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Labour market polarization in South Africa

A decomposition analysis

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Abstract: There is evidence from developed countries that technical change affects not only the employment intensity of production, but also the occupational composition of employment. The use of artificial intelligence, automation, and robots has changed the skills composition of employment. A range of 'routine' tasks are being replaced by machines which has led to polarization: a relative increase in higher level and in lower level jobs. This paper is concerned with examining the extent to which labour market polarization has taken place in South Africa over the period 1993–2017. A decomposition method is used in which change in employment can be attributed to changes in occupational mix, technology, and economic structure as well as an economic growth effect. The polarization we find is mild. This may be because technology in South Africa lags elsewhere. Furthermore, the low rates of investment in South Africa means that uptake of new technology is slow.

Key words: decomposition, labour market, polarization, tasks, occupations

JEL classification: J21, J24, C65

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Note: Some typographical errors in Equations 5, 7, and 8 were corrected in May 2021.

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1 Introduction

South Africa's economic growth is constrained in part by shortages of skilled labour. There have been several government initiatives to address such shortages, including a Skills Development Act (1998), various National Skills Development Strategies (NSDS), and the establishment of Sector Education and Training Authorities (SETAs), designed to enhance the supply of needed skills. There are 21 SETAs, established in 2005, which raise levies to fund training based on estimates of potential skills shortages. Although some have performed well, there has been discussion in policy circles about the need to reformulate the overall skills strategy. In 2013, the Minister of Higher Education and Training released a *White Paper for Post-School Education and Training: Building an Expanded, Effective and Integrated Post-School System* (WP-PSET) (DHET 2013). In November 2015, the Department of Higher Education and Training (DHET) initiated consultations around a *National Skills Development Strategy and Sector Education Training Authorities Landscape Proposal* (NSLP). This aimed, inter alia, at providing a more focussed mandate for SETAs, and transforming them into permanent specialised service delivery units within DHET. It was anticipated that these consultations would lead to a replacement of the NSDS III, which was due to end on 1 April 2018. However, in December 2016, its term was extended to 31 March 2020.

Understanding the drivers of the demand for skills and their future trajectories will strengthen DHET's capacity to use the re-mandated SETAs effectively. However, predicting those trajectories is difficult and uncertain. All forecasts are conditional on the continuing validity of the premises upon which they are based. For employment forecasts, these premises include inter alia the technologies that undergird employment demands. Future technical change is inherently unknowable in any detail. We may be fairly confident about broad trends, such as industry becoming more capital intensive, but it is difficult to know the extent of this intensification and how it will vary across sectors.

The pace and nature of technological change today makes 'forecasting' technical change even more difficult than in some previous periods. There is growing evidence from elsewhere that technical change affects not only the employment intensity of production, but also the occupational composition of employment. In particular, there is solid evidence that the use of artificial intelligence, automation, and robots has changed the skills composition of employment in developed countries. A range of 'routine' tasks—those for which complete instructions can be written down—are being replaced by machines. Many of these tasks are carried out by middle level occupations, so their replacement has led to polarization: a relative increase in higher level jobs that perform tasks which require initiative and judgement ('abstract labour') and in lower level jobs, which require some kind of human interaction ('manual labour'), and a relative decline in the middle level jobs that can be routinized ('routine labour'). There has been an explosion of studies on the polarizing effects of the new technologies, particularly in developed countries (see, for example: Autor et al. 2003; Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor and Salomons 2018; Bárány and Siegel 2018).

It is likely that South Africa will follow a similar path, especially as much of its technological development is adapted from global technology. This polarizing trend will happen on top of South Africa's already high structural unemployment. This will likely create a dynamic that is different from that found in developed countries. While some displaced workers from the middle may be able to transition from routine labour to abstract, others will find themselves competing in the already over-supplied market for manual labour.

Since South Africa's technology is heavily influenced by global technology with a lag, it is probably less useful to 'predict' future skills demands based on past trends in South Africa itself than it is to examine the economy-wide consequences of South Africa following the same technological trajectory as the rest of the world. Such trends also have potentially profound implications for skills development programmes that DHET wishes to develop. This paper lays a basis for modelling to analyse prospective economy-wide changes.

2 Method and data

2.1 Decomposition

There are several drivers of change in the use of skills in the economy. They are:

1. Output growth: other things equal, use of all skills rises as output grows;
2. Structural change: since occupational shares in sector employment vary, changes in the sectoral structure of the economy will, other things being equal, change the demand for skills;
3. Technical change: changes in demand for skills are driven by technical change. Technical change can be further decomposed into:
    a. changes in the demand for labour *vis a vis* capital;
    b. changes in the occupational mix of that labour.

In this paper, we undertake an empirical decomposition of past trends in employment by occupation and industry and output to explore how occupational composition of employment has changed in South Africa, and how each of the above drivers has contributed to it.

We can specify a labour-output ratio for sector *a*, as

$$\lambda_a \equiv \frac{L_a}{X_a} \tag{1}$$

where L_a is the total employment in sector *a* and X_a is total output.

We define the share of occupation *o* in sector *a*, $\theta_{a,o}$, as the ratio of the employment in that occupation, $L_{a,o}$, to the total employment in the sector, L_a:

$$\theta_{a,o} \equiv \frac{L_{a,o}}{L_a} \equiv \frac{L_{a,o}}{\sum_o L_{a,o}} \tag{2}$$

We can decompose these definitions as follows.[1] Firstly, the change in employment in a sector can be split into a component emanating from the change in the labour-output ratio (keeping output constant) and one emanating from a change in output (keeping the labour-output ratio constant):

$$\Delta L_a = X_a \cdot \Delta\lambda_a + \lambda_a \cdot \Delta X_a \tag{3}$$

where Δ denotes the change in a variable between two periods ($\Delta L \equiv L_{t2} - L_{t1}$, etc).

[1] For expositional purposes, we assume an exact decomposition so that we can ignore the covariance terms. We include these in the empirical application.

The change in the number of workers in occupation *o* in sector *a* can similarly be broken into a component emanating from the change in the occupational mix of employment in the sector and one coming from the change in the level of employment in that sector:

$$\Delta L_{a,o} = L_a \cdot \Delta\theta_{a,o} + \theta_{a,o} \cdot \Delta L_a \tag{4}$$

Substituting (3) into (4) we can write

$$\Delta L_{a,o} = \lambda_a \cdot X_a \cdot \Delta\theta_{a,o} + \theta_{a,o} \cdot (X_a \cdot \Delta\lambda_a + \lambda_a \cdot \Delta X_a) \tag{5}$$

and simplifying gives

$$\Delta L_{a,0} = \underbrace{\lambda_a \cdot X_a \cdot \Delta\theta_{a,o}}_{\substack{\text{occupational mix}\\ \text{effect}}} + \underbrace{\theta_{a,o} \cdot X_a \cdot \Delta\lambda_a}_{\substack{\text{labour intensity}\\ \text{effect}}} + \underbrace{\theta_{a,o} \cdot \lambda_a \cdot \Delta X_a}_{\text{output effect}} \tag{6}$$

We can then move to the economy-wide effects, adding changes in the sectoral composition of output:

$$L_o \equiv \sum_a \theta_{a.o} \cdot L_a \equiv \sum_a \theta_{a.o} \cdot \frac{L_a}{X_a} \cdot \frac{X_a}{X} \cdot X \equiv \sum_a \theta_{a,o} \cdot \lambda_a \cdot \phi_a \cdot X \tag{7}$$

where X is the total output in the economy ($X = \sum_a X_a$).

This allows us to break the output effect in (6) into a growth effect and a sectoral composition effect. Combining (6) and (7) we can write:

$$\Delta L_o \equiv \underbrace{\sum_a \lambda_a \cdot \phi_a \cdot X \cdot \Delta\theta_{a,o}}_{\text{occupation mix effect}} + \underbrace{\sum_a \theta_{a,o} \cdot \phi_a \cdot X \cdot \Delta\lambda_a}_{\text{technical change effect}} + \underbrace{\sum_a \theta_{a,o} \cdot \lambda_a \cdot X \cdot \Delta\phi_a}_{\text{structural change effect}} + \underbrace{\sum_a \theta_{a,o} \cdot \lambda_a \cdot \phi_a \cdot \Delta X}_{\text{growth effect}} \tag{8}$$

Equation (8) shows how the change in the overall use of an occupation can be decomposed into these four components. Like all such accounting decompositions, it is true by definition, rather than a causal analysis. However, it can provide a useful starting point for framing the analysis. To be able to say something about future trends in occupational use, we need to say something about possible past trends in each of these components.

The above decomposition is used in the next section to investigate trends in South Africa's occupational structure between 1996 and 2017. We emphasise that while this might give us an idea of drivers, it does not tell us causes. Each component can itself be the outcome of interaction between different forces. For example, if we see that sectoral change accounts for a large change in occupational use, we do not know whether that change has been driven by external factors, such as global demand, or domestic, such as the reduction of importance of mining. If occupational mix is significant, we do not know whether this was a response to changing demand because of technology shifts or because of shortages in supply of skills.

2.2 Data

We use the Post-Apartheid Labour Market Series (PALMS) 1993–2017 (Kerr and Wittenberg 2017) and extract employment for 1-digit industries (coded as *jobindcode*) and 1-digit occupations (coded as *jobocccode*) as shown in Table 1 below.

