How large is the wage penalty in the labour broker sector? Evidence for South Africa using administrative data.

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Abstract

The public debate on the growing temporary employment services, or labour broker, sector in South Africa has been largely centred around the issue of decent work, and specifically the wage and non-wage benefits afforded to temporary workers. However, there has been limited empirical research in this area given that it is not possible to accurately identify temporary employment services as a stand-alone sector in South Africa's recent labour force surveys. In 2015, SARS and National Treasury (SARS-NT) made company and employee income tax data available for research purposes. It is the only South African dataset from the last decade that explicitly captures which firms are labour brokers and also contains individual employee wages. This paper makes use of the SARS-NT panel data from 2011 to 2015 to examine whether there is a wage penalty for employees in the labour broker sector and, if so, the magnitude of the wage differential. In the estimation strategy we control for individual and time fixed effects. In addition, we examine temporary employee wage differentials before and after their temporary employment spell. The reason for this is that temporary workers could 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 labour broker wage penalty in South Africa is an important first step to help inform debates on the role and value of this sector in the South African labour market.

Keywords: temporary employment services; wage differentials; administrative data; South Africa

JEL codes: J31; J41

1. Introduction

The use of temporary employment[1] has grown both globally and in South Africa (Deakin 2002; Benjamin, Bhorat, and van der Westhuizen 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, Sato, and Wakasugi 2011; Saha, Sen, and Maiti 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 were to foreign markets (Matsuura, Sato, and Wakasugi 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, Sen, and Maiti 2013). In South Africa, it has been suggested that trade liberalisation led to firms externalising employment because of the drive to lower wages in sectors where there is increased competition (Theron 2005).

Given the context in which temporary employment grows, it is widely expected that there is 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, Sen, and Maiti 2013), Portugal (Boeheim and Cardoso 2007), Germany (Pfeifer 2012), Britain (Brown and Sessions 2005) and the U.S. (Houseman 2001; Segal and Sullivan 1997). In the U.S., it was found that after controlling for demographic information and particularly skill level and work experience, the earnings differential for temporary workers declined substantially relative to the raw wage differential (Houseman 2001). International evidence on the size of the wage penalty for temporary workers after adjusting for demographic factors, job characteristics or controlling for fixed effects suggests a penalty ranging from 6 per cent in the UK (Booth, Francesconi, and Frank 2002) to around 20 per cent in France and the U.S. (Blanchard and Landier 2002; Segal and Sullivan 1997). Picchio (2006) estimates a wage penalty for temporary workers of around 12-13 percent in Italy, but this declines with 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 persists for temporary workers is in terms of non-wage benefits. Temporary workers have been found to have far lower 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 both in terms of wage and non-wage 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 wage and non-wage benefits afforded to temporary workers (Bhorat, Cassim, and Yu 2016). The focus on wage and non-wage discrimination in this sector resulted in amendments being made to that part of the Labour Relations Act (LRA) that governs temporary employment in early 2015. The new legislation attempted

[1] Temporary workers, as defined here, are employed by staffing agencies, where these agencies 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. TES workers can also be distinguished from seasonal, temporary or part-time contingent workers who typically can be employees of the company that hired them, and who are usually let go when the work is complete.

to better regulate the TES industry and offer greater protection to temporary workers. However, there is little empirical evidence on the extent of either wage or non-wage discrimination against temporary 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 bi-annual 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 percent) were reported as being employed by a labour broker, and 274 000 (2.5 percent) by a contractor or agency. It has been suggested that this is too low an estimate for South Africa (Budlender 2013). Misreporting on the sector of employment or the nature of the employment contract is a well-known problem in household surveys (Segal and Sullivan 1998), and particularly when there is proxy-reporting as in the LFSs.

The QLFS, which replaced the LFS in 2008, did not include a similar question. However, to try and identify TES workers, Benjamin, Bhorat, and van der Westhuizen (2010) and Bhorat, Cassim, and Yu (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, where 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 cognisant of the limitations of the QLFS data, Bhorat, Cassim and Yu (2016) estimated that there were just under 1 million temporary jobs in 2014.[3]

Given the broad list of categories 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 percent of the workers recorded in this industry are likely to be security guards and 15 percent 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 is likely to be employed internally by the company (rather than the TES firm). Budlender (2013) further noted that while over 93 percent of the workers falling under this code are employees,

[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, Cassim and Magadla (2016) examine earnings differentials in the TES sector using the sub-sector Business Activities N.E.C and find a wage penalty of around 10 percent when examining compliant firms (defined as firms [INSERT], and just under 40 percent 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 center, 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. Temporary workers are different in that they come from staffing agencies, where these agencies are ultimately responsible for the salary, taxes and benefits of the leased employee.

59 per cent of the employees are recorded as having permanent contracts, 22 percent have contracts of limited duration, and 19 per cent have contracts of unspecified duration. Budlender (2013) 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 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, the 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 dataset 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 examine whether there is a wage penalty for employees in the labour broker sector and the magnitude of the wage differential. 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 and value 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; lists the main variables used and their definitions; and lastly, summarises some of the main advantages and disadvantages of using the data for this research.

Structure of the data

This paper uses an unbalanced employee panel dataset 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 – end February 2015)[7]. The dataset was created from employee income tax certificates submitted by employers (IRP5 and

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[5] There have only been a handful of research papers that have used these data in the past two years. The research has mostly covered the employment tax incentive (Ebrahim, Leibbrandt, and Ranchhod 2017; Chatterjee and Macleod 2016) 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 (for eg. the 2011 tax year refers to 1 March 2010 to 28 February 2011). Pieterse, Kreuser, and Gavin (2016) showed that 85 per cent of firms have their financial year at the end of February.

