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Book Chapter

The Evolution of Earnings and Employment in South Africa: Tasks, Occupations and Gender, 2000-2015

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July 2020

Abstract

Whilst there is consensus that routine-biased technical change has contributed to patterns of job and wage polarisation in industrialised economies, there is less evidence about whether the same conclusions can be drawn for developing labour markets. We employ two measures of routine cognitive work to investigate the association between occupational routine task intensity and wage and employment changes in South Africa between 2000 and 2015. Although wage change is polarised between 2000 and 2015, it is unlikely that routine-biased technical change is a key factor here. Instead, growth at the bottom is likely related to minimum wage growth whilst growth at the top end, is likely linked to increasing returns to skills and higher education. That said, high levels of routine cognitive task intensity in clerking occupations likely has undermined their wages. Clerking occupations are mainly filled by women in South Africa and occupy the upper middle of the South African wage distribution. Employment change is related to the premature deindustrialisation of the economy: manufacturing is in decline and services are the main source of GDP and job growth. Although historical and context-specific reasons are more likely behind the decline of the primary and secondary sectors in South Africa, the fact that many services jobs are non-routine is probably not a coincidence. We note the growth of low-paid services work commonly associated with the casualisation of the labour market over the same period. As routine manufacturing jobs have less and less prospect of ever re-appearing, the existence of jobs like security services work are 'protected' to some extent by their non-routine nature and the need to be performed on site. [269 words]

1 Introduction

The extent to which highly routine jobs can be replaced by computer or machine technology is an important explanation for the patterns behind growing inequality in industrialised economies (Goos et al. 2014). So far, this explanation has not been so thoroughly tested in developing country cases. In this paper, we consider South Africa, a country with extreme labour market inequality (Wittenberg 2017*b*,*c*), the persistence and form of which has already been studied in a burgeoning literature. The role of structural transformation (Edwards & Lawrence 2008, Bhorat, Rooney & Steenkamp 2016, Bhorat et al. 2020), changing returns to education (Finn & Leibbrandt Submitted, Branson et al. 2012), labour market institutions (Kerr & Wittenberg 2017*b*, Bhorat et al. Submitted), and other historical and social factors (Mosomi 2019, Casale & Posel 2011) in maintaining inequality in South Africa have been closely examined. With a special focus on gender, the goal of this paper is to review some of the descriptive evidence for how well a routine-work explanation is associated with changes in the South African labour market using a measure of routine task intensity.

Extreme gendered occupational sorting by women (Casale & Posel 2011) makes routine-biased technical change more relevant for men than women. Women cluster relatively evenly into non-routine work in the form of domestic work and personal care further down the wage distribution; and highly routine work in the form of clerks further up the wage distribution. The persistence of this clustering makes it difficult to apply a task-based logic to change in female employment and the persistence of the pattern has more to do with gender norms and discrimination in South Africa, than technology (Mosomi 2019).

For men then, we find tasks are more relevant for explaining employment changes than wage changes. The influence of minimum wages and other State and institutional intervention in wage-setting means that changes in the wage structure are sometimes de-linked from changes in employment composition, especially at the bottom of the wage distribution. Even in terms of employment though, it is unlikely that routine work by itself represents a pivotal explanation for South African labour market inequality and instead falls into a supporting role for the more important drivers already identified in the literature. In particular, employment composition has been profoundly impacted by the rapid structural transformation of the economy from one based on agriculture, mining and manufacturing to one that is finance and services-led (Bhorat et al. 2020); and routine work has, to an extent, interacted with this change.

The contraction of the South African primary and secondary sectors have complicated historical and context-specific explanations (Bhorat et al. 2020). However, it is not by chance that most new jobs in South Africa have been in the least-routine sector: services. The nature of many of the fastest-growing service jobs, (e.g. personal care, security work) make them difficult to offshore or outsource to a machine. This pattern of premature de-industrialisation, or tertiarisation, of the South African economy does not necessarily mean it is destined to overcome inequality, though. As high-skilled professional and technical service jobs have grown, so too have menial service jobs - security guards, personal care, street sweepers and garbage collectors.

In the future, non-routine work is perhaps going to be more important in South Africa, represented mainly by the services sector. Understanding how the services sector will challenge or maintain inequality is an important research agenda. At the bottom and middle of the wage distribution, the fact that service work is non-routine is 'protective', meaning it ensures the continued need for human beings to do these jobs. At the top end, growth in services, even so-called tradeable services, has been pulled by growing local and global demand according to both South Africa's current comparative advantage and position as a destination of outsourced service work in the global value chain.

Following an introduction of our data in the next section, we describe inequality in the South African labour market and provide an overview of its main drivers in Section 3. The routine-biased technical change literature is discussed in Section 4 with reference to both developed and developing economies. Following this set-up, we investigate the evolution of earnings and employment across distributions of wages and skill focusing on gender in Section 5. Two measures of routine task intensity are introduced and described in Section 6. We test the association between our measures of routine work and occupational earnings and employment change in Section 7. A more thorough test of the association between routine work and earnings change controlling for other important drivers of inequality is carried out in Section 8. A decomposition of the role of routine work on the wage Gini is reported in Section 9. Section 10 concludes.

2 Data

The data used is version 3.2 of the Post-apartheid Labour Market Series (PALMS) which is a harmonized series of South African labour force surveys for the years 1995-2015 curated by DataFirst at the University of Cape Town (Kerr et al. 2017). The original data for the series comes from annual nationally representative cross-sectional labour force surveys collected by Statistics South Africa (StatsSA), the national statistics bureau, since 1995. These were the October Household Surveys (1995-1999), Labour Force Surveys (2000-2007), and the Quarterly Labour Force Surveys (2008-current). Earnings information for the Quarterly Labour Force Surveys is sourced from the Labour Market Dynamics Surveys for the corresponding years. The original surveys all survey approximately 30 000 dwelling units based on about 3 000 Primary Sampling Units drawn from the Master Sample of the most recent census at the time. A stratified, two-stage cluster sampling design is employed in each case, stratified at the provincial level. Data is self-reported to the enumerator (or by proxy in the case of an absent respondent) and covers the spectrum from basic demographic and household information to detailed labour market data.

PALMS harmonizes variable definitions across the different surveys to reach the most consistent series possible over the time period. PALMS also provides two weights not provided in the original nationally-released data and which we use in our analysis. The first is a cross-entropy weight, called 'ceweight2', that employs a more consistent demographic model than the weights released with the original data. This weight is therefore recommended for analysis across surveys (Kerr & Wittenberg 2017*a*) and we use it when estimating counts or shares of people. The second weight is the 'bracket weight', which corrects estimates of the earnings data for those who responded with bracket, instead of Rand currency, amounts. The bracket weight is a combination of the inverse probability of responding with a bracket, multiplied by the ceweight2. We use this weight when estimating wages. Our sample is limited to all employees between the age of 15 and 64.

Occupational information is available in PALMS up to the four-digit level and is based on the South African Standard Classification of Occupations (SASCO) from 2003 (Statistics South Africa 2003). SASCO 2003 is based on the International Standard Classification of Occupations (ISCO) from 1988 (ISCO-88).[1] There are some minor differences between SASCO 2003 and ISCO-88, such as the classification of mini bus taxi drivers. We merge our task variables discussed below into PALMS on occupational codes at the four-digit level. About ten percent of observations did not merge in the pre-2000 (October Household Survey) period, causing concerns about the quality of the occupational coding in these data sets. As such, our period of study covers 2000-2015, where 2015 is the latest year with available earnings data. Wittenberg (2017*a*) has also raised concerns about certain quarters of the Quarterly Labour Force Survey. Specifically, quarter three in 2012 and 2014 appear to include an anomalously higher number of high earners compared to the other surveys, therefore this data has been excluded from this analysis.

3 Inequality and its drivers in South Africa

Today, South Africa has amongst the highest levels of income inequality in the world. The Gini coefficient using all countries for which we have data between 2012-2016 was 0.37 - South Africa's Gini coefficient was the highest in this group and came in at 0.63 (World Bank 2020). Inequality in labour market income accounts for over 80% of the country's aggregate income inequality (Hundenborn et al. 2018). This influence is partly because labour market income overwhelmingly constitutes the dominant share of household income in the country, compromising the welfare of people and households without access to a wage. Access to a wage is by no means guaranteed, since South Africa also suffers from critically high levels of unemployment. The broad unemployment rate exceeded 30% in 2010 and has remained above this mark since then (DPRU 2017). Questions about who is able to secure employment and whose employment has become increasingly tenuous are therefore of critical importance in the project to deconstruct South African income inequality.

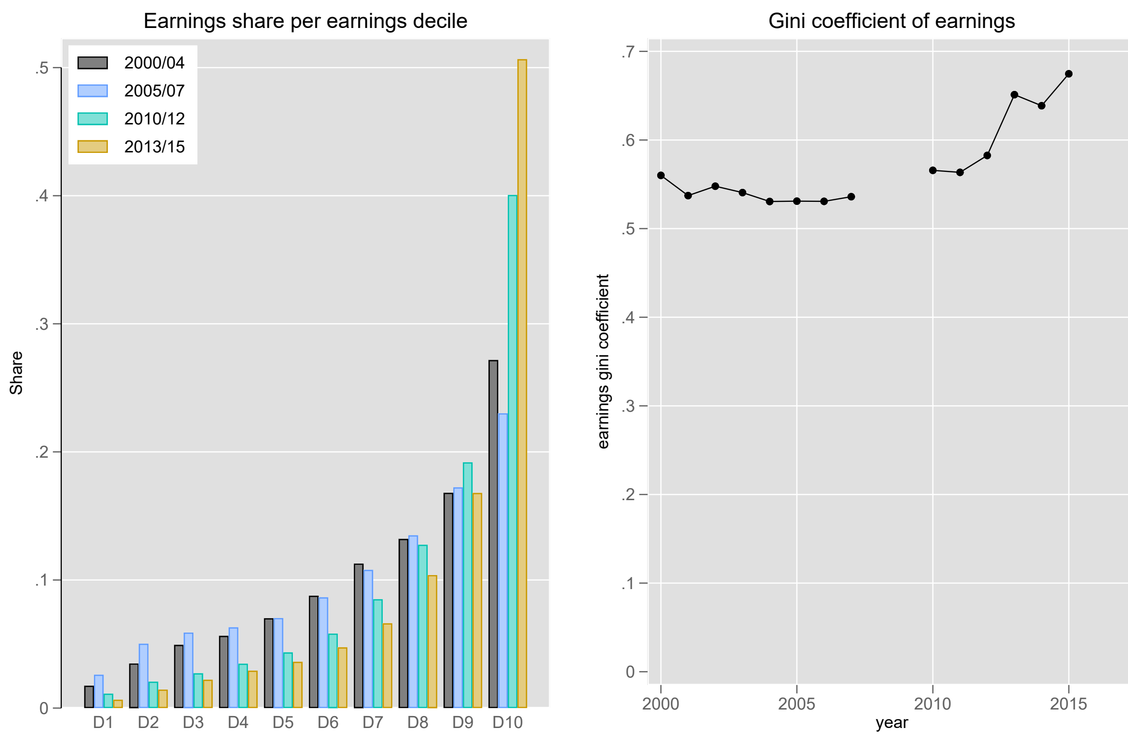
Figure 1 describes how earnings inequality in South Africa has worsened over the period 2000-2015, reaching astonishing levels by global standards from an already-high base. The first panel in Figure 1 plots the share of earnings going to each earnings decile in four time periods between 2000 and 2015. The share accruing to the top decile has generally increased over time and stood at about 27% in the 2000/4 period. By 2013/5, the top ten percent earned more than half of total earnings - a striking level of earnings concentration. The share of earnings going to the top decile has roughly doubled in the 10-15 years between the data pooled in years 2000-4 and 2013-5. Conversely, the trend for deciles 1 through 8 has been one of a declining earnings share. The decline has been most consistent for those in the very middle (deciles 6 and 7); whilst those at the bottom and in deciles 8 and 9, enjoyed some growth in earnings share especially in the 2005/7 period.

The second panel in Figure 1 reveals that the wage Gini coefficient has exceeded 0.5 throughout the period of study, reinforcing that high earnings inequality is a structural feature of the South African labour market. The steep jump in the Gini between 2012 and 2013 has been flagged in previous research as an unrealistic year-on-year change, potentially signalling problems with the underlying wage data

[1] Note that a new version of SASCO was released in 2012 based on ISCO-08 but inspection of the data makes it clear that these codes are not being applied to the labour market data yet. Particularly, SASCO 2012 yields far too few domestic workers whereas SASCO 2003 yields the right amount.

(Wittenberg 2017*a*). Alternatively, this could be a problem created during the imputation of earnings for bracket respondents or non-respondents in the QLFS period, since only fully-imputed earnings data has been released in this period.

Figure 1: Wage inequality in the South African labour market, 2000-2015



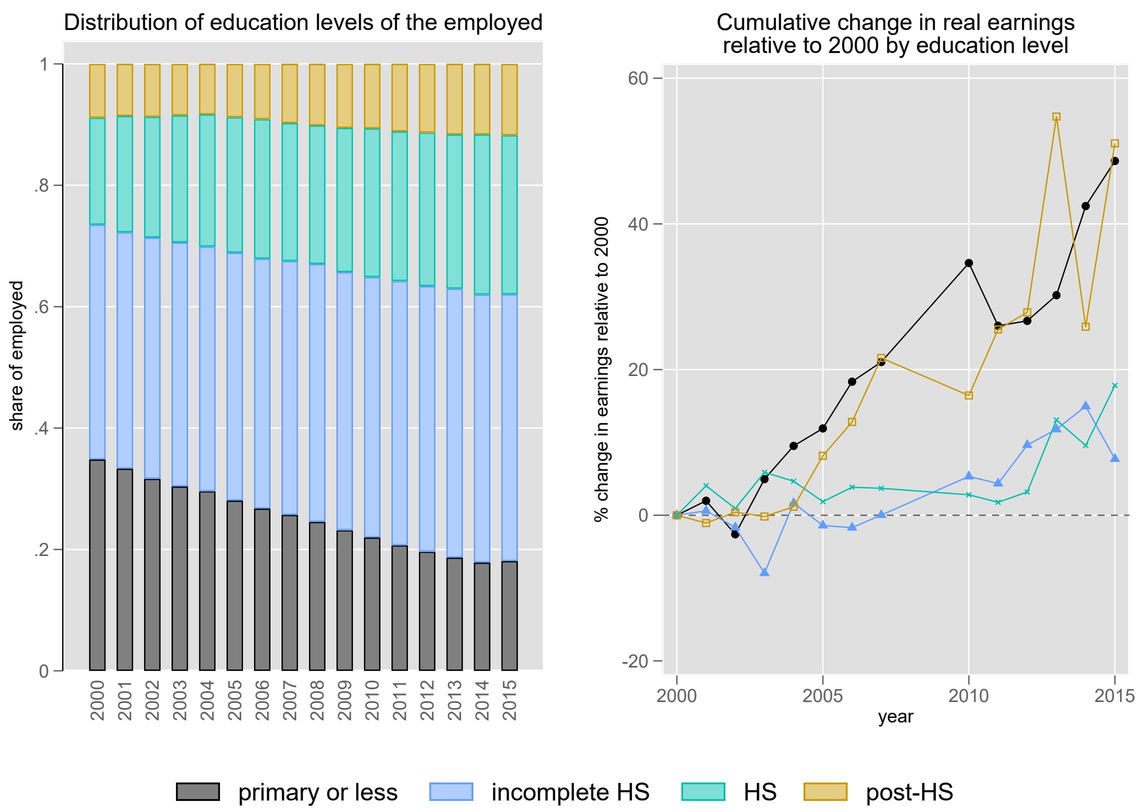
Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees with non-missing wage and hours of work data.

A key explanation for earnings inequality is that it is reproducing inequality in the schooling market (Branson et al. 2012, Finn & Leibbrandt Submitted). Only a small share of the employed have post-secondary education, including certificates or diplomas (with or without a high school graduation) as well as higher degrees. The share of the employed with this type of qualification increased from about 8% in 2000 to just under 15% in 2015 - with higher degrees roughly making up half of that portion. The jump in earnings between the high school-educated and the post-secondary-educated is wide - on average between 2000-2015, the post-secondary educated earned about 2.3 times the earnings of the high-school educated and also enjoyed much steeper growth in their earnings over the same period.

