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Routine Biased Technological Change in a Middle-income Country: the Case of South Africa

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1 Introduction

After several decades of decreasing wage inequality, the late 1970s saw a reversal of this trend as wage gaps between workers of different skill and occupation classes started widening in several countries (Autor et al. 2005, Katz & Autor 1999, Autor et al. 1998). Different hypotheses have been formulated to explain this trend, including rising international trade and offshoring (Wood 1998), a slowdown in the growing supply of better educated workers (Katz & Murphy 1992), changing wage-setting norms and institutions (DiNardo et al. 1996), and skill-biased technical change (Katz & Autor 1999, Bound & Johnson 1992).[1,2] The skill-biased technical change (SBTC) hypothesis, which posits that technological progress favours more skilled workers, is supported by evidence that skilled workers are complements to advances in ICT (Autor & Handel 2013, Górka et al. 2017) and that firms that adopted more technologies and invested more in capital also tended to hire more highly skilled workers (Fernandez 2001, Bartel & Lichtenberg 1987, Greenwood & Yorukoglu 1997).[3,4]

However, this hypothesis failed to predict a more recent phenomenon observed across many developed country labour markets: shrinking employment shares and slower wage growth for middle-skilled occupations relative to high- and low-skilled occupations (Autor et al. 2003, Goos & Manning 2007). This shortcoming led to the development of the theory of routine-biased technical change (RBTC) (Autor et al. 2003).[5] This theory views the production process as consisting of a number of different tasks, which are often usefully categorised into three types (Autor & Handel 2013): *man-*

[1]The same phenomenon is also referred to as skill-biased *technological* change (see for example Goos et al. (2014).

[2]For surveys describing the foundation for skill-biased technical change in economic models see Acemoglu (2002) and Hornstein et al. (2005).

[3]For example, Krusell et al. (2000) discusses suggestive evidence that rapid increases in the capital stock beginning in the 1960s, together with its strong complementarity to skilled labour, contributed to the observed increase in relative demand for skills.

[4]For a clear and comprehensive early discussion of capital-skill complementarity, see Griliches (1969, 1970).

[5]Noteworthy revisions to the model have since been made by Goos & Manning (2007), and later by Acemoglu & Autor (2011).

ual tasks, typically requiring physical exertion and direct personal interaction; *abstract tasks*, which require soft skills, intuition, reasoning or some form of higher-level cognitive exertion; and *routine tasks*[6]. Manual tasks are typically performed by low-skilled workers, routine tasks by middle-skilled workers, and abstract tasks by high-skilled workers. RBTC postulates that technological progress allows the automation of a growing share of routine tasks, which incentiveses firms to replace the middle-skilled workers who perform such "codifiable" tasks with computer-based systems. In contrast, low-skilled and high-skilled workers perform a larger share of non-routine manual or cognitive tasks, both of which are harder to automate, making these workers less dispensable and raising the relative demand for their services. Several studies have confirmed that the shrinking share of middle-skilled occupations corresponds with a reduced demand for occupations with high routine task intensity (RTI) in developed economies, including the US (Autor & Handel 2013, Autor & Dorn 2013, Autor et al. 2006), UK (Goos & Manning 2007), and parts of Europe (Spitz-Oener 2006, Matthes et al. 2014, Fernández-Macías & Bisello 2016).

A few recent studies have also looked for evidence of RBTC in developing countries. These studies have confirmed that RBTC may also affect labour markets in middle and low-income countries (World Trade Organization 2017), despite the fact that production processes in these countries tend to be less exposed to routinisation than in developed economies (Das & Hilgenstock 2018). Kim et al. (2019) find that the occupational distribution in South Korea was characterised by a decline in middle-skilled occupations accompanied by increases in low- and high-skilled occupations, as predicted by RBTC.[7] Similar findings have also been reported for Brazil between 1996 and 2006 (Almeida et al. 2017). Both studies used RTI index measures linked to US-based occupational schemes to confirm that occupations in routine-intensive occupations were

[6]Initial work on the tasks framework by Autor et al. (2003) presented five categories of occupations, and it is only in more recent work that that has been scaled down to three, as in Goos et al. (2014), Acemoglu & Autor (2011), and Autor & Handel (2013).

[7]Note that even though South Korea gave up its 'developing' country status towards the end of 2019, it was still classified as a developing country for the total number of years included in the study, 1993 to 2015.

more vulnerable to job losses.[8] More broadly, the evidence for RBTC in developing countries is mixed (Maggie Fu et al. 2020, Longmuir et al. 2020). In fact, in some developing countries the adoption of technologies appear to disproportionately benefit those with middle to advanced levels of education at the expense of those with less education.

Many studies in this literature rely on occupational task requirements from the US labor market — often the Dictionary of Occupational Titles (DOT), or its successor the Occupational Information Network (O*NET) — to calculate RTI measures for other countries. For example, US-based RTI measures were used to test for the existence of RBTC in 16 European countries (Goos & Manning 2007, Fonseca et al. 2018, Anghel et al. 2014).[9] This measure may provide a reasonable approximation of the RTI of jobs in countries with labour markets and production processes similar to the US. However, it is presumably less appropriate when investigating the effects of RBTC in developing countries with very different economic structures, factor costs and labour market institutions. This approach has been critiqued by Raquel & Biagi (2018) who warn that using RTI measures from dissimilar countries can lead to measurement error and misleading conclusions. In this study, therefore, we use RTI measures based on developing country data to study the South African labor market. We compare results for two different developing-country based measures to those based on the US DOT.

South Africa presents an interesting case study to investigate the effects of RBTC in a middle-income country for several reasons. First, South Africa experienced the same labour market trends between 1970 and 1994 that have been ascribed to SBTC in developed country labour markets (Bhorat & Hodge 1999). It is therefore natural to investigate whether we can also find evidence of RBTC in the South African labour market since the 1990s. Secondly, South Africa remains one of the most un-

[8] Additional evidence is also presented for Colombia and Mexico (Ariza & Bara 2020, Medina & Suárez 2010).

[9] Although DOT/O*NET is used by the majority of empirical studies in this literature, there are various other less-widely used occupation classification schemes as well. Examples would be the Princeton Data Improvement Initiative Survey (PDII) for the US (Autor & Handel 2013), the Programme for the International Assessment of Adult Competencies (PIAAC) (Marcolin et al. 2016) and the European Working Condition Survey (EWCS) (Fernández-Macías & Hurley 2017, Sebastian 2018).

equal countries in the world with a Gini coefficient of 0.65 as of 2014 (Hundenborn et al. 2016). Much of this inequality is due to wage differences between race groups, where black workers were historically disadvantaged by discriminatory policies enacted during the apartheid era, and continue to be disadvantaged by poorer access to high-quality schools and high-value social networks. These disadvantages may mean that black middle-skilled workers are less able to adapt to the adoption of new skill-biased technologies than their more privileged white counterparts. Thirdly, South Africa has a surplus of unskilled workers who experienced high unemployment and low wages, even before the advent of SBTC. Limited access to tertiary education also means that South Africa did not experience the same substantial increase in highly skilled workers that contributed to the shift from middle- to high-skilled occupations in some developed countries (Salvatori 2018). Fourthly, the South African labour market is also characterised by high unemployment, a sizeable informal sector, and wages that are influenced by trade unions and minimum wages, which differentiates it from the labour markets in developed countries, where most of the evidence for routine-biased technical change has been found.

No existing studies have explicitly examined the effect of RBTC on the South African labour market, although a hollowing-out of the skills distribution has been documented (Bhorat & Hodge 1999, Bhorat et al. 2014). Bhorat et al. (2014) also look at the presumed task composition of jobs — occupations are classified into one or more of five task categories[10] using the schema developed by Firpo et al. (2011) for the US — and show that jobs that consist of routine tasks have experienced a decline in wages over the 2001-12 period.

Against this backdrop, this study sets out to make the following contributions to the expanding literature on the effects of routine-biased technological change in developing countries. The first contribution is to analyse trends in wages and the occupational distribution in the South African labour market between 1997 to 2015, to see whether

[10] These categories are: information and communication technology (ICT), automation/routinisation, face-to-face, on-site, and decision-making/analytic.

there is any evidence that RBTC affected South African labour market outcomes. Secondly, we investigate whether a declining share of middle-skilled workers offset by the relative growth of low- or high-wage jobs, the informal sector, or unemployment, and whether this experience differs between workers of different population groups or genders. The third contribution is to gauge the robustness of the results to using different measures of routine task intensity. We compare the results from using US-based measures of RTI to those obtained from data on occupational tasks in developing countries recently collected by the World Bank. Finally, we also explore whether wage and employment trends that are consistent with RBTC may have been driven by other causes: specifically international trade or changes in labour supply.

The paper provides several interesting results. We observe the same hollowing out of the occupational distribution that has been ascribed to RBTC in developed country labour markets. However, South Africa experienced a larger increase in low-wage occupations and a smaller increase in high-wage occupations than is typically observed in developed countries. These occupational shifts are restricted to the private sector; public sector employment appears not to have responded to changes in the relative productivity of workers. Furthermore, direction of movement away from middle-skilled occupation is highly correlated to race and gender: the male, white and Indian population groups experience an increasing share of high-skilled occupations, whereas female and black workers experience an increasing share of low-skilled occupations. We find no indication that employment shifted from middle-skilled occupations into informal employment, unemployment or economic inactivity. Wage trends across occupations are also consistent with the predictions of RBTC. Unlike what has been observed in developed country labour markets, wages of low-skilled occupations have not increased very much, possibly due to the large supply of unemployed workers who can fill these jobs.

A decomposition of occupational shifts reveals that middle-skilled jobs are disappearing mostly due to within-industry changes in how production occurs, and that these tasks are increasingly performed by lower-skilled workers. However, unlike what has been observed elsewhere, there is no displacement of middle-skilled workers to high-skilled occupations within industries. Instead, the increasing share of high-skilled workers appears to be driven completely by between-industry shifts in which industries that have historically employed a large share of high-skilled workers (e.g. financial or social services) are expanding.