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 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. Whilst 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, Kreuser, and Gavin (2016), in their detailed discussion of the construction and features of the panel, provide different ways to think of a firm and their employees using the CIT and IRP5 panel datasets, 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 for the same firm 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 are either 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 organisations. While these individuals are dropped from the CIT panel, they are still included in the IRP5 panel. In the IRP5 data, we therefore do not think of a firm 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 after 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 month, an IT3(a) form is provided to an employee. If an employee earns less than R2000 per month in a given tax year and no employee tax was deducted, the employee is not issued with an IRP5 or an IT3(a) form. 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, as well as 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

[8] The construction of the firm level panel, created using CIT records, is detailed by Pieterse, Kreuser, and Gavin (2016). For this analysis, we use the IRP5 panel data and construct firm level characteristics from the data available in those records.

set of employee/job characteristics (namely, length of contract within the tax year and age of employee) and firm characteristics (firm size and industry the firm operates in).

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. This came out of a consultation between SARS and Statistics South Africa. The binary indicator can be matched to both the CIT panel and the IRP5 panel using the PAYE reference number.

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 summarises the methods and decision-making processes used to deal with multiple job records, overlapping job contracts and coding errors.

The raw IRP5 dataset is an unbalanced panel at the job contract-level for the years 2011 to 2015.[9] In the raw panel, multiple IRP5 entries can exist per individual per firm in a particular year, which essentially means that an individual may have multiple entries for the same job contract. This could be because of a revision to the IRP5 in the event of a mistake or a change to the employment duration, but we are unable to tell which version of the contract was revised and thus which is the most recent version (Chatterjee and Mcleod 2016). We therefore have to take a number of decisions such that an individual has one entry per job contract for a given firm in a given year. However, a person may have multiple job contracts in a year *in different firms*, some of which could overlap. About 80 percent of individuals have just one job contract per year.

There are two main steps to clean the data such that it can be used in an individual-level fixed effects estimation. First, where the same job contract appears multiple times per person per year, we take a number of decisions such that there is only one job per person per firm. Second, we identify "main jobs" such that job contracts are not overlapping. We end up with a panel of individuals at the job contract-level, where each person may have a number of sequential jobs per year (at different firms). Lastly, we remove observations that are not required for the particular analysis. The resulting sample will be referred to as the "main job sample". The steps taken are detailed below:

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 (where the duration of all contracts is less than or equal to one year), we add the contract duration as well as the earnings, essentially collapsing the IRP5 entries into one observation. Therefore multiple contracts at the same firm that are shorter than one year are taken as one job contract.[10]

[9] The raw IRP5 panel for 2011 to 2015 has just under 90 million observations.
[10] For simplicity, job contracts were identified by a unique identifier made up of the ID and PAYE reference number and collapsed such that there was one job per firm per year in the panel. A similar method was used by Bhorat et al. (2017).

ii. **Multiple overlapping IRP5 entries at the same firm.** Where contracts overlap[11] we use a similar approach to clean the data as was done in Pieterse et al. (2016). Where the same IRP5 entry appears more than once in a given year, the primary job is taken as the job with the longest job duration (i.e. days in a year). If information on job duration does not exist, the job with the highest earnings is used as the main job, and in cases where earnings were the same and there are duplicate entries, the IRP5 form that appears first in the panel is used. Overall, we drop around 20 percent of the observations that we began with. This leaves us with only one job contract per individual per firm in a given year but as noted above, a person may have multiple jobs in a year in different firms.[12]

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 to their main job), then we need to identify the individual's primary job. Firstly, we rank all job contracts per person chronologically. Secondly, we create an indicator for those contracts that overlap. Of the overlapping job contracts, we create an indicator for the job with the highest earnings which is taken as the "main job" for that period. We drop around 8 million observations that are considered to be second jobs or piecemeal jobs as they are not the highest earning job during that period. 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 and the sequential jobs are in different firms).

iv. **Missing ID numbers.** We drop observations with no ID numbers or passport numbers[13] as this does not allow us to track individuals over time.

v. **Merging in the labour broker indicator.** The labour broker indicator is merged into the dataset matching on the PAYE reference number.

vi. **Outliers.** We remove 7 observations that appear to be outliers in the income distribution, where annual earnings were in excess of R1 billion (suggesting these were reporting errors).

vii. **Age cut off.** Lastly, we limit the sample to those between the ages of 16 and 65 years old.

Table 1 presents the number of individuals[14] and job contracts in the constructed *main job sample*.

Table 1: Description of Employee-Firm Panel, 2011 to 2015 (16-65 years)

Tax year	Job contracts	Individuals
2011	10 336 148	8 556 501
2012	11 047 988	8 957 401
2013	11 289 988	9 164 339
2014	11 605 556	9 370 578
2015	11 924 825	9 528 038
Total	56 204 505	45 576 857

Source: Authors' estimates based on IRP5 data.

[11] It is not clear why contracts would overlap at the firm, and while each contract could refer to an actual job contract, multiple overlapping contracts could also be revisions and therefore decisions are taken as to which contract is likely to be the most correct one to use for the analysis.

[12] This results in an unbalanced panel of around 74 million observations.

[13] This excludes around 600 000 observations.

[14] 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. However, total employment including the informal sector was estimated to be 15.06 million individuals. This means that the sample of IRP5 data in Table 1 captures around 81 percent of formal employment and 63 percent of total employment according to the household survey data.

Description of variables used

Job duration

Job duration is estimated as the 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 a year however. So for permanent employees, for example, the job contract length would be recorded as the maximum length of a 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 input errors of the start and end date, some job duration records are estimated to be negative (around 3 percent) and these are indicated as "missing" in the dataset.