In the United States (US), the rate of earnings growth increases monotonically with education level, meaning earnings for the most highly educated increased far faster than those for the least well-educated (Autor et al. 2019). Figure 2 reveals that South Africa departs from this pattern in that the rate of earnings growth has been U-shaped across education level. Earnings growth for the most and least well-educated have roughly kept apace of each other and improved steadily over time, with a noticeable depression in the growth of earnings for those with any level of high school education. This pattern can in part be explained by compositional changes amongst the education levels of the employed, shown in the first panel of Figure 2

The most important education composition trend, shown in the first panel of Figure 2, is the expansion of people with partial or completed high school education, partly a consequence of the implementation of free schooling after *apartheid*. In 2000, slightly more than half of the employed (55%) fell into this combined group; by 2015, a full 70% of the employed had some level of high school education, an increase of 27%. The share of high-school graduates increased the most rapidly from 17.6% of the employed in 2000 to 26.2% in 2015, a 48% increase. Crucially, although access to high school improved over the post-*apartheid* period, schooling quality has not kept pace (Spaull 2013), undermining the quality of the signal sent by a high school certificate. The upshot has been that the swelling of the ranks of the high-school educated undermined the returns to this qualification and instead bolstered returns to those with post-secondary education, which in turn, became a more trustworthy signal for employers.

Figure 2: Changes in composition and returns by education level amongst South African employees

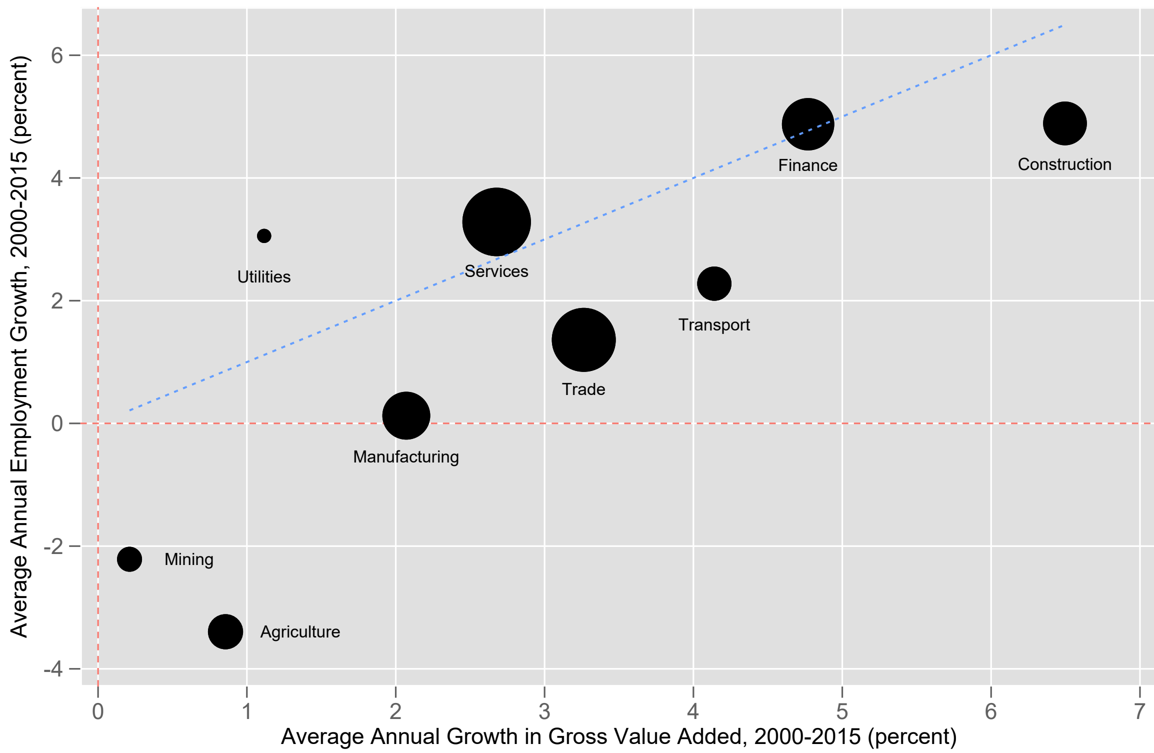


Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees with non-missing wage and hours of work data in the second panel.

Whilst education is key for understanding changing wage premia, changes in the sectoral composition of the economy are crucial for understanding employment shifts (Bhorat, Rooney & Steenkamp 2016). South Africa has followed a pattern of 'premature de-industrialisation' in which the manufacturing sector never rose to prominence as an engine of the economy after the decline of agriculture (Bhorat et al. 2020). Protectionism in the late apartheid era undermined the efficiency of the manufacturing industry resulting in the sector yielding rapidly to more competitive trading partners when South Africa opened its borders to world trade in the mid-1990s (Edwards & Lawrence 2008). As a consequence of this transformation, the employment share of the tertiary sector increased extensively. Financial and community, social, and personal services accounted for almost 80% of the increase in employment between 2001 and 2014 (Bhorat, Rooney & Steenkamp 2016).

Figure 3 describes changes across industrial sectors in the economy: The y-axis reports employment growth; the x-axis reports growth in value added to GDP; and the bubbles are weighted by the 2015 size of employment. Sectors above the 45 degree blue line experienced labour-absorbing growth over the period. The contraction of agriculture, mining and manufacturing is evident compared to the rise of services represented by the services bubble, but also finance, trade, transport and construction. In this case, the services bubble is community, social, and personal services, such as care workers, teachers, press, and, police, for example.

Figure 3: Changes in employment and gross value added by sector in South Africa, 2000-2015



Source: Own calculations using data from South African Reserve Bank version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights; Bubbles weighted by the number of employed in 2015

4 Routine-biased technical change as a driver of inequality

The extent to which routine-biased technical change is behind South African inequality has not received as much attention as other explanations so far. The role of routine-biased technical change in explaining rising inequality in industrialised economies is the subject of an extensive and growing literature (Acemoglu & Autor 2011, Autor & Dorn 2009, Firpo et al. 2011, Autor 2014, Autor et al. 2019, Goos et al. 2014, Autor et al. 2003). The twin phenomena of job and wage 'polarisation' have been documented in many developed countries in which employment share and earnings grow more quickly for high- and low-skilled jobs, relative to mid-skilled (Goos et al. 2014). This pattern has been linked to the types of tasks people are performing in their jobs as opposed to their education, i.e. the skill-biased technical change hypothesis.

Tasks are defined as discrete activities (e.g. picking or sorting) as opposed to skills which are capabilities (e.g. reading, numeracy) (Autor et al. 2003). Autor et al. (2003) distinguish between routine versus non-routine tasks and manual versus cognitive tasks. Routine tasks are those which a computer can be programmed to perform; and the manual-cognitive distinction is largely a blue collar-white collar one. A classic example of a routine manual worker is a machine operator; whereas a non-routine manual worker would be a care worker. Similarly, a classic example of a routine cognitive job is a bookkeeper; whilst a non-routine cognitive job would be an engineer or manager, for example.

Routine tasks are considered most prone to labour-replacing automation by machines or computer technology, thus undermining demand and earnings for routine jobs. Many jobs that are high in routine task-content are clustered in the middle of the (industrialised-country) wage distribution, like manufacturing operators and assemblers, but also white-collar office jobs, like clerks and bookkeepers (Autor et al. 2019). As computer technology increasingly replaces these routine tasks, these occupations grow more slowly than the comparatively less-routine jobs at the poles of the wage distribution, in a pattern called 'job polarisation'. Accordingly, job polarisation is often accompanied by 'wage polarisation', a pattern whereby the wages of these mid-skill routine occupations are eroded relative to those that are either low- or high-skilled ones (Autor & Dorn 2009).

A much smaller literature examines whether job polarisation exists in developing countries (Crankshaw 2017, Maloney & Molina 2016) and investigations of wage polarisation are even rarer (Bhorat et al. Submitted). Whilst there is consensus that job polarisation is pervasive in industrialised economies (Goos et al. 2014), the developing-country literature has reached less certain conclusions. This is most likely owed to key structural differences not only between developed and developing country labour markets, but to extensive diversity within developing markets. Important questions for economists are to what degree these polarisation patterns do or do not apply to developing economies; and to unpack what is behind such patterns. It is by no means obvious that polarisation patterns of either type should emerge in developing economies or, even if they do, that the drivers of such patterns will be the same as those in developed labour markets. In the next section we closely inspect to what degree changes in earnings and employment in South Africa can be described as polarised.

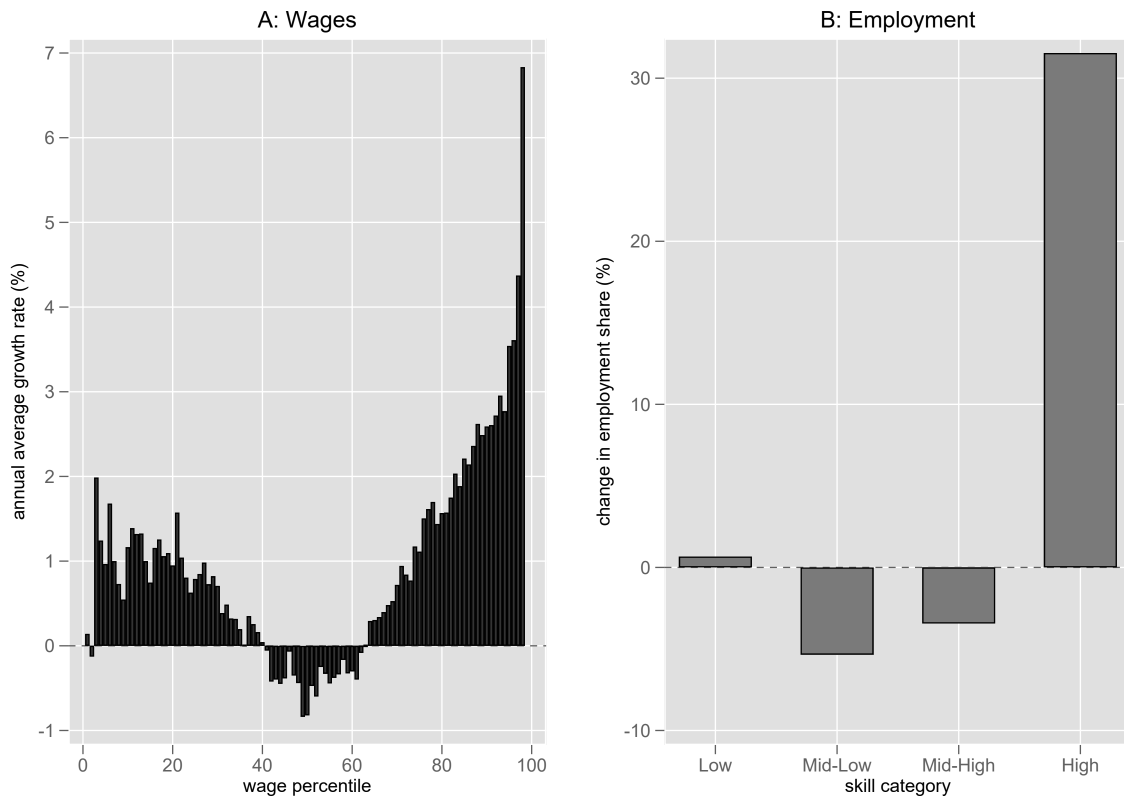
5 Earnings and Employment Change and Gender in South Africa

Initial descriptions of how earnings and employment have changed over the period 2000-2015 are presented in Figure 4 for employees. The average annual growth rate (AAGR) of earnings displays a U-shaped pattern across the percentiles. Wages have grown at the bottom and top of the wage distribution but have shrunk in real terms in the middle. This pattern could be described as polarising, and has already been noted by researchers closely studying the South African labour market (Wittenberg 2017*b*,*c*).

However, there appears to be no corresponding job polarisation in Figure 4. Panel B plots the change in employment share across four major skill groups set out by the South African Standard Classification of Occupations (SASCO) which adjust the International Standard Classification of Occupations (ISCO) skill categorisation for the South African context. One-digit occupations are divided into four skill categories: Domestic workers and elementary occupations are classified as low-skilled. Machine operators, trades workers, skilled agriculture, service workers, and clerks fall under mid-low skill. Technicians are mid-high skill; and, professionals and managers are highly skilled (Statistics South Africa 2003). Based on this classification, changes in employment share are 'professionalising', or 'skills-biased': only high-skilled occupations can be described as growing in a robust sense. The same pattern was detected by Crankshaw (2017) for the economically important province of Gauteng. Mid-skilled occupations do appear to be shrinking more quickly than low-skilled, but low-skilled occupations can hardly be described as growing.

Usually, job and wage polarisation accompany each other, since declining job market demand and declining wage growth for highly routine occupations are two outcomes of the same underlying explanation of technology replacing routine tasks. The mismatch between the wage and employment changes is likely related to minimum wages. South Africa set nine minimum wages sectorally over the period of study. Table 1 details when different minimum wages were implemented; how these levels were increased over time; as well as what share of the employed in 2014 were covered by a sectorally determined minimum wage. In 2014, 38.6% of the employed were covered by minimum wage legislation. Key constituencies at the bottom of the income distribution are farm workers and domestic workers. Both of these groups were covered by a minimum wage early in our study period, 2002. Domestic workers alone represented 8.6% of employees in 2014 and farm workers are notable for experiencing large real increases which happened mainly in 2012 and 2013 (Bhorat, Caetano, Jourdan, Kanbur, Rooney, Stanwix & Woolard

Figure 4: Distributional changes in wage and employment growth in South Africa, 2000-2015



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees. Panel B compared change between a pooled period of 2000-2004 and 2013-2015.

2016). Minimum wages for domestic work and farm workers are very likely key factors driving wage growth at the bottom of the wage distribution.

Note to eds: I'm not sure why this citation isn't collapsing to 'et al.'? Maybe you have some LaTex know-how I don't.

A quite distinct picture emerges by gender when earnings and employment change are plotted in Figure 5: women exhibit wage polarisation, but not employment polarisation, and the opposite is true for men. Earnings AAGR is plotted on an axis of Rands so that the patterns by gender are comparable. Female earnings growth displays a very distinctive U-shape, whilst male earnings growth displays a more monotonic pattern with low-earning men experiencing either negative or negligible wage growth.

Wage growth at the bottom end of the female wage distribution is very likely the result of the domestic worker minimum wage, since as many as 16% of women were domestic workers in 2013/5 according to Table 2. Over time, though, the domestic work share of female employment has been shrinking as women shift into services instead. This move is behind the positive growth in mid-low skilled work in Figure 5. By contrast men continue to be employed in elementary labourer occupations but have lost ground in traditional mid-skilled occupations like machine operators and assemblers and trades work.

This divergence by gender points to gender being an important dimension for explaining wage patterns and inequality in South Africa. This is well within expectations given the findings of an extensive local and international literature on the topic of gender in the South African labour market (Mosomi 2019, Casale & Posel 2011). A question for this paper, is how does a task-based explanation apply to men and women when they display the different patterns in Figure 5.

