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How large is the wage penalty in the labour broker sector?

Evidence for South Africa using administrative data

Aalia Cassim[1] and Daniela Casale[2]

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Abstract: Public debate on the temporary employment services, or labour broker, sector in South Africa has focused on temporary workers' wages and benefits. Empirical research is limited: temporary employment services cannot be accurately identified in recent labour force surveys. In 2015, South Africa Revenue Services and the National Treasury made company and employee income tax data available which explicitly captures labour brokers and employee wages. We use this to examine whether there is a wage penalty for labour broker employees and, if so, its magnitude. We control for individual and time fixed effects. Such empirical evidence is important in debates on the sector's role in the South African labour market.

Keywords: temporary employment services, wage differentials, administrative data, South Africa
JEL classification: J31, J41

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[1] AMERU (African Microeconomic Research Unit), School of Economic and Business Sciences, University of the Witwatersrand, Johannesburg, and National Treasury, Pretoria, South Africa, corresponding author: aalia.cassim@treasury.gov.za; [2] AMERU, School of Economic and Business Sciences, University of the Witwatersrand, Johannesburg, South Africa.

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Information and requests: publications@wider.unu.edu

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

The use of temporary employment[1] has grown both globally and in South Africa (Deakin 2002; Benjamin et al. 2010). In part, this is related to firms requiring lower adjustment costs in certain economic environments, such as poor macroeconomic conditions (Holmlund and Storrie 2002) or when there is a need to become more competitive (Matsuura et al. 2011; Saha et al. 2013). Holmlund and Storrie (2002) find that poor macroeconomic conditions in Sweden in the 1990s resulted in employers offering more temporary contracts, and employees being more willing to accept this form of employment. In Japan, global competition in tradable goods led to a rapid increase in temporary employment, specifically in those sectors where the bulk of sales was to foreign markets (Matsuura et al. 2011). Similarly in India, both pro-worker labour institutions and increased import penetration led to greater use of contract labour in the Indian manufacturing sector (Saha et al. 2013). In South Africa, it has been suggested that trade liberalization led to firms externalizing employment because of the drive to lower wages in sectors where there has been increased competition (Theron 2005).

Given the context in which temporary employment grows, it is widely expected that there would be a wage differential between temporary workers and non-temporary workers (Lass and Wooden 2017). Indeed, a wage penalty for temporary workers has been found in a number of countries, including India (Saha et al. 2013), Portugal (Boeheim and Cardoso 2007), Germany (Pfeifer 2012), Britain (Brown and Sessions 2005), and the US (Segal and Sullivan 1997; Houseman 2001). International evidence on the size of the wage penalty for temporary workers, after adjusting for demographic factors and job characteristics or controlling for fixed effects, suggests a penalty ranging from 6 per cent in the UK (Booth et al. 2002) to around 20 per cent in France and the US (Segal and Sullivan 1997; Blanchard and Landier 2002). Picchio (2006) estimates a wage penalty for temporary workers of around 12–13 per cent in Italy, but this declines with the seniority of temporary workers, with a reduction in the wage gap of about 2.3 percentage points after one year of tenure.

While the wage gap tends to decline after controlling for certain characteristics, where the gap does persist for temporary workers is in terms of benefits, such as pension, medical aid, and unemployment insurance. Temporary workers have been found to have far lower levels of access to benefits than permanent workers, even after controlling for factors such as race, education, and location (Houseman 2001). This suggests that employers use labour brokers as a way to lower costs in terms of both the base wage and benefits.

In South Africa, the public debate on temporary employment services (TES), often referred to as the labour broker sector, has largely centred around the issue of decent work, and specifically the wages and benefits afforded to temporary workers (Bhorat et al. 2016). The focus on discrimination in this sector resulted in amendments being made in early 2015 to the part of the Labour Relations Act (LRA) that governs temporary employment. The new legislation attempted to better regulate the TES industry and offer greater protection to temporary workers. However, there is little empirical evidence on the extent of a penalty to temporary employment service sector

[1] Temporary workers, as defined here, are employed by staffing agencies, which are ultimately responsible for the salary, taxes, and benefits of the leased employee. When a company contracts with a staffing agency for temporary help, the company pays the staffing agency a set fee for the leased worker. Temporary employment services workers can also be distinguished from seasonal, temporary, or part-time contingent workers, who typically are employees of the company that hired them and who are usually let go when the work is complete.

workers in South Africa, mostly because current South African labour force surveys do not explicitly capture this sector.

Before they were replaced by the Quarterly Labour Force Surveys (QLFS), the earlier biannual Labour Force Surveys (LFS) for the years 2000 to 2007 did ask employees whether they were employed by a labour broker. The final LFS survey, conducted in September 2007, provided an estimate of 11 million employees in the country, of whom 37 000 (0.3 per cent) were reported as being employed by a labour broker, and 274 000 (2.5 per cent) by a contractor or agency. It has been suggested that this is too low an estimate for South Africa (Budlender 2013). Misreporting on sector of employment or nature of employment contract is a well-known problem in household surveys (Segal and Sullivan 1998), and particularly when there is proxy reporting as in the LFS.

The QLFS, which replaced the LFS in 2008, did not include a similar question. However, to try and identify TES workers, Benjamin et al. (2010) and Bhorat et al. (2016) used the standard industry classification code 889, *Business Activities Not Elsewhere Classified*, which falls under the broader category *Finance and Business Services*, and which includes, among a number of other activities, 'labour recruitment and provision of staff; activities of employment agencies and recruiting organisations; hiring out of workers (labour broking activities)'.[2] Although it is not possible to separate out the TES sector from the other activities listed under the general code 889, Benjamin et al. (2010) attempted to estimate the size of the TES sector and arrived at a figure of just over 600 000 TES workers in 2008. Budlender (2013) undertook a similar exercise and found that between 2008 and 2012 the number tended to increase year on year, reaching over 865 000 in 2012. The only exception to the steady increase was for 2009, when the number recorded was closer to 883 000, suggesting that the global financial crisis may have resulted in an increased use of temporary employment services. Also cognizant of the limitations of the QLFS data, Bhorat et al. (2016) estimated that there were just under 1 million temporary jobs in 2014.[3]

Given the broad list of activities within the classification, Budlender (2013) suggests that the 889 code is not a good proxy for TES workers. According to her analysis for 2012, 44 per cent of the workers recorded in this industry are likely to be security guards and 15 per cent are likely to be cleaners in offices, hotels, and the like. These workers are outsourced,[4] not temporary agency workers. Of the rest, the bulk are likely to be employed internally by the company (rather than the TES firm). Budlender (2013) further noted that while over 93 per cent of the workers falling under this code are employees, 59 per cent of the employees are recorded as having permanent contracts, 22 per cent have contracts of limited duration, and 19 per cent have contracts of unspecified duration. Budlender (2013: 3) writes that 'while there is widespread agreement that a large number of workers are employed by temporary employment agencies in South Africa, and that the number

[2] The category also includes 'disinfecting and exterminating activities in buildings; investigation and security activities; building and industrial plant activities; photographic activities; packaging activities; other business activities; credit rating agency activities; debt collecting; agency activities; stenographic, duplicating, addressing, mailing list or similar activities; other business activities'.

[3] Bhorat et al. (2015) examine earnings differentials in the TES sector using the subsector *Business Activities N.E.C.* and find a wage penalty of around 10 per cent when examining firms that comply with unemployment insurance and other benefits, and closer to 40 per cent when examining non-compliant firms. The concerns around the data outlined above are, however, noted.

[4] Outsourcing is when a company decides to eliminate internal staff or a department that previously handled a specific function, such as a call centre, human resources, shipping, payroll, or accounting. Many companies have chosen to do away with internal departments by outsourcing non-core departmental functions to companies or independent contractors that provide these services for a fee.

has grown over time, there is similarly widespread agreement that the available numbers are estimates based on various assumptions rather than more reliable "counts" of the phenomenon'.

In 2015, South Africa Revenue Services (SARS) and the National Treasury (NT) made company and employee income tax administrative data available for research purposes.[5] It is the first South African data set from the last decade that explicitly captures which firms are labour brokers and also contains individual employee wages. This paper makes use of the administrative panel data for the years 2011 to 2015 to explore whether there is a wage penalty for employees in the labour broker sector, examining both the base wage (the salary less contributions to medical aid, unemployment insurance, pension, etc.) and the total income received from a company. Although the data do not contain many demographic or job characteristics, the panel nature of the data allows us to control for time and individual fixed effects. In other words, we can examine variation in wages for employees who switched between TES and non-TES jobs over the period of the panel. In addition, we examine the temporary employee wage differentials before and after the temporary employment spell. The reason for this is that temporary workers often accept such jobs due to factory closure or after being laid off, and thus wage differentials may reflect the circumstances in which they accept the job rather than the job itself (Segal and Sullivan 1998). Providing empirical evidence on the earnings differential between labour broker workers and other workers in South Africa is an important first step to help inform debates on the role of this sector in the South African labour market. [6]

The rest of the paper is structured as follows. Section 2 describes the data and definitions used in the analysis. Section 3 presents the descriptive analysis. Section 4 explains the methodology. Section 5 presents the econometric analysis and Section 6 concludes.