Earnings

Each IRP5 form reports gross taxable income, gross retirement income and gross non-retirement fund income. The sum of these variables provides *total earnings* for a specific job contract. As outlined above, some decision rules had to be applied in cases where there were multiple IRP5 contracts per person for the same firm in a given year. In cases where contracts do not overlap, earnings and job duration were summed given that an individual appeared in the same firm in consecutive periods. In cases where there were multiple IRP5 entries per job per person where contracts do overlap, the contract with the longest duration or highest earnings was kept. This essentially leaves us with one IRP5 entry per person per firm in a given year.

Daily earnings are estimated 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. We use monthly earnings instead of daily earnings for the analysis as monthly earnings are used to decide whether an employer will submit an IRP5 form for an employee (monthly earnings are used by Ebrahim, Leibbrandt, and Ranchhod 2017 and Chatterjee and Mcleod 2016).

Firm size

The IRP5 data does not include a variable indicating firm size and therefore this variable is imputed, taking into account that not all workers on a firm's pay roll 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 (Ebrahim, Leibbrandt, and Ranchhod 2017; Bhorat et al. 2017; Pieterse, Kreuser, and Gavin 2016).

Advantages and disadvantages of the dataset 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 that 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 gross 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 dataset only contains tax registered firms, and among those, only the firms that actually completed a tax return in the relevant period. This means that employees of unregistered, small, young or informal TES firms, which may be of particular interest in the South African context (as the employees in those firms may be the most vulnerable), have not been captured (Pieterse, Kreuser, and Gavin 2016). Also, as noted earlier, the IRP5/IT3(a) forms apply only to those earning more than R2000 a month, which means the lowest-wage workers will be excluded from the dataset. 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 would also be excluded.

Another limitation of the dataset 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 can 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.

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 are such a small proportion of total employment in the firm (Kvasnicka 2008).

3. Descriptive Statistics

Employment Trends

Table 2 presents employment in the TES and non-TES sectors at the job contract, individual and firm levels. TES employment has consistently made up around 5-6 percent of total employment between 2011 and 2015. This is true if 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 was relatively stable from 2011 to 2013, the proportion declined in 2014 and 2015. In absolute terms, the number of TES employees grew between 2011 and 2014 and then fell to 2013 levels in 2015. 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 either using this broad category from the QLFS overestimates the size of the TES sector or the QLFS is picking up many more low-paid workers which are not included in the SARS data.

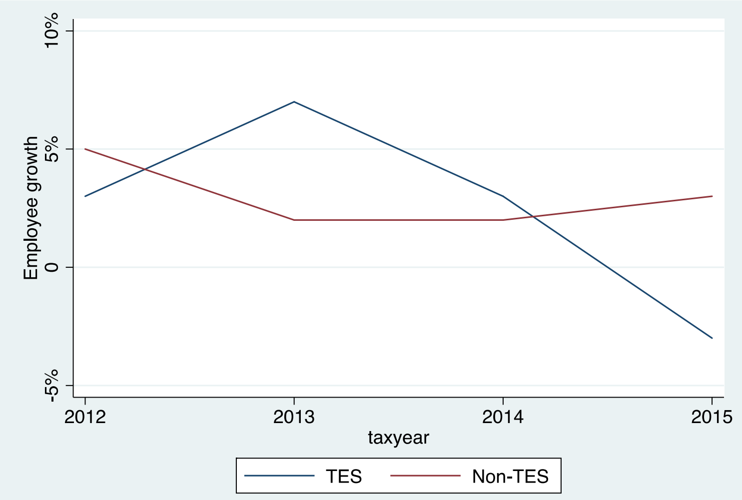
Table 2: Contracts, individuals and firms in the IRP5 data, by TES/non-TES status

Tax year	Job contracts			Individuals			Firms (Entities with payroll)		
	TES	Non-TES	Share	TES	Non-TES	Share	TES	Non-TES	Share
2011	541 849	9 794 299	5.53%	488 395	8 068 106	6.05%	627	267 026	0.23%
2012	564 906	10 483 082	5.47%	503 609	8 453 792	5.89%	644	270 567	0.24%
2013	604 864	10 685 124	5.47%	538 445	8 625 894	6.01%	665	273 706	0.24%
2014	623 707	10 981 849	5.37%	554 818	8 815 760	5.92%	680	276 665	0.25%
2015	603 645	11 321 180	5.06%	539 940	8 988 098	5.67%	636	279 184	0.23%

Source: Authors' estimates based on IRP5 data.
Note: This is the "main job" sample as defined in Section 2. In terms of the number of firms, Section 2 explains that there may be more than one payroll per firm so the firm numbers are likely to overstate the number of independent firms.

Figure 1 presents growth rates for TES and non-TES employment at the job contract level between 2012 and 2015. The figure suggests that TES employment and non-TES employment growth rates moved in opposite directions. For example, when the growth rate in TES employment increased between 2012 and 2013, the growth rate in non-TES employment declined. Similarly, while the growth rate in TES employment declined between 2013 and 2015 (and was even negative in 2015), the growth rate in non-TES employment increased. The decline in the TES sector in the final year may be related to employers pre-empting the amendments to the LRA regarding TES employment introduced in January 2015 that made the conditions around temporary hire more stringent. (This will form the subject of future research, as more years of data in the IRP5 panel become available.)

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



Source: Authors' estimates based on IRP5 data.
Note: This is the "main job" sample as defined in Section 2 and is at the job contract level.