Table 1: 1-digit industries and 1-digit occupations used by PALMS and in the decomposition analysis

Industries	Occupations	Occ. Code
1. Agriculture, hunting, forestry and fishing	1. Legislators, senior officials and managers	Man
2. Mining and quarrying	2. Professionals	Prof
3. Manufacturing	3. Technical and associate professionals	Tch
4. Utilities	4. Clerks	Clr
5. Construction	5. Service workers and shop and market sales workers	Srv
6. Trade	6. Skilled agricultural and fishery workers	Sag
7. Transport	7. Craft and related trades workers	Trd
8. Finance	8. Plant and machine operators and assemblers	Mch
9. Services	9. Elementary Occupation	Ele

Source: authors' construction based on Kerr and Wittenberg (2017).

Data was extracted and annualized for the period 1996–2017. Domestic worker services are not dealt with consistently throughout the period in the underlying data. We therefore added them in with the *9. Services* industry and the *9. Elementary Occupations* where necessary. Residual employment by industry and occupation is identified in some but not all the data points. The average share across all data points is small at 0.12 per cent and this data is therefore removed from the working set.

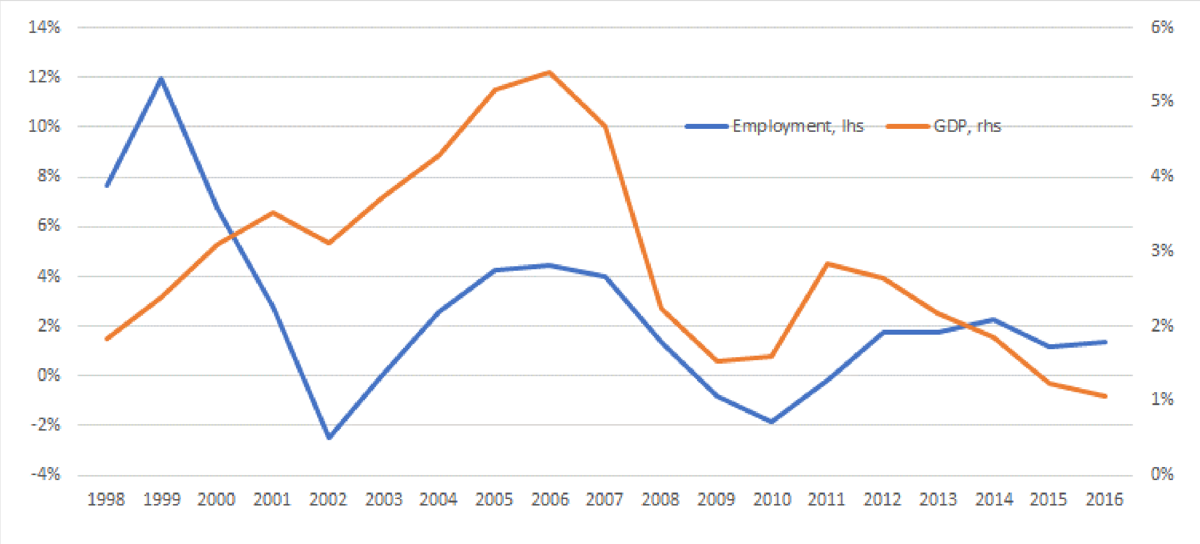
We combined the employment data with GDP data for 1-digit industries obtained from Statistics South Africa (SSA 2018). These industries line up with PALMS 1-digit industries except for the last two (general government services and personal services), which we aggregated into a single industry to match *9. Services* in Table 1 above.[2]

We analyse trends across the whole period and within three sub-periods (see below). In order to reduce the influence of our choice of start and end years for our periods, we use three-year averages for each, reducing the full period of analysis to 1997–2016.

Figure 1 below shows the three-year moving averages for total employment and GDP. The 1999 spike in employment growth is followed by a rapid decline to 2001, while GDP growth continues to rise at the start. At the other end of the time period, from 2011 onwards, growth in GDP declines, while growth in employment is relatively stable in the 1.5 to 2 per cent range from 2012 onwards.

[2] Note that up to 2006, the sum of the industries' value added does not match Stats South Africa's (Stats SA) published total value added at constant basic prices. We make sure that industry shares add to unity so that there is a difference between the implicit total value added that we work with and the Stats SA published total value added at constant basic prices.

Figure 1: Total GDP (at constant basic prices) and employment rates of change, 1996/98–2015/17



Source: authors' construction based on Kerr & Wittenberg (2017) and SSA (2018).

Peak GDP growth was in 2006, after which a downturn began, lasting until 2010. Recovery starts in 2010 for employment and stabilizes between 1.5 and 2 per cent. GDP growth also increases initially but after two years it starts to decline. It seems reasonable to identify the following subperiods:

- Upswing: 1997–2006
- Downturn: 2006–2010
- Recovery: 2010–2016

The pace of technical change in an economy will be driven in part by the pace of investment, since technology is generally embedded in new equipment and machinery. Because investment and GDP growth are correlated, we would expect a faster rate of adoption when growth is fast than when it is slow. South Africa's economic growth since the end of apartheid has varied. With the three distinct phases identified above, the economic growth rate rose until 2006. Then there was the period of the financial recession, 2007–2009, followed by slow recovery since 2010.

3 Results of decomposition at 1-digit level

In this section, we present results of the decomposition at 1-digit occupation level and for the various elements of the decomposition model.

3.1 Full period: 1997–2016

Results of the decomposition model described in the previous section are reported for the full period (1996/98–2015/17) in the next table. In the first panel, absolute values are shown for the starting year (column 1) and the ending year (column 3) of the period of observation. Total absolute changes are shown in column 2 and in columns 4–7 for the decomposition elements, representing the impact of change in the occupational mix, technical change, change in industry structure and change in growth respectively.

The overall change and impacts can be seen in row 10. Employment increased by 5.6 million over the full period. The total occupational impact cancels out while the impact of technical change (i.e. changes in the employment-output ratio), given the same average occupational and industry shares and no economic growth, resulted in a decline of employment by about 0.93 million. If only industry shares had changed, while everything else had remained unchanged, employment would have increased by just over 310,000. Thus, a shift has taken place over the full period towards somewhat more employment intensive industries. The effect shown in column 7 relies solely on economic growth while keeping labour-(net)output ratios and industry and occupation shares constant. With over 6.2 million it makes the highest contribution. In relative terms (off a normalized base, see appendix), this is larger than total change with the technical change effect outweighing the structural change effect, although both are relatively small.

Table 2: Results of a decomposition of employment for the full period 1996/98–2015/17

	1	2	3	4	5	6	7	8	9	10	11	12
	Employment in Starting Period 1996/98	Total Change in Employment	Employment in End Period 2015/17	Occupational Mix Effect	Technical Change Effect	Structural Change Effects	Growth Effect	Total	Occ. Mix Eff.	Tech. Chg. Eff.	Str. Chg. Eff.	Gr. Eff.
					Change in employment			Percentage change in employment (%)				
1. Legislators, senior officials and managers	642,203	677,370	1,319,574	195,970	-83,199	78,173	486,426	71.3	20.6	-8.8	8.2	51.2
2. Professionals	598,761	221,341	820,102	-176,239	22,680	2,463	372,437	30.4	-24.2	3.1	0.3	51.2
3. Technical and associate professionals	1,006,889	390,219	1,397,108	-262,268	-401	18,883	634,005	31.5	-21.2	0.0	1.5	51.2
4. Clerks	856,044	727,454	1,583,499	57,501	-50,671	99,478	621,146	59.9	4.7	-4.2	8.2	51.2
5. Service workers and shop and market sales workers	1,120,966	1,171,504	2,292,470	210,231	-9,215	123,422	847,065	70.8	12.7	-0.6	7.5	51.2
6. Skilled agricultural and fishery workers	267,354	-187,971	79,383	-207,783	-50,852	-27,081	97,746	-98.4	-108.8	-26.6	-14.2	51.2
7. Craft and related trades workers	1,365,212	456,556	1,821,768	-334,683	-185,932	138,529	838,642	27.9	-20.4	-11.3	8.5	51.2
8. Plant and machine operators and assemblers	950,726	244,593	1,195,318	-50,221	-253,541	-24,247	572,602	21.9	-4.5	-22.7	-2.2	51.2
9. Elementary Occupation	2,540,927	1,944,188	4,485,115	567,491	-318,353	-95,542	1,790,592	55.6	16.2	-9.1	-2.7	51.2
10. Total	**9,349,083**	**5,645,255**	**14,994,338**	**0**	**-929,484**	**314,079**	**6,260,660**	**46.1**	**0.0**	**-7.6**	**2.6**	**51.2**

Note: percentage change is calculated over the whole period, off a normalized employment base as explained in the appendix.

Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

In terms of occupational mix (column 4), managers (row 1) grow by almost 200,000, service and shop workers (row 5) increase by just over 200,000, and elementary occupations (row 9) by almost 600,000. This is at the cost of the other occupations. The negative overall impact of technical change (column 5) effects all occupations except professionals. Change in the industry structure (column 6) favours all occupations except skilled agricultural workers, machine operators and elementary occupations. Economic growth (column 7 and 12) had a uniform impact across all occupations by definition; the growth effect measures the effect of total GDP growth which is the same for all sectors. See the appendix for more detail.

3.2 Upswing: 1997–2006

As discussed in the previous section, the upswing period lasted from 1997 to 2006. Growth in employment clocked in indeed at a robust 36.21 per cent over the period (off the normalized base), and added just over 4 million to workers in employment. Interestingly, during this period, the technology (i.e. employment intensity) changed to the point that this component of total employment growth added more than 0.7 million workers. It appears that technology change was inversely related to economic growth during this period. The impact of the latter (economic growth) therefore contributed less to overall employment (30 per cent) than the sum of the components.

