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Offshoring within South African manufacturing firms

An analysis of the labour market effects

Anmar Pretorius,[1] Carli Bezuidenhout,[1] Marianne Matthee,[*2] and Derick Blaauw[1]

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Abstract: In South Africa, the manufacturing sector—important for growth and employment creation—has shown declining growth, poor productivity performance, decreased labour demand, and increased imports of intermediate goods (offshoring activities). Offshoring influences jobs and wages differently depending on the type of industry and worker. We provide a nuanced view of offshoring in South Africa, using firm- and employer–employee-level data to disentangle its impact on the labour market in terms of capital- and labour-intensive industries and skilled and unskilled workers. Contrary to previous findings in developed countries, we find that offshoring generally lowers employment in manufacturing firms, and seems to increase the percentage of unskilled workers and lower the percentage of skilled workers. There are indications that increased narrow offshoring increases the cohort of unskilled workers, particularly in ultra-labour-intensive industries. As offshoring gains momentum, worker-level earnings increase in capital- and labour-intensive industries but decrease in ultra-labour-intensive industries.

Key words: offshoring, firm-level data, employer–employee data, employment, skills, wages

JEL classification: F14, F16

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1 Introduction

Manufacturing is the engine of economic growth: Cantore et al. (2017) argue that their own evidence shows that this is still the case, even though the role of manufacturing in generating growth has been questioned as a result of evidence from, for example, India and the failure of industrialization in Africa. Thirlwall (1983) explains that Kaldor's laws on manufacturing are based on the premise that manufacturing displays dynamic returns to scale. Faster growth in the manufacturing sector leads to faster growth in the economy. Kaldor's laws, which state this relationship between manufacturing growth and GDP growth, have also been tested in an African context by Wells and Thirlwall (2004). The authors find that growth in manufacturing is indeed more closely associated with GDP growth than in sectors such as agriculture and services. However, Cantore et al. (2017) argue that not all types of manufacturing value added contribute to growth, and that increased productivity and technological change are key to growth (for example in the case of China).

In South Africa, the manufacturing sector's contribution to GDP has been steadily declining (e.g. 20 per cent in 1994 versus under 14 per cent in 2019; South African Market Insights 2019) and has displayed poor productivity performance (albeit heterogeneous between different industries within the sector) (Kreuser and Newman 2018). Declining growth in the industry resulted in approximately 250,000 job losses between 2005 and 2014. Of this, the largest decline in jobs was in the textiles industry (91,000). An exception was in the petroleum and chemicals industry, which created 20,000 jobs (Stats SA 2016). This calls for a nuanced approach in detailing the relationship between manufacturing and employment growth, considering industries as per their intensity level (being capital- or labour-intensive) (Zalk 2014). Indeed, South Africa's economy is highly capital-intensive, with costly labour being increasingly substituted by capital. Moreover, labour-intensive sectors also faced severe competition from low-wage countries after 1995, which resulted in many companies being shut down (World Bank 2018).

Another trend in the manufacturing sector has been increasing imports of intermediate inputs, for example in the South African metals and engineering sector. The percentage increased from approximately 22 per cent 20 years ago to approximately 35 per cent in recent years (Creamer 2015). Creamer (2015) explains this trend by detailing rising domestic production costs (including significant increases in electricity and labour) and production volatility (e.g. strikes and power disruptions). This signifies South African manufacturers' increasing involvement in fragmented production networks as a result of engaging in offshoring activities.

As the international literature has shown, these offshoring activities have consequences for manufacturing firms' labour demand (for both skilled and unskilled workers) and for wages paid to workers within a firm. For South Africa this has pertinent importance, as finding the solutions to employment creation within the manufacturing sector is challenging, given the current context of the large unskilled workforce. Bhorat and Rooney (2017), in their analysis of the manufacturing sector, surmise that it has had a greater demand for skilled workers, relative to semi-skilled and unskilled workers. Indeed, they explain that in absolute terms, '59 000 highly-skilled jobs in manufacturing were created in the South African economy between 2001 and 2014, while 149 000 semi-skilled jobs were lost, and unskilled jobs grew by 9 000" (Bhorat and Rooney 2017: 9). The question that arises is to what extent offshoring plays a role in these dynamics. Labour demand and firm dynamics (including entry and exit) are complex within the formal-plus-informal and multi-segment context of the South African labour market. The issue of offshoring is one of the knowledge gaps for efficient and focused policy formulation.

This paper aims to address this gap by answering the following question: what are the labour market impacts (i.e. in wages and employment levels) of offshoring within South African manufacturing firms? The focus of the paper is both on firm level and worker level. Firm-level analysis reveals the extent to which South African manufacturing firms are engaged in offshoring, while the worker-level data provide an indication of the individual wages and number of employees per firm (with different skills levels) subject to offshoring shocks. Understanding the labour market effects of importing activities within fragmented production networks provides first-time firm- and worker-level insights for South Africa that will assist policymakers in laying the path for South Africa's inclusive growth targets, specifically in employment creation within the manufacturing sector.

The paper is organized as follows: Section 2 provides a brief overview of the international literature; Section 3 provides the South African literature context; Section 4 details the South African manufacturing sector; Section 5 contains the data discussion, descriptive statistics, and empirical results; and Section 6 concludes.

2 Literature overview

Worldwide, production has become much more fragmented due to firms' increasing offshoring activities (Bandyopadhyay et al. 2017). Different prices for factors allow firms to be efficiency seekers, thereby acquiring better or cheaper resources to enlarge their gains from trade (that arise from specialization) (Bottini et al. 2007; Hummels et al. 2016). External factors such as lower trade barriers and decreased transport and international telecommunication costs have also contributed to the rise in global production networks (Andersson et al. 2016; Bottini et al. 2007). Offshoring within the manufacturing sector can therefore be defined as the geographical disaggregation of specified production tasks, where component production occurs in a foreign country (Hummels et al. 2016).

How does offshoring affect employment levels and wages? Traditionally, offshoring has been critically viewed within the public domain of developed countries, where it is claimed that low-skilled jobs are exported to developing countries, resulting in large-scale job losses and rising wage inequality (within the home country) (Bottini et al. 2007; Hsieh and Woo 2005; Hummels et al. 2016). However, the association between offshoring and labour outcomes is not that straightforward. Hummels et al. (2014), using Danish data, explain that although offshoring can lead to the displacement of workers (through the importation of an input/intermediate good that was previously produced within the firm), acquiring more cost-effective foreign inputs could have a positive effect through enhanced productivity, which in turn leads to higher output, employment levels, and wages. However, this is linked to the skills level of the worker, as offshoring tends to increase the wages of high-skilled workers and decrease wages for low-skilled workers. Feenstra and Hanson (2003) concur with this finding in their study on US data—offshoring results in a lower demand for low-skilled workers and a higher demand, coupled with higher wages, for high-skilled workers.

A vast body of theoretical and empirical literature has emerged over the last two decades on the labour consequences of offshoring (as detailed by Hummels et al. 2016). Andersson et al. (2016) summarize that most of the empirical literature uses industry-level data, where employment data within the industries are garnered at plant level. They furthermore state that only a limited number of studies employ firm-level data. An even more limited number of studies make use of matched employer–employee data. Hummels et al. (2016) explain that this type of data has only recently been used to study the offshoring effects on labour market outcomes. Such data have information on firm and worker characteristics and allow researchers to track workers over time. In particular, Hummels et al. (2016: 44) state that 'Matched employer–employee data allow researchers to accurately measure offshoring, and cleanly identify the causal effects of offshoring on wages'. A further contribution of this paper is therefore to the international literature in the application of offshoring using employer–employee data within a developing-country context.

3 South African literature context

Various South African studies have considered the labour market effect of increased exports. Edwards (2001) provides a summary of some of the earlier literature. This includes one of the first studies in this field, by Bell and Cattaneo (1997). Exports did increase employment in manufacturing between 1985 and 1993, but decreases in the labour coefficients of exports compared with manufacturing and imports reduced the growth rate of employment as a result of an increase in exports (Edwards 2001). Edwards (1999) extended the time period to 1997 in order to take into account the impact of the tariff liberalization programme initiated in 1994. The results were generally consistent with the Bell and Cattaneo (1997) study. In his 2001 paper, Edwards' results did not support the notion that trade liberalization was the reason for the decline in employment since the late 1980s, although export-led employment growth was unable to reduce unemployment (Edwards 2001).

However, no specific reference to the impact of offshoring is available. Pretorius and Blaauw (2005), for example, analysed industry data for the period 1993 to 2001, and found that the higher the ratio of exports to domestic sales, the more workers are employed—but this applied to highly skilled workers and not to semi- and unskilled workers. A follow-up study by Pretorius and Blaauw (2018) does consider the impact of imported inputs on industry employment levels. Highly skilled and skilled employment respond positively to increases in the ratio between imported and local inputs for manufacturing; the same observation is not made for the semi- and unskilled categories of employment.

This paper builds on previous trade- and labour-related studies conducted on the SARS (South African Revenue Service) administrative data (see Edwards et al. 2018; Matthee et al. 2017, 2018). Matthee et al. (2018) examine the characteristics of manufacturing exporters, while Matthee et al. (2017) add an understanding of the labour dynamics of this manufacturing sector. Edwards et al.'s (2018) study has a wider scope, including importers of intermediate inputs: they found that importing intermediates increases exports, especially for imports that are sourced from developed countries. They also found that two-way traders (importing inputs and exporting output) are more productive, employ more workers, and pay higher wages than exporters only or importers only.