Regression analysis confirms that occupations with higher routine task intensity experienced slower wage growth and decreasing employment shares over this period. Although these results are relatively robust across different measures of RTI, we find that using a measure of RTI constructed from US data —- an approach that has been followed in several other developing countries — can produce highly attenuated regression coefficients or misleading conclusions. Finally, we also find that the observed wage and employment trends across occupations are more consistent with the RBTC than with explanations based on international trade or shifts in labour supply.

The remainder of this paper is organised as follows. Section 2 discusses the various data sources used in our analysis. Section 3 presents descriptive trends in South African labour market outcomes for the three skill groups between 1997 and 2015. Section 4 uses regression analysis to estimate the effect of occupational routine task intensity on wages and employment shares, and to explore the validity of alternative explanations for these trends. Finally, section 5 concludes.

2 Data Sources

2.1 Employment and wages

This study uses three sources of data. The first is the Post-Apartheid Labour Market Series (PALMS) created by DataFirst at the University of Cape Town (UCT). PALMS was created by harmonising nationally representative microdata from 61 household surveys conducted by Statistics South Africa (StatsSA) between 1995 and 2017 (Kerr et al. 2013). It consists of the October Household Surveys (OHS) (1994-1999), the bi-annual Labour Force Surveys (2000-2007) and the 2008 to 2017 Quarterly Labour Force Surveys. These surveys include individual responses to questions regarding wages, employment status, and industry and occupation of employment. Occupations are largely classified using the internationally recognised four-digit method prescribed by the United Nations' International Standard Classification of Occupations; the ISCO-88.[11] Although the PALMS data has been harmonised with respect to most labour market variables, the codes used to classify occupations are internally inconsistent and were therefore harmonised by us to ensure consistency across all surveys.

The sample used for the empirical analysis in this chapter is limited to employed individuals of working age (16 to 64) with monthly wage values that were greater than zero and non-missing. Total (or aggregate) employment is calculated from individual responses to questions pertaining to employment and their respective survey weights.[12] In addition, informal sector workers were omitted, based on evidence that sampling and questionnaire design inconsistencies makes it very difficult to compare informal employment across survey waves (Kingdon & Knight 2007, Altman 2008, Casale et al. 2005, Burger & Yu 2007). The implication of this omission is that our analysis is re-

[11] The ISCO was developed by the International Labour Office (ILO) in Geneva in 1957 and has had several iterations: ISCO-58, ISCO-68, ISCO-88, and the most recent 2007 version, the ISCO-08. The main reason for the different versions is to have a classification of occupations that takes into account developments in the world of work.

[12] PALMS provides cross-entropy weights which are more consistent over time than the sampling weights provided by Stats SA (Branson & Wittenberg 2014).

stricted to the effect of RBTC on the formal labour market, which, at 69.5 percent of total employment in 2015, remains the single largest source of employment in South Africa (StatsSA 2015).

2.2 Task content

The literature on RBTC is relatively young and continually expanding, so it is not surprising that some unresolved methodological issues remain.[13] One such an issue regards how to measure the routine task intensity of occupations. This issue arises partly from the fact that information on tasks is not commonly collected by representative surveys, which means that researchers face binding data limitations when choosing the best measure of routine task intensity (RTI). What researchers have typically done is to map the occupation variable codes to a database containing information on task content of occupations. An early example of this approach is Autor et al. (2003) who created a measure of RTI from task data obtained from the DOT and applied this measure to US labour market data.[14] Given the success of this approach, other researchers proceeded to use this same data on tasks to study the labour markets of countries other than the US. This is potentially problematic, especially when applying this measure in the context of a developing country.

In 2012, the World Bank launched an initiative called the Skills Towards Employability and Productivity (STEP) Measurement Program. The STEP survey is a first-of-its-kind attempt to collect and systematically measure information on job-relevant skills in developing countries. In addition to conceptually drawing inspiration from the very influential DOT, the STEP survey items are drawn from the survey of Skills, Technology, and Management Practices (STAMP) which is a two-wave nationally rep-

[13]For a more extensive discussion of these issues, see Raquel & Biagi (2018).

[14]One important feature of the DOT is that it divides job-relevant skills according to their level of involvement with "data, people, and things" which conveniently correspond to cognitive, interpersonal, and manual skills making it easier to categorise skills accordingly (Pierre et al. 2014). Further, note also that more recent work tends to opt for the O*NET, which is a successor to the DOT.

resentative survey of US wage and salary workers (Pierre et al. 2014). Items were then chosen and adapted to developing country contexts in various ways. For example, the survey design team made sure to include skills that are relevant to agriculture, which is an important economic activity in developing countries (Pierre et al. 2014). Between 2012 and 2017, STEP household surveys were conducted in 12 low- and middle-income countries (LICs and MICs).[15] The STEP survey samples are representative of the population of non-institutionalised adults 15 to 64 years of age living in private dwellings in urban areas. The household surveys collect background information of all household members age six and over and more detailed information, including employment history and occupational skills, for one individual respondent who is randomly selected among all adult household members.

Using the data on occupational skills, we construct a measure of RTI as follows. First, we map survey items to four task categories (see table 1), following Lo Bello et al. (2019) but with some adjustments. The task categories are abstract analytical, abstract interpersonal, routine (including routine cognitive and routine manual), and non-routine manual tasks. We first standardise each survey item and then take the sum across all items within a task category. This sum is again standardised to obtain four individual-level task indexes that each have a mean of zero and unit standard deviation. The individual-level task indexes for all of the 12 countries are then aggregated to the ISCO-88 2-digit occupation level, which can be mapped to the occupational codes in South Africa's employment data in order to apply the STEP task indexes to South Africa. As an alternative, we applied the same procedure to the sub-sample of STEP survey respondents from Colombia and Macedonia, which are the two richest countries in the data and the only two with GDP per capita levels close to that of South Africa.

[15]These 12 countries are : Armenia, Azerbaijan, Bolivia, Colombia, Georgia, Ghana, Kenya, Lao PDR, Macedonia, Ukraine, Vietnam, and Yunnan Province in China.

Table 1: STEP survey items per task category

Task category	STEP survey item	Variable name	Variable type
Abstract (non-routine analytical and interactive)	Thinking at work	m5b_q09 (Wave 1) m5b_q10 (Wave 2) m6b_q10 (Wave 3)	Categorical (1-5)
	Learning at work	m5b_q15 (Wave 1) m5b_q17 (Wave 2) m6b_q17 (Wave 3)	Categorical (1-5)
	Contact with clients/suppliers	m5b_q04*m5b_q05 (Wave 1) m5b_q05*m5b_q06 (Wave 2) m6b_q05*m6b_q06 (Wave 3)	Categorical (0-10)
	Formal presentation to clients	m5b_q10 (Wave 1) m5b_q12 (Wave 2) m6b_q12 (Wave 3)	Binary
	Supervising co-workers	m5b_q11 (Wave 1) m5b_q13 (Wave 2) m6b_q13 (Wave 3)	Binary
Routine (routine cognitive and manual skills)	Routine math tasks	m5a_q18_1—m5a_q18_4 (Wave 1 & 2) m6a_q13_1—m6a_q13_4 (Wave 3)	Categorical (0-4)
	Operate	m5b_q08 (Wave 1) m5b_q09 (Wave 2) m6b_q09 (Wave 3)	Binary
	Autonomy at work	m5b_q12 (Wave 1) m5b_q14 (Wave 2) m6b_q14 (Wave 3)	Categorical (1-10)
	Repetitiveness at work	m5b_q14 (Wave 1) m5b_q16 (Wave 2) m6b_q16 (Wave 3)	Categorical (1-4)
Manual (non-routine manual skills)	Driving	m5b_q06 (Wave 1) m5b_q07 (Wave 2) m6b_q07 (Wave 3)	Binary
	Repair	m5b_q07 (Wave 1) m5b_q08 (Wave 2) m6b_q08 (Wave 3)	Binary

Following Autor & Handel (2013) , the task variables are used to create a composite measure of routineness, the RTI index. This index measures the routine intensity of an occupation and is—in the current literature—the main measure of an occupation's susceptibility to the impact of recent technological progress (Goos et al. 2014).

In addition, this study also uses an RTI index developed by Goos et al. (2014) based on the widely used US DOT task measures.[16] This dataset was also merged with the South African employment data by matching the 2-digit ISCO-88 occupation codes. In section 4.1, all three of these measures — both versions of the RTI index developed from the STEP survey, and the RTI index based on U.S DOT task measures — will be used to estimate the effect of RBTC on South African wages and the occupational distribution. Doing so allows us to gauge the extent to which using RTI measured derived from countries with dissimilar labour markets can produce misleading results.

To see how these different RTI measures directly compare to each other, Table 2 below presents all three of these task measures for the 2-digit ISCO-88 occupation codes. Column 1 represents the RTI calculated using information from all 12 countries, column 2 does the same for information from Colombia and Macedonia only, while column 3 shows the RTI measure derived from US labour market occupational definitions.[17]

[16]This is the same index used in such papers as Autor & Handel (2013), Autor & Dorn (2013), Mahutga et al. (2018)

[17]This data was shared with us by Anna Salomons.