Table 3 presents descriptive statistics for TES and non-TES job contracts for the year 2014.[15] The vast majority of TES contracts, 76 percent, are less than 12 months. The most common job contract length for the TES sector is more than 6 months but less than a year (37 percent). In contrast, for non-TES employment, the most common job contract length is a year or more (52 percent). In terms of firm size,

[15] 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.

the majority of TES employment, 78 percent, is in TES firms that have more than 1000 employees, whereas only 39 percent of non-TES employment is in very large firms of more than 1000 employees.

Table 3: Descriptive Statistics (2014)

	TES		Non-TES	
	Proportion	***N***	***Proportion***	***N***
Contract duration				
less than 15 days	4.21%	26 072	1.97%	200 577
15 to 30 days	5.38%	33 335	2.94%	299 980
1 to 3 months	14.85%	91 970	9.88%	1 007 248
3 to 6 months	14.83%	91 868	11.47%	1 169 637
6 months to under a year	36.73%	227 533	21.84%	2 227 384
A year or more	24.00%	148 682	51.91%	5 294 841
Total	*100%*	*619 460*	*100%*	*10 199 667*
Firm Size				
Small	1.41%	8 803	29.13%	3 185 857
Medium	5.13%	31 991	18.16%	1 986 198
Large	15.74%	98 196	13.81%	1 510 112
1000+	77.72%	484 717	38.89%	4 252 849
Total	*100%*	*623 707*	*100%*	*10 935 016*
Age				
16-29	52.87%	305 477	32.42%	3 281 323
30-39	29.07%	167 953	29.15%	2 949 465
40-49	12.04%	69 548	20.00%	2 024 433
50-65	6.03%	34 838	18.42%	1 864 523
Total	*100%*	*577 816*	*100%*	*10 119 744*
Industry				
Agriculture	2.16%	13 454	7.91%	862 959
Mining	0.82%	5 094	3.85%	419 637
Manufacturing	3.52%	21 967	15.53%	1 694 747
Utilities	0.07%	417	1.09%	119 500
Construction	5.26%	32 776	3.34%	364 149
Trade	1.79%	11 141	11.15%	1 216 812
Transport	0.34%	2 092	3.83%	418 350
Tourism	0.04%	278	2.73%	297 440
Financial	82.18%	512 512	32.32%	3 526 683
Government	0.00%	0	11.87%	1 295 325
Non-Government Community Services	3.84%	23 929	6.39%	697 683
Total	*100.00%*	*623 660*	*100%*	*10 913 285*

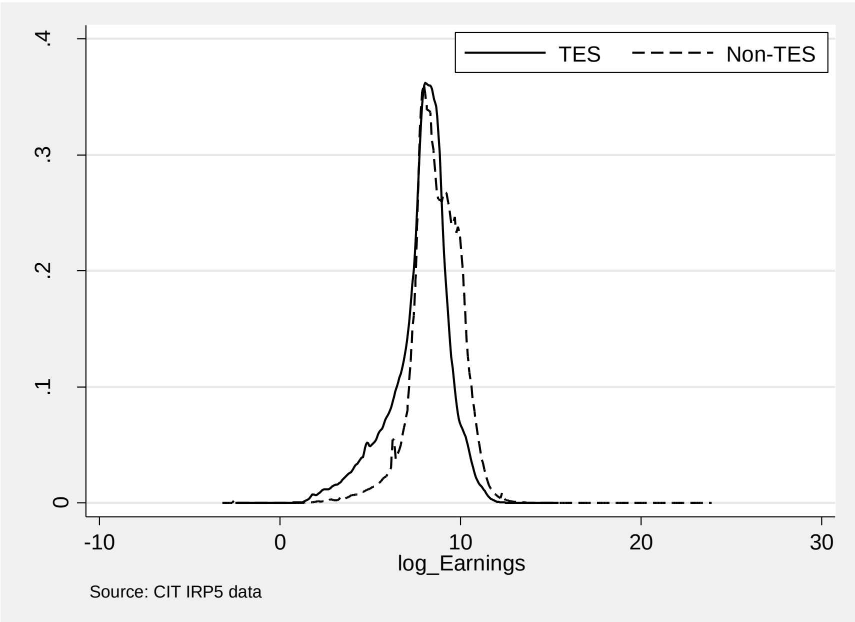
Source: Authors' estimates based on IRP5 data.
Note: This is the "main job" sample as defined in Section 2 and is at the job contract level.

TES employees are also younger than non-TES employees with more than half (53 percent) of all TES job contracts filled by individuals between 16 and 29 years old relative to 32 percent of non-TES employees. This finding further motivates why we need to better understand this sector, as it may play a key role in absorbing young people into employment, in the context of a narrow youth unemployment rate of around 39 percent.[16] In terms of industry, TES firms are concentrated in the Finance and Business Services sector (82 percent) followed by the Construction sector (5 percent). These are also the sectors where employment growth has been observed over the last two decades according to LFS data (Bhorat, Cassim, and Yu 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 suggests that the former consists of more 'vulnerable' employees, given that they are younger and employed on shorter contracts.

Wage differentials

Figure 2 shows the kernel density of the log of monthly wages for TES and non-TES jobs in 2014. While the peak of the TES earnings distribution is at almost the same level as the non-TES earnings distribution, the non-TES distribution's tail extends far further right than the TES distribution. In addition, the TES distribution extends further left than the non-TES distribution and is also wider towards the left. This suggests there are a larger proportion of TES workers along the lower end of the earnings distribution than non-TES employees.

Figure 2: Earnings kernel density, 2014



Source: Authors' estimates based on IRP5 data.
Note: This is the "main job" sample as defined in Section 2 and is at the job contract level.

