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Wage polarization in a high-inequality emerging economy

The case of South Africa

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Abstract: Earnings growth in South Africa displayed a U-shaped pattern across the earnings percentiles between 2000 and 2015, resembling wage polarization in the industrialized world. We investigate whether the drivers of this example of wage polarization in an emerging economy resemble those explored for industrialized ones. These are: skills-biased technical change; changing sectoral composition; the role of labour market institutions; and how occupational task content interacts with technology. A recentred influence function regression is run on a series of South African labour force datasets merged with the Occupational Information Network to explore the relevance of these four frameworks for explaining earnings inequality between 2000 and 2015. Labour market institutions are crucial to the U-shape. Wage growth at the bottom end has mainly been shored up by minimum wages, without which we expect wage growth there would have resembled the weaker growth of the middle of the distribution.

Key words: inequality, minimum wages, recentred influence function, South Africa, tasks, wage polarization

JEL classification: J31, J24, C21

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1 Introduction

South Africa is potentially the most unequal society in the world. Its Gini coefficient increased from 0.66 in 1993 to 0.70 in 2008 and stood at 0.65 in 2014 (Hundenborn et al. 2016; Leibbrandt et al. 2012). The labour market is the major driver of this inequality, accounting for more than 80 per cent of total inequality in 1993 and 2008 (Leibbrandt et al. 2012). The wage Gini has increased over the post-apartheid period from a coefficient of 0.58 in 1995 to 0.69 by 2015—a rise of 19 per cent. These aggregate measures, though, can conceal the structural patterns propping up inequality, making it important to interrogate the underlying dynamics. Our initial descriptive evidence suggests that South Africa has experienced non-monotonic changes in real wages over the period 2000–2015, growing in a distinctly U-shaped pattern across the percentiles of the wage distribution. This U-shaped wage growth pattern—or wage polarization—has also been observed in several industrialized countries, most notably the United States. The latter has been the point of departure for a burgeoning literature on drivers of labour market inequality in advanced economies (Acemoglu and Autor 2011; Katz and Murphy 1992). The focus of this paper, then, is to investigate the relevance of various compelling explanations for wage polarization within the context of a high-inequality developing country, with quite distinct labour market features compared with the industrialized cohort.

Key features of the South African labour market that might shape expectations about wage inequality include its dualistic nature, high and persistent levels of structural unemployment, and discouraged work-seekers. Earnings are astonishingly concentrated: from 2005 to 2010, the top decile of wage earners accounted for about 40 per cent of the total wage bill (Wittenberg 2017a). Unsurprisingly, then, numerous authors have described the labour market as segmented (Heintz and Posel 2008; Kingdon and Knight 1999).[1] The labour market reproduces and reinforces the advantage of a small portion of well paid, highly skilled people for whom jobs are easily obtained, secure, and well regulated. Conditions are much more fragile for the larger remainder, who, in the midst of high open unemployment, compete for work in a stagnant job market, where jobs in many cases have only tenuous job security and lack the types of benefits that come with standard employment (Bhorat et al. 2016a). Unemployment is a defining feature of the economy: the narrow and broad unemployment rates were 29.1 per cent and 38.7 per cent in 2019, respectively (Stats SA 2020). Although South Africa has low levels of informality by developing country standards (Vanek et al. 2014), the informally employed still form an important part of the labour market. A large constituent of the informally employed are domestic workers, almost exclusively female, who, along with farm workers, are amongst the most vulnerable and lowest earners in the country.[2]

In such a set-up, a monotonic growth pattern may be more in line with expectations than a U-shaped one. Specifically, better wage growth at the bottom end of the wage distribution relative to the middle is puzzling given two stylized facts about South Africa: there is a large pool of unemployed people and people at the bottom and in the middle of the wage distribution are more homogeneous in terms of skills and socio-economic characteristics than in an industrialized

[1] Although the line of segmentation varies between informal–formal (Kingdon and Knight 1999), rural–urban (Bhorat and Leibbrandt 2001), and segmentation within informal (Heintz and Posel 2008) and formal markets (du Toit and Neves 2007), the key idea is that for a smaller elite portion, the labour market reinforces advantages and vice versa.

[2] Informal employment is low by developing-country standards at about 34.6 per cent in 2012 (Cassim et al. 2016). In comparison, informal employment is estimated to account for about 66 per cent of total non-agricultural employment in the Sub-Saharan region (Vanek et al. 2014). Nevertheless, South Africa's level of informality still far exceeds that in the industrialized world.

economy. The literature on inequality in South Africa is a well-developed one and numerous scholars have put forward explanations for its persistent structure. We select four frameworks based on important explanations for inequality in the literature, as well as on our understanding of the South African context. Our approach is to unify these competing and complementary narratives into a coherent conceptual framework to try to explain wage polarization in post-apartheid South Africa.

A leading explanation for wage polarization in the industrialized world has been the influence of occupational task content on earnings growth (Acemoglu and Autor 2011; Autor et al. 2003; Firpo et al. 2011). We use task content information from the Occupational Information Network (O*NET) to investigate the changing task content of occupations as one explanation for wage polarization. This represents a contribution to this literature, since most work on tasks in emerging economies has focused on employment, and not wage, polarization. A second, older, explanation for inequality in the literature is skills-biased technical change (Tinbergen 1974). This is particularly compelling in South Africa given inequality in the education sector (van der Berg et al. 2011). Our understanding of the South African context leads us to also investigate the role played by the structural transformation of the economy from one based mainly on agriculture, mining, and manufacturing to one that is driven by services, finance, and business as the isolated apartheid economy was integrated into world markets. This changing sectoral composition brings with it changes in employment and wage setting. Finally, the state has played an active role in the labour market and the lives of the poor in post-apartheid South Africa by promulgating minimum wages, dispensing social grants, expanding the public wage bill, and incorporating trade unions into a formal alliance with the ruling political party. We therefore also investigate the influence of labour market institutions in shaping the earnings growth pattern. Note that the first three of these frameworks can broadly be assigned to structural change, which can be contrasted with the fourth framework, labour market institutions. Structural change is interpreted as the inexorable and often irreversible effects of technology, globalization, and international trade on an economy.

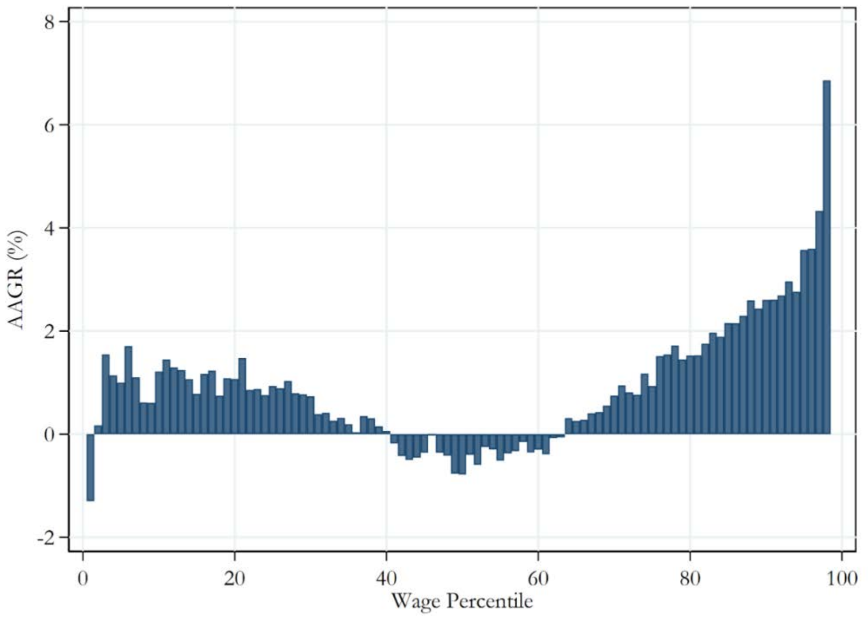
The change in wages between the early 2000s and mid 2010s is analysed using a recentred influence function-regression (RIF-regression) of wage ventiles, which is subsequently decomposed to interpret the influence of each framework at different parts of the distribution. In this way, the analysis explicitly takes a disaggregated approach, looking across the percentiles of the distribution. Our findings are that each of the frameworks appears to have played a role in forming the U-shaped earnings growth pattern and, although this work remains descriptive in nature, we cannot ascribe the shape to one framework alone. Different frameworks are more relevant in different portions of the distribution: minimum wages largely account for growth at the bottom. In the middle, wages were undermined not only by a decline in mining and manufacturing but also because increasing automation undermined returns to routine work clustered here. Increasing returns to the highly educated performing non-routine tasks continue to reinforce growth at the top. Whilst scholars have started to investigate employment polarization in the developing world (Maloney and Molina 2016; World Bank Group 2016), to our knowledge this is the first description and analysis of wage polarization in a developing country.

The paper is organized as follows: the next section sets up the four frameworks within which we can explain inequality and goes into further detail on the South African economy in each regard. Section 3 introduces our data as well as the RIF methodology and the decomposition. A descriptive overview of each of the frameworks using data follows in Section 4. We then present our RIF-regression results, followed by an in-depth discussion of the decomposition in Section 5. Section 6 concludes.

2 Wage inequality in South Africa: a descriptive overview

The average annualized growth rate (AAGR) of real monthly earnings is plotted across wage percentiles for all employees in the South African labour market for every year in the period 2000 to 2015 in Figure 1. There is a stark U-shape across the distribution, similar to the wage polarization observed in the developed world. Growth in wages at the bottom of the distribution hovered around 1 per cent per year on average. Then, from about the 30th to the 70th percentile, this decreased to less than 1 per cent real wage growth on average over the period. In the middle of the distribution, between about the 40th and the 60th percentile, workers experienced negative growth on average. After about the 70th percentile, wage growth increased steeply and monotonically until the end of the distribution, reaching a growth rate of over 3 per cent in the top decile. Growth at the top was much stronger than at the bottom from about the 80th percentile, resulting in an increase in aggregate inequality as the 'rich got richer'. Overall, though, while there was positive growth in real wages at both the bottom and top end of the distribution, the middle experienced very weak and sometimes negative wage growth. This result is among the first descriptions of the wage polarization in a middle-income country.[3]

Figure 1: Annual average growth rate of real earnings for employees in South Africa, 2000–2015



Note: sample consists of all employees of working age with non-missing wage and hours of work data.

Source: own calculations using Post-Apartheid Labour Market Series (PALMS) data, adjusted using sampling weights.

It is important to consider the distribution of skill when thinking about wages in a developing country. One way in which the South African labour market is distinct from that of industrialized economies is that it is dualistic and highly unequal. What this means is that individuals are more homogeneous in terms of occupation and skill until much higher up in the wage distribution, compared with industrialized economies. Occupations that would be found in the middle of the distribution in industrialized economies occur further up in South Africa.

[3] Other authors identifying non-monotonic growth in South Africa are Levy et al. (2015) and Wittenberg (2017a).

To show this, Table 1 reports the most common occupations in the bottom third, middle third, next 20 percentiles, and top 15 percentiles in 2000–2002 and 2013–2015. Low-skilled occupation types like domestic cleaning, protective services[4], motor vehicle driving, and certain types of labouring are amongst the most prevalent right up until the 85th percentile.[5]

Table 1: Most frequent occupations in different portions of the hourly wage distribution, 2000–2002 and 2013–2015

2000–2002	**2013–2015**
Bottom: 1st–35th hourly wage percentiles	
1. 913: Domestic and related helpers, cleaners, and launderers 2. 921: Agricultural and fishery labourers 3. 611: Market gardeners and crop growers 4. 832: Motor vehicle drivers and related workers 5. 932: Manufacturing labourers	1. 913: Domestic and related helpers, cleaners, and launderers 2. 921: Agricultural and fishery labourers 3. 516: Protective services 4. 832: Motor vehicle drivers and related workers 5. 931: Mining and construction labourers
Middle: 36th–65th hourly wage percentiles	
1. 913: Domestic and related helpers, cleaners, and launderers 2. 832: Motor vehicle drivers and related workers 3. 932: Manufacturing labourers 4. 516: Protective services 5. 833: Agriculture and other mobile plant operators	1. 913: Domestic and related helpers, cleaners, and launderers 2. 921: Agricultural and fishery labourers 3. 516: Protective services 4. 932: Manufacturing labourers 5. 522: Shop salespersons and demonstrators
Bottom of the top: 66th–85th hourly wage percentiles	
1. 516: Protective services 2. 414: Library, mail, and related clerks 3. 331: Primary education teaching associate professionals 4. 832: Motor vehicle drivers and related workers 5. 412: Numerical clerks	1. 419: Other office clerks and clerks NEC (except customer service clerks) 2. 516: Protective services 3. 832: Motor vehicle drivers and related workers 4. 913: Domestic and related helpers, cleaners, and launderers 5. 931: Mining and construction labourers 6. 122: Productions and operations managers/ department managers 14. 241: Business professionals
Top of the top: 86th–100th hourly wage percentile	
1. 331: Primary education teaching associate professionals 2. 339: Teaching and associate professionals NEC 3. 232: Secondary education teaching professionals 4. 122: Productions and operations managers/ department managers 5. 516: Protective services 10. 241: Business professionals	1. 123: Other managers/department managers 2. 122: Productions and operations managers/ department managers 3. 241: Business professionals 4. 419: Other office clerks and clerks NEC (except customer service clerks) 5. 331: Primary education teaching associate professionals

Notes: the bullet numbers refer to the ranking of the occupations in terms of frequency in the respective portion of the wage distribution. The three-digit numbers correspond to the three-digit SASCO occupational codes. NEC = not elsewhere classified.

Source: PALMS.

[4] In the bottom and middle, this is usually the code 5169: protective service workers NEC. This includes security guards, a common job in South Africa. In the top third, though, this is usually code 5162, which is police officers.

[5] The continued prevalence of domestic workers and labourers even this high up in the distribution is related to our analysis being at the hourly level. Domestic and labouring work is often ad hoc and many of these workers will not be working full time.

Domestic workers, protective service workers, and labourers mainly occupy the bottom of the distribution, but manufacturing labourers crop up in the middle in both periods. Notably, shop salespersons also appear in the top five occupations in the middle of the end period—likely an indicator of the rise of service jobs over time. Clerks and teachers are concentrated in the top third of the wage distribution, whereas in industrialized economies these occupations would predominantly be found in the middle of the distribution (Autor 2014). Business professionals (accountants and personnel professionals, for example) and managers of various types only really start appearing in substantial numbers in the top 15 percentiles. This means that, although the bottom and the middle of the distribution are dominated by low- to semi-skilled workers and look similar in terms of the types of jobs people have, they have very different earnings growth profiles. The following descriptive analysis investigates the potential drivers of this wage polarization. Section 3 describes the data and methodology used in this analysis.