Table 2: A comparison of RTI index measures

ISCO-88	**12 country STEP RTI**	**2 country STEP RTI**	**US based RTI**
High-paying occupations			
11	-2.51	-2.47	-0.57
12	-0.71	-0.47	-0.65
13	-1.36	-1.31	-1.45
21	-0.69	-0.51	-0.73
22	-0.77	-0.69	-0.91
23	-0.91	-0.96	-1.47
24	-1.02	-1.06	-0.64
31	-0.88	-1.01	-0.29
32	0.05	0.26	-0.23
34	-0.90	-0.91	-0.34
Middle-paying occupations			
41	-0.03	-0.03	2.41
42	0.25	0.71	1.56
71	0.81	0.60	-0.08
72	0.15	0.07	0.58
73	0.61	0.42	1.74
74	0.94	0.88	1.38
81	1.57	1.65	0.45
82	1.41	1.51	0.62
83	-0.45	-0.20	-1.42
Low-paying occupations			
51	-0.13	0.01	-0.50
52	0.03	-0.19	0.17
61	0.85	0.51	0.14
62	0.73		0.47
91	0.49	0.50	0.14
92	0.71	1.03	0.38
93	1.77	1.68	0.57

In columns 1 and 2, the STEP-derived RTI index variables were calculated as the log of the ratio of routine to non-routine task variables for the entire 12 and 2 country's respectively. These two RTI index variables were then standardised to have a mean of 0 and a standard deviation 1. Theoretically, the RTI index is highest for high-paying occupations, and lowest for low-paying occupations. A high score on the RTI index therefore implies that that particular job is more routine intense, whereas a low value implies less routine intensity. What immediately stands out is that across all three measures, the RTI index values are lowest for high-paying occupations. However, unlike the US and a majority of EU countries where middle-paying occupations have noticeably higher RTI index occupations relative to low- and high-paying workers (as seen in column 3), here both the low- and middle-paying occupations have a comparably high RTI-index. This is consistent with the finding of Dicarlo et al. (2016) that the skill content of occupations is similar across developing countries, but differs between developing countries and the US. One implication of this finding is that using a US-based measure of RTI may produce misleading results due to substantial measurement error. It is also worth pointing out that even though low-paying jobs tends to have a relatively high RTI value on average, certain low-paying occupations entail low routine task intensity,

3 Descriptive Statistics

The model of RBTC makes a very clear prediction about the evolution of employment and wages for the different occupational classes. Individuals who engage in highly routine occupations are expected to experience a decrease in wages and in their employment share due to a decline in their relative productivity as their tasks become increasingly performed by technological advancements. Since these highly routine occupations are typically found in the middle of the wage and skills distribution, this predicts a decrease in wages and employment for occupations in the middle of the wage distribution. By the same token, the model predicts that low- and high-skilled workers should see an increase in wages and employment share. Finding descriptive results that are in favour of these trends is prima facie evidence pointing to the likely existence of RBTC in the South African labour market. In section 3.1 this chapter discusses the employment trends of the skill classes, followed by a discussion of the wage trends in section 3.2.

3.1 Trends in employment

3.1.1 General occupation trends

This section provides an overview of the overall changes in employment shares. We follow Goos et al. (2014) in classifying each occupation into exactly one of three types — low, middle and high — by ordering the 27 unique two-digit occupations by their mean wage. This leads to *high paid occupations* that are made up of the top three high-earning managerial occupations (11 to 13), professional occupations (31 to 34), and associate professionals (41 and 42); *middle-paid occupations* that consist of clerical occupations (41 and 42), crafts and other related occupations (71 to 74), and plant and machine operators and assemblers (81 to 83); and *low-paid occupations* that are made up of sales, personal, protective, and agricultural workers (51,52,61 and 62), labourers in agricultural, mining, construction, and manufacturing related work (92,93) and other low-skilled sales and services occupations (91). Coincidentally, this classification matches that of Goos et al. (2014).[18]

The descriptive analysis starts by looking at the changing composition of employment in the private sector—where market forces are most likely to quickly reflect changes in labour demand—and in the public sector, between 1997 and 2015.

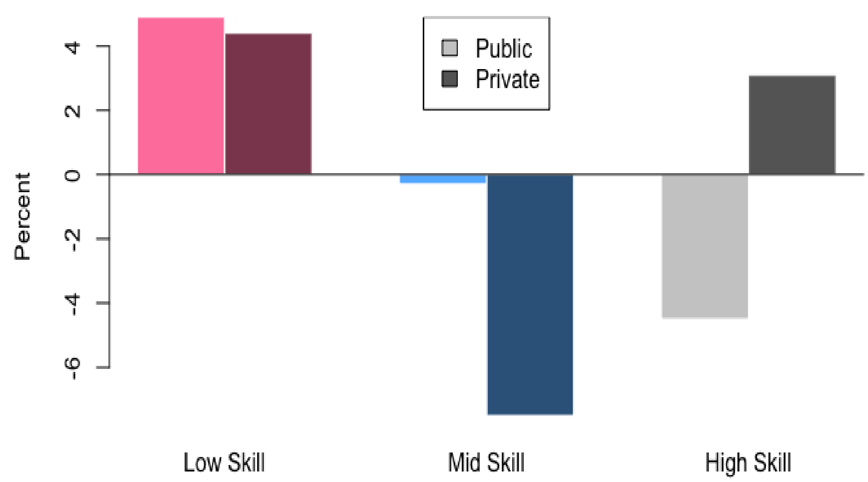

Figure 1: Changes in employment shares in the private and public sector (1997 - 2015)

Figure 1 shows that changes in employment shares in the private sector follow the typical U-shaped trend reported in high income countries (Goos et al. 2014). This is due to a significant decline in the share of middle-skilled occupations, while the relative shares of low- and high-skilled occupations increased. This pattern is exactly what we would expect to see if RBTC is causing the automation of routine tasks previously performed predominantly by workers in middle-skilled occupations. A feature that

[18]Note that while using wages to proxy for skills/routine is a crude approach compared to using an RTI index itself, this same approach has previously been used to demonstrate the secular bifurcation of the occupation structures in both the US (Autor 2019), and Europe (Goos et al. 2014) into high-wage, high-education, high-skill occupations on the one hand, and low-skill, low-wage occupations on the other.

distinguishes the shape observed in South Africa from those observed in most developed economies is that the declining employment share of middle-skilled occupations is offset mainly by an increase in the share of low- rather than high-skilled occupations. High-skilled occupations increased their share of total employment from 20.5 percent in 1997 to 23.5 percent in 2015, while low-skilled occupations increased from 33.2 to 38.7 per cent in the same period.

Employment shifts in the public sector show no signs of polarisation, but a substantial shift from high- to low-skilled employment, suggesting that RBTC has not affected employment outcomes in the public sector.

3.1.2 Occupational trends across demographic subgroups

The overall employment trends demonstrate that South Africa experienced the same hollowing-out of the skills distribution reported elsewhere, and that loss of middle-skilled jobs coincided with a larger increase in lower- than higher-skilled jobs. However, this overall trend does not tell us how the benefits and burdens of adjustment were distributed across racial and gender groups. Figure 3 shows the change in the shares of workers of different race groups employed in the three occupational groups between 1997 and 2015.

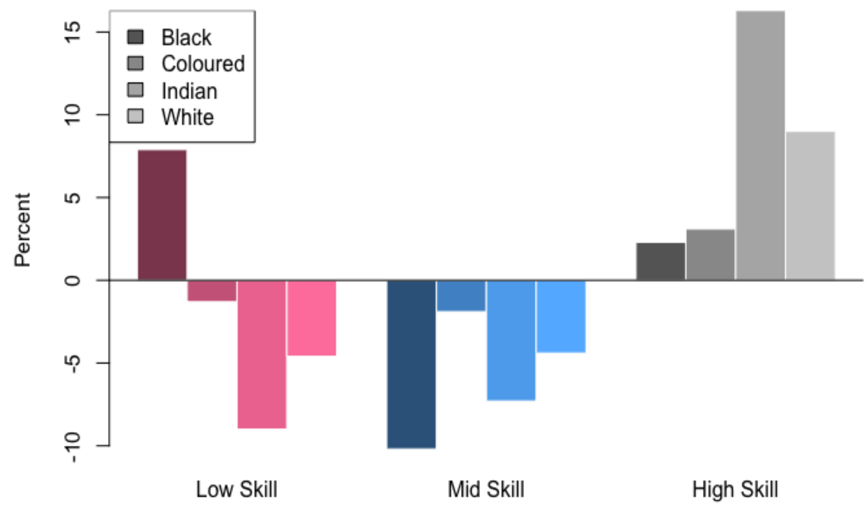

Figure 2: Private sector changes in occupational employment shares by race (1997-2015)

Disaggregating the employment share changes by race shows that black workers experienced the largest decrease in middle-skill employment which was predominantly offset by increases in low-skill employment, and minimal increases in high-skilled occupations. This differs strikingly from the white, Indian, and coloured workforce, who experienced a decline in both low- and middle-skill employment shares and an increase in high skilled work. While it is beyond the scope of this chapter to determine specifically what channels led to the apparent disadvantage of the black worker, it is probable that the increases in low-skilled occupations for black workers may point to some enduring effects of apartheid. This may have disadvantaged black workers in several ways including: leading black learners to dysfunctional schools which do not transfer adequate skills to students thereby having long-term productivity effects; disproportionate levels of educational attainment that differ by race group, with more white and Asian learners completing post-secondary (thus high-skilled) education than their black and coloured counterparts, entrenched discriminatory hiring and firing practices, and creating and reinforcing social spheres where white workers have access to powerful networks that are not available to black workers. Consequently, with the decline in middle-skilled jobs, it is possible that black workers find themselves increasingly relegated to low-skilled occupations as opposed to being able to adjust to the demands and requirements of high-skilled occupations.

In addition to employment share changes disaggregated by race, Figure 3 reports employment share shifts for both genders.