Table 3: Results of a decomposition of employment for the upswing period 1996/98–2005/07

	1 Employment in Starting Period 1996/98	2 Total Change in Employment	3 Employment in End Period 2005/07	4 Occupational Mix Effect	5 Technical Change Effect	6 Structural Change Effects	7 Growth Effect	8 Total	9 Occ. Mix Eff.	10 Tech. Chg. Eff.	11 Str. Chg. Eff.	12 Gr. Eff.
				Change in employment				Percentage change in employment (%)				
1. Legislators, senior officials and managers	642,203	306,600	948,804	-18,771	37,632	46,946	240,794	38.7	-2.4	4.7	5.9	30.4
2. Professionals	598,761	102,433	701,194	-103,302	37,320	-31,317	199,732	15.6	-15.7	5.7	-4.8	30.4
3. Technical and associate professionals	1,006,889	279,349	1,286,238	-90,800	58,526	-39,532	351,155	24.2	-7.9	5.1	-3.4	30.4
4. Clerks	856,044	425,555	1,281,599	-1,733	52,489	51,713	323,086	40.0	-0.2	4.9	4.9	30.4
5. Service workers and shop and market sales workers	1,120,966	568,671	1,689,637	-86,232	175,738	54,741	424,424	40.7	-6.2	12.6	3.9	30.4
6. Skilled agricultural and fishery workers	267,354	205,435	472,789	102,215	54,873	-62,927	111,274	56.1	27.9	15.0	-17.2	30.4
7. Craft and related trades workers	1,365,212	540,466	1,905,678	-117,063	76,572	85,417	495,540	33.1	-7.2	4.7	5.2	30.4
8. Plant and machine operators and assemblers	950,726	290,413	1,241,139	15,277	-73,778	10,650	338,264	26.1	1.4	-6.6	1.0	30.4
9. Elementary Occupation	2,540,927	1,398,080	3,939,008	300,409	306,257	-178,793	970,207	43.8	9.4	9.6	-5.6	30.4
10. Total	**9,349,083**	**4,117,002**	**13,466,085**	**0**	**725,628**	**-63,102**	**3,454,476**	**36.2**	**0.0**	**6.4**	**-0.6**	**30.4**

Note: percentage change is calculated over the whole period, off a normalized employment base as explained in the appendix.

Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

During the upswing period, the occupational mix shifted towards employment of elementary occupations, skilled agricultural workers, and to a lesser degree towards machine operators, away from the other occupations. Technical change benefitted all occupations except machine operators. The change in economic structure offers a mix set of impacts with elementary occupations carrying most of the burden of a shift towards industries that use them to a lesser degree. As mentioned in section 3.1, economic growth had a uniform impact across all occupations by definition.

3.3 Downturn: 2006–2010

During the economic downturn total employment increased by about 355,000 workers. While the economic growth effect is still almost 10 per cent over the period, equivalent to 1.35 million workers, the shift towards lower labour intensity causes a similar decline. As a result, the change in economic structure is comparable to the overall growth in employment.

Table 4: Results of a decomposition of employment for the downturn period 2005/07–2009/11

	1	2	3	4	5	6	7	8	9	10	11	12
	Employment in Starting Period 2005/07	Total Change in Employment	Employment in End Period 2009/11	Occupational Mix Effect	Technical Change Effect	Structural Change Effects	Growth Effect	Total	Occ. Mix Eff.	Tech. Chg. Eff.	Str. Chg. Eff.	Gr. Eff.
				Change in employment				Percentage change in employment (%)				
1. Legislators, senior officials and managers	948,804	179,872	1,128,676	116,861	-64,005	24,145	102,871	17.3	11.2	-6.2	2.3	9.9
2. Professionals	701,194	60,758	761,952	-29,747	-7,117	25,201	72,421	8.3	-4.1	-1.0	3.4	9.9
3. Technical and associate professionals	1,286,238	276,552	1,562,790	124,051	-30,262	41,988	140,775	19.4	8.7	-2.1	2.9	9.9
4. Clerks	1,281,599	181,073	1,462,672	70,269	-50,978	25,784	135,998	13.2	5.1	-3.7	1.9	9.9
5. Service workers and shop and market sales workers	1,689,637	240,563	1,930,200	113,924	-96,252	43,741	179,151	13.3	6.3	-5.3	2.4	9.9
6. Skilled agricultural and fishery workers	472,789	-383,803	88,986	-262,194	-161,401	14,890	24,901	-152.4	-104.1	-64.1	5.9	9.9
7. Craft and related trades workers	1,905,678	-197,357	1,708,321	-220,696	-226,793	70,242	179,891	-10.9	-12.1	-12.5	3.9	9.9
8. Plant and machine operators and assemblers	1,241,139	-55,487	1,185,652	-41,808	-89,774	-44,077	120,172	-4.6	-3.4	-7.4	-3.6	9.9
9. Elementary Occupation	3,939,008	52,292	3,991,299	129,340	-605,310	131,022	397,240	1.3	3.2	-15.1	3.3	9.9
10. Total	**13,466,085**	**354,464**	**13,820,548**	**0**	**-1,331,891**	**332,935**	**1,353,421**	**2.6**	**0.0**	**-9.7**	**2.4**	**9.9**

Note: percentage change is calculated over the whole period, off a normalized employment base as explained in the appendix.

Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

During this period, a move towards higher skilled occupations such as managers, technical, clerical, and services workers can be observed. All occupations are negatively impacted by the technical change effect, albeit in varying degrees. Skilled agricultural workers, trades workers, and elementary occupations suffer most. Shifts in the industry structure during this period benefit all occupations except machine operators.

3.4 Recovery: 2010–2016

Employment increases by about 1.2 million over the recovery period 2010–2016, just over 8% over the normalized base. In contrast to the earlier upswing period, the recovery period is characterized by a shift towards lower overall labour intensity which takes some of the gloss away from the economic growth effect. Industry structure switches towards higher labour-intensive industries but the contribution is modest. Thus, if the economic structure and technology had remained the same, 1.7 million would have been added to employment.

Table 5: Results of a decomposition of employment for the recovery period 2009/11–2015/17

	1 Employment in Starting Period 2009/11	2 Total Change in Employment	3 Employment in End Period 2015/17	4 Occupational Mix Effect	5 Technical Change Effect	6 Structural Change Effects	7 Growth Effect	8 Total	9 Occ. Mix Eff.	10 Tech. Chg. Eff.	11 Str. Chg. Eff.	12 Gr. Eff.
				Change in employment				Percentage change in employment (%)				
1. Legislators, senior officials and managers	1,128,676	190,898	1,319,574	100,236	-68,871	14,944	144,589	15.6	8.2	-5.6	1.2	11.8
2. Professionals	761,952	58,150	820,102	-40,095	-10,634	15,338	93,542	7.3	-5.1	-1.3	1.9	11.8
3. Technical and associate professionals	1,562,790	-165,682	1,397,108	-317,559	-47,447	23,611	175,713	-11.1	-21.3	-3.2	1.6	11.8
4. Clerks	1,462,672	120,827	1,583,499	5,914	-89,444	24,258	180,099	7.9	0.4	-5.9	1.6	11.8
5. Service workers and shop and market sales workers	1,930,200	362,270	2,292,470	207,270	-144,180	50,077	249,102	17.2	9.8	-6.8	2.4	11.8
6. Skilled agricultural and fishery workers	88,986	-9,603	79,383	-25,985	10,578	-4,257	10,060	-11.3	-30.5	12.4	-5.0	11.8
7. Craft and related trades workers	1,708,321	113,447	1,821,768	-623	-81,378	-13,337	208,785	6.4	0.0	-4.6	-0.8	11.8
8. Plant and machine operators and assemblers	1,185,652	9,666	1,195,318	-23,876	-82,838	-24,511	140,892	0.8	-2.0	-6.9	-2.1	11.8
9. Elementary Occupation	3,991,299	493,816	4,485,115	94,718	-118,451	16,632	500,918	11.6	2.2	-2.8	0.4	11.8
10. Total	**13,820,548**	**1,173,790**	**14,994,338**	**0**	**-632,665**	**102,755**	**1,703,700**	**8.1**	**0.0**	**-4.4**	**0.7**	**11.8**

Note: percentage change is calculated over the whole period, off a normalized employment base as explained in the appendix