2 Data and definitions

This section outlines the structure of the SARS-NT panel data; describes some of the complexities of the data and how these were dealt with; defines the main variables used in the analysis; and lastly, summarizes some of the advantages and disadvantages of using the data for this research.

2.1 Structure of the data

This paper uses an unbalanced employee panel data set made available by SARS and the NT for the tax years 2011 (i.e. 1 March 2010 to end February 2011) to 2015 (1 March 2014 to end February 2015).[7] The data set was created from employee income tax certificates submitted by employers (IRP5 and IT3(a)) to SARS. The unit of analysis is essentially at the *job contract* level, as it includes records of employment for tax-paying firms over the period. However, the data can be collapsed to the individual level, as the records also contain a person ID number. Each IRP5- or IT3(a)-submitting entity is identified through a Pay As You Earn (PAYE) reference number which can

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[5] There have been only a handful of research papers that have used these data in the past two years. The research has mostly covered the employment tax incentive (Chatterjee and Macleod 2016; Ebrahim et al. 2017) and wage inequality among employees (Bhorat et al. 2017).

[6] This paper is the first in Aalia Cassim's PhD thesis. Future work will examine whether TES employment acts a stepping-stone to more permanent work, particularly among the youth, and whether there were disemployment effects in the TES sector following the 2015 amendments to the Labour Relations Act.

[7] The years in the IRP5 panel refer to the period 1 March of the previous year to the end of February of that year regardless of a firm's financial year. Pieterse et al. (2016) showed that 85 per cent of firms have their financial year end at the end of February.

be linked to the Company Income Tax (CIT) records submitted to SARS for that entity, allowing us to identify the firm an employee is employed in. While we do not use the firm-level panel[8] or CIT data for this particular analysis, linking the CIT data with the employee or IRP5 data enables researchers to examine both worker and firm performance in a given year.

Pieterse et al. (2016), in their detailed discussion of the construction and features of the panel, provide different ways to think of a firm and its employees using the CIT and IRP5 panel data sets, also highlighting the complexity of the data:

- A CIT-registered firm may have multiple PAYE numbers because they have different branches.
- An individual can appear in two different PAYE-registered entities but work at a single firm only, as they may have an employee record for the head office and the branch.
- An individual may also have more than one IRP5 form because there are revisions to IRP5 forms associated with the same firm (PAYE number).
- An individual may have more than one IRP5 form in the same year because they either are performing two jobs simultaneously or have sequential jobs in the same year.

A company tax reference number is not always linked to a PAYE reference number. This can happen when firms do not have any workers, such as a company that earns rental income to benefit from lower company tax rates, or a bank nominee company that holds significant assets on behalf of investment companies or pension funds. Only 21–23 per cent of firms in the CIT data can be matched to IRP5 data (Pieterse et al. 2016). In addition, there are IRP5 forms that cannot be linked to a firm, such as for employees of government organizations. While these individuals are dropped from the CIT panel, they are still included in the IRP5 panel. In the IRP5 data, we therefore think of a firm not as a CIT-registered entity but as a PAYE-registered entity, as we are interested in employers and their employees.

As noted above, the employee database contains information from individual-level employee tax certificates (IRP5 and IT3(a)) submitted by PAYE-registered entities. All employers must register with SARS within 21 business days of becoming an employer, unless none of the employees are liable for normal tax. Where no employee tax was deducted from remuneration and the employee receives R2000 or more per year, an IT3(a) form is provided to the employee. If an employee earns less than R2000 in a given tax year and no employee tax was deducted, the employee is not issued with an IRP5 or an IT3(a) form. The IRP5 certificates of all employees in a company must be submitted within 60 days of the end of the tax year. The IRP5 and IT3(a) forms issued by employers are reconciliation forms that include details of the total amount paid by that employer to the employee, as well as the total amount of tax paid, skills development levy payments, unemployment insurance fund (UIF) payments, pension and medical aid contributions, and the periods worked in the year of assessment. In addition to providing information on earnings, data from these forms can be used to generate employment estimates, and to identify a limited set of employee/job characteristics (namely, length of contract within the tax year and gender and age of employee) and firm characteristics (firm size and industry in which the firm operates).

Importantly for the purposes of this research, the SARS-NT panel has a binary indicator which identifies TES or labour broker firms according to their PAYE reference number. Labour brokers are identified through an IRP30A form that they are expected to submit to SARS, which absolves

[8] The construction of the firm-level panel, created using CIT records, is detailed by Pieterse et al. (2016). For this analysis, we use the IRP5 panel data and the firm-level characteristics that are available in those same records.

the client firms from having to deduct tax from any payments made to a labour broker, as the labour broker is responsible for paying tax on behalf of their employees. The binary indicator can be matched to both the CIT panel and the IRP5 panel using the PAYE reference number.

2.2 Challenges and cleaning process

There are a number of challenges one faces when working with the SARS-NT panel, given the complexity of the data. This sub-section describes the data further and summarizes the methods and decision-making processes used to deal with multiple job records, overlapping job contracts, and coding errors.

The raw IRP5 data set is an unbalanced panel at the job contract level for the years 2011 to 2015. About 80 per cent of individuals have just one job contract per year; however, for the rest, multiple entries per year exist and decisions need to be taken on how best to 'clean' the data for use in a fixed-effect analysis. Our aim is to be left with a panel of individuals with information at the job contract level, where each person may have a number of sequential (or non-overlapping) jobs per year either at the same firm or at different firms. We refer to the resulting sample as the 'main job sample'. The steps taken to arrive at this sample are detailed below, along with some other sample restrictions:

i. **Multiple IRP5 entries at the same firm that do not overlap.** Where there are multiple IRP5 entries for the same firm that do not overlap—so for example, where a person has one job contract from March to June and another from July to September at the same firm—we keep the job entries as separate job contracts.
ii. **Multiple overlapping IRP5 entries at the same firm.** Where contracts at the same firm overlap, we use the average earnings and average days for the overlapping contracts. While some of the overlapping contracts have different start and end dates, a large proportion of these contracts appear to be duplicates and some have the same start date, end date, and earnings. Overall, these 'duplicate' observations make up around 24 per cent of the original sample (leaving us with 69 million out of the original sample of 90 million job contracts after the averaging process).[9] This leaves us with only one job contract per individual per firm in a given year, unless there are contracts that do not overlap, as noted above in (i), or a person has multiple jobs in a year in different firms.
iii. **Overlapping contracts at different firms.** In cases where individuals have job contracts at different firms that are overlapping (for instance, when someone undertakes ad hoc or contract work simultaneously with their main job), we need to identify the individual's primary job. We take the job with the highest earnings as the 'main job' for that period. We drop approximately a further 5 million job contract observations that are considered to be secondary jobs or piecemeal jobs as they are not the highest-earning job during that period (leaving us with 64 million observations). Thus we end up with a panel of individuals at the job contract level, where each person may have a number of sequential job contracts per year (as long as the jobs are not overlapping).
iv. **Missing ID numbers.** We drop around 350 000 observations with no ID numbers or passport numbers, as this would prevent us from tracking individuals over time.

[9] It is not entirely clear why contracts would overlap at the firm; while each contract could refer to an actual job contract, multiple overlapping contracts are most likely to be IRP5 revisions. Revisions to the IRP5 might be submitted in the event of a mistake or a change to the employment duration. Unfortunately, we are unable to tell which version of the contract was revised and thus which is the most recent version, hence the averaging approach adopted (Chatterjee and Mcleod 2016).

v. **Comparing like with like.** Given that we are comparing TES sector workers to the rest of the employed population, it is important that we compare like with like. Therefore, we remove observations in which individuals earned more than R10 million per year as these are likely to be CEOs and directors of companies who are not comparable to TES sector workers. Upon removing them, we exclude around 3000 non-TES sector contracts and 11 TES contracts. In addition, we remove those earning less than R2000 per year (or R167 per month) because they should not be included in the tax database. They are likely to be reporting errors, or it could be the case that a human resources employee unnecessarily included IRP5 forms for all workers despite the criterion discussed above. This results in a further loss of less than 1 per cent of the overall sample (around 1 million of 64 million observations, of which 204 000 involve TES jobs).

vi. **Age cut-off.** Lastly, we limit the sample to those between the ages of 16 and 65.