It is here where this paper contributes to and expands the body of existing work on administrative data by investigating offshoring within the South African manufacturing context. As indicated above, the literature on offshoring considers the importation of intermediate inputs, and it has labour implications for workers in the manufacturing industry.

4 Brief overview of the South African manufacturing sector

Approximately one hundred years ago, South Africa was an economy dominated by mining and agriculture. The expansion of the mining sector brought with it increased demand for complementary products such as processed foods and textiles. The government responded in the

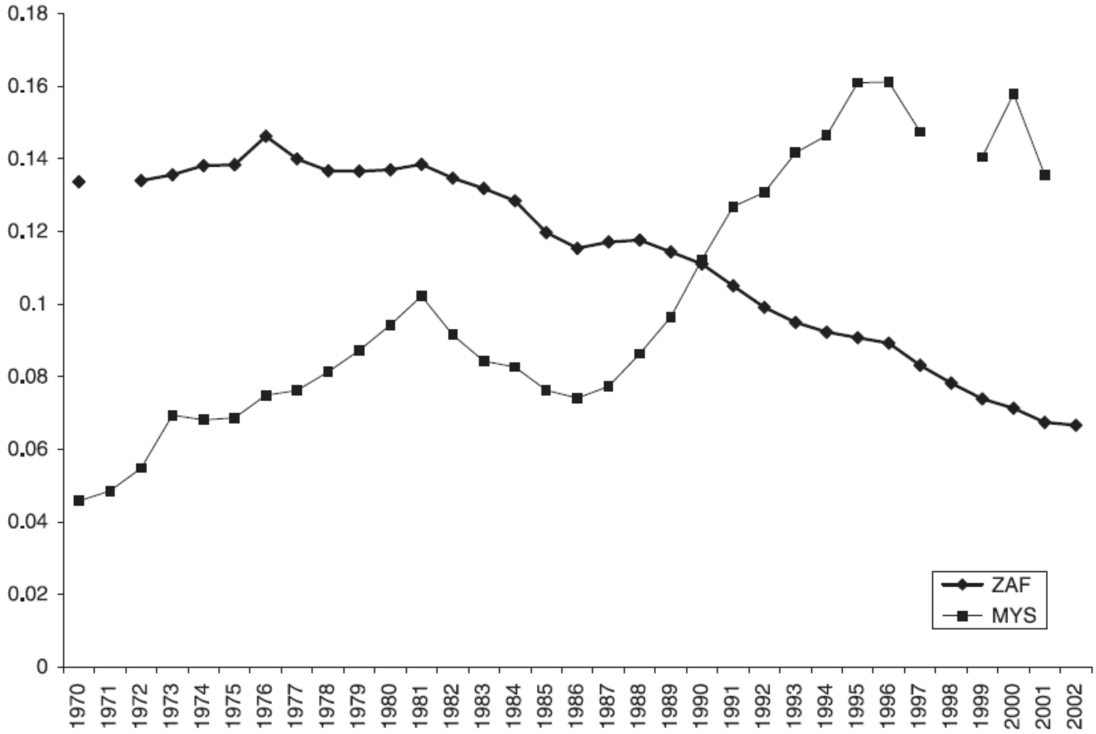
1920s and commenced providing relatively cheap electricity and steel for use by industry in a bid to assist South African manufacturing. During this time, a number of state-owned businesses became the dominant force in local manufacturing. This process continued after the Second World War, and the government played an important role in establishing industries in the areas of chemicals, oil from coal, and armaments. As a result, manufacturing and its contribution grew until the 1980s. In fact, according to Rodrik (2008), in the mid-1980s South Africa had a larger manufacturing base than Malaysia. Approximately 12 per cent of South Africa's total labour force was employed in manufacturing, compared with less than 8 per cent in Malaysia (Rodrik 2008).

The 1980s saw a number of factors impacting negatively on local manufacturing. There were droughts, coupled with an economic downswing. Gold prices displayed increasing levels of volatility, and sanctions and disinvestment also resulted in declining manufacturing in the country. As a result, the three factors which historically were responsible for a competitive South African manufacturing sector—i.e. cheap labour, inexpensive and reliable electricity supply, and government subsidies and tariffs—were slowly eroded in that period (Bhorat and Rooney 2017). This process continued into the 1990s, when South Africa's integration into the world economy was accompanied by new challenges.

The globalized world into which South Africa now emerged brought with it brutal competition from other developing countries, especially in South-East Asia (Bhorat and Rooney 2017). Suddenly, the South African government, having to adhere to its obligations to the World Trade Organization (WTO), had almost no room any more to implement protectionist policies (Bhorat and Rooney 2017). Furthermore, productivity did not keep pace with the increase in wages (Bhorat and Rooney 2017), rendering many industries unable to deal with the competition they faced from countries in South-East Asia.

The results for the South African manufacturing industry were indeed calamitous. Going back to the preceding comparison, the picture in relation to Malaysia completely reversed. By 1990, Malaysia's manufacturing industry employed 16 per cent of its labour force (Rodrik 2008). In South Africa, in stark contrast, the share of the labour force who found work in manufacturing consistently decreased to below 7 per cent by 2000 (Rodrik 2008). Figure 1 illustrates this reversal graphically.

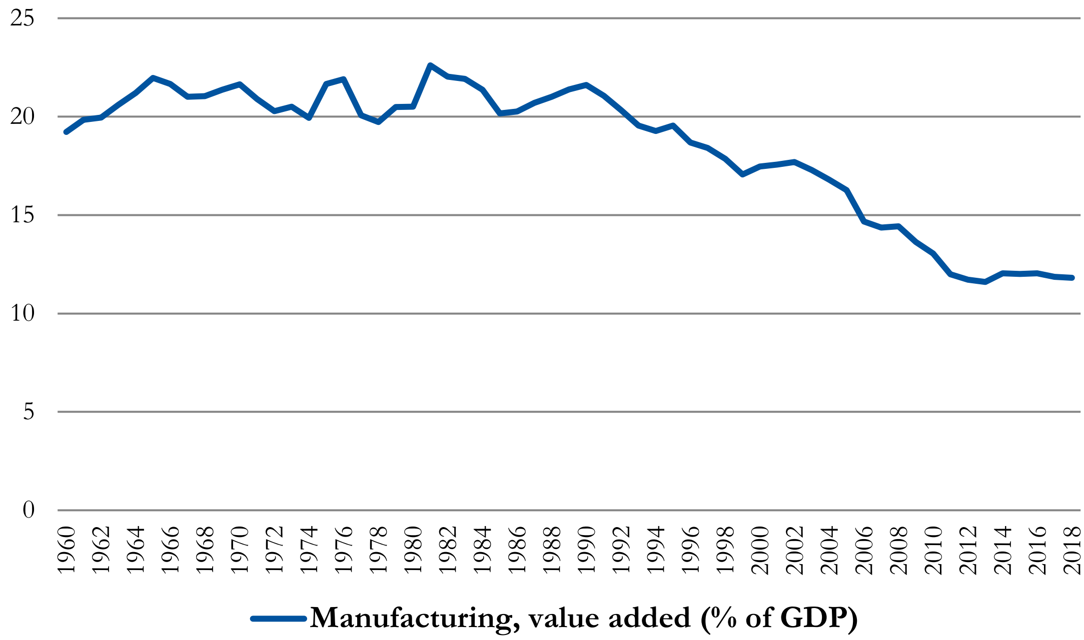
Figure 1: Comparing the percentage of the labour force employed in manufacturing between South Africa and Malaysia, 1970–2002



Source: Rodrik (2008: 775); reproduced here with permission.

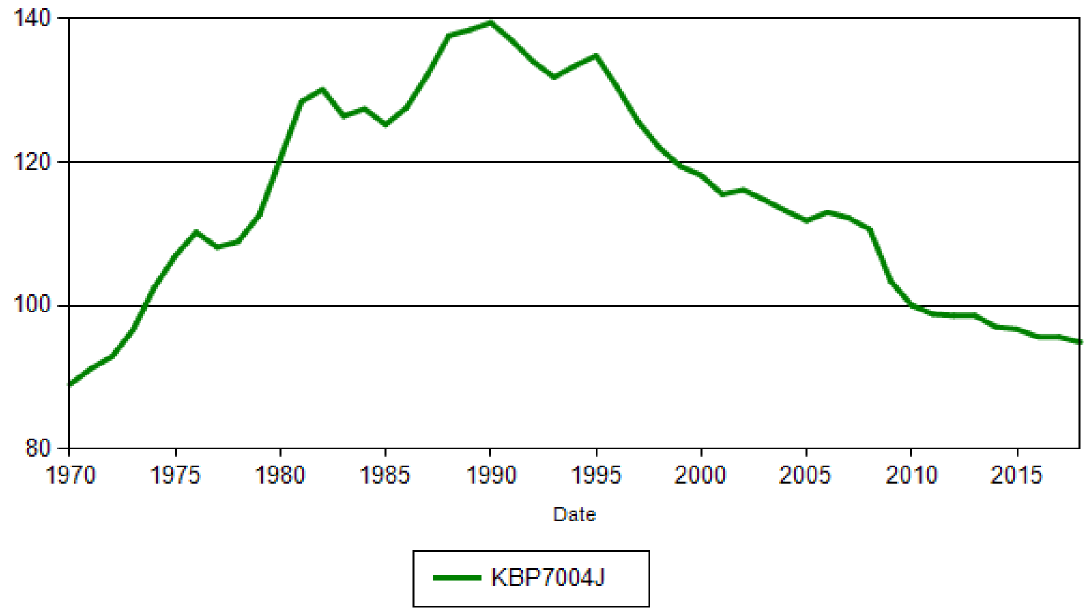
Data from the South African Reserve Bank (SARB 2019) and the World Bank (2019) point to a continuation of this declining trend since 2001 and to the impact it has on South African manufacturing employment—see Figures 2 and 3.