3 Data and econometric method

The data used is the Post-Apartheid Labour Market Series (PALMS), which is a harmonized series of South African labour force surveys for the years 1995–2015 (Kerr et al. 2017). The original data for the series are based on the annual nationally representative cross-sectional labour force surveys collected by Statistics South Africa (Stats SA) since 1995. These were the October Household Surveys (1995–1999), Labour Force Surveys (2000–2007), and Quarterly Labour Force Surveys (2008–present). Earnings information for the Quarterly Labour Force Surveys is sourced from the Labour Market Dynamics Surveys for the corresponding years.[6] The original data cover approximately 30,000 dwelling units and include basic demographic and household information as well as detailed labour market data. PALMS harmonizes variable definitions across the different surveys to establish the most consistent series possible over the total period.

PALMS covers the years 1994 until 2017, with earnings data up to 2015, and is updated each time Statistics South Africa releases a new annual labour market survey. We use data from 2000 to 2015, as about 10 per cent of observations did not merge with the Occupational Information Network (O*NET) task data in the pre-2000 period, resulting in concerns about the quality of the occupational coding in these data sets. The public sector employment variable is also less reliable for these earlier data sets (Kerr and Wittenberg 2017), meaning that the 1994–1999 October Household Survey data sets in PALMS are less reliable for both the task and the institutional frameworks in our conceptual set-up. Wittenberg (2017b) has also raised concerns about certain quarters of the Quarterly Labour Force Survey—the surveys that make up the PALMS earnings data from 2010 onwards. Specifically, quarter three in both 2012 and 2014 appear to include an anomalously higher number of high earners compared with the other surveys,[7] so we have excluded them from our analysis. Our sample is limited to all employees between the ages of 15 and 64 with wages greater than zero and non-missing data for hours worked. We limit the sample

[6] Earnings data were not collected for the first two years of the Quarterly Labour Force Survey, so the PALMS series lacks earnings data for 2008 and 2009.

[7] A change that happened between the LFS and QLFS period was that Stats SA released fully imputed wage data with no way of identifying who was and who was not imputed. This has led Wittenberg (2017b) to worry that, depending on the imputation method, the whole top tail may have been shifted in the process. Our research is concerned with a difference in wages across a period, and too many higher earners at the end of the period could bias our results. We therefore take the precaution to remove these quarters from our analysis.

in this way because the labour market institutions as well as wage-setting mechanisms are more relevant to employees than to the self-employed.

3.1 Regression and decomposition

We use constructed hourly wage data from PALMS to run a recentred influence function (RIF) or unconditional quantile regression, as developed by Firpo et al. (2009). This technique allows us to estimate the impact of changing the distribution of explanatory variables on the unconditional quantiles of the outcome variable (Firpo et al. 2009). The ability of the RIF-regression to differentiate between effects at different points of the distribution is an important advantage when we are considering a range of explanations for the pattern of wage growth. Much of the literature on wage inequality in advanced economies has focused on developing the theory and evidence behind the task content framework, resulting in a consensus that task content is of primary importance in explaining wage polarization in the developed world. However, Firpo et al. (2011) argue that the importance of task content-based explanations in accounting for *total* change in the wage distribution over time is less well understood. Their employment of an RIF-regression using United States wage data allows them to perform this more comprehensive type of analysis and reach a more nuanced conclusion.[8]

The RIF-regression has advantages over a standard conditional quantile regression when the effect of a given covariate on a specific quantile of the outcome variable differs over levels of other covariates (Borah and Basu 2015). While a conditional quantile regression produces estimates which are conditioned on the mean value of all other covariates, the unconditional quantile regression estimates the effect of changing a covariate by one unit, keeping the full distribution of all other covariates the same (Borah and Basu 2013). This provides more interpretable and policy-relevant results than the standard conditional quantile regression assumptions. The estimated coefficients can be used to perform a detailed decomposition of the gap along the distribution into the compositional and structural components, as well as to determine the contribution of each of the explanatory variables to these components.

An RIF-regression makes use of the recentred influence function of the outcome variable instead of the outcome variable itself on the left-hand side of the regression. In the case of quantiles, the Influence Function (IF) (Y, Q_τ) for the τth quantile is given by:

$$IF\ (y; Q_\tau) = \frac{\tau - II\{y \leq q_\tau\}}{f_y\ (q\tau)} \tag{1}$$

where f_y is the marginal density function of Y and $II\{\cdot\}$ is an indicator function. The RIF of the τth quantile is:

$$RIF\ (y; Q_\tau) = q_\tau +\ IF\ (y; Q_\tau) \tag{2}$$

For our purposes, the RIF of the log of hourly wages is employed in equation (3), which sets up our regression. We run an RIF-regression of the log of hourly wages on our four frameworks in the PALMS data for 2000–2002 and 2013–2015, weighted using the bracket weight. We pool years at the beginning and end of the period to improve the precision of the estimates and to compensate for data problems that may be idiosyncratic to particular quarters.[9] At the beginning of the period

[8] They find that task content and de-unionization were central to wage changes in the 1980s and 1990s, but that from the 2000s these factors were much less important than offshorability.

[9] Firpo et al. (2011) also do this.

in our data, surveys were conducted twice a year and so our base period consists of the six surveys conducted over the three years 2000–2002. Surveys were carried out four times a year at the end of the period, so our end period consists of 11 surveys between 2013 and 2015, with the exclusion of quarter three of 2014 due to concerns described earlier.[10] The RIF-regression takes the form:

$$RIF(hourly\ wage) = \beta^*SBTC + \beta^*INST + \beta^*SECTOR + \beta^*TASKS + \beta^*X + \varepsilon \quad (3)$$

The vector *SBTC* represents the skills-biased technical change framework and consists of four education dummies: less than complete secondary education, complete secondary education, diploma or certificate post-secondary education, and degreed post-secondary education. *INST* represents the labour market institution framework and consists of a union membership dummy and a public sector employment dummy. A limitation is our inability to control adequately for minimum wage legislation since only one sector-specific minimum wage (of an eventual nine) was promulgated at the beginning of 2000. We should partly be able to observe the effect of minimum wages in cases where there is overlap with our sector dummies. These fall into the *SECTOR* vector, which stands for the change in sectoral composition framework. There are 10 sector dummies. Finally, *TASKS* consists of five task content variables coded using O*NET data and described in detail below (Section 3.2). The vector X includes the general controls of age, age squared, marital status, gender, and race.

The results of the RIF-regressions are extended by using an Oaxaca-Blinder detailed decomposition along the quantiles of the wage distribution. This allows us to decompose changes in real wages between our base (2000–2002) and end (2013–2015) periods into the total compositional (Δx) and wage structure (Δβ) effect for different percentiles of the distribution. We begin with the linear models of:

$$w^{base} = x^{base}\beta^{base} + \varepsilon^{base} \quad (4)$$

$$w^{end} = x^{end}\beta^{end} + \varepsilon^{end} \quad (5)$$

where w^i is the outcome variable of the wage in 2000–2002 and 2013–2015. As long as E(ε^{end})=E(ε^{base}) =0, the mean outcome difference between the base and end periods can be decomposed as:

$$\Delta w = x^{end\prime}\beta^{end} - x^{base\prime}\beta^{base}\ x^{end} \quad (6)$$

$$\Delta w = (x^{end} - x^{base})'\beta^{base} + x^{base'}(\beta^{end} - \beta^{base}) + (x^{end} - x^{base})'(\beta^{end} - \beta^{base}) \quad (7)$$

$$\Delta w = E + C + EC \quad (8)$$

where x^{end} and x^{base} are the vectors of means of the regressors (including the constants) for the end and base periods, respectively. In other words, the change in wages between 2000–2002 and 2013–2015 is decomposed into one part that is due to differences in endowments (E), one part that is due to differences in coefficients (C), and a third part that is due to the interaction between coefficients and endowments (EC). This analysis was also conducted in STATA 15 using the *oaxaca8.ado* package.

[10] Analysis was conducted using the rifreg.ado package in STATA 15.

3.2 Coding task content

To measure task content, we use the Occupational Information Network (O*NET). O*NET is an American survey of very detailed occupational demands such as work context, activities, and skills.[11] These data are merged with South African occupational codes in PALMS at the three-digit level. We follow methodology by Jensen and Kletzer (2010) and Firpo et al. (2011) to code five task content variables. The categories are listed and described in detail in Table 2 and respectively relate to (1) the information content of a job; (2) the level of automation or routinization of a job; (3) the need for face-to-face contact; (4) how necessary it is to be on site for work; and (5) the importance of decision-making or analysis in the job. Firpo et al. (2011) interpret jobs with high levels of information content and automation (task categories 1 and 2) as likely to be affected by technology and more susceptible to being offshored. Generally, jobs that include more automated or routine tasks are unambiguously more vulnerable to substitution by technology and offshoring. However, jobs with high information content could be either substituted or complemented by technology. The repetitive elements of jobs with high information content (e.g. 'documenting/ recording information' in Table 2) make them vulnerable to substitution by technology—for example, bookkeeping tasks. However, the information content category also includes work activities that could be complemented by technology—for example, 'analysing data or information' and 'interacting with computers'. We therefore expect ambiguous impacts for jobs with high information content.

In the Firpo et al. (2011) framework, jobs with more face-to-face, on-site, and decision-making tasks are less susceptible to being offshored. This is because these jobs require personal interaction, require physical presence at the site of work, and benefit from the worker staying local and accessible, respectively. The decision-making or analytic category is similar to the Autor et al. (2003) non-routine cognitive task category. Autor et al. (2003) suggest that this category stands to gain from the adoption of computer technology, since computers increase the productivity of these types of tasks. The impact of technology on on-site and face-to-face jobs is less clear-cut, especially because these are characteristics of a diverse range of jobs spanning the wage distribution. For example, working on-site is relevant to both informal street food vendors and certain types of managers. Similarly, both a call-centre operator and a manager require high levels of interpersonal contact and relationship management (i.e. the face-to-face category).[12] These two criteria are therefore better indicators of non-offshorability than technological impact.

[11] In the absence of task data specifically collected for South Africa, the best we can achieve is an approximation from the American data, although questions remain about how applicable American task data are to South African occupations. Task data from other countries do exist, although these are mainly European countries, and only a handful of developing countries are included in these surveys. We refer the reader to Hardy et al. (2018) and Lewandowski et al. (2019) for comparisons between various task data sets. The overall conclusion is that task measures are consistent amongst these different data sets.

[12] Note that part of the tension here arises from South Africa being both the sender and receiver of offshore labour. For example, South Africa has a well developed and continuously growing call-centre industry, but many local manufacturing jobs have been cut because production is cheaper overseas. Our expectations are therefore less rigid than they would be in an advanced economy.

Table 2: Detailed description of tasks in each task category from O*NET data

	Task category	Characteristics from O*NET
1	Information content	Getting information (JK) Processing information (JK) Analysing data or information (JK) Interacting with computers (JK) Documenting/Recording information (JK)
2	Automation/Routinization	Degree of automation Importance of repeating same tasks Structured versus unstructured work (reverse) Pace determined by speed of equipment Spend time making repetitive motions
3	Face-to-face	Face-to-face discussions Establishing and maintaining interpersonal relationships (JK,B) Assisting and caring for others (JK,B) Performing for or working directly with the public (JK,B) Coaching and developing others (B)
4	On-site	Inspecting equipment, structures, or material (JK) Handling and moving objects Controlling machines and processes Operating vehicles, mechanized devices, or equipment Repairing and maintaining mechanical equipment
5	Decision-making	Making decisions and solving problems (JK) Thinking creatively (JK) Developing objectives and strategies Responsibility for outcomes and results Frequency of decision making

Note: 'JK' is a work activity used in Jensen and Kletzer (2010); 'B' is a work activity used or suggested by Blinder (2007).

Source: reproduced from Firpo et al. (2011: Appendix Table A2), with permission.

O*NET has data for every occupation on the 'importance' and 'level' of work activity and the frequency of five levels of work context—work activity and work context are O*NET classifications. For work activities, a Cobb-Douglas weight of two-thirds to 'importance' and one-third to 'level' is arbitrarily assigned, following Blinder (2007) and Firpo et al. (2011). Work context is captured by multiplying frequency by level. This can be summarized as:

$$TC_{jh} = \sum_{k=1}^{A_h} I_{jk}^{2/3} L_{jk}^{1/3} + \sum_{l=1}^{C_h} F_{jl} * V_{jl}$$

where TC_h is the score for occupation j in category h, $h = 1,\ldots,5$; A_h is the number of work activity elements, and C_h is the number of work context elements; I is 'importance'; L is 'level'; F is frequency; and V, value of the level. We then scale these measures to vary in an interval [0;1] by dividing by the maximum of the full distribution. This scaling makes it easier to compare occupations across each category, but the values of the measures themselves have no specific unit.

The distribution of task content by occupation is reported in Appendix Table A1. Expectations are that computer technology can either substitute or complement tasks with high information content depending on how routine the task is. For example, managers, professionals, and clerks all have high scores for information content, but clerks have much higher scores for automated or routine work. This could indicate a differential impact of computer technology across these occupations, with clerks likely to be substituted but managers and professionals likely to be complemented. At the lower end of the skills spectrum, we can compare operators/assemblers with elementary workers.[13] Both of these occupations involve manual work—they both get low scores for decision-making or analytic work—and yet the operators/assemblers have higher scores for automation or routinization than the elementary workers. Autor et al. (2003) show that it is routine manual work that is replaced by technology or offshored, while non-routine manual work remains steady in terms of employment and wages. It is therefore in line with expectations that the share of elementary workers expanded by 3.86 percentage points between 2000–2002 and 2013–2015, whilst the share of operators/assemblers contracted by 3.28 percentage points. Service-related occupations have the highest scores for face-to-face task content.

Appendix Table A2 indicates that tasks overlap with sectors in predictable ways. Agriculture and domestic services have the lowest information content scores, whereas the finance sector has the highest. Agriculture, manufacturing, mining, and construction have the highest scores for on-site work. According to the Firpo et al. (2011) task framework, on-site work should protect against offshoring. Manufacturing and mining, though, also coincide with the highest levels of automated and routine work. The service sector has some of the lowest scores for on-site work, but the highest need for interpersonal contact (the face-to-face task category). This combination is reflective of call-centre operators, for example. The section that follows provides a descriptive overview of the role of the four frameworks in explaining this pattern.