Table 1 presents the number of individuals and job contracts in the final constructed *main job sample* of working-age individuals. Over the five-year panel, there are around 45 million individual observations and around 50.5 million job contract observations.[10]

Table 1: Description of employee panel, 2011 to 2015 (16–65 years)

Tax year	Job contracts	Individuals
2011	9 603 863	8 593 848
2012	10 043 436	8 900 761
2013	10 216 097	9 096 931
2014	10 170 368	9 135 393
2015	10 473 427	9 370 194
Total	50 507 191	45 097 127

Source: Authors' estimates based on IRP5 data.

2.3 Description of variables used

Job duration

Job duration is estimated as the number of days between the start date and the end date of the term of employment reported in the IRP5 or IT3(a) form. The variable is truncated at one year, however. So for permanent employees, for example, the job contract length would be recorded as the maximum length of one tax year. As such, a '365-day contract' may refer to someone who is actually employed in a one-year contract or to someone employed for a duration of longer than a year in a particular job. Due to errors in the inputting of the start and end date, some job duration records are estimated to be negative (around 3 per cent), and these are indicated as 'missing' in the data set.

Earnings

Each IRP5 form reports *gross non-retirement fund income* (the salary paid to an individual from which contributions to medical aid and UIF are deducted), *non-taxable income* (which includes arbitration

[10] Given the different methods of data collection, one would not expect to find correspondence between the employment numbers from the SARS-NT data and the QLFS data. Nonetheless, it is interesting to compare the overall figures. According to the QLFS Quarter 1 of 2015, 11.68 million people were employed in the formal sector including agriculture. Total employment including the informal sector was estimated to be 15.06 million individuals. This means that in 2015, for example, the sample of IRP5 data in Table 1 captures around 80 per cent of formal employment and 62 per cent of total employment according to the household survey data.

awards, purchased annuities, travel reimbursements, subsistence allowances, uniform allowances, and other allowances) and *gross retirement income* (or pension contributions). The sum of these three variables provides *total earnings* for a specific job contract.[11] To estimate the earnings penalty, we use as dependent variables both *total earnings* and what we refer to as the *base salary*. The *base salary* is the gross non-retirement fund income (which already excludes pension contributions) less the contributions made to medical aid and UIF.

We use monthly earnings for the analysis (as do Ebrahim et al. 2017 and Chatterjee and Macleod 2016). First, daily earnings are calculated using *total earnings* for a specific contract divided by the length of that contract (*job duration*). From this, monthly earnings are estimated by multiplying daily earnings by working days in a month.

Firm size

The IRP5 data do not include a variable indicating firm size and therefore this variable is imputed, taking into account that not all workers on a firm's payroll were employed for the entire year. Firm size is the total number of employees at the firm, weighted by the number of days an employee worked in a given year. Similar methods were employed in other studies using the IRP5 data (Pieterse et al. 2016; Bhorat et al. 2017; Ebrahim et al. 2017).

In addition, the IRP5 includes *date of birth* (used to calculate age) and *gender*. An industry variable, which is self-reported by the firm, is merged in from the CIT data matching on a firm's PAYE reference number.

2.4 Advantages and disadvantages of the data set in the context of the research project

There are clearly a number of advantages offered by the data. These include the larger sample size than in the labour force survey data; the longitudinal nature of the data, which allows us to track firms and individuals over time (and therefore control for individual fixed effects in identifying the wage penalty); more reliable reporting of income than in household surveys; and, importantly for this work, the ability to accurately identify firms (and therefore employees) in the TES sector.

However, there are also a number of potential limitations. The data set only contains tax-registered firms and, among these, only the firms that actually completed a tax return in the relevant period. This means that employees of unregistered, small, very young, or informal TES firms, which may be of particular interest in the South African context (as the employees in these firms may be the most vulnerable), have not been captured (Pieterse et al. 2016). However, in terms of comparability when estimating the wage penalty for TES vs non-TES workers, of course low-wage workers or workers in informal firms in the non-TES sector are also excluded from the data.

Another limitation of the data set is that there is no information on the number of hours worked per day/month in the job contract. This means any monthly wage difference between workers may be due to differences in the hourly wage or differences in the number of hours worked in a month, and we are unable to differentiate between these two factors.

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[11] For simplicity we use the term *total earnings*, but more specifically this variable represents total gross earnings as it still includes the tax portion.

Finally, TES workers are not differentiated from administrative staffing personnel working in the TES firm. This is unlikely to be a significant problem, however, given that staffing personnel constitute such a small proportion of total employment in the firm (Kvasnicka 2008).

3 Descriptive statistics

3.1 Employment trends

Table 2 presents employment in the TES and non-TES sectors at the job contract and individual levels. TES employment consistently made up between 4 and 5 per cent of total employment between 2011 and 2015. This is true whether we consider individuals employed in the TES sector as a proportion of all employed individuals, or TES job contracts as a proportion of total job contracts. While TES employment as a proportion of total employment increased and then stabilized between 2013 and 2014, the proportion declined in 2015. In absolute terms, the number of TES employees grew between 2011 and 2013 and then fell to 2012 levels by 2015, while non-TES employment continued to grow.[12]

Table 2: Job contracts and individuals by TES/non-TES status

Tax year	Job contracts			Individuals		
	TES	Non-TES	Share	TES	Non-TES	Share
2011	413 924	9 189 939	4.31%	400 584	8 193 264	4.66%
2012	454 587	9 588 849	4.53%	438 140	8 462 621	4.92%
2013	477 531	9 738 566	4.67%	459 606	8 637 325	5.05%
2014	475 951	9 694 417	4.68%	459 840	8 675 553	5.03%
2015	451 638	10 021 789	4.31%	436 323	8 933 871	4.66%

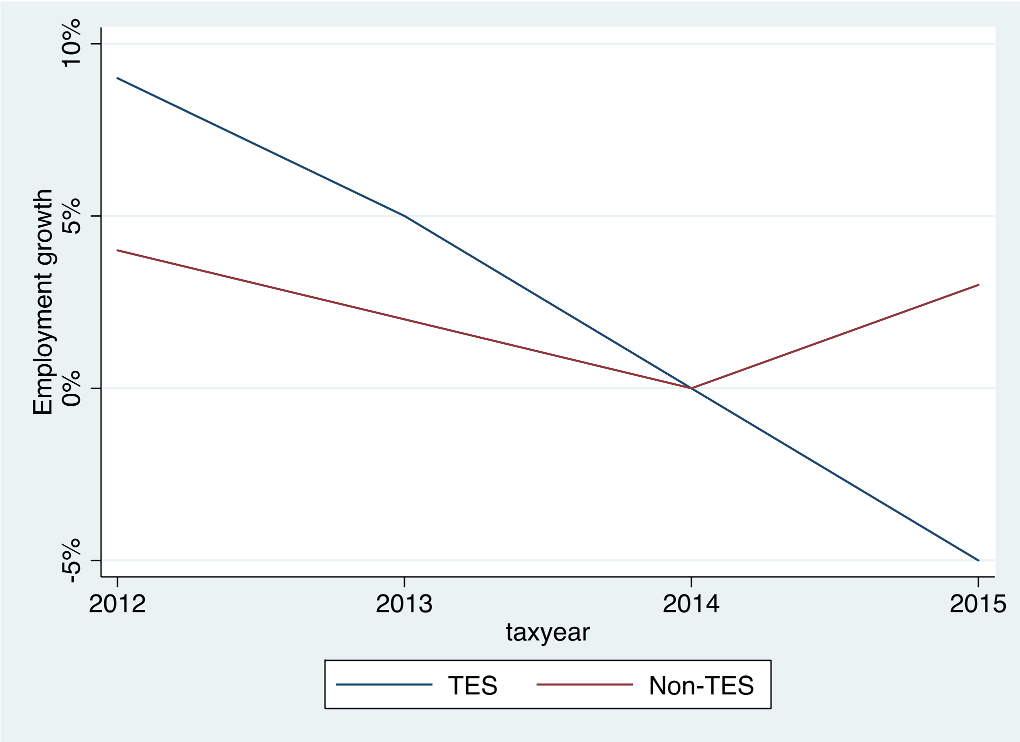
Note: This is the 'main job' sample as defined in Section 2.

Source: Authors' estimates based on IRP5 data.