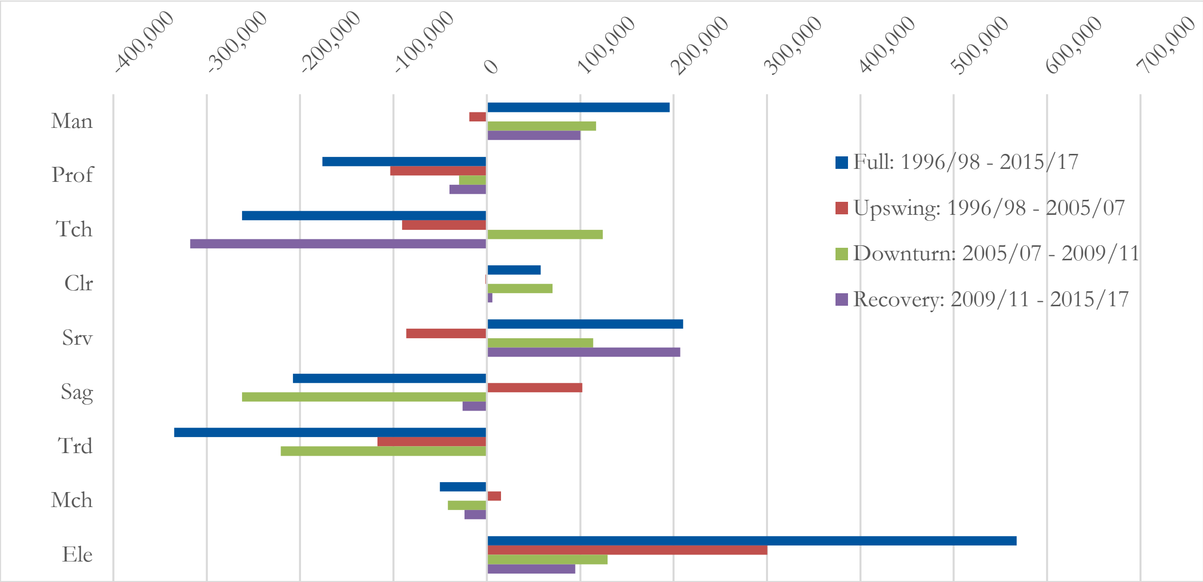
Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

The occupational mix effect during the recovery period shows a tendency to favour managers, service workers, and elementary occupations. The occupational shift is mainly away from technical workers, the significance of which will be discussed later in more detail. The technical change effect is negative for all occupations except skilled agricultural workers. The industry structure changed to the modestly benefit of most occupations but shifted away from industries that used trades workers and machine operators more.

3.5 Occupational mix effect

The results can also be summarized by focusing on the elements of the decomposition across the subperiods. Figure 2 shows that over the full, upswing, and recovery periods, manager, services and shop workers, and elementary occupations gained. Most other occupations appeared to have lost out. The increase in skilled agricultural workers seems to be a bit of an outlier. The consistent decline of professionals is somewhat of a surprise.

Figure 2: Occupational mix effect for all periods and all occupations

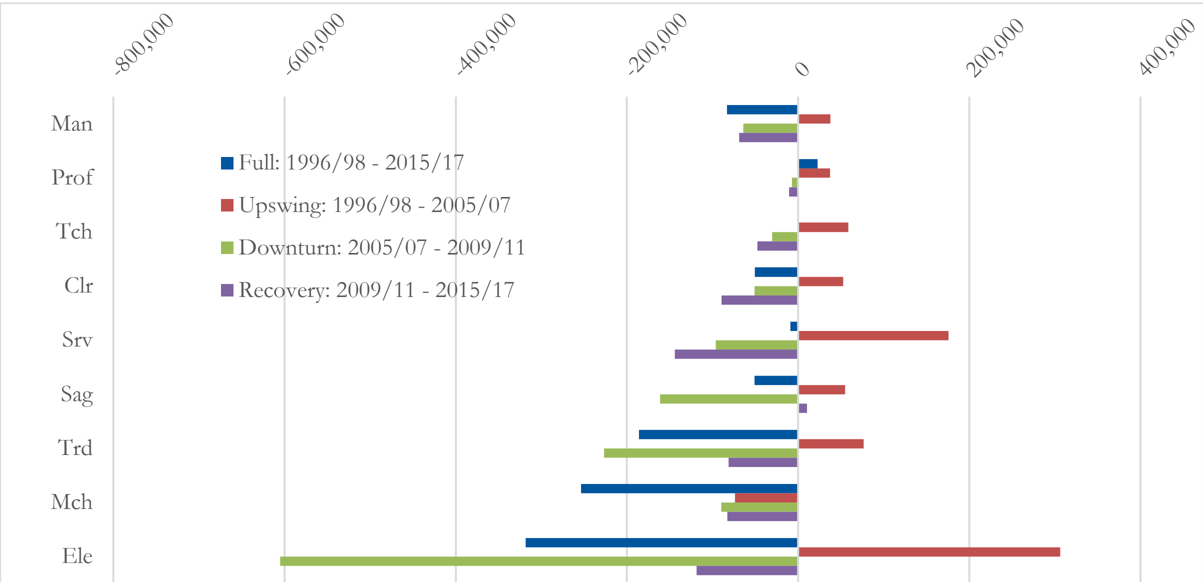


Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

3.6 Technical change effect

The technical change effects are largely negative during the full, downturn, and recovery periods but positive during the upswing period. This seems unusual as in times of upswing, on would expect higher capacity utilization would result in labour productivity going up. Likewise, in economic downturns, firms may decide to hang onto their workforce in order to avoid costly search costs, thereby reducing labour productivity. Perhaps the generous amount of overarching slack in the labour market is an explanation here.

Figure 3: Technical change effect for all periods and all occupations

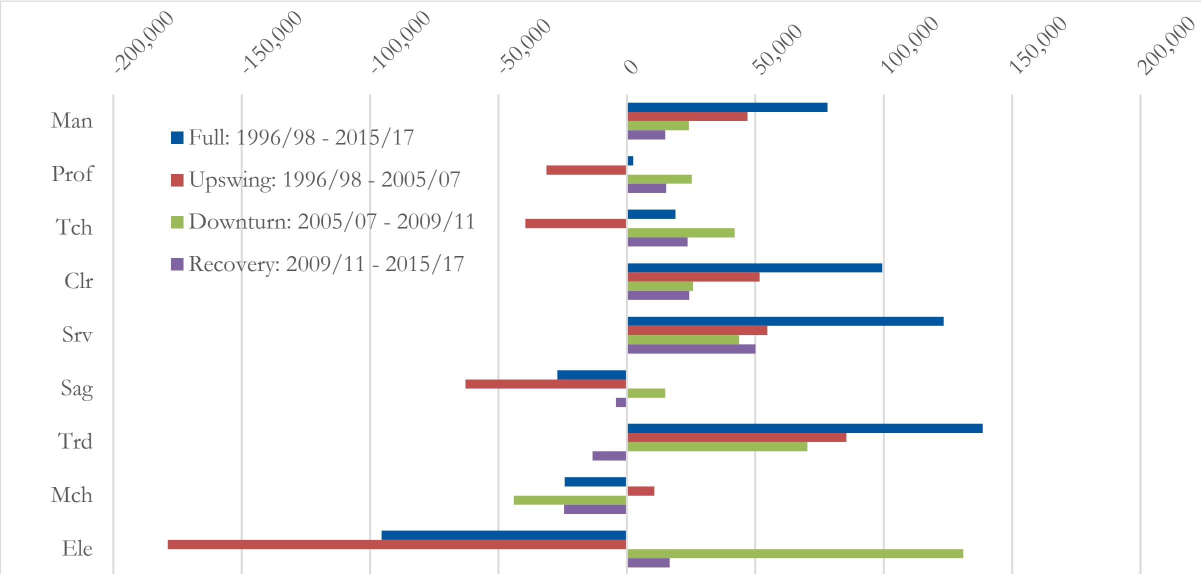


Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

3.7 Structural change effect

The structural change effects offer a mixed bag of results. Most strikingly, during the upswing period, there was a shift away from industries that employed elementary occupations, which reversed during the downturn. However, this reversal was not enough to create a positive effect over the whole period. This was also the case for skilled agricultural workers, albeit to a lesser degree. The perverse shift during the upswing period also applies to professional and technical occupations. Positive impacts of structural change are recorded for trades and services workers, clerks, and managers even during the downturn period.

Figure 4: Structural change effect for all periods and all occupations

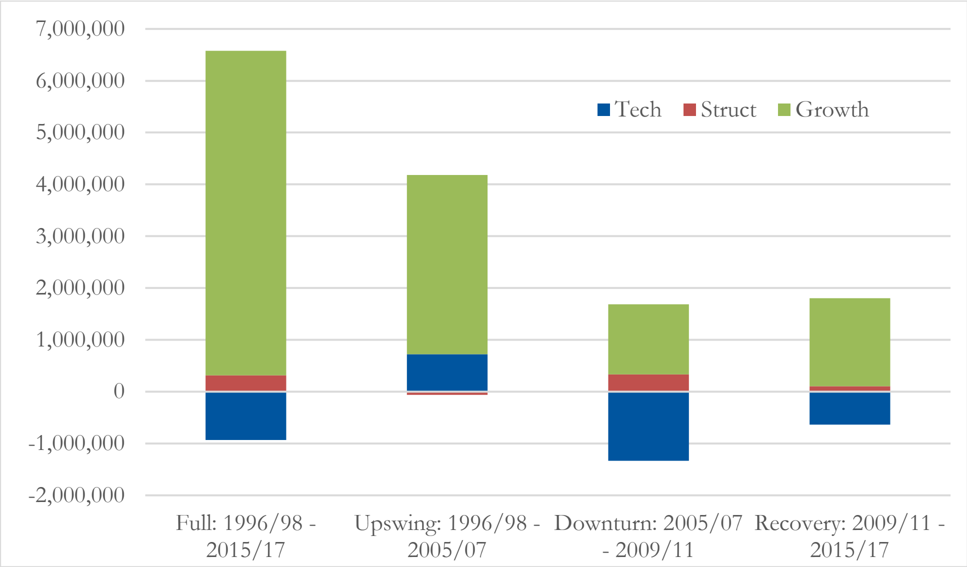


Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

3.8 Summary of overall effects

It is no surprise to see in Figure 5 below that the economic growth effect dominates the proceeding here. As discussed earlier, the overall impacts of the technical change element of the decomposition is somewhat counterintuitive in that it is not just negative during the full and recovery periods but also during the downturn period. In addition, the impact is positive during the upswing, the first ten years of the full period. The economic structure element plays a rather modest role in the greater scheme of things.

