proportion of non-FCFs employing workers with FCF experience**
2014	4.03	59.30
2015	2.70	60.28
2016	3.40	61.30

Source: SARS–NT panel (own calculations)
Note: sample–largest connected group

4.5.2 Methodology

In this section, the production function established in Balsvik (2011) is used to estimate the productivity spillovers. FCF spillovers are defined as the relationship between a non-FCF's productivity and the share of FCF-experienced workers in non-FCFs. There are three types of labour: incumbent workers (L_{inc}), newly hired workers from FCFs (L_{FCF}) and newly hired workers from non-FCFs ($\mathrm{L}_{non-FCF}$), where L_{FCF} and $\mathrm{L}_{non-FCF}$ are weighted by a positive premium δ. Thus, with three types of labour, effective labour use (L^{*}) in the Cobb-Douglas production function is:

$$L^{*} = \mathrm{L}_{inc} + \mathrm{L}_{non-FCF}(\delta_n) + \mathrm{L}_{FCF}\left(\delta_f\right) = L\left(1 + \delta_n + \delta_f\right) \quad (4)$$

Spillovers occur when workers move between FCFs and non-FCFs. Thus, the share of new hires with FCF experience (s_{it}) as well as the share of newly hired workers with non-FCF experience in the total use of labour ($nons_{it}$) are included in the estimation. This makes it possible to measure a spillover as the differential impact of hiring a worker with FCF experience over hiring a worker with non-FCF experience. Thus, effective labour use, including the productivity premium and share of new hires, is:

$$L^{*} = L\left(1 + \delta_n + \delta_f\right) = L\left(1 + \delta_n(nons_{it}) + \delta_f\ (s_{it})\right) \quad (5)$$

In log-linear form, labour input L:

$$L = \beta_L \ln L + \beta_L \delta s + \beta_L \delta nons \quad (6)$$

Thus, the following Cobb-Douglas production function (in log-linear form) is estimated:

$$lnY_{it} = \beta_K lnK_{it} + \beta_C lnC_{it} + \beta_L lnL_{it} + \boldsymbol{\beta_L \delta s_{it}} + \boldsymbol{\beta_L \delta nons_{it}} + v_i + v_j + v_t + v_t * v_{ind} + \varepsilon_{it} \quad (7)$$

Where:

- ln Y, ln K, ln C and ln L are the natural logs of output, capital, cost of sales and days of weighted employment in plant i, year t;
- $\boldsymbol{s_{it}}$ is the share of new hired labour with FCF experience (main variable of interest - share_FCF);
- $\boldsymbol{nons_{it}}$ is the share of new hired labour with non-FCF experience (share_non_FCF);
- v_i worker fixed effects;
- v_j firm fixed effects;
- v_t year dummies;
- $v_t * v_{ind}$ time and industry interaction; and
- ε_{it} is the idiosyncratic error term.

The estimation of $\boldsymbol{s_{it}}$ requires FCF experience, which is defined as having worked for an FCF for one or more of the last two years. The workers in a non-FCF with FCF experience are counted and the number is divided by the total number of employees in the firm. The same is done with the share of workers with non-FCF experience. The main interest is the share of workers with FCF experience; thus, the regressions are restricted to workers moving from FCFs to non-FCFs.

Firm, worker and time fixed effects are included to capture any permanent differences in productivity levels between different industries and different workers. Time and industry interactions are also included in addition to the time/year dummies controlling for correlation between the share of workers with FCF experience at the firm level and any industry-specific business cycles or any average impact on all firms in a given year.

The analysis also includes running regressions across different dimensions (i.e. gender, wage quantiles and technology). However, equation 6 is used, summing across L (where L=male/female; low, med_low, med_high and high wage; low, med and high tech):

$$lnY_{it} = \beta_K lnK_{it} + \beta_C lnC_{it} + \beta_L lnL_{it} + \sum \boldsymbol{\beta_L \delta s_{it}} + \sum \boldsymbol{\beta_L \delta nons_{it}} + v_i + v_j + v_t + v_t * v_{ind} + \varepsilon_{it} \quad (8)$$

4.6 Empirical results

4.6.1 General spillovers

Table 4-13 presents the results from estimating equation 7. The variable and co-efficient of interest is that of the share of workers with FCF experience (share_FCF). As indicated in the previous section, FCF experience is defined as having worked for an FCF for one or more of the last two years. The workers in a non-FCF with FCF experience are counted and the number is divided by the total number of employees in the firm. The same is done with the share of workers with non-FCF experience. It is important to note that evidence of spillovers indicates that the presence of workers with previous FCF and non-FCF experience is correlated with higher productivity in the firms they move to. As a consistency check for the production function, the sum of the labour, capital and cost of sales coefficients comes to approximately 1, as expected in a Cobb-Douglas production function.

The results show a positive coefficient of 0.0239, which is significant at the 10% level when controlling for both worker and firm fixed effects (see column 1 in **Table 4-13**). When this is combined with the labour input coefficient, δ = 0.1741. This implies that job changers coming from FCFs contribute on average 17.41% more to the productivity of the firm than incumbent FCF workers. In Norway, δ was 27% (Balsvik, 2011).

The share of FCFs and non-FCFs are also interacted with labour and the co-efficient of the share of FCFs is found to be insignificant. This indicates that firm size plays a role in the explanation of spillovers. As such, the sample is divided into above and below the median firm size (see columns 2 and 3). The median firm size in these regressions is 138 workers. There is only evidence of spillovers from FCFs to non-FCFs below the median. When the size of the sending firms is included (see columns 3 and 4), there is strong evidence of spillovers from FCFs that are above the median firm size to non-FCFs, and there are significant negative spillovers from small FCFs to domestic firms. This indicates that spillovers from FCFs occur when workers with FCF experience move to a non-FCF (local/domestic firm) that is below the median firm size, i.e. small non-FCFs, and that these spillovers mainly occur through FCFs above the median firm size.

Table 4-13: Spillovers from new hires in non-FCFs

Log real output	All firms to non-FCF	All firms to above median firm size non-FCF	All firms to below median firm size non-FCF	Above median firms to non-FCF	Below median firms to non-FCF
lncapital	0.0770**	0.0839**	0.0723**	0.101**	0.0484**
	(0.00223)	(0.00315)	(0.00314)	(0.00328)	(0.00297)
lncos	0.654**	0.638**	0.671**	0.600**	0.725**
	(0.00293)	(0.00414)	(0.00421)	(0.00388)	(0.00432)
lnlab	0.198**	0.162**	0.206**	0.216**	0.161**
	(0.00390)	(0.00701)	(0.00714)	(0.00547)	(0.00556)
share_FCF	0.0239+	-0.0179	0.162**	0.0642**	-0.151**
	(0.0139)	(0.0184)	(0.0236)	(0.0171)	(0.0277)
share_non_FCF	0.131**	0.124**	0.0769*	0.120**	0.184**
	(0.0224)	(0.0354)	(0.0310)	(0.0372)	(0.0295)
significant productivity premium (δ)					
share_FCF	0,1741	none	0,044	0,1518	negative
share_non_FCF	0,067	0,038	0,1291	0,096	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	11,564	6,141	5,410	6,098	5,445
R-squared	0.949	0.918	0.919	0.947	0.952

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Contrary to Balsvik (2011), this study finds that hiring workers from non-FCFs also has positive spillovers for other non-FCFs, adding 6.7% to the productivity of the firm, which is significant at the 1% level (see column 1). When disaggregating by the median firm size, there is evidence of spillovers from non-FCF-experienced workers to non-FCFs both above and below the median. However, spillovers mainly come from non-FCFs that are above the median firm size. This result indicates that there are domestic firms that are productive and also have positive spillovers to other domestic firms. Notably, the spillovers between non-FCFs are small in magnitude but more significant than the coefficient from FCFs. Based on the findings in Chapter 3, trading firms (exporters and/or importers) account for the most employment in the sample (**Table 3-4**). In this chapter, trading firms are included as domestic firms. Thus, it is not surprising to find positive spillovers between non-FCFs, particularly when firms that are simultaneously exporters and importers are classified as local firms. Further, there is a great deal of worker mobility between non-FCFs. As such, their coefficients are more accurately estimated.

Table 4-14: Spillovers from new hires in FCFs

Log real output	Worker moving to FCFs Firm fixed effects	 Firm and worker fixed effects
lncapital	0.0462**	0.0445**
	(0.00261)	(0.00257)
lncos	0.648**	0.641**
	(0.00336)	(0.00333)
lnlab	0.237**	0.249**
	(0.00390)	(0.00390)
share_FCF	0.0539**	0.0681**
	(0.0134)	(0.0132)
share_non_FCF	0.0217	0.0214
	(0.0197)	(0.0194)
significant productivity premium (δ)		
share_FCF	0,1831	0,1809
share_non_FCF	none	none
Firm fixed effects	Yes	Yes
Worker fixed effects	No	Yes
Year dummies	Yes	Yes
Year-Industry dummies	Yes	Yes
Observations	11,991	11,991
R-squared	0.949	0.950

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Movement from non-FCFs to FCFs (i.e. the share of workers with non-FCF experience in FCFs) is also explored as a consistency check. There should not be any evidence of spillovers from movement in this direction, given the premia found in FCFs compared to non-FCFs. Estimating equation 7 for the share of non-FCF workers in FCFs confirms this theory as the share_non_FCF coefficient is not significant. There is no evidence of spillovers from non-FCF-experienced workers moving to FCFs. However, FCF-experienced workers coming from other FCFs contribute positively and significantly to the new FCFs' productivity (see **Table 4-14**).

Looking at the descriptive statistics as well as the results so far, there are fewer FCFs than non-FCFs, although FCFs contribute substantially to output and employment. Further, there is a wage premium for FCFs, which is higher at the top end of the distribution and higher in large firms. The fact that the wage premium is higher at the top end of the distribution suggests that high-skilled workers embody more productivity than lower-skilled workers. After controlling for both observed and unobserved worker and firm characteristics, the FCF wage premium is found to be positive for firms above the median firm size and negative for those below the median. The FCF worker wage premium is positive above and below the median firm size. However, the FCF worker premium above the median is higher than the premium of FCF workers below the median firm size. This indicates that there is heterogeneity across firm size. Finally, the results show that there is evidence of spillovers from workers moving from FCFs to non-FCFs and not the other way around. On average, there is evidence of spillovers from both FCFs to non-FCFs and between non-FCFs. However, when disaggregating by median firm size, only spillovers from FCFs to non-FCFs below the median remain, and there are spillovers from non-FCFs to non-FCFs below and above the median firm size. One potential explanation for this is the presence of trading firms in the classification of local firms, which highlights the important role played by domestically owned trading firms.

The results in this section have shown that there are spillovers from FCFs to non-FCFs. It is also important to explore whether there is any evidence of spillovers using different dimensions, such as gender, wage quantiles and technology.

4.6.2 Spillovers across different dimensions

In this section, the analysis focuses on whether there is any evidence of spillovers across other dimensions, such as gender, wages and technology levels. Only around a third of the movers in the manufacturing sector are female for both FCFs and non-FCFs. Further, there are fewer female FCF movers relative to female non-FCF workers (see

Table D-1 in Appendix C). There is evidence of spillovers from both male FCF- and non-FCF-experienced workers when they move to non-FCFs. However, there is no evidence of spillovers from female FCF-experienced workers. The gender difference could indicate the different types of jobs held by males and females in the manufacturing sector. It is also possible that male workers could have the types of jobs where spillovers are more likely to occur – for example, males might work on a production line whereas females might have cleaning jobs where spillovers are more difficult. The coefficient for female non-FCF workers is higher than the labour coefficient, which is likely due to the standard deviation of the estimate. However, this is taken to indicate a significant premium of zero (see column 1 in **Table 4-15**).