Figure 1 presents growth rates for TES and non-TES employment at the individual level between 2012 and 2015. While the growth rates followed a similar downward trend between 2012 and 2014, growth rates diverged thereafter. The declining growth rate in the TES sector in the final year may be related to employers pre-empting the amendments to the LRA regarding TES employment which were introduced in January 2015 and which made the conditions around temporary hire more stringent. (This will form the subject of future research, as additional years of data in the IRP5 panel become available.)

[12] It is worth noting that based on the QLFS estimates, there were just under 1 million individuals in the *Business Services N.E.C.* category in 2014, which suggests that using this broad category from the QLFS overestimates the size of the TES sector (as has been noted in previous research; Budlender 2013),. It is possible, however, that the QLFS is picking up more low-paid workers who are not included in the SARS data.

Figure 1: Growth of TES relative to non-TES employment



Note: This is the 'main job' sample as defined in Section 2 and is at the individual level.

Source: Authors' estimates based on IRP5 data.

Table 3 presents descriptive statistics for TES and non-TES job contracts for the year 2014.[13] TES employees are younger than non-TES employees, with around half of all TES job contracts filled by individuals between 16 and 29 years old, relative to 32 per cent of non-TES contracts. This finding further motivates the need to better understand this sector, as it may play a key role in absorbing young people into employment, especially in the context of a youth unemployment rate of around 39 per cent in South Africa.[14] In terms of gender, males dominate the TES sector, with around two-thirds of job contracts filled by male employees relative to 56 per cent of job contracts in the non-TES sector. The vast majority of TES contracts, 74 per cent, are for less than 12 months. The most common job contract length for the TES sector is more than six months but less than a year (39 per cent). In contrast, for non-TES employment, the most common job contract length is a year or more (53 per cent).

In terms of firm size, the majority of TES employment, 73 per cent, is in TES firms that have more than 1000 employees, whereas only 39 per cent of non-TES employment is in very large firms of more than 1000 employees. In terms of industry, the greatest concentration of TES firms is in the finance and business services sector (84 per cent), followed by the construction sector (4 per cent). These are also the sectors where employment growth has been observed over the last two decades according to LFS data (Bhorat et al. 2016). As we would expect, non-TES firms are more widely spread across the different industrial categories. Overall, the key descriptive characteristics of TES employment relative to non-TES employment indicate that TES

[13] Employment (and therefore employee characteristics) in 2015 may have been affected by the LRA amendments if there was a disemployment effect. For this reason, we use 2014 data here for illustrative purposes.

[14] This estimate is based on data from the QLFS, quarter 1, 2017, and uses the narrow or 'searching' definition of unemployment.

employment is more likely to be held by young, male employees, employed on short contracts (of less than a year) and in firms with more than 1000 employees.

Table 2: Characteristics of TES vs non-TES employment, 2014

	TES		**Non-TES**	
	Proportion	***N***	***Proportion***	***N***
Age				
16–29	50.45%	233 125	31.94%	2 962 962
30–39	30.09%	139 075	29.92%	2 775 132
40–49	12.50%	57 759	20.82%	1 931 280
50–65	6.96%	32 170	17.32%	1 606 752
Total	100%	462 129	100%	9 276 126
Gender				
Female	33.14%	164 893	43.78%	3 983 691
Male	66.86%	332 614	56.22%	5 116 353
Contract duration				
less than 15 days	3.13%	14 843	1.75%	164 617
15 to 30 days	4.44%	21 040	2.52%	236 790
1 to 3 months	12.64%	59 938	8.79%	826 120
3 to 6 months	14.83%	70 295	10.98%	1 031 592
6 months to less than a year	38.94%	184 636	23.47%	2 205 659
A year or more	26.03%	123 409	52.49%	4 932 108
Total	100%	474 161	100%	9 396 886
Firm size				
Small (0–50)	1.82%	8 693	26.28%	2 553 459
Medium (51–250)	6.49%	30 946	19.47%	1 891 747
Large (251–1000)	18.55%	88 390	15.34%	1 490 886
Very large (more than 1000)	73.13%	348 440	38.92%	3 781 714
Total	100%	476 469	100%	9 717 806
Industry				
Agriculture	1.53%	7 293	8.58%	827 997
Mining	1.12%	5 340	4.27%	412 415
Manufacturing	3.08%	14 661	16.79%	1 620 096
Utilities	0.08%	377	1.27%	122 366
Construction	4.34%	20 664	3.58%	345 562
Trade	2.23%	10 612	12.13%	1 169 929
Transport	0.76%	3 634	4.23%	408 106
Tourism	0.06%	285	2.78%	268 496
Financial	83.73%	398 929	25.73%	2 482 196
Government	0.00%	0	13.39%	1 291 725
Non-government community services	3.08%	14 655	7.24%	698 292
Total	100%	476 450	100%	9 647 180

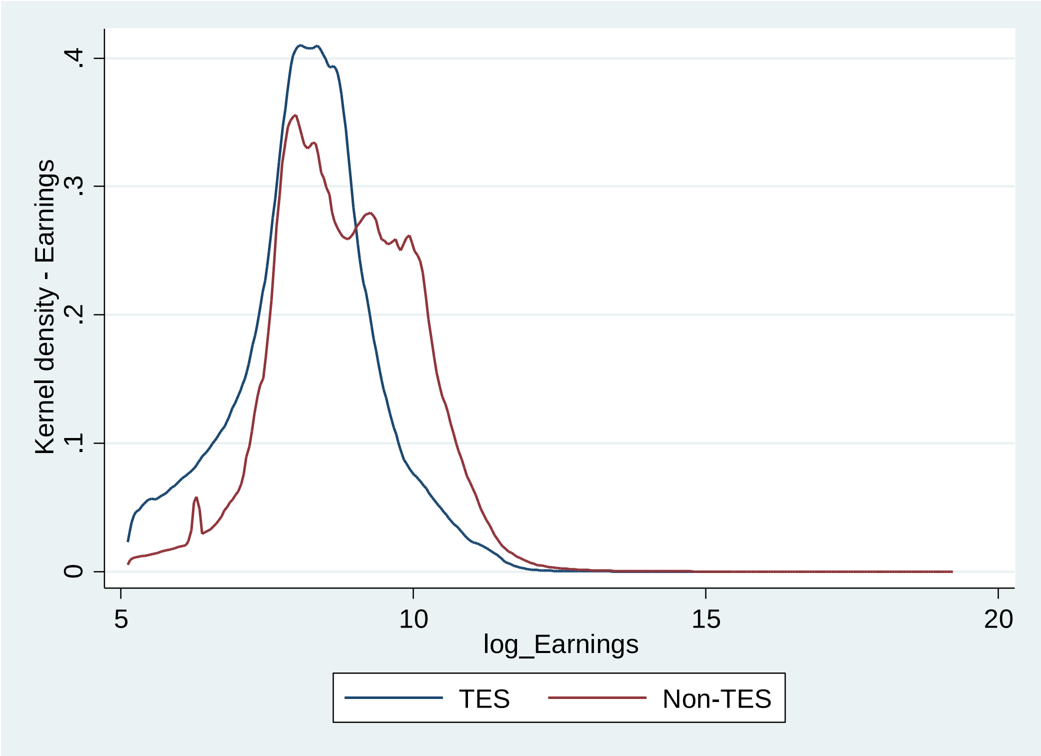
Note: This is the ’main job’ sample as defined in Section 2 and is at the job contract level.

Source: Authors’ estimates based on IRP5 data.

3.2 Wage differentials

Figure 2 shows the kernel density of the log of monthly wages for TES and non-TES jobs in 2014. The non-TES earnings distribution sits to the right of the TES earnings distribution as expected, and has a much longer upper tail.

Figure 2: Earnings kernel density, 2014



Note: This is the 'main job' sample as defined in Section 2 and is at the job contract level.

Source: Authors' estimates based on IRP5 data.

Table 4 presents the mean monthly total earnings in TES and non-TES job contracts, as well as the ratio of TES to non-TES earnings at the mean and the 25th, 50th, and 75th percentiles, for the full sample and disaggregated by age of employee, gender, job duration, firm size, and industry. For the full sample, TES wages are 50 per cent of non-TES wages at the mean and 59 per cent at the median. The wage differential is lower at the bottom of the earnings distribution, with TES wages around 67 per cent of non-TES wages at the 25th percentile, but 43 per cent at the 75th percentile.