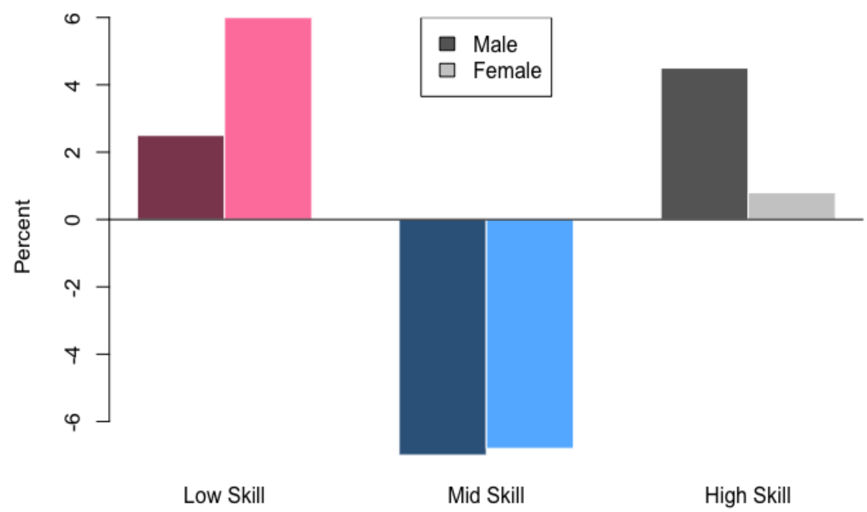

Figure 3: Private sector changes in occupation employment shares by gender (1997-2015)

We can observe the same U-shaped pattern we saw in Figures 1 and 2, signifying the polarisation of employment for both male and female workers. However, the share of female workers employed in low-skill occupations grew much more than the share of male workers. In contrast, male employment increased much more in high-skilled occupations.

The trends so far discussed for the private sector hold even if we express private sector employment as a fraction of the entire labor force, including public sector workers and a residual ”Outside formal employment category” which is made up of workers from the informal sector, as well as those that were unemployed, and not economically active.[19] This allows us to see whether the decrease in middle-skilled employment coincided with increases in public employment or those outside formal employment, which may suggest that these workers are displaced to other sectors rather than just other occupations within the private sector.

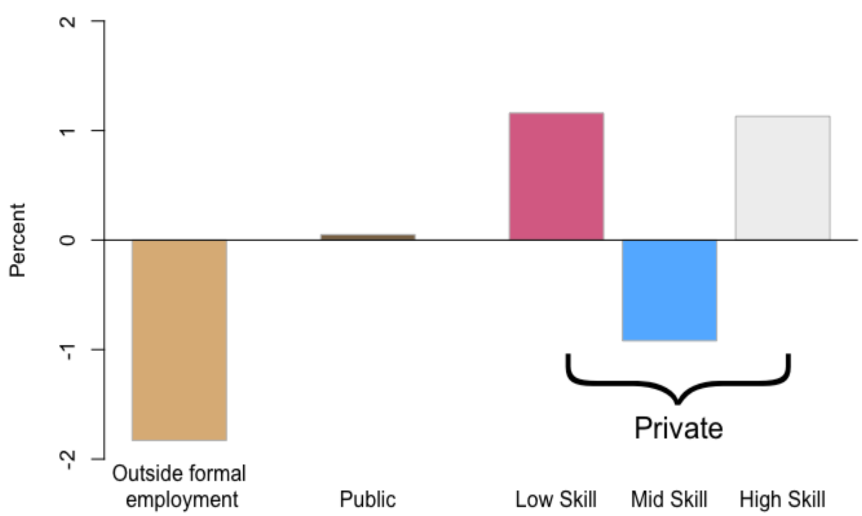

Figure 4: Private sector changes in occupational employment shares among working age adults (1997-2015)

Indeed, Figure 5 affirms that the trends discussed up to this point persist even after accounting for the entire working-age population. Most workers who lose their middle-wage jobs appear to be either absorbed in low- or high-wage occupations within the

[19]The period under investigation was marked by a large increase in labour force participation, and changes in survey questionnaire design which results in improved capturing of informal sector workers, so accurately distinguishing the trends in informal sector employment, labour force participation and unemployment is not possible. However, since we are primarily concerned that RBTC may have resulted in lower formal sector employment and that those who lost their jobs wound up in either the informal sector, unemployment or economically inactive, our ”Outside of formal employment” category allows us to test that hypothesis.

formal private sector, and there is no indication of large displacement into informal employment, unemployment or economic inactivity.

3.1.3 Detailed occupational analysis

While classifying skills into these three broad types does a lot by way of observing the general employment trends, there still remains the question of which occupations actually drive these trends, and how those differ by demographic features. Tables 1 and 2 attempt to answer these questions. Table 3 begins by reporting the initial 1997 proportions of the 27 unique two-digit occupations by race and gender. This sets the context by showing the occupational composition of the demographic groups. Table 4 reports only those occupations that had employment share gains or drops of four or more percentage points where the average percentage point change for all occupations was 1.6.[20]

[20] The full version of these changes is available in Appendix A.

Table 3: Employment shares by race and gender, 1997

Occupations ranked by mean earnings	ISCO-88 code	Male	Female	Black	White	Indian	Coloured
High paying occupations							
Legislators and senior officials	11	0.39	0.84	0.32	1.24	0.53	0.25
Corporate managers	12	2.43	1.77	0.57	7.34	3.73	0.98
General managers	13	6.8	5.14	3.65	13.6	12.26	4.46
Physical, mathematical, and engineering professionals	21	2.06	0.43	0.71	4.82	0.7	0.68
Life science and health professionals	22	0.14	0.29	0.12	0.46	0.25	0.02
Teaching professionals	23	0.36	0.49	0.23	1.06	0.1	0.2
Other professionals	24	2.23	2.67	1.01	6.31	4.45	1.3
Natural and engineering science associate professionals	31	2.49	2.53	1.34	5.19	3	3.03
Life science and health associate professionals	32	0.1	0.5	0.2	0.25	0.1	0.24
Teaching associate professionals	33	0.1	0.24	0.15	0.1	0.15	0.15
Other associate professionals	34	3.52	6.35	2.65	9.98	5.35	2.59
Middling occupations							
Office clerks	41	4.29	14.44	4.17	13.73	14.71	7.44
Customer service clerks	42	1.64	11.32	3.86	5.41	7.87	4.24
Extraction and building trades workers	71	10.69	1.35	10.13	4.11	3.23	6.72
Metal, machinery, and related trade workers	72	8.01	0.91	6.02	7.21	4.26	4.46
Precision, handicraft, craft printing, and related trade workers	73	0.9	0.81	0.85	0.64	1.62	1.06
Other craft and related trade workers	74	2.17	7.15	3.94	0.85	6.37	5.37
Stationary plant and related operators	81	1.67	0.38	1.72	0.72	0.7	0.67
Machine operators and assemblers	82	4	4.26	4.79	0.85	4.54	5.72
Drivers and mobile plant operators	83	13.71	1.12	13.93	3.17	4.31	6.75
Low-paying occupations							
Personal and protective service workers	51	5.78	5.92	7.35	3.79	1.26	4.26
Models, salespersons and demonstrators	52	3.74	8.23	4.56	5.07	11.27	4.88
Skilled agricultural and fishery workers	61	2.22	2.01	2.88	0.51	0.19	2.35
Subsistence agricultural and fishery workers	62	0.04		0.05			
Sales and service elementary occupations	91	3.09	5.17	5.03	1	1.43	3.05
Agricultural, fishery and related labourers	92	4.95	5.89	4.91	0.18	0.24	15.11
Labourers in mining, construction, manufacturing, and transport	93	12.47	9.8	14.86	2.41	7.38	14.01
Cumulative Totals		100	100	100	100	100	100

Table 3 shows that white and Indian workers had a relatively large proportion of their workers working in high-paying jobs such as managerial (12, 13) and professional (24, 34) occupations compared to black and coloured workers in 1997. This is likely an artefact of the apartheid regime which disadvantaged black and coloured workers by excluding them from high quality schools, tertiary education, and powerful social networks that are often key in obtaining employment in highly skilled occupations. Among the middle-paid workers, occupations seem to be split more along gender lines than was the case with high-paying occupations. Jobs in office and customer service clerk occupations (41,42) appear to be predominantly performed by white and Indian females.

As expected, while all occupations experienced some level of growth or decline in employment share during the 1997 to 2015 period, the observed trends were not driven by all the occupations. Indeed, a handful of occupations can be singled out as being particularly important in driving the employment share changes.[21] Table 4 presents these occupations.

[21] To be easily distinguishable, the demographic group within these selected occupations that experienced a percentage point gain or drop of more than four percentage points is reported in bold.

Table 4: Levels & Changes in Selected Employment Shares by race and gender, 1997-2015

Skill level	Occupations ranked by mean earnings	ISCO-88 code	Sub-group	Percent in 1997	Perecent in 2015	Percent point change
H	Corporate managers	12	Black	0.57	3.63	3.06
			White	**7.34**	**24.28**	**16.94**
			Indian	**3.73**	**17.69**	**13.96**
			Coloured	**0.98**	**6.27**	**5.29**
			Male	**2.43**	**9.27**	**6.84**
			Female	**1.77**	**7.06**	**5.29**
M	Other craft and related trade workers	74	Black	3.94	2.14	-1.8
			White	0.85	0.36	-0.49
			Indian	**6.37**	**0.53**	**-5.84**
			Coloured	5.37	1.57	-3.8
			Male	2.17	1.41	-0.76
			Female	**7.15**	**2.07**	**-5.08**
	Drivers and mobile plant operators	83	Black	**13.93**	**7.49**	**-6.44**
			White	3.17	1.06	-2.11
			Indian	4.31	3.37	-0.94
			Coloured	6.75	5.68	-1.07
			Male	**13.71**	**9.3**	**-4.41**
			Female	1.12	0.55	-0.57
L	Sales and service elementary occupations	91	Black	**5.03**	**10.28**	**5.25**
			White	1	0.76	-0.24
			Indian	1.43	1.39	-0.04
			Coloured	**3.05**	**7.67**	**4.62**
			Male	3.09	4.67	1.58
			Female	**5.17**	**12.72**	**7.55**
	Labourers in mining, construction etc	93	Black	14.86	12.29	-2.57
			White	2.41	1.47	-0.94
			Indian	**7.38**	**1.87**	**-5.51**
			Coloured	**14.01**	**9.59**	**-4.42**
			Male	12.47	10.51	-1.96
			Female	9.8	7.91	-1.89
	Personal and protective service workers	51	Black	**7.35**	**13.22**	**5.87**
			White	3.79	3.03	-0.76
			Indian	1.26	2.34	1.08
			Coloured	4.26	6.96	2.7
			Male	5.78	9.14	3.36
			Female	**5.92**	**11.55**	**5.63**

Table 4 shows that the increase in employment shares in high-skilled workers seen in Figures 1 to 4 is predominantly due to large shifts in white and Indian workers specifically into the corporate manager occupation. This increase was also more pronounced for males than for females. Among low-paying occupations, even though there was an overall increase in their employment share, one also sees that among the Indian and coloured sub-population, employment shares fell drastically in cases where they worked as labourers in mining, construction and manufacturing. On the other hand, the increases within the low-paying occupations appear to be predominantly driven by increases in employment shares among black and coloured female workers in sales and service elementary occupation and black female workers in personal and protective services. Interestingly, even though Table 2 revealed that low-paying occupations in low- and middle-income economies tend to be quite routine task intensive on average, the two occupations that experienced the largest increases in employment shares had relatively low routine task intensity.