Table 4 presents the ratio of TES to non-TES monthly earnings at the mean and at the 25th, 50th and 75th percentiles, for the full sample and disaggregated by the categories described above, namely job duration, firm size, age of employee and industry (only ratios are shown here, with the absolute wage values presented in Appendix 1). For the full sample, TES wages are 62 percent of non-TES wages at the mean and 60 percent at the median. The wage differential is much larger at both ends of the distribution (as would be expected given Figure 2), with TES wages only around 47-48 percent of non-TES wages at the 25th and 75th percentiles.

[16] This estimate is based on data from the QLFS, Quarter 1, 2017.

Table 4: Monthly Earnings of TES relative to Non-TES Jobs (2014)

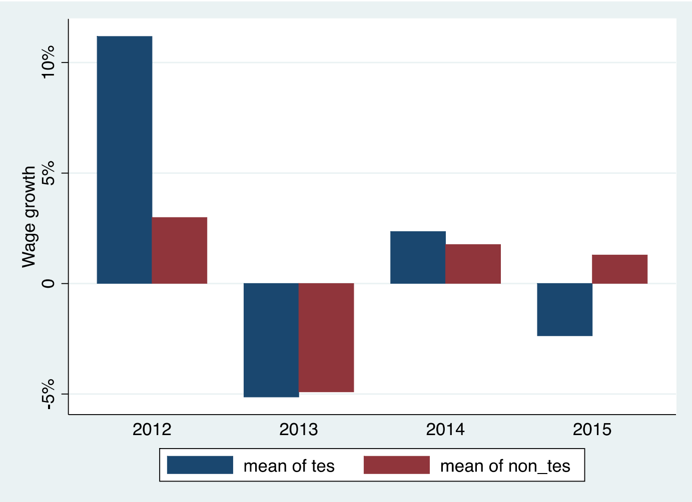
	Ratio TES/Non-TES			
	Mean	p25	p50	p75
Overall	0.62	0.47	0.60	0.48
Length of contract				
Less than 15 days	0.23	0.74	0.67	0.51
15- 30 days	0.77	0.95	1.22	1.22
1- 3 mths	0.61	0.89	1.17	1.17
3- 6 mths	0.67	0.79	0.95	0.83
6 months - less than 1 year	0.55	0.59	0.78	0.62
1 Year or more	0.27	0.11	0.25	0.28
TES firm size				
Small	0.79	1.64	1.79	1.74
Medium	1.15	1.37	1.53	1.24
Large	0.58	0.74	0.78	0.61
1000+	0.33	0.37	0.35	0.30
Age				
16-29	0.62	0.42	0.73	0.66
30-39	0.46	0.53	0.60	0.47
40-49	0.30	0.53	0.50	0.44
50-65	0.71	0.89	0.74	0.70
Industry				
Agriculture	0.93	0.82	1.27	1.51
Mining	0.66	0.69	0.78	0.67
Manufacturing	0.35	0.95	1.00	0.77
Utilities	0.60	0.40	0.38	0.52
Construction	1.04	0.93	1.27	1.46
Trade	0.38	0.56	0.59	0.46
Transport & Communications	0.25	0.18	0.27	0.26
Tourism	1.18	2.23	2.07	1.34
Financial Services	0.34	0.47	0.69	0.50
Non-Government Community Services	0.30	0.09	0.14	0.24

Source: Authors' estimates based on IRP5 data.
Note: This is the "main job" sample as defined in Section 2 and is at the job contract level.

While the ratio of TES to non-TES earnings is fairly inconsistent across the categories, there are a few noticeable patterns. Firstly, barring job contracts of less than 15 days (which make up a very small proportion of all contracts and are potentially driven by outliers), the wage penalty associated with TES employment appears to increase, the longer the contract length. One of the largest TES wage penalties is for job contracts of a year or more, particularly pronounced at the 25th percentile (where the ratio of TES to non-TES earnings is only 0.11). Secondly, 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). Thirdly, 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 40 to 49 year olds compared to jobs held by younger workers (16 to 29 years) and older workers (50 to 65 years). Lastly, in terms of sector, mean wage penalties are most extreme for financial services (where the bulk of TES employment is located), transport and communications, trade and non-government community services.

Figure 3 shows that the annual growth rate of mean real monthly wages moved in the same direction for the TES and non-TES sectors between 2012 and 2014. However, in 2012, the growth rate in the TES sector was much higher than in the non-TES sector (by almost five times). In 2015, growth rates diverge, with wages in the TES sector declining while wages in the non-TES sector increased. The decline in real monthly wages may be reflective of a decline in the hourly wage or in the number of hours worked (which again could be related to the LRA amendments).

Figure 3: Annual Wage Growth



Source: Authors' estimates based on IRP5 data.
Notes: This is the "main job" sample as defined in Section 2 and is at the job contract level.
Wages are monthly real wages using 2015 as the base year.

While these results provide a first insight into the distribution of wages and 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 non-TES jobs. We describe the empirical strategy to account for these differences in the next section.

4. Empirical strategy

Internationally, several studies have been conducted examining the temporary employment wage penalty using various 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 percent in Spain. Blanchard and Landier (2002) use an employment survey and identify a wage gap of 20 percent in France with a Pooled Ordinary Least Squares (POLS) method. In Britain, Booth, Francesconi, and Frank (2002) make use of household survey data and find a wage gap of between 13 and 15 percent when using POLS and a wage gap of between 6 and 10 percent 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 percent 13 percent in Italy. Hagen (2002), using the German socio-economic survey, employs matching estimators and a Dummy Endogenous Variable model controlling for self-selection, and finds a penalty of 23 percent in West Germany. In the U.S., Segal and Sullivan (1998) use administrative employee data controlling for worker and time fixed effects and find a wage gap of 15 to 20 percent.