Disaggregating by above and below the median firm size (columns 2 and 3 in **Table 4-15**), there is evidence that positive spillovers from FCF-experienced male workers are only in domestic firms below the median firm size. The results also find evidence of spillovers from female FCF workers to non-FCFs below the median. Further, spillovers mainly occur from male workers in FCFs that are above the median firm size. There are negative spillovers from male and female FCF workers coming from FCFs below the median firm size. Hlatshwayo et al. (2019) found that negative spillovers occur in South Africa and that, on average, workers are more likely to move from low-productivity to high-productivity firms, which lowers the average productivity of the receiving firm. This is likely due to the significant skills deficit in the South African labour market as well as the low level of generalpurpose/soft-technology worker capabilities. As such, an important mechanism for technology transfers in the future may therefore be driven by investments in firm-level training initiatives.

After disaggregating, the premium for non-FCF male workers is not significant for non-FCFs below and above the median. However, non-FCF female workers have a positive premium in firms below the median. There is evidence of positive spillovers from female and male workers in non-FCFs above the median firm size and a zero premium for male and female non-FCF workers in domestic firms below the median. The most robust productivity spillovers come from male FCF workers; these spillovers remain for non-FCFs below the median and come from FCFs above the median.

Table 4-15: Spillovers to non-FCFs controlling for human capital: gender

Log real output	All firms to non-FCF	All firms to above median firm size non-FCF	All firms to below median firm size non-FCF	Above median firms to non-FCF	Below median firms to non-FCF
lncapital	0.0771**	0.0844**	0.0721**	0.101**	0.0486**
	(0.00223)	(0.00316)	(0.00315)	(0.00329)	(0.00297)
lncos	0.654**	0.638**	0.672**	0.600**	0.724**
	(0.00293)	(0.00414)	(0.00423)	(0.00387)	(0.00433)
lnlab	0.197**	0.160**	0.205**	0.216**	0.161**
	(0.00392)	(0.00704)	(0.00715)	(0.00548)	(0.00559)
share_FCF_male	0.0449**	0.00335	0.183**	0.0917**	-0.157**
	(0.0157)	(0.0206)	(0.0263)	(0.0188)	(0.0321)
share_FCF_female	-0.0333	-0.0818**	0.0981*	-0.0236	-0.128**
	(0.0251)	(0.0306)	(0.0459)	(0.0301)	(0.0473)
share_non_FCF_male	0.0936**	0.0514	0.0492	0.0931*	0.173**
	(0.0258)	(0.0441)	(0.0348)	(0.0416)	(0.0352)
share_non_FCF_female	0.220**	0.241**	0.159**	0.181**	0.214**
	(0.0398)	(0.0532)	(0.0616)	(0.0694)	(0.0495)
productivity premium (δ)					
share_FCF_male	0,1521	none	0,022	0,1243	negative
share_FCF_female	none	negative	0,1069	none	negative
share_non_FCF_male	0,1034	none	none	0,1229	0
share_non_FCF_female	0	0	0,046	0,035	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	11,564	6,141	5,410	6,098	5,445
R-squared	0.949	0.919	0.919	0.948	0.952

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

In the absence of education in the data, human capital is controlled for by estimating equation 8 using the share of workers with FCF experience by wage quantiles. Thus, the analysis now focuses on spillovers across wage quantiles. On a monthly basis, low-wage workers earn less than R3545.49, low medium-wage workers earn between R3545.49 and R6526.38, medium high-wage workers earn between R6526.38 and R11 883.37, and high-wage workers earn more than R11 883.37. The number of movers by wage quantiles can be found in **Table D-2** in Appendix C.

Table 4-16: Spillovers to non-FCFs controlling for human capital: wage quantiles

Log real output	All firms to non-FCF	All firms to above median firm size non-FCF	All firms to below median firm size non-FCF	Above median firms to non-FCF	Below median firms to non-FCF
lncapital	0.0768**	0.0835**	0.0710**	0.100**	0.0474**
	(0.00223)	(0.00315)	(0.00314)	(0.00330)	(0.00297)
lncos	0.655**	0.636**	0.675**	0.601**	0.725**
	(0.00294)	(0.00416)	(0.00423)	(0.00390)	(0.00433)
lnlab	0.198**	0.162**	0.198**	0.216**	0.158**
	(0.00391)	(0.00702)	(0.00722)	(0.00548)	(0.00557)
share_FCF_low	-0.0271	0.0132	-0.0191	0.0366	-0.232**
	(0.0296)	(0.0337)	(0.0652)	(0.0340)	(0.0658)
share_FCF_low_med	-0.0500*	-0.00608	-0.0408	0.0233	-0.312**
	(0.0254)	(0.0307)	(0.0458)	(0.0296)	(0.0523)
share_FCF_med_high	0.0843**	-0.0410	0.358**	0.123**	-0.105*
	(0.0252)	(0.0331)	(0.0430)	(0.0297)	(0.0486)
share_FCF_high	0.0537*	-0.0320	0.182**	0.0653*	-0.0906+
	(0.0240)	(0.0332)	(0.0360)	(0.0279)	(0.0481)
share_non_FCF_low	0.0990	-0.0959	0.194*	0.159	0.130
	(0.0689)	(0.103)	(0.0972)	(0.102)	(0.0923)
share_non_FCF_low_med	0.0671	0.115	0.0590	0.0828	0.0533
	(0.0508)	(0.0789)	(0.0680)	(0.0808)	(0.0642)
share_non_FCF_med_high	0.126**	0.223**	-0.0942+	0.157*	0.201**
	(0.0338)	(0.0538)	(0.0508)	(0.0611)	(0.0482)
share_non_FCF_high	0.113**	0.0824	0.0828	0.0883	0.151**
	(0.0381)	(0.0579)	(0.0526)	(0.0552)	(0.0523)
productivity premium (δ)					
share_FCF_low	none	none	none	none	negative
share_FCF_low_med	negative	none	none	none	negative
share_FCF_med_high	0,1137	none	0	0,093	negative
share_FCF_high	0,1443	none	0,016	0,1507	negative
share_non_FCF_low	none	none	0,004	none	none
share_non_FCF_low_med	none	none	none	none	none
share_non_FCF_med_high	0,072	0	negative	0,059	0
share_non_FCF_high	0,085	none	none	none	0,007
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	11,564	6,141	5,410	6,098	5,445
R-squared	0.949	0.919	0.920	0.948	0.952

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

On average, there is evidence of positive productivity spillovers from both medium high- and high-wage workers with FCF and non-FCF experience. However, the productivity premium from FCF-experienced workers is higher at 11.37% for medium high-wage workers and 14.43% for high-wage workers compared to non-FCF medium high-wage workers at 7.2% and high wage workers at 8.5% (see column 1 in **Table 4-16**). However, there are significant negative spillovers from FCF low medium-wage workers. Disaggregating by above and below the median firm size reveals positive spillovers for high-wage workers moving to non-FCFs below the median and a zero premium for medium high-wage workers. There is also evidence of spillovers from high-wage and medium high-wage FCF workers moving from FCFs above the median firm size. On average, there is only evidence of spillovers from medium high-wage and high-wage non-FCF workers. Medium high-wage non-FCF workers moving to other non-FCFs below the median have significant positive spillovers as well as high-wage workers from non-FCFs below the median.

These results suggest that low-wage workers, whether from FCFs or non-FCFs, have similar skills levels and do not significantly affect the productivity of the non-FCF they are joining. They learn their new tasks quickly and are easily absorbed into the new firm. Medium high- and high-wage workers from FCFs and non-FCFs increase the productivity of the non-FCFs they are joining. This could indicate that higher-wage workers have similar characteristics, whether they work in an FCF or a non-FCF. As such, both types of workers add to the productivity of the firm. This supports the earlier finding of a higher wage premium at the top end of the distribution. Notably, the most robust spillovers are from high-wage FCF workers; these hold when they move to non-FCFs below the median and when they come from FCFs that are above the median.

The United Nations Industrial Development Organization (UNIDO) manufacturing sector technology intensity definition is used to create a technology indicator.[49] The International Standard Industrial Classification (ISIC) 4 industry classifications are used to group them by technology intensity – for example, low-tech industries include clothing & textiles and food products; medium-tech industries include rubber & plastic products and base metals; and high-tech industries include chemical products and motor vehicles.[50]

On average, there are significant positive productivity spillovers (greater than zero) for workers from medium-technology FCFs (see column 1 in **Table 4-17**). There are negative spillovers from low- and high-technology FCFs as well as low-technology non-FCFs. Notably, on average, there are no spillovers between non-FCFs. When disaggregating by median firm size, there is only evidence of

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[49] https://stat.unido.org/content/learning-center/classification-of-manufacturing-sectors-by-technological-intensity-%28isic-revision-4%29;jsessionid=4F51485549B935DF0EBB431975AB7E15

[50] Medium high and high technology (high): Chemicals and chemical products; Pharmaceuticals; Computer, electronic and optical products; Machinery and equipment n.e.c.; Motor vehicles, trailers and semi-trailers; Other transport equipment except ships and boats. Medium technology: Rubber and plastics products; Other non-metallic mineral products; Basic metals; Other manufacturing except medical and dental instruments; Repair and installation of machinery and equipment. Low technology: Food products; Beverages; Tobacco products; Textiles; Wearing apparel; Leather and related products; Wood and products of wood and cork; Paper and paper products; Printing and reproduction of recorded media; Coke and refined petroleum products; Fabricated metal products except weapons and ammunition; Furniture.

positive non-zero spillovers from medium- and high-technology non-FCFs to non-FCFs above the median. There is also evidence of spillovers from high-technology non-FCFs above the median. In terms of FCFs, there is only evidence of spillovers from medium- and low-technology FCFs above the median to non-FCFs.

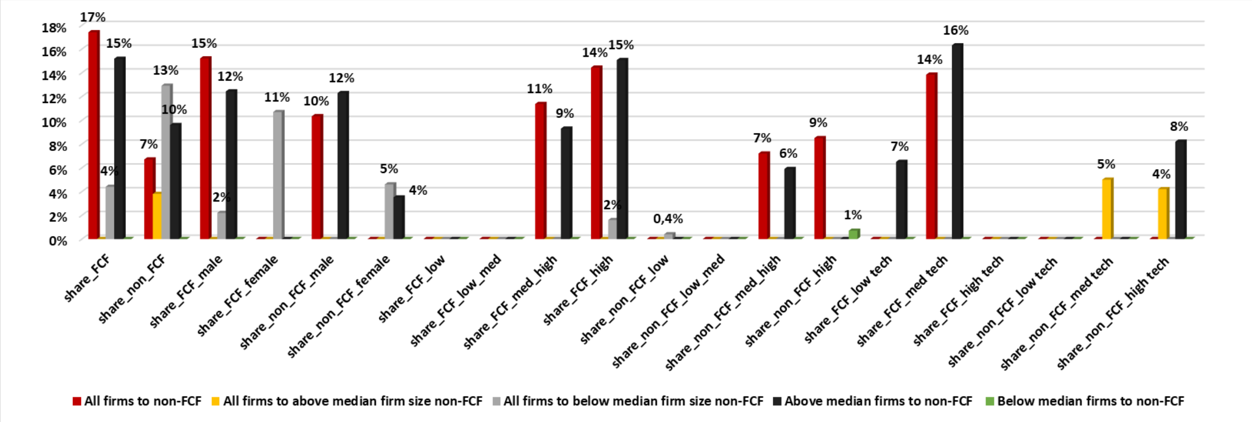
Table 4-17: Spillovers to non-FCFs controlling for human capital: technology