Figure 5: Summary of overall effects for all periods



Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

4 The task-based approach to labour markets[3]

The foregoing analysed the effects of changes in various drivers of occupational employment, taking the standard occupational definitions as given. Recent developments in labour market economics have raised some criticisms of this approach, particularly regarding displacement of labour by computers, and suggested a task-based approach would be better. We outline this approach in this section, before making a preliminary application of it to South Africa in section 5.

The traditional model of production in economics postulates that outputs depend upon inputs of services from primary factors of production, and upon technology. The primary factors are typically capital and labour but can be—and commonly are—disaggregated into whatever granular detail the data can support. This allows labour services to be differentiated by different skill types, frequently identified with occupations. There can be substitution between factors as their relative prices vary. Thus, the traditional canonical model—using skill differentiation based on occupations—would model computers as bringing down the price of machines embodying the new technology, leading to them displacing labour.

However, Autor et al. (2003) observed that computers do not substitute for occupations but rather for tasks. Furthermore, although the machines might substitute for some tasks, they complement others. The task-based approach to production identifies, both conceptually and empirically, which tasks might be substituted, and which might be complemented. Where instructions for tasks can be codified so that they can be carried out following an exact routine, computers can substitute for humans. They cannot do so for tasks that require analytical skills and judgement, or human interaction. Indeed, not only can computers not substitute for humans, they may enhance human productivity in such tasks, hence the complementarity.

[3] This section provides a brief account of the task-based approach to production. A fuller exploration of the area is undertaken in a companion paper (Davies and van Seventer, forthcoming)

On this basis, Autor et al. (2003) identify four categories of tasks with different implications for human-computer interactions. These are summarized in Table 6.

Table 6: Predictions of task model for the impact of computerization on four categories of workplace tasks

		Routine	**Non-routine**
Analytical and interactive	Examples	Record-keeping	Forming/testing hypotheses
		Calculation	Medical-diagnosis
		Repetitive customer service (e.g. bank teller)	Legal writing
			Persuading/selling
			Managing others
	Computer impact	*Substantial substitution*	*Strong complementarities*
Manual	Examples	Picking or sorting	Janitorial-services
		Repetitive-assembly	Truck driving
	Computer impact	*Substantial substitution*	*Limited opportunities for substitution or complementarity*

Source: authors' adaptation, based on Table 1 in Autor et al. (2003).

Autor et al.'s (2003) framework has been developed and refined in subsequent work, largely by David Autor and his co-authors (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Atalay et al. 2018; Autor 2013; Autor and Handel 2013). Although the approach was developed in the context of recent technological change, it seems to provide the basis for thinking about production more generally. It suggests ways of going behind the notion of 'labour' and 'capital' substitution to consider a more nuanced explanation of what it is about labour and capital that facilitates substitution between them and among different varieties of each.[4]

Acemoglu and Autor (2011) argue that the 'canonical' model treats occupations (or skill categories), as static. An occupation today is assumed to deliver the same services that it did decades ago. However, there is plenty of evidence that this is not the case. Autor (2013) provides many illustrative examples.

Although the approach has been useful in a range of applications, and holds promise for further development in the future, it is still in an early stage, especially as regards empirical application. Occupational classification systems have collected data on tasks for some time, but the development of a clear system of classification is still problematic. Autor and colleagues have worked with task data in the Dictionary of Occupational Titles (DOT, National Academy of Sciences, 1971). The German system of occupations (BIBB, Federal Institute for Vocational

[4] As with many recent developments in economics, the view of production processes as assemblages of tasks is not new to economics. Adam Smith's iconic description of a pin factory is task-based. Early developments in linear programming were often related to efficient allocation of tasks. However, computers have made it possible to handle the large data required to properly implement task-based analysis, complementing the skills of economists and raising their productivity.

Education and Training) has detailed task descriptions and they have been done developing overarching classifications, but as yet there is no single system. Autor (2013) appealed for researchers to build on existing attempts, rather than developing their own, but it seems that this has not been heeded.

In South Africa, the Organising Framework for Occupations (OFO) (DHET 2013) does have task descriptions; but it is difficult to bring them into a coherent framework. In practice, this means that the task-based approach falls back on classifying occupations by what is perceived to be their dominant tasks, which is the approach we adopt in Section 5 below.

In addition, when confronted to the development of these technologies, some of the early observations on the possibilities of computers carrying out human tasks seem rather outdated. Their range has expanded. Experiments with self-driving vehicles suggest that Autor et al.'s (2003) placement of 'truck driving' in Table 6 could be wrong. Deep Mind's AlphaGo suggests that self-instructing computers could begin to do a range of problem-solving tasks that have hitherto been considered as requiring human inputs.

5 Results of task-based decomposition

Following Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018), we adopt the 1-digit occupations mapping to the 'abstract', 'routine', and 'manual' task-based categories as shown in Table 7.

Table 7: Industries and occupations used in the decomposition analysis

Broad Task	Occupations
Abstract	1. Legislators, senior officials and managers
Abstract	2. Professionals
Routine	3. Technical and associate professionals
Routine	4. Clerks
Manual	5. Service workers and shop and market sales workers
Routine	6. Skilled agricultural and fishery workers
Routine	7. Craft and related trades workers
Routine	8. Plant and machine operators and assemblers
Manual	9. Elementary Occupation

Sources: adapted from Kerr and Wittenberg (2017); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018).

The decomposition model described in section 2.1 above is applied to the three categories shown in the first column of Table 7. The first four rows of Table 8 show results for the whole period. The most important element of the decomposition is the occupational effect reported in column 4 and 9. Routine tasked labour has declined by almost 0.8 million workers. This represents 15 per cent over the whole period off the normalized base. Manual tasked labour has increased by almost the same, with small gains for abstract labour. This labour market polarization is enhanced by the technical change effect (column 10). All categories suffer but routine labour loses out more relatively. The structural change effect (column 11) does not work particularly well in favour of manual labour. Rather, routine labour benefits more from shifts in shares toward industries that demand them more. However, in the end, both abstract and manual labour benefit proportionally more (column 8) than routinized labour.

Further down in Table 8, it can be seen that broadly, except for the upswing period 1996/98–2005/07, routine tasked labour performed worse than the other groups in terms of occupational shift effects (columns 4 and 9) and overall change in employment (columns 2 and 8).

Table 8: Decomposition of change in employment for broad tasks and selected periods

			1	2	3	4	5	6	7	8	9	10	11	12
			Start of Period	Total Change	End of Period	Occu-pational Mix Effect	Technical Change Effect	Structural Change Effect	Growth Effect	Total Chg.	Occ. Mix Eff.	Tech. Chg. Eff.	Str. Chg. Eff.	Gr. Eff.
	Task	Period	Numbers							Percentage change (%)				
1	Total	Full	9,349,083	5,645,255	14,994,338	0	-929,484	314,079	6,260,660	46.1	0.0	-7.6	2.6	51.2
2	Abstract	Full	1,240,965	898,712	2,139,676	19,731	-60,519	80,636	858,863	53.5	1.2	-3.6	4.8	51.2
3	Routine	Full	4,446,225	1,630,852	6,077,077	-797,453	-541,397	205,562	2,764,140	30.2	-14.8	-10.0	3.8	51.2
4	Manual	Full	3,661,893	3,115,692	6,777,585	777,722	-327,568	27,880	2,637,657	60.4	15.1	-6.4	0.5	51.2
5	Total	Upswing	9,349,083	4,117,002	13,466,085	0	725,628	-63,102	3,454,476	36.2	0.0	6.4	-0.6	30.4
6	Abstract	Upswing	1,240,965	409,033	1,649,998	-122,073	74,951	15,629	440,526	28.2	-8.4	5.2	1.1	30.4
7	Routine	Upswing	4,446,225	1,741,217	6,187,442	-92,104	168,682	45,321	1,619,319	32.7	-1.7	3.2	0.9	30.4
8	Manual	Upswing	3,661,893	1,966,751	5,628,644	214,177	481,995	-124,052	1,394,632	42.8	4.7	10.5	-2.7	30.4
9	Total	Downturn	13,466,085	354,464	13,820,548	0	-1,331,891	332,935	1,353,421	2.6	0.0	-9.7	2.4	9.9
10	Abstract	Downturn	1,649,998	240,630	1,890,628	87,114	-71,122	49,345	175,293	13.6	4.9	-4.0	2.8	9.9
11	Routine	Downturn	6,187,442	-179,021	6,008,421	-330,378	-559,208	108,827	601,737	-2.9	-5.4	-9.2	1.8	9.9
12	Manual	Downturn	5,628,644	292,855	5,921,499	243,264	-701,562	174,762	576,391	5.0	4.2	-12.0	3.0	9.9
13	Total	Recovery	13,820,548	1,173,790	14,994,338	0	-632,665	102,755	1,703,700	8.1	0.0	-4.4	0.7	11.8
14	Abstract	Recovery	1,890,628	249,048	2,139,676	60,141	-79,505	30,282	238,130	12.4	3.0	-3.9	1.5	11.8
15	Routine	Recovery	6,008,421	68,656	6,077,077	-362,129	-290,529	5,764	715,550	1.1	-6.0	-4.8	0.1	11.8
16	Manual	Recovery	5,921,499	856,086	6,777,585	301,988	-262,631	66,708	750,020	13.5	4.8	-4.1	1.1	11.8

Note: percentage change is calculated over the whole period, off a normalized employment base as explained in the appendix. Full: 1996/98 – 2015/17, Upswing 1996/98 - 2005/07, Downturn: 2005/07 - 2009/11, Recovery: 2009/11 - 2015/17

Source: authors' calculations based on Kerr & Wittenberg (2017) and SSA (2018).