4 Four frameworks for understanding wage inequality in South Africa

4.1 Framework 1: changes in aggregate demand and sectoral composition

Since the end of apartheid in the mid-90s, the South African economy has undergone enormous changes over a very short period. Many of these changes have been 'structural'—that is, related to the formidable and far-reaching trends of ever-tightening globalization, advancing computer technology, and international trade. These structural factors influence a country's import–export mix and affect which industry sectors face the most competition from offshoring and cheap imports, as well as which sectors thrive (Bhorat and Rooney 2017). In the last few decades, the economy has rapidly transformed from one based on agriculture, manufacturing, and mining to one that is business-, services-, and finance-led (Bhorat and Rooney 2017). Between 2001 and 2014, the mining sector contracted by a third and manufacturing, by 20 per cent; the finance sector, on the other hand, expanded by 30 per cent. The changing sectoral composition of the economy is not without implications for employment and wages. This change disadvantaged the low- and semi-skilled to the benefit of the high-skilled. The employment share of the tertiary sector increased dramatically between 2001 and 2014, whilst there was little change in that of the secondary sector, and the primary sector halved its share (Bhorat and Rooney 2017).

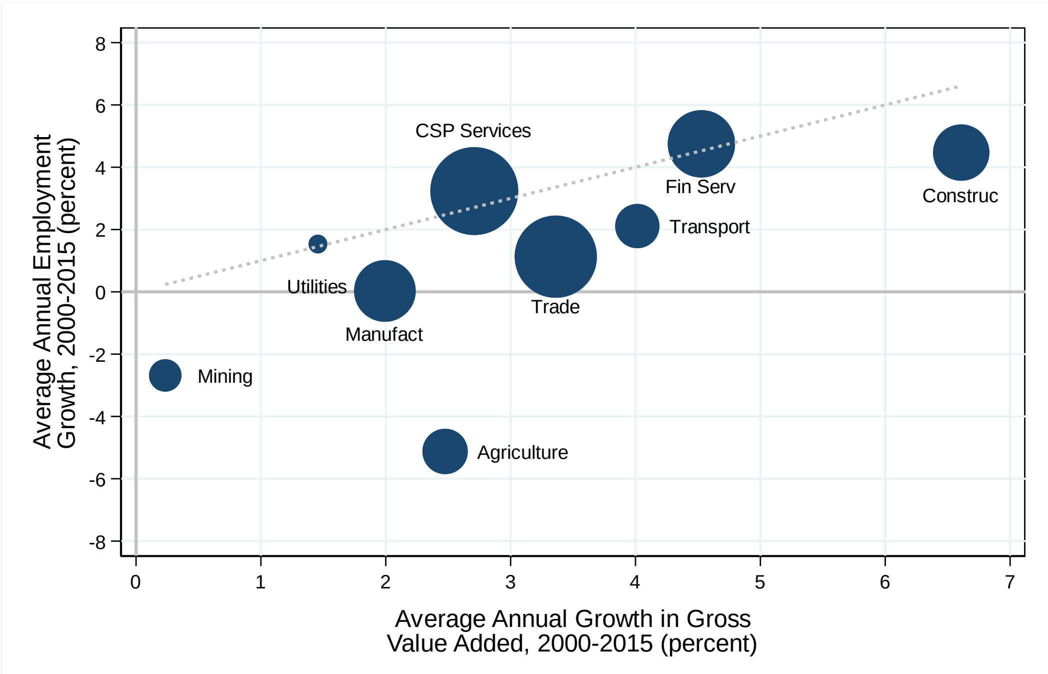
The influence of changing sectoral composition on aggregate labour demand patterns is an important piece of the puzzle for our understanding of wage polarization in South Africa. On the one hand, this is a key reason for an increase in wage inequality, because the economy is growing in ways that benefit highly skilled, and therefore better remunerated, workers—for example, those in the finance sector. Meanwhile, in the middle of the distribution, semi-skilled, medium-paid jobs in manufacturing and mining are whittled away by offshoring and labour-replacing technologies.

[13] Elementary workers are mainly unskilled labourers in manufacturing, agriculture, and mining. Operators/assemblers operate machinery in often the same sectors. Most of the growth in the elementary occupation category between 2000 and 2015 came from waste collectors, mining and construction labourers, and transport labourers and freight handlers. In other words, this was likely the effect of public sector employment and construction.

Changing sectoral make-up is also useful for explaining the growth of wages at the bottom end of the wage distribution via the expansion of what Goos and Manning (2007) term 'lousy' jobs—that is, low-paying jobs in the services sector. Together, financial, community, social, and personal services accounted for almost 80 per cent of the change in employment between 2001 and 2014 (Bhorat and Rooney 2017). Structural change in aggregate demand, then, is one framework that could be used to explain wage polarization in South Africa.

In Figure 2, we plot the AAGR of value added to GDP by sector against the corresponding AAGR of employment, with bubbles weighted by the size of employment in 2015. Sectors above the dotted line have experienced labour-intensive growth. The overarching shift in aggregate demand has been away from mining and manufacturing towards a services-oriented economy. The CSP services and financial services sectors have exhibited strong growth in both output and employment and together represent a large portion of the employed. In contrast, the mining sector has declined, shed jobs over the period on average, and represents only a small number of the employed in 2015. Growth in manufacturing has imploded in terms of both output and employment. Agriculture has fared even worse than manufacturing and also experienced high job losses on average over the period. The collapse of the last two sectors is concerning, since both were important absorbers of South Africa's oversupply of low-skilled labour at the beginning of the post-apartheid period.

Figure 2: Changes in employment and contribution to GDP by sector, 2000–2015



Note: bubbles weighted by the number of employed in 2015.

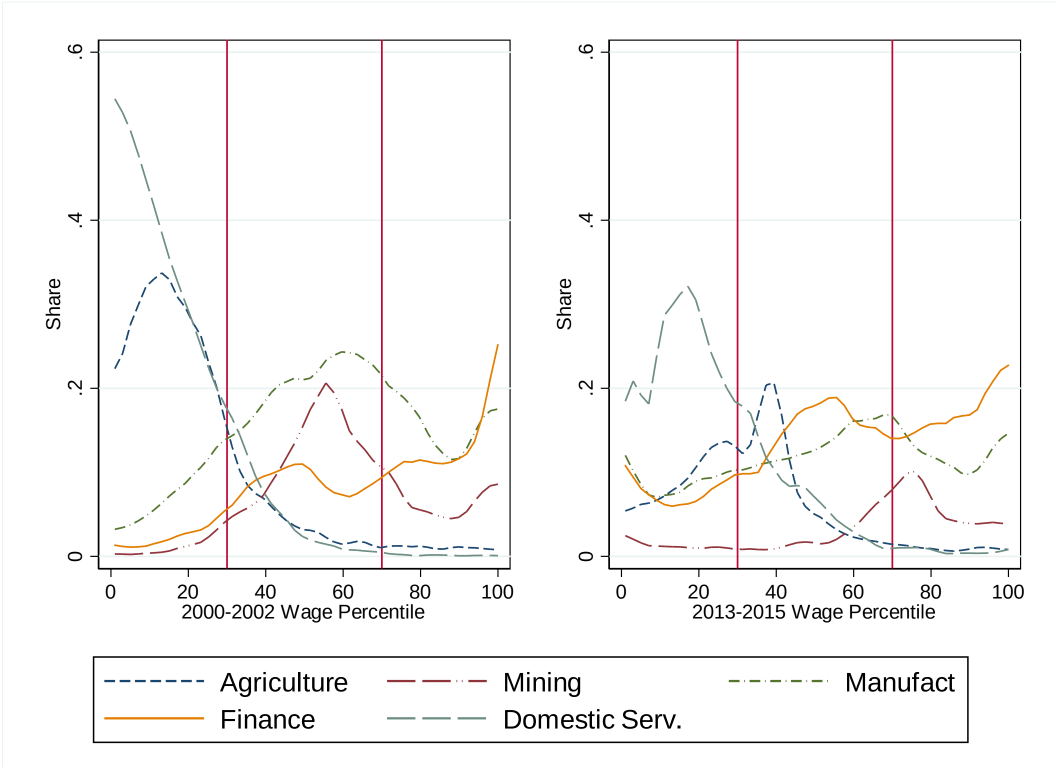
Source: own calculations using data from South African Reserve Bank and PALMS, adjusted using sampling weights.

To understand how sectoral shifts interact with wages, Figure 3 plots the share of workers in five pertinent sectors at each percentile of the wage distribution.[14] Reference lines divide the wage distribution into three sections based on the U-shaped wage growth shown in Figure 1; that is

[14] Data for the remaining sectors are reported in Appendix Figure A1.

positive wage growth at the bottom (percentiles 0 to 29), roughly sub-1 per cent down to negative wage growth in the middle (percentiles 30 to 70), and positive wage growth at the top (percentiles 71 to 100). The smoothed polynomials are interpreted as the share of workers working in a given sector per wage percentile; that is, all plot lines sum to one in each wage percentile (over all 10 sector categories plotted in Figure 3 and Appendix Figure A1). For example, about 20 per cent of people were employed in manufacturing at the 70th percentile in 2000–2002.

Figure 3: Local polynomial regression: Share of employed in selected sectors per wage percentile, 2000–2002 and 2013–2015



Notes: sample consists of all employees of working age with non-missing wage and hours of work data; reference lines on the x-axis are at the 30th and 70th percentiles; density is interpreted as the proportion of jobs in that wage percentile in that sector.

Source: own calculations using PALMS data, adjusted using sampling weights.

Figure 3 shows growth in the share of financial services workers across the distribution. The effects of such a compositional shift will certainly be felt throughout the economy, as this was the second biggest sector in 2000–2002 (18.13 per cent of employed) and the biggest in 2013–2015 (23.14 per cent of the employed). As financial services is one of the fastest-growing sectors in terms of employment, the distribution shown in Figure 3 is potentially an important driver of wage growth at the top and bottom of the wage distribution. The surge in services at the bottom end (Appendix Figure A1) is partly a result of expansion in personal care (of the elderly and of children), cooks and cleaners in the hospitality industry, security guards and police officers, and sweepers and odd-job labourers. On the other hand, the decline of manufacturing and mining is evident. In the middle of the distribution, semi-skilled work in these sectors has been replaced by less skilled work such as agricultural and domestic work (also construction and trade: see Appendix Figure A1)—partially explaining weak wage growth in the middle. The effect of minimum wages for the domestic services and agricultural sectors is also apparent from the rightward shift of these distributions between 2000–2002 and 2013–2015. Minimum wages are therefore likely propping up wage growth at the bottom.

4.2 Framework 2: skill-biased technical change

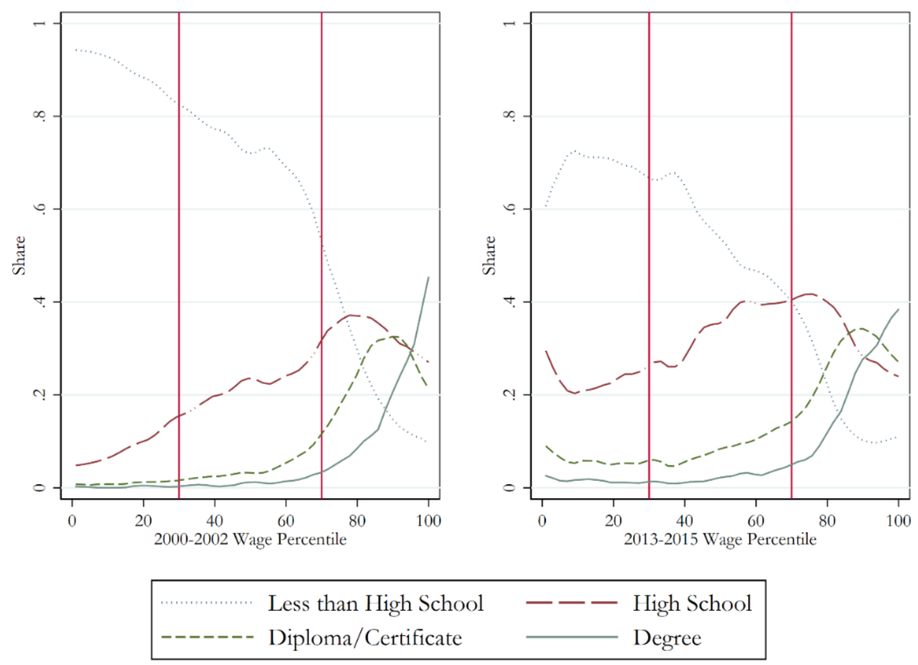
The impact of technology on the labour market is an important and diverse topic in economics, classically understood with Tinbergen's (1974, 1975) original model of skill-biased technical change. In this model, changes in the wage structure for high- and low-skilled workers are explained by an education premium (high school/college premium), which is itself modulated by the relative supply and demand for skills. Technology is usually assumed to be 'skills-biased'; that is, it is factor-augmenting in favour of high-skilled workers. Skills-biased technology raises inequality through expanding the level and variance of the wage distribution. A consequence of this process is Tinbergen's race between technology and skill supply as more and more people have invested in higher education in the latter half of the 20th century in industrialized economies (Acemoglu and Autor 2011). For example, Acemoglu and Autor (2011) show that returns to education (the college/high school wage premium) rose monotonically across the distribution in the United States during the 1980s and 1990s.

This model is compelling in the South African case. The use of technology has surged over the past two decades in South Africa: The proportion of internet users increased from 1.6 per cent of the population in 1997 to 54 per cent in 2016. Further, the number of secure internet servers in the country increased from 521 in 2001 to 6,962 in 2016, an expansion of 1,240 per cent (World Bank 2018). At the same time, South Africa has a dual education market, the majority of the population receiving a very poor education and a small, wealthy elite enjoying high-quality schooling in preparation for entry into higher education institutions. It has been well documented (Branson et al. 2012; van der Berg et al. 2011) that returns to the top end of the wage distribution have increased significantly over the post-apartheid period, whilst returns to those with less than post-secondary education have stagnated. Skills-biased technical change is therefore a second compelling framework for explaining wage inequality in South Africa.

Appendix Table A3 reveals that there have been important compositional changes in education levels over the period under consideration. South Africans have become more educated in general: in 2000–2002, two-thirds of the wage-employed had less than a high school education; by 2013–2015, this had dropped to less than half. Most of this drop was absorbed by a surge in the number of people completing high school. The share of high school graduates increased substantially, from about 20 per cent of employees in 2000–2002 to about 30 per cent in 2013–2015. In 2000–2002, 7.9 per cent and 4.3 per cent of the employed held diplomas/certificates and degrees, respectively, and both of these shares increased by less than six percentage points by 2013–2015. This means that the major compositional change in education over the period came in the form of an expansion of new high school graduates and a decrease in individuals holding less than a high school qualification. Figure 4 illustrates this clearly. There is a noticeable decrease in the incidence of employees with less than high school education below the 70th percentile. At the same time, there has been an increase in the share of high school educated in the middle of the distribution. Finally, even in 2013–2015, having post-secondary education remained comparatively rare.