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 individual-specific effects at the employee level, where the variation in the earnings of individuals that switch into and out of TES employment over time is exploited. To put this into context, in 2012, for example, 55 percent of TES job contracts were held by those who switched into the sector from a non-TES job while in the same year, 3 percent of all non-TES job contracts were held by those that had previously held a TES job. This suggests that there is substantial movement into and out of the sector (a similar pattern is observed for other tax years).

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 OLS model that treats the data as if it were cross-sectional:

$$Y_{ijt} = \lambda TES_{ijt} + \varepsilon_{ijt} \qquad (1)$$

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

$$Y_{ijt} = \alpha_i + \beta_t + \lambda TES_{ijt} + \varepsilon_{ijt} \qquad (2)$$

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 dataset, in the next specifications we include controls for the time-varying factors that we do have information on. We include employee age, A_{it}, and age-squared, A_{it}^2, (as a proxy for experience):

$$Y_{ijt} = \alpha_i + \beta_t + \lambda TES_{ijt} + A_{it} + A_{it}^2 + \varepsilon_{ijt} \quad (3)$$

Further, we include a vector of job/firm characteristics (X_{itj}), namely, job contract duration, size of the firm, and industry. This model recognises 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.

$$Y_{ijt} = \alpha_i + \beta_t + \lambda TES_{ijt} + A_{it} + A_{it}^2 + X_{itj} + \varepsilon_{ijt} \quad (4)$$

Lastly, we examine temporary workers' wages before and after their temporary employment spell. The reason for this, as Segal and Sullivan (1998) point out, is that 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. To explore this further, we follow the approach in Segal and Sullivan (1998) and include dummy variables that reflect the job before and after the temporary employment spell. As they 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 five below includes a set of dummies ${Before^k}_{ijt}$ where at year *t*, *k* is 1 for the first (non-TES) job prior to the temporary employment spell and 2 for two jobs prior to the temporary employment spell. Therefore ${Before^1}_{ijt} = 1$ for the first job prior to the temporary employment spell and 0 for all other jobs held by the individual, and ${Before^2}_{ijt} = 1$ for two jobs prior to the temporary spell and 0 for other jobs held by the individual. The set of dummies ${After^k}_{ijt}$ is similarly included to represent the first and second jobs after the temporary employment spell. This specification therefore adds four additional dummy variables. The coefficient on the before and after dummies measures the effect on earnings *k* jobs before or after the temporary employment spell.

$$Y_{ijt} = \alpha_i + \beta_t + A_{it} + A_{it}^2 + {TES^k}_{ijt}\lambda^k + {Before^k}_{ijt}\lambda^k + {After^k}_{ijt}\lambda^k + X_{it} + \varepsilon_{ijt} \quad (5)$$

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 5 presents the econometric results for equations 1 to 4 outlined above. The coefficient on the TES variable in the simplest OLS specification (1) is -0.823 indicating a wage penalty of 56.09 percent. When we control for individual fixed effects (in 2A), the coefficient on TES declines only marginally to -0.817 (se of 0.001). This is surprising, as we would have expected a larger 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 -0.815, (a wage penalty of around 55.73%), suggesting that year effects also do not have a substantial bearing on real wage penalties.

In order to control for work experience, as per equation 3, we include employee age and age-squared. The coefficient on the TES dummy now declines noticeably to -0.709 which is equivalent to a penalty of 50.78 percent. Interestingly, when controls for industry, firm size and job contract duration are included in specification 4, the fall in the wage penalty is largest. The coefficient on the TES variable is now -0.375 which is equivalent to a wage penalty of 31.27 percent. The coefficients on the firm size dummies are all negative and significant, indicating that, compared to small firms, wages are lower in firms with a larger number of employees. The contract duration dummies are also negative and significant, suggesting that workers in contract lengths of 15 days to one year or more earn less on average, compared to those with contracts of less than 15 days. Except for the financial services sector, the coefficients on the industry categories are all positive and significant, indicating higher wages relative to the agricultural sector. The negative and significant coefficient on the financial services sector variable suggest that, on average, wages are lower in this industry relative to Agriculture, after controlling for various factors.

Table 5: Econometric Results: Estimating the TES wage penalty

	1	2A	2B	3	4
TES	-0.823***	-0.817***	-0.815***	-0.709***	-0.375***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2012			0.084***	0.056***	0.050***
			(0.000)	(0.000)	(0.000)
2013			0.065***	0.008***	0.001***
			(0.000)	(0.000)	(0.000)
2014			0.128***	0.042***	0.031***
			(0.000)	(0.000)	(0.000)
2015			0.183***	0.033***	0.026***
			(0.000)	(0.000)	(0.000)
Age				0.162***	0.149***
				(0.000)	(0.000)
Age^2				-0.002***	-0.001***
				(0.000)	(0.000)
Medium					-0.073***
					(0.001)
Large					-0.163***
					(0.001)
1000+					-0.353***
					(0.001)
15 to 30 days					-0.733***
					(0.001)
30 to 60 days					-0.859***
					(0.001)
3 to 6 months					-0.925***
					(0.001)
6 months to less than 1 year					-0.979***
					(0.001)
1 year +					-0.929***
					(0.001)
Mining					0.927***
					(0.002)
Manufacturing					0.366***
					(0.001)
Utilities					0.615***
					(0.002)
Construction					0.281***
					(0.001)
Trade					0.166***
					(0.001)
Transport					0.473***
					(0.001)
Tourism					0.123***
					(0.002)
Financial					-0.012***
					(0.001)
Govt					0.826***
					(0.001)
Non-Govt Community Services					0.028***
					(0.001)
_cons	8.509***	8.678***	8.584***	5.132***	6.202***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)
Individual fixed effects	No	Yes	Yes	Yes	Yes
N	52,516,526	52,516,526	52,516,526	52,516,526	52,516,526