The key link between the task explanation and the role of gender is occupations. The task explanation for wage and employment change is operationalised at an occupational level by measuring what types

Table 1: Selected details about the implementation and evolution of sectoral minimum wages in South Africa

Sectoral Determination	Implemented	% real increase between implementation and 2015	% of total employees in 2014
Farm Workers	2002	90	5.1
Forestry	2003	81	0.3
Domestic workers	2002	41	8.6
Wholesale & retail	2003	28	10.5
Contract Cleaning	1999	27	5.7
Taxi	2005	23	1.9
Hospitality Workers	2007	15	2.5
Private Security	2001	14	4
			38.6

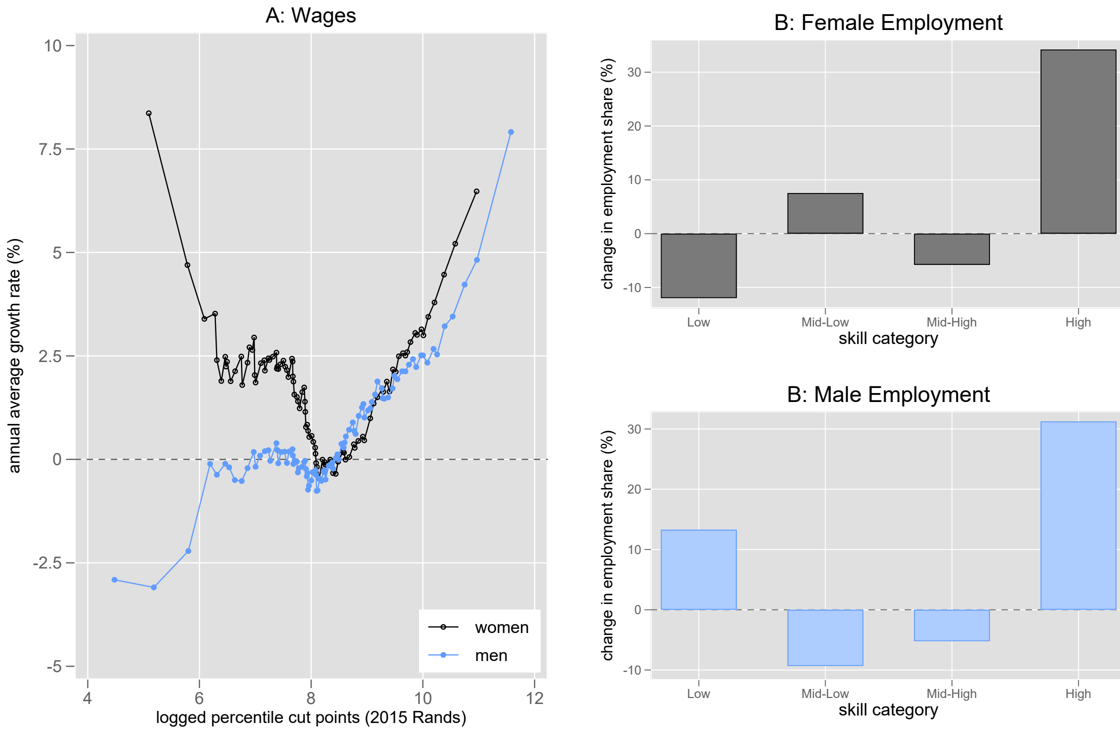
Source: compiled from Figure 10 and Table 2 in Bhorat, Caetano, Jourdan, Kanbur, Rooney, Stanwix & Woolard (2016)

of tasks a given occupation is doing. First of all, the South African labour market is loaded towards low-skilled work: a quarter of men and more than a third (35.6%) of women worked in elementary occupations, including domestic work in 2013-2015. Secondly, severe occupational sorting by gender means men and women in South Africa are sorting into very different types of tasks. Table 2 reveals the severity of gendered occupational sorting in South Africa. Women are highly concentrated in three main occupations: domestic work (16.2% in 2013-2015), personal care (11.8%), and clerks (19.2%); these three occupations together made up 47.2% of female employment in 2013-2015. By contrast, men are more evenly distributed across different occupations, with concentration in elementary labourer work (19.2%), drivers and mobile plant operators (10.3%), trades work (9.3%), and protective services (10.9%); these four occupations make up about 49.7% of male employment in 2013-2015. Managers and professionals altogether make up about 12.7% and 11.2% of male and female employment in the later period, respectively.

Female work is then split between highly non-routine cleaning and care work (27% between domestic work and personal care) and highly routine clerking (19.2%) Between 2000-2004 and 2013-20015, female employment share contracted substantially in domestic work, and expanded notably in personal care (by 80.1%) and more modestly in customer-related clerking occupations (by 6.2% overall), meaning women are mainly moving into non-routine but also into routine work. Revisiting Figure 5, this move out of domestic work and into services is behind the employment pattern in Panel B.

The expansion of male employment into protective services (by 27%) represents a step towards more non-routine work; whereas other traditional male occupations which are more routine, like trades work and plant machine operator and assembly work, saw a contraction in male employment share (by 7.9 and 18.7% percent respectively). The continued importance of elementary occupations and especially labourer occupations for men meant male low-skilled work grew in Figure 5. This may have been behind the negative wage growth for low-earning men in Panel A of Figure 5. Labourers in mining, construction, manufacturing and transport grew by 19.4% between 2000/4 and 2013/5 and this could be the outcome of, for example, men losing technical jobs as machine operators and assemblers being re-hired on a more casual basis as a labourer in the same sector. Investigating whether these are indeed the same people is beyond the scope of this paper, but elsewhere researchers have documented the 'casualisation' of the South African labour market (Budlender 2013, Bhorat, Cassim & Yu 2016). The precariousness of temporary and casual work undermines worker bargaining power to demand protections they are entitled to by law, e.g. minimum wages. Furthermore, the growth of these other types of labourers was several times faster than the growth of minimum-wage covered agricultural workers. Hence, non-minimum wage covered job growth exceeded minimum-wage covered for men, which may explain negative wage change at the lower end of the distribution in Figure 5.

Figure 5: Distributional changes in wage and employment growth in South Africa by gender, 2000-2015



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees. Panel B compared change between a pooled period of 2000-2004 and 2013-2015.

Table 2: One- and Two-Digit Occupational Share of Male and Female Wage-Employment between 2000 and 2015

	Two Digit Occupation	Men			Women		
	One Digit Occupation	**2000-2004**	**2013-2015**	**% Change**	**2000-2004**	**2013-2015**	**% Change**
11	Legislators and senior officials	0.2	0.5	175.8	0.1	0.3	211.5
12	Corporate managers	4.3	6.3	45.3	2.3	4.4	95.0
13	Managers of small enterprises	1.0	0.4	-62.0	0.5	0.2	-66.8
1	**Legislators, senior officials and managers**	**5.6**	**7.2**	**29.4**	**2.9**	**4.9**	**69.8**
21	Physical, mathematical and engineering science professionals	1.0	1.7	66.7	0.3	0.5	53.6
22	Life science and health professionals	0.4	0.5	37.0	0.8	1.2	51.1
23	Teaching professionals	1.3	1.0	-26.7	2.7	1.8	-32.7
24	Other professionals	1.4	2.3	66.3	1.6	2.7	73.8
2	**Professionals**	**4.1**	**5.5**	**33.8**	**5.4**	**6.3**	**15.4**
31	Physical and engineering science associate professionals	3.1	3.1	2.3	1.2	1.2	2.4
32	Life science and health associate professionals	0.5	0.5	6.2	3.8	3.0	-21.4
33	Teaching associate professionals	2.3	1.7	-22.8	6.4	5.9	-9.1
34	Other associate professionals	3.1	3.1	-1.5	3.3	3.8	15.8
3	**Technical and associate professionals**	**8.9**	**8.4**	**-5.2**	**14.7**	**13.8**	**-5.8**
41	Office clerks	5.0	5.0	-1.3	11.8	11.9	0.9
42	Customer services clerk	1.6	1.5	-9.0	6.8	7.2	6.2
4	**Clerks**	**6.7**	**6.4**	**-3.2**	**18.6**	**19.2**	**2.8**
51	Personal and protective services worker	8.5	10.9	27.6	6.6	11.8	80.1
52	Models, salespersons and demonstrators	3.5	3.6	1.6	4.1	3.6	-11.0
5	**Service workers and shop and market sales workers**	**12.1**	**14.5**	**20.0**	**10.6**	**15.4**	**45.3**
61	Skilled agricultural and fishery workers	3.2	0.4	-87.1	0.6	0.3	-55.9
62	Subsistence agricultural and fishery workers	0.1	0.0	-68.6	0.0	0.0	-77.5
6	**Skilled agricultural and fishery workers**	**3.2**	**0.4**	**-86.7**	**0.7**	**0.3**	**-57.5**
71	Extraction and building trades workers	10.7	9.3	-13.0	0.7	0.6	-4.3
72	Metal, machinery and related trades workers	6.4	6.4	0.4	0.3	0.3	14.8
73	Precision, handicraft, craft printing and related trades workers	0.7	0.6	-14.2	0.4	0.2	-42.0
74	Other craft and related trades workers	1.2	1.2	-3.5	1.8	1.3	-29.0
7	**Craft and related trades workers**	**19.0**	**17.5**	**-7.9**	**3.1**	**2.5**	**-21.3**
81	Stationary plant and related operators	2.2	1.7	-23.5	0.2	0.2	11.1
82	Machine operators and assemblers	3.5	2.9	-19.2	3.5	1.9	-45.7
83	Drivers and mobile plant operators	12.5	10.3	-17.8	0.3	0.4	29.1
8	**Plant and machine operators and assemblers**	**18.2**	**14.8**	**-18.7**	**4.0**	**2.6**	**-36.7**
91	Sales and services elementary occupations (excl. Domestic Workers)	4.3	5.5	28.0	7.4	9.8	32.2
92	Agricultural, fishery and related labourers	9.2	9.6	5.1	5.6	4.3	-24.0
93	Labourers in mining, construction, manufacturing and transport	8.1	9.6	19.4	4.2	4.8	14.6
9	**Elementary Occupation**	**21.5**	**24.8**	**15.0**	**17.3**	**19.0**	**9.9**
10	**Domestic workers**	**0.8**	**0.5**	**-33.2**	**22.7**	**16.2**	**-28.6**
	Two Digit	100.0	100.0		100.0	100.0	
	One Digit	**100.0**	**100.0**		**100.0**	**100.0**	

Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

5.1 Earnings and employment change by skill percentile

Another way to view employment and earnings change by occupation is across what is termed the 'skill percentile'. The skill percentile ranks occupations at the three- or even four-digit level according to their (employment-weighted) mean log wage. This allows for a more disaggregated look at skill. However, it also makes assumptions about the link between skill and wages, which do not always hold, and that occupations can be accurately represented by their mean wage, which is not always the case. This is a problem when occupations themselves have very dispersed wage distributions. A good example of this are 'General Managers' which include some very modest and some very lucrative earners. These concerns aside, the skill percentile is a common analytic tool for researchers studying job polarisation (Autor & Dorn 2009, Acemoglu & Autor 2011).

An advantage of the skill percentile over the main occupation groupings or skill categories is that it can provide a more granular picture by ranking (in our case) at the three-digit occupational code level. This is important especially for services, which is one of the fastest-expanding occupation categories but which is also very heterogeneous, making it hard to know whether the main group is low- or mid-skill.[2] For example, stall and market sales persons are below the 10th skill percentile. Housekeeping and restaurant service workers (cooks, cleaners, and wait staff) fall below the 30th skill percentile. Beauticians, hairdressers, barbers, and, personal care of children, the elderly, and other home-based care workers come shortly before the 50th skill percentile. Protective services workers are above the 60th percentile and fashion models are at the 86th percentile. The skill percentile breaks down the large services group and places specific occupations at points in the distribution that more closely align with our idea of skill. The skill percentile further holds occupations in a fixed position on the axis, meaning changes can securely be attributed to a given occupation, as opposed to analysis by wage percentiles where in individuals can shift up and down the distribution over time.

Figure 6 plots employment change over sub-periods between 2000 and 2015 for men and women across the skill percentiles. Note these data are plotted on a common skill percentile, but the y-axis represents change in the share of either total male or total female employment. In agreement with Figure 4, there is little indication of employment polarisation for either men or women when using this more detailed way to classify occupations by skill. In fact, women are arguably displaying an inverted polarisation pattern: Moving out of low-skilled occupations (almost exclusively domestic work) and dispersing into mid-skilled ones, particularly those around the 30th to 70th percentiles (e.g. cashiers, service clerks, personal care). The adjustment of the composition of male employment has been less extreme; although both men and women then saw a decline in upper-middle occupations between the 70th and 80th percentiles - office clerks, secretaries and some more highly-skilled manufacturing work - before a slight uptick for the most highly skilled occupations, being managers and professionals of various types.

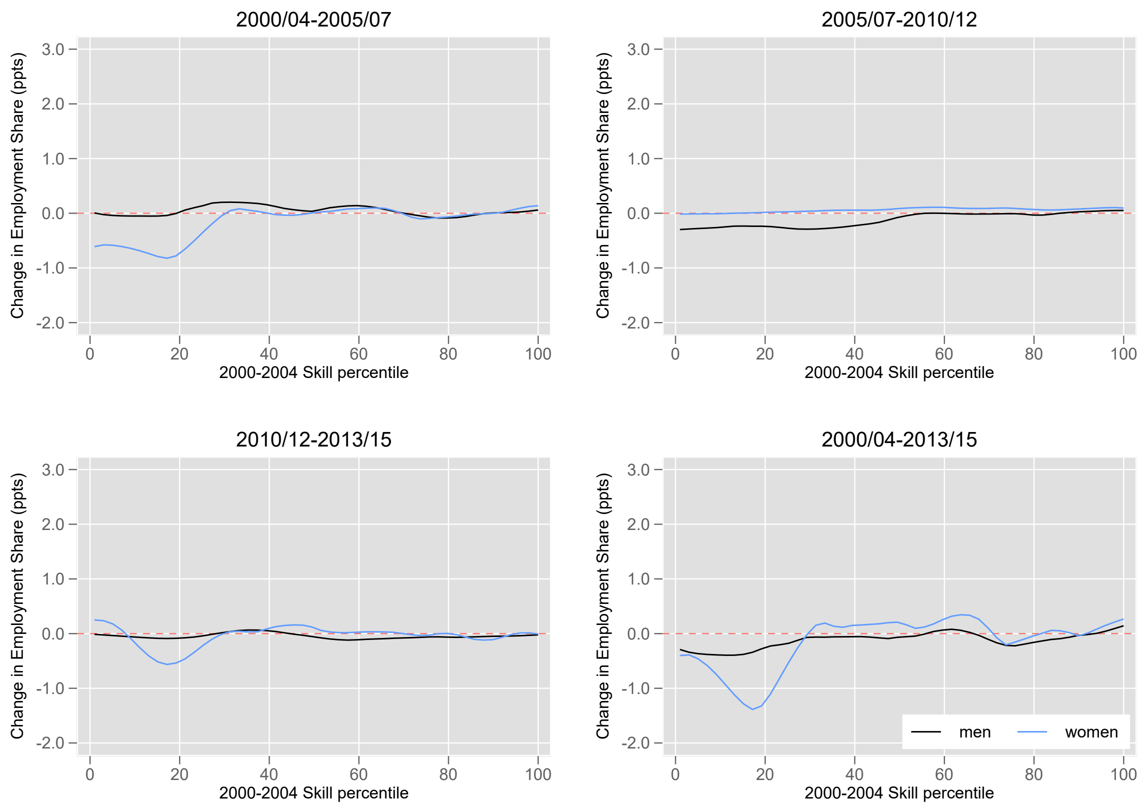
Figure 7 plots earnings change across the skill percentiles and quite different patterns emerge compared to those for employment. There is a pro-poor wage growth pattern between 2000/4 and 2005/7 when many minimum wages were being implemented (see Table 1). The period immediately after the 2008 Global Financial Crisis (2010/2-2013/5) saw a gouging-out of wage growth for upper middle occupations. We return to these occupations in more detail later on. The overall period presents a polarised pattern, with growth most muted for the same occupations that suffered the most during the post-crisis period.

In the literature from the United States, wage polarisation across the skill percentiles mirrors employment polarisation also across the skill percentiles. In contrast, in South Africa at low skill percentiles, wages are growing for precisely the occupations where employment share contracted (Figure 6 and 7). As already discussed, this is likely the consequence of minimum wages. The task explanation therefore plays only a weak role in explaining wage change at this point in the distribution.

The main point of agreement across the skill percentiles between employment and earnings is contraction around the 70-80th percentiles. South Africa's wage change across the skill percentile for the overall period in the bottom right-hand panel of Figure 7 is perhaps better described as a backwards J-shape, or hockey stick, than a U-shape. The trough of the polarisation pattern occurs later in the South African skill distribution than in industrialised countries because of the outsized share of low-skilled work

[2] And researchers will reach different conclusions about whether South Africa exhibits employment polarisation, for example, if they allocate services to mid or low skill

Figure 6: Employment change across the skill percentile in South Africa by gender, 2000-2015



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

in South Africa's employment make-up.[3] The occupations occupying percentiles 70 through 90 were some technical trades workers (e.g. electricians, mechanics); teachers of various types; nurses; but mainly clerks and administrative staff of various types (secretaries, bookkeepers, accountants, numerical clerks). In South Africa, these conventionally mid-skilled occupations occur much higher in the distribution and highly skilled work is compacted into the top decile of the distribution. This concentration is partly an outcome of historical inequality in the schooling sector resulting in skills being generally in short supply.