This changing composition affects the 'race' between skill supply and technology, which is usually assumed to be skill-biased. As is typical, wages increase monotonically with education level (see Appendix Table A3). Average earnings for the university degree educated, though, have increased substantially in the period (by 49.6 per cent), in contrast to earnings for other education categories. The next highest increase was experienced by those with high school education and came in at 13.2 per cent. In other words, the increase in average earnings for the degree educated was more than four times greater than the second biggest increase.

Figure 4: Local polynomial regression: Education level per wage percentile, 2000–2002 and 2013–2015



Notes: sample consists of all employees of working age with non-missing wage and hours of work data; reference lines on the x-axis are at the 30th and 70th percentiles; density is interpreted as the proportion of jobs in that wage percentile classified as having the relevant education level.

Source: own calculations using PALMS data, adjusted using cross-entropy weights.

4.3 Framework 3: tasks

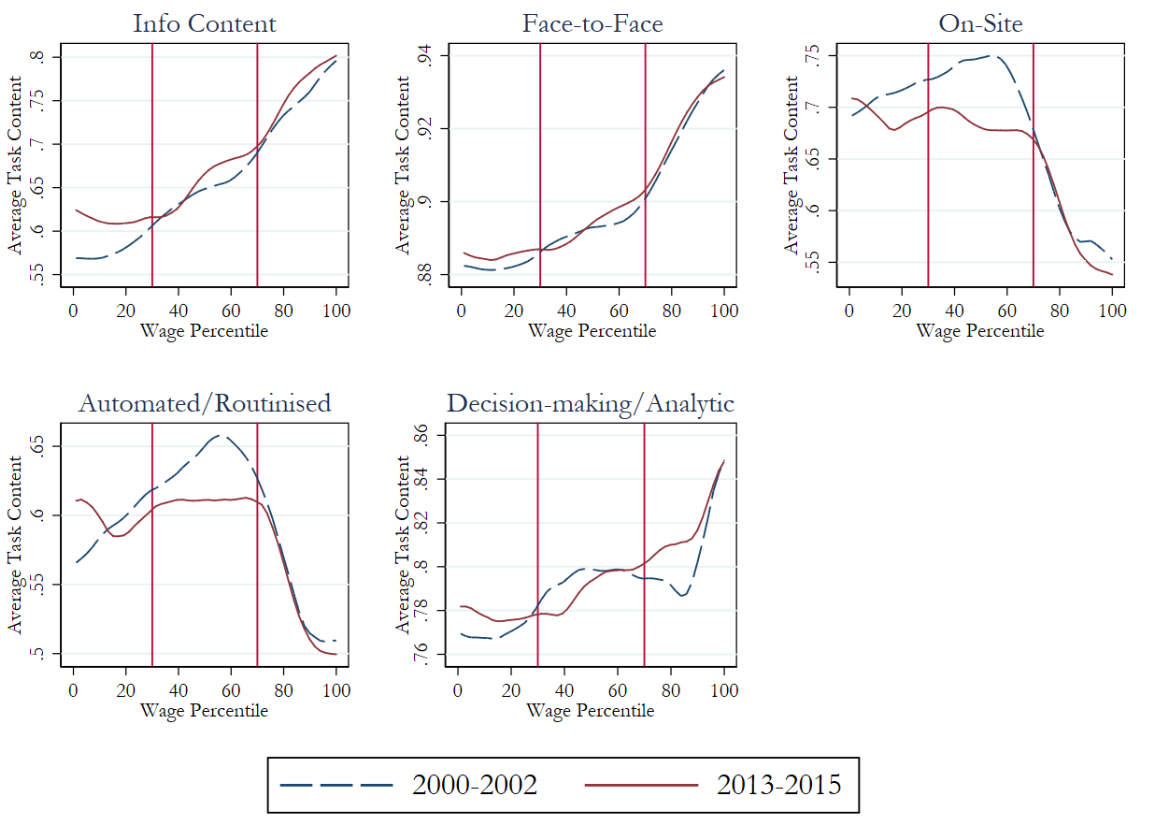
Whilst the Tinbergen model can help explain inequality driven by increasing premia at the top end of the distribution, it cannot explain the 'missing middle' or U-shape of the wage distribution. That is, this framework can explain the wage growth at the top half of the U-shape, but it is not helpful in understanding the wage growth at the bottom half of the U-shape. Since technical change is incorporated in the model as a factor-augmenter, it does not explain how technologies might supplant certain occupations or tasks. It is also unhelpful for understanding the impact of offshoring or explaining why certain occupations would experience negative earnings growth (Acemoglu and Autor 2011: 1118).

In an effort to better explain wage polarization, an influential literature on the interaction of technological change on skill content, or tasks, has developed that represents an augmentation of the original Tinbergen model. Since the seminal paper by Autor et al. (2003), a number of scholars have argued that technology can complement or substitute different tasks, thereby enhancing or depressing wage growth, respectively (Acemoglu and Autor 2011; David et al. 2006; Firpo et al. 2011; Goos and Manning 2007). This framework thus has the potential to explain differential impacts on wages at different points in the distribution. Autor et al. (2003) identify four task categories: routine versus non-routine tasks, each of these being either manual or cognitive in nature. It was argued that in the era of large-scale computer adoption in the United States, routine tasks—whether manual (such as picking or sorting) or cognitive (e.g. calculation or record-keeping)—were highly susceptible to being substituted by computers. In contrast, computer technology is usually complementary for non-routine cognitive tasks such as research, selling, or managing, leading to increased productivity and increased returns for these tasks. Such tasks are typically high-skilled and therefore already well remunerated compared with routine work.

However, not all lower skilled work is necessarily susceptible to substitution. Autor, Levy, and Murnane (2003) explain that non-routine manual tasks such as cleaning, cooking, and driving services have a limited capacity for both substitution and complementation by technology. The authors show that the U-shaped earnings growth curve in the United States can partially be explained empirically by medium-skilled workers performing routine cognitive tasks being substituted by computer technology when it was adopted on a large-scale in the 80s and 90s. At the same time, low-skilled non-routine work, like cleaning, was somewhat protected—thus engendering a 'missing middle'. This wage polarization was accompanied by a similar employment polarization fuelled by lower job growth for medium-skilled occupations relative to low- and high-skilled jobs. Given the level and structure of inequality in South Africa, it is not only the bottom third, but also the middle third of the distribution that is dominated by low-skilled occupations throughout the post-apartheid period (e.g. cleaners, drivers, and security guards). Occupations typically classified as medium- and high-skilled (such as teachers, general managers, and clerks) only really start to emerge from the 70th and 80th wage deciles in 2015. This implies that the 'missing middle' in South Africa may represent a different typology of workers and skill sets, relative to those observed in developed country labour markets.

Figure 5 plots smoothed average task content across the wage distribution for 2000–2002 and 2013–2015.

Figure 5: Local polynomial regression: Task content per wage percentile, 2000–2002 and 2013–2015



Notes: sample consists of all employed adults of working age with non-missing wage and hours of work data; reference lines on the x-axis are at the 30th and 70th percentiles; density is interpreted as the average task content of jobs at the relevant wage percentile.

Source: own calculations using PALMS data, adjusted using sampling weights.

The average task content has no specific unit, so comparisons can be made within but not between task categories. The distribution of task content across the distribution is in line with expectations. Analytic or decision-making task content is concentrated at the top end, whilst on-site and routine work is found at the bottom and (mainly) in the middle of the distribution. Information content and face-to-face content increases monotonically across the distribution.

The clearest change is the collapse of on-site and automated work in the middle of the distribution. This is most likely a reflection of the contraction of the manufacturing and mining sectors, which score highly on on-site task content (see Appendix Table A2). High base levels of on-site and routine task content may be indicative of vulnerability to offshoring and replacement by technology in this portion of the distribution, respectively, endangering wage growth. The main change at the top end appears to be a broadening of the importance of work that involves decision-making. This would be expected to boost wages, since this type of work is harder to offshore and automate.

4.4 Framework 4: labour market institutions

So far, the discussion has focused on the effect of structural change, be it through evolving sectoral composition, Tinbergen's skills-biased technical change, or the task framework. Labour market institutions, though, are another factor that could influence and shape the wage distribution outcomes observed for South Africa in the post-apartheid period. With the advent of democratic rule, the state intensified its pro-poor policies through, for example, widening and deepening social security provisions and, from 1999 onwards, a more active promulgation of sectoral minimum wage laws. In 1999, contract cleaning was the first sector to be subject to minimum wage legislation, followed by civil engineering and private security in 2001. By 2015, there were nine sectoral minimum wages covering 31 per cent of the formal sector (ILO 2015).[15] Most of these sectors experienced annual real increases in their wages; agricultural workers in particular experienced steep real increases in the mid-2010s (Bhorat et al. 2016b).

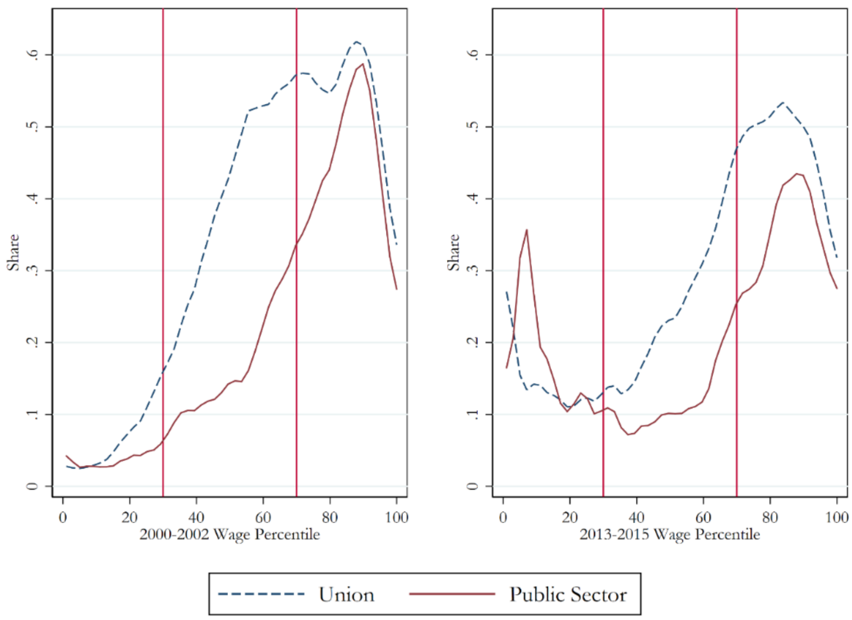
In addition, trade unions remain firmly entrenched in the South African labour market, and importantly are part of a formal political tripartite alliance with the ruling party. However, the influence of trade unions has waned due to a trend of casualization and informalization in the labour market. Union membership in the private sector declined by 11.2 percentage points, from 35.6 per cent to 24.4 per cent, between 1997 and 2013 (Bhorat et al. 2015). Simultaneously, the use of temporary employment services—whose employees are difficult to unionize—has grown annually by 8.7 per cent over the past two decades (Bhorat et al. 2014). Yet, despite this overall erosion of trade union representation, public sector unions in South Africa have witnessed a rise in their membership. Between 1997 and 2013, public sector union membership rose by just over half a million members (14 percentage points), resulting in a unionization level of 70 per cent for the public sector in 2013 (Bhorat et al. 2015). Analysis by Bhorat et al. (2015: 29) describes the rise of a 'new labour elite' in the South African labour market from the 2000s, typified by a unionized public sector employee. These workers are older and better educated on average than non-agricultural private sector employees and are reaping wage premia specifically at higher levels of the wage distribution. Overall, the bottom end of the U-shape could be propped up by minimum wages; meanwhile, de-unionization in the middle of the distribution could be related to an erosion of real wages for those workers. At the top end, elite capture of union membership and public sector employment could raise returns for this section of the distribution. Labour market

[15] This will change when the new national minimum wage comes into effect.

institutions are therefore likely to be an important factor in explaining South African wage polarization.

In terms of the present research, although average wages increased more for non-union members than unionized ones during the period under study, a union premium existed in both years (see Appendix Table A3). Average earnings for union members were about 43 per cent higher than those of the non-unionized in the end period. A public sector wage premium also exists in both 2000–2002 and 2013–2015, although it narrowed over time. Figure 6 shows that there has been a hollowing-out of both union membership and public sector employment in the middle of the distribution—echoing the U-shape in Figure 1. Union membership and public sector employment are most prevalent at the top end, although there have been important increases at the bottom end. Therefore, while unions and government employment have played a role in supporting the most vulnerable, it is the richest who have benefited the most, and largely to the cost of those in the middle.

Figure 6: Local polynomial regression: Union membership and public sector employment per wage percentile, 2000–2002 and 2013–2015



Notes: sample consists of all employed adults of working age with non-missing wage and hours of work data; reference lines on the x-axis are at the 30th and 70th percentiles; density is interpreted as the proportion of jobs in that wage percentile classified as being union members or public sector employees.

Source: own calculations using PALMS data, adjusted using sampling weights.

The descriptive evidence already suggests some important trends. Aggregate shifts towards services and finance, combined with jobs at the top end of the wage distribution typically requiring more decision-making or analytic tasks carried out by people with university degrees, have likely reinforced returns in the top deciles. Not only are jobs at the top end more analytic and more in demand, but only a small proportion of the population is qualified to carry them out. Interestingly, relatively wealthier workers are more likely to be unionized than those at the bottom end of the wage distribution. Labour market institutions like trade unions are conventionally designed to protect those earning relatively lower wages. However, there is rapid de-unionizing in the middle of the distribution, while public sector employment has hollowed out for the same group. Even though workers in the middle of the distribution are more educated in general, they have increasingly found themselves in routine manual jobs, such as manufacturing, which has collapsed in the face of global competition (Bhorat and Rooney 2017). As manufacturing and mining have imploded, semi-skilled work in these sectors has been replaced by work in agriculture and trade, which is less skilled and therefore also less well remunerated.[16]

At the bottom end of the distribution, it is likely that the expansion of minimum wages throughout the 2000s has served to prop up wage growth. While there was only one sector covered by a minimum wage in 2000, by 2014, 46 per cent of employees were covered by a sectoral minimum wage.[17] Increases in the value of the minimum wage have been rapid, with real wage increases between 2007 and 2015 ranging from 14 per cent in the private security sector to 90 per cent in the agriculture sector (Bhorat et al. 2016b). There has also been an increase in public sector employment at the bottom end due to the government's public works programme contributing to low-wage employment in construction and services. Section 5 presents a more comprehensive empirical assessment of the driving forces behind the missing middle in South Africa, using an RIF-regression and its detailed decomposition.