Figure 2: South Africa: Manufacturing value added (% of GDP), 1960–2017



Source: Authors' construction based on World Bank (2019).

Figure 3: Index of employment in the private sector: Manufacturing



Note: The y-axis represents an index where the base year is 2010.

Source: Authors' construction based on SARB (2019).

The decline in the share of manufacturing in South Africa's GDP has been an almost constant feature since 1990. According to Bhorat and Rooney (2017), manufacturing declined by 20 per cent between 2001 and 2014. In 2001, the manufacturing sector was the third-largest employment sector for all employed individuals (at 14.7 per cent). As a result of its decline, the statistic in 2014 was 11.3 per cent (Bhorat and Rooney 2017). The beneficiaries in this period were evidently skilled workers, in both absolute and relative terms. At the same time, the price was paid by semi-skilled workers (Bhorat and Rooney 2017).

However, the South African manufacturing sector was still the fourth-largest contributor (13.5 per cent) to economic activity in 2014 (all data in this paragraph: Stats SA 2016). It remains an important part of the economy despite the fact that the annual growth of the sector declined from 5.9 per cent in 2010 to 0.1 per cent in 2014. Earnings in the industry did, however, increase from R634,318 million to just over R2 trillion in 2014. The highest-earning sector in the industry is petroleum and chemical products (34 per cent), followed by food and beverages (17 per cent); metals and machinery (17 per cent); transport equipment (15 per cent); other (12 per cent); and wood, paper, and publishing (6 per cent). Metals and machinery employ the most workers (21 per cent), followed by food and beverages (19 per cent); petroleum and chemical products (15 per cent); other (15 per cent); wood, paper, and publishing (11 per cent); textiles and clothing (10 per cent); and transport equipment (9 per cent). Large firms contribute 82 per cent of income and employ 46 per cent of the manufacturing workforce. The numbers for medium, small, and micro-firms vary only slightly. The average annual salary of the entire manufacturing sector is R183,417; the highest salaries are earned in the petroleum and chemical sector (R265,871) and the lowest in the textile sector (R69,443).

Looking at the history of manufacturing in South Africa, Zalk (2014) makes the point that there was no stand-alone factor that could be identified as being responsible for its decline. However, the inertia of South Africa's manufacturing sector can be primarily linked back to two factors (Bhorat and Rooney 2017; Rodrik 2008). The first is the development of an ample supply of cheap labour in countries such as China, India, Vietnam, and Indonesia. Secondly, South Africa's skills shortage makes it very difficult to move up the manufacturing value chain (Bhorat and Rooney 2017). The last decade has brought with it additional pressure, such as significant increases in the price of electricity coupled with an unreliable supply thereof. This decreases already-flagging levels of profitability for the manufacturing sector even further.

Zalk (2014) argues that these factors must be dealt with collectively in order to improve the outlook and capacity of the South African manufacturing sector. He highlights key industries where capital and labour are complements rather than substitutes as areas where improved manufacturing and job creation can be achieved. These include sectors such as the fabrication of metals and plastics and transport equipment, and sections of the agro-processing sector. In these industries, employment actually increases with a rise in capital investment (Zalk 2014). Another area with scope to raise employment in conjunction with increased investment, mentioned by Zalk, is segments of the automotive value chain. This would, for example, be found in expanding the vehicle assembly segment (capital-intensive), while at the same time growing the range and depth of automotive components that are to be produced locally. These are considerably less capital-intensive than the assembly portion (Zalk 2014). Zalk (2014) applies the same reasoning to the manufacturing of components for the renewable energy sector.

However, for South Africa to capitalize on any of these possibilities, the current school system must be reformed to provide the skills necessary to reap these potential benefits. The reason for this is summarized by Bhorat and Rooney (2017), who conclude that the evidence speaks to an increase in the skills intensity in South African manufacturing, with an increase in the demand for skilled jobs, but with job losses in the semi and low-skilled occupations (Bhorat and Rooney 2017). Along with this, the issue of political and policy uncertainty requires immediate attention if the current downward spiral is to be addressed.

5 Empirical analysis

5.1 Variables employed

Hummels et al. (2014: 1604) describe broad offshoring as the 'total value of imports by manufacturing firm per year' and narrow offshoring as 'purchases of inputs belonging to the same industry as that of the producing firm'. They go on to state that narrow offshoring takes place when a firm imports goods classified in the same HS4 category as the products that the firm sells—both domestic and internationally. Therefore, the closer the imported products are to the final product, the more likely it is that labour within the firm could have produced it and that job losses may occur if imports increase.[1]

Our broad offshoring measure is provided in the company income tax (CIT) panel as the total rand value of imports (variable name: cust_imp_total).[2] Since the data set does not provide an indication of the HS4 codes of products sold domestically, we disregard the domestic sales classification criterion and define narrow-offshoring firms (narrow offshorers) as those firms for which the HS4 code of their most recurrent/most traded imported product and the HS4 code of

[1] Narrow offshoring within the context of manufacturing firms therefore excludes firms that merely resell imported goods—in which case the importing firm would be classified as belonging to 'wholesale and retail'. Narrow offshoring manufacturing firms are still engaged in value-added activities.

[2] The SARS and National Treasury (NT) firm-level panel provides administrative data on CIT, IRP5, and customs records, accessible only to contracted researchers. For further background see Pieterse et al. (2016).

their most recurrent exporting product coincide (variables: cust_mainHS4import and cust_mainHS4export). This definition may be more limiting and narrower than the one proposed by Hummels et al. (2014), but it is very appropriate within the context of the available data.

We investigate the labour market effects of offshoring within South African manufacturing firms at firm level as well as at employer–employee level. Firstly, the CIT-IRP5 panel data available on 19 May 2019 are utilized for the firm-level analysis. This panel consists of matched firm-level data from three tax forms, namely the CIT form, customs transaction form, and worker-level tax form (IRP5 certificates). In addition to cust_imp_total, the following list of variables is utilized; g_sales to measure sales, k_ppe to measure capital, irp5_empl_weight to measure number of employees, x_labcost to measure employee expenses, ISIC4 code to classify the type of manufacturing firm, and HS4 product code of most traded good per firm to create the narrow-offshoring dummy (as discussed above).

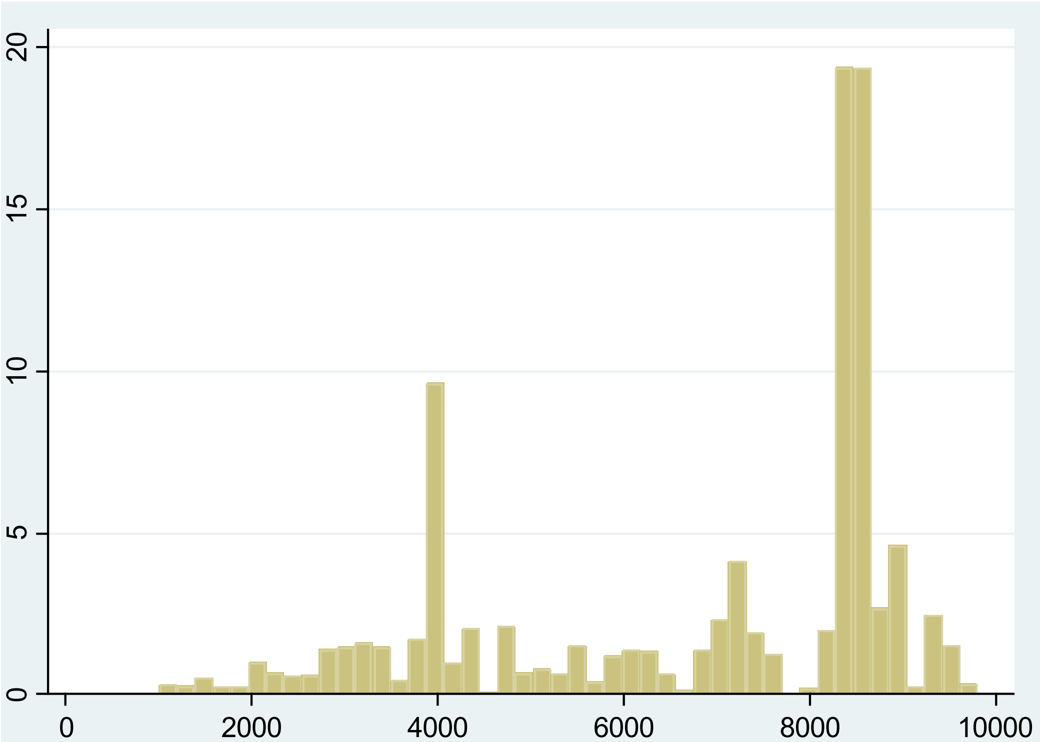
While the IRP5 data include no measure of education level or skilling, by using the raw IRP5 data we are able to create a variable indicating the percentage of employees in a firm earning 'skilled' and 'unskilled' salaries. This is a novel contribution, since similar studies merely considered monthly salaries of R20,000 and above to represent 'skilled' workers—see Edwards et al. (2018). Our skills threshold is determined from Quantec's average salaries for low-skilled and high-skilled workers in the manufacturing industry for 2010 to 2017 (Quantec 2018). Their mean salary for all skilled workers in manufacturing (in a specific year) is used as yardstick. We then calculate the percentage of workers in each firm who earned more than this mean salary to get the percentage of skilled workers per firm. The same is done for unskilled workers: the mean salary for all unskilled workers in the manufacturing sector is calculated and all workers earning this amount or less are considered to be unskilled.