During the recession period of 2005/07–2009/11 and the subsequent recovery period (2009/11–2015/17), there is stronger evidence of routinized labour falling behind. This is not only the case for the occupational shift element of the decomposed change in employment but also for the technical change and the structural shift elements, albeit to a lesser degree and not for the technical change effect during the downturn, where manual labour suffers more. The overall period also shows a bias against routine tasked labour, except for the structural shift element.

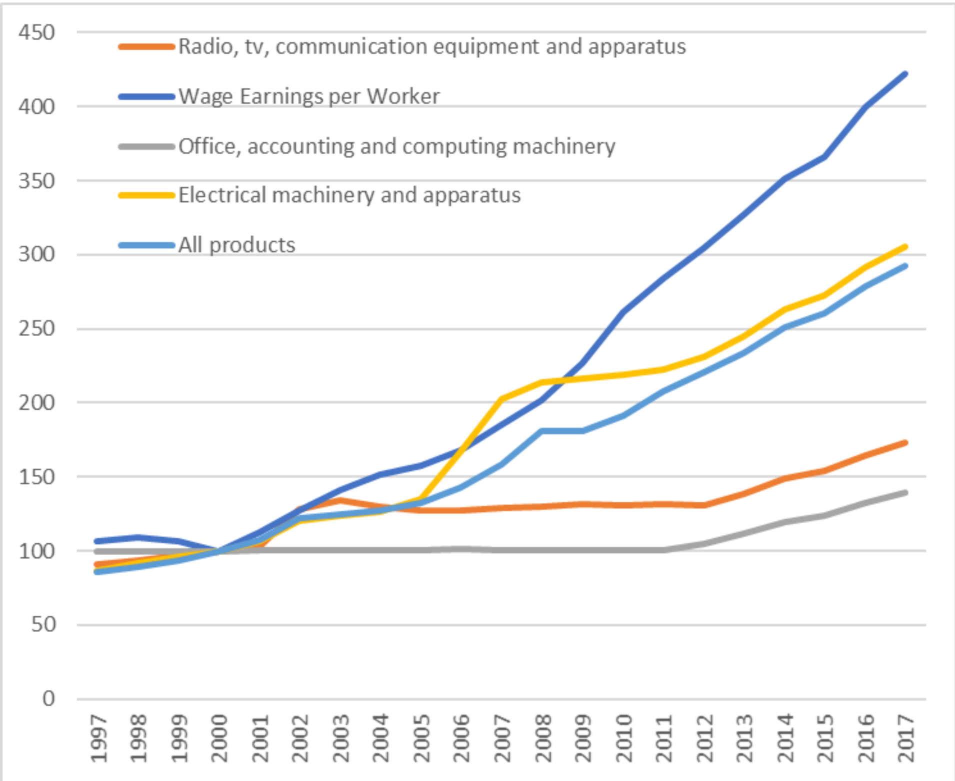
In a recent paper on labour market polarization in developed and developing countries, Das and Hilgenstock (2018) note that there are different views on whether developing countries are already faced with labour market polarization forces. On one hand, disputing the view that falling middle skilled employment shares are suggestive of polarization, the authors argue that it ignores possible shifts within broad occupations away from routine tasks. On the other hand, they claim that developing economies are still subject to 'ongoing structural transformation' (Das and Hilgenstock 2018: 6–7). Our decomposition analysis allows us to consider the latter and we find some evidence in this regard for South Africa. However, the strongest shifts that we find are of the first kind—i.e. the occupational shifts (keeping all other forces fixed)—although we acknowledge that our analysis is subject to the shortcoming of rather broad occupation groups.

A related distinction made by Das and Hilgenstock (2018: 6) is that high initial exposure to routinization (i.e. during an earlier period) is associated with lower subsequent exposure, while at a lower range of initial exposure, higher exposure is associated with a subsequent *rise* in exposure, which they explain by structural change. We find it difficult to ascertain whether South Africa has a relatively high exposure to routinization compared to other countries or whether it is relatively low and rising or not, in particular if we account for the 2006–10 downturn period. If anything, the results presented above suggest that routinization has become more pronounced during the last subperiod (2010–2016) compared to the first subperiod (1997–2006).

Yet another observation by Das and Hilgenstock (2018: 7) considers technological change as an important driver of polarization due to rapid rise in productivity of ICT and declining capital costs thereof, which offers a motivation for firms to routinize labour. While this may be a strong force in developed countries, it is argued that this may not be the case in developing countries. Using the decomposition analysis described above for South Africa we found some very weak evidence that technical change causes a shift away from routinized toward abstract and/or manual tasked labour (row 15, column 10 of Table 8).

One way to find out is to track wage earnings per unit of employment as a proxy for wage costs against the PPI of the production of ICT related equipment, as a proxy of capital costs as is attempted in the next figure.

Figure 6: Wage costs and PPIs for selected ICT related product groups (2000=100)



Source: authors' calculations based on various publications of Statistic South Africa's (PPIs), South African Reserve Bank, National Accounts (wage earnings), and PALMS data (Kerr and Wittenberg 2017, total employment).

Framed as an index, Figure 6 shows that wage cost have outstripped of what we consider here as a proxy for capital costs of ICT related production, in particular during the latter stage of the period of observation. Although, this supports the broad impact of the technical change element of the decomposition, it does not say much about task-based or any other group of labour.

Das and Hilgenstock (2018) also refer to globalization as a factor that has an impact on labour market polarization. The idea here is that, through deeper integration into global value chains, globalization could bring about structural change that may shift production towards more routine tasked jobs. Kummritz and Quast (2016: 19), using a global Input-Output framework in which South Africa is represented, find South Africa' integration into global value chains is fairly low due to its focus on raw material and its location far away from production networks. This is reflected by the relatively low impact of the structural change element in our decomposition analysis. In section 3.1, one can note that machine operators were impacted negatively by the structural change element of the decomposition. Indeed, this appears to be counterintuitive, because the impact on skilled agricultural workers is also negative. The latter makes sense given the ongoing shift out of agriculture. The negative impact on machine operators is, however, offset by gains in technical (3) and trades (7) workers which are both mapped to routine tasked labour, highlighting the rather crude filter on the data used in this analysis. Nevertheless, Table 8 suggests that routine tasked labour benefitted over the period from structural change effect of the decomposition. In summary, the evidence from the decomposition analysis concords with findings elsewhere.

Conclusions

This paper has been concerned with examining the extent to which labour market polarization has taken place in South Africa over the period 1993 to 2017. A decomposition method was used in which change in employment can be attributed to changes in the occupational mix, technology, and the economic structure as well as to an economic growth effect. The decomposition method was applied at the 1-digit occupation level and at a broad task-based level where the latter is an aggregation of the former. The period of observation covers the years 1996 to 2017. To deal with outliers, three year moving averages are used. For full period 1996/98–2015/17, subperiods are identified to emphasize an upswing period 1996/98–2005/07, a downturn period 2005/07–2009/11, and a recovery period 2009/11–2015/17.

We find that the economic growth effect dominates the effects of the other components of the decomposition. During the positive growth periods, managers, services and shop workers, and elementary occupations gained. Most other occupations appeared to have lost out. The technical change effects are unusual in that they are largely negative during the downturn but positive during the upswing period. One would have expected the opposite, in times of upswing, higher capacity utilization would result in labour productivity to go up. Likewise, in economic downturns, firms may decide to hang onto their workforce in order to avoid costly search costs, thereby reducing labour productivity. Perhaps the generous amount of overarching slack in the labour market is an explanation here. The structural change effects offer a mixed bag of results without a clear pattern amongst the occupation groups.

At the broad task level, we focus mainly on the occupational mix effect, and find that routine tasked labour has declined while manual tasked labour has increased with small gains for abstract labour. This is not only the case for the occupational shift element of the decomposed change in employment but also for the technical change and the structural shift elements, albeit to a lesser degree. The overall period also shows a bias against routine tasked labour across all components of the decomposition. In support of other literature, we find some evidence for developing countries that the ongoing process of structural change—which has progressed to a higher degree in developed economies—throws somewhat of a spanner in the works by recording moderate gains across the board, including routinized labour. There is also some modest support for the observation made elsewhere that technical change in developing countries has had a limited impact on the bias against routinized labour.

While the decomposition method used uncovers some patterns, it does not determine causality. The patterns we find are consistent with the hypothesis that the new technology causes polarization but there are other possible explanations. Shortages of skilled labour associated with 'routine' tasks could lead to polarization of employment. (One could test this since it would mean wage rates rise rather than equipment prices falling).

However, the polarization we find is rather mild. We think that is because the technology in South Africa lags elsewhere. Furthermore, the low rates of investment in South Africa—driven by a number of factors—means that the uptake of new technology is slow.

We will explore scenarios in which South Africa does adopt the new technology in a separate paper.