5 Determinants of wage inequality in South Africa: a dynamic analysis

Before discussing the results of the decomposition, we present some key features of the RIF-regressions for each period. This discussion is based on the full RIF-regressions for the 10th, 50th and 90th percentiles in both 2000–2002 and 2013–2015, as reported in Appendix Table A4, as well as the plotted coefficients for education and task content shown in Appendix Figure A2; and for institutional variables and selected sectors, as shown in Appendix Figure A3. The RIF-regressions show that returns to those with high school education follow an inverse U-shape across the distribution and that this shifts substantially downwards between 2000–2002 and 2013–2015 (the base group is those with less than high school education). Returns to diploma/certificates and degrees are mostly monotonic across the distribution, with pronounced positive returns for degree holders at the top end.

Returns to high ICT task content show a consistently inverted-U shape at both ends of the period. In other words, returns to this task content are highest towards the 'top of the middle' of the distribution and lower than we expected at the top end. However, returns remain stable over time for the top end, but a significant rightward shift of only the left-hand leg of the inverted-U in 2013–2015 indicates falling returns for those situated below about the 60th percentile. The coefficients for automated work follow an inverted U-shape in 2000–2002. By 2013–2015, there has been a hollowing in the middle of the distribution. At the 50th percentile, the coefficient on automated tasks has decreased by 47 per cent. The coefficients on face-to-face task content stand out for having very large standard errors, meaning that they are imprecisely estimated and should be cautiously interpreted. Despite the confidence intervals around the series being wide as a result, the improvement in returns at the bottom end in 2013–2015 is still marked enough that they do not overlap. Returns to on-site work have systematically decreased across the distribution. Lastly, the coefficients for decision-making or analytic tasks are U-shaped in 2000–2002, with the middle of the U dipping deeply into negative returns. By 2013–2015, though, returns to this task type are all positive and increasing relatively uniformly across the distribution.

[16] Our own calculations show that about a third of those working in the trade sector in 2015 were street vendors, and the next largest category was shop salespersons and demonstrators; both of these occupations are unskilled.

[17] This figure is only for those employees earning below the Basic Conditions of Employment Act (BCEA) threshold of R205,433.30 (c. US$11,000) per annum.

The RIF-regression coefficients for public sector employment and union membership show clearly how richer employees have captured returns to these institutions to the detriment of poorer quantiles. Both public sector employment and union membership display a collapse in returns at the bottom end whilst the top end stays intact and improves, respectively. Firpo et al. (2011) also find a drop in the contribution of union membership to wages at the bottom end in the United States in 1988–1990 and 2000–2002, but the hollowing-out in South Africa is more extreme and the steep increase in returns at the top end is unique.

All sector effects are relative to the base of the transport sector, chosen for its size and relative stability over the period (see Appendix Figure A1).[18] The impact of minimum wages is evident in the agriculture and domestic services sectors. In agriculture, returns in the 10th percentile have more than doubled between the two periods. For domestic work, returns at the 10th percentile are negative in 2000–2002 but become positive in 2013–2015. Returns to occupation in the financial services sector have remained relatively stable between the base and end periods, with an increase in returns evident below the 20th percentile. Overall, returns in the financial sector are U-shaped. Coefficients for the manufacturing sector are estimated with relatively large standard errors. With this in mind, there still appears to have been a statistically significant fall in returns to this sector in the middle of the distribution.

In order to better understand the changes in these coefficients over time, we decompose overall change in the log real hourly wage at each percentile into compositional (endowment), wage structure (coefficient), and interaction effects. Consistent with wage polarization in the developed world (Firpo et al. 2011), the total effect is U-shaped (Figure 7). In 2013–2015, the median wage was 3 per cent higher than it was in 2000–2002. Meanwhile, the lower and upper ends of the distribution saw more extensive growth. Wages at the 25th and 75th percentiles in 2013–2015 were 26 and 20 per cent higher than what they were in 2000–2002, respectively.

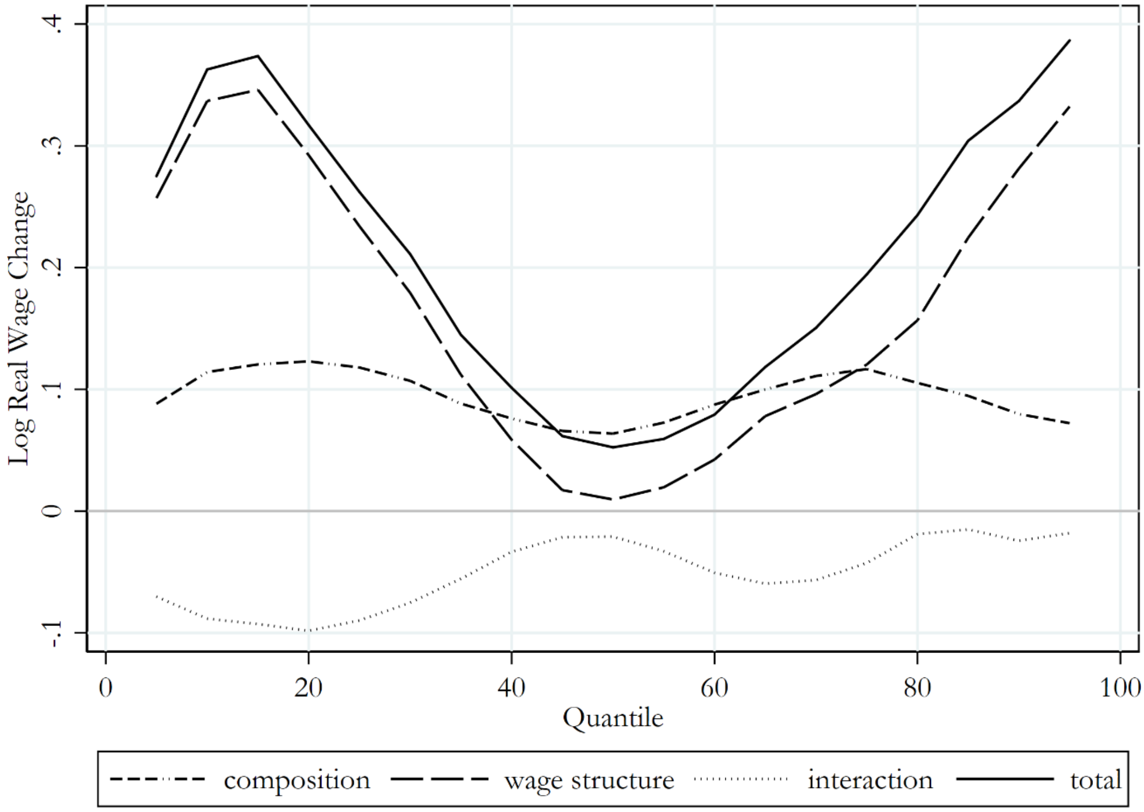
The total wage change is decomposed into compositional and wage structure components, as well as their interaction, per equation (8) (Section 3.1). The compositional component is the proportion of the wage gap that is explained by changing characteristics of the employed, and the wage structure component is the proportion that is explained by changes in returns. Specifically, the compositional component plots the change in real wages in 2000–2002 if the employed had the x-characteristics (level of education, gender, age, etc.) of the employed in 2013–2015, holding the wage structure in 2000–2002 constant. The wage structure component plots the change in real wages in 2000–2002 if the employed had the β-returns of the employed in 2013–2015, holding the worker characteristics in 2000–2002 constant. Lastly, the interaction is the simultaneous effect of changes in coefficients and endowments.

The wage structure component is more important and predominantly accounts for the U-shaped nature of the wage change. Wage changes accounted for by the characteristics of the employees (wage composition effects) also reflect the U-shape, but to a much weaker degree. In contrast, Firpo et al. (2011) find that the compositional effect increased monotonically across the distribution when wages were polarizing in the US of the 1990s, and the wage structure effect was driving the result. For South Africa, this means that there have been both inequality-increasing and inequality-decreasing effects of change in the composition of the labour market, but that overall

[18] From Figure A1, the utilities sector may seem like a better choice because it is more stable. However, it is very small, representing only 1 per cent and less than 1 per cent of the sample in 2000–2002 and 2013–2015, respectively (Table A2). It is usually understood that the choice of base does not affect inference and should be determined by ease of interpretation only. Peng and MacKenzie (2014) suggest that very small bases may result in losses in efficiency and precision of estimation.

these have been driven by wage structure effects. Changes in returns—that is, the frameworks identified by this paper (skills-biased technical change, structural sectoral change, the influence of technology on task content, and the role of labour market institutions)—explain wage polarization to a large extent, and help us understand how inequality has increased overall.

Figure 7: Decomposition of total change into compositional, wage structure, and interaction effects, 2000–2002 to 2013–2015

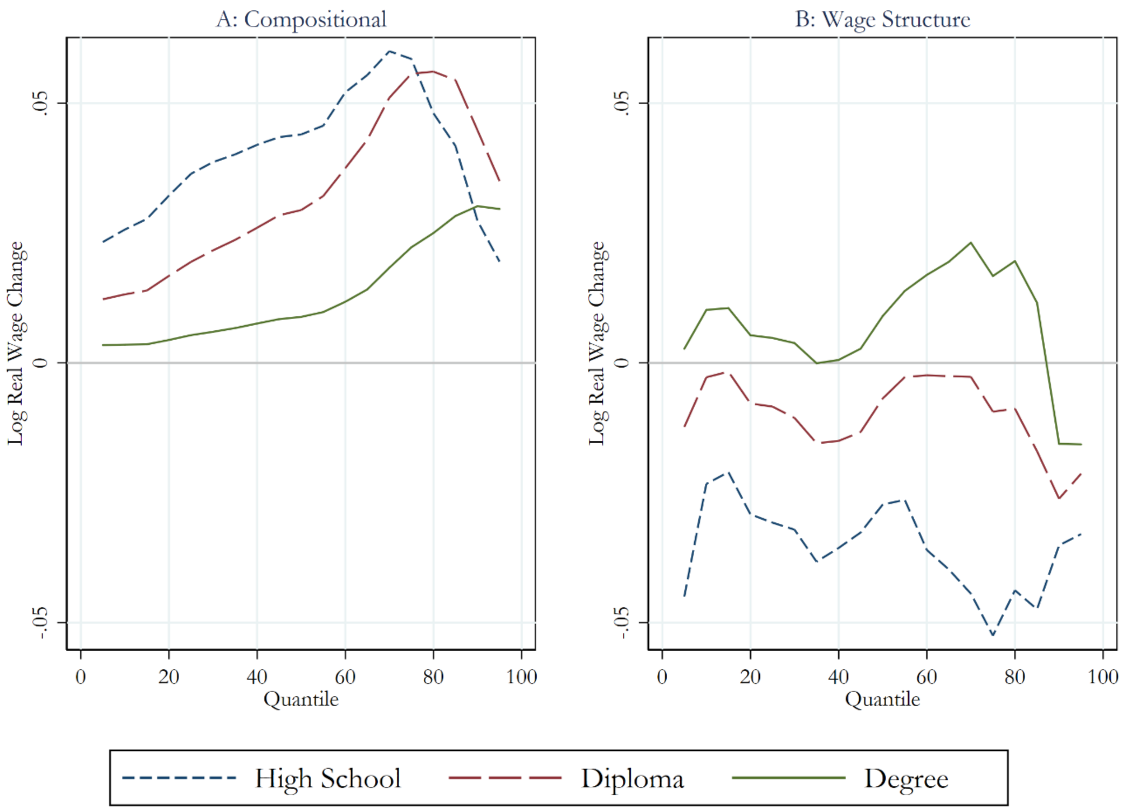


Note: sample consists of all employees of working age with non-missing wage and hours of work data.

Source: own calculations using PALMS data, weighted using sampling weight.

Figure 8 provides a detailed decomposition of the compositional and wage structure effects on wage growth for three education categories, with less than high school education as the base group. Changes in the composition of education amongst the employed has resulted in positive wage growth across the distribution in Panel A. The increase in returns to high school due to compositional changes relative to less than high school are large and increase across the distribution before turning down at about the 70th percentile. This large compositional effect fits in with the swelling of the ranks of high school graduates between 2000–2002 and 2013–2015 observed in Figure 4. The share of high school-educated employees increased substantially (by approximately 10 percentage points). The smallest compositional effect comes from the change in share of the degree educated compared with those with less than high school—and like diploma/certificate education, degree education increases almost monotonically over the whole distribution. Compositionally, the gains from higher education have benefited those at the top end of the distribution the most.

Figure 8: Detailed decomposition of the compositional and wage structure effects of education level



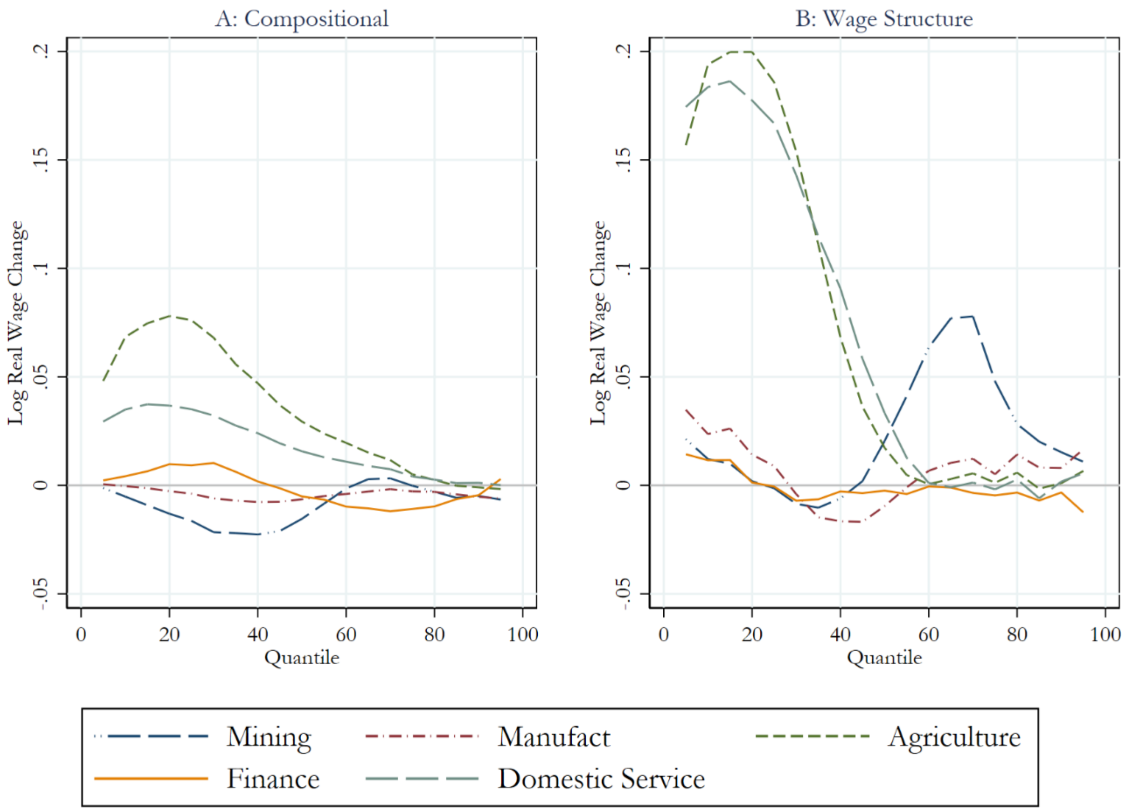
Note: sample consists of all employees of working age with non-missing wage and hours of work data.