Secondly, to create an employer–employee matched data set (of the manufacturing sector), the CIT-IRP5 panel data at firm level are matched onto the employee-level data (IRP5 certificates). The raw IRP5 data are adjusted to remove duplicate certificates, multiple job spells, and invalid periods worked (see Table A1, Appendix A). The IRP5 certificates include information on the number of days an individual worked in a specific job (start and end date), their income earned (in South African rand value), and their birth date (from which their age can be determined). As the numbers of days worked differs between jobs, the monthly wage variable is calculated by taking the income and dividing it by the number of days worked (to get the daily wage equivalent). This is then multiplied by 30 to get the monthly equivalent wages. Even though the final panel data set is from 2010 to 2017, the tenure of each job was calculated by using the IRP5 data from 2010 to 2016. The reason for not including 2017 is that there were many missing values in the 2017 data (at the time when we accessed the IRP5 panel) and the income variable was not consistent with previous years. To create a measure of firm size, the number of employees per firm was calculated using a full-time equivalent over each year (i.e. number of days worked across all workers in a firm/365).

5.2 Offshoring vs narrow offshoring

What do manufacturing firms import? While Danish firms mainly import raw materials (see Hummels et al. 2014), the same is not true for South African manufacturing firms. Information supplied in the firm-level panel identifies the HS4 codes of the most recurrent import product per firm—see Figure 4.

Figure 4: Most imported products per HS4 classification



Note: The vertical axis shows the percentage of firms for which the specific HS4 product code on the horizontal axis is their main import—for all firms across all years in the panel.

Source: Authors' construction based on SARS-NT panel data.

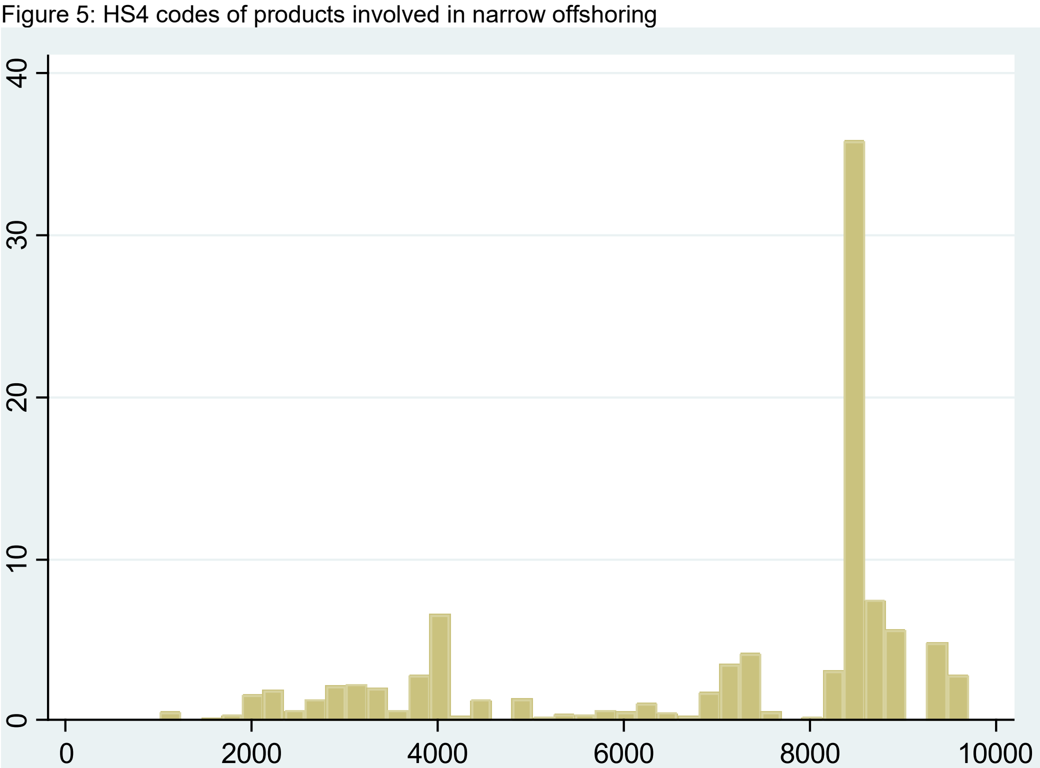
The spikes in Figure 4 appear around the following HS2 categories:

- 84: 'Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof'
- 90: 'Optical, photographic, cinematographic, measuring, checking, medical or surgical instruments and apparatus; parts and accessories'
- 39: 'Plastics and articles thereof'

Raw materials, according to Hummels et al. (2014: 1604), fall into the HS2 categories 01–15, 25–27, 31, and 41. From Figure 4, it is evident that raw materials are not that important in the import basket of South African firms. As a further classification of the imports reflected in Figure 4, the HS4 categories were converted into their respective broad economic categories. According to this classification, 18.53 per cent of South African firms' imports are capital goods, 65.21 per cent intermediate goods, and 13.57 per cent consumer goods. (The remaining 2.69 per cent could not be classified.)

Focusing only on the narrow offshorers, Figure 5 displays the HS4 code on the horizontal axis and the percentage of firms involved in narrow offshoring according to our restricted narrow definition.

Figure 5: HS4 codes of products involved in narrow offshoring



Note: The y-axis shows the percentage of firms for which the specific HS4 code is their main imported product

Source: Authors' construction based on SARS-NT panel data.

The major spikes in Figure 5 correspond with the spikes in Figure 4. However, as expected, not all of the imported products feature simultaneously as exports. The following products, on HS2 level, are those most often observed in narrow offshoring:

- 84: 'Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof'
- 87: 'Vehicles; other than railway or tramway rolling stock, and parts and accessories thereof'
- 90: 'Optical, photographic, cinematographic, measuring, checking, medical or surgical instruments and apparatus; parts and accessories'
- 88: 'Aircraft, spacecraft and parts thereof'
- 85: 'Electrical machinery and equipment and parts thereof; sound recorders and reproducers; television image and sound recorders and reproducers, parts and accessories of such'
- 94: 'Furniture; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings; lamps and lighting fittings, n.e.s.; illuminated signs, illuminated name-plates'
- 73: 'Iron or steel articles'
- 39: 'Plastics and articles thereof'

How many firms are involved? The CIT firm-level data span the period 2010 to 2017, with the number of firms increasing until 2014 and then declining to 2017. Table 1 compares the number of firms in three different samples between 2010 and 2017.

Table 1: Comparing number of firms in manufacturing categories over time

	2010					2014					2017				
	All	Offshorers		Narrow		All	Offshorers		Narrow		All	Offshorers		Narrow	
	Firms #	Firms #	%	Firms #	%	Firms #	Firms #	%	Firms #	%	Firms #	Firms #	%	Firms #	%
All firms	23,966	6,185	25.81	985	4.11	27,925	7,282	26.08	1,231	4.41	23,315	6,493	27.85	1,013	4.34
1010	1,357	281	20.71	24	1.77	1,639	348	21.23	46	2.81	1,354	335	24.74	32	2.36
1011	364	109	29.95	12	3.30	513	134	26.12	13	2.53	547	145	26.51	17	3.11
1012	36	13	36.11	2	5.56	40	17	42.50	2	5.00	53	23	43.40	3	5.66
1013	1,066	346	32.46	27	2.53	1,180	364	30.85	37	3.14	974	307	31.52	22	2.26
1014	832	240	28.85	19	2.28	1,051	245	23.31	22	2.09	892	220	24.66	22	2.47
1015	270	104	38.52	13	4.81	331	125	37.76	11	3.32	277	107	38.63	7	2.53
1016	1,256	133	10.59	10	0.80	1,489	188	12.63	23	1.54	1,202	170	14.14	21	1.75
1017	520	177	34.04	12	2.31	599	202	33.72	15	2.50	485	166	34.23	17	3.51
1018	829	127	15.32	12	1.45	884	122	13.80	15	1.70	739	120	16.24	8	1.08
1019	147	28	19.05	6	4.08	157	43	27.39	9	5.73	127	30	23.62	9	7.09
1020	1,041	361	34.68	57	5.48	1,258	426	33.86	84	6.68	1,091	385	35.29	67	6.14
1021	407	165	40.54	45	11.06	457	166	36.32	45	9.85	350	156	44.57	32	9.14
1022	1,534	469	30.57	56	3.65	1,786	570	31.91	64	3.58	1,493	526	35.23	57	3.82
1023	568	109	19.19	9	1.58	576	122	21.18	13	2.26	497	117	23.54	18	3.62
1024	1,119	248	22.16	38	3.40	1,275	282	22.12	39	3.06	1,059	219	20.68	30	2.83
1025	2,810	548	19.50	102	3.63	3,186	646	20.28	123	3.86	2,697	564	20.91	86	3.19
1026	357	158	44.26	24	6.72	379	169	44.59	28	7.39	293	141	48.12	17	5.80
1027	829	358	43.18	58	7.00	946	413	43.66	75	7.93	770	349	45.32	62	8.05
1028	1,565	565	36.10	146	9.33	1,674	642	38.35	160	9.56	1,466	590	40.25	151	10.30
1029	391	124	31.71	36	9.21	457	150	32.82	46	10.07	421	147	34.92	40	9.50
1030	259	104	40.15	26	10.04	293	124	42.32	34	11.60	232	99	42.67	23	9.91
1031	865	143	16.53	23	2.66	993	162	16.31	35	3.52	848	155	18.28	28	3.30
1032	4,255	1,068	25.10	193	4.54	5,366	1,402	26.13	251	4.68	4,416	1,236	27.99	217	4.91
1033	1,289	207	16.06	35	2.72	1,396	220	15.76	41	2.94	1,032	186	18.02	27	2.62