While the ratio of TES to non-TES earnings is fairly inconsistent across the categories, there are a few noticeable patterns. First, the mean TES wage penalty is larger in the middle of the age distribution. In other words, the TES wage penalty is larger among jobs held by 30- to 49-year-olds than jobs held by younger workers (16- to 29-year-olds) and older workers (50- to 65-year-olds). Second, at the purely descriptive level, the mean wage penalty in the TES sector is only slightly higher for females than males. Third, excluding job contracts of less than 15 days (which make up a very small proportion of all contracts), the wage penalty associated with TES employment appears to increase the longer the contract length. There is a particularly large TES wage penalty for job contracts of a year or more. Fourth, there appears to be a wage *premium* for TES jobs in firms classified as small (with 50 employees or less) through to medium firms (with 51–250 employees), while a wage penalty exists for TES jobs in large firms (with 251–1000 employees) and particularly in firms with more than 1000 employees (where the vast majority of TES employment is recorded). Lastly, in terms of industry, mean TES wage penalties are most extreme for transport and communications, financial services (where the bulk of TES employment is located), and trade.

Table 3: Monthly total earnings for TES and non-TES jobs, 2014

	Total earnings (mean)[a]		Ratio TES/non-TES			
	TES (ZAR)	Non-TES (ZAR)	Mean	p25	p50	p75
Overall	7 215.63	14 417.72	0.50	0.67	0.59	0.43
Age						
16–29	4 658.91	7 075.66	0.66	0.69	0.82	0.68
30–39	7 663.95	13 625.55	0.56	0.71	0.64	0.49
40–49	10 964.90	19 506.70	0.56	0.65	0.51	0.45
50–65	15 798.93	23 137.91	0.68	0.64	0.57	0.62
Gender						
Female	5 093.35	12 037.70	0.42	0.40	0.48	0.35
Male	7 409.49	16 379.04	0.45	0.53	0.54	0.40
Length of contract						
less than 15 days	11 133.16	36 927.03	0.30	0.64	0.50	0.46
15 to 30 days	8 168.71	10 818.93	0.76	0.95	1.18	1.21
1 to 3 months	8 033.33	12 069.08	0.67	0.93	1.16	1.15
3 to 6 months	7 168.19	9 731.61	0.74	0.92	1.00	0.86
6 months to less than 1 year	6 282.08	10 090.69	0.62	0.88	0.86	0.65
A year or more	7 608.56	17 417.64	0.44	0.34	0.32	0.32
TES firm size						
Small (0–50)	18 686.01	12 338.71	1.51	1.64	1.72	1.71
Medium (50–250)	15 398.35	11 895.94	1.29	1.38	1.57	1.44
Large (50–1000)	7 716.65	14 658.78	0.53	0.77	0.74	0.52
Very large (more than1000)	6 079.44	17 203.58	0.35	0.50	0.33	0.29
Industry						
Agriculture	5 900.61	5 789.50	1.02	0.96	1.29	1.47
Mining	15 727.81	24 592.81	0.64	0.71	0.78	0.64
Manufacturing	9 941.84	15 532.49	0.64	0.99	0.94	0.67
Utilities	20 463.12	31 161.57	0.66	0.36	0.41	0.54
Construction	11 717.86	10 869.28	1.08	1.15	1.39	1.46
Trade	4 271.00	8 883.72	0.48	0.62	0.62	0.50
Transport & communications	8 077.84	20 856.21	0.39	0.48	0.52	0.48
Tourism	7 393.25	6 695.09	1.10	2.16	2.00	1.22
Financial services	6 863.01	16 033.80	0.43	0.61	0.68	0.44
Non-government community services	6 826.55	12 561.06	0.54	0.51	0.52	0.46

Notes: This is the 'main job' sample as defined in Section 2 and is at the job contract level. [a] The average US$–ZAR exchange rate for 2014 was R10.86–US$1.

Source: Authors' estimates based on IRP5 data.

The divergence between base salary and total earnings

One of the contentions in the labour broker debate is that benefit-related contributions are substantially larger in the non-TES than the TES sector, which could partly drive the earnings penalty. To get a sense of this in the South African context, Table 5 presents the mean *base salary*[15] of TES and non-TES workers, as well as the TES/non-TES ratio of these earnings at the mean and the 25th, 50th, and 75th percentiles, for the full sample and disaggregated by the categories described in Table 4. Compared with the *total earnings* wage differentials shown in Table 4, the mean and median wage penalties are substantially lower. TES wages are now 74 per cent and 88 per cent of non-TES wages respectively. While similar patterns across the categories are observed to those in Table 4, the lower wage penalties (or higher premiums in some cases) indicate that benefits such as retirement and medical aid contributions are responsible for a large part of the wage differential between the TES and non-TES sectors.

The gap between total and base earnings between sectors is particularly large at the upper end of the distribution, evident from comparing the TES/non-TES ratios in Tables 4 and 5 at the 25th, 50th, and 75th percentiles. In Table 4, for total earnings, the ratios decline as one moves up the distribution, while in Table 5 the ratios are similar across the distribution. This is shown more clearly in Figure 3, which presents the ratio of base to total earnings by income category. Below R2000, workers (regardless of sector) receive minimal benefits and the ratio of base to total earnings is close to 1. Thereafter, we see greater divergence in the base-to-total-earnings ratio between the TES and non-TES sectors. For monthly earnings above R15 000, for example, we see the non-TES base-to-total-earnings ratio ranging from 0.5 to 0.6, while for the TES sector the ratio is always above 0.8.

While these results provide a first insight into the wage penalties for TES workers, of course TES workers may be different from non-TES workers in terms of skill or human capital, or the nature of TES jobs may be different from that of non-TES jobs. We describe the empirical strategy to account for these differences in the next section.

[15] This is gross non-retirement fund income (i.e. income excluding the pension) less contributions to medical aid and UIF.

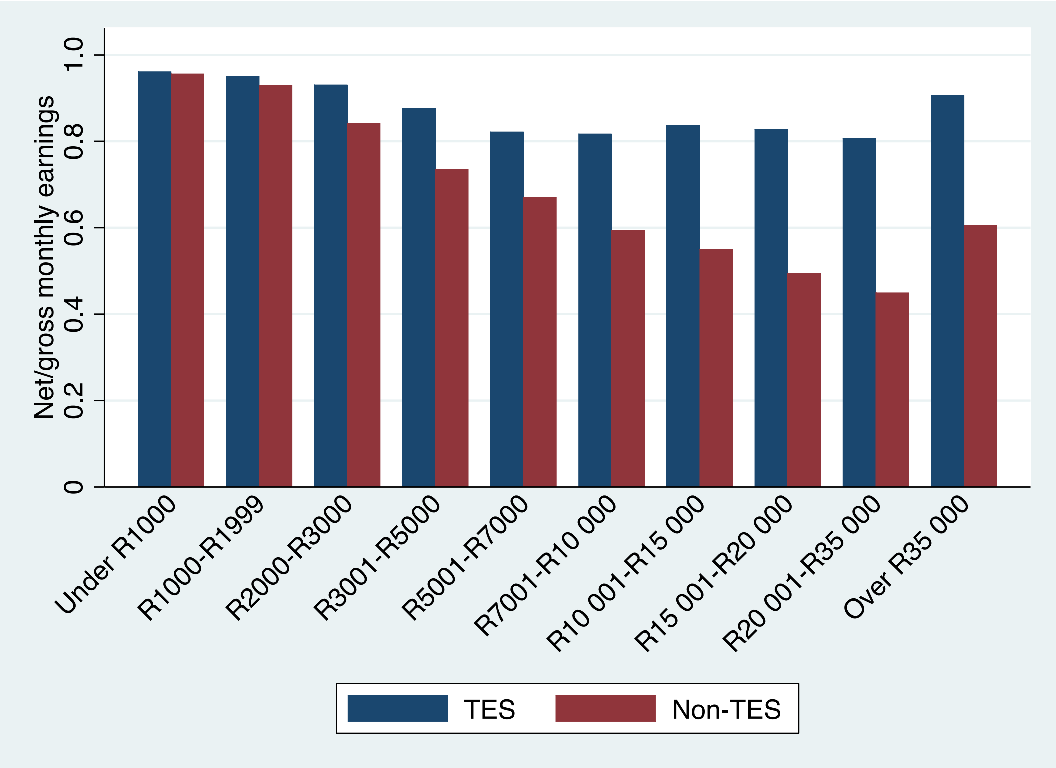
Table 4: Monthly base salary for TES and non-TES jobs, 2014