Log real output	All firms to non-FCF	All firms to above median firm size non-FCF	All firms to below median firm size non-FCF	Above median firms to non-FCF	Below median firms to non-FCF
lncapital	0.0744**	0.0855**	0.0569**	0.0987**	0.0467**
	(0.00226)	(0.00315)	(0.00313)	(0.00335)	(0.00298)
lncos	0.655**	0.633**	0.690**	0.600**	0.723**
	(0.00295)	(0.00417)	(0.00421)	(0.00395)	(0.00433)
lnlab	0.196**	0.161**	0.194**	0.216**	0.159**
	(0.00394)	(0.00701)	(0.00702)	(0.00552)	(0.00558)
share_FCF_low tech	-0.0657*	0.252**	-0.170**	0.151**	-0.245**
	(0.0310)	(0.0502)	(0.0411)	(0.0438)	(0.0435)
share_FCF_med tech	0.0576**	-0.0544**	0.700**	0.0529**	-0.0662
	(0.0165)	(0.0189)	(0.0378)	(0.0187)	(0.0497)
share_FCF_high tech	-0.106**	0.485**	-0.183**	0.0319	-0.230**
	(0.0333)	(0.0925)	(0.0362)	(0.0479)	(0.0460)
share_non_FCF_low tech	-0.0795+	0.0488	-0.0412	-0.0920	-0.0559
	(0.0408)	(0.0680)	(0.0506)	(0.0609)	(0.0528)
share_non_FCF_med tech	0.207**	0.111+	-0.267**	0.268**	0.203**
	(0.0328)	(0.0618)	(0.0476)	(0.0531)	(0.0531)
share_non_FCF_high tech	0.217**	0.119*	0.271**	0.134+	0.271**
	(0.0385)	(0.0533)	(0.0541)	(0.0704)	(0.0466)
productivity premium (δ)					
share_FCF_low tech	negative	0	negative	0,065	negative
share_FCF_med tech	0,1384	negative	0	0,1631	none
share_FCF_high tech	negative	0	negative	none	negative
share_non_FCF_low tech	negative	none	none	none	none
share_non_FCF_med tech	0	0,05	negative	0	0
share_non_FCF_high tech	0	0,042	0	0,082	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	11,564	6,141	5,410	6,098	5,445
R-squared	0.949	0.920	0.925	0.948	0.952

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

The negative coefficients and lack of spillovers from high-technology FCF worker spillovers could be due to the low number of movers in this category relative to the others. High-technology FCFs have the lowest number of movers from FCFs to non-FCFs (see **Table D-3** in Appendix C). Further, spillovers are only possible based on the absorptive capacity of the local firms (Fosfuri et al., 2001). As such, high-technology FCFs might be using technology that is very advanced and difficult to transfer through worker mobility. Thus, the most robust spillovers arise through workers in medium technology-intensity industries; these mainly occur through FCFs above the median and have a zero premium for workers moving to FCFs below the median.

Figure 4-4: Summary of positive spillovers from FCFs and non-FCFs



Note: Regressions presented in **Table 4-13**,**Table 4-15**, **Table 4-16** and **Table 4-17**

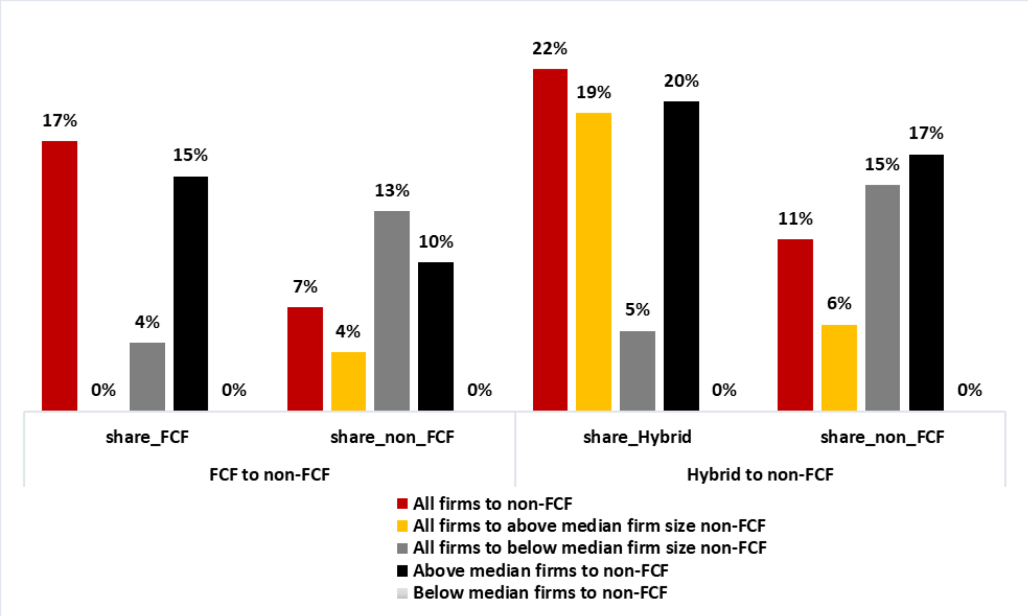
Overall, there is evidence of job changers coming from FCFs, contributing on average 17.41% more to the productivity of the non-FCF compared to incumbent non-FCF workers. However, there is only robust evidence of spillovers to non-FCFs below the median. This indicates that spillovers mainly occur when workers with FCF experience move to a non-FCF (domestic firm) that is below the median firm size, i.e. small non-FCFs, and when movers come from FCFs above the median (see **Figure 4-4**). Using gender, the most robust productivity spillovers come from male FCF workers. After disaggregating by median firm size, spillovers remain for non-FCFs below the median and for FCFs above the median. Using wage quantiles, the most robust spillovers are from high-wage FCF workers; these hold when they move to non-FCFs below the median and when they come from FCFs that are above the median. Finally, using technology intensity, the most robust spillovers arise through workers in medium technology-intensity industries; these mainly occur through FCFs above the median and have a zero premium for workers moving to FCFs below the median. These results indicate that the most robust spillovers occur from FCFs above the median and are mainly received by domestic firms below the median.

4.6.3 Spillovers from hybrid FCFs

In Chapter 3, the analysis was centred on a niche subset of firms called hybrid FCFs which use a combination of trading and FDI. As an additional check, spillovers from these firms are explored as they are likely to have more spillovers to domestic firms. There is evidence of more significant and larger spillovers from hybrid FCFs to non-FCFs (see **Figure 4-5**). Further, the spillovers from hybrid

FCFs to non-FCFs are larger and as significant as those between non-FCFs. There is also evidence of spillovers from hybrid FCFs to non-FCFs above and below the median – with larger spillovers in non-FCFs above the median. This indicates that hybrid FCFs have more significant spillovers for larger domestic firms.

Figure 4-5: Spillovers from FCFs and hybrids to non-FCFs



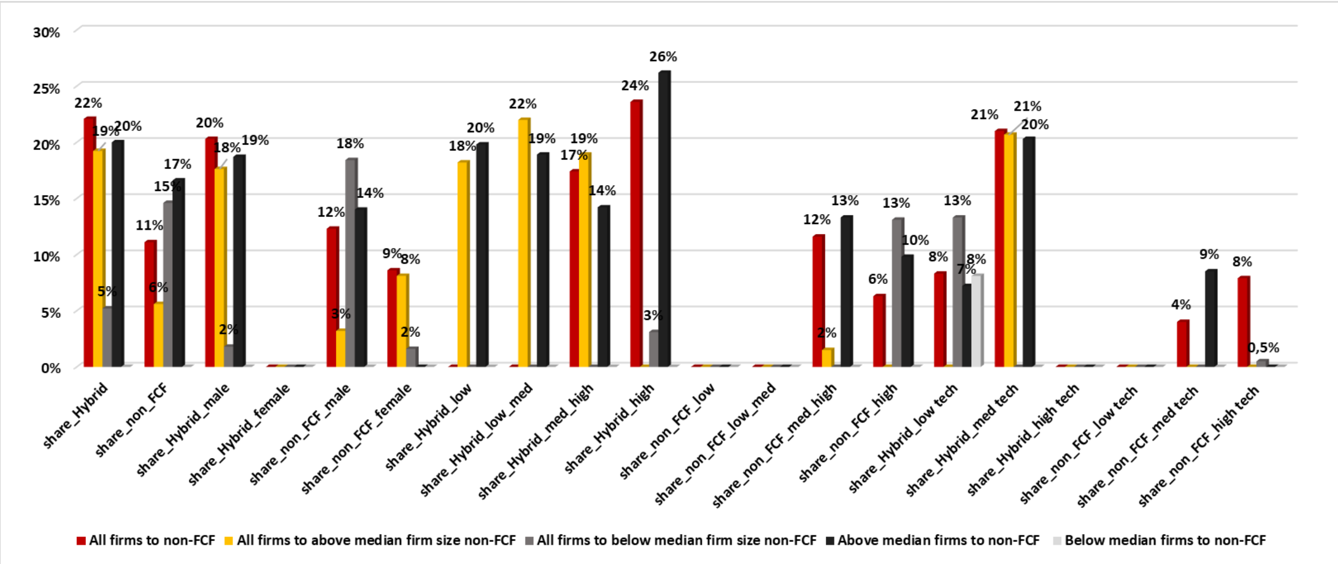
Note: Regressions presented in **Table 4-13** and **Table D-4** in Appendix C.

The hybrid FCF spillovers are also analysed across different dimensions, i.e. gender, wage quantiles and technology. A summary of the positive spillovers is given in **Figure 4-6** and the regressions are presented in Appendix C. The results for technology spillovers stand out and reveal that there is a great deal of heterogeneity. On average, there are only spillovers from low-tech and medium-tech hybrid FCFs. There are negative spillovers from high-tech hybrid FCFs. Low-tech hybrid FCFs mainly have spillovers to non-FCFs below the median, while medium-tech hybrid FCFs have spillovers to non-FCFs above the median. Low-tech firms above and below the median have positive spillovers in non-FCFs. However, only hybrid FCFs above the median have positive spillovers for non-FCFs. The lack of positive spillovers from high-tech hybrid firms confirms the notion that spillovers are only possible to the extent that local firms can absorb them (Fosfuri et al., 2001). Thus, the most robust spillovers arise through workers in low and medium technology-intensity industries. There are no spillovers in low-tech non-FCFs. However, there are spillovers from medium- and high-tech non-FCFs. However, there are only positive spillovers from high-tech non-FCFs to other non-

FCFs below the median, and only medium-tech non-FCFs above the median have positive spillovers to non-FCFs.

Overall, this section highlights that larger and more significant spillovers emanate from hybrid FCFs, and technology spillovers are more pronounced through hybrid FCFs.

Figure 4-6: Summary of positive spillovers from hybrid FCFs and non-FCFs



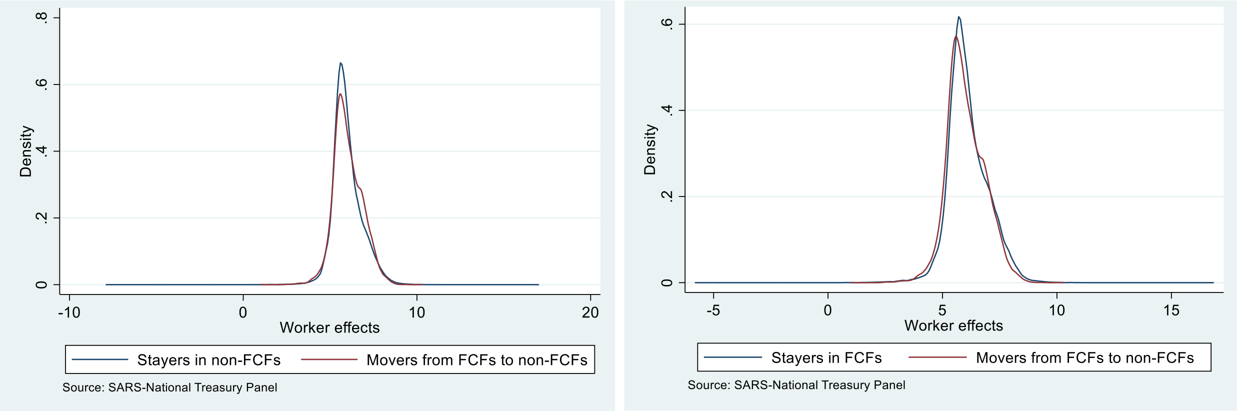
Note: Regressions presented in **Table D-4, Table D-5, Table D-6** and **Table D-7**

4.7 Wage premium from mobility

All the results presented thus far confirm that there is a positive correlation between the share of workers with FCF experience in non-FCFs and the productivity of non-FCFs in South Africa. This was done by looking at firm-level productivity. The next step is to establish whether FCF workers are rewarded when they enter non-FCFs compared to incumbent workers in non-FCFs, i.e. is experience from an FCF rewarded in non-FCFs? This will be done by looking at individual-level outcomes, which are wages.