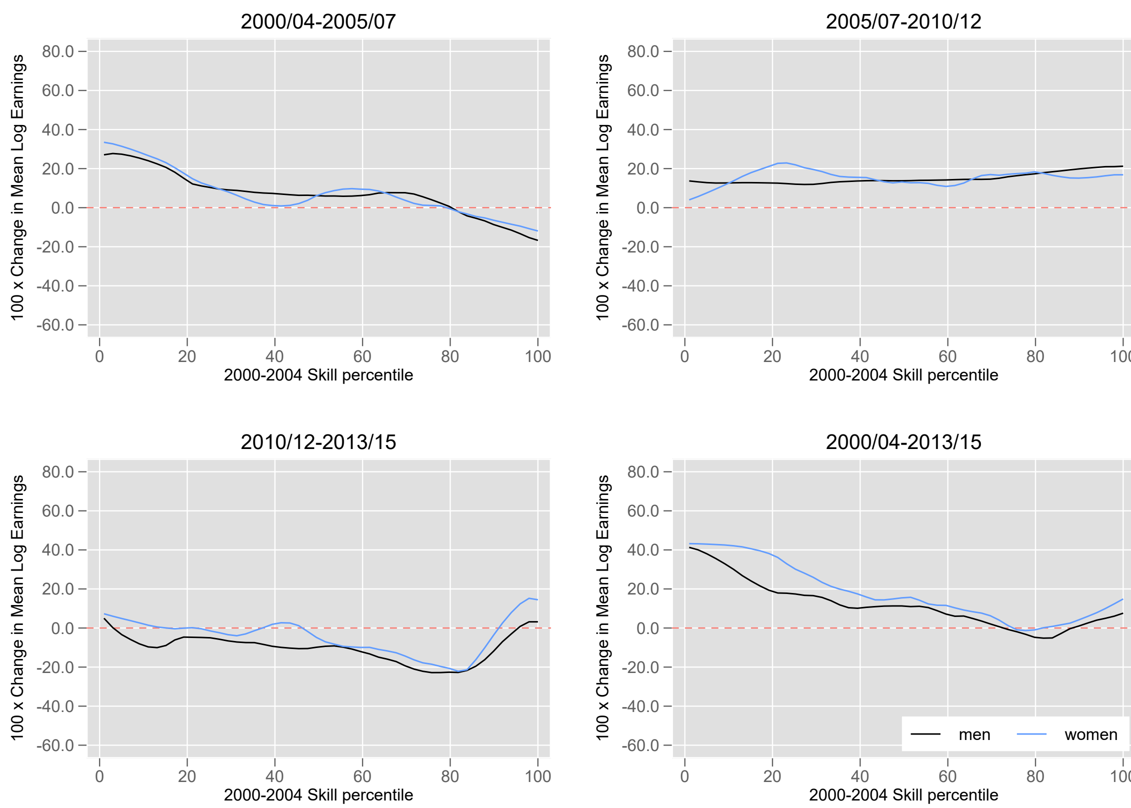
These occupations just listed are the same ones that experienced severe wage shrinkage in the 2010/12-2013/15 period immediately following the 2008 Global Financial Crisis. Generally, these occupations are also out of the reach of minimum wages and are divided into a highly routine (e.g. clerks) and highly non-routine cluster (e.g. teachers and nurses). Women are over-represented at this portion of the skill percentile, making up the bulk of clerks, teachers and nurses. The task explanation could be more relevant for this portion of the skill percentile in South Africa, although this requires closer examination given the co-existence of routine and non-routine jobs in the same skill percentiles.

Notably this wage polarisation shape is the case for both men and women, whereas, when wage change is plotted across wage percentiles as in Figure 4, men at the bottom of the distribution appear to have lost ground. Some of the reasons for the discrepancy between the skill percentile pattern in Figure 7 and the wage percentile pattern in Figure 4 is that the y-axis in the former only considers change in the mean wage per three-digit occupation. This could be hiding detail from occupations where wages are more

[3]Elementary occupations (including domestic work) comprised just under 30% of employees in all periods.

dispersed which would be captured in the wage percentile figure which then displays more extreme male wage loss at the bottom of the distribution and more extreme wage gains at the top of the distribution for both genders. Indeed, runaway wage growth at the top end is an important aspect of earnings inequality in South Africa and is better captured in Figure 4 (Wittenberg 2017*b*,*a*).

Figure 7: Wage change across the skill percentile in South Africa by gender, 2000-2015



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

In sum, very different wage growth patterns by gender are reconciled when looking at wage growth across occupations in the skill percentile. This suggests that an occupational framework is relevant to wage change in South Africa, and specifically for white-collar office jobs, like clerks. This may be because minimum wage policies have de-linked employment and earnings patterns specifically at the bottom end of the distribution. Next we explore whether tasks are an important explanation in this regard by introducing a task variable and describing its distribution in South Africa.

6 Measuring Task Intensity in South Africa

We use a routine task intensity index (RTI) to quantify the share of routine work relative to other types of work in a given occupation. The RTI is a composite of task measures from Acemoglu & Autor (2011). Acemoglu & Autor (2011)'s task measures are based on a detailed publicly-available occupational survey called the Occupational Information Network (O*NET) collected by the United States' Department of Labour (National Center for O*NET Development 2020). Information is collected on a range of occupational details such as abilities, skills, activities, and work context.

The component task measures which Acemoglu & Autor (2011) create and which we replicate using the O*NET data are: routine cognitive; non-routine analytic; and, non-routine interpersonal. Routine cognitive (r_{cog}) measures the importance of repeating the same task; being exact and accurate; and how structured work activities are. Routine cognitive work is closely associated with administrative clerks. Non-routine analytic ($nr_{analytic}$) captures the level of creative thinking, analysis, and interpretation someone does and is associated with highly technical professions, like engineering. Non-routine interpersonal ($nr_{interpersonal}$) measures the importance of inter-personal relationships, and how much guiding and coaching is involved in the job. This task type is closely associated with managers and teachers for example.[4] We omit routine manual work (commonly associated with machine operators) for consistency with our second measure, described shortly, but also because routine manual and routine cognitive are quite distinct forms of routine work. We choose to focus on the latter and keep the concept being measured clear. These components are combined into an O*NET RTI for four-digit occupation i using the following formula from Lewandowski et al. (Submitted):

$$RTI_i = ln(r_{cog,i}) - ln(\frac{nr_{analytic,i} + nr_{interpersonal,i}}{2}) \tag{1}$$

To ensure all task components are transparently weighted, we compress the variation of each component to vary between zero and one. We then use a crosswalk between the American Standard Occupational Classification (SOC) system and ISCO-88 on which SASCO 2003 is based. For occupations that don't merge because they exist in SASCO 2003 and not in ISCO-88, we allocate the average value of the RTI at the two digit occupation level. Once our measure is in the labour market data, we standardise it. A one standard deviation change is then relative to the distribution of routine work in the South African labour market.

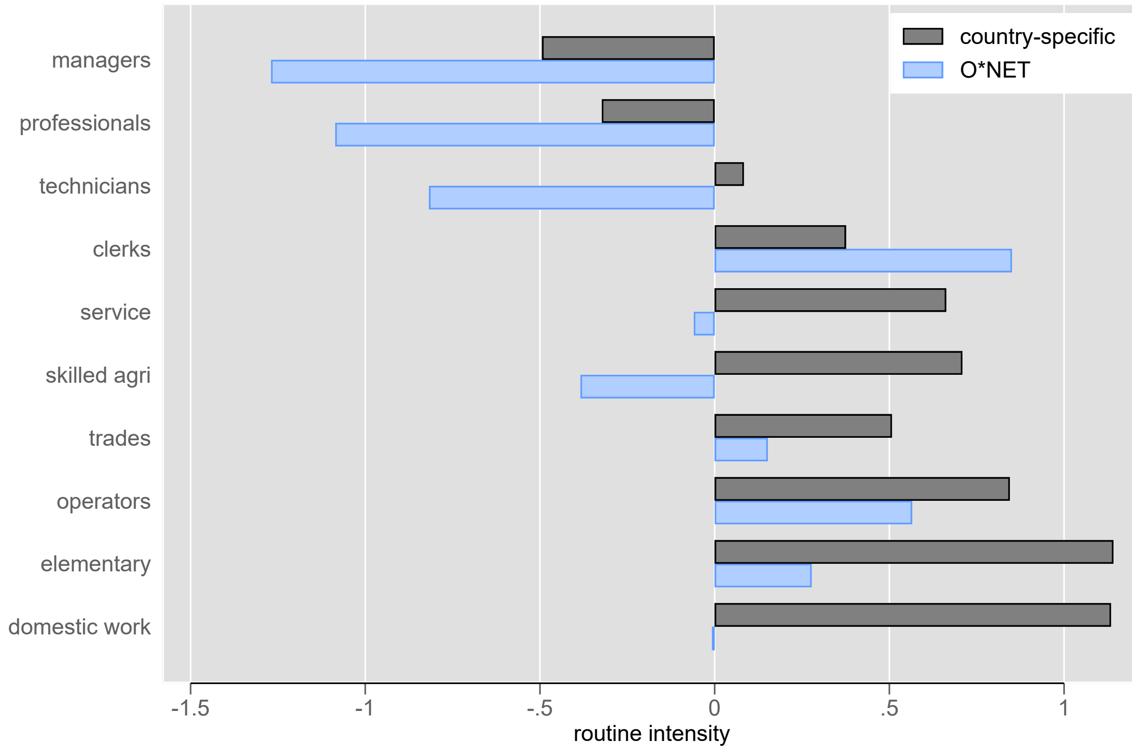
An important consideration is that O*NET is thoroughly embedded in an industrialised American context and it may be inappropriate to directly apply these measures to a developing country context like South Africa. As such, we also consider a second RTI constructed in the same way but which has been adjusted for the South African country context by Lewandowski et al. (Submitted). Lewandowski et al. (Submitted) use task data from the World Bank's Skills toward Employment and Productivity (STEP) surveys from 45 countries (note, only 5 of these are developing countries and only two of those are African) to predict how the RTI for a given occupation should be adjusted from a baseline one digit ranking using country-specific measures for GDP, skill, technology uptake and other factors. The authors noted that the measurement of manual work was not consistent across countries and did not distinguish between routine and non-routine manual work in their data set and so they omitted this measure. This country-specific RTI (CS RTI) was made available to us at the two-digit level and we merge it into PALMS accordingly. This RTI has also been standardised.

Figure 8 shows that indeed there are some important differences between how O*NET and the country-specific RTI rank routine intensity by main occupation code. Two major differences are the ranking on clerks and domestic workers. The country-specific RTI ranks clerks as having a medium level of routine intensity and domestic workers as highly routine. By contrast, the O*NET measure ranks clerks as having the highest level of routine intensity and domestic workers fall behind machine operators, trades workers, and other elementary workers in their level of routine intensity. So far, the O*NET measure more accurately reflects our intuitions about how routine work should be distributed in South Africa. Most economists familiar with the South African labour market would probably agree that a machine operator or a clerk are both more likely to lose their jobs to a machine or a computer well before a domestic worker or a personal care worker. The reason the country-specific RTI is so different could be that the one-digit baseline used in the prediction model was based on a sample of European countries which are also not necessarily comparable to South Africa.

We plot the distribution of both RTI measures across the skill and wage percentiles in Figure 9. The differences between the two measures are in line with what we would expect given how each ranks the one-digit occupations. The O*NET RTI follows an inverted-U shape across both the wage and skill distributions, whilst the country-specific RTI declines almost monotonically also across both. It appears

[4]See Appendix A for detail on O*NET measures in each component

Figure 8: O*NET and Country-specific Routine Task Intensity by Main Occupation Code



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

that the country-specific RTI has a very close correlation with skill as measured by the skill percentile. On the other hand, the O*NET RTI is less related to skill and quite clearly is capturing a completely different dimension of work activity. In Table 3 we report correlation coefficients strongly supporting this idea. The correlation coefficient between main occupation code (decreasing in skill) and the country-specific RTI is as high as 0.94 suggesting the country-specific RTI is an almost exact proxy for skill. By contrast, the same coefficient for the O*NET RTI is 0.36. The country-specific RTI is as correlated with education and skill category as the main occupation code. For these reasons, we favour the O*NET RTI and where it is practical to only present one set of results, we present those from the O*NET RTI.

Looking at the O*NET RTI, work for both men and women below the 70th wage percentile became slightly less routine between 2000-2004 and 2013-2015; and, slightly more routine above this mark, especially women. The former change is likely due to both men and women moving into non-routine personal and protective services; whilst the latter is probably related to the decline in teachers. Teaching occupations come in at more than two standard deviations below mean of the O*NET RTI making them the second least routine occupation only after legislators and senior officials (See Appendix Table 7). The substantial contraction of teaching professionals and teaching associate professionals for both men and women reported in Table 2 is likely behind the increase in average RTI above the 70th percentile since this is also where both of these occupations are located in the income distribution.

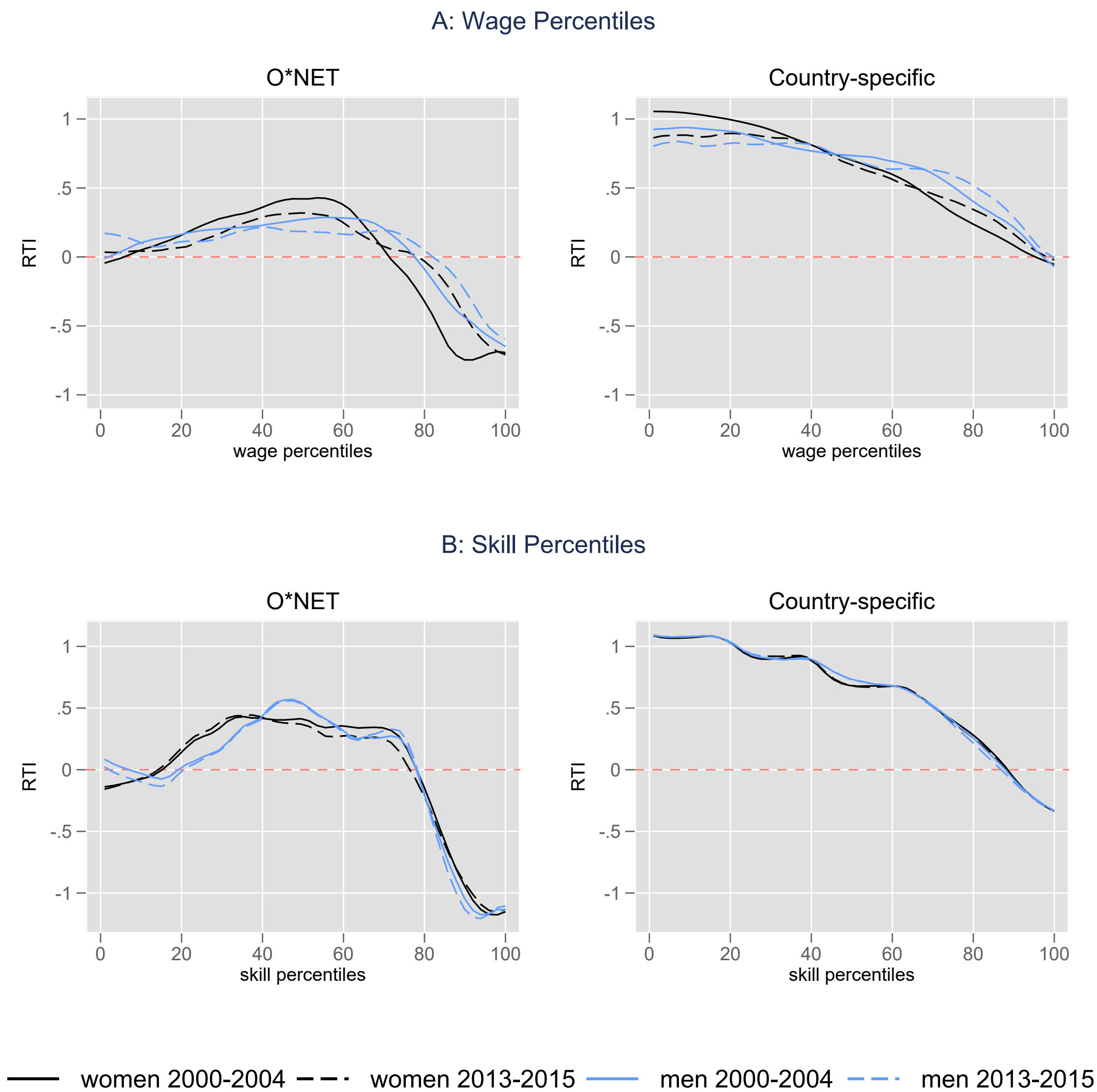
The adjustment of the distribution of routine work across the wage distribution is more obvious than across the skill percentile. The main change across the skill percentile is that women between the 50th and 80th skill percentiles became slightly less routine by the end of the period (reflecting teacher decline), but otherwise the distribution is highly stable over time. The skill percentile holds occupations fixed whilst occupations are free to shift up and down the wage percentiles. Greater change over time across the wage percentiles could be the result of both occupational recomposition across the wage distribution as well as changes in returns.

Table 3: Pearson correlation coefficients for selected variables

	Main Occupation	**Years Education**	**SASCO Skill Cat**	**O*NET RTI**	**Country-specific RTI**
Main Occupation	1				
Years Education	-0.57	1			
SASCO Skill Cat	-0.88	0.517	1		
O*NET RTI	0.36	-0.21	-0.36	1	
Country-specific RTI	0.94	-0.54	-0.95	0.4	1

Source: own calculations the Post-apartheid Labour Market Series Version 3.2
Notes: adjusted using sampling weights; pairwise handling of missing values on a total sample of 990 159 covering years 2000-2015; all coefficients significant at the 5% level.