	Base salary[a]		Ratio TES/non-TES			
	TES (ZAR)	Non-TES (ZAR)	Mean	p25	p50	p75
Overall	6 212.60	8 353.37	0.74	0.84	0.88	0.83
Age						
16–29	4 053.32	4 643.81	0.87	0.86	0.98	0.96
30–39	6 496.80	7 758.41	0.84	0.90	0.94	0.88
40–49	9 431.06	10 698.97	0.88	0.90	0.93	0.92
50–65	13 761.54	13 008.44	1.06	1.09	1.14	1.21
Gender						
Female	5 062.98	6 416.70	0.79	0.82	0.90	0.89
Male	6 612.43	9 583.10	0.69	0.80	0.83	0.75
Length of contract						
less than 15 days	9 937.22	34 726.10	0.29	0.54	0.45	0.39
15 to 30 days	7 243.66	8 522.22	0.85	0.96	1.19	1.36
1 to 3 months	6 855.13	10 002.12	0.69	0.92	1.14	1.29
3 to 6 months	6 183.89	6 890.88	0.90	1.02	1.10	1.06
6 months to less than 1 year	5 376.65	6 362.34	0.85	1.10	1.09	0.94
A year or more	6 543.80	8 385.15	0.78	0.55	0.69	0.70
TES firm size						
Small (0–50)	16 807.59	10 239.11	1.64	1.55	1.91	1.85
Medium (50–250)	13 467.50	7 764.41	1.73	1.65	2.01	2.11
Large (250–1000)	6 576.07	8 405.64	0.78	1.09	1.08	0.95
Very large (more than 1000)	5 215.17	7 483.88	0.70	0.81	0.79	0.79
Industry						
Agriculture	4 566.65	4 361.72	1.05	0.79	1.15	1.44
Mining	15 629.61	14 388.52	1.09	1.57	1.39	1.25
Manufacturing	7 455.39	8 983.23	0.83	1.50	1.38	1.06
Utilities	19 276.81	16 301.98	1.18	0.72	0.95	1.10
Construction	9 414.59	7 969.14	1.18	1.41	1.42	1.53
Trade	4 026.57	5 408.68	0.74	1.48	1.03	0.83
Transport & communications	7 275.56	11 254.65	0.65	0.93	0.97	0.95
Tourism	7 393.25	4 526.17	1.63	3.76	2.44	1.83
Financial services	5 922.62	10 928.67	0.54	0.83	0.79	0.66
Non-government community services	6 667.29	7 469.99	0.89	0.88	0.96	0.84

Note: This is the 'main job' sample as defined in Section 2 and is at the job contract level.

Source: Authors' estimates based on IRP5 data.

Figure 3: Ratio of base/total earnings for TES and non-TES sectors by income category, 2014



Source: Authors' estimates based on IRP5 data.

4 Econometric strategy

Several studies examining the temporary employment services wage penalty have been conducted internationally, using a variety of methods depending on the data available. Combining firm and labour force survey data, Tohario and Serrano (1993) employ an Ordinary Least Squares (OLS) regression and find a wage penalty of 8.5 to 10.8 per cent in Spain. Blanchard and Landier (2002) use an employment survey and identify a wage gap of 20 per cent in France with a Pooled Ordinary Least Squares (POLS) method. In Britain, Booth et al. (2002) make use of household survey data and find a wage gap of between 13 and 15 per cent when using POLS and a wage gap of between 6 and 10 per cent when using fixed effects, suggesting that not accounting for the impact of time-invariant factors results in an overestimation of wage penalties. Using household survey data and an Instrumental Variable approach, Picchio (2006) finds a wage penalty of around 13 per cent in Italy. Hagen (2002), using the German socioeconomic survey, employs matching estimators and a Dummy Endogenous Variable model controlling for self-selection, and finds a penalty of 23 per cent in West Germany. In the US, Segal and Sullivan (1998) use administrative employee data controlling for worker and time fixed effects and find a wage gap of 15 to 20 per cent.

Given the lack of human capital variables and other individual and job characteristics in the SARS-NT data, we rely on the panel nature of the data to estimate the wage penalty (as in Segal and Sullivan 1998, who had administrative data structured in a similar way to ours). We use a fixed-effects strategy which controls for time-invariant individual-specific effects at the employee level, where the variation in the earnings of individuals who switch into and out of TES employment over time is exploited. To put this into context, in Table 6 we examine transition between the TES and non-TES sectors for consecutive years for those individuals that have one job contract per year (81 per cent of the main jobs sample). While using a subset of data where individuals have just one job contract per year may underestimate the number of switches, it still gives us an indication of the movement between sectors. Of those individuals that had a TES job in 2011, 147 707 (85 per cent) stayed in the TES sector in 2012 while 27 007 (15 per cent) moved into the non-TES sector. Of those that were in the non-TES sector in 2011, the majority remained in the non-TES sector, with 29 418 moving into the TES sector (this accounts for less than 1 per cent of the non-TES sector). In absolute terms, more individuals move into the TES sector than out of it between 2011 and 2012. The percentages transitioning into and out of the TES sector are similar across the years, except in the final year, with the percentage of workers transitioning out of the TES sector rising by about 2 percentage points between 2014 and 2015. This could be related to amendments to the LRA that resulted in stricter hiring conditions for TES workers.

Table 5: Transitions matrices for consecutive years over the panel, 2011–2015

	Share (%)	Number	Share (%)	Number	Share (%)	Number
	TES 2012		**Non-TES 2012**		**Total**	
TES 2011	84.54	147 707	15.46	27 007	100.00	174 714
Non-TES 2011	0.56	29 418	99.44	5 203 347	100.00	5 232 765
	TES 2013		**Non-TES 2013**		**Total**	
TES 2012	84.45	159 773	15.55	29 430	100.00	189 203
Non-TES 2012	0.53	28 570	99.47	5 390 911	100.00	5 419 481
	TES 2014		**Non-TES 2014**		**Total**	
TES 2013	84.75	167 180	15.25	30 077	100.00	197 257
Non-TES 2013	0.53	29 886	99.47	5 620 918	100.00	5 650 804
	TES 2015		**Non-TES 2015**		**Total**	
TES 2014	82.41	163 342	17.59	34 872	100.00	198 214
Non-TES 2014	0.44	25 373	99.56	5 761 315	100.00	5 786 816

Notes: The table only includes individuals who have stayed in the panel for every year, and therefore the totals will differ to those in Table 2. Around 10 milllion observations were dropped. The unit of analysis is the individual.

Source: Authors' estimates based on IRP5 data.

We describe the various specifications we estimate below, closely following the formulation in Segal and Sullivan (1998), although modified to reflect our own data structure. We begin by estimating a simple POLS model that treats the data as if they were cross-sectional:

$$Y_{ij} = \lambda TES_{ij} + \varepsilon_{ij} \tag{1}$$

where Y_{ij} is the log of real monthly earnings for individual *i* in job *j*, TES_{ij} is a dummy variable for whether the individual is in a job in the TES sector or not, λ is the temporary work earnings penalty, and ε_{ij} is the error term. This model is unlikely to capture the true wage differential, of course, as temporary workers are likely to be different from non-temporary workers. Therefore, we control for the time-invariant characteristics of employees (such as race, gender, education, etc.) using a standard fixed-effects model and including year dummies to control for time fixed effects:

$$Y_{ij} = \alpha_i + \beta_t + \lambda TES_{ij} + \varepsilon_{ij} \tag{2}$$

where β_t are the fixed effects for each year and control for annual wage growth, and α_i are the individual-specific constants and control for the time-invariant characteristics of TES and non-TES workers.

Although we have very few variables in the SARS-NT data set, in the next specifications we include controls for the time-varying factors that we do have information on. We include employee age in the form of three age dummies (as a proxy for experience):

$$Y_{ij} = \alpha_i + \beta_t + \lambda TES_{ij} + Age\_30to39_i + Age\_40to49_i + Age\_50to65_i + \varepsilon_{ij} \quad (3)$$

Further, we include a vector of job/firm characteristics (X_{ij})—namely, job contract duration, size of the firm, and industry. This model recognizes that part of the TES wage penalty might be due to differences in the nature of the job itself or the type of firm it is located in.

$$Y_{ij} = \alpha_i + \beta_t + \lambda TES_{ij} + Age\_30to39_i + Age\_40to49_i + Age\_50to65_i + X_{ij} + \varepsilon_{ij} \quad (4)$$