Source: Authors' construction based on SARS-NT panel data.

The current sample includes a total of 23,966 manufacturing firms in 2010, of which 25.81 per cent imported one or more product and 4.11 per cent engaged in narrow offshoring—i.e. their main imports and main exports were classified in the same HS4 product code. The number of manufacturing firms increased to 27,925 in 2014 and declined to 23,315 in 2017. Despite the number of manufacturing firms decreasing between 2010 and 2017, the percentage of offshorers and narrow offshorers increased in the same period: 25.81 per cent were offshorers in 2010 compared with 27.85 per cent in 2017; and 4.11 per cent were narrow offshorers in 2010 compared with 4.34 per cent in 2017. This may indicate increased importing activity by manufacturing firms in general, or it may indicate that the firms present throughout the time period 2010 to 2017 tended to be the ones engaging in imports.

In order to refine the analysis, the number of firms is also reported per ISIC4 industry—see Appendix A, Table A2, for a description of each ISIC4 code. Interestingly, there are offshorers as well as narrow offshorers in each of the industries. The percentage of firms engaging in offshoring increased between 2010 and 2017 in 17 out of the 24 industries, while the percentage of narrow offshorers increased in 14 out of the 24 industries.

In 2017, the highest percentage of importers (48.12 per cent of all firms) were in 1026, 'Manufacture of computer, electronic and optical products', followed by 1027, 'Manufacture of electrical equipment' with 45.32 per cent; 1021, 'Manufacture of pharmaceuticals, medicinal chemical and botanical products' with 44.57 per cent; and 1012, 'Manufacture of tobacco products' with 43.40 per cent. The industries with the fewest importing firms were 1016, 'Manufacture of wood and of products of wood and cork, except furniture' (14.14 per cent); 1018, 'Printing and reproduction of recorded media' (16.24 per cent); 1033, 'Repair and installation of machinery and equipment' (18.02 per cent); and 1031, 'Manufacture of furniture' (18.28 per cent).

Narrow offshorers, as a percentage of the total number of firms, were the highest in 1028, 'Manufacture of machinery and equipment n.e.c.' (10.30 per cent), followed by 1030, 'Manufacture of other transport equipment' (9.91 per cent); 1029, 'Manufacture of motor vehicles, trailers and semi-trailers' (9.50 per cent); and 1021, 'Manufacture of pharmaceuticals, medicinal chemical and botanical products' (9.14 per cent). The lowest percentage of offshorers was in 1018, 'Printing and reproduction of recorded media' (1.08 per cent); 1016, 'Manufacture of wood and of products of wood and cork, except furniture' (1.75 per cent); and 1013, 'Manufacture of textiles' (2.26 per cent).

Considering the 1,013 narrow offshorers in 2017, most firms were from 1032, 'Other manufacturing' (21.42 per cent); 1028, 'machinery and equipment' (14.91 per cent); 1025, 'Manufacture of fabricated metal products, except machinery and equipment' (8.49 per cent); and 1027, 'Manufacture of electrical equipment' (6.12 per cent)—accounting for 50.94 per cent of all narrow offshorers. This list corresponds with the specific products (at HS4 level) identified in Figure 5, as those were the main import and export products.

In order to compare key indicators across the three categories of manufacturing firms, Table 2 provides a profile by summarizing the mean values across all firms included in the panel across all the years.

Except for the percentage of unskilled workers, all indicators show the same trend. The mean values for the total sample of manufacturing firms are the lowest; they then increase for the group of firms that import and are the highest for the group engaging in narrow offshoring. In this regard, the mean number of workers employed in manufacturing firms is 47, compared with 95 in importing firms and 110 in narrow-offshoring firms. The rand amount of sales also increases across the three columns of Table 2. The mean net profit as a percentage of sales, however, shows a declining trend across the three columns. Narrow offshorers realized a mean value of 7.90 per cent net profit as a percentage of sales, compared with a higher 10.69 per cent for all manufacturing firms. The amount of capital per worker increases relatively more between importer and narrow offshorer, while the mean salary per worker for narrow offshorers does not increase proportionally with the other indicators.

The above corresponds with Amiti and Davis's (2011) study on Indonesian manufacturing firms, in which they found that exporters pay 8 to 28 per cent higher wages, importers pay 15 to 47 per cent higher wages, and two-way traders 25 to 66 per cent higher wages than non-traders do (depending on the controls implemented). The picture regarding number of workers in Table 2 also corresponds with the finding of Edwards et al. (2018) that two-way traders employ more workers than firms engaging in only imports or only exports. However, they also found that two-way traders pay higher wages than one-way traders. This is not what is reflected in Table 2. Narrow offshorers in general pay lower wages than all offshorers.

Table 2: Mean values for key indicators in the firm-level panel

	All manufacturing firms	All offshorers	Narrow offshorers
Sales	78,700,000	249,000,000	448,000,000
Number of workers	47	95	110
Imports	-	22,500,000	68,700,000
Sales per worker	2,231,640	4,110,221	4,803,972
Import per worker	-	773,236	1,226,280
Capital per worker	279,171	565,952	1,192,112
Salary per worker	221,272	338,628	262,131
% skilled workers	5.59	9.30	13.75
% unskilled workers	73.97	65.34	57.01
Net profit	8,410,779	24,100,000	35,400,000
Profit as % of sales	10.69	9.68	7.90

Note: All amounts in rand.

Source: Authors' construction based on SARS-NT panel data.

5.3 Theoretical foundation

Our regression analysis focuses on labour demand and wages in manufacturing. The theoretical basis for the specification is found in the literature. Andersson et al. (2017) estimate labour demand as a function of the level of capital in the firm and the level of output (or production). They further add the relative wage between skilled and unskilled workers when estimating demand specifically for skilled or unskilled workers. Previous studies on this data set also included output as a proxy for firm size (see Edwards et al. 2018 and Matthee et al. 2018 as examples).

The theoretical basis of the empirical analysis is found in Hsieh and Woo (2005) and based on previous work from Berman et al. (1994) and Feenstra and Hanson (1996). This is illustrated in Equation 1:

$$\Delta D_{tj} = \beta_1 \Delta Out_{tj} + \beta_2 \Delta \ln\left(\frac{K_{tj}}{Y_{tj}}\right) + \beta_3 \Delta lnY_{tj} \qquad (1)$$

Their dependent variable is skilled worker wages as a ratio of the total wage bill. It is explained on the right-hand side by a proxy for offshoring (outsourcing), the capital–output ratio, and total output. The two important variables are the dependent variable and the outsourcing variable. The capital–output ratio controls for technological change and output controls for cyclical changes. The underlying assumptions include: variable labour cost, a cost function with constant returns to scale, and an objective of cost minimization. The relationship is estimated in differences. Changes in relative wages are then left out of the equation due to differences in worker quality across different industries.

5.3.1 Specification

Our specification builds on the above and includes various fixed effects (FE): fixed time effects, industry effects, and firm (or job-spell) effects. In order to further refine the analysis regarding offshoring, two dummy variables are added. The first tests for a change in the intercept for narrow offshorers ($dumnarrow_{tj}$ = 1 if firm is classified as a narrow offshorer) and the second for a different slope for narrow offshorers (by including $Out_{tj} * dumnarrow_{tj}$).