Unsurprisingly, given what we know to expect in the presence of RBTC, there are two main drivers for the decline in the middling-occupations: drivers and mobile plant operators and craft and related workers. These include jobs like wood and leather cutting, clothes-sorting, knitting, cement and concrete mixing, ice cream and cheese-making, and various types of mining and construction work like sorting and excavating. Such occupations are jobs with high routine task intensity and are therefore prone to replacement by advancements in ICT. These are occupations predominantly performed by black and Indian male and female workers.

In summary, it appears that among the highly skilled workers, there has been a relative increase in labour demand for corporate managers which includes jobs like production, operation, and department managers; school principals and deans; chief executive officers; and bank managers. At the lower end of the skills distribution, relative labour demand has increased for jobs like security personnel, barbers, waiters, maids, cleaners, and nannies — all jobs that cannot be automated and are low in routine task intensity. Furthermore, these jobs are predominantly performed by black and coloured workers.

3.1.4 Decomposition of changes in occupational shares

The changes in the occupational structure of the workforce documented above could reflect a process of structural change, in which industries that use middle-skilled workers more intensively have experienced a decrease in their share of production, while all industries continue to produce with the same mix of low-, middle- and high-skilled workers. On the other hand, the declining share of middle-skilled occupations could be driven by a general trend, observed across all industries, in which production is increasingly performed with more high- and low-skilled workers, and with fewer middle-skilled workers. To shed some light on this, we decompose the change in occupation shares into a within-industry component (which is driven by changes in occupational shares *within* industries, while keeping industry shares constant) and a *between*-industry component (due to changing industry shares, while keeping occupational shares constant). Following Autor et al. (1998), this is achieved using the standard equation given by

$$\Delta P_{jt} = \sum_k \left(\Delta E_{kt}\gamma_{jk}\right) + \sum_k \left(\Delta \gamma_{jkt} E_k\right) = \Delta P_{jt}^b + \Delta P_{jt}^w \tag{1}$$

where ΔP_{jt} is the change in the aggregate share of total employment for occupation j between years t and τ, E_{jkt} is the employment of occupation j in year t and industry k as a share of total employment in year t, $E_{kt} = \sum_j E_{jkt}$ is total employment in industry k in year t, $\gamma_{jkt} = E_{jkt}/E_{kt}$ is the group j share of employment in industry k in year t, $\gamma_{jk} = (\gamma_{jkt} + \gamma_{jk\tau})/2$, and $E_k = (E_{kt} + E_{k\tau})/2$. The resulting first term (ΔP_{jt}^b) represents the changes in the aggregate proportion of workers due to changes in employment shares *between* industries, and the second term (ΔP_{jt}^w) reflects the changes in the aggregate proportion of workers due to changes in employment shares *within* industries. Table 5 below reports the results of Equation 1 above.

Table 5: Between and within decomposition

	Overall	Between	Within
Low	5.22	-0.49	5.71
Middle	-5.82	-2.56	-3.26
High	0.60	3.05	-2.45

Table 5 shows that for middle-skilled and especially low-skilled occupations, within-industry forces explain relative employment shifts more than between-industry forces. In their work, Bhorat et al. (2014) find a similar result, showing further that the within-industry component constituted between 86 to 96 percent of aggregate demand shifts in the 2001 to 2012 period. Broadly, the increasing share of low-skilled jobs is mainly driven by finance, services and agricultural industries, while manufacturing and finance industries account for most of the declining share of middle-skilled jobs.

Regarding the middle-skill occupations, both the between and within components are negative. What this shows is that for these groups of workers, not only is there a relative demand shift away from their kind of jobs within their industry, but also industries that are relatively middle-skilled intensive are declining in importance. Practically, this means a middle-skilled worker cannot easily leave their industry and hope to find work that requires similar skills in another industry. Table 5 further shows that the increasing share of high-skilled occupations is driven entirely by between-industry shifts, which are party offset by a negative within-industry contribution. Industries like finance and services that employ a large proportion of high-skilled workers are expanding, while the share of high-skilled occupations within industries is declining. [22]

3.2 Trends in wages

The theory of RBTC makes strong predictions about trends in employment shares of the different occupation groups, which was shown to also characterise the South African

[22]See Table 4 in Appendix B that reports the detailed between and within decomposition for each industry.

labour market between 1997 and 2015. In addition, we would expect a decrease in relative wages for middle-skilled occupation in labour markets where wages are determined mainly by market forces. However, if non-market forces—like minimum wages or trade union bargaining—are crucial factors in determining wages, then the effect of such factors may drown out the effect of labour demand so that the effect of technological growth is only observable in employment shares. To this end, Figure 5 plots the average annualised growth rate of real earnings across percentiles in the private sector of the South African labour market between 1997 and 2015.

As can be observed, wage growth varied substantially across the wage distribution. Wage growth was lowest for workers in the bottom decile of the distribution and for workers around the median. Above the median, wage growth rises more or less linearly, implying increasing inequality in the top half of the wage distribution.

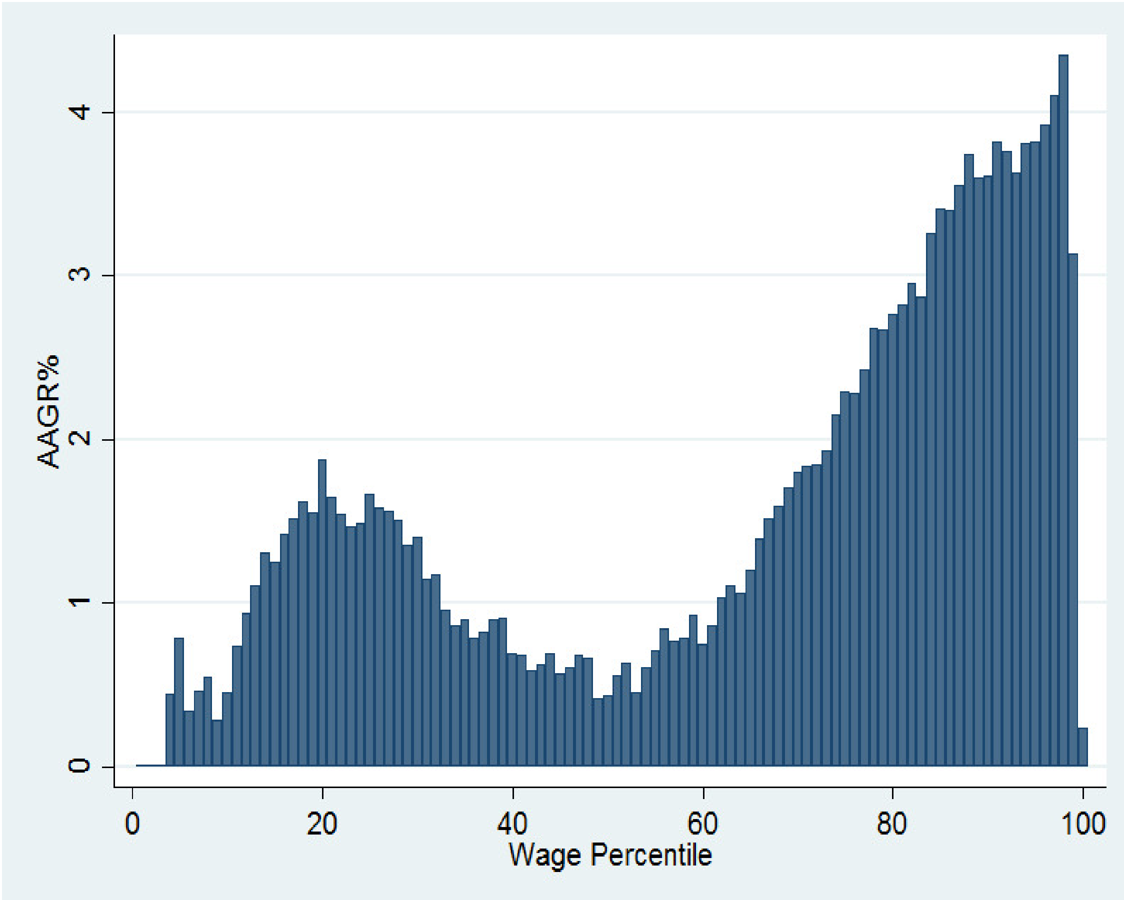

Figure 5: Annual average growth rate of private sector mean real earnings (South Africa, 1997-2015)

The fact that wages at the top grew much more rapidly than in the middle of the distribution is in line with the predictions of RBTC, which suggests that middle-skilled workers experienced slower productivity growth than highly skilled workers. In a labour market with very low unemployment and competitively determined wages, we would also have expected to see the wages of low-skilled workers expand more rapidly than those of their middle-skilled counterparts. This is not what we observe, however, which may reflect the particular South African context, where there is an oversupply of low-skilled workers and the wages for low-skilled workers are partly determined by institutional factors.