Source: own calculations using PALMS data, weighted using sampling weights.

Examining the wage structure effect of education in Panel B, the returns to education levels are inverted in their ranking compared with the compositional effects in Panel A. There was upward pressure on wages as the number of high school graduates swelled and employees became more educated in general; however, this was undermined by negative returns to high school education across the distribution. The degree-educated are the only group to enjoy positive structural returns to their qualification. This wage structure is distinctly U-shaped, with the degree-educated in the middle of the distribution experiencing change in returns from their education that is close to zero. The shape of the change in returns to the degree-educated in particular reflects the overall shape in Figure 7, with the bottom seeing growth, the middle stagnating, and the top growing the most. This result—the collapse of returns to high school in favour of tertiary education, even though the supply of both groups increased—is consistent with what happened in the United States (Acemoglu and Autor 2011). There is an additional nuance in the South African case: it is specifically the university-educated who have benefited, since tertiary education in the form of diplomas/certificates also suffered a negative change in returns. This point emphasizes the deeper inequality in the South African labour market and how this is realized through education differentials in particular.

We now move to the sector effects (Figure 9), all relative to the transport sector as reference group. Five of the most pertinent sectors are presented in this figure and the rest are reported in Appendix Figure A4. There are important compositional and wage structure effects, although the wage structure effects dominate. The compositional effect reflects the change in the distribution of wages between the two periods that is due to changes in the distribution of workers across sectors. In Panel A, we observe a positive compositional effect in the domestic services and agricultural sectors at the bottom end of the distribution. This may be reflective of the contraction in the employment shares of both these sectors. Compositional effects in the mining sector, though, were opposite over the same portion of the distribution, whilst compositional effects on wage growth in the manufacturing sector were little different from zero.

Figure 9: Detailed decomposition of the compositional and wage structure effects for selected sectors, 2015–2001



Notes: sample consists of all employees of working age with non-missing wage and hours of work data; base category is the transport sector. Sectors not shown here are reported in the Appendix.

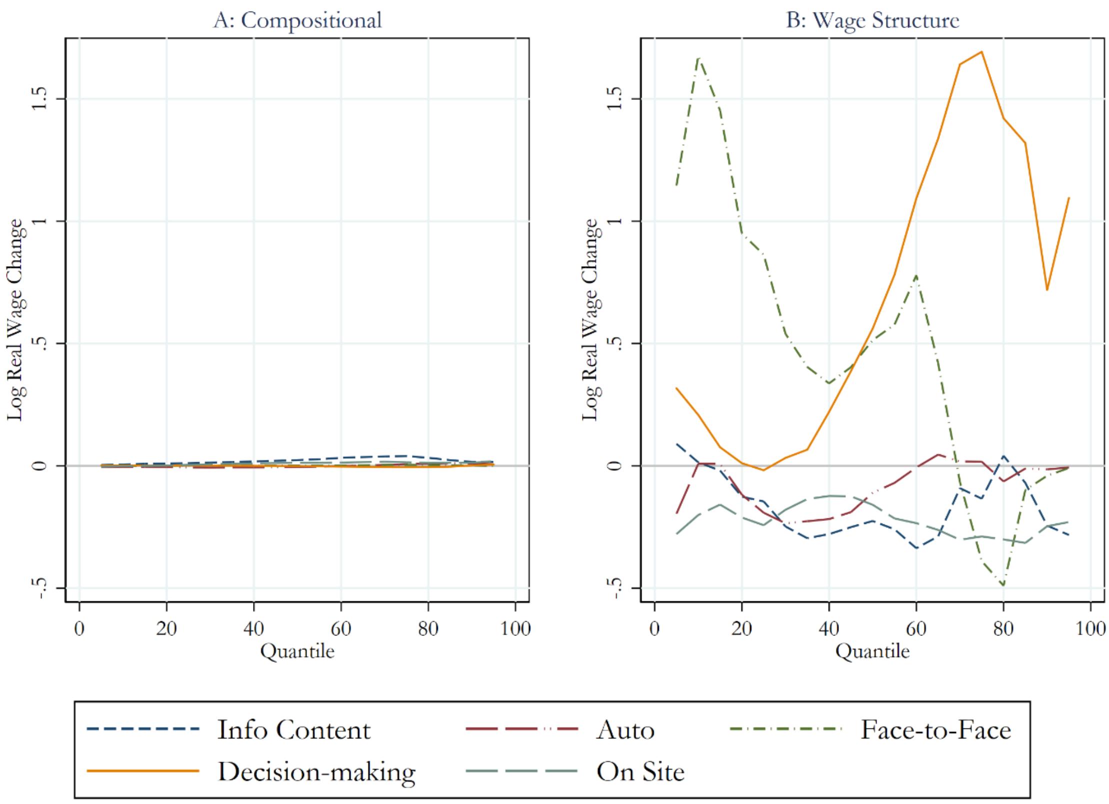
Source: own calculations using PALMS data, weighted using sampling weights.

Structurally, the introduction of minimum wages in the domestic services and agricultural sectors clearly inflated wage growth at the bottom end of the distribution. This aligns with positive wage growth at the bottom end of the total effect, as shown in Figure 7. Although the mining sector itself is clearly in decline (see Figure 2 and related discussion), working in this sector was associated with positive wage change for the upper half of the distribution. Some of these increases could be explained by widespread industrial action by mineworkers from about 2010, in which they advocated for higher wages (Department of Labour 2010). Strike action brought extraction to a standstill in 2014, particularly in the platinum belt, with the longest wage strike in South African history (Department of Labour 2014). Structural returns in both the manufacturing sector (Figure 9) and CSP services sector (Figure A4) display a quasi U-shape, both dipping into negative change in returns in the middle of the distribution. If we look across the distribution, returns increased in all sectors at the bottom end, whilst a reduction in the returns to manufacturing and CSP services explains the weaker growth in the middle. The surge in returns at the top end for those working in CSP services is likely to be closely related to the growth in public sector wages over the period.

This sectoral decomposition overall provides little insight into the increase in wages at the top end, and it is clear that the financial services sector is not what is driving growth at the top despite the growth in employment in this sector over the period.

Figure 10 plots the composition and wage structure effects of the five task content variables. The wage structure effects are far more substantial than the compositional ones. Evaluating panel B, the only task types to contribute to positive returns across the distribution are decision-making and face-to-face work. The change in returns to face-to-face tasks decreases overall across the distribution, while the change in returns to analytic tasks increases, effectively leaving the middle least rewarded. Occupations with the highest decision-making scores are professionals and managers, who are mostly clustered at the top end of the distribution. The premium on decision-making could be a consequence of complementarity with the increasing use of technology, difficulty in offshoring, and the sizeable growth experienced by the sectors requiring these skills over the period (e.g. business and finance; see Figure 2).

Figure 10: Detailed decomposition of the compositional and wage structure effects of task scores, 2015–2001



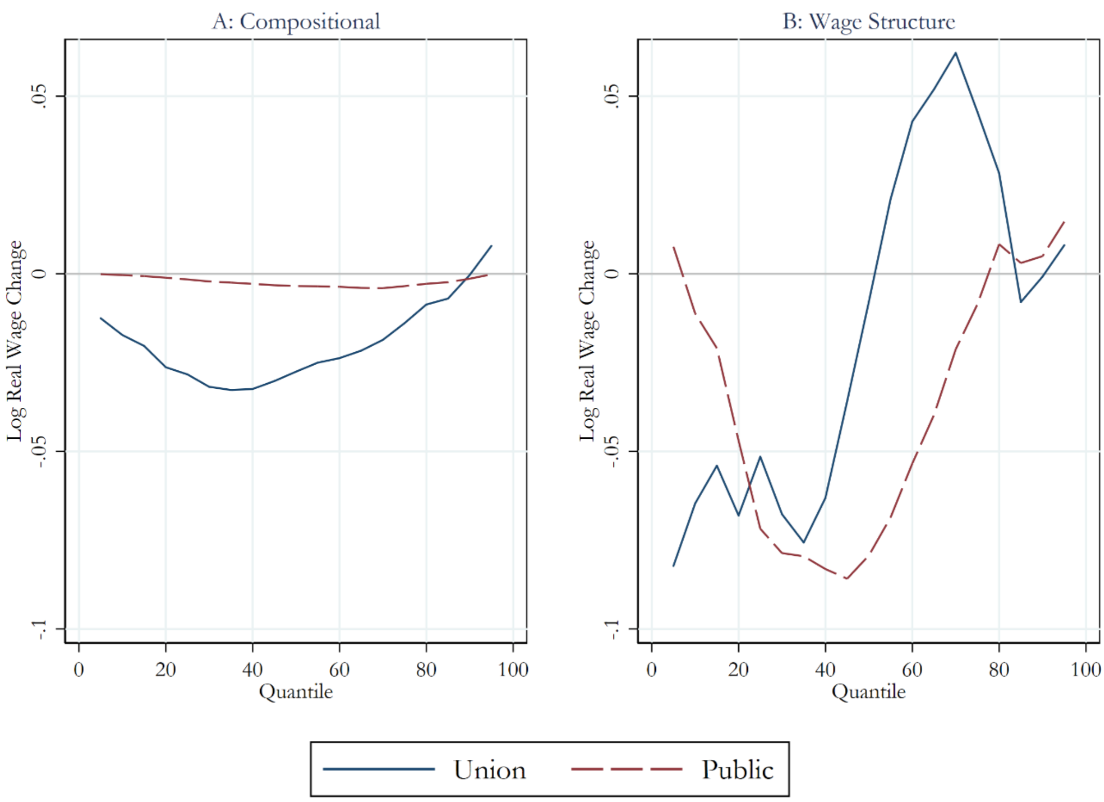
Note: sample consists of all employed adults of working age with non-missing wage and hours of work data

Source: own calculations using PALMS data, weighted using sampling weights.

Firpo et al. (2011) argue that on-site and face-to-face task content is difficult to offshore and therefore should have a protective effect on wages. Figure 10 indicates that growth at the bottom end can be explained by an increase in the returns to face-to-face work—although this variable must be interpreted with caution given the high standard errors flagged earlier. Along with automated and ICT task content, on-site task content generally experiences a decline in returns. The returns to automated task types are U-shaped, with those in the middle of the distribution experiencing negative returns. The descriptive section shows that the middle of the distribution is typified by high levels of on-site and routine work, meaning that negative change in the wage structure will explain poor wage growth for these individuals. On the other hand, routine work is expected to be undermined by technology; indeed, returns are eroded especially in the middle and lower portions of the distribution. The RIF-regression showed that ICT task content was most important for explaining wages in the 'top of the middle' of the distribution, and this is precisely where returns have declined.

We now turn to the last of our four explanations: institutions. Figure 11 plots a detailed decomposition of the compositional and wage structure effects for union membership and public sector employment. The compositional effect of union membership follows a U-shape that is almost exclusively negative. Changes in the composition of union membership contributed negatively to wages for most portions of the distribution, but were most pronounced for those in the middle. This reflects the pattern of de-unionization in the middle of the distribution during this period. The union wage structure effect, on the other hand, is deeply negative until just before the 60th percentile, whereafter it is strongly positive before dipping below zero again at about the 85th percentile. This means that, although some unionized workers have seen their returns increase, there are substantially fewer individuals reaping these rewards. From this analysis, it appears that positive returns to being a union member are becoming localized in the upper half of the distribution. A similar conclusion can be drawn about public sector employment. Returns and the change in returns appear to have remained stable at the top end, but have deteriorated below the 80th percentile. As union membership and public sector employment are usually tools for protecting the wages of low-skilled workers, these institutional trends are particularly concerning.

Figure 11: Detailed decomposition of the compositional and wage structure effects of union membership and public sector employment, 2015–2001



Note: sample consists of all employed adults of working age with non-missing wage and hours of work data.

Source: own calculations using PALMS data, weighted using sampling weights.

To summarize the effects of these competing and complementary explanations, inequality-decreasing wage growth at the bottom of the wage distribution can primarily be attributed to the expansion and increases of minimum wages over the period. The share of unionized and public sector workers increased in the bottom third, but this change does not appear to be what is driving wage growth; if anything, it is undermining it. Workers did become more educated at the bottom end, which was reflected in a positive compositional effect, but this was dampened by a negative wage structure effect. The growth of low-paid service sector jobs, some of which are minimum-wage protected, may have contributed to positive wage growth at the bottom. In addition, jobs at the bottom end of the distribution increasingly required face-to-face contact, making them more difficult to offshore.

The muted wage growth in the middle of the distribution was also driven by a combination of factors. The major compositional effect was the swelling of the ranks of the high school educated compared with the less than high school educated. The result was that many more similarly educated people were competing for jobs that were easy to offshore and substitute with technology. At the same time, the sectors employing large numbers of individuals in the middle of the distribution—mining and manufacturing—were collapsing. Work susceptible to automation and replacement by technology were common in this portion of the distribution. Although it is clear that workers in the middle are vulnerable to wage erosion due to the effects just described, they are the least protected by labour market institutions. Unguarded by minimum wages, these workers are left to weather the effects of technology, sectoral adjustment, and evolving education composition on their own. De-unionization and weak returns from both union membership and public sector employment serve to undermine wage growth in the middle even further.

Finally, inequality-increasing wage growth at the top end of the distribution has been reinforced by tasks, sectoral make-up, institutions, and education. Only a small portion of the employed are highly educated, and returns to university degrees in particular have increased over the period. These positive returns are likely a consequence of increasing returns to analytic and decision-making tasks and most economic growth being in sectors requiring this type of work from highly-skilled workers, such as finance and business. Labour market institutions have further secured advantage at the top end, where returns to unionization and public sector employment in particular have increased.

6 Conclusion

The analysis in this paper, to our knowledge, constitutes the first investigation of the drivers of a missing middle in wage growth in an emerging economy. We examined the contribution of four major explanations for wage polarization in South Africa: skills-biased technical change; changing sectoral composition influencing aggregate labour demand; the effect of technology on tasks; and the role of institutions. The first three frameworks are interpreted as competing and complementary ideas about the effects of technology, globalization, and trade on the labour market (i.e. structural change), which are contrasted with the impact of the fourth framework, institutions. All four frameworks are important for different portions of the wage distribution. Using a methodology similar to that of Firpo et al. (2011), we run a detailed decomposition to quantify the contribution of each of these factors to the pattern of wage growth in South Africa. Both wage structure and compositional effects contributed to an overall U-shaped change in wages, but the wage structure effects were overwhelmingly more important.