The k-densities of workers moving from FCFs to non-FCFs compared to workers who are already in non-FCFs indicate that the distribution of worker effects is quite similar; however, FCF-experienced workers remain slightly to the right of non-FCF workers (**Figure 4-7a**). These workers are also compared to workers who stay in FCFs and find that they are slightly to the left of the FCF stayers (**Figure 4-7b**). This shows that workers moving from FCFs to non-FCFs have lower worker fixed effects compared to workers in the firm that they are coming from.

Figure 4-7: Movers from FCFs to non-FCFs (a) vs non-FCF stayers and (b) vs FCF stayers



Source: SARS–NT panel
Note: sample-largest connected group

The wage equation for non-FCF workers is estimated and compared to new hires from FCFs as well as other non-FCFs. Thus, the following wage equation from Balsvik (2011) is estimated:

$$W_{it} = \beta_0 + \sum \beta_1 \mathrm{FCF}_{j(i,t)} + \sum \beta_2 \mathrm{nonFCF}_{j(i,t)} + \beta_3' X_{it} + \beta_4' F_{j(i,t)} + \mathrm{v}_j + \mathrm{v}_t + \mathrm{v}_t * \mathrm{v}_{ind} + \varepsilon_{it} \quad (9)$$

Where:

- i denotes a worker (i=1….N) at time t (t=1….T) in firm j (j=1.....J);
- W_{it} is the log monthly wage;
- $\mathrm{FCF}_{j(i,t)}$ is a dummy indicating a new worker in firm j from an FCF and tenure (less/greater than 3 years)/gender/wage quantiles;
- $\mathrm{nonFCF}_{j(i,t)}$ is a dummy indicating a new worker in firm j from a non-FCF and tenure (less/greater than 3 years)/gender/wage quantiles;
- X_{it} is a vector with K observable characteristics, i.e. age, age squared, age cubed, gender;
- $F_{j(i,t)}$ is a vector of firm characteristics, i.e. firm size and output per worker;
- v_j firm fixed effects;
- v_t year dummies;
- $\mathrm{v}_t * \mathrm{v}_{ind}$ industry and year interaction terms; and
- ε_{it} is the idiosyncratic error term.

Equation 9 is estimated to try and determine whether there are any returns to tenure through a wage premium. Like Balsvik (2011), worker fixed effects are not included in these regressions as they would capture the difference between the workers. The results indicate a positive wage premium for FCF workers with more than a three-year tenure at an FCF before moving (10.3%) and a negative spillover of FCF workers with less than a three-year tenure compared to all non-FCF stayers (see **Table 4-18**). This result holds for FCF workers with more than a three-year tenure moving to non-FCFs below and above the median firm size. FCF workers with less than a three-year tenure are not significantly different to non-FCF stayers. These results align with the theoretical framework where transfers can only occur after a worker has received training in the FCFs' technology which will enable them to transfer it. Thus, finding a wage premium only for workers with more than a three-year tenure in an FCF supports this theory. Workers hired from other non-FCFs, i.e. between non-FCFs, with more than a three-year tenure are not paid significantly differently to non-FCF stayers in the firm they are moving to, while those with less than a three-year tenure receive a negative premium. However, workers with more than a three-year tenure receive a positive premium when moving to other non-FCFs below the median firm size. Using all stayers as the base category, Balsvik (2011) found a wage premium of 6.9% for FCF workers with more than a three-year tenure and 3.3% for similar workers in non-FCFs.

Table 4-18: Wage premium by tenure

Base category	All non-FCF stayers			non-FCF stayers with more than 3 year tenure			non-FCF stayer with less than 3 year tenure		
Dep: Log monthly wage	All firms	Above median firm size	Below median firm size	All firms	Above median firm size	Below median firm size	All firms	Above median firm size	Below median firm size
FCF to non-FCF less than 3 year tenure	-0.0147*	-0.0438**	0.00873	-0.0719**	-0.104**	-0.0439**	0.150**	0.122**	0.167**
	(0.00680)	(0.00974)	(0.00925)	(0.00669)	(0.00951)	(0.00917)	(0.00733)	(0.0107)	(0.00981)
FCF to non-FCF more than 3 year tenure	0.103**	0.144**	0.0674*	0.0476*	0.0876*	0.0162	0.289**	0.319**	0.255**
	(0.0243)	(0.0388)	(0.0307)	(0.0238)	(0.0377)	(0.0304)	(0.00255)	(0.0415)	(0.0317)
Between non-FCF less than 3 year tenure	-0.0980**	-0.140**	-0.0502**	-0.156**	-0.199**	-0.104**	0.0675**	0.0213**	0.112**
	(0.00360)	(0.00505)	(0.00500)	(0.00359)	(0.00499)	(0.00500)	(0.00415)	(0.00594)	(0.00566)
Between non-FCF more than 3 year tenure	0.00998	-0.00201	0.0724**	-0.0419**	-0.0600**	0.0275+	0.196**	0.194**	0.236**
	(0.0109)	(0.0152)	(0.0153)	(0.0107)	(0.0148)	(0.0151)	(0.0116)	(0.0165)	(0.0159)
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	No	No	No	No	No	No	No	No	No
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,028,502	479,135	549,367	824,233	380,274	443,959	285,718	136,553	149,165
R-squared	0.256	0.357	0.178	0.232	0.334	0.158	0.314	0.399	0.231

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

These movers are also compared to non-FCF stayers with more or less than a three-year tenure. The results show that FCF workers with more than a three-year tenure have a premium relative to non-FCF stayers with more or less than a three-year tenure in non-FCFs above and below the median. The only exception is that FCF workers with more than a three-year tenure are not paid significantly differently from non-FCF stayers with more than a three-year tenure below the median. FCF workers with less than a three-year tenure have a negative premium relative to non-FCF workers with more than a three-year tenure. However, they have a positive wage premium relative to non-FCF workers with less than a three-year tenure. All non-FCF workers with more and less than a three-year tenure have a wage premium relative to non-FCF workers with less than a three-year tenure. This holds for non-FCFs above or below the median. However, compared to non-FCF stayers with more than a three-year tenure, all new non-FCF hires have a negative premium, with the exception of non-FCF hires with more than a three-year tenure which are not significantly different. It should be noted that while there is robust evidence of a wage premium for workers with a tenure of three years or more, a longer panel could allow a more nuanced analysis of the returns to tenure. For example, transfers of knowledge might take longer to translate into productivity increases and a longer timeframe for the analysis would allow for a more accurate estimation.

Table 4-19: Wage premium by gender

Base category	non-FCF stayer (male and female)			non-FCF stayer (male)			non-FCF stayer (female)		
Dep: Log monthly wage	All firms	Above median firm size	Below median firm size	All firms	Above median firm size	Below median firm size	All firms	Above median firm size	Below median firm size
FCF to non-FCF male	0.308**	0.285**	0.309**	0.228**	0.449**	0.203**	0.449**	0.495**	0.372**
	(0.00787)	(0.0117)	(0.0104)	(0.00787)	(0.00837)	(0.00818)	(0.00837)	(0.00853)	(0.00949)
FCF to non-FCF female	0.0398**	0.0450**	0.0373*	-0.0683**	0.192**	-0.110**	0.192**	0.257**	0.0863**
	(0.0125)	(0.0169)	(0.0180)	(0.0124)	(0.0129)	(0.0127)	(0.0129)	(0.0127)	(0.0141)
Between non-FCF male	0.225**	0.199**	0.234**	0.143**	0.369**	0.118**	0.369**	0.420**	0.291**
	(0.00445)	(0.00652)	(0.00595)	(0.00457)	(0.00520)	(0.00499)	(0.00520)	(0.00573)	(0.00641)
Between non-FCF female	-0.0550**	-0.0829**	0.0381**	-0.175**	0.0998**	-0.221**	0.0998**	0.165**	-0.0158*
	(0.00617)	(0.00802)	(0.00932)	(0.00625)	(0.00669)	(0.00662)	(0.00669)	(0.00695)	(0.00785)
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	No	No	No	No	No	No	No	No	No
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,028,502	479,135	549,367	702,446	349,165	434,730	407,505	255,176	233,778
R-squared	0.253	0.352	0.178	0.249	0.333	0.212	0.263	0.334	0.209

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Turning to gender, the results indicate that male FCF movers receive a wage spillover relative to all non-FCF stayers, male non-FCF stayers and female non-FCF stayers in non-FCFs above and below the median (see **Table 4-19**). The same holds for female FCF movers when compared to all non-FCF stayers and female non-FCF stayers. However, the male FCF premium is higher than that received by female FCF movers. Compared to male non-FCF stayers, female FCF movers have a negative wage spillover to all firms and those below the median; however, they have a positive spillover to non-FCFs above the median. There are similar trends between non-FCF male and female movers. However, female non-FCF movers have a negative premium compared to all non-FCF stayers and those above the median. They also have a negative premium compared to female non-FCF workers in non-FCFs below the median.

In terms of wage quantiles, the results indicate that the most consistent premia for FCF and non-FCF movers are received by medium high- and high-wage quantile workers (see

Table ***4-20***). FCF and non-FCF movers in low-wage quantiles have negative premia across the board, the only exception being FCF low-wage movers, who are not significantly different from low-wage non-FCF stayers in non-FCFs above the median. FCF and non-FCF low medium-wage movers display the same trend, with both receiving a negative premium compared to all non-FCF stayers. However, they receive a premium compared to low-wage non-FCF stayers both above and below the median.

Table 4-20: Wage premium by wage quantiles

Base category	non-FCF stayer			non-FCF stayer low		
Dep: Log monthly wage	All firms	Above median firm size	Below median firm size	All firms	Above median firm size	Below median firm size
FCF to non-FCF low	-0.772**	-0.625**	-0.920**	-0.0417**	-0.00584	-0.118**
	(0.0130)	(0.0168)	(0.0195)	(0.0109)	(0.0107)	(0.0104)
FCF to non-FCF low_med	-0.0783**	-0.0237	-0.151**	0.786**	0.779**	0.758**
	(0.0129)	(0.0180)	(0.0180)	(0.0109)	(0.0107)	(0.0105)
FCF to non-FCF med_high	0.313**	0.332**	0.280**	1.298**	1.277**	1.294**
	(0.0132)	(0.0208)	(0.0168)	(0.0112)	(0.0111)	(0.0107)
FCF to non-FCF high	1.199**	1.262**	1.139**	2.278**	2.240**	2.289**
	(0.0114)	(0.0177)	(0.0147)	(0.00989)	(0.00989)	(0.00955)
Between non-FCF low	-0.777**	-0.615**	-0.896**	-0.0720**	-0.0310**	-0.150**
	(0.00643)	(0.00827)	(0.00985)	(0.00576)	(0.00592)	(0.00592)
Between non-FCF low_med	-0.0811**	0.00369	-0.167**	0.771**	0.761**	0.752**
	(0.00654)	(0.00896)	(0.00930)	(0.00597)	(0.00621)	(0.00609)
Between non-FCF med_high	0.288**	0.243**	0.283**	1.290**	1.263**	1.291**
	(0.00679)	(0.0103)	(0.00889)	(0.00628)	(0.00660)	(0.00636)
Between non-FCF high	1.149**	1.139**	1.132**	2.220**	2.183**	2.231**
	(0.00645)	(0.00987)	(0.00838)	(0.00611)	(0.00649)	(0.00623)
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	No	No	No	No	No	No
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,028,502	479,135	549,367	260,140	179,539	162,050
R-squared	0.313	0.403	0.242	0.588	0.678	0.677

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Overall, there is evidence of a wage premium paid to new entrants coming from FCFs with more than a three-year tenure. Further, there is also evidence of spillovers to movers across gender and wage quantiles. The most robust wage premia are paid to both FCF and non-FCF male movers as well as FCF and non-FCF medium high- and high-wage movers. One limitation of this analysis is that bargaining councils are not included in the analysis. Bassier (2021) used the SARS-NT panel from 2008 to 2018 to assess the impact of centralised bargaining on spillovers and the wage structure. He found that following large wage increases mandated by bargaining council contracts, firms that are not part of bargaining councils, but are connected to them through worker mobility, also increased their wages, reflecting spillovers between BC and non-BC firms. This indicates that the wage spillovers estimated in this chapter could be higher due to BC-related wage increases and spillovers between BC and non-BC firms. As such, further research is required to extend the analysis in this chapter to include BCs.