Figure 9: Distribution of occupational cognitive routine intensity in South Africa according the same index using different data sources, 2000-2015



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

7 Investigating occupational routine task content

To investigate the role of routine work in explaining wage and employment changes we run two sets of regressions and a decomposition. The first of these is a series of simple regressions following the specification of Sebastian (2018) in investigating job polarisation in Spain. As expected, the author found a negative linear relationship meaning that the employment share of the most routine jobs grew the least. We run the following specification by gender:

$$\Delta E_j = \beta_0 + \beta_1 log(RTI_{j,t-1}) \tag{2}$$

$$\Delta logY_j = \beta_0 + \beta_1 log(RTI_{j,t-1}) \tag{3}$$

where ΔE_j is the percentage change in employment share of two-digit-level occupation j between time period $t-1$ and t; $\Delta logY_j$ is the change in log earnings for the two-digit occupation j between time period $t-1$ and t; $RTI_{j,t-1}$ is the O*NET-based index of routine task intensity for occupation j in time period $t-1$. We weight all regressions by employment share in period $t-1$. For completeness, we run the same specification for the country-specific RTI but report it in the appendix.

7.1 Regression Results

The results of our simple regressions are in Table 4 with graphical depictions of the full period result in Figure 10. The numbers on the bubbles in Figure 10 correspond to the two-digit occupational codes in Table 2, as does the change reported on the y-axis for employment. The sample size is small at only 27 two-digit occupations meaning significance was difficult to achieve. Nonetheless, we interpret the direction and size of the coefficients.

There does not appear to be a very strong relationship between RTI and earnings change; coefficients are close to zero. This conclusion is confirmed in the earnings results in Figure 10. Note the strong wage change for agricultural labourers for men (bubble 92) and essential sales and services (bubble 91, dominated by domestic workers) for women. This aligns with increases in minimum wages for these groups and the role these types of interventions have played in potentially de-linking wage change from a routine tasks explanation. Such interventions could explain the positive association between RTI and wage change for women in Table 4: a standard deviation increase in RTI increased women's wages by 3.9 percent over the whole period.

Results for employment are stronger and in particular for men. A one standard deviation increase in the routine intensity of an occupation led to a statistically significant reduction of 18.23 percentage points in that occupation's employment share. Men have moved largely out of routine work like machine operation and assembly (bubble 82) and into non-routine work like protective services (bubble 51), corporate management (bubble 12), and elementary labourer work (bubble 93). Although elementary labourer work is still relatively routine, it is less routine than machine operation and assembly. As such, the pattern of changing male employment has followed the logic of routine-biased technical change more consistently than that for women. The negative correlation between female employment change and routine work is diluted by counter-theoretical changes at the poles of the RTI. Figure 10 shows women moving out of highly non-routine teaching (bubbles 23 and 33) and into highly routine clerking (bubble 42).

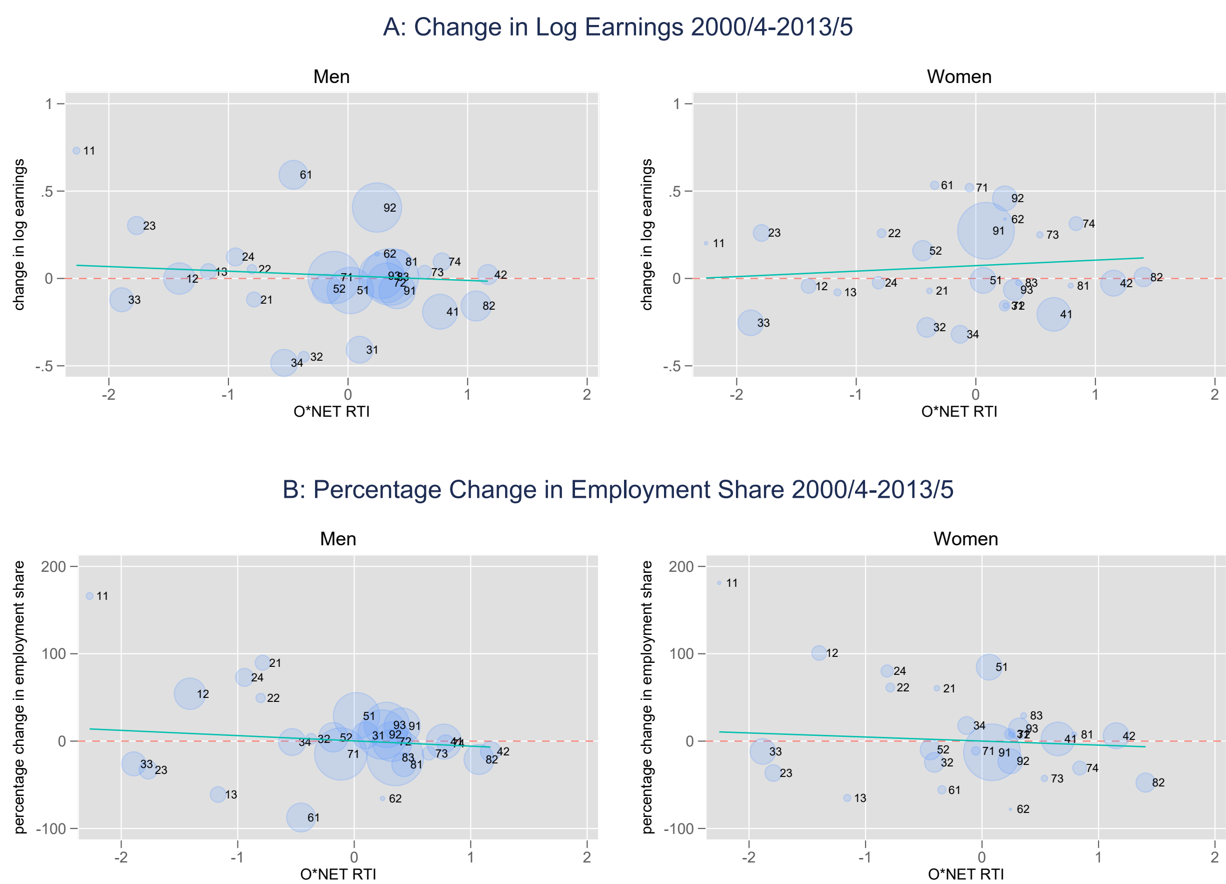
The results for the country-specific RTI are in Appendix Table 8 and Figure 13. The figure reveals though that there is a more quadratic relationship between the country-specific RTI and wage and employment change which corresponds with patterns observed across the skill percentile. It is unsurprising that the country-specific RTI patterns mirror the skill percentile one given that this measure is so closely related to skill.

Table 4: Regression output for employment and earnings changes for two-digit occupations and O*NET-measured routine task intensity in South Africa, 2000-2015

	Change in Log Earnings				**Percentage Change in Employment Share**			
	2005/7-2000/4	**2010/2-2005/7**	**2013/5-2010/2**	**2013/5-2000/4**	**2005/7-2000/4**	**2010/2-2005/7**	**2013/5-2010/2**	**2013/5-2000/4**
				WOMEN				
O*NET RTI	0.0211	0.0189	0.0149	**0.0392**	-3.838	-4.094	3.553	**-10.07**
	(0.0323)	(0.0290)	(0.0281)	**(0.0581)**	(4.704)	(5.702)	(3.560)	**(10.66)**
_cons	0.112***	0.0177	-0.0677**	**0.0502**	0.0656	-0.0779	0.0632	**11.70**
	(0.0256)	(0.0232)	(0.0221)	**(0.0441)**	(3.727)	(4.575)	(2.806)	**(8.094)**
N	27	27	27	**27**	27	27	27	**27**
				MEN				
O*NET RTI	0.0172	-0.00997	-0.0273	**-0.00883**	-0.104	-8.378	2.852	**-18.23***
	(0.0450)	(0.0349)	(0.0269)	**(0.0632)**	(6.377)	(6.398)	(3.385)	**(8.294)**
_cons	0.115***	-0.00897	-0.0907***	**-0.000997**	0.00496	0.226	0.00106	**8.866**
	(0.0289)	(0.0215)	(0.0174)	**(0.0396)**	(4.085)	(3.950)	(2.194)	**(5.195)**
N	27	27	27	**27**	27	27	27	**27**

Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees. Standard errors in parenthesis. * p<0.05, ** p<0.01, *** p<0.001.

Figure 10: Employment weighted scatter plot of change in earnings and employment against O*NET routine task intensity index at the two-digit occupational level, 2000/4-2013/5



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees. Bubble size corresponds to size of employment in 2000/4. Bubble number correspond to two-digit occupational codes, listed in Table 2.

8 Routine Work and Other Explanations for Inequality

Even if routine-biased technical change is mildly associated with employment change, how does it compare to other prominent explanations for wage inequality? To answer this question, we run a fuller specification for wage change. We consider the role of explanations such as skill-biased technical change (controlling for education and occupation); structural transformation (controlling for industrial composition); labour market institutions (controlling for trade unions and public sector employment); and, finally routine-biased technical change (with the RTI).

We run a RIF regression, also known as an unconditional quantile regression, developed by (Firpo et al. 2009). This regression makes use of the recentered influence function (RIF) of the outcome variable instead of the outcome itself, and allows us to estimate the relative importance of different variables at different points of the wage distribution. A RIF regression is run for the base period 2000-2004 and an end period 2013-2015. The specification is as follows for each sex separately and each time period (t):

$$RIF(logearnings)_t = \beta_0 + \beta_1 AGE_t + \beta_2 AGE_t^2 + \beta_3 YRSEDUC_t + \beta_4 POPGROUP_t + \beta_5 IND_t + \beta_6 OCC_t + \beta_7 UNION_t + \beta_8 PUBLIC_t + \beta_9 RTI_t \epsilon \quad (4)$$

where AGE and AGE^2 are age in years and age in years squared; $YRSEDUC$ is the years of education variable provided in the PALMS data; $POPGROUP$ are three race group dummies with the omitted (base) category being Africans; IND are nine main industry dummies with the omitted (base) category being agriculture; OCC are also nine main occupation dummies with the omitted (base) category being senior managers; $UNION$ is a dummy for union membership; $PUBLIC$ is a dummy for employment in the public sector; and lastly RTI is either the O*NET RTI or country-specific RTI. The RIF regressions are weighted using the 'bracketweight' in PALMS.

Following this, we use an Oaxaca-Blinder decomposition to understand at which points of the wage distribution changes in the wage structure or composition of the employed have been more influential. The oaxaca-blinder decomposition decomposes the change in mean wages between two periods into effects owed to changes in the wage structure (coefficient effect), the composition of employment (endowment effect), and their interaction. The endowment effect is defined as the expected change in mean wages for employees in 2000/4, had they had the predictor levels (i.e. characteristics) of those in 2013/5. The coefficient effect is defined as the expected change in mean wages for employees in 2000/4, had they had the regression coefficients (i.e. wage structure) of those in 2013/5 (Jann 2008). We then run a detailed decomposition for each covariate.

8.1 RIF Regression Results

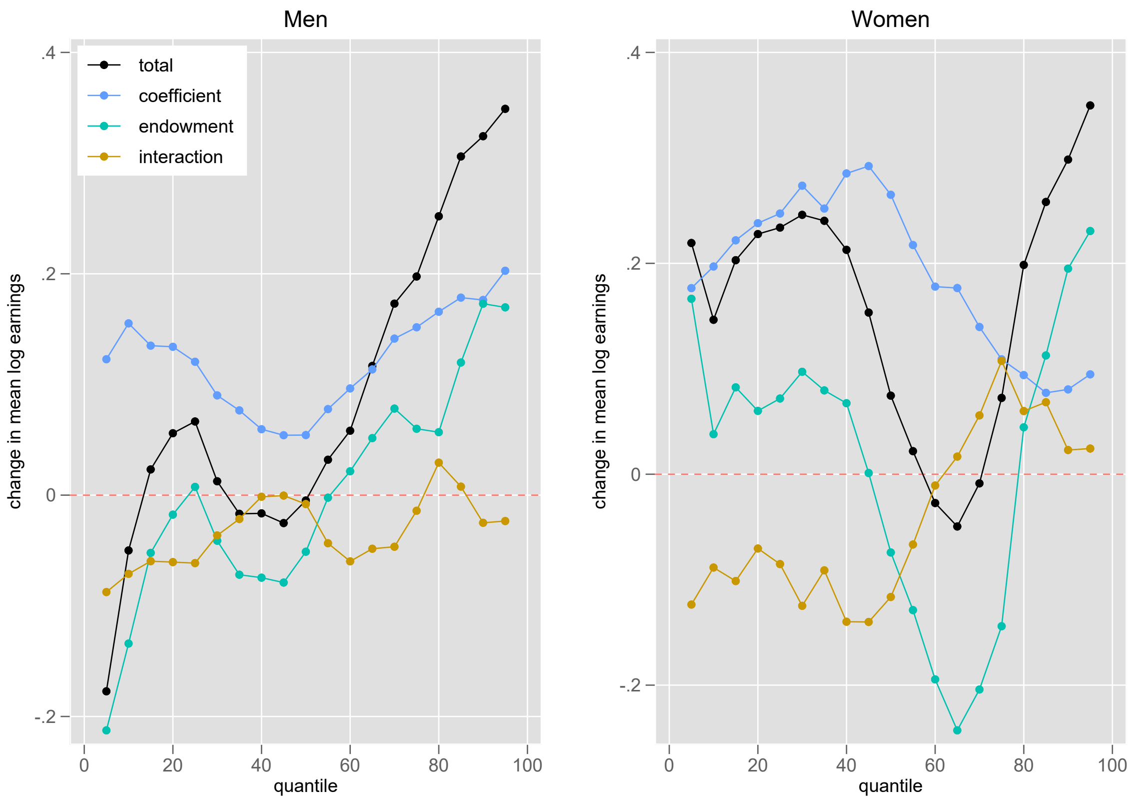
The total change in mean wages between the base and end periods, as well as the division into coefficient, endowment and interaction effects are plotted in Figure 11. The detailed RIF regression output is in Appendix Tables 9 and 10 for men and women, respectively.[5] The overall changes for men and women mirror the gender differences initially described in Figure 5: wage change is U-shape for women, but negative for men at the bottom of the distribution. Important roles are played by both changes in the wage structure (coefficient effect) and composition of the employed (endowment effect). For both men and women, the coefficient effect lies above the endowment effect for most wage quantiles. This means that changes in the wage structure have served to increase wages between the early 2000s and mid 2010s; but this has been offset to some extent by changes in the composition of employment. For men at the bottom end, it is compositional changes that undermined wage change; whereas, for women at the top end, compositional changes supported wage change.

For women, changes in endowments in Figure 11 especially seemed to undermine wages between the 60th and 80th wage quantiles. Table 2 can again assist in understanding which occupations declined and which grew over this period. Previously we have noted that an important change at this point of the wage distribution for women was the decline in teachers, and to a lesser extent nurses (under code 32 in Table 2). Teachers in particular have strong unions protecting wages for those who remain employed (Mahlangu & Pitsoe 2011, Msila 2014) so fewer teachers would likely affect wage change.

By contrast, Table 2 reports the growth of residual business occupation categories of 'other professionals' and 'other associate professionals' which often capture business and administrative work (e.g. bookkeeping). This trend could indicate women moving into less protected temporary employment work which could undermine wages. Temporary employment services are not directly identified in South African labour market data. Researchers have reached some consensus that the industry code "Business Not Elsewhere Classified" may be capturing the spread of temporary work (Budlender 2013, Bhorat, Cassim & Yu 2016). The share of both of these residual categories in female Business Not Elsewhere Classified increased over time. This could be an indication of the increased casualisation of women's work, but it could also be a real increase in residual business categories. For men, the endowment effect undermined wages at the bottom end. We have previously discussed the continuing importance of

[5]Results for the RIF decompositon using the country-specific measure are in the Appendix Figures 14 and 15 and the detailed RIF regression output in Appendix Tables 11 and 12.