Lastly, we examine temporary workers' wages before and after their temporary employment spell. The reason for this is that, as Segal and Sullivan (1998) point out, temporary workers might accept a temporary job because of some setback such as a factory closure or after being laid off, and thus wage differentials may reflect the circumstances in which workers accept the job rather than the job itself. If this is the case, the earnings received in periods far removed from the temporary employment spell may not be a good comparison but those immediately prior to the temporary spell will be. To explore this further, the approach in Segal and Sullivan (1998) is followed and dummy variables that reflect the jobs before and after the temporary employment spell are included. As Segal and Sullivan did, for the sake of simplicity we exclude individuals that had more than one temporary employment spell over the period, so that our sample of individuals in TES employment were employed in non-TES jobs before and after the temporary employment spell. As such, Equation 5 below includes a set of dummies where $1Before_{ij}$ is the (non-TES) job prior to the temporary employment spell and $2Before_{ij}$ is two jobs prior to the temporary employment spell. Therefore $1Before_{ij} = 1$ for the first job prior to the temporary employment spell and 0 for all other jobs held by the individual, and $2Before_{ij}$=1 for two jobs prior to the temporary spell and 0 for other jobs held by the individual. The set of dummies $1After_{ij}$ and $2After_{ij}$ is similarly included to represent the first and second jobs after the temporary employment spell. This specification therefore adds four additional dummy variables. The coefficients on the before and after dummies measure the earnings penalty in the jobs before and after the temporary employment spell.

$$Y_{ijt} = \alpha_i + \beta_t + TES^k{}_{ijt}\lambda^k + Age\_30to39_i + Age\_40to49_i + Age\_50to65_i + 1Before_{ij} + 2Before_{ij} + 1After_{ij} + 2After_{ij} + X_{it} + \varepsilon_{ijt} \quad (5)$$

Segal and Sullivan (1998) find that wage differentials are negative before the TES spell, which they suggest is associated with the circumstances leading to workers having lower wages even before entering a TES spell.

5 Results

Table 7 presents the econometric results for the equations outlined above, where monthly *total earnings* is the dependent variable. The coefficient on the TES variable in the simplest POLS specification (1) is −0.656, indicating a wage penalty of 48.11 per cent. When we control for individual fixed effects (in 2A), the coefficient on TES declines substantially to −0.394 (se of 0.001), equivalent to a wage penalty of 32.57 per cent. This is unsurprising, as we would expect a large difference in the time-invariant characteristics between TES and non-TES workers. In specification 2B, in addition to the individual-specific fixed effects, we also include year dummies to control for time-specific effects. The coefficient hardly changes at −0.383 (a wage penalty of around 31.82 per cent), suggesting that year effects do not have a substantial bearing on real wage penalties.

To control for work experience, as per Equation 3, we include age dummies. The coefficient on the TES dummy declines marginally to −0.382 (a penalty of 31.61 per cent). The results suggest, as expected, that relative to the 16–29 age cohort, older workers earn more (with the quadratic effect evident from the lower coefficient for the 50–65 age group compared with the 40–49 age group). Interestingly, when controls for job contract duration, firm size, and industry are included progressively in specifications 4A, 4B, and 4C, the change in the wage penalty is relatively small. The coefficient on the TES variable in the final specification is −0.377, which is equivalent to a wage penalty of 31.41 per cent. The coefficients on the firm size dummies are all negative and significant, indicating that, compared with small firms, wages are on average lower in firms with a larger number of employees. The contract duration dummies are positive and significant for the first two categories (less than 15 days and between 15 to 30 days), suggesting that workers in contract lengths of very short duration earn more on average than those in contracts of one year or more (the omitted category). However, those in contracts of more than 30 days but less than a year earn less on average than workers in contracts of a year or longer. Except for the trade, tourism, non-government community services, and financial services sectors, the coefficients on the industry categories are all positive and significant, indicating higher wages relative to the agricultural sector.[16]

[16] In addition, we ran the regressions with a panel including only individuals with one job contract per year (47 625 823 observations compared with 58 488 963 in Table 7), to see if those who switched frequently within years were driving the results. However, the coefficients ranged from −0.685 to −0.317, only slightly lower than what is observed in Table 7.

Table 7: Estimating the TES wage penalty (dependent variable: log of monthly total earnings)

	1	**2A**	**2B**	**3**	**4A**	**4B**	**4C**
TES	−0.656***	−0.394***	−0.383***	−0.382***	−0.380***	−0.384***	−0.377***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2012			0.051***	0.047***	0.047***	0.050***	0.050***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2013			0.108***	0.100***	0.100***	0.102***	0.102***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2014			0.184***	0.171***	0.171***	0.172***	0.170***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
2015			0.247***	0.230***	0.230***	0.229***	0.227***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Age: 30–39				0.100***	0.100***	0.097***	0.099***
				(0.001)	(0.001)	(0.001)	(0.001)
Age 40–49				0.136***	0.136***	0.131***	0.131***
				(0.001)	(0.001)	(0.001)	(0.001)
Age 50–65				0.114***	0.114***	0.109***	0.103***
				(0.001)	(0.001)	(0.001)	(0.001)
Medium (50–250)					−0.013***	−0.014***	−0.014***
					(0.000)	(0.000)	(0.000)
Large (250–1000)					−0.014***	−0.014***	−0.016***
					(0.001)	(0.001)	(0.001)
Very large					−0.014***	−0.022***	−0.025***
					(0.000)	(0.000)	(0.000)
Less than 15 days						0.643***	0.648***
						(0.001)	(0.001)
15 to 30 days						0.004***	0.005***
						(0.001)	(0.001)
30 to 60 days						−0.083***	−0.082***
						(0.000)	(0.000)
3 to 6 months						−0.092***	−0.091***
						(0.000)	(0.000)
6 months to less than 1 year						−0.084***	−0.083***
						(0.000)	(0.000)
Mining							0.089***
							(0.001)
Manufacturing							0.020***
							(0.001)
Utilities							0.069***
							(0.002)
Construction							0.014***
							(0.001)
Trade							−0.030***
							(0.001)
Transport							0.051***
							(0.001)
Tourism							−0.032***
							(0.001)
Financial							−0.023***
							(0.001)

Government							0.046***
							(0.001)
Non-govt community services							−0.086***
							(0.001)
_cons	8.931***	8.918***	8.797***	8.728***	8.738***	8.770***	8.772***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
N	58 488 963	58 488 963	58 488 963	58 488 963	58 488 963	58 488 963	58 488 963

Notes: The dependent variable is the log of monthly total earnings, deflated such that 2015 is the base year. The 2011 financial year, agriculture, small firms, and contracts of a year or more are the omitted categories. * p<=0.1, ** p<=0.05, *** p<=0.01.

Source: Authors' estimates based on IRP5 data.

Table 8 shows the same set of estimations as in Table 7, but using the *base salary* as the dependent variable, i.e. gross non-retirement fund income net of medical aid and UIF contributions. We find that the earnings differentials are much lower than when total earnings were used as the dependent variable. The coefficient in specification 1 from the POLS estimation is −0.274 (a wage penalty of 23.97 per cent), versus a coefficient of −0.656 (a wage penalty of 48.11 per cent) in Table 7. In the final specification, 4C (fixed effects including all controls), the coefficient on the TES dummy is −0.068 (a wage penalty of 6.57 per cent), versus a coefficient of −0.377 (a wage penalty of 31.41 per cent) in Table 7. This suggests that, on average, the TES wage penalty is driven to a large extent by the benefit contributions afforded to those in the non-TES sector.

Table 8: Estimating the TES wage penalty (dependent variable: log of monthly base salary)

	1	**2A**	**2B**	**3**	**4A**	**4B**	**4C**
TES	−0.274***	−0.149***	−0.141***	−0.140***	−0.049***	−0.061***	−0.068***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2012			0.044***	0.042***	0.044***	0.044***	0.044***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2013			0.087***	0.083***	0.085***	0.089***	0.089***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2014			0.140***	0.133***	0.135***	0.139***	0.180***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
2015			0.183***	0.174***	0.177***	0.185***	0.225***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Age: 30–39				0.056***	0.059***	0.065***	0.065***
				(0.001)	(0.001)	(0.001)	(0.001)
Age 40–49				0.077***	0.082***	0.091***	0.090***
				(0.001)	(0.001)	(0.001)	(0.001)
Age 50–65				0.060***	0.067***	0.075***	0.071***
				(0.001)	(0.001)	(0.001)	(0.001)
Medium (50–250)					−0.184***	−0.180***	−0.180***
					(0.001)	(0.001)	(0.001)
Large (250–1000)					−0.288***	−0.276***	−0.278***
					(0.001)	(0.001)	(0.001)
Very large					−0.400***	−0.384***	−0.385***
					(0.001)	(0.001)	(0.001)
Less than 15 days						1.192***	1.189***
						(0.001)	(0.001)
15 to 30 days						0.275***	0.275***
						(0.001)	(0.001)
30 to 60 days						0.185***	0.186***
						(0.001)	(0.001)
3 to 6 months						0.098***	0.098***
						(0.000)	(0.000)
6 months to less than 1 year						0.027***	0.028***
						(0.000)	(0.000)
Mining							0.003**
							(0.001)
Manufacturing							−0.039***
							(0.001)
Utilities							0.082***
							(0.002)
Construction							0.016***
							(0.001)
Trade							−0.162***
							(0.001)
Transport							−0.014***
							(0.001)
Tourism							−0.100***
							(0.002)
Financial							−0.014***
							(0.001)

Government							−0.025***
							(0.001)
Non-govt community services							−0.102***
							(0.001)
_cons	8.299***	8.293***	8.199***	8.161***	8.403***	8.324***	8.326***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
N	56 955 731	56 955 731	56 955 731	56 955 731	56 955 731	56 955 731	56 955 731

Notes: The dependent variable is the log of the monthly base salary, deflated such that 2015 is the base year. The 2011 financial year, agriculture, small firms, and contracts of a year or more are the omitted categories. The sample size is not the same as in Table 7, as some firms may not have reported on gross non-retirement fund income that makes up the base salary. * p<=0.1, ** p<=0.05, *** p<=0.01.