4.8 Conclusion

FCFs are important for South Africa's economic growth as they contribute substantially to employment and output. They are also more productive and pay higher wages. This chapter examined the extent to which productivity spillovers arise through worker mobility from FCFs to non-FCFs in South Africa. Further, it explored whether workers benefit from mobility in terms of wages.

There is evidence of productivity spillovers from workers moving from FCFs to non-FCFs and no evidence of spillovers in the opposite direction. On average, the results show evidence of spillovers from both FCFs to non-FCFs and between non-FCFs. However, when disaggregating by median firm size, only spillovers from FCFs to non-FCFs below the median remain. This indicates that the most robust spillovers occur in small domestic companies. Further, there is robust evidence of spillovers from FCFs above the median. As such, these spillovers come from large FCFs and are received mostly by small domestic firms.

When looking at spillovers across different dimensions, i.e. gender, wage quantiles and technology, there is, on average, evidence of positive spillovers from hiring both male FCF and non-FCF workers as well as medium high and high-wage workers from FCFs and non-FCFs. Disaggregating by median firm size, only male FCF workers and high-wage FCF workers have positive spillovers in domestic firms below the median firm size. Only workers from medium technology FCFs have productivity spillovers that are higher than zero. However, there is no evidence of spillovers greater than zero, after disaggregating by median firm size.

The results provide strong evidence of productivity spillovers from male FCF workers and high-wage FCF workers to non-FCFs below the median firm size. The results suggest that most FCF workerembodied knowledge is carried by male and high-wage workers. The gender difference could indicate the different types of jobs held by males and females in the manufacturing sector. It is also possible that male workers have the types of jobs where spillovers are more likely to occur – for example, males might work on a production line whereas females might have cleaning jobs where spillovers are more difficult. Further, there are fewer female workers employed in the sector. Finding that high-wage workers are important for spillovers to occur is unsurprising, given that the wages are related to the skill level of a worker. Previous studies have shown that the extent of transfer of spillovers depends on the seniority, skill and exposure that the worker had while working in an FCF. Using technology intensity, the most robust spillovers arise through workers in medium technology-intensity industries; these mainly occur through FCFs above the median. Restricting the sample to hybrid FCF spillovers reveals larger and more significant spillovers to non-FCFs above and below the median.

In terms of wage spillovers, a wage premium is paid to new entrants coming from FCFs with more than a three-year tenure. There is also evidence of spillovers to movers across gender and wage quantiles. The most robust wage premia are paid to both FCF and non-FCF male movers as well as FCF and non-FCF medium high and high-wage movers.

From a policy perspective, these results indicate that the skill level of workers is important for FCF spillovers through worker mobility. Essentially this shows that FCFs have ‘better’ workers and when they move to local firms there are benefits for the firms that hire them. This indicates that there are benefits to working in externally focused firms. As such, it is important for South Africa to ensure that firms (particularly FCFs) invest in training their workers in the use of new technologies or machinery, process innovations, high-quality intermediate inputs and management techniques. Thus, it is important for any support provided by the government to include training requirements, particularly for incentives designed to attract FDI. Another way to get workers with similar exposure to externally focused firms is by getting people who work in the international context to be allowed to work in South Africa through more efficient work visa processes. This is not limited to workers with high skills at the top of the distribution; lower skill levels could also benefit. However, given the high unemployment rate in the South African economy, this would be difficult for government to implement.

Chapter 5: Conclusion

5.1 Summary of findings

This thesis significantly adds to the understanding of wage dynamics, trade-related wage premia and productivity spillovers from foreign-connected firms (FCFs). This is important in view of the high levels of inequality in South Africa, of which wage inequality is a major component. The thesis uses a tax administration linked employer–employee dataset to gain new insights into wages, trade and productivity in the manufacturing sector. Firstly, the study estimates the contribution of observable and unobservable worker and firm characteristics to wage levels and growth. Secondly, it provides a more detailed understanding of trading manufacturing firms by extending the exporter premium theory to include exporters–importers (EXIM) and hybrid firms. Thirdly, the study explores the existence of spillovers from FCFs to local firms and the extent to which and how such spillovers occur.

Chapter 2 shows that worker effects dominate firm effects in both wage levels and growth. However, firm fixed effects are relatively more important for low-wage workers. Further, the importance of firm fixed effects increases with firm size. In South Africa, Bhorat et al. (2017), using the SARS–NT tax administration panel dataset, found that worker fixed effects are more important than firm fixed effects in explaining the variation in wage levels. However, their analysis is conducted across all the sectors in the South African economy and does not look at wage growth. As such, this is the first study to look at wage growth, taking into account unobserved worker and firm heterogeneity in South Africa. One of the main findings in this chapter is that worker fixed effects explain a higher proportion of wage growth in low-wage workers compared to wage levels. One possible explanation for this is the low bargaining power that low-wage workers have when they take a job compared to their wage growth where their employers have had time to observe them. Overall, workers who stay in the same job tend to have higher wage levels. However, workers who change jobs receive higher wage growth. The only workers who this does not apply to are low-wage workers, indicating that movement at the low end of the wage distribution is likely to be involuntary; it also reflects the small wage difference across firm sizes at the lower end of the wage distribution, likely due to the wage determination processes in the sector. As such, low-wage movers are unlikely to experience high wage growth, even if they move to a large firm. More importantly, wage growth for low-wage workers is very different to the rest of the distribution, and for these workers, staying in the same job is very important for their wage growth.

In Chapter 3, the wage premia for trading and foreign-owned firms in South Africa are estimated. Theoretical models by Helpman et al. (2004), Grossman et al. (2006) and Bernard et al. (2018) extend the Melitz (2003) model on firm heterogeneity and show that FDI firms are more productive than firms that only serve foreign markets through exports. Further, the literature indicates that the most productive firms are more likely to export, import and engage in FDI. As such, this chapter extends the South African literature on the exporter wage premium (Matthee et al., 2018; Rankin, 2001; Rankin & Schoër, 2013) and highlights Edwards et al. (2018) who distinguished between the wages of firms that only export, only import, and are both exporters and importers. To my knowledge, internationally the only studies in the literature that have done this are Tanaka (2015) for Japan and Schröeder (2020) for Germany. Further, this chapter extends the literature by distinguishing between firms that are simultaneously exporters and importers and are pure exporters and importers. As such, this thesis is the first to empirically estimate the wage premium by differentiating between pure exporters/importers and firms that are both importers and exporters, as well as domestically owned and foreign-owned FCFs. The results indicate that hybrid firms pay the highest wage premium, followed by domestic FCFs, EXIM, exporters and importers. Hybrid firms are most likely the group of firms that previous South African studies have referred to as ‘super-exporters’. Thus, the chapter concludes that it is the combination of exposure to foreign markets through imported inputs, export sales and FDI that leads to the highest wage premia.

Lastly, Chapter 4 explores whether the presence of FDI firms leads to any spillovers for local firms. Fosfuri et al. (2001) and Glass and Saggi (2002) provide theoretical frameworks that identify worker mobility as a channel for spillovers between FDI and local firms. Following Balsvik (2011), this chapter estimates productivity and wage spillovers for workers moving from FCFs to non-FCFs. In South Africa, productivity spillovers have only been estimated for exporters, R&D and training (Hlatshwayo et al., 2019) as well as horizontal, forward and backward spillovers (Sørensen, 2020), making this the first study to estimate spillovers from FDI in South Africa using linked employer–employee data. There is robust evidence of positive productivity spillovers from FCFs to small, local firms; however, these mainly occur through high-wage workers. This is unsurprising, given that previous studies have shown that the extent of transfer of spillovers depends on the seniority, skill and exposure that the worker had while working at an FCF. In terms of wages spillovers, this chapter found positive spillovers to new entrants coming from FCF workers with more than a three-year tenure. This supports the theoretical framework for spillovers which requires workers to be trained and to understand the technology well enough to be able to transfer it to a local firm. Thus, a worker takes around three years to fully understand the technology and systems used by FCFs, for which they are rewarded when moving to a local firm.

Overall, this thesis highlights the difference in wage levels and growth for different types of workers, particularly how different wage growth is for low-wage workers compared to other workers. Tenure is important for low-wage workers. Given the high levels of wage inequality in South Africa, it is important to understand which firms pay the highest wages. Thus, various types of manufacturing firms are ranked according to the wage premia they pay. The results indicate that hybrid firms pay the highest wages. However, this is a niche group of firms which are likely to increase inequality unless local firms are able to compete with them. Thus, the possibility of spillovers between FCFs and non-FCFs is explored using worker mobility as a channel for spillovers. There is evidence of positive productivity and wage spillovers through worker mobility. As such, this highlights the importance of workers moving between FCFs and non-FCFs so that there is knowledge sharing, allowing local firms to increase their productivity.

5.2 Policy implications

There are five broad policy issues that all policymakers are encouraged to take into consideration when designing new reforms for the manufacturing sector. The first is the importance of training and the substantial role played by FCFs through training; the second is that worker mobility is important for spillovers between FCFs and local firms as such mobility should be encouraged after there has been enough time for the worker to master the technology/methods used in the FCF; the third is the importance of tenure for the wage growth of low-wage workers; the fourth is that it is the combination of using imported inputs, having exports and engaging in FDI that yields the most productive firms; and the fifth is an acknowledgement of the nuances underlying how firms become trading or hybrid firms.

An underlying issue in South Africa is the current skills shortage, which results in a high skills premium. As such, policymakers need to focus on improving training and skills development in the country. This is reinforced by the finding that the skill level of workers is important for FCF spillovers through worker mobility. Workers embody the know-how they acquire from on-the-job training as well as the skills to operate sophisticated machinery. As such, it is important for firms (particularly FCFs) to invest in training their workers in the use of new technologies or machinery, process innovations, high-quality intermediate inputs and management techniques. Thus, it is important for any support provided by the government to include training requirements, particularly for incentives designed to attract FDI. Further, policy should encourage worker mobility among workers who have been at the same FCF for at least three years, which is important for the transfer of knowledge in the sector. These results show that FCFs have 'better' workers and when they move to local firms there are benefits for the firms that hire them. This indicates that there are benefits to working in externally focused firms. As such, policymakers should explore ways to encourage the movement of workers from FCFs to local firms after at least three years at an FCF, as this is important for the transfer of knowledge in the sector. Another way to get workers with similar exposure to externally focused firms is by getting workers with experience in the international context to be allowed to work in South Africa through more efficient work visa processes. This is not limited to workers with high skills at the top of the distribution; lower skill levels could also benefit. However, given the high unemployment rate in the South African economy, this would be difficult for government to implement.