The main policy implications we are concerned with are those for skill training. If the 'routine' skills are becoming relatively redundant, does that imply a need to focus supply of labour in other directions? The emphasis on Science, Technology, Engineering, and Mathematics (STEM) may not necessarily prepare people for abstract labour. If new entrants are unable to use their skills, it not only has implications for their earnings and future careers, but also for social discontent. Should training be focused on soft skills? Although there is a notion that people can move into abstract labour, what proportion of the population can do this?

Is the scope for complementarity restricted by the shortage of abstract skills? While the computer technology can create demand for abstract labour, if there are shortages, that demand will simply raise the income of those providing that labour, probably worsening polarization in the labour market and inequality in South Africa.

To explore this we need a model, which we do in the next paper (Davies and van Seventer, forthcoming).

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Appendix: derivation of decomposition with average weights

In the text we derive the decomposition in theory, without worrying too much about details of the empirical application. In this appendix, we pay more attention to the empirical application. We also explain why we use the normalized occupational employment as the base for percentage calculations.

Decomposition algebra

In the text, the final decomposition is given as

$$\Delta L_o \equiv \underbrace{\sum_a \lambda_a \cdot \phi_a \cdot X \cdot \Delta\theta_{a,o}}_{\text{occupation mix effect}} + \underbrace{\sum_a \theta_{a,o} \cdot \phi_a \cdot X \cdot \Delta\lambda_a}_{\text{technical change effect}} + \underbrace{\sum_a \theta_{a,o} \cdot \lambda_a \cdot X \cdot \Delta\phi_a}_{\text{structural change effect}} + \underbrace{\sum_a \theta_{a,o} \cdot \lambda_a \cdot \phi_a \cdot \Delta X}_{\text{growth effect}} \tag{1}$$

Implicitly, all the coefficients and variables used as weights for each set of changes are measured in the initial period. However, if these weights are used, the decomposition will not be exhaustive, since we ignore the interaction between changes in the various elements.

To illustrate, assume we are decomposing into only the growth and structural change effects. We could write the output of sector *a* as the product of total output, X, and the sector share, ϕ_a:

$$X_a \equiv \phi_a \cdot X \tag{2}$$

If we were dealing with very small changes, we could decompose (2) by differentiating it totally:

$$dX_a \equiv \phi_a \cdot dX + X \cdot d\phi_a \tag{3}$$

The effect of the change in X on the change in ϕ_a is ignored because we assume both changes are infinitesimal. The decomposition is <u>exhaustive</u>. Furthermore, the decomposition in (3) is <u>reversible</u>. We will get the same decomposition whether we work with change from period 0 to 1 or its reverse from 1 to 0.

With large discrete changes, both these attributes depend on the weights used. With discrete changes, (3) has to be written in differences:

$$\Delta X_a \equiv X_a^1 - X_a^0 \equiv \underbrace{\phi_a \cdot \Delta X}_{\text{Growth effect}} + \underbrace{X \cdot \Delta\phi_a}_{\text{Structural change effect}} + \underbrace{\Delta X \cdot \Delta\phi_a}_{\text{Interaction effect}} \tag{4}$$

There is now an interaction term—a covariance—which could be large if the discrete changes are large. The decomposition is therefore not exhaustive. Furthermore, it is not reversible. When we move from period 0 to period 1, we have

$$\Delta X_a \equiv \phi_a^0 \cdot \Delta X + X^0 \cdot \Delta\phi_a + \Delta X \cdot \Delta\phi_a \tag{5}$$

However, if we reverse this, and move from period 1 back to period 0, we would have

$$\Delta X_a \equiv \phi_a^1 \cdot \Delta X + X^1 \cdot \Delta\phi_a + \Delta X \cdot \Delta\phi_a \tag{6}$$

Although the overall change we are trying to explain, and the changes in each of the components, are the same, we assign different weights to the components, and thus have a different decomposition. Therefore, if X has grown, and ϕ_a has fallen, we will assign a greater impact to changes in ϕ_a and a smaller one to changes in X when we measure from period 0 to period 1 than when we measure from period 1 to period 0.

A standard way of circumventing both these problems is to average the weights between the two periods:

$$\Delta X_a \equiv \bar{\phi}_a \cdot \Delta X + \bar{X} \cdot \Delta \phi_a \tag{7}$$

where $\bar{\phi}_a = \frac{1}{2}\left(\phi_a^0 + \phi_a^1\right)$ and $\bar{X} = \frac{1}{2}\left(X^0 + X^1\right)$.

We can show this is exhaustive—there is no interaction term—by expanding the terms in (7):

$$\begin{aligned}
\Delta X_a &\equiv \frac{\phi_a^0 + \phi_a^1}{2} \cdot \left(X^1 - X^0\right) + \frac{X^0 + X^1}{2}\left(\phi_a^1 - \phi_a^0\right) \\
2 \cdot \Delta X_a &\equiv \left(\phi_a^0 + \phi_a^1\right) \cdot \left(X^1 - X^0\right) + \left(X^0 + X^1\right)\left(\phi_a^1 - \phi_a^0\right) \\
&\equiv \cancel{\phi_a^0 X^1} - \phi_a^0 X^0 + \phi_a^1 X^1 \cancel{- \phi_a^1 X^0} \cancel{+ \phi_a^1 X^0} + \phi_a^1 X^1 - \phi_a^0 X^0 \cancel{- \phi_a^0 X^1} \\
&\equiv 2\phi_a^1 X^1 - 2\phi_a^0 X^0 \\
&\Rightarrow \Delta X \equiv \phi_a^1 X^1 - \phi_a^0 X^0
\end{aligned}$$

And since the weights are the same whether moving from period 0 to 1 or period 1 to 0, this decomposition is reversible. This is the method adopted in the paper.

When there are three terms in the formula to be decomposed, there are some further complications. Say we have sector *a* employment, L_a, as the product of total output, X, the sector share, ϕ_a, and the employment-output ratio, λ_a:

$$L_a \equiv \lambda_a \cdot \phi_a \cdot X \tag{8}$$

Then, change in sector *a* employment is

$$\Delta L_a \equiv \Delta \lambda_a \cdot \bar{\phi}_a \cdot \bar{X} + \bar{\lambda}_a \cdot \Delta \phi_a \cdot \bar{X} + \bar{\lambda}_a \cdot \bar{\phi}_a \cdot \Delta X \tag{9}$$

$$\begin{aligned}
\Delta L_a \equiv &\left(\lambda_a^1 - \lambda_a^0\right)\frac{1}{2}\left(\phi_a^1 + \phi_a^0\right)\frac{1}{2}\left(X^1 + X^0\right) \\
&+ \frac{1}{2}\left(\lambda_a^1 + \lambda_a^0\right)\left(\phi_a^1 - \phi_a^0\right)\frac{1}{2}\left(X^1 + X^0\right) \\
&+ \frac{1}{2}\left(\lambda_a^1 + \lambda_a^0\right)\frac{1}{2}\left(\phi_a^1 + \phi_a^0\right)\left(X^1 - X^0\right)
\end{aligned} \tag{10}$$

$$\begin{aligned}4\Delta L_a \equiv &\left(\lambda_a^1-\lambda_a^0\right)\left(\phi_a^1+\phi_a^0\right)\left(X^1+X^0\right)\\ &+\left(\lambda_a^1+\lambda_a^0\right)\left(\phi_a^1-\phi_a^0\right)\left(X^1+X^0\right)\\ &+\left(\lambda_a^1+\lambda_a^0\right)\left(\phi_a^1+\phi_a^0\right)\left(X^1-X^0\right)\end{aligned}\tag{11}$$

$$\begin{aligned}4\Delta L_a \equiv &\left(\lambda_a^1\phi_a^1+\lambda_a^1\phi_a^0-\lambda_a^0\phi_a^1-\lambda_a^0\phi_a^0\right)\left(X^1+X^0\right)\\ &+\left(\lambda_a^1\phi_a^1-\lambda_a^1\phi_a^0+\lambda_a^0\phi_a^1-\lambda_a^0\phi_a^0\right)\left(X^1+X^0\right)\\ &+\left(\lambda_a^1\phi_a^1+\lambda_a^1\phi_a^0+\lambda_a^0\phi_a^1+\lambda_a^0\phi_a^0\right)\left(X^1-X^0\right)\end{aligned}\tag{12}$$

$$\begin{aligned}4\Delta L_a \equiv &\left(\lambda_a^1\phi_a^1X^1+\lambda_a^1\phi_a^0X^1-\lambda_a^0\phi_a^1X^1-\lambda_a^0\phi_a^0X^1+\lambda_a^1\phi_a^1X^0+\lambda_a^1\phi_a^0X^0-\lambda_a^0\phi_a^1X^0-\lambda_a^0\phi_a^0X^0\right)\\ &+\left(\lambda_a^1\phi_a^1X^1-\lambda_a^1\phi_a^0X^1+\lambda_a^0\phi_a^1X^1-\lambda_a^0\phi_a^0X^1+\lambda_a^1\phi_a^1X^0-\lambda_a^1\phi_a^0X^0+\lambda_a^0\phi_a^1X^0-\lambda_a^0\phi_a^0X^0\right)\\ &+\left(\lambda_a^1\phi_a^1X^1+\lambda_a^1\phi_a^0X^1+\lambda_a^0\phi_a^1X^1+\lambda_a^0\phi_a^0X^1-\lambda_a^1\phi_a^1X^0-\lambda_a^1\phi_a^0X^0-\lambda_a^0\phi_a^1X^0-\lambda_a^0\phi_a^0X^0\right)\end{aligned}\tag{13}$$