Figure 11: Oaxaca-Blinder decomposition of the change in wages across wage quantiles into the coefficient, endowment, and interaction effect for South Africa, 2000/4-2013/5



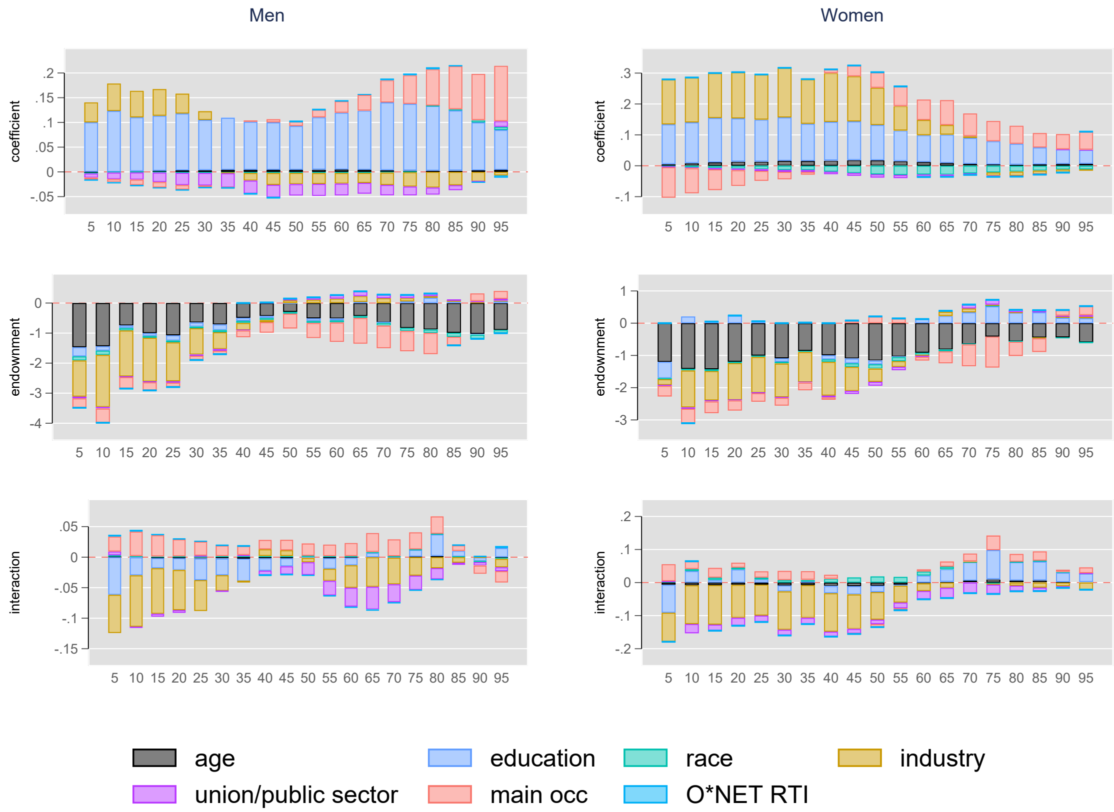
Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

low-skilled elementary labourer work for men. Here, men are also potentially becoming more 'casualised' since non-minimum wage covered labourers grew faster than farm workers, but a thorough test of the increase of casualisation for either men or women is beyond the scope of this paper.

Figure 12 summarises the results of each set of variables, besides the constant term. The figure shows that the O*NET RTI is not very important in any regard for explaining the change in wages between these two periods when we control for other explanations. The light blue that represents the RTI is barely visible in all plots. This is not very surprising considering the results of the simple regressions for two digit occupations in Table 4.

Instead, we see that changes in returns to years of education are crucial for explaining changes in the wage structure. This effect dwindles slightly as we move up the wage distribution for women, but the opposite is the case for men. The endowment effect on the other hand, is driven by age, which could also be proxying for experience which Finn & Leibbrandt (Submitted) found to be important. Changes in industry and occupation are important for both the coefficient and endowment effect. Industry accounts for wage structure effects at the bottom end, whilst occupation (arguably proxying for skill) becomes more important at the top end. This lines up with the notion that minimum wages which intersect closely with low-income industries like agriculture and domestic work, play an important role at the bottom end. For men, changes in unions and public sector employment also undermined wage growth.

Figure 12: Detailed decomposition of the change in wages across wage quantiles, 2000/4-2013/5



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

9 Decomposing the Gini

A final decomposition investigates the contribution of tasks and occupations to the wage Gini. In Table 5 we calculate the wage Gini coefficient in different time periods and undertake various decompositions to understand the contribution of occupations and task content to wage inequality. Two counterfactual decompositions are also estimated: one holding occupational employment shares constant but allowing wages to change over time ("Shares constant" column); and the second holding occupational mean wages constant and allowing occupational employment shares to fluctuate over time ("Means constant").

As discussed previously in this paper, earnings inequality is trending upwards over time and the jump in the last period may reflect data quality issues. Comparing the two counterfactual scenarios allows us to ascertain to what degree changes in the Gini were driven by changes in employment composition versus earnings. The Gini increased very similarly in both counterfactuals suggesting it has been both employment and earnings changes that explain earnings inequality. However, if we ignore the last period, changes in occupational composition look narrowly more important.

The Shapley decomposition reveals that inequality between and within occupations equally contribute to overall inequality in the first period; but, over time, the within-occupation contribution becomes gradually more important. This conclusion also applies across both counterfactual scenarios and once again, there is a large step-up in the last period. The growing significance of the contribution of within-occupation inequality explains why wage growth patterns across the wage percentiles differed from those across the skill percentiles, as already discussed.

Inequality between occupations is high, existing in a range between 0.38-0.43. The concentration index estimates the Gini coefficient sorting occupations by the (inversely ordered) RTI. The between-occupation Gini and the concentration index are equal when average earnings by occupation and average earnings sorted by RTI are perfectly correlated, i.e. the concentration index measures how closely RTI is associated with the between-occupation Gini. The O*NET RTI accounts for an increasing share of between-occupation wage inequality. The counterfactual analysis suggests this is owed to both changes in the wage structure and the composition of the employed, with the latter being marginally more important. This result coheres with previous discussions about the rising importance of services which are generally non-routine. In a final demonstration that the country-specific RTI is measuring skill rather than routine work, the concentration index is almost one in all cases.

Table 5: Decomposition of the wage Gini coefficient by occupation and gender

	Actual				**Shares constant**				**Means constant**			
	2000-2004	**2005-2007**	**2010-2012**	**2013-2015**	**2000-2004**	**2005-2007**	**2010-2012**	**2013-2015**	**2000-2004**	**2005-2007**	**2010-2012**	**2013-2015**
Overall Gini	0.56	0.55	0.56	0.66	0.56	0.55	0.56	0.64	0.56	0.56	0.59	0.65
Shapley Decomposition:												
Between-occupation	0.28	0.27	0.25	0.28	0.28	0.26	0.24	0.27	0.28	0.28	0.29	0.28
%	0.51	0.48	0.44	0.43	0.51	0.48	0.43	0.42	0.51	0.50	0.49	0.42
Within-occupation	0.27	0.28	0.31	0.38	0.27	0.28	0.32	0.37	0.27	0.28	0.30	0.38
%	0.49	0.52	0.56	0.57	0.49	0.52	0.57	0.58	0.49	0.50	0.51	0.58
Gini between occupations	0.41	0.39	0.38	0.43	0.41	0.39	0.37	0.41	0.41	0.41	0.43	0.43
Concentration Index:												
O*NET RTI	0.18	0.19	0.22	0.27	0.18	0.15	0.17	0.22	0.18	0.19	0.26	0.24
%	0.44	0.47	0.57	0.63	0.44	0.38	0.46	0.53	0.44	0.46	0.61	0.56
CS RTI	0.40	0.38	0.37	0.43	0.40	0.37	0.36	0.41	0.40	0.40	0.42	0.42
%	0.97	0.96	0.98	0.98	0.97	0.96	0.97	0.98	0.97	0.97	0.98	0.98

Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

10 Discussion and Conclusion

Between 2000 and 2015, the South African labour market underwent a process of wage polarisation, but employment can better be described as skills-biased rather than polarising. In spite of this, the routine-biased technical change hypothesis is more relevant for explaining employment than wage changes in South Africa. Across the skill percentile, South African wage change resembles a backwards J-shape, or hockey stick, more than the U-shape classically associated with wage polarisation, due to the greater prevalence of low-skilled work in South Africa. Wage growth for low-income earners is more likely driven by the onset and maintenance of minimum wage legislation, especially for domestic workers for women and farm workers for men, than routine-biased technical change. The occupations found in the trough of the J are those typically found in the middle of industrialised country wage distributions: nurses, teachers, administrative workers, and various white-collar office clerks. Routine-biased technical change is likely an important factor for the decline in office clerk wages. However, other factors were at play for the overall fortunes of occupation in the trough of the J: Earnings for these occupations shrank severely in real terms following the 2008 Global Financial crisis, suggesting that the recession played a role. The share of (highly non-routine) teaching jobs declined, the wages for which are well-protected by strong trade unions (Mahlangu & Pitsoe 2011, Msila 2014); and, in their place other office and business administration occupation categories grew (often without corresponding wage growth) which are possibly associated with the casualisation of the South African labour market. Therefore, whilst computer and other technology is very likely undermining the wages for office clerks occupying the upper middle of the South African wage distribution, the Global Financial Crisis, minimum wages, and casualisation are also important for explaining the overall pattern of polarisation.

Due to women clustering in a few care, cleaning, and clerk-based occupations, the routine-biased technical change hypothesis is more relevant for men who are more evenly distributed across occupations in the economy. Even so, routine-biased technical change is more relevant for male employment than wage changes: Occupational routine intensity significantly predicted negative employment change for men between 2000 and 2015. This may be because routine intensity has interacted with the rapid structural transformation of the South African economy whereby the primary and secondary sectors have declined and services, business and finance have risen to prominence. It is tempting to rationalise this change by pointing out that agriculture, mining and manufacturing are relatively routine, whilst services are non-routine. However, there are instead complex historical and context-specific reasons behind the contraction of mining and agriculture in South Africa (Bhorat et al. 2020). The manufacturing sector has collapsed mainly in the face of global competition. When South Africa opened its borders to international trade at the end of apartheid, the manufacturing sector was unable to compete internationally after years of apartheid isolation had rendered the sector much less efficient than other trading partners (Edwards & Lawrence 2008). In this more global sense, perhaps South African manufacturing has been influenced by the adoption of more advanced machine and computer technologies in its trading partners. However, although mining, manufacturing, and agriculture are amongst the most routine sectors of the economy, it is not clear that routine-biased technical change played a decisive role in their decline from a local viewpoint.

Even if routine-biased technical change is less important for explaining why South Africa's primary and secondary sectors have declined, it likely is of importance for explaining why the tertiary sector has grown. Firpo et al. (2011) describe how certain job task qualities can 'protect' work from being offshored: The need for work to be done on-site, for example, can 'protect' the existence of that job (e.g. a security worker, or personal care worker). These two qualities - being non-routine and requiring physical presence on-site - have probably contributed towards the flourishing of the personal and protective services sector in South Africa as a low-skilled alternative to increasingly scarce manufacturing jobs. These jobs are not necessarily well-paid (most personal care workers earn less than the median wage) and are associated with the growth of temporary employment services, suggesting these jobs are unprotected in important ways (Bhorat, Cassim & Yu 2016).

At the other end of the wage distribution, jobs in services are growing for different reasons. The GDP contribution of the financial and business services sector grew at about 4.8% per year between 2000 and 2015 (see Figure 3), making it the fastest growing sector only after construction. In other words, job growth here is stoked by South Africa's comparative advantage in financial services; however, we also expect service jobs to be growing due to South Africa's status as a destination of offshored service jobs. The documented rise in call centres in Cape Town is testament to this (Benner 2006). The need for jobs to be performed on-site is less important at this point in the distribution and perhaps flexibility in this regard has contributed to job growth here.

This variation within the services sector should be monitored and examined in order to understand how the process tertiarisation will challenge or, more likely, reinforce existing earnings inequality. For example, what factors, along with non-routine intensity, are behind the growth of low-skilled personal and protective services? What are the implications for gender and inequality given that women are mainly sorting into personal care services and men into protective services? And, how will the wage structure adjust to jobs that are growing because they can't be off-shored versus jobs that are growing because they are actively contributing to economic growth? These are some important questions this analysis has illuminated. Routine-biased technical change may therefore play a more important role in the future for South Africa; and importantly, a quite different role to the one played in industrialised countries.

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11 Appendix A: Component task measures method

This appendix describes how we made the task measures routine cognitive (r_{cog}); non-routine analytic ($nr_{analytic}$); and non-routine interpersonal ($nr_{interpersonal}$). We use data from the O*NET databases on occupational 'Work Context' and 'Activties'. Table 6 below details which 'task elements' in O*NET went into each measure along with their description. The elements for these three task measures are combined as follows:

$$T_{jh} = \sum_{k=1}^{A_h} I_{jk}^{\frac{2}{3}} L_{jk}^{\frac{1}{3}} + \sum_{l=1}^{C_h} CX_{jl} \tag{5}$$

where T_{jh} is the score for occupation j for task measure h, where h is non-routine analytic, non-routine interpersonal, and routine cognitive. A_h are the 'Work Activity' elements and C_h are the 'Work Context' elements. Elements from the 'Activities' data set included measures for both level (L) and importance (I). These were combined in a Cobb-Douglas fashion applying a weight of two-thirds to importance and one-third to level following Firpo et al. (2011). CX are the scores from the 'Work Context' data. We scale each element to vary [0;1] before we combine them so that when they are summed, they are equally weighted. Once we have created each task measure, we once again compress the variance to [0;1].

Table 6: O*NET components of Acemoglu & Autor (2011) task measures

Element ID	Task description
Non-routine cognitive analytic	
4.A.2.a.4	Analyzing data/information
4.A.2.b.2	Thinking creatively
4.A.4.a.1	Interpreting information for others
Non-routine cognitive interpersonal	
4.A.4.a.4	Establishing and maintaining personal relationships
4.A.4.b.4	Guiding, directing and motivating subordinates
4.A.4.b.5	Coaching/developing others
Routine cognitive	
4.C.3.b.7	Importance of repeatng the same tasks
4.C.3.b.4	Importance of being exact or accurate
4.C.3.b.8	Structured v. unstructured work (reverse)

12 Appendix B: Summary of routine task intensity by occupation

Table 7: Mean routine task intensity index per two-digit occupation code

	Two Digit Occupation	O*NET RTI		Country-specific RTI	
		Men	Women	Men	Women
11	Legislators and senior officials	-2.26	-2.25	-0.60	-0.60
12	Corporate managers	-1.24	-1.18	-0.49	-0.49
13	Managers of small enterprises	-1.18	-1.05	-0.49	-0.49
21	Physical, mathematical and engineering science professionals	-0.69	-0.62	-0.51	-0.51
22	Life science and health professionals	-0.93	-0.78	-0.07	-0.07
23	Teaching professionals	-1.83	-1.84	-0.35	-0.35
24	Other professionals	-1.07	-0.82	-0.31	-0.31
31	Physical and engineering science associate professionals	0.11	0.30	-0.07	-0.07
32	Life science and health associate professionals	-0.45	-0.40	0.39	0.39
33	Teaching associate professionals	-1.89	-1.87	0.07	0.07
34	Other associate professionals	-0.58	-0.31	0.05	0.05
41	Office clerks	0.76	0.61	0.35	0.35
42	Customer services clerk	1.26	1.25	0.42	0.42
51	Personal and protective services worker	0.03	0.11	0.64	0.64
52	Models, salespersons and demonstrators	-0.39	-0.53	0.71	0.71
61	Skilled agricultural and fishery workers	-0.45	-0.35	0.71	0.71
62	Subsistence agricultural and fishery workers	0.24	0.24	0.71	0.71
71	Extraction and building trades workers	-0.18	-0.09	0.56	0.56
72	Metal, machinery and related trades workers	0.34	0.24	0.40	0.40
73	Precision, handicraft, craft printing and related trades workers	0.66	0.53	0.48	0.48
74	Other craft and related trades workers	0.79	0.88	0.60	0.60
81	Stationary plant and related operators	0.46	0.75	0.79	0.79
82	Machine operators and assemblers	1.03	1.37	0.82	0.82
83	Drivers and mobile plant operators	0.32	0.36	0.87	0.87
91	Sales and services elementary occupations	0.34	0.09	1.13	1.13
92	Agricultural, fishery and related labourers	0.24	0.24	1.15	1.15
93	Labourers in mining, construction, manufacturing and transport	0.25	0.26	1.14	1.14