4 Estimation Results

This section moves beyond using descriptive statistics to investigate whether the predictions of RBTC can help us understand South African labour market trends between 1997 and 2015. In section 4.1 we start by using multivariate regressions to explore the trends in wages by occupational group. Although we have already demonstrated that employment trends across broad occupational groups — and to a lesser extent, also wage trends across the same groups — support the hypothesis that RBTC is affecting South African labour market trends, the discussion in section 2.2 noted that this occupational grouping is not the ideal measure of the routine task intensity. We may be concerned that these trends are driven by some other factors that vary across occupations. In order to address this concern, we use regression analysis and the recently gathered STEP data to confirm that the trends observed for the low-, middle- and high-skilled occupation groups are indeed driven by the routine task intensity of individual occupations, rather than by some other inter-occupational differences. We also check how robust the results are to the choice of RTI measure, and discuss the implications for the practice of using RTI measures from the US to investigate the effects of RBTC in other countries.

In section 4.2 we explore two alternative explanations for the observed wage and occupational employment trends. The first is that South African firms may have experienced changing occupational demand due to shifts in international trade. The second is that the reduced share of middle-skilled workers may reflect changes in the composition of labour supply, as found in the UK (Salvatori 2018). We find that neither explanation is supported by our data.

4.1 Regression analysis

We begin our regression analysis by investigating the relationship between wages and occupation skill level or routine intensity. We estimate a reduced-form OLS regression with log of wages as the dependent variable and three predictor variables: the type of labour, — measured either through dummy variables for low-, medium-, or high-skilled occupations, or using the occupation-level RTI index —; a linear time trend variable to account for expected year-on-year changes; and an interaction term between the type of labour and a linear time trend.[23] We are primarily interested in the interaction effect, since this represents differences in wage trends across occupations. RBTC predicts that workers in occupations with high routine intensity experience slower than average wage growth. The results from this regression analysis are presented in Table 6.

[23]This follows work by Firpo et al. (2011), Goos et al. (2014).

Table 6: Wage regression with RTI time trend interactions

	Dependent Variable: Log of Wages			
	(1)	(2)	(3)	(4)
Year	0.00615***	0.00671***	0.00697***	0.00939***
	(0.000381)	(0.000254)	(0.000255)	(0.000261)
RTI		-0.434***	-0.488***	-0.108***
		(0.00326)	(0.00330)	(0.00265)
RTI*Year		-0.00664***	-0.00430***	-0.00264***
		(0.000304)	(0.000307)	(0.000245)
High Skill	1.328***			
	(0.00647)			
Middle Skill	0.511***			
	(0.00570)			
High Skill*Year	0.00116*			
	((0.000584)			
Middle Skill*Year	-0.00159**			
	(0.000533)			
N	494660	467039	467009	493124
R^2	0.248	0.150	0.163	0.020

Point estimates with Standard errors in parentheses. Dependent variable is the log of wages. Column (1) presents estimation results for wages against skill levels and trend. Columns (2) - (4) present regression results for wage against three variant measures of RTI based on the respective reference sample data. In column (2) RTI based on all 12 countries in STEPS data, in Column (3) RTI is based on Colombia and Macedonia data and RTI in column (4) is derived from US based DOT task measures

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results in column 1 compare wage growth across skill levels, with low-skill workers as the base group. Consistent with the descriptive results discussed in section 3, the interactions between time trend (Year) and skill groups indicate that both high- and low-skill occupations experienced positive wage growth relative to middle-skilled workers during this period. This confirms the polarisation of employment in the South African labour market.

Columns 2-4 in Table 6 presents results for three more models that test whether differences in wage growth across occupations were associated with the routine task intensity of these occupations (as predicted by the RBTC model). As discussed in section 2, there are three measures of RTI that we could use in our analysis. In column 2 we use the RTI variable based on data for all 12 countries included in the STEP data. The variable used in column 3 is based on data from Colombia and Macedonia, which have GDP per capita similar to South Africa and are therefore more likely to have occupational RTI values similar to South Africa. Finally, the measure in column 4 is from Goos et al. (2014) which is derived from US-based DOT task measures.

Given that skill content of occupations has been found to be similar across developing countries, but to differ between developing countries and the US (Dicarlo et al. 2016) we would expect the STEP measures to provide a more reliable indication of the routine task intensity of South African occupations than those based on the US data. The literature on measurement error suggests that variables that contain more noise and less informative variation usually cause attenuation bias in regression coefficients, provided that the measurement error is roughly classical in nature. Based on what we know about the different measures, and the assumption that deviations between the RTI of occupations in South Africa and elsewhere is roughly uncorrelated to the model residual, we may expect the coefficients on the US measure and its interaction with time to be biased towards zero.

Comparing the models in columns 2, 3 and 4, we observe that all confirm that occupations that require the execution of more routine tasks have experienced slower wage growth over this period than those that perform more non-routine tasks. This is in line with predictions of the RBTC model, and serves to confirm that the wage trends observed across occupation groups were (at least partly) driven by the routine task intensity of these occupations. Furthermore, we can see that the RTI measure derived from US data (in column 4) produces much smaller coefficients and a lower R-squared value than those obtained with the STEP measures. This is consistent with the hypothesis that extrapolating the routine task intensity of occupations in developed countries to developing country settings can induce measurement error problems. Regarding which of the two STEPS measures — used in columns 2 and 3 — is more appropriate, the evidence is mixed. The measure used in column 3 produces a higher R-squared and RTI coefficient, but a lower RTI-time interaction coefficient than the measure used in column 2. We are inclined to conclude that the measure that only uses information from comparable middle-income countries produces a less noisy RTI index. However, the fact that this measure is constructed from relatively small samples across only two countries may in itself make the measure more noisy and less reliable, which could explain the attenuated RTI-time interaction coefficient. Regardless of which of these measures is more appropriate, the results clearly show that wage trends operate via a reduced demand for occupations that have a high RTI. Overall, these findings are consistent with those reported in Bhorat et al. (2014) for the 2001 to 2012 period, which also found that occupations that are more routine intensive have recorded lower wage growth.

One concern with the specifications in Table 6 may be that the linear time trend assumption is overly restrictive. To address this, we re-estimated the models with interactions between RTI and year dummies. The coefficients of these interaction terms (for both STEP measures of RTI) are presented in Figure 6 in the appendix. It clearly shows a negative wage trend for occupations that involve more routine tasks.

In order to further scrutinise the descriptive analysis on trends in occupational employment shares discussed in section 3, we use a similar specification as in Table 6 to explore the role of RTI in employment trends. The unit of observation is the 2-digit occupation-year pair, and the dependent variable is calculated as the share of the occupation in total private sector employment in a that year. The results from these regressions are reported in Table 7.

Table 7: Employment share regression with RTI time trend interactions

	Dependent Variable: Share of Workers			
	(1)	(2)	(3)	(4)
Year	-0.000669***	0.000191**	0.000207***	0.000236***
	(0.0000989)	(0.0000587)	(0.0000595)	(0.0000568)
RTI		0.0254***	0.0257***	0.0830***
		(0.00555)	(0.00510)	(0.00181)
RTI*Year		-0.000313***	-0.000261***	0.000127*
		(0.0000602)	(0.0000620)	(0.0000587)
High Skill	-0.104***			
	(0.00251)			
Low Skill	-0.00515			
	(0.00266)			
High Skill*Year	0.00131***			
	((0.000124)			
Low Skill*Year	0.00112***			
	(0.000152)			
Occupation (2 digit)	Y	Y	Y	Y
N	1145	1082	1070	1125
R^2	0.907	0.896	0.894	0.897

Point estimates with Standard errors in parentheses. Dependent variable is the Share of Workers. Column (1) presents estimation results for the share of workers against skill levels and trend. Columns (2) - (4) present regression results for the share of workers against three variant measures of RTI based on the respective reference sample data. In column (2) RTI based on all 12 countries in STEPS data, in Column (3) RTI is based on Colombia and Macedonia data and RTI in column (4) is derived from US based DOT task measures.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficients on year (again the linear time trend) and year-skill interactions in column 1 confirm that high and low skilled occupations grew, while middle-skilled occupations shrank. In addition, the estimates in columns 2 and 3 (using the 12 and 2 country STEP measures of RTI respectively) show that routine-intensive occupations experienced a decline in employment shares. This suggests that middle-skilled occupations shrank because these occupations often entail performing easily automatable routine tasks, which is consistent with the predictions of RBTC. Interestingly, the estimates in column 4 that use the RTI measure based on the US occupation schemes, shows exactly the opposite. We interpret this as additional evidence that occupational taks measures based on developed country labour markets may not be well suited for analyses of developing country labor markets.

4.2 Alternative explanations

The preceding analysis demonstrated that between 1997 and 2015 middle-skilled occupations in South Africa experienced a shrinking employment share and slower wage growth compared to high- and low-skilled occupations. We also presented evidence that this was at least partly driven by a reduced demand for occupations with a high RTI. This is consistent with the predictions of RBTC, which postulates that these changes are due to technological change. However, there exists alternative theories that are also consistent with these trends.