Structural effects have altered the South African economy in important ways. Since the end of apartheid, South Africa has evolved from an economy based on agriculture, manufacturing, and mining to one that is finance- and services-led. This change has had important implications for jobs, since it favours the highly skilled to the detriment of the semi- and low-skilled. The collapse of manufacturing, mining, and agriculture coincided with the offshoring and technology-substitution of routine or easily automated work, typical of these sectors. Analytic, decision-making, and creative tasks such as those required by highly skilled finance and business sector workers saw increasing returns to wages. Furthermore, there has been an increase in 'lousy' low-paid and low-skilled service sector jobs in the bottom third of the distribution. This, coupled with the implementation of minimum wages at the bottom end, has contributed to wage growth at the bottom relative to the middle.

At the same time that the economy was changing in these important ways, the education shares of the employed were also shifting. The employed became more educated in general over the period 2000–2002 to 2013–2015—a change mainly accounted for by an increase in high school graduates compared with those with less than high school education. The diploma/certificate and degree qualified also expanded, but at a much slower rate. Wages in 2013–2015 were positively affected by the employed being more educated than in 2000–2002. However, this benefit was undermined by wide-ranging changes to the way in which education was remunerated as a consequence of the structural changes just described. The labour market was confronted with a glut of high school graduates who were qualified to do medium-skilled routine manual or routine cognitive work—just the types of tasks that were easily offshored or substituted by technology. It was the university educated (only 7.37 per cent of employees in 2013–2015) who were able to meet the growing demand for analytic work that aligned well with growth in the finance and business sectors. The advantage created by a more educated workforce was undermined by an elitist wage structure partly formed by the structural change wrought on the economy by technology, globalization, and trade.

Labour market institutions that could and indeed should have guarded the vulnerable against the structural effects just described have largely failed to do so. Positive wage returns to union membership and public sector employment have accrued mainly to the upper middle and top third, and de-unionization has been strong in the middle of the distribution. However, the broad roll-out of minimum wages has been critical to sheltering the bottom third of the wage distribution. Without the set of minimum wages introduced during the decade of the 2000s, the bottom of the wage distribution would almost certainly look much like the middle, if not worse. Unfortunately, the inequality-decreasing impact of minimum wages was too small to compensate for the astonishing concentration of advantage at the top end as a result of both structural change and the role played by labour market institutions. Aggregate inequality has thus remained high and even increased slightly in post-apartheid South Africa, cementing the country's position as one of the most unequal societies in the world.

With these conclusions in mind, South Africa's recent strengthening of minimum wage laws could tentatively be welcomed. In a rapidly changing world of work, however, it is unclear whether traditional wage protection of this kind is an answer to labour market vulnerability. Further research is needed to understand the drivers of inequality at different parts of the wage distribution in the developing world, which is already home to most of the world's most precarious jobs. This paper has demonstrated the complexity behind wage polarization and inequality in an emerging market. A combination of global forces related to advancing technology and increasing globalization has interacted with local trends in the schooling sector and the set-up of labour market institutions to exacerbate earnings inequality in South Africa. It is only by fully understanding these dynamics that South Africa and other emerging markets can begin to prepare themselves for the fourth industrial revolution.

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Appendix

Table A1: Average task content scores by occupations in 2001 and 2015

	2000–2002							2013–2015							Change 2015–2001	
	ICT	Auto	On site	Face-to-face	Decision-making	N	%	ICT	Auto	On site	Face-to-face	Decision-making	N	%	N	%
Managers	0.82	0.44	0.53	0.97	0.95	2,376.09	4.18	0.83	0.45	0.52	0.96	0.94	8,319.50	6.09	5,943.41	1.91
Professionals	0.84	0.39	0.44	0.94	0.82	2,626.57	4.62	0.87	0.42	0.42	0.94	0.82	7,913.88	5.79	5,287.32	1.17
Technicians	0.78	0.46	0.52	0.94	0.77	6,533.18	11.48	0.78	0.46	0.52	0.94	0.78	14,879.99	10.89	8,346.81	- 0.59
Clerks	0.77	0.72	0.44	0.89	0.77	6,511.03	11.44	0.80	0.69	0.44	0.89	0.77	16,840.69	12.33	10,329.67	0.89
Service	0.70	0.52	0.63	0.91	0.82	6,420.46	11.28	0.70	0.52	0.63	0.91	0.82	20,353.69	14.90	13,933.23	3.62
Skilled agric. workers	0.62	0.57	0.80	0.93	0.79	1,855.50	3.26	0.63	0.62	0.85	0.91	0.82	488.85	0.36	-,1,366.65	- 2.90
Craft workers	0.61	0.62	0.88	0.90	0.84	7,261.95	12.76	0.61	0.61	0.88	0.90	0.84	14,470.69	10.59	7,208.74	- 2.17
Operators/assemblers	0.62	0.75	0.86	0.86	0.78	7,085.08	12.45	0.63	0.73	0.85	0.86	0.77	12,531.31	9.17	5,446.23	- 3.28
Elementary workers	0.56	0.64	0.75	0.88	0.74	10,404.84	18.28	0.56	0.65	0.77	0.88	0.75	30,244.14	22.14	19,839.30	3.86
Domestic workers	0.56	0.54	0.63	0.87	0.78	5,681.34	9.98	0.56	0.54	0.63	0.87	0.78	10,549.54	7.72	4,868.20	- 2.26
						56,912.18	100.00						136,594.46	100.00	79,682.28	0.00

Note: sample consists of all employed adults of working age with non-missing wage and hours of work data.

Source: own calculations using PALMS data, weighted using sampling weights.

Table A2: Average task content scores by sector in 2001 and 2015

	2001							2015							Change 2015–2001	
	ICT	Auto	On site	Face-to-face	Decision-making	N	%	ICT	Auto	On site	Face-to-face	Decision-making	N	%	N	%
Agriculture	0.54	0.62	0.78	0.88	0.75	5,406.30	9.50	0.54	0.61	0.76	0.88	0.74	7,826.81	5.73	2,420.51	-3.77
Mining	0.64	0.71	0.87	0.91	0.84	3,416.92	6.00	0.65	0.68	0.85	0.91	0.83	4,546.33	3.33	1,129.41	-2.67
Manufacturing	0.66	0.69	0.74	0.88	0.78	8,840.05	15.53	0.67	0.69	0.73	0.89	0.78	16,160.66	11.83	7,320.61	-3.70
Utilities	0.70	0.60	0.72	0.92	0.83	567.36	1.00	0.74	0.59	0.71	0.92	0.83	1,323.11	0.97	755.75	-0.03
Construction	0.60	0.61	0.85	0.91	0.86	3,054.54	5.37	0.61	0.62	0.84	0.92	0.85	10,021.14	7.34	6,966.59	1.97
Trade	0.68	0.61	0.65	0.90	0.79	8,533.84	14.99	0.68	0.62	0.63	0.90	0.79	23,061.19	16.88	14,527.35	1.89
Transport	0.70	0.63	0.69	0.89	0.80	3,012.89	5.29	0.70	0.62	0.69	0.89	0.79	7,918.00	5.8	4,905.11	0.51
Finance	0.79	0.58	0.53	0.91	0.81	5,303.50	9.32	0.78	0.56	0.56	0.91	0.82	18,798.16	13.76	13,494.66	4.44
CSP services	0.73	0.49	0.56	0.92	0.79	11,622.33	20.42	0.73	0.51	0.57	0.92	0.79	33,753.78	24.71	22,131.45	4.29
Domestic services	0.57	0.54	0.66	0.88	0.78	6,867.97	12.07	0.55	0.55	0.65	0.87	0.77	13,149.73	9.63	6,281.77	-2.44
						56,912.18	100.00						136,594.50	100.00	79,682.28	0.00

Note: sample consists of all employed adults of working age with non-missing wage and hours of work data.

Source: own calculations using PALMS data weighted using ceweight2.

Table A3: Earnings and number of jobs by education level and labour market institution

	Average hourly earnings in rands			Count of jobs in ’000s		
	2000–2002	**2013–2015**	**Change**	**2000–2002**	**2013–2015**	**Change***
Education level						
Less than high school	23.13	25.55	2.43	32,547.50	56,418.29	23,870.79
			10.49%	67.79%	48.08%	-19.71pp
High school	45.30	51.28	5.98	11,451.84	36,624.17	25,172.33
			13.20%	20.11%	31.21%	11.10pp
Diploma/Certificate	86.97	95.82	8.85	5,085.69	15,652.40	10,566.72
			10.17%	7.85%	13.34%	5.49pp
Degree	121.40	181.66	60.26	2,968.76	8,645.78	5,677.02
			49.64%	4.25%	7.37%	3.12pp
Institutions						
Union members	52.87	69.43	16.56	17,783.62	32,719.40	14,935.78
			31.33%	31.46%	28.28%	-3.18pp
Non-union members	32.91	48.13	15.22	33,125.04	82,964.29	49,839.25
			46.26%	68.54%	71.72%	3.18pp
Public sector	66.40	76.84	10.44	11,399.12	24,039.44	12,640.32
			15.72%	18.51%	20.31%	1.80pp
Private sector	32.30	48.59	16.29	41,020.50	94,337.86	53,317.36
			50.43%	81.49%	79.69%	-1.80pp
Total	39.75	54.33	14.58%	56,912.18	136,594.46	79,682.28
				100.00%	100.00%	

Notes: sample consists of all adult employees of working age and with non-missing hours and earnings data; earnings are in real 2016 rands; percentages reported in parentheses; *the change here represents the marginal difference in the percentage shares for 2000–2002 and 2013–2015.

Source: own calculations using PALMS data, adjusted using the bracket weight.

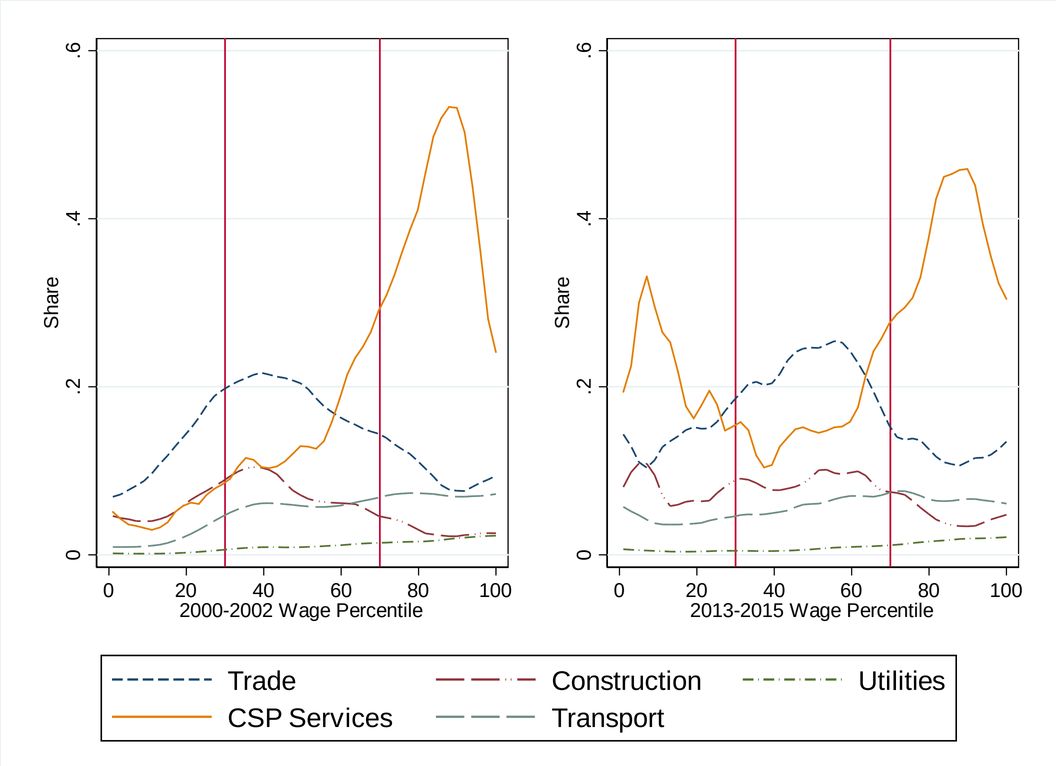
Table A4: RIF-regression: Unconditional quantile regression coefficients on log of hourly wages