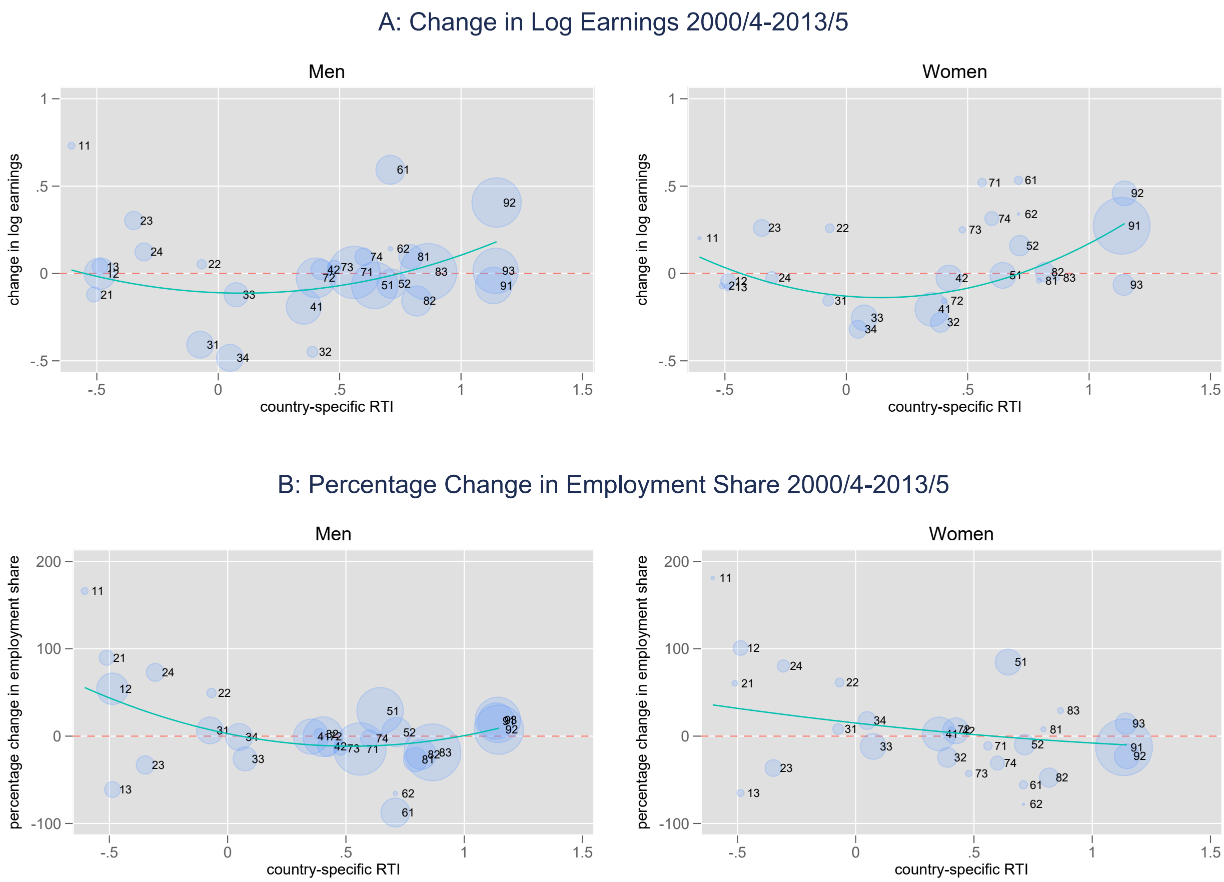
13 Appendix C: Simple regression results for the country-specific RTI

Table 8: Regression output for employment and earnings changes for two-digit occupations and Country-specific routine task intensity in South Africa, 2000-2015

	Change in Log Earnings				**Percentage Change in Employment Share**			
	2005/7-2000/4	**2010/2-2005/7**	**2013/5-2010/2**	**2013/5-2000/4**	**2005/7-2000/4**	**2010/2-2005/7**	**2013/5-2010/2**	**2013/5-2000/4**
				WOMEN				
CS RTI	0.175***	0.116**	0.0148	**0.272*** **	-18.53*	-12.71	8.801	**-35.79***
	(0.0398)	(0.0401)	(0.0438)	**(0.0695)**	(6.819)	(8.759)	(5.365)	**(14.70)**
_cons	-0.00310	-0.0539	-0.0767*	**-0.115***	12.23*	7.832	-5.135	**33.39****
	(0.0327)	(0.0319)	(0.0338)	**(0.0548)**	(5.590)	(6.987)	(4.145)	**(11.58)**
N	27	27	27	**27**	27	27	27	**27**
				MEN				
CS RTI	0.119	0.0453	-0.0111	**0.133**	-3.110	-19.06*	9.646*	**-22.12***
	(0.0583)	(0.0444)	(0.0354)	**(0.0743)**	(8.876)	(7.703)	(3.985)	**(10.40)**
_cons	0.0424	-0.0367	-0.0845**	**-0.0790**	1.903	11.54	-5.424	**21.57***
	(0.0446)	(0.0342)	(0.0267)	**(0.0573)**	(6.783)	(5.925)	(3.005)	**(8.031)**
N	27	27	27	**27**	27	27	27	**27**

Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees. Standard errors in parenthesis. * p<0.05, ** p<0.01, *** p<0.001.

Figure 13: Employment weighted scatter plot of change in earnings and employment against country-specific routine task intensity index at the two-digit occupational level, 2000/4-2013/5



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees. Bubble size corresponds to size of employment in 2000/4. Bubble number correspond to two-digit occupational codes, listed in Table 2.

14 Appendix D: Additional RIF-Regression Output

Table 9: RIF regression output using the O*NET RTI for men

Depvar: log real earnings		**2000-2004**			**2013-2015**	
Quantile:	**15**	**50**	**85**	**15**	**50**	**85**
O*NET RTI	0.090***	0.012**	-0.014	0.073***	0.032***	-0.023**
	[0.010]	[0.005]	[0.011]	[0.012]	[0.005]	[0.007]
Age	0.079***	0.053***	0.078***	0.040***	0.041***	0.028***
	[0.004]	[0.002]	[0.005]	[0.005]	[0.003]	[0.004]
Age squared	-0.001***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Years of education	0.060***	0.051***	0.070***	0.053***	0.051***	0.073***
	[0.002]	[0.001]	[0.002]	[0.003]	[0.002]	[0.002]
Union member	0.106***	0.152***	0.038**	0.246***	0.432***	0.071***
	[0.015]	[0.010]	[0.012]	[0.017]	[0.012]	[0.017]
Public Sector	0.195***	0.405***	0.349***	-0.213***	0.137***	0.326***
	[0.016]	[0.015]	[0.036]	[0.030]	[0.018]	[0.029]
Race: Coloured	0.452***	0.234***	0.211***	0.043**	0.040**	0.068***
	[0.016]	[0.011]	[0.023]	[0.022]	[0.013]	[0.017]
Race: Indian/Asian	0.228***	0.464***	0.424***	0.002	0.188***	0.057
	[0.015]	[0.020]	[0.061]	[0.038]	[0.029]	[0.049]
Race: White	0.200***	0.589***	1.680***	0.002	0.364***	0.769***
	[0.011]	[0.012]	[0.044]	[0.022]	[0.017]	[0.035]
Industry: Mining	1.958***	0.768***	0.038*	0.073*	1.112***	0.195***
	[0.028]	[0.017]	[0.022]	[0.042]	[0.025]	[0.033]
Industry: Manufacturing	1.687***	0.577***	-0.081***	-0.158***	0.578***	-0.023
	[0.029]	[0.015]	[0.022]	[0.037]	[0.019]	[0.022]
Industry: Utilities	1.689***	0.548***	0.173*	-0.035	0.607***	-0.047
	[0.038]	[0.033]	[0.105]	[0.066]	[0.043]	[0.076]
Industry: Construction	1.490***	0.207***	-0.196***	-0.138***	0.417***	-0.176***
	[0.034]	[0.017]	[0.024]	[0.039]	[0.020]	[0.022]
Industry: Trade	1.523***	0.290***	-0.400***	-0.169***	0.428***	-0.243***
	[0.031]	[0.015]	[0.024]	[0.037]	[0.018]	[0.021]
Industry: Transport	1.586***	0.358***	-0.107**	-0.177***	0.438***	0.003
	[0.032]	[0.019]	[0.034]	[0.041]	[0.023]	[0.030]
Industry: Finance	1.752***	0.355***	-0.151***	-0.097**	0.459***	-0.147***
	[0.031]	[0.019]	[0.038]	[0.037]	[0.020]	[0.026]
Industry: CSP Services	1.609***	0.485***	-0.114**	-0.304***	0.455***	-0.130***
	[0.032]	[0.018]	[0.038]	[0.043]	[0.022]	[0.030]
Industry: Domestic Services	-0.348***	-0.02	-0.008	-1.496***	-0.049**	-0.007
	[0.062]	[0.016]	[0.018]	[0.063]	[0.019]	[0.017]
Occupation: Professionas	-0.238***	-0.171***	0.150*	-0.029	-0.078***	0.161**
	[0.021]	[0.024]	[0.090]	[0.022]	[0.018]	[0.060]
Occupation: Technicians	-0.134***	-0.072***	-0.840***	-0.410***	-0.629***	-1.423***
	[0.018]	[0.018]	[0.076]	[0.029]	[0.022]	[0.052]
Occupation: Clerks	-0.199***	-0.133***	-1.666***	-0.510***	-0.688***	-1.851***
	[0.029]	[0.023]	[0.080]	[0.039]	[0.027]	[0.058]
Occupation: Services worker	-0.165***	-0.507***	-1.704***	-0.488***	-1.000***	-2.044***
	[0.025]	[0.021]	[0.072]	[0.030]	[0.021]	[0.047]
Occupation: Skilled Agriculture	-0.217***	-0.621***	-1.919***	-0.878***	-1.080***	-2.291***
	[0.058]	[0.028]	[0.070]	[0.116]	[0.061]	[0.059]
Occupation: Trades worker	-0.175***	-0.415***	-1.717***	-0.505***	-0.883***	-1.941***
	[0.024]	[0.020]	[0.070]	[0.031]	[0.021]	[0.048]
Occupation: Operator	-0.057**	-0.389***	-1.938***	-0.671***	-0.925***	-2.228***
	[0.027]	[0.021]	[0.070]	[0.035]	[0.023]	[0.047]
Occupation: Elementary	-0.388***	-0.662***	-1.892***	-0.968***	-1.228***	-2.205***
	[0.029]	[0.021]	[0.069]	[0.034]	[0.021]	[0.046]
Occupation: Domestic Worker	-0.162	-0.652***	-1.936***	-1.166***	-1.258***	-2.234***
	[0.123]	[0.033]	[0.073]	[0.140]	[0.036]	[0.051]
constant	3.693***	6.399***	8.465***	6.647***	7.023***	9.928***
	[0.082]	[0.052]	[0.117]	[0.110]	[0.062]	[0.092]
r2	0.359	0.443	0.428	0.078	0.279	0.312
N	78932	78932	78932	92766	92766	92766

Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using bracket weights. Sample restricted to employees. Standard errors in parenthesis. * p<0.05, ** p<0.01, *** p<0.001. Base groups: Race = African; Industry = Agriculture; Occupation = Managers.

Table 10: RIF regression output using the O*NET RTI for women

Depvar: log real earnings	**2000-2004**			**2013-2015**		
Quantile:	**15**	**50**	**85**	**15**	**50**	**85**
O*NET RTI	0.073***	0.045***	-0.049***	0.042***	0.018***	-0.074***
	[0.009]	[0.009]	[0.008]	[0.009]	[0.005]	[0.009]
Age	0.063***	0.063***	0.051***	-0.004	0.011***	0.024***
	[0.004]	[0.005]	[0.005]	[0.004]	[0.003]	[0.004]
Age squared	-0.001***	-0.001***	-0.001***	0	-0.000*	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Years of education	0.092***	0.073***	0.035***	0.097***	0.061***	0.071***
	[0.003]	[0.003]	[0.002]	[0.003]	[0.001]	[0.002]
Union member	0.085***	0.272***	0.059***	0.386***	0.459***	0.264***
	[0.012]	[0.021]	[0.013]	[0.014]	[0.012]	[0.020]
Public Sector	0.073***	0.706***	0.359***	-0.449***	-0.032**	0.367***
	[0.018]	[0.031]	[0.034]	[0.020]	[0.013]	[0.025]
Race: Coloured	0.308***	0.461***	0.132***	0.032*	0.123***	0.056**
	[0.016]	[0.023]	[0.018]	[0.016]	[0.012]	[0.017]
Race: Indian/Asian	0.198***	0.772***	0.147**	0.02	0.206***	0.057
	[0.013]	[0.041]	[0.051]	[0.030]	[0.029]	[0.056]
Race: White	0.128***	0.839***	0.747***	0.011	0.335***	0.668***
	[0.012]	[0.025]	[0.038]	[0.017]	[0.014]	[0.035]
Industry: Mining	0.672***	1.570***	0.133	-0.830***	0.602***	-0.032
	[0.048]	[0.095]	[0.107]	[0.059]	[0.044]	[0.072]
Industry: Manufacturing	0.531***	1.101***	-0.102***	-0.552***	0.395***	-0.124***
	[0.038]	[0.041]	[0.031]	[0.036]	[0.024]	[0.030]
Industry: Utilities	0.539***	1.040***	0.214	-0.508***	0.387***	0.433***
	[0.080]	[0.105]	[0.145]	[0.066]	[0.056]	[0.127]
Industry: Construction	0.049	0.557***	-0.172***	-1.466***	0.234***	-0.243***
	[0.081]	[0.072]	[0.044]	[0.053]	[0.028]	[0.033]
Industry: Trade	0.543***	0.652***	-0.323***	-0.616***	0.307***	-0.280***
	[0.036]	[0.041]	[0.026]	[0.034]	[0.021]	[0.021]
Industry: Transport	0.516***	1.167***	0.033	-0.681***	0.484***	-0.079
	[0.043]	[0.060]	[0.069]	[0.045]	[0.032]	[0.058]
Industry: Finance	0.597***	1.298***	0.058	-0.642***	0.442***	-0.136***
	[0.035]	[0.042]	[0.040]	[0.035]	[0.021]	[0.026]
Industry: CSP Services	0.474***	0.989***	-0.242***	-0.835***	0.223***	-0.262***
	[0.037]	[0.044]	[0.034]	[0.037]	[0.021]	[0.023]
Industry: Domestic Services	-1.163***	-0.194**	-0.080**	-1.501***	-0.051	0.002
	[0.163]	[0.065]	[0.033]	[0.129]	[0.056]	[0.070]
Occupation: Professionas	-0.161***	-0.321***	0.123	0.024	-0.014	0.165**
	[0.031]	[0.050]	[0.098]	[0.017]	[0.017]	[0.066]
Occupation: Technicians	0.009	-0.247***	-0.702***	-0.131***	-0.335***	-1.234***
	[0.032]	[0.049]	[0.091]	[0.020]	[0.018]	[0.058]
Occupation: Clerks	-0.026	-0.328***	-1.303***	-0.177***	-0.350***	-1.621***
	[0.036]	[0.051]	[0.089]	[0.025]	[0.020]	[0.057]
Occupation: Services worker	-0.042	-1.012***	-1.509***	-0.272***	-0.729***	-1.880***
	[0.036]	[0.057]	[0.087]	[0.024]	[0.020]	[0.055]
Occupation: Skilled Agriculture	-0.054	-1.394***	-1.616***	-0.877***	-1.049***	-1.992***
	[0.127]	[0.093]	[0.087]	[0.129]	[0.068]	[0.086]
Occupation: Trades worker	0.003	-1.308***	-1.539***	-0.142***	-0.704***	-1.758***
	[0.046]	[0.074]	[0.091]	[0.041]	[0.036]	[0.065]
Occupation: Operator	0.052	-1.025***	-1.616***	-0.399***	-0.858***	-2.118***
	[0.047]	[0.072]	[0.092]	[0.043]	[0.037]	[0.063]
Occupation: Elementary	0.046	-1.433***	-1.628***	-0.727***	-1.049***	-2.110***
	[0.039]	[0.058]	[0.086]	[0.028]	[0.021]	[0.054]
Occupation: Domestic Worker	0.802***	-1.316***	-1.599***	0.273**	-0.983***	-2.137***
	[0.165]	[0.083]	[0.091]	[0.129]	[0.057]	[0.087]
constant	4.112***	5.580***	9.108***	6.936***	7.234***	9.708***
	[0.107]	[0.123]	[0.128]	[0.090]	[0.061]	[0.101]
r2	0.241	0.594	0.371	0.132	0.353	0.31
N	61196	61196	61196	87893	87893	87893

Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using bracket weights. Sample restricted to employees. Standard errors in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Base groups: Race = African; Industry = Agriculture; Occupation = Managers.