The first alternative theory is that the reduced demand for routine occupations is due to international trade. If automation in developed countries lowers the costs of goods produced using routine-intensive tasks, then South African consumers may switch to consuming these foreign-produced goods. This would reduce the demand for workers who perform such routine intensive tasks domestically, as we observe in our data. We test this hypothesis by including time-varying measures of industry-specific import and export shares in our wage regressions from Table 6, to see whether this explains away the effect of RTI on wages. The data on import and export shares are retrieved from Quantec[24], but is only available for four industries: agriculture, forestry, and fishing; mining and quarrying; manufacturing; and electricity, gas, and water. We re-estimate the models in columns 2 and 3 in Table 6 (which use the 12 and 2 country STEP RTI measures) in two ways: by restricting the data to the four industries for which we have trade measures, and by including all industries while setting the trade

[24] The data can be accessed from their website (https://www.quantec.co.za).

measures to zero for industries without trade data. The result of these regressions are reported in Table 8, along with the same regression without the trade measures.[25]

Table 8: Wage regression with RTI time trend interactions, export, and import shares

	Dependent Variable: Log of Wages							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	0.00671***	0.00380***	0.00697***	0.00425***	0.0246***	-0.0324***	0.0228***	-0.0295***
	(0.000254)	(0.000258)	(0.000255)	(0.000259)	(0.000519)	(0.000773)	(0.000528)	(0.000777)
RTI	-0.434***	-0.438***	-0.488***	-0.493***	-0.286***	-0.280***	-0.403***	-0.390***
	(0.00326)	(0.00325)	(0.00330)	(0.00329)	(0.00521)	(0.00507)	(0.00527)	(0.00515)
RTI*Year	-0.00664***	-0.00873***	-0.00430***	-0.00630***	-0.00542***	-0.00676***	-0.00152**	-0.00167***
	(0.000304)	(0.000305)	(0.000307)	(0.000309)	(0.000515)	(0.000501)	(0.000518)	(0.000506)
Export Share		0.0727***		0.121***		1.105***		1.018***
		(0.0104)		(0.0104)		(0.0160)		(0.0157)
Import Share		0.133***		0.0910***		-0.0900***		-0.0927***
		(0.00778)		(0.00773)		(0.00810)		(0.00798)
N	467032	467032	467002	467002	159920	159920	159893	159893
R^2	0.150	0.156	0.163	0.169	0.087	0.139	0.123	0.166

SAMPLE: Columns 1-4 are full sample while Columns 5-8 limit the sample to 4 industries
RTI Measure: Columns 1,2,5 and 6 use the 12 country RTI measure while columns 3,4,7 and 8 use the 2 country RTI measure
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression estimates reveal that controlling for industry-time specific import and export shares does not diminish the estimated effect of RTI on wage changes. In fact, the regression coefficients are marginally larger in absolute magnitude after adding the trade measures as controls. This result is consistent across all four specifications and indicates that the observed trend of more routine task intensive occupations experiencing slower wage growth was not driven by changing patterns in international trade.

The second alternative explanation for the observed job polarisation is that it may be caused by changes in the distribution of educational attainment in the South African labour force. In the United Kingdom, it was found that the move away from middle- to high-skilled occupations was largely driven by the increase in the share of people with tertiary education (who tend to work in highly-skilled occupations) and a decrease in the share of people with secondary education (who often work in middle-skilled

[25]Since the occupational employment shares that serve as the outcome variable in the regressions reported in Table 7 do not vary across industries, we are unable to use the same approach to test for the effect of international trade on trends in the occupational distribution.

occupations) (Salvatori 2018). In order to investigate the relevance of this hypothesis for South Africa, Table 9 below reports the changes in the share of people with different levels of educational attainment.

Table 9: Changes in labour supply by educational attainment (1997 - 2015)

	1997	**2015**	**Diff**
Primary	28.21%	10.23%	-17.98%
Incomplete secondary	38.42%	31.18%	-7.24%
Secondary+	30.22%	48.47%	18.25%
Tertiary	3.15%	10.11%	6.96%

We can see that the decrease in the share of workers in middle-skilled occupations coincided with a large increase in the share of workers with secondary levels of education who typically perform middle-skilled jobs. Furthermore, in South Africa, the large downward mobility from middle- to low-skilled workers occurred despite an increase in educational attainment. The one aspect of this hypothesis that may be relevant for South Africa is that the unusually small increase in upward mobility may be attributable to the relatively low share of workers with tertiary education, which could act as a barrier to upward mobility. We can therefore conclude that, unlike the experience in the UK, changes in labour supply and the composition of educational attainment of the labour force did not contribute to the observed changes in the South African occupational distribution.

5 Conclusion

This study investigates whether RBTC had any impact on the labour market of a large, middle-income developing country: South Africa. In line with the predictions of RBTC we find evidence of job polarisation, characterised by an increased employment share and slower wage growth in middle-skilled occupations compared to low- and high-skilled occupations. Regression analysis shows that occupations that involve a high share of routine tasks—whose workers happen to be those in the middle of the skills distribution—experienced a decline in employment and wages over time. We also find that this trend is unlikely to be driven by changing patterns in international trade or the composition of labour supply.

Although we observe many of the same trends that have been attributed to RBTC in developed country labour markets, we also see a few notable differences. Whereas in most countries the increase in high-skilled occupations is larger than the increase in low-skilled occupations, the opposite is true for South Africa. These movements appear to be differentiated by race and gender, with the advantaged groups (male, white, and Indian) being more likely to move into high-skilled occupations and the disadvantaged groups (female and black) more likely to move into less-skilled occupations. The decrease in middle-skilled jobs also occurred despite an increase in the share of secondary school graduates who typically perform these jobs. It is possible that opportunities of upward mobility offered by RBTC were constrained by the lack of access to higher education (and high quality primary and secondary education) for all but the most privileged groups. This suggests that technological progress is likely to continue deepening inequality along historical lines, until improved equality in access to education is achieved. On a more optimistic note, there is no indication that RBTC is currently contributing to unemployment or informality.

Potential policy responses to address the anticipated widening of the wage gap would need to focus on up-skilling middle-skilled workers from disadvantaged groups to facilitate movement up the skills ladder. This could be achieved by improving schooling quality, greater access to tertiary education retraining programmes for retrenched middle-skilled workers, or affirmative action policies. Our results also indicate that the public sector did not experience the same decrease in middle-skilled employment, which points to a potentially important role for public sector employment in dampening the effects of technological progress on wage inequality.

This paper was not able to address several important questions which are left for future research. The absence of a representative South African panel data set that spans the period under consideration means that our empirical analysis required using a series of cross-section surveys. This meant that we could not observe what happened to individual workers who lost their middle-skilled jobs. We were also not able to identify the mechanisms that determined whether workers moved up or down the skills distribution. The study also uses reduced form regressions to analyse labour market trends, rather than estimating these labour market outcomes as equilibrium outcomes determined by factor costs and a production function that experienced differential growth in productivity across occupations.

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Appendix

A Tables

Table 10: Levels and changes in employment shares by race and gender, 1997-2015

Occupations ranked by mean earnings	ISCO-88 code	Sub-group	Percent in 1997	Perecent in 2015	Percent point change
Legislators and senior officials	11	Black	0.3	0.06	-0.3
		Coloured	0.2	0.09	-0.1
		Indian	0.5	0.05	-0.5
		White	1.3	0.53	-0.8
		Male	0.4	0.17	-0.2
		Female	0.8	0.12	-0.7
Corporate managers	12	Black	0.6	3.66	3.1
		Coloured	1	6.31	5.3
		Indian	3.7	17.7	14.0
		White	7.4	24.32	16.9
		Male	2.4	9.36	7.0
		Female	1.8	7.08	5.3
General managers	13	Black	3.6	1.78	-1.8
		Coloured	4.5	1.7	-2.8
		Indian	12.4	6.81	-5.6
		White	13.4	7.26	-6.2
		Male	6.7	3.83	-2.9
		Female	5.03	1.72	-3.3
Physical, mathematical, and engineering professionals	21	Black	0.7	0.37	-0.4
		Coloured	0.6	0.14	-0.5
		Indian	0.6	1.96	1.4
		White	5.0	3.65	-1.3
		Male	2.1	1.36	-0.7
		Female	0.4	0.49	0.1
Life science and health professionals	22	Black	0.1	0.05	-0.1
		Coloured	0.0	0.05	0.0
		Indian	0.3	0.14	-0.1
		White	0.5	0.98	0.5
		Male	0.2	0.21	0.1
		Female	0.3	0.26	0.0
Teaching professional	23	Black	0.2	0.03	-0.2
		Coloured	0.2		-0.2
		Indian	0.1		-0.1
		White	1.0	0.17	-0.8
		Male	0.32	0.04	-0.3
		Female	0.5	0.08	-0.4

Occupations ranked by mean earnings	ISCO-88 code	Sub-group	Percent in 1997	Perecent in 2015	Percent point change
Other professionals	24	Black	1.0	1.5	0.5
		Coloured	1.3	1.6	0.3
		Indian	4.5	6.7	2.2
		White	6.3	6.6	0.3
		Male	2.2	2.3	0.0
		Female	2.7	3.3	0.6
Natural and engineering science associate professionals	31	Black	1.3	2.13	0.8
		Coloured	3.1	2.73	-0.3
		Indian	3.1	6.36	3.3
		White	5.2	5.64	0.5
		Male	2.5	3.8	1.3
		Female	2.4	1.9	-0.6
Life science and health associate professionals	32	Black	0.2	0.2	0.0
		Coloured	0.2	0.3	0.1
		Indian	0.1	0.4	0.3
		White	0.3	0.4	0.2
		Male	0.1	0.2	0.1
		Female	0.5	0.5	0.0
Teaching associate professionals	33	Black	0.1	0.1	0.0
		Coloured	0.2	0.08	-0.1
		Indian	0.2		-0.2
		White	0.1	0.1	0.0
		Male	0.1	0.01	-0.1
		Female	0.22	0.2	0.0
Other associate professionals	34	Black	2.6	3.2	0.6
		Coloured	2.6	4.0	1.3
		Indian	5.4	7.0	1.6
		White	9.9	9.6	-0.3
		Male	3.5	3.7	0.2
		Female	6.2	6.1	-0.1
Office clerks	41	Black	4.1	5.7	1.6
		Coloured	7.3	9.9	2.6
		Indian	14.7	18.3	3.6
		White	13.5	14.1	0.6
		Male	4.2	4.2	0.0
		Female	14.3	14.8	0.5
Customer services clerks	42	Black	3.9	6.4	2.5
		Coloured	4.2	7.0	2.8
		Indian	7.9	6.5	-1.4
		White	5.3	3.3	-2.0
		Male	1.6	1.9	0.2
		Female	11.2	12.1	0.9