Different dependent variables are included to replace Y_{tj}: number of manufacturing workers (workers), percentage of skilled workers (skilled_per), percentage of unskilled workers (unskilled_per), salary per worker (salaryperw), and individual income (lis). The empirical model will try to explain these dependent variables for all of the manufacturing firms in the panel and a few sub-samples. The sub-samples include: all the firms classified as narrow offshorers, all the firms in capital-intensive industries, firms in labour-intensive industries, and firms in ultra-labour-intensive industries.[3]

Even though Equation 1 is specified in a difference format, estimations are first done in levels (see Equations 2 and 3) and then in differences (see Equations 4 and 5).

$$Y_{tj} = \beta_1 lnOut_{tj} + \beta_2 \ln\left(\frac{K_{tj}}{Y_{tj}}\right) + \beta_3 lnY_{tj} \tag{2}$$

$$Y_{tj} = \beta_1 lnOut_{tj} + \beta_2 lnOut_{tj} * dumnarrow_{tj} + \beta_3 dumnarrow_{tj} + \beta_4 \ln\left(\frac{K_{tj}}{Y_{tj}}\right) + \beta_5 lnY_{tj} \tag{3}$$

$$\Delta Y_{tj} = \beta_1 \Delta lnOut_{tj} + \beta_2 \Delta \ln\left(\frac{K_{tj}}{Y_{tj}}\right) + \beta_3 \Delta lnY_{tj} \tag{4}$$

$$\Delta Y_{tj} = \beta_1 \Delta lnOut_{tj} + \beta_2 \Delta lnOut_{tj} * dumnarrow_{tj} + \beta_3 dumnarrow_{tj} + \beta_4 \Delta \ln\left(\frac{K_{tj}}{Y_{tj}}\right) + \beta_5 \Delta lnY_{tj} \tag{5}$$

The following variables are represented in these firm-level equations:

$lnOut_{tj}$: total imports as proxy for outsourcing (log imports)

[3] Intermediate capital-intensive firms as a group are not included in the analysis.

$\ln\left(\frac{K_{tj}}{Y_{tj}}\right)$: capital–output ratio measured as total value of capital plant and equipment to total sales (log capout)

Y_{tj}: total sales (log sales)

Overall, the panel regressions in levels format did not render significant results—see tables in Appendix B. The differenced equation (similarly to the specification used by Hsieh and Woo 2005) led to more statistically significant estimates.

5.3.2 Instrumental variables

Additional to the above specification, the use of instrumental variables is essential in the analysis in order to address possible endogeneity. A brief explanation of the endogeneity problem follows. This analysis revolves around the impact of imported inputs on a firm's labour demand. A firm can, due to endogenous reasons, import more inputs, which would influence its labour demand. For example, a more productive firm would import more inputs, pay higher wages, export more, and be more capital-intensive. Therefore, an endogeneity problem can occur when examining the effect of imported inputs on a firm's labour demand. Are the changes in labour demand due to a firm being more productive, or is it because the firm has started importing more inputs due to an exogenous reason? The solution would be to find an exogenous shock that would result in a firm importing more inputs, irrespective of its productivity and wage structure. This requires the use of an instrument. Usually, a major change in policy would act as such an instrument. However, in the absence of such policy changes (i.e. where the trade environment is stable, without significant changes in trade policy), it is suggested in the literature that an import flow, namely world export supply (WES), be used (see for example Andersson et al., 2017; Balsvik and Birkeland 2012; Hummels et al. 2014).

Suppose firm i imports product p from country c. The WES instrument would be country c's export of product p to the rest of the world, minus South Africa, in year t. Now suppose there is a shock that changes the export supply of product p by country c. This shock could be the result of an increase in the supply by country c due to more product varieties and better-quality products being offered, higher productivity, and lower wages and costs. The importing of product p by firm i from country c will therefore be affected by this shock—firm i will import more and this will subsequently impact its labour demand. The change in labour demand is then completely exogenous to/does not correlate with the firm's own wage-setting and productivity. This will differ across all importing firms, as they each import a different mix of product p.

Hummels et al. (2016) conclude that these instruments are particularly well suited to employer–employee data, where endogeneity is likely to be a serious concern. Similarly to Kreuser and Newman (2018) and Matthee et al. (2018), tests will be performed to confirm the validity of the chosen instrumental variables. Various F-tests as well as Hansen's J-test will be employed to test for under-identification, weak identification, excluded instruments, and over-identification.

We intended to follow Andersson et al. (2017) and Hummels et al. (2014) by using world export supply as instrumental variable. Data were obtained from COMTRADE on an HS4 level for each country-year observation (UN COMTRADE 2019). Anderson et al. (2017: 245) explain that to obtain a firm-level instrument, 'world export supply (demand) in year t will be multiplied with the offshoring intensity in year t_1 for each firm i matched at the country, c, and product level, p':

$$WES_{it} = \sum_{cp} \frac{M_{i,t-1,c,p}}{Q_{i,t-1}} \times WE_{t,c,p} \qquad WID_{it} = \sum_{cp} \frac{E_{i,t-1,c,p}}{Q_{i,t-1}} \times WI_{t,c,p} \tag{6}$$

In order to replicate their instrument, we used import data at HS4 level for all firms in the panel. When we tried to match the indicated HS4 codes for firm-level imports, at least 10 per cent of the codes provided in the firm-level panel could not be matched with trade data from the COMTRADE database. In other words, 10 per cent of the HS4 codes listed in the firm-level panel do not exist or did not match codes in the COMTRADE database (these codes are not in the Harmonised System: Revisions, 1988, 1996, 2002, 2007, 2012, 2017, and combined). Therefore, two alternative instruments were constructed. From COMTRADE, we obtained the total value of world export supply and subtracted the value of all South African exports. The remaining world export supply therefore includes all of the potential world exports available to South African firms for imports, and the dollar values are converted to South African rand values. Our WES instrument is consequently calculated as:

$$WESIV_{it} = \frac{Total\ firm\ level\ imports_{it-1}}{WES_{t-1}} \times\ WES_t$$

As an alternative instrument, we obtained the rand value of total South African manufacturing imports from the Quantec database and constructed a 'South African manufacturing' instrument in almost the same way:

$$SAmanuIV_{it} = \left(\frac{Total\ firm\ level\ imports_{it-1}}{Total\ South\ African\ manufacturing\ imports_{t-1}}\right) \\ \times\ Total\ South\ African\ manufacturing\ imports_t$$

Two additional instruments were tested, along with the two described above. A WESIV, in dollar terms, was used together with the rand–dollar exchange rate; and the mere lag of firm-level imports was also tested. In the end, the best results were obtained from the SAmanuIV and WESIV. In some of the regressions reported in Section 5.4.1, these two instruments rendered the same results. Therefore, the later regressions in Section 5.4.3 included only SAmanuIV.

Regressions where imports are instrumented are estimated in Stata using the xtivreg2 command. Various test statistics are generated to test for under-identification (Kleibergen Paap LM), weak identification (Kleibergen Paap Wald F, Cragg-Donald Wald F), first-stage F, F-test of excluded instruments first stage, over-identification (Hansen J), and endogeneity.

5.4 Empirical results

5.4.1 Offshoring and employment

Three different measures are used to determine the impact of offshoring on employment. Firstly, the total number of manufacturing workers per firm is considered and then the percentage of skilled workers, followed by the percentage of unskilled workers.

To start the empirical analysis, we first consider firm-level employment, by estimating Equation 4 (in differences) with dlworkers (change in log of number of workers) as dependent variable. Table 3 reports regression results from the firm-level panel. Apart from the log of imports, the impact of offshoring is also tested by including an interactive variable, log imports multiplied by narrow offshoring. Column 1 indicates the impact of offshoring on employment for the complete sample of manufacturing firms. Because it is expected that there will be heterogeneity and substantial differences between the various manufacturing industries, the regressions are also run for three sub-samples of the panel to test whether the impact of offshoring differs between firms with differing capital (labour) intensities.

Various measures are available to determine the factor intensity of production. Since the data is primarily provided in an accounting and tax environment, we do not base such classification on capital labour ratios calculated from this dataset. As an alternative measure, we use the classification of the South African manufacturing sector as described and employed in Edwards (2001)[4]. Regression results are reported for the total panel of manufacturing firms, as well as for three sub-groups—labour-intensive, capital-intensive, and ultra-labour-intensive industries. Results for intermediate capital-intensive industries are not reported, as they did not render statistically significant results.[5]

Table 3: Regression results with log number of workers as dependent variable—including all dummies and variables in differences, and without firm fixed effects

	1	2	3	4
	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**
log imports	0.0016229	0.0015454	−0.0050035#	−0.0018047
	(.0021436)	(0.0034999)	(0.0032798)	(0.0062848)
	[0.449]	[0.659]	[0.127]	[0.774]
log imports*narrow	0.001353***	−0.00056	0.0018589	0.0007736
	(0.0004996)	(0.0008038)	(0.0015944)	(0.0017916)
	[0.007]	[0.486]	[0.244]	[0.666]
dumnarrow	−0.020391***	0.0036512	−0.0326246*	0.0363319#
	(.0064219)	(0.0092826)	(0.0174881)	(0.0236058)
	[0.001]	[0.694]	[0.062]	[0.124]
log capout	.0070164***	0.0089552***	0.0070966	0.0001203
	(.0017575)	(0.0029361)	(0.0039288)	(0.006071)
	[0.000]	[0.002]	[0.071]	[0.984]
log sales	0.2106811***	0.2240805***	0.2002549***	0.2404576***
	(0.0144596)	(0.0250555)	(0.0495634)	(0.0600261)
	[0.000]	[0.000]	[0.000]	[0.000]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Instruments	No	No	No	No
Observations	31,417	10,626	5,238	2,155
R-squared	0.0881	0.0928	0.0833	0.0650

Notes: Robust standard errors in parentheses; probability in square brackets; ***p<0.01, **p<0.05, *p<0.1, #p<0.15.

Source: Authors' construction based on SARS-NT panel data.