Notes: 1. The dependent variable is the log of monthly earnings, deflated such that 2015 is the base year.
2. The 2011 financial year, Agriculture, Small firms and "contracts less than 15 days" are the omitted categories.
* p<=0.1 ** p<=0.05 *** p<=0.0

As a sensitivity test, we then estimate the same set of specifications shown in Table 5, but on a sample which excludes the top one percent of the income distribution.[17] Since the top one percent includes those earning the highest salaries and potentially bonuses/dividends, they may not be directly comparable to those employed in TES firms, biasing the wage penalty upwards. The results are shown in Appendix 2. The coefficients on the TES dummy are now smaller, but only marginally so. In the final specification (4), the coefficient declines to -0.325 which is equivalent to a wage penalty of 27.75 percent, compared to the wage penalty of 31.27 percent from specification 4 using the full sample in Table 5. (Additional sensitivity tests will be conducted in future work on this paper.)

Finally, Table 6 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.[18] For comparsion we first rerun equation 4, 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 6). The coefficient on TES employment for this reduced sample is larger than for the full sample used above in Table 5 (-0.508 vs -0.375). However, of interest are the dummy variables representing the jobs before and after the temporary employment spell shown in Column 2. The coefficients on the dummies representing 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). The coefficient on the dummy “1 job prior to the temp job” of -0.192 (which is equivalent to a 17.50 percent penalty) is larger than the coefficient on the dummy “2 years prior to the temp job” of -0.044 (which is equivalent to a 4.30 percent penalty). The coefficients on the dummies for the jobs after temporary work are also negative but less so than the coefficients on the dummies for the years prior to entering TES (coefficients of -0.060 and -0.004 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 the temp spell. The coefficient on the TES dummy (-0.558) is larger than in Column 1 (0.508) because the jobs just before and just after the TES spell, during which wages tend to be lower than outside the two job prior and two job 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] Removing the top one percent of the income distribution excludes around eight percent of non-TES contracts and under one percent of TES contracts suggesting that the TES contracts are underrepresented at the top of the income distribution.

[18] Excluding those with more than one TES job spell, excludes around 30 percent of the TES contracts and three percent of non-TES contracts.

Table 6: Econometric results including before and after effects

	4	5
TES	-0.508***	-0.558***
	(0.001)	(0.001)
2012	0.046***	0.045***
	(0.000)	(0.000)
2013	-0.004***	-0.006***
	(0.000)	(0.000)
2014	0.024***	0.022***
	(0.000)	(0.000)
2015	0.018***	0.014***
	(0.000)	(0.000)
Age	0.150***	0.150***
	(0.000)	(0.000)
Age^2	-0.001***	-0.001***
	(0.000)	(0.000)
Medium	-0.078***	-0.077***
	(0.001)	(0.001)
Large	-0.169***	-0.168***
	(0.001)	(0.001)
1000+	-0.364***	-0.363***
	(0.001)	(0.001)
15 to 30 days	-0.778***	-0.778***
	(0.001)	(0.001)
30 to 60 days	-0.901***	-0.901***
	(0.001)	(0.001)
3 to 6 months	-0.962***	-0.962***
	(0.001)	(0.001)
6 months to less than 1 year	-1.013***	-1.014***
	(0.001)	(0.001)
1 year +	-0.964***	-0.965***
	(0.001)	(0.001)
Mining	0.895***	0.892***
	(0.002)	(0.002)
Manufacturing	0.342***	0.340***
	(0.001)	(0.001)
Utilities	0.562***	0.560***
	(0.002)	(0.002)
Construction	0.236***	0.234***
	(0.001)	(0.001)
Trade	0.152***	0.150***
	(0.001)	(0.001)
Transport	0.442***	0.439***
	(0.001)	(0.001)
Tourism	0.107***	0.106***
	(0.002)	(0.002)
Financial	-0.039***	-0.040***
	(0.001)	(0.001)
Government	0.781***	0.780***
	(0.001)	(0.001)
Non-Govt Community Services	-0.041***	-0.042***
	(0.001)	(0.001)
2 jobs prior		-0.044***
		(0.001)
1 job prior		-0.192***
		(0.001)
1 job post		-0.060***
		(0.001)
2 jobs post		-0.004***
		(0.001)
_cons	6.228***	6.236***
	(0.004)	(0.004)
Fixed Effects	Yes	Yes
N	49,582,177	49,582,177

Notes: 1. The dependent variable is the log of monthly earnings, deflated such that 2015 is the base year.
2. The 2011 financial year, Agriculture, Small firms and "contacts less than 15 days" are the omitted categories.
* p<=0.1 ** p<=0.05 *** p<=0.

6. Concluding discussion

In this paper, we attempted to estimate the wage penalty associated with being in the TES or labour broker sector, using the recently released SARS-NT firm-employee panel data for 2011 to 2015. We find that there is a large penalty associated with TES employment, even after controlling for worker-specific fixed effects and time effects. The raw wage penalty diminishes substantially when controlling for job contract duration, firm size and industry. Nonetheless, even in our fullest specification, comparing wages during a TES job spell relative to wages at other times in someone's career suggests a wage penalty of around 30 percent. 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 percent found using the SARS-NT data for South Africa is higher than that found in international literature cited in this paper, where the maximum wage penalty found was 23 percent. However, the results found in this literature are not directly comparable to those found in this paper, 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 used administrative data with a limited set of variables to estimate the TES wage penalty for the U.S. They found a differential of 15 to 20 percent, which is still lower than what was found in this study.