Source: Authors' estimates based on IRP5 data.

Finally, Table 9 presents the estimation of Equation 5, where dummies associated with the two jobs before and after entering the TES sector are included. As explained above, we exclude those who had more than one TES job spell in the panel.[17] For comparison we first rerun Equation 4C, i.e the specification with time dummies, individual fixed effects, and a full set of controls, using this reduced sample (shown in column 1 of Table 9). The coefficient on TES employment for this reduced sample is only slightly larger than for the full sample used in Table 7 (−0.387 vs −0.377). However, of interest are the coefficients on the dummy variables representing the jobs before and after the temporary employment spell shown in column 2. The coefficients on the dummies representing non-TES jobs before the temporary employment spell are negative, suggesting that periods prior to entering into a TES contract are associated with events leading to workers having lower wages even before they joined a TES firm (as per Segal and Sullivan 1998). The coefficient on the dummy '1 job prior to the temp job' of −0.305 (which is equivalent to a 26.28 per cent penalty) is larger than the coefficient on the dummy '2 jobs prior to the temp job' of −0.131 (which is equivalent to a 12.28 per cent penalty). The coefficients on the dummies for the jobs after the temporary employment spell are also negative, but less so than the coefficients on the dummies for the period prior to entering the TES sector (coefficients of −0.068 and −0.006 for one and two jobs post the TES spell respectively). This suggests that while the coefficients are still negative, the wage penalty is far smaller in the period after the temporary employment spell and tends to decline for successive jobs after this spell. The coefficient on the TES dummy (−0.494) in column 2 is larger than that in column 1 (−0.387) because the jobs just before and just after the TES spell, during which wages tend to be lower than for the periods outside the 'two jobs prior and two jobs post' window, are removed from the non-TES comparison group. The largest differential is still observed in the period associated with being in a TES firm.

[17] Around 10 million observations were dropped, or 17 per cent of the sample from Table 7.

Table 6: Econometric results including before and after effects

	4C	5
TES	−0.387***	−0.494***
	(0.001)	(0.001)
Age: 30–39	0.096***	0.095***
	(0.001)	(0.001)
Age 40–49	0.126***	0.126***
	(0.001)	(0.001)
Age 50–65	0.097***	0.099***
	(0.001)	(0.001)
2012	0.050***	0.049***
	(0.000)	(0.000)
2013	0.101***	0.100***
	(0.000)	(0.000)
2014	0.171***	0.170***
	(0.001)	(0.001)
2015	0.228***	0.224***
	(0.001)	(0.001)
Medium (50–250)	−0.015***	−0.015***
	(0.000)	(0.000)
Large (250–1000)	−0.015***	−0.016***
	(0.001)	(0.001)
Very large (1000+)	−0.025***	−0.026***
	(0.000)	(0.000)
Less than 15 days	0.649***	0.653***
	(0.001)	(0.001)
15 to 30 days	0.001*	0.004***
	(0.001)	(0.001)
30 to 60 days	−0.084***	−0.080***
	(0.000)	(0.000)
3 to 6 months	−0.091***	−0.087***
	(0.000)	(0.000)
6 months to less than 1 year	-0.082***	-0.080***
	(0.000)	(0.000)
Mining	0.087***	0.087***
	(0.001)	(0.001)
Manufacturing	0.019***	0.017***
	(0.001)	(0.001)
Utilities	0.068***	0.067***
	(0.002)	(0.002)
Construction	0.011***	0.008***
	(0.001)	(0.001)
Trade	−0.031***	−0.031***
	(0.001)	(0.001)
Transport	0.050***	0.047***
	(0.001)	(0.001)
Tourism	−0.033***	−0.033***
	(0.001)	(0.001)
Financial	−0.024***	−0.028***
	(0.001)	(0.001)
Government	0.044***	0.045***
	(0.001)	(0.001)

Non-govt community services	−0.087***	−0.088***
	(0.001)	(0.001)
2 jobs prior		−0.131***
		(0.001)
1 job prior		−0.305***
		(0.001)
1 job post		−0.068***
		(0.001)
2 jobs post		−0.006***
		(0.001)
_cons	8.775***	8.785***
	(0.001)	(0.001)
Fixed effects	Yes	Yes
N	48 172 843	48 172 843

Notes: The dependent variable is the log of monthly total earnings, deflated such that 2015 is the base year. The 2011 financial year, agriculture, small firms, and contracts of a year or more are the omitted categories. * p<=0.1, ** p<=0.05, *** p<=0.01.

Source: Authors' estimates based on IRP5 data.

6 Concluding discussion

In this paper, we attempted to estimate the wage penalty associated with being in the TES or labour broker sector in South Africa, using the recently released SARS-NT employee panel data for 2011 to 2015. We find that there is a large penalty associated with TES employment, even after various controls are introduced. The raw total earnings penalty of close to 50 per cent diminishes substantially (by 15 percentage points or a third of its original size) when controlling for individual fixed effects, suggesting that TES and non-TES workers have different time-invariant characteristics. The penalty declines slightly further when controlling for year effects and the time-varying characteristics available in the data—namely, age, job contract duration, firm size, and industry. Nonetheless, even in our fullest specification, comparing wages during a TES job spell with wages at other times in someone's career suggests a wage penalty of around 30 per cent when using total earnings. However, some of this effect appears to be due to factors associated with the circumstances of the worker rather than the job itself, as there is a penalty, albeit a smaller one, also on the non-TES jobs just prior to the temporary job spell.

The penalty of around 30 per cent found using the SARS-NT data for South Africa is higher than that found in the international literature cited in this paper, where the maximum wage penalty found was 23 per cent. However, the results are not directly comparable, as most of the work uses household, labour, or firm surveys in which the data and thus the controls available are substantially different to those available in administrative employee data. The paper which uses data and methods most similar to ours is Segal and Sullivan (1998), which uses administrative data with a limited set of variables to estimate the TES wage penalty for the US. They found a differential of 15 to 20 per cent, which is still lower than that found in this study.

We also found that a large part of the TES wage penalty—24 percentage points, or close to 80 per cent of its original size—is due to differences in the benefit contributions (for pension, medical aid, and UIF) for TES versus non-TES workers. The penalty declines to 6 per cent when using the base salary rather than total earnings as the dependent variable. The descriptive statistics suggest that the benefit gap is much higher at the upper end of the income spectrum, whereas at the lower end, workers in both sectors receive few such benefits.

It is possible that the size of the penalty might fall further if we were able to control for additional factors. While we use a fixed-effects estimation strategy to control for time-invariant characteristics at the individual level, we have not been able to control for an extensive set of time-varying individual or job characteristics. Controlling for occupation, skill level, or union coverage, for example, might affect the results, as literature elsewhere has shown that these are also important determinants of earnings (Booth et al. 2002). Further, since we do not have data on hours worked, we cannot tell whether the earnings differential is related to differences in the actual hourly wage versus the number of hours worked.

Despite the limitations of the SARS-NT data set when examining wage differentials, it does at least provide the opportunity to explore the labour broker wage penalty using a more reliable identifier for the sector than is available in South Africa's labour or household surveys. In addition, the data provide the opportunity to explore other interesting and policy-relevant issues related to this under-examined sector. For example, the gender indicator was only recently released by SARS-NT and in further analysis one could explore whether women in the TES sector are particularly disadvantaged relative to their TES male peers. Second, as more years of data become available, it would be useful to examine the impact of the amendments to the LRA of 2015 on both TES firms and their employees. The trade-off between protection of temporary employees and the potential disemployment effects has been the subject of some debate, but empirical analysis has not been possible. Third, in line with the international literature, we could also examine whether temporary employment spells are a stepping-stone into the non-TES permanent labour market, particularly for young workers.

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