Table 3 reports different responses to offshoring for firms of different capital/labour intensities. With some of the dummy and interactive terms found to be significant, it seems as if there is a difference between the reactions of general and narrow offshorers. However, due to the potential impact of endogeneity, the analysis is extended to include instrumental variables—see Table 4.

[4] A list of the ISIC4 classification codes, descriptions, and factor intensity classification appears in Appendix A (Tables A2 and A3).

[5] All values sourced from the tax sources are reported in nominal values. Similarly to Edwards et al. (2018), the nominal values are used in the regression analysis, combined with year fixed effects.

Table 4: Regression results with log number of workers as dependent variable—variables in differences and including instrumental variables

	1	2
	All manufacturing	**All manufacturing**
log imports	−0.0194***	−0.0196***
	(0.0061)	(0.0061)
	[0.001]	[0.001]
log imports*narrow	0.0007	
	(0.0005)	
	[0.189]	
log capout	0.0039*	0.0039*
	(0.0021)	(0.0021)
	[0.064]	[0.064]
log sales	0.0995***	0.0997***
	(0.0214)	(0.0214)
	[0.000]	[0.000]
Year FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
Observations	144,449	144,449
R-squared	0.0071	0.0069

Notes: Robust standard errors in parentheses; probability in square brackets; ***p<0.01, **p<0.05, *p<0.1, #p<0.15.

Source: Authors' construction based on SARS-NT panel data.

None of the sub-groups rendered significant results with the instrumental variable specification. Table 4 therefore only reports on the results for all manufacturing firms. All the test statistics confirm the validity of the instrument. The first results column includes the slope dummy variable and the second excludes the slope dummy variable. While the slope dummy variable is not significant in the equation, both specifications confirm the negative and statistically significant effect of offshoring on the level of employment. As firm-level imports increase, the number of workers employed by manufacturing firms decreases.

5.4.2 Offshoring and skills level

Secondly, we consider employment according to skills level. Similar international studies, particularly from Scandinavia, are based on detailed information about individuals: education level, union membership, marital status, etc. The South African IRP5 data/worker-level data contain no such information—and the biggest shortcoming is the lack of an education indicator or skills-level proxy. Previous studies on CIT data used a salary of R20,000 per month as a proxy for skilled workers (see Edwards et al. 2018). We employ an alternative approach. An alternative source of time-series data on the manufacturing sector, Quantec (2018), provides annual data regarding the number of unskilled, semi-skilled, and skilled workers employed. It also provides the annual total wage bill for each of these three categories of workers. We used these data to calculate the average monthly salary per worker in the skilled and unskilled categories.[6] Information on worker level, i.e. data from the IRP5 panel, allows us to calculate what percentage of workers falls into these two categories for each firm. For manufacturing firms in this panel, on average, 5.59 per cent of their workers are considered to be skilled and 73.97 per cent to be unskilled—and the trend observed in Table 2 again repeats for the other two groupings. The skilled percentage for importing firms increases to 9.30 per cent and the unskilled decreases to 65.34 per cent, while narrow offshorers

[6] We therefore exclude the middle grouping or skills level.

employ relatively greater numbers of skilled workers, at 13.75 per cent of their workforce, and the fewest unskilled workers, at 57.01 per cent of the workforce.

Tables B7 to B12 in Appendix B report on the regressions estimated with the percentage of skilled workers as dependent variable. Out of all of these regressions, Table B8, with estimates in level format, indicates that narrow-offshoring firms in ultra-labour-intensive industries employ a larger percentage of skilled workers compared with normal offshorers, but as narrow offshorers increase their imports, the percentage of skilled workers in their labour force declines. This observation is in line with the descriptive statistics in Table 2 indicating a higher percentage of skilled workers for narrow offshorers compared with broad offshorers. However, in order to confirm that this observation is not due to endogeneity, the regression is run using instrumental variables.

Table 5: Regression results with % of skilled workers as dependent variable—variables in differences and including instrumental variables

	1 **All manufacturing**	2 **Narrow offshorers**
log imports	−0.2200* (0.1289) [0.090]	−0.9662** (0.4444) [0.030]
log capout	0.1337* (0.0862)	0.2748 (0.3581)
log sales	0.4670 (0.4110)	−0.9975 (1.0971)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
Observations	14,460	2,358
R-squared	0.0032	0.0101

Notes: Robust standard errors in parentheses; probability in square brackets; ***p<0.01, **p<0.05, *p<0.1, #p<0.15.

Source: Authors' construction based on SARS-NT panel data.

Table 5 contains results for the instrumental variable specification (Equation 4) for all manufacturing firms (Column 1) and the sub-group of narrow offshorers (Column 2). The test statistics confirm the validity of the instrument for the narrow equation, but for all manufacturing firms the endogeneity test is not conclusive. As imports increase across all offshorers (all manufacturing firms that import), the percentage of skilled workers decreases. This is statistically significant at 10 per cent. Column 2 repeats the estimation for the subgroup of all narrow offshorers. As the narrow offshorers increase imports their percentage of skilled workers also declines, and at a rate of four times more than reported in Column 1.

Table 6 reports the results with the percentage of unskilled workers as dependent variable. The model is run in a differenced format and includes the narrow-offshorer slope dummy—Equation 5 specification. The first two rows of Table 6 suggest that offshoring has a definite impact on the percentage of unskilled workers across various sectors.

Increased imports increase the percentage of unskilled workers for labour-intensive firms in general (significant at 11.1 per cent), while increased narrow offshoring increases the percentage of unskilled workers for all manufacturing firms (only significant at 15.1 per cent), for capital-intensive firms (significant at 14.2 per cent), and for ultra-labour-intensive firms (significant at 2.1 per cent).

Table 6: Regression results with percentage of unskilled workers as dependent variable—variables in differences including dummies

	1 All manufacturing	2 Labour-intensive	3 Capital-intensive	4 Ultra-labour-intensive
log imports	0.0155965 (0.1008378) [0.877]	0.2526718# (0.1586955) [0.111]	−0.0116012 (0.1877621) [0.951]	−0.1730618 (0.3054464) [0.571]
log imports*narrow	0.0471575# 0(.0328397) [0.151]	−0.0023846 0.0626677 [0.970]	0.1272428# (0.0866836) [0.142]	0.2797307** (0.1205099) [0.021]
dumnarrow	−0.5618276 0(.6668807) [0.400]	−0.1878228 1.277957 [0.883]	−2.543182 1.804599 [0.159]	−2.723429 2.747441 [0.322]
log capout	0.1677173* (0.1012189) [0.098]	−0.0060124* 0.1691163 [0.972]	−0.480507** 0.2166863 [0.027]	0.1636054 0.1835201 [0.373]
log sales	−0.4302132 0.5612376 [0.443]	−0.5158068 0.9997171 [0.606]	−2.229917# 1.469214 [0.129]	1.947713 1.498104 [0.194]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	22,969	7,811	3,828	2,157
R-squared	0.0007	0.0008	0.0036	0.0080

Notes: Robust standard errors in parentheses; probability in square brackets; ***p<0.01, **p<0.05, *p<0.1, #p<0.15.

Source: Authors' construction based on SARS-NT panel data.

According to Table 6, there is a definite difference in response to offshoring depending on the factor intensity of manufacturing firms. Replicating the analysis in Table 6 while using instrumental variables indicates a statistically significant impact of narrow offshoring only for the sub-group of ultra-labour-intensive firms—see Table 7.

The test statistics generally confirm the validity of the instrument for the narrow equation, but the weak instrument criteria are not convincing. Table 7 suggests that increased imports from narrow offshorers increase the percentage of unskilled workers in manufacturing firms belonging to ultra-labour-intensive industries. While there are also indications of this trend in other industries, the instrumental variable specification does not render statistically significant results for the other sub-samples.

The empirical analysis on employment (Sections 5.4.1 and 5.4.2) indicates an overall decrease in manufacturing employment with increased imports/offshoring and an accompanying relative increase in the unskilled labour force or decrease in the skilled labour force. This is similar to the findings of Stone and Bottini (2012: 21). They analysed firm-level data for various OECD countries and came, among others, to the following conclusions: 'high technology offshoring leads to a reduction in labour demand' and 'there is a positive relationship between labour demand for medium and low skilled workers and the manufacturing content of exports'. Our definition of narrow offshoring relates directly to the manufacturing content of exported manufacturing products. Their explanation that the imports of cheaper inputs (cheaper than locally produced inputs) can increase exports and then lead to a higher demand for lower-skilled workers may also be the driver behind similar trends observed in our regression analysis. Feenstra and Hanson (2003) report the opposite for US firms—in their sample, offshoring resulted in lower demand for low-skilled workers and higher demand for high-skilled workers. If one considers South Africa to be a developing country, it is to be expected that the South African labour market would respond differently from the US market. Section 2 discussed the experience of developed countries exporting low-skilled jobs to developing countries.