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 controlled for time-varying individual characteristics. In addition, we only control for a limited set of job characteristics. Controlling for, for example, occupation, skill level, job tenure or union coverage, might affect the results, as literature elsewhere has shown these are also important determinants of earnings (Booth et al. 2000). Further, since we do not have data on hours worked, we cannot tell whether the earnings differential is related to differences in the actual wage versus the number of hours worked.

Despite the limitations of the SARS-NT dataset 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 the QLFSs. In addition, the data provide the opportunity to explore other interesting and policy-relevant issues related to this under-examined sector. First, as a next step, we could also explore differentials in the composition of the gross wage of TES relative to non-TES jobs (in other words, what proportion of the gross wage is made up of medical aid, pension and other monetary benefits reported in the IRP5 data across sectors). 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. In particular, we would consider the trade-off between protection of temporary employees and the potential disemployment effects. Third, in line with the international literature, we can 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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Appendix 1: Raw monthly earnings

Appendix Table A.1: Monthly earnings (in Rands), 2014

	Mean			Median		
	TES	Non-TES	Ratio	TES	Non-TES	Ratio
Overall	6 374.37	10 268.23	0.62	3 215.82	5 374.43	0.60
Length of contract						
Less than 15 days	11 207.66	48 340.31	0.23	4 774.56	7 125.30	0.67
15- 30 days	8 079.66	10 534.45	0.77	4 130.61	3 383.33	1.22
1- 3 mths	7 719.42	12 599.97	0.61	3 777.94	3 216.54	1.17
3- 6 mths	6 444.45	9 688.12	0.67	3 298.97	3 484.53	0.95
6 months - less than 1 year	5 315.04	9 662.06	0.55	3 319.05	4 272.22	0.78
1 Year or more	5 558.95	20 700.10	0.27	2 174.41	8 658.17	0.25
TES firm size						
Micro	17 593.55	22 152.42	0.79	8 985.76	5 031.46	1.79
Small	13 158.94	11 490.80	1.15	6 865.71	4 499.41	1.53
Medium	8 046.60	13 973.58	0.58	3 993.62	5 106.82	0.78
Large	5 300.48	16 106.79	0.33	2 887.32	8 148.30	0.35
Age						
16-29	4 120.95	6 627.84	0.62	2 573.32	3 520.50	0.73
30-39	7 053.40	15 238.30	0.46	3 794.11	6 357.02	0.60
40-49	9 715.72	32 084.16	0.30	4 365.11	8 707.00	0.50
50-65	13 955.18	19 682.48	0.71	5 826.10	7 865.39	0.74
Industry						
Agriculture	5 249.70	5 625.00	0.93	3 094.41	2 443.11	1.27
Mining	14 870.32	22 544.14	0.66	8 954.48	11 514.67	0.78
Manufacturing	10 167.44	28 770.88	0.35	6 771.75	6 770.22	1.00
Utilities	17 860.24	29 592.77	0.60	8 451.43	22 530.95	0.38
Construction	10 693.07	10 295.53	1.04	6 138.11	4 825.26	1.27
Trade	3 151.70	8 250.88	0.38	2 336.86	3 932.65	0.59
Transport & Comm	4 790.75	18 899.30	0.25	3 034.55	11 157.42	0.27
Tourism	7 417.13	6 267.35	1.18	6 522.42	3 158.52	2.07
Financial Services	5 926.11	17 432.62	0.34	3 061.32	4 422.26	0.69
Non-Govt Community Services	5 006.12	16 610.43	0.30	2 062.71	14 428.70	0.36

Source: Authors' estimates based on IRP5 data.
Note: This is the "main job" sample as defined in Section 2 and is at the job contract level.

Appendix 2

Appendix Table A.2: Regression results (without top 1% of income distribution)

	1A	1B	2	3	4
	b/se	b/se	b/se	b/se	b/se
TES	-0.805***	-0.801***	-0.799***	-0.701***	-0.325***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2012			0.079***	0.053***	0.048***
			(0.000)	(0.000)	(0.000)
2013			0.059***	0.006***	0.001*
			(0.000)	(0.000)	(0.000)
2014			0.123***	0.042***	0.032***
			(0.000)	(0.000)	(0.000)
2015			0.176***	0.033***	0.029***
			(0.000)	(0.000)	(0.000)
Age				0.163***	0.146***
				(0.000)	(0.000)
Age^2				-0.002***	-0.001***
				(0.000)	(0.000)
Medium					-0.075***
					(0.001)
Large					-0.171***
					(0.001)
1000+					-0.375***
					(0.001)
15 to 30 days					-0.566***
					(0.001)
30 to 60 days					-0.700***
					(0.001)
3 to 6 months					-0.748***
					(0.001)
6 months to less than 1 year					-0.792***
					(0.001)
1 year +					-0.728***
					(0.001)
Mining					0.934***
					(0.002)
Manufacturing					0.364***
					(0.001)
Utilities					0.619***
					(0.002)
Construction					0.276***
					(0.001)
Trade					0.166***
					(0.001)
Transport					0.464***
					(0.001)
Tourism					0.124***
					(0.002)
Financial					-0.044***
					(0.001)
Govt					0.960***
					(0.001)
Non-Govt Community Services					0.055***
					(0.001)
_cons	8.477***	8.641***	8.551***	5.128***	6.085***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)
Fixed effects	No	Yes	Yes	Yes	Yes
N	51,975,887	51,975,887	51,975,887	51,975,887	51,975,887

Notes: 1. The dependent variable is the log of monthly earnings, deflated such that 2015 is the base year.
2. The 2011 financial year, Agriculture, Small firms and "contacts less than 15 days" are the omitted categories.
* p<=0.1 ** p<=0.05 *** p<=0.01