Occupations ranked by mean earnings	ISCO-88 code	Sub-group	Percent in 1997	Perecent in 2015	Percent point change
Extraction and building trades workers	71	Black	10.2	6.2	-4.0
		Coloured	6.7	4.7	-2.1
		Indian	3.3	2.5	-0.8
		White	4.1	4.8	0.7
		Male	10.8	8.7	-2.1
		Female	1.4	0.9	-0.5
Metal, machinery, and related trade work	72	Black	6.1	4.5	-1.6
		Coloured	4.4	5.1	0.7
		Indian	4.3	5.2	0.8
		White	7.3	6.8	-0.5
		Male	8.1	8.0	-0.1
		Female	0.9	0.5	-0.4
Precision, handicraft, craft printing, and related trade workers	73	Black	0.9	0.5	-0.4
		Coloured	1.1	0.8	-0.3
		Indian	1.7	0.7	-1.0
		White	0.7	0.6	-0.1
		Male	0.9	0.6	-0.3
		Female	0.8	0.4	-0.4
Other craft and related trade workers	74	Black	4.0	2.2	-1.8
		Coloured	5.4	1.6	-3.9
		Indian	6.5	0.5	-6.0
		White	0.9	0.4	-0.5
		Male	2.2	1.4	-0.8
		Female	7.3	2.1	-5.2
Stationary plant and related operators	81	Black	1.7	2.2	0.4
		Coloured	0.6	1.0	0.3
		Indian	0.7	0.3	-0.5
		White	0.8	0.6	-0.2
		Male	1.7	2.4	0.7
		Female	0.4	0.4	0.0
Machine operators and assemblers	82	Black	4.8	4.1	-0.7
		Coloured	5.8	4.8	-1.0
		Indian	4.5	3.3	-1.2
		White	0.9	0.6	-0.3
		Male	4.0	3.6	-0.4
		Female	4.3	3.3	-1.0
Drivers and mobile plant operators	83	Black	13.9	7.5	-6.3
		Coloured	6.7	5.7	-1.0
		Indian	4.2	3.4	-0.8
		White	3.2	1.0	-2.2
		Male	13.7	9.4	-4.4
		Female	1.1	0.6	-0.5

Occupations ranked by mean earnings	ISCO-88 code	Sub-group	Percent in 1997	Perecent in 2015	Percent point change
Personal and protective service workers	51	Black	7.4	13.2	5.9
		Coloured	4.1	6.9	2.8
		Indian	1.3	2.3	1.1
		White	3.8	3.0	-0.8
		Male	5.8	9.2	3.4
		Female	5.9	11.4	5.5
Models, salaespersons and demonstrators	52	Black	4.6	4.7	0.0
		Coloured	4.9	5.1	0.2
		Indian	11.5	6.7	-4.8
		White	5.2	2.9	-2.4
		Male	3.8	4.3	0.5
		Female	8.4	4.8	-3.7
Skilled agricultural and fishery workers	61	Black	2.9	0.6	-2.4
		Coloured	2.3	0.7	-1.7
		Indian	0.2	0.1	-0.1
		White	0.5	0.2	-0.3
		Male	2.3	0.5	-1.8
		Female	2.04	0.5	-1.5
Subsistence agricultural and fishery workers	62	Black	0.05	0	-0.1
		Coloured	0	0.02	0.0
		Indian	0	0	0.0
		White	0	0	0.0
		Male	0.04	0	0.0
		Female	0	0.01	0.0
Sales and service elementary occupations	91	Black	5.0	10.4	5.4
		Coloured	3.0	7.7	4.7
		Indian	1.5	1.4	-0.1
		White	1.0	0.8	-0.2
		Male	3.1	4.7	1.7
		Female	5.1	12.7	7.6
Agricultural, fishery and related labourers	92	Black	5.0	6.5	1.6
		Coloured	15.4	12.5	-2.8
		Indian	0.2	0.2	-0.1
		White	0.2	0.2	0.0
		Male	5.0	5.7	0.7
		Female	6.01	6	0.0
Labourers in mining, construction, manufucturing, and transport	93	Black	14.9	12.4	-2.5
		Coloured	14.1	9.6	-4.4
		Indian	6.92	1.9	-5.1
		White	2.3	1.5	-0.9
		Male	12.5	10.6	-1.9
		Female	9.9	7.9	-1.9

B Changes in Occupation Employment Shares

Table 11: Full sample vs private sector sample

	1997		2015		Difference	
	Private	**Full**	**Private**	**Full**	**Private**	**Full**
Low	33.9	31.6	38.2	36.2	4.4	4.6
Middle	45.6	39.3	38.1	33.9	-7.5	-5.4
High	20.6	29.1	23.7	29.9	3.1	0.8

Table 12: Private Sector Changes in Occupation Employment Shares by Gender

	1997		2015		Diference	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Low	32.5	37.3	35.0	43.3	2.5	6.0
Middle	47.1	41.8	40.1	35.0	-7.0	-6.8
High	20.4	21.0	24.9	21.7	4.5	0.8

Table 13: Private Sector Changes in Occupational Employment Shares by Race

	1997				2015				Difference			
	Black	**Coloured**	**Indian**	**White**	**Black**	**Coloured**	**Indian**	**White**	**Black**	**Coloured**	**Indian**	**White**
Low	39.8	43.9	21.6	13.1	47.7	42.6	12.6	8.5	7.9	-1.3	-9.0	-4.6
Middle	49.4	42.3	47.7	36.7	39.2	40.4	40.5	32.3	-10.2	-1.9	-7.3	-4.4
High	10.8	13.9	30.7	50.3	13.1	17.0	47.0	59.3	2.3	3.1	16.3	9.0

C Other tables

Table 14: Between and Within Industry Decompositon of the Increase in the Share of Workers in Employment, 1997-2015

	Low		Middle		High	
	Between	Within	Between	Within	Between	Within
Agriculture, hunting, forestry and fishing	-2.32	0.62	-0.56	-0.54	-0.14	-0.08
Mining and quarrying	-0.71	0.43	-1.70	-0.08	-0.42	-0.35
Manufucturing	-1.75	-0.86	-4.23	0.73	-1.46	0.13
Utilities	-0.08	-0.15	-0.27	0.05	-0.10	0.11
Construction	0.49	0.47	1.22	-0.84	0.28	0.36
Trade	0.45	0.29	0.37	-0.43	0.20	0.14
Transport	-0.14	-0.10	-0.47	-0.42	-0.20	0.52
Finance	2.47	1.04	2.50	-1.37	3.11	0.33
Services	1.09	3.96	0.59	-0.35	1.78	-3.61

D Figures

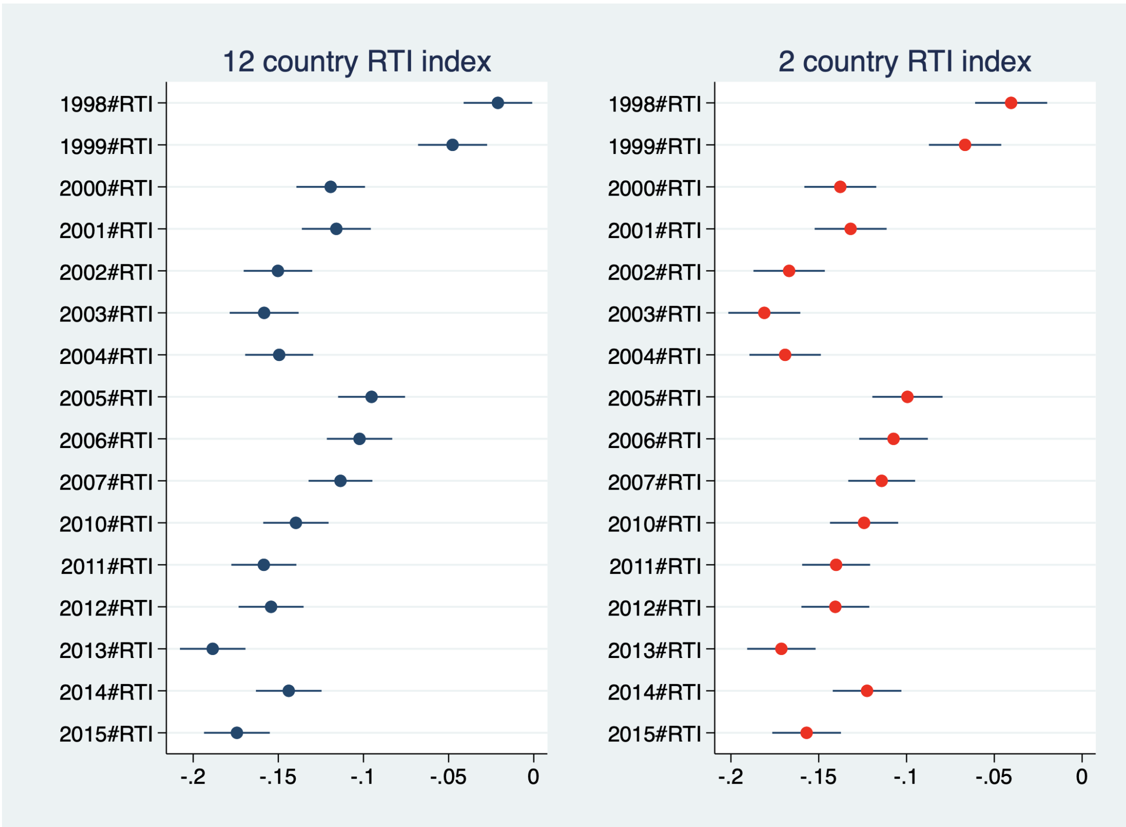

Figure 6: Estimated interaction effects between RTI and survey year
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About the authors

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About FoWiGS

The Future of Work in the Global South (FoWiGS) is an initiative supported by the International Development Research Centre (IDRC) and coordinated by the Center for the Implementation of Public Policies Promoting Equity and Growth (CIPPEC).

It aims at understanding the implications of technological change on jobs from a Global South perspective bringing data, knowledge, and policy frameworks to build evidence-based narratives on the future of work in developing countries.

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