$$\begin{aligned}4\Delta L_a \equiv &\lambda_a^1\phi_a^1X^1\cancel{+\lambda_a^1\phi_a^0X^1}\cancel{-\lambda_a^0\phi_a^1X^1}\cancel{-\lambda_a^0\phi_a^0X^1}\cancel{+\lambda_a^1\phi_a^1X^0}\cancel{+\lambda_a^1\phi_a^0X^0}\cancel{-\lambda_a^0\phi_a^1X^0}-\lambda_a^0\phi_a^0X^0\\ &+\lambda_a^1\phi_a^1X^1\cancel{-\lambda_a^1\phi_a^0X^1}\cancel{+\lambda_a^0\phi_a^1X^1}-\lambda_a^0\phi_a^0X^1+\lambda_a^1\phi_a^1X^0\cancel{-\lambda_a^1\phi_a^0X^0}\cancel{+\lambda_a^0\phi_a^1X^0}-\lambda_a^0\phi_a^0X^0\\ &+\lambda_a^1\phi_a^1X^1+\lambda_a^1\phi_a^0X^1+\lambda_a^0\phi_a^1X^1\cancel{+\lambda_a^0\phi_a^0X^1}\cancel{-\lambda_a^1\phi_a^1X^0}-\lambda_a^1\phi_a^0X^0-\lambda_a^0\phi_a^1X^0-\lambda_a^0\phi_a^0X^0\end{aligned}\tag{14}$$

$$\begin{aligned}4\Delta L_a \equiv &\lambda_a^1\phi_a^1X^1-\lambda_a^0\phi_a^0X^0\\ &+\lambda_a^1\phi_a^1X^1-\lambda_a^0\phi_a^0X^1+\lambda_a^1\phi_a^1X^0-\lambda_a^0\phi_a^0X^0\\ &+\lambda_a^1\phi_a^1X^1+\lambda_a^1\phi_a^0X^1+\lambda_a^0\phi_a^1X^1-\lambda_a^1\phi_a^0X^0-\lambda_a^0\phi_a^1X^0-\lambda_a^0\phi_a^0X^0\end{aligned}\tag{15}$$

$$\begin{aligned}4\Delta L_a \equiv &3\lambda_a^1\phi_a^1X^1-3\lambda_a^0\phi_a^0X^0\\ &-\lambda_a^0\phi_a^0X^1+\lambda_a^1\phi_a^1X^0+\lambda_a^1\phi_a^0X^1+\lambda_a^0\phi_a^1X^1-\lambda_a^1\phi_a^0X^0-\lambda_a^0\phi_a^1X^0\end{aligned}\tag{16}$$

$$\begin{aligned}4\Delta L_a \equiv &3\lambda_a^1\phi_a^1X^1-3\lambda_a^0\phi_a^0X^0+\lambda_a^1\phi_a^1X^1-\lambda_a^1\phi_a^1X^1+\lambda_a^0\phi_a^0X^0-\lambda_a^0\phi_a^0X^0\\ &-\lambda_a^0\phi_a^0X^1+\lambda_a^1\phi_a^1X^0+\lambda_a^1\phi_a^0X^1+\lambda_a^0\phi_a^1X^1-\lambda_a^1\phi_a^0X^0-\lambda_a^0\phi_a^1X^0\end{aligned}\tag{17}$$

$$\begin{aligned}4\Delta L_a \equiv &4\lambda_a^1\phi_a^1X^1-4\lambda_a^0\phi_a^0X^0\\ &-\lambda_a^1\phi_a^1X^1+\lambda_a^1\phi_a^1X^0+\lambda_a^1\phi_a^0X^1-\lambda_a^1\phi_a^0X^0\\ &+\lambda_a^0\phi_a^0X^0-\lambda_a^0\phi_a^0X^1+\lambda_a^0\phi_a^1X^1-\lambda_a^0\phi_a^1X^0\end{aligned}\tag{18}$$

$$\begin{aligned}4\Delta L_a \equiv &4\lambda_a^1\phi_a^1X^1-4\lambda_a^0\phi_a^0X^0\\ &-\lambda_a^1\left[\phi_a^1X^1-\phi_a^1X^0-\phi_a^0X^1+\phi_a^0X^0\right]\\ &+\lambda_a^0\left[\phi_a^0X^0-\phi_a^0X^1+\phi_a^1X^1-\phi_a^1X^0\right]\end{aligned}\tag{19}$$

$$
\begin{aligned}
4\Delta L_a \equiv\ & 4\lambda_a^1\phi_a^1X^1 - 4\lambda_a^0\phi_a^0X^0 \\
& -\lambda_a^1\left[\phi_a^1\left(X^1 - X^0\right) - \phi_a^0\left(X^1 - X^0\right)\right] \\
& +\lambda_a^0\left[-\phi_a^0\left(X^1 - X^0\right) + \phi_a^1\left(X^1 - X^0\right)\right]
\end{aligned} \tag{20}
$$

$$
\begin{aligned}
4\Delta L_a \equiv\ & 4\lambda_a^1\phi_a^1X^1 - 4\lambda_a^0\phi_a^0X^0 \\
& -\lambda_a^1\left[\left(\phi_a^1 - \phi_a^0\right)\left(X^1 - X^0\right)\right] \\
& +\lambda_a^0\left[\left(\phi_a^1 - \phi_a^0\right)\left(X^1 - X^0\right)\right]
\end{aligned} \tag{21}
$$

$$
\begin{aligned}
4\Delta L_a \equiv\ & 4\lambda_a^1\phi_a^1X^1 - 4\lambda_a^0\phi_a^0X^0 \\
& -\left(\lambda_a^1 - \lambda_a^0\right)\left(\phi_a^1 - \phi_a^0\right)\left(X^1 - X^0\right)
\end{aligned} \tag{22}
$$

$$4\Delta L_a \equiv 4\lambda_a^1\phi_a^1X^1 - 4\lambda_a^0\phi_a^0X^0 - \Delta\lambda_a\Delta\phi_a\Delta X \tag{23}$$

$$\Delta L_a \equiv \lambda_a^1\phi_a^1X^1 - \lambda_a^0\phi_a^0X^0 - \frac{1}{4}\Delta\lambda_a\Delta\phi_a\Delta X \tag{24}$$

There is thus an interaction term.

If, however, we re-write (8) as

$$L_a \equiv \lambda_a \cdot X_a \tag{25}$$

(which is equivalent, since $X_a \equiv \phi_a \cdot X$), we can then write the decomposition as

$$\Delta L_a \equiv \Delta\lambda_a \cdot \overline{X}_a + \overline{\lambda}_a \cdot \Delta X_a \tag{26}$$

and we can proceed similarly to the two-variable decomposition of equation (7) above. The interaction term seems to disappear. This is because the interaction is subsumed in the weights.

The same problem arises when we go to the four-component formula. We can circumvent it by substituting L_a for $\lambda_a\phi_a X$.

Presenting results as percentages

Having decomposed the overall change into the four components, it is convenient to calculate the results as percentage rather than absolute changes. However, the choice of base upon which to calculate the percentages is influenced by the choice of weights. Since we use average weights, we calculate the percentage changes with reference to an average. Our decomposition is essentially of the equation for the employment in activity *a* of occupation *o*:

$$L_{a,o} = \theta_{a,o} \cdot \lambda_a \cdot \phi_a \cdot X \tag{27}$$

However, since we use average weights, the correct reference levels for changes in $L_{a,o}$ should use the same weights.

$$\overline{L}_{a,o} = \overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \overline{X} \tag{28}$$

We therefore present percentages based on this normalized level of occupational employment in activities. Thus, the four effects in percentages are:

Growth effect: $$\frac{\Delta L^G_{a,o}}{\overline{L}_{a,o}} = \frac{\overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \Delta X}{\overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \overline{X}} = \frac{\Delta X}{\overline{X}}$$

Structural Change Effect: $$\frac{\Delta L^S_{a,o}}{\overline{L}_{a,o}} = \frac{\overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \Delta\phi_a \cdot \overline{X}}{\overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \overline{X}} = \frac{\Delta\phi_a}{\overline{\phi}_a}$$

Technical Change Effect: $$\frac{\Delta L^T_{a,o}}{\overline{L}_{a,o}} = \frac{\overline{\theta}_{a,o} \cdot \Delta\lambda_a \cdot \overline{\phi}_a \cdot \overline{X}}{\overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \overline{X}} = \frac{\Delta\lambda_a}{\overline{\phi}_a}$$

Occupational Mix Effect: $$\frac{\Delta L^O_{a,o}}{\overline{L}_{a,o}} = \frac{\Delta\theta_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \overline{X}}{\overline{\theta}_{a,o} \cdot \overline{\lambda}_a \cdot \overline{\phi}_a \cdot \overline{X}} = \frac{\Delta\theta_{a,o}}{\overline{\theta}_{a,o}}$$

We can see that the growth effect will be the same for all activities and occupations, as it should be, since they are all being driven by the same change in GDP. The structural change effects will be the same for all occupations within each activity (although they will differ across activities). Again, this is as it should be. Similarly, the technical change effect will be the same for all occupations within each sector.

It is also easy to see that these regularities in the results will not arise unless the weights in the denominator are not the same as in the numerator. If we use the average coefficients in the decomposition but calculate the percentage based on, say, the initial year coefficients, the growth effects will not be uniform across all sectors and occupations, etc.