This study finds that worker fixed effects explain a higher proportion of wage growth in low-wage workers compared to wage levels. One possible explanation for this is the low bargaining power that low-wage workers have when they take a job compared to their wage growth where their employers have had time to observe them. This indicates that tenure is important for low-wage workers. However, it is also important for firms to have reskilling programmes to assist low-wage workers move into jobs and activities that require more advanced skills, thus supporting their wage growth and boosting the demand for low-wage workers.

The finding that it is the combination of importing, exporting and FDI that results in the highest wage premia highlights the importance of policymakers ensuring that firms can source inputs from abroad cost-effectively and are equipped to take up more export opportunities. Given the current export-led growth focus of South Africa's industrial policy, it is important to ensure a balance between supporting local industry and sourcing certain intermediate inputs globally. Further, the Economic Reconstruction and Recovery Plan (ERRP) emphasises industrialisation through localisation and a reduction in imports of final and intermediate imports. The Re-imagined Industrial Strategy (RIS) national sector masterplans are also anchored in increased localisation and lower imports. However, this research indicates that it is important for policymakers to note that even with increased localisation, trading firms and FCFs still need to be part of global and regional value chains through exporting and importing to remain internationally competitive.

Given the higher productivity and wages paid by trading and foreign-owned firms, an important consideration is whether it is possible to have more of these firms. Two important aspects need to be highlighted from a policymaking perspective: (1) whether exporters and hybrid firms are born or made, and (2) whether more productive firms self-select into exporting or if they become more productive from learning-by-exporting. There is a branch of the literature on born-global and gradual-global firms. However, the evidence in the literature is mixed, with some studies finding higher sales and employment in born-global firms relative to other exporters (Choquette et al., 2017) and other studies finding that, over time, born-global firms do not outperform other exporters in terms of size and growth (Ferguson et al., 2021). Regarding self-selection and learning-by-exporting, Bezuidenhout et al. (2019) found that in South Africa firms entering exporting need to have similar productivity levels as existing exporters to compete in the export market. This indicates that there is some level of self-selection into exporting. The literature indicates that there are nuances that need to be considered when designing policies directed towards increasing export participation. It is also evident that firms are likely to require support, which facilitates entry of competitive firms into the export market and ensures that, upon entry, they are able to export consistently and realise export sales of around 10% of their output.

5.3 Future research

One of the limitations of this study is that it does not include BCs in the analysis. The inclusion of BCs would allow for a more accurate analysis of wage levels and growth as well as spillovers. In the absence of controlling for BCs, it is possible that this thesis has overestimated the spillovers due to worker mobility, as some of the wage increases presented also include wage increases mandated by BCs. One of the main findings in this thesis is that job stability is important for low-wage workers, given that changing jobs is unlikely to result in higher wages for these workers. Further research is required to test the robustness of the tenure dynamics presented in this thesis. A panel dataset with a longer time period is required. If the returns to tenure for low-wage workers hold over a longer period, it will be important for policymakers to explore which labour-market reforms are required to improve low-wage tenure, particularly in large firms.

The absence of an indicator for skills in the SARS-NT panel is another limitation of this study. The main implication of not including skills in the analysis is that the worker fixed effects have potentially been overestimated. As such, for more accurate and robust research, it is essential for the SARS-NT panel to include information on skills or job descriptions, i.e. manager, assembly line worker, and so on.

It is important to be able to identify unemployment spells in the data, especially when analysing wage levels and growth. Some of the literature has shown that the estimation of worker and firm fixed effects differs based on whether a worker is hired from unemployment or from another job. As such, the inclusion of Unemployment Insurance Fund (UIF) data in the SARS-NT panel would open up more avenues for research and allow for a more accurate analysis of job transitions.

Additional research is required to assess the impact of hybrid firms on wage inequality, especially within-firm wage inequality, as well as the impact of FCFs on the gender wage gap. Moreover, it is essential to conduct further research on the impact of competition on job mobility due to the high wage premia paid by FCFs – which they could use to prevent workers moving to non-FCFs, while in the process limiting the potential for spillovers through worker mobility. Lastly, additional research is required to understand the absorptive capacity of South Africa firms as well as the mechanisms required to improve the scope for increased spillovers from FCFs to domestic firms. This research is important for policymakers and would help inform both the country's industrial policy and innovation policy.

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Appendices

Appendix A: Data overview

Table A-1: Chapter 2 cleaning

Description	Number of observations	%
IRP5	104 831 788	100%
Observations dropped		
labour brokers	3 671 014	4%
Missing industry	4 185 795	4%
Missing ID number	4 315 636	4%
Duplicate certificate number	268 643	0%
Nature of person not individual	11 792 256	11%
Top 1%	5 136 977	5%
Duplicate job entries	853 552	1%
Non-manufacturing	63 975 640	61%
Total	10 632 275	10%

Table A-2: Chapter 3 and 4 cleaning

Description	Number of observations	%
IRP5	104 831 788	100%
Observations dropped		
labour brokers	3 671 014	4%
Missing industry	4 185 795	4%
Missing ID number	4 315 636	4%
Duplicate certificate number	268 643	0%
Nature of person not individual	11 792 256	11%
Duplicate job entries	7 755 341	7%
Multiple job spells	802 331	1%
Top 1%	4 805 065	5%
Non-manufacturing	60 476 046	58%
Missing CIT numbers	28 918	0%
Total observations after merge with CIT	6 730 743	6%

Appendix B: Job mobility and wage growth

Table B-1: Summary of wage level groups

	Number of workers	Number of firms	Number of groups	Number of movers	Number of estimable effects
Total	3,229,063	56,693	293	509,033	4,477
Female	1,147,769	49,084	1019	161,729	28,994
High income (q4)	257,439	29,795	1073	33,864	11,137
Low income (q1)	498,468	29,598	887	33,293	7567
Male	2,081,360	53,358	380	347,257	40,448
High income (q4)	476,935	34,161	1004	67,397	15,939
Low income (q1)	907,785	41,688	822	80,726	21,221
Firm size					
10–49	845,581	26,676	342	55,746	21,757
50–99	585,532	6163	24	26,478	5739
100–499	1,149,858	3926	2	90,753	3290
500–999	451,713	475	2	18,313	473
1000–49,999	882,214	248	1	46,354	247

Note 1: All the numbers presented, including workers in firms with no movers

Note 2: Where there is only one group it means all the firms in that category had movers

Note 3: Firms employing 1–9 employees had too many small, connected groups, thus preventing estimation.

Table B-2: Summary of wage growth groups

	Number of workers	Number of firms	Number of groups	Number of movers	Number of estimable effects
Total	2,218,428	52,365	800	204,730	33,886
Female	762,241	45,158	1751	61,997	18,091
High income (q4)	211,786	26,463	1095	17,838	6989
Low income (q1)	227,445	23,195	671	5848	2623
Male	1,456,211	49,219	925	142,715	29,618
High income (q4)	402,787	30,139	1130	37,594	10,632
Low income (q1)	433,844	35,113	1357	15,626	8161
Firm size					
10–49	558,006	25,081	1877	18,705	11,897
50–99	362,543	5642	311	7845	3373
100–499	724,105	3751	3	32,279	3569
500–999	284,463	448	2	6978	417
1000–49999	583,571	240	2	20,902	238

Note 1: All the numbers presented, including workers in firms with no movers

Note 2: Firms employing 1–9 employees had too many small, connected groups, thus preventing estimation.

Table B-3: Variance decomposition across the full sample, gender and income level

	Wage levels			Wage growth		
Z	Mean	Std.Dev	Cov(lmwage,Z) / Var(lmwage)	Mean	Std.Dev	Cov(lmwage,Z) / Var(lmwage)
Total						
WE	4.279074	0.9098051	.5636502	3.013183	.5444191	.41561039
FE	-.5454053	.6047237	.26346799	-1.563472	.4756485	.06711732
xb	5.202235	.2964134	.08187553	-1.408347	.0460792	.0019842
Residual	2.11e-12	.3615156	.09100628	-6.34e-12	.3208598	.51528809
Female						
WE	5.055535	.9769017	.59464339	1.316624	.4650084	.40967104
FE	-.4040086	.6920556	.27920914	-.0100501	.380784	.10219882
xb	3.993963	.1884938	.0333853	-1.275018	.0369401	-.00012981
Residual	-3.85e-12	.371478	.09276217	3.54e-12	.3342256	.48825995
Male						
WE	3.324051	.9007501	.57623825	3.095621	.5639434	.41800133
FE	-.493611	.5902935	.24894942	-1.486188	.4995839	.05124081
xb	6.255011	.2956061	.08312834	-1.56314	.0493539	.00365311
Residual	8.30e-13	.3510003	.091684	-5.64e-12	.312403	.52710475
Female_LI						
WE	-.0450538	.8600272	.53255056	4.389904	1.108121	.60445467
FE	9.697247	.7198288	.32836809	-.6854293	.9433984	.1529519
xb	-2.441613	.1026202	.00304749	-3.90591	.1140212	-.00542565
Residual	1.43e-12	.3800516	.13603387	3.39e-11	.41943	.24801908
Female_HI						
WE	5.892048	.5244799	.78874489	6.497392	.3710345	.63507773
FE	.1018932	.2409453	.08640835	.0564558	.2189575	.03679894
xb	4.137607	.1177874	.030962	-6.441823	.0665064	.02671059
Residual	1.12e-12	.1692655	.09388476	4.17e-13	.2116686	.30141275
Male_LI						
WE	8.307413	.9423038	.60815352	4.983574	1.178205	.66125831
FE	-1.393872	.761804	.27193878	-1.117415	1.034876	.08628576
xb	.8086568	.0473915	.00451147	-3.976487	.110703	-.00421671
Residual	-4.55e-12	.3244387	.11539624	1.75e-11	.3699545	.25667264
Male_HI						
WE	5.92438	.5241075	.79271515	9.972391	.3664355	.58812171
FE	-.0432501	.2272101	.06793129	-.0782852	.2305753	.05854471
xb	4.629385	.1347216	.04150022	-9.787214	.0963292	.03915351
Residual	1.16e-12	.1716004	.09785333	-8.27e-12	.2148357	.31418007

Note 1: Worker fixed effects (WE) - θ_i, Firm fixed effects (FE) - $\psi_{j(i,t)}$, Observable characteristics (xb) – β and the Residual/error term - ε_{it}.

Note 2: The coefficients are estimated from equation 1.

Table B-4: Variance decomposition by firm-size category

	Wage levels			Wage growth		
Z	Mean	Std.Dev	Cov(lmwage,Z) / Var(lmwage)	Mean	Std.Dev	Cov(lmwage,Z) / Var(lmwage)
10 to 49						
WE	4.547939	1.044789	.73921516	1.707722	.7988567	.46823497
FE	-.4668932	.6932983	.1576731	-.0562203	.7480621	.03890064
xb	4.728364	.2284815	.02723293	-1.620621	.0597676	-.0005256
Residual	-2.49e-12	.2744737	.07587882	-3.74e-12	.2940672	.49338998
50 to 99						
WE	5.704469	1.006467	.65559885	4.066088	1.112345	.59507071
FE	-.9693455	.7235649	.22139861	-.6665125	.9176818	.03439557
xb	4.117675	.2572747	.07417366	-3.358832	.5837494	.02754981
Residual	1.33e-12	.2307965	.04882887	.2300463	.2300463	.3429839
100 to 499						
WE	6.496987	.8649979	.54545779	.919368	.5333128	.53597393
FE	-.4245569	.5546859	.27145848	.1902268	.3330597	.05475753
xb	2.818789	.3854466	.1228265	-1.067164	.3149918	-.0101622
Residual	4.25e-12	.2803773	.06025723	-7.19e-12	.265416	.41943074
500 to 999						
WE	-.3859019	1.722545	.6769908	1.759353	.4957767	.56316186
FE	.1598072	.6023965	.28071506	.0387914	.4046301	.05948129
xb	9.183968	1.375412	-.15245945	-1.749268	.056875	.00485225
Residual	7.48e-14	.2524231	.04475359	-1.74e-12	.2457341	.3725046
1000 to 49999						
WE	.423326	1.063505	.56639156	1.65796	.370474	.42443129
FE	-.3981927	.7759925	.32708876	-.0792347	.2434688	.13662339
xb	9.135506	.3397491	.03775591	-1.526642	.0571369	.0010153
Residual	1.08e-12	.3773023	.06876377	1.39e-11	.3387803	.43793002

Note 1: Worker fixed effects (WE) - θ_i, Firm fixed effects (FE) - $\psi_{j(i,t)}$, Observable characteristics (xb) – β and the Residual/error term - ε_{it}.
Note 2: The coefficients are estimated from equation 1.