Table 11: RIF regression output using the country-specific RTI for men

Depvar: log real earnings	**2000-2004**			**2013-2015**		
Quantile:	**15**	**50**	**85**	**15**	**50**	**85**
Country-specific RTI	-0.396***	-0.655***	-0.750**	0.055	-0.541***	-0.287*
	[0.072]	[0.079]	[0.229]	[0.112]	[0.079]	[0.147]
Age	0.080***	0.054***	0.078***	0.040***	0.041***	0.027***
	[0.004]	[0.002]	[0.005]	[0.005]	[0.003]	[0.004]
Age squared	-0.001***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Years of education	0.060***	0.051***	0.069***	0.053***	0.051***	0.073***
	[0.002]	[0.001]	[0.002]	[0.003]	[0.002]	[0.002]
Union member	0.108***	0.153***	0.039***	0.250***	0.432***	0.069***
	[0.015]	[0.010]	[0.012]	[0.017]	[0.012]	[0.017]
Public Sector	0.195***	0.404***	0.334***	-0.213***	0.134***	0.324***
	[0.017]	[0.015]	[0.036]	[0.030]	[0.018]	[0.029]
Race: Coloured	0.451***	0.233***	0.201***	0.046**	0.039**	0.066***
	[0.016]	[0.011]	[0.023]	[0.022]	[0.013]	[0.017]
Race: Indian/Asian	0.234***	0.459***	0.401***	0.002	0.187***	0.057
	[0.015]	[0.020]	[0.061]	[0.037]	[0.028]	[0.049]
Race: White	0.200***	0.583***	1.659***	0.006	0.355***	0.763***
	[0.011]	[0.012]	[0.044]	[0.022]	[0.017]	[0.035]
Industry: Mining	1.981***	0.755***	0.033	0.076*	1.105***	0.190***
	[0.029]	[0.017]	[0.022]	[0.042]	[0.025]	[0.033]
Industry: Manufacturing	1.720***	0.562***	-0.104***	-0.134***	0.574***	-0.037*
	[0.029]	[0.015]	[0.022]	[0.037]	[0.019]	[0.023]
Industry: Utilities	1.706***	0.521***	0.157	-0.03	0.594***	-0.055
	[0.039]	[0.034]	[0.103]	[0.066]	[0.043]	[0.076]
Industry: Construction	1.488***	0.215***	-0.177***	-0.150***	0.421***	-0.168***
	[0.035]	[0.017]	[0.024]	[0.039]	[0.020]	[0.022]
Industry: Trade	1.545***	0.279***	-0.401***	-0.162***	0.429***	-0.246***
	[0.031]	[0.015]	[0.024]	[0.037]	[0.018]	[0.021]
Industry: Transport	1.607***	0.344***	-0.109**	-0.163***	0.438***	-0.005
	[0.032]	[0.019]	[0.034]	[0.041]	[0.023]	[0.029]
Industry: Finance	1.781***	0.333***	-0.160***	-0.077**	0.454***	-0.160***
	[0.031]	[0.018]	[0.038]	[0.037]	[0.020]	[0.026]
Industry: CSP Services	1.607***	0.482***	-0.101**	-0.317***	0.453***	-0.125***
	[0.032]	[0.018]	[0.038]	[0.043]	[0.022]	[0.029]
Industry: Domestic Services	-0.356***	-0.022	-0.009	-1.498***	-0.051**	-0.007
	[0.063]	[0.016]	[0.018]	[0.063]	[0.019]	[0.017]
Occupation: Professionas	-0.157***	-0.076**	0.240**	-0.015	0.006	0.193**
	[0.024]	[0.024]	[0.093]	[0.026]	[0.022]	[0.064]
Occupation: Technicians	0.140***	0.274***	-0.458**	-0.388***	-0.326***	-1.290***
	[0.040]	[0.044]	[0.140]	[0.064]	[0.047]	[0.095]
Occupation: Clerks	0.347***	0.450***	-1.066***	-0.402***	-0.156**	-1.654***
	[0.063]	[0.070]	[0.209]	[0.100]	[0.072]	[0.138]
Occupation: Services worker	0.418***	0.264**	-0.876**	-0.463***	-0.340***	-1.743***
	[0.084]	[0.091]	[0.272]	[0.130]	[0.092]	[0.176]
Occupation: Skilled Agriculture	0.351***	0.165*	-1.037***	-0.858***	-0.400***	-1.977***
	[0.103]	[0.096]	[0.279]	[0.176]	[0.112]	[0.185]
Occupation: Trades worker	0.354***	0.244**	-0.994***	-0.457***	-0.306***	-1.691***
	[0.073]	[0.079]	[0.236]	[0.113]	[0.081]	[0.153]
Occupation: Operator	0.638***	0.493***	-0.958**	-0.624***	-0.148	-1.882***
	[0.098]	[0.106]	[0.311]	[0.153]	[0.108]	[0.202]
Occupation: Elementary	0.408***	0.413**	-0.693*	-0.939***	-0.299**	-1.777***
	[0.119]	[0.128]	[0.376]	[0.184]	[0.129]	[0.243]
Occupation: Domestic Worker	0.616***	0.417**	-0.741**	-1.155***	-0.343**	-1.804***
	[0.169]	[0.130]	[0.375]	[0.228]	[0.132]	[0.242]
constant	3.348***	6.060***	8.144***	6.574***	6.727***	9.826***
	[0.089]	[0.063]	[0.153]	[0.122]	[0.072]	[0.115]
r2	0.358	0.444	0.427	0.078	0.279	0.312
N	79191	79191	79191	92766	92766	92766

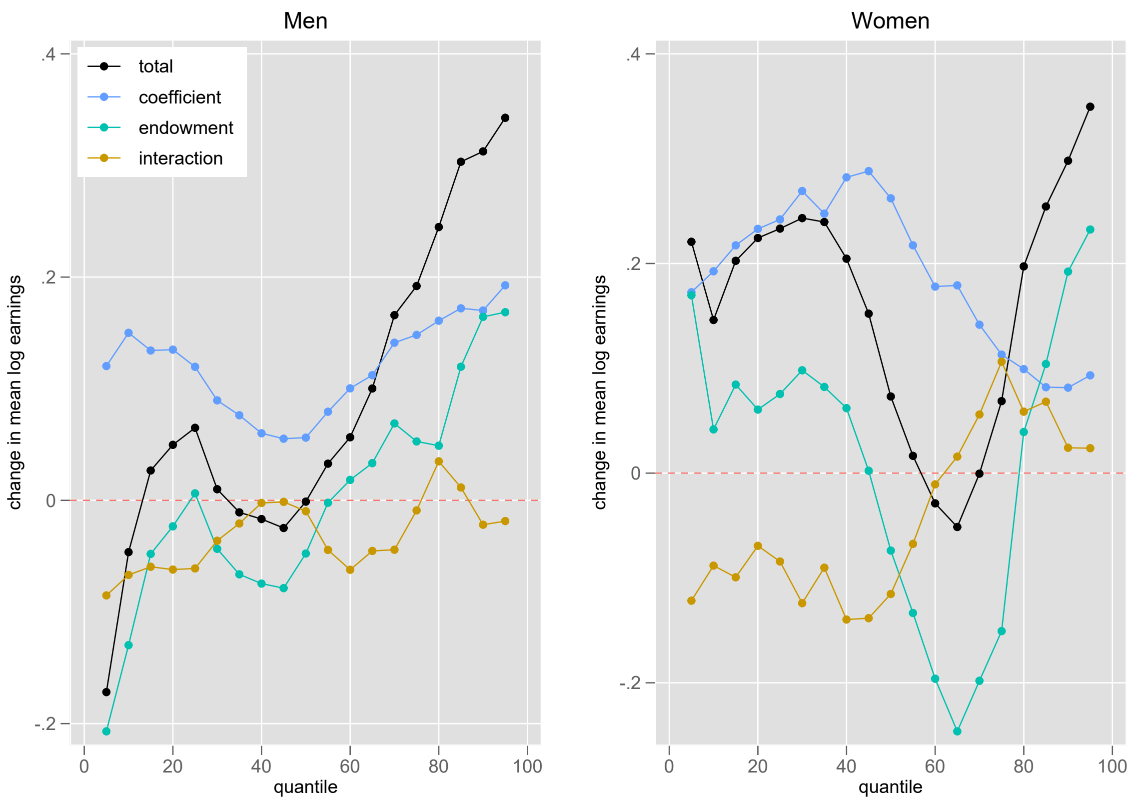
Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using bracket weights. Sample restricted to employees. Standard errors in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Base groups: Race = African; Industry = Agriculture; Occupation = Managers.

Table 12: RIF regression output using the country-specific RTI for women

Depvar: log real earnings	**2000-2004**			**2013-2015**		
Quantile:	**15**	**50**	**85**	**15**	**50**	**85**
Country-specific RTI	0.021	-0.101	-0.672***	0.115	0.119*	-0.502***
	[0.044]	[0.086]	[0.174]	[0.070]	[0.061]	[0.143]
Age	0.063***	0.063***	0.051***	-0.003	0.011***	0.023***
	[0.004]	[0.005]	[0.005]	[0.004]	[0.003]	[0.004]
Age squared	-0.001***	-0.001***	-0.001***	0	-0.000*	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Years of education	0.091***	0.073***	0.036***	0.097***	0.061***	0.072***
	[0.003]	[0.003]	[0.002]	[0.003]	[0.001]	[0.002]
Union member	0.085***	0.272***	0.061***	0.385***	0.458***	0.267***
	[0.012]	[0.021]	[0.013]	[0.014]	[0.012]	[0.020]
Public Sector	0.063***	0.700***	0.361***	-0.453***	-0.033**	0.372***
	[0.018]	[0.031]	[0.034]	[0.020]	[0.013]	[0.025]
Race: Coloured	0.314***	0.465***	0.131***	0.032**	0.124***	0.056**
	[0.016]	[0.023]	[0.018]	[0.016]	[0.012]	[0.017]
Race: Indian/Asian	0.206***	0.777***	0.142**	0.02	0.207***	0.056
	[0.013]	[0.041]	[0.051]	[0.030]	[0.029]	[0.056]
Race: White	0.134***	0.841***	0.744***	0.008	0.335***	0.669***
	[0.012]	[0.025]	[0.038]	[0.017]	[0.015]	[0.035]
Industry: Mining	0.679***	1.572***	0.107	-0.827***	0.605***	-0.045
	[0.048]	[0.094]	[0.107]	[0.059]	[0.044]	[0.072]
Industry: Manufacturing	0.553***	1.112***	-0.133***	-0.537***	0.403***	-0.158***
	[0.038]	[0.041]	[0.031]	[0.036]	[0.024]	[0.030]
Industry: Utilities	0.559***	1.049***	0.184	-0.494***	0.397***	0.391**
	[0.080]	[0.105]	[0.146]	[0.066]	[0.056]	[0.127]
Industry: Construction	0.044	0.552***	-0.178***	-1.469***	0.233***	-0.241***
	[0.081]	[0.073]	[0.043]	[0.053]	[0.028]	[0.034]
Industry: Trade	0.559***	0.662***	-0.329***	-0.609***	0.309***	-0.290***
	[0.036]	[0.041]	[0.026]	[0.034]	[0.021]	[0.021]
Industry: Transport	0.527***	1.172***	0.017	-0.671***	0.489***	-0.101*
	[0.043]	[0.060]	[0.069]	[0.045]	[0.032]	[0.058]
Industry: Finance	0.621***	1.310***	0.025	-0.628***	0.449***	-0.167***
	[0.035]	[0.042]	[0.040]	[0.035]	[0.021]	[0.026]
Industry: CSP Services	0.471***	0.990***	-0.231***	-0.837***	0.221***	-0.257***
	[0.037]	[0.044]	[0.034]	[0.037]	[0.021]	[0.023]
Industry: Domestic Services	-1.195***	-0.216***	-0.066**	-1.529***	-0.062	0.049
	[0.164]	[0.065]	[0.032]	[0.129]	[0.056]	[0.070]
Occupation: Professionas	-0.140***	-0.289***	0.221**	0.009	-0.034	0.253***
	[0.031]	[0.052]	[0.103]	[0.022]	[0.021]	[0.073]
Occupation: Technicians	0.041	-0.157**	-0.317**	-0.186***	-0.401***	-0.956***
	[0.042]	[0.072]	[0.142]	[0.046]	[0.041]	[0.107]
Occupation: Clerks	0.123**	-0.139	-0.834***	-0.194**	-0.418***	-1.334***
	[0.046]	[0.086]	[0.175]	[0.063]	[0.056]	[0.137]
Occupation: Services worker	0.03	-0.836***	-0.802***	-0.355***	-0.844***	-1.394***
	[0.059]	[0.112]	[0.218]	[0.082]	[0.072]	[0.173]
Occupation: Skilled Agriculture	0.021	-1.214***	-0.882***	-0.975***	-1.174***	-1.462***
	[0.136]	[0.137]	[0.225]	[0.153]	[0.099]	[0.191]
Occupation: Trades worker	0.121**	-1.118***	-0.925***	-0.196**	-0.800***	-1.349***
	[0.061]	[0.116]	[0.205]	[0.085]	[0.073]	[0.164]
Occupation: Operator	0.215**	-0.777***	-0.858***	-0.464***	-0.979***	-1.608***
	[0.068]	[0.132]	[0.246]	[0.101]	[0.089]	[0.200]
Occupation: Elementary	0.142*	-1.192***	-0.625**	-0.853***	-1.217***	-1.400***
	[0.078]	[0.149]	[0.296]	[0.116]	[0.101]	[0.239]
Occupation: Domestic Worker	0.912***	-1.065***	-0.605**	0.165	-1.143***	-1.461***
	[0.179]	[0.161]	[0.297]	[0.171]	[0.114]	[0.249]
constant	4.019***	5.466***	8.857***	6.943***	7.270***	9.556***
	[0.107]	[0.128]	[0.151]	[0.095]	[0.067]	[0.121]
r2	0.24	0.594	0.371	0.132	0.353	0.309
N	61229	61229	61229	87893	87893	87893

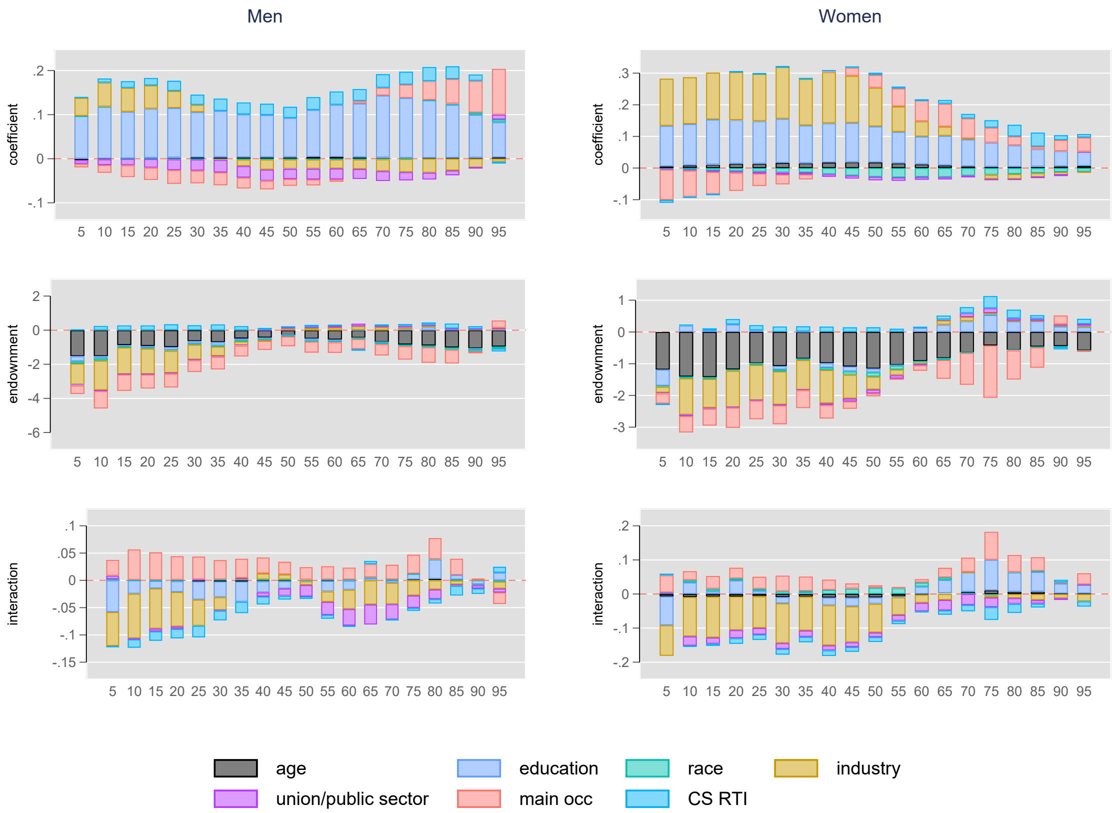
Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using bracket weights. Sample restricted to employees. Standard errors in parenthesis. * p<0.05, ** p<0.01, *** p<0.001. Base groups: Race = African; Industry = Agriculture; Occupation = Managers.

Figure 14: Oaxaca-Blinder decomposition of the change in wages across wage quantiles into the coefficient, endowment, and interaction effect for South Africa using the country-specific RTI, 2000/4-2013/5



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.

Figure 15: Detailed decomposition of the change in wages across wage quantiles using the country-specific RTI, 2000/4-2013/5



Source: own calculations using version 3.2 of the Post-apartheid Labour Market Series adjusted using sampling weights. Sample restricted to employees.