Years:	**2001**			**2015**		
Quantiles:	**10**	**50**	**90**	**10**	**50**	**90**
Female	-0.165***	-0.169***	-0.203***	-0.025*	-0.208***	-0.244***
	[0.017]	[0.012]	[0.023]	[0.013]	[0.008]	[0.013]
Age	0.080***	0.044***	0.058***	0.024***	0.019***	0.014***
	[0.005]	[0.003]	[0.005]	[0.004]	[0.002]	[0.003]
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]
Race: Coloured	0.622***	0.406***	0.181***	0.024	0.159***	0.149***
	[0.019]	[0.014]	[0.020]	[0.017]	[0.010]	[0.013]
Race: White	0.298***	0.813***	1.084***	0.066***	0.460***	0.787***
	[0.012]	[0.016]	[0.047]	[0.018]	[0.013]	[0.029]
Race: Indian/Asian	0.329***	0.679***	0.186***	-0.011	0.265***	0.044
	[0.016]	[0.025]	[0.055]	[0.033]	[0.023]	[0.041]
Married/Cohabitating	-0.038**	0.100***	0.074***	0.077***	0.118***	0.068***
	[0.016]	[0.011]	[0.018]	[0.013]	[0.007]	[0.011]
Union member	0.268***	0.428***	0.005	0.079***	0.405***	0.003
	[0.012]	[0.014]	[0.022]	[0.014]	[0.009]	[0.014]
Public sector employment	0.044**	0.434***	0.172***	-0.011	0.047***	0.198***
	[0.018]	[0.020]	[0.038]	[0.021]	[0.012]	[0.021]
Edu: high school	0.268***	0.460***	0.286***	0.161***	0.334***	0.124***
	[0.017]	[0.016]	[0.024]	[0.015]	[0.010]	[0.011]
Edu: Diploma/Certificate	0.320***	0.713***	1.084***	0.288***	0.635***	0.787***
	[0.019]	[0.021]	[0.057]	[0.021]	[0.013]	[0.025]
Edu: Degree	0.259***	0.654***	2.225***	0.439***	0.812***	1.951***
	[0.020]	[0.025]	[0.075]	[0.024]	[0.015]	[0.041]
Task: ICT	0.308***	1.251***	0.854***	0.330***	0.908***	0.478***
	[0.080]	[0.086]	[0.157]	[0.081]	[0.053]	[0.085]
Task: Auto	0.383***	0.394***	-0.872***	0.397***	0.209***	-0.895***
	[0.064]	[0.055]	[0.093]	[0.065]	[0.038]	[0.059]
Task: Face-to-face	-0.293	1.141***	1.090**	1.572***	1.712***	1.060***
	[0.266]	[0.223]	[0.334]	[0.270]	[0.154]	[0.204]
Task: On-site	0.045	-0.465***	-0.475***	-0.250***	-0.696***	-0.836***
	[0.049]	[0.049]	[0.096]	[0.055]	[0.035]	[0.057]
Task: Decision-making	0.503***	-0.333***	0.367	0.766***	0.376***	1.278***
	[0.101]	[0.091]	[0.224]	[0.097]	[0.063]	[0.129]
Sector: Agriculture	0.110***	0.328***	0.104*	0.264***	0.587***	0.298***
	[0.027]	[0.033]	[0.055]	[0.041]	[0.026]	[0.044]
Sector: Mining	0.013	0.220***	0.180***	0.172***	0.155***	0.235***
	[0.024]	[0.028]	[0.050]	[0.032]	[0.019]	[0.031]
Sector: Manufacturing	0.014	0.093*	-0.008	0.121**	0.170***	0.205**
	[0.060]	[0.052]	[0.108]	[0.061]	[0.038]	[0.083]
Sector: Utilities	-0.064*	-0.066*	-0.032	0.279***	0.109***	-0.009
	[0.036]	[0.034]	[0.057]	[0.036]	[0.022]	[0.033]
Sector: Construction	-0.078**	-0.147***	-0.184***	0.099**	-0.085***	-0.026
	[0.027]	[0.028]	[0.048]	[0.031]	[0.019]	[0.030]
Sector: Trade	-1.631***	-0.701***	0.022	0.197***	-0.538***	0.032
	[0.042]	[0.027]	[0.046]	[0.038]	[0.020]	[0.029]
Sector: CSP services	0.025	-0.014	-0.320***	0.059*	-0.069***	-0.149***
	[0.022]	[0.027]	[0.055]	[0.031]	[0.019]	[0.032]
Sector: Finance	0.079**	-0.095**	-0.085	0.216***	-0.124***	-0.124***
	[0.026]	[0.031]	[0.063]	[0.030]	[0.019]	[0.032]
Sector: Domestic service	-1.309***	-0.587***	-0.044	0.087**	-0.334***	-0.031
	[0.042]	[0.028]	[0.048]	[0.036]	[0.020]	[0.028]
r2	0.200	0.464	0.315	0.018	0.275	0.226
N	82,044.000	82,044.000	82,044.000	158,690.000	158,690.000	158,690.000

Notes: standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.001; standard errors adjusted using sample weights; base category for the race dummies is African; base category for education dummies is having less than high school; base category for the sector dummies is the utilities sector.

Source: PALMS 2001 and 2015.

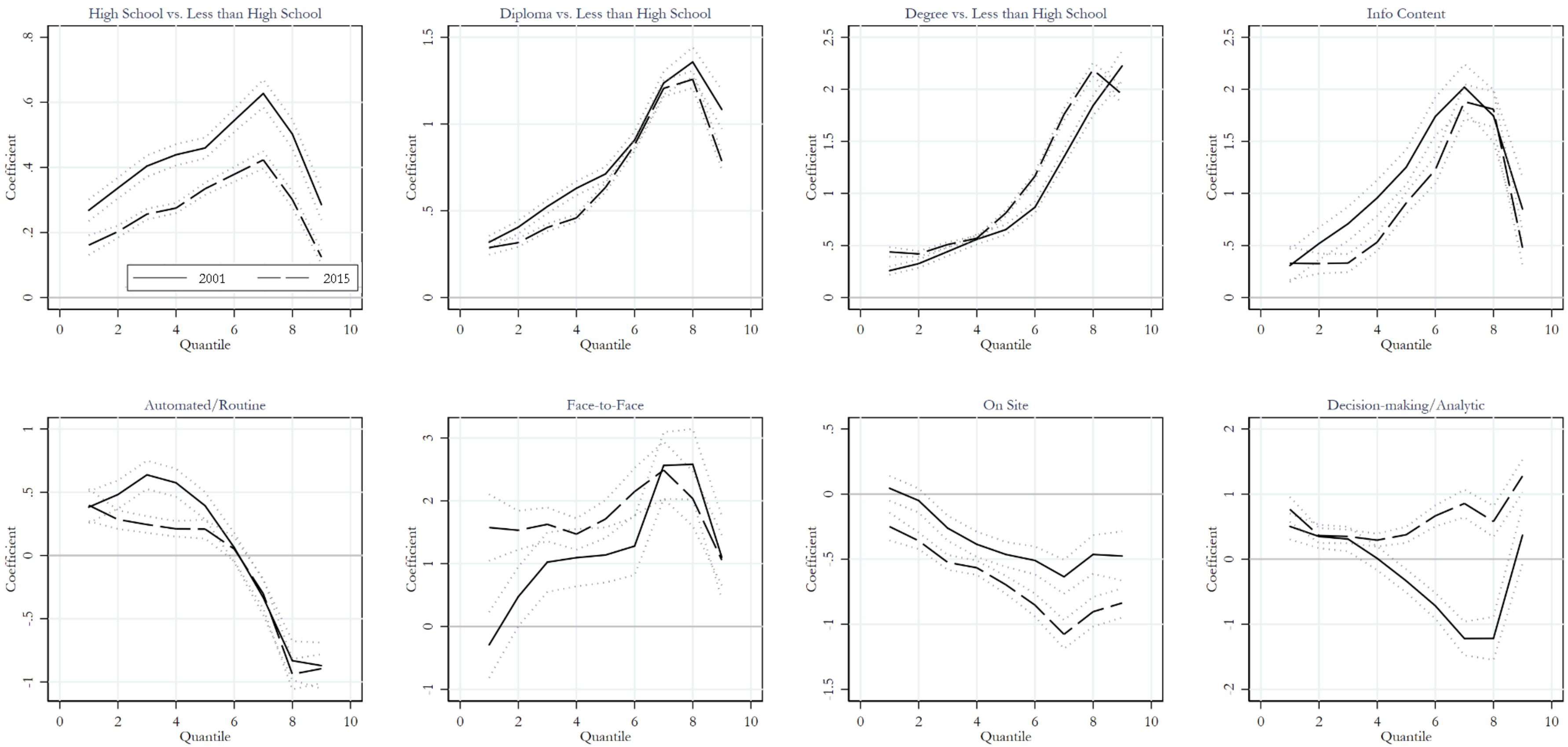
Figure A1: Local polynomial regression: Share of employed in remaining sectors not reported in text per wage percentile, 2000–2002 and 2013–2015



Notes: sample consists of all employed adults of working age with non-missing wage and hours of work data; reference lines on the x-axis are at the 30th and 70th percentiles; density is interpreted as the proportion of jobs in that wage percentile classified as having the relevant task content.

Source: own calculations using PALMS data, adjusted using sampling weights.

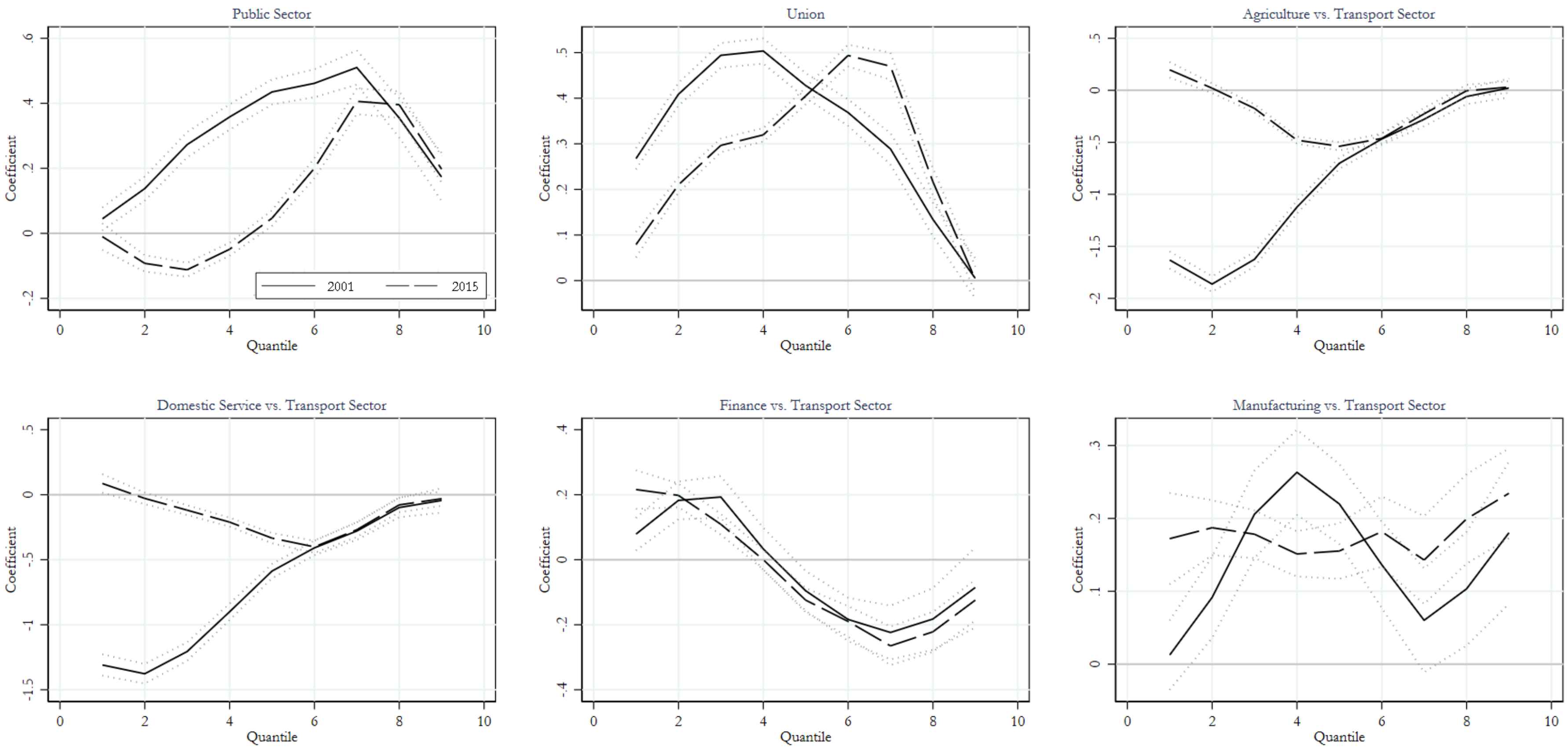
Figure A2: RIF-regression coefficients for education dummies and task content, with 95 per cent confidence intervals



Notes: sample consists of all employed adults of working age with non-missing wage and hours of work data; 95 per cent confidence intervals for respective years graphed with dotted lines.

Source: own calculations using PALMS data, weighted using sampling weights.

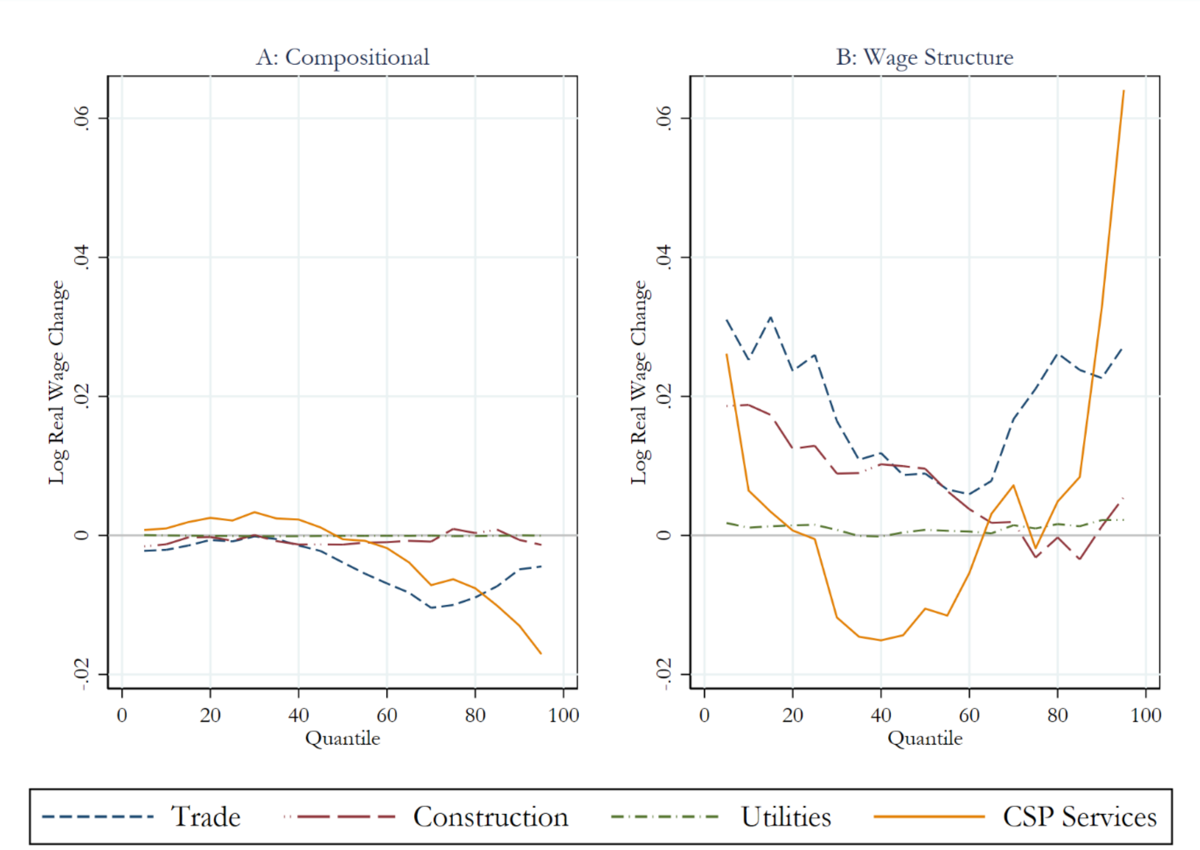
Figure A3: RIF-regression coefficients for selected sector dummies and labour market institutions, with 95 per cent confidence intervals



Notes: sample consists of all employed adults of working age with non-missing wage and hours of work data; 95 per cent confidence intervals for respective years graphed with dotted lines.

Source: own calculations using PALMS data, weighted using sampling weights.

Figure A4: Detailed decomposition of the compositional and wage structure effects for selected sectors not reported in text, 2015–2001



Notes: sample consists of all employed adults of working age with non-missing wage and hours of work data; base category is the utilities sector.

Source: own calculations using PALMS data, weighted using sampling weights.