Table B-5: Variance decomposition across the full sample, gender and income level, including firm characteristics

	Wage levels			Wage growth		
Z	Mean	Std.Dev	Cov(lmwage,Z)/ Var(lmwage)	Mean	Std.Dev	Cov(lmwage,Z)/ Var(lmwage)
Total						
WE	4.442474	.9306924	.6757247	2.710744	.5853935	.4403546
FE	-.5681278	.5310191	.2307353	-1.509669	.5314707	.0713118
xb	5.278864	.2998878	.0419085	-1.154381	.0484815	.0019867
Residual	1.24e-12	.2375762	.0516316	-6.04e-12	.2597514	.486347
Female						
WE	5.055535	.9769017	.6430835	1.007299	.4283331	.4372365
FE	-.4040086	.6920556	.2676978	-.0118854	.3538505	.0900228
xb	3.993963	.1884938	.035592	-.9551897	.0471901	-.0018896
Residual	-3.85e-12	.371478	.0536268	4.85e-12	.2736937	.4746304
Male						
WE	3.324051	.9007501	.6407178	4.070424	.8885661	.362038
FE	-.493611	.5902935	.2075736	-.5674653	.5246947	.0696588
xb	6.255011	.2956061	.0991736	5.789345	.2768533	-.0404443
Residual	8.30e-13	.3510003	.052535	1.45e-12	.2309533	.3175962
Female_LI						
WE	7.875671	.6638492	.4499898	1.442097	.7069189	.5327641
FE	.0946248	.5700997	.3626709	.0506079	.5909597	.1647303
xb	-.2584457	.2233812	.0431411	-1.555218	.0994568	.0008081
Residual	3.02e-12	.2228627	.1441982	-1.17e-11	.2918007	.3016976
Female_HI						
WE	6.411188	.5078455	.8281962	4.576638	.3936892	.6353468
FE	.1474176	.2480846	.0594622	.0383338	.2552281	.0458955
xb	3.772419	.0992198	.0296037	-4.500266	.0880256	.0434754
Residual	-4.38e-12	.1445456	.082738	7.71e-13	.1872384	.2752823
Male_LI						
WE	8.096148	.7920175	.590718	1.857502	.9895844	.6619542
FE	-.6882197	.7031015	.2669665	-.6234952	.8423381	.1125226
xb	.3513768	.0887698	.0199185	-1.356413	.136961	.0006842
Residual	2.16e-12	.2035636	.1223971	6.62e-12	.2788304	.224839
Male_HI						
WE	5.328849	.5607997	.8157298	5.692727	.3351899	.5548052
FE	-.0753434	.2391175	.0579281	-.0332846	.2150735	.0595653
xb	5.194868	.1498314	.0526805	-5.559632	.1082744	.0543368
Residual	9.42e-13	.1512353	.0736617	-2.24e-12	.1909139	.3312928

Note 1: Worker fixed effects (WE) - θ_i, Firm fixed effects (FE) - $\psi_{j(i,t)}$, Observable characteristics incl. firm size and lagged firm size (xb) – β and the Residual/error term - ε_{it}.
Note 2: The coefficients are estimated from equation 1.

Table B-6: Variance decomposition across the full sample, gender and income level, including match effects

Z	Wage levels Mean	Wage levels Std.Dev	Wage levels Cov(lmwage,Z) / Var(lmwage)	Wage growth Mean	Wage growth Std.Dev	Wage growth Cov(lmwage,Z) / Var(lmwage)
Total						
WE	9.264905	1.414471	.791064	-1.301771	.6968722	.4542961
FE	.1485663	.6473363	.2843404	.0241902	.330399	.0810011
ME	.0000127	.227067	.0320719	-.0000953	.1122009	.0422092
xb	.4728302	.8642942	-.1669407	1.247027	.5357914	-.0441838
Residual	1.62e-12	.2929164	.0594644	1.72e-11	.3031495	.4666775
Female						
WE	8.730944	1.133165	.6694316	-.9379761	.7070665	.4381675
FE	-.0006809	.6982413	.2851958	-.0045489	.4175742	.1069044
ME	.0000196	.2059088	.0279855	-.0001565	.1010705	.0311757
xb	-.0824088	.4264716	-.0470061	.9321561	.4919025	-.0268215
Residual	-3.28e-12	.3111952	.0643933	2.51e-13	.3200815	.450574
Male						
WE	9.777648	1.611276	.8889097	-1.115761	.7181714	.4671369
FE	.225584	.6582212	.2792489	.0269779	.3387107	.0680939
ME	9.72e-06	.2330253	.0333502	-.0000547	.1106578	.04381
xb	-.9123537	1.098441	-.2610749	1.099287	.5550747	-.055949
Residual	2.14e-13	.2829558	.0595661	4.59e-12	.2942993	.4769081
Female_LI						
WE	5.302454	1.123714	.6329069	-3.765459	1.910558	.4705983
FE	-.2354915	.7354141	.0922684	-.0597707	.8896932	.3695859
ME	.0000327	.1580564	.0110341	.0001555	.0879518	.0266211
xb	2.420735	.8741724	-.0117866	3.534819	1.692295	.0129874
Residual	-1.09e-11	.3291339	.2755772	5.14e-12	.3675588	.1202073
Female_HI						
WE	10.58363	.7831308	.8929053	-2.28013	1.025857	.8988953
FE	.1305514	.2457975	.0750498	.0077442	.2802036	.0389991
ME	6.69e-08	.0698929	.0171841	-.0002157	.0571775	.0136596
xb	-.400224	.5502473	-.0712446	2.307202	.9164103	-.2020638
Residual	1.56e-12	.1503448	.0861053	-2.63e-12	.2030162	.2505099
Male_LI						
WE	-.191377	.6630081	.6225064	-3.389907	1.694657	.7690026
FE	6.020724	.953235	.2848174	.0181297	.8148056	.1024493
ME	.0000399	.1475701	.021979	.0001662	.0791448	.0073093
xb	1.717983	.3943398	-.0198778	3.013242	1.307989	-.0987513
Residual	-3.08e-12	.2986257	.0905751	-4.65e-12	.386326	.2199902
Male_HI						
WE	.2230427	.280902	1.068035	-4.12822	1.679192	1.043185
FE	11.80947	1.077703	.0810688	-.0177454	.4396422	.0649363
ME	-5.79e-08	.0907123	.0193037	-.000291	.0953017	.0254266
xb	-1.602289	.8335131	-.2428746	4.11896	1.588154	-.4377545
Residual	-8.09e-13	.155563	.0744673	-1.75e-12	.2048749	.3042066

Note 1: Worker fixed effects (WE) - θ_i, Firm fixed effects (FE) - $\psi_{j(i,t)}$, Match fixed effects (ME) - Ω_{ij}, Observable characteristics (xb) – β and the Residual/error term - ε_{it}.
Note 2: The coefficients are estimated from equation 6.

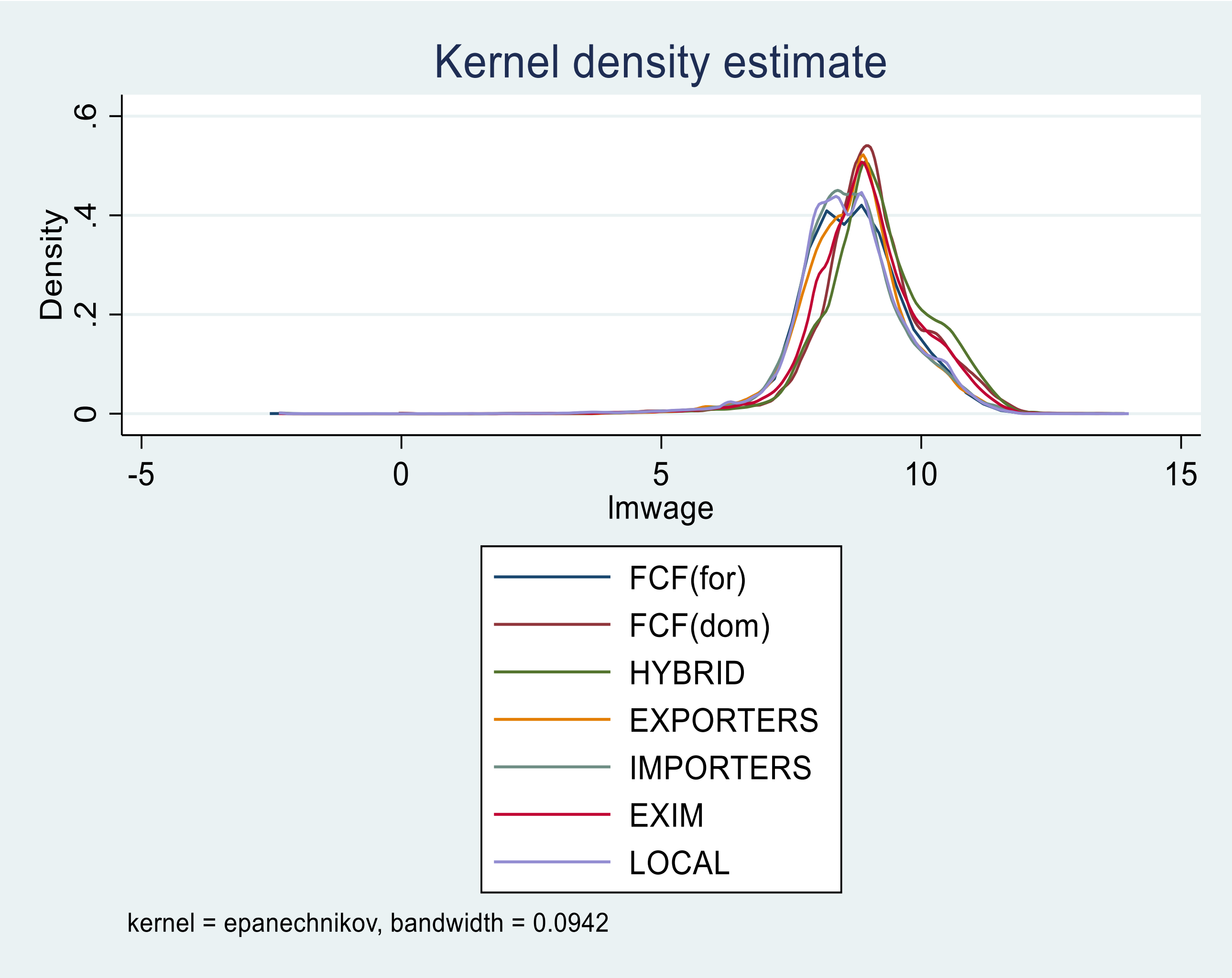
Appendix C: Wage premium for foreign-connected firms and exporters

Table C-1: Number of firms by manufacturing subsector, 2014

	All	FCF(for)	FCF(dom)	HYBRID	EXIM	EXPORT	IMPORT	LOCAL
Manufacturing of food products	**1 235**	184	*	55	223	78	58	690
Manufacturing of beverages	**354**	28	*	16	84	41	17	184
Manufacturing of tobacco products	**26**	*	*	*	*	*	*	12
Manufacturing of textiles	**804**	105	*	55	221	50	76	352
Manufacturing of wearing apparel	**653**	92	*	31	145	44	58	315
Manufacturing of leather and related products	**217**	23	*	14	77	15	17	86
Manufacturing of wood and wood of product	**1 084**	219	*	26	102	72	48	643
Manufacturing of paper and paper product	**456**	75	*	29	121	32	35	194
Printing and reproduction of recorded media	**672**	126	*	16	82	48	25	391
Manufacture of coke and refined petroleum	**123**	23	*	*	19	*	*	71
Manufacture of chemicals and chemical products	**950**	103	*	83	277	75	54	441
Manufacture of pharmaceuticals, medicinal products	**331**	32	*	31	111	21	26	142
Manufacture of rubber and plastic products	**1 415**	212	*	93	346	123	105	629
Manufacture of other non-metallic minerals	**443**	64	*	19	78	31	27	243
Manufacture of basic metals	**1 027**	185	*	38	164	55	48	575
Manufacture of fabricated metal products	**2 563**	422	*	107	427	176	117	1 421
Manufacture of computer, electronic and optical products	**299**	26	*	29	106	*	37	122
Manufacture of electrical equipment	**775**	84	*	61	261	48	75	305
Manufacture of machinery and equipment	**1 418**	172	*	123	473	85	83	605
Manufacture of motor vehicles, trailers and semi-trailers	**361**	49	*	39	97	32	15	167
Manufacture of other transport equipment	**232**	25	*	30	81	14	15	96
Manufacture of furniture	**754**	130	*	21	105	67	31	420
Other manufacturing	**3 939**	542	*	208	869	249	252	2 026
Repair and installation of machinery and equipment	**1 053**	200	*	32	126	37	51	639

*less than 10 observations

Figure C-1: K-density of the full wage distribution



Appendix D: Worker mobility as a channel for spillovers from foreign-connected firms

Table D-1: Number of movers by gender

	Gender			
	FCF to non-FCF movers		Between non-FCF movers	
	Male	Female	Male	Female
2013	1 356	460	5 078	2 187
2014	2 643	927	9 920	4 257
2015	3 512	1 435	13 275	5 858
2016	4 364	1 624	15 017	7 378

Source: SARS–NT panel
Note: sample–largest connected group

Table D-2: Number of movers by wage quantiles

	Wage quantiles							
	FCF to non-FCF movers				Between non-FCF movers			
	Low	Low_med	Med_high	High	Low	Low_med	Med_high	High
2013	404	384	388	641	1 848	1 604	1 707	2 171
2014	770	788	789	1 224	3 901	3 036	3 390	3 994
2015	1 058	1 122	1 234	1 539	5 146	4 839	4 471	5 005
2016	1 587	1 554	1 271	1 581	5 768	6 348	5 194	5 402

Table D-3: Number of movers by technology

	Technology					
	FCF to non-FCF movers			Between non-FCF movers		
	Low	Medium	High	Low	Medium	High
2013	840	584	394	3 678	2 568	1 076
2014	1 599	1 132	844	7 068	4 612	2 641
2015	2 361	1 683	907	9 570	6 540	3 290
2016	2 597	2 194	1 198	11 869	7 415	3 397

Source: SARS–NT panel
Note: sample–largest connected group

Table D-4: Spillovers from hybrid firm new hires in non-FCFs

Log real output	All firms to non-FCF	All firms to above median firm	All firms to below median firm	Above median firms to non-	Below median firms to non-
lncapital	0.0854**	0.102**	0.0826**	0.0944**	0.0677**
	(0.00298)	(0.00539)	(0.00335)	(0.00401)	(0.00424)
lncos	0.562**	0.506**	0.618**	0.517**	0.681**
	(0.00374)	(0.00567)	(0.00476)	(0.00463)	(0.00602)
lnlab	0.296**	0.270**	0.249**	0.324**	0.198**
	(0.00509)	(0.00998)	(0.00792)	(0.00655)	(0.00796)
share_Hybrid	0.0752**	0.0777**	0.197**	0.124**	-0.0916**
	(0.0159)	(0.0245)	(0.0214)	(0.0197)	(0.0282)
share_non_FCF	0.185**	0.214**	0.103**	0.158**	0.211**
	(0.0268)	(0.0477)	(0.0326)	(0.0413)	(0.0340)
significant productivity premium (δ)					
share_Hybrid	0,2208	0,1923	0,052	0,2	negative
share_non_FCF	0,111	0,056	0,146	0,166	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	9,026	4,634	4,384	5,75	3,261
R-squared	0.930	0.871	0.919	0.924	0.947

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Table D-5: Spillovers from hybrids to non-FCFs by gender

Log real output	All firms to non-FCF	All firms to above median firm	All firms to below median firm	Above median firms to non-	Below median firms to non-
lncapital	0.0856**	0.102**	0.0828**	0.0940**	0.0677**
	(0.00299)	(0.00541)	(0.00335)	(0.00401)	(0.00426)
lncos	0.562**	0.506**	0.619**	0.517**	0.681**
	(0.00374)	(0.00568)	(0.00477)	(0.00463)	(0.00604)
lnlab	0.295**	0.270**	0.247**	0.325**	0.198**
	(0.00510)	(0.0100)	(0.00796)	(0.00655)	(0.00799)
share_Hybrid_male	0.0920**	0.0983**	0.229**	0.138**	-0.0927**
	(0.0176)	(0.0274)	(0.0233)	(0.0215)	(0.0318)
share_Hybrid_female	0.0171	0.0287	0.0507	0.0594	-0.0829
	(0.0302)	(0.0398)	(0.0478)	(0.0370)	(0.0519)
share_non_FCF_male	0.172**	0.238**	0.0629+	0.185**	0.205**
	(0.0309)	(0.0604)	(0.0362)	(0.0456)	(0.0407)
share_non_FCF_female	0.209**	0.189**	0.231**	0.0184	0.223**
	(0.0479)	(0.0692)	(0.0662)	(0.0823)	(0.0554)
productivity premium (δ)					
share_Hybrid_male	0,203	0,17617	0,018	0,187	negative
share_Hybrid_female	none	none	none	none	none
share_non_FCF_male	0,123	0,032	0,1841	0,14	0
share_non_FCF_female	0,086	0,081	0,016	none	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	9,026	4,634	4,384	5,750	3,261
R-squared	0.930	0.871	0.919	0.924	0.947

Standard errors in parentheses

** p<0.01, * p<0.05, + p<0.1

Table D-6: Spillovers from hybrids to non-FCFs by wage quantile

Log real output	All firms to non-FCF	All firms to above median firm	All firms to below median firm	Above median firms to non-	Below median firms to non-
lncapital	0.0848**	0.101**	0.0811**	0.0931**	0.0665**
	(0.00299)	(0.00542)	(0.00336)	(0.00403)	(0.00428)
lncos	0.562**	0.506**	0.621**	0.517**	0.681**
	(0.00375)	(0.00568)	(0.00480)	(0.00465)	(0.00603)
lnlab	0.295**	0.269**	0.241**	0.324**	0.196**
	(0.00509)	(0.0100)	(0.00804)	(0.00656)	(0.00795)
share_Hybrid_low	0.0542	0.114*	0.00741	0.126**	-0.0526
	(0.0356)	(0.0444)	(0.0640)	(0.0429)	(0.0660)
share_Hybrid_low_med	0.0395	0.0761+	0.0526	0.135**	-0.175**
	(0.0298)	(0.0402)	(0.0435)	(0.0365)	(0.0508)
share_Hybrid_med_high	0.121**	0.107*	0.340**	0.182**	-0.106*
	(0.0284)	(0.0427)	(0.0398)	(0.0340)	(0.0511)
share_Hybrid_high	0.0591*	0.0316	0.210**	0.0621*	-0.0762
	(0.0262)	(0.0431)	(0.0325)	(0.0313)	(0.0474)
share_non_FCF_low	0.0881	-0.0412	0.152	0.0555	0.0781
	(0.0921)	(0.157)	(0.108)	(0.136)	(0.115)
share_non_FCF_low_med	-0.00226	-0.0755	0.0120	-0.0887	0.00979
	(0.0662)	(0.110)	(0.0772)	(0.102)	(0.0776)
share_non_FCF_med_high	0.179**	0.281**	-0.0285	0.191**	0.250**
	(0.0413)	(0.0687)	(0.0543)	(0.0685)	(0.0547)
share_non_FCF_high	0.232**	0.307**	0.110*	0.226**	0.249**
	(0.0430)	(0.0777)	(0.0513)	(0.0583)	(0.0594)
productivity premium (δ)					
share_Hybrid_low	none	0,182	none	0,198	none
share_Hybrid_low_med	none	0,2199	none	0,189	negative
share_Hybrid_med_high	0,174	0,189	0	0,142	negative
share_Hybrid_high	0,2359	none	0,031	0,2619	none
share_non_FCF_low	none	none	none	none	none
share_non_FCF_low_med	none	none	none	none	none
share_non_FCF_med_high	0,116	0,015	none	0,133	0
share_non_FCF_high	0,063	0	0,131	0,098	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	9,026	4,634	4,384	5,750	3,261
R-squared	0.930	0.872	0.919	0.924	0.947

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Table D-7: Spillovers from hybrids to non-FCFs by technology

Log real output	All firms to non-FCF	All firms to above median firm	All firms to below median firm	Above median firms to non-	Below median firms to non-
lncapital	0.0818**	0.104**	0.0789**	0.0910**	0.0635**
	(0.00302)	(0.00545)	(0.00333)	(0.00405)	(0.00433)
lncos	0.563**	0.505**	0.628**	0.518**	0.680**
	(0.00376)	(0.00577)	(0.00483)	(0.00469)	(0.00600)
lnlab	0.297**	0.265**	0.235**	0.324**	0.201**
	(0.00517)	(0.0100)	(0.00811)	(0.00663)	(0.00808)
share_Hybrid_low tech	0.214**	0.364**	0.102+	0.252**	0.120+
	(0.0426)	(0.0692)	(0.0538)	(0.0548)	(0.0628)
share_Hybrid_med tech	0.0870**	0.0582*	0.400**	0.121**	-0.130**
	(0.0185)	(0.0253)	(0.0302)	(0.0215)	(0.0455)
share_Hybrid_high tech	-0.128**	0.0499	-0.144**	-0.0899	-0.207**
	(0.0359)	(0.122)	(0.0349)	(0.0611)	(0.0403)
share_non_FCF_low tech	0.0183	0.320**	-0.0806	0.0429	-0.0619
	(0.0533)	(0.0924)	(0.0610)	(0.0766)	(0.0666)
share_non_FCF_med tech	0.257**	0.0511	-0.0282	0.239**	0.333**
	(0.0368)	(0.0833)	(0.0462)	(0.0525)	(0.0567)
share_non_FCF_high tech	0.218**	0.299**	0.230**	0.0337	0.275**
	(0.0484)	(0.0713)	(0.0620)	(0.0901)	(0.0525)
productivity premium (δ)					
share_Hybrid_low tech	0,083	0	0,133	0,072	0,081
share_Hybrid_med tech	0,21	0,2068	0	0,203	negative
share_Hybrid_high tech	negative	none	negative	none	negative
share_non_FCF_low tech	none	0	none	none	none
share_non_FCF_med tech	0,04	none	none	0,085	0
share_non_FCF_high tech	0,079	0	0,005	none	0
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes	Yes
Observations	9,026	4,634	4,384	5,750	3,261
R-squared	0.931	0.872	0.922	0.924	0.948

Standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1