Table 7: Regression results with percentage of unskilled workers as dependent variable—variables in differences and including instrumental variable

	Ultra-labour-intensive
log imports	0.1857
	(0.5971)
log imports*narrow	0.2258**
	(0.1141)
	[0.048]
log capout	0.3235
	(0.3028)
log sales	2.3164
	(2.6744)
Year FE	Yes
Industry FE	Yes
Firm FE	Yes
Observations	1278
R-squared	0.0189
Under-identified	31.723
Kleibergen Paap rk LM stat	0.000%
Weak ident Cragg-Donald	
KP rk LM	228.44
	54.28 (0.00%)
Hansen J	0.00% exact id
Under-identified	0.00%
Weak instrument	0.75 (cannot reject)
Endog test (H0 exo)	0.5681 (cannot reject)

Notes: Robust standard errors in parentheses; probability in square brackets; ***p<0.01, **p<0.05, *p<0.1, #p<0.15.

Source: Authors' construction based on SARS-NT panel data.

5.4.3 Offshoring and wages

The firm-level panel provides a very crude indicator for salary per worker in the form of total labour cost per firm divided by the number of workers per firm. We use this indicator as a first proxy for firm-level salaries. Tables B19 to B24 in Appendix B summarize the regression results with log of salary per worker as dependent variable. Across most of the specifications, there are indications that firms in ultra-labour-intensive industries increase their salary per worker if narrow offshorers increase their imports, but these narrow offshorers do start the salary per worker at a lower level than the general offshorers. Estimations including instrumental variables do not confirm any statistically significant impact of offshoring on the firm-level proxy of wage level (or salary per worker). There are some indications that increased imports increase salary per worker for labour-intensive firms, but this is only significant at 13 per cent.

Finally, we analyse worker-level salaries by estimating Equation 4 and adding more control variables. While the above analysis of salary per worker is based on a crude indicator of salary per worker, data from the IRP5 panel provide a potentially more reliable estimate of individuals' monthly earnings (income). Due to the large number of observations in the combined IRP5 panel, the following results were obtained from a random sample of 20 per cent of the total observations, limited only to workers in the manufacturing industry.

Tables B25 and B26 in Appendix B summarize the estimates, including firm fixed effects. However, a better-suited specification would include job-spell fixed effects, which account for fixed effects of the specific period of employment and are more closely related to the individual earning the income than the firm paying the salary. Table 8 reports on the regressions.

Table 8: Regression results with log monthly earnings per worker as dependent variable—basic regression in differences and job fixed effects

	1 All manufacturing	2 Labour-intensive	3 Capital-intensive	4 Ultra-labour-intensive	5 Narrow offshorers
log imports	0.0048222***	0.0089341***	0.0048801***	−0.0061351**	−0.0070469***
	0.0007626	0.0015528	0.001278	0.0031156	0.0024522
	[0.000]	[0.000]	[0.000]	[0.049]	[0.004]
log capout	−0.0059388***	0.0009924	0.0031522#	−0.0207287***	0.0047293**
	0.0010221	0.0018937	0.0021388	0.0028872	0.002203
	[0.000]	[0.600]	[0.141]	[0.000]	[0.032]
log sales	0.0390392***	0.0797753***	0.0579953***	−0.0285388**	0.0375813***
	0.0050108	0.0093136	0.0112081	0.0138808	0.0103883
	[0.000]	[0.000]	[0.000]	[0.040]	[0.000]
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Job FE	Yes	Yes	Yes	Yes	Yes
Observations	323,690	80,493	64,333	29,328	66,653
R-squared	0.0003	0.0015	0.0008	0.0034	0.0009

Notes: Robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1; all regressions include additional control variables for age, age^2, tenure, and tenure^2.

Source: Authors' construction based on SARS-NT panel data.

Increased imports (offshoring) increase individual monthly earnings for manufacturing employees overall (Column 1). However, a further breakdown into factor intensity classification reveals that increased imports increase monthly income in capital-intensive (Column 3) and labour-intensive (Column 2) industries, but decrease individual monthly income for workers in ultra-labour-intensive industries (Column 4). Firms engaging in narrow offshoring generally pay lower individual wages as offshoring increases (Column 5). Hummels et al. (2014) conclude that offshoring increases the wages of highly skilled workers and lowers those of unskilled workers. If one expects workers in capital-intensive industries to be more highly skilled than workers in ultra-labour-intensive industries—even though this is a crude assumption to make—the wage impact of offshoring in Table 8 corresponds generally with the international experience.

For robustness, the analysis reported in Table 8 was replicated, including the instrumental variable for imports. However, the various test statistics do not confirm the validity of the instrument. Previous studies on similar South African IRP5 data did not utilize instrumental variables. One reason for this may be the nature of the worker-level data, being linked to a specific individual rather than a firm. In the absence of a valid instrumental variable, and the previous use of instruments in similar analyses, we consider the analysis reported in Table 8 to be sufficient.

6 Conclusion

South Africa's fledgling democracy is faced with the trilemma of low and stagnant economic growth, persistently high and increasing levels of long-term structural unemployment, and widening inequalities on various fronts in society. Government has responded with a range of policy initiatives to combat the entrenched socioeconomic challenges of South Africa. Fourie (2015) tracks a number of these initiatives.

From 2004, several relatively focused initiatives, such as the Expanded Public Works Programme, industrial policy action plans (IPAPs; DTI 2017, 2018) and the National Development Plan (NDP; National Planning Commission 2013), were established. A key aim of both the IPAP (2017/2018–2019/2020) and the NDP is to achieve shared and inclusive growth through decent jobs, especially in labour-intensive sectors. It is, however, acknowledged that there are severe skills shortages and mismatches in the labour market.

Perceived skills shortages influence the ability of the manufacturing sector to enhance its capacity to create economic and employment multipliers across value chains. Indeed, statistics show that although manufacturing GDP has increased over the last decade, manufacturing employment has decreased (DTI 2017). The backdrop to these findings is a continuous process of capital-deepening as labour as a production factor is substituted by capital in the production process. Furthermore, there has been a trend of increasing imports of intermediate inputs as a result of increasing domestic production costs (e.g. for electricity and labour) and production volatility (e.g. strikes and power disruptions). These production uncertainties have led to South African manufacturing firms' increasing involvement in offshoring activities.

Offshoring occurs when manufacturing firms form part of fragmented production networks. We consider offshoring in the manufacturing sector from two perspectives, namely 'broad' and 'narrow'. Broad offshoring is considered to be all imports from manufacturing firms. This percentage increased from around 26 per cent to around 28 per cent between 2010 and 2017. Black et al. (2018) argue that import penetration in South Africa's manufacturing sector has increased—the result of which we also see in our evidence in that employment opportunities are lost as broad offshoring increases. Moreover, the percentage of skilled workers decreases as imports increase across all offshorers. This may suggest that the type of goods imported are imported for reasons of cost-effectiveness—as do the findings of Stone and Bottini (2012) for OECD countries—or that these skills may not be as readily available as they previously were.

We define narrow offshoring in a particular way which is suited to the administrative data used. We classify as narrow offshorers any manufacturing firms that import goods (or intermediaries) in the same HS4 category in which they export (here we make the assumption that re-exporters are classified in retail or wholesale ISIC sectors, not in the manufacturing sector). Previous studies utilizing the SARS administrative data have considered two-way traders (e.g. Edwards et al. 2018). We provide a narrower classification of two-way traders that we argue brings us closer to considering these firms as being part of a fragmented production network (as we control for endogeneity using instrumental variables).

Within the context of South Africa, this is of particular interest. The importance of inclusive growth in South Africa is reinforced by the country's persistent inequality, poverty, and unemployment. However, achieving inclusive growth in an era of fragmented production networks (through global value chains (GVCs) or multinational organisations (MNOs) poses a number of labour market challenges to policymakers. As explained in the literature review, involvement in fragmented production networks has consequences for firms' labour demand and for the wages paid to workers within a firm. For South Africa this has pertinent importance, as finding the solutions to employment creation within the manufacturing sector in South Africa is a delicate operation. The NDP summarizes the situation:

> The proposals in the plan take cognisance of the fact that South Africa is a middle-income country. On the one hand, it cannot compete in low-skilled industries because cost structures are already too high. On the other hand, the country lacks the skills to compete with advanced manufacturing countries such as Germany. South Africa therefore needs to compete in the mid-skill manufacturing and service areas, and niche markets that do not require large economies of scale. (National Planning Commission 2013: 115)

Our results show that as narrow offshorers increase their imports, the percentage of skilled workers declines. This is in contrast to the experiences of developed countries, where the percentage of skilled workers increases relative to that of unskilled workers (see for example Andersson et al. 2016). However, from a South African policy perspective, our results are encouraging given South Africa's large semi- and unskilled workforce. In particular, our results show that the percentage of unskilled workers increases as narrow offshorers increase imports in ultra-labour-intensive industries (such as wearing apparel; leather and related products; wood and food products; and furniture). We also show that on an employer–employee level, the wages of labour- and capital-intensive firms increase as offshorers increase their imports, while the wages for ultra-labour-intensive workers decrease. Narrow offshorers do not necessarily pay higher wages as imports increase.

Therefore, a comment by Black et al. (2018: 7) highlighting the policy context from an industrial policy perspective is useful:

> The nature of industrial policy must depend on context and the South African context is one of massive structural unemployment. Thus, industrial policy should focus on improving economy-wide efficiency and should support more employment-intensive growth. Incentives should subsidise labour and training rather than capital investment, electricity and infrastructure for capital-intensive firms.

In this we are arguing not for the abandonment of a supportive environment for higher-skilled advanced manufacturing firms, but rather that (both trade and industrial) policy should take a balanced approach to take the context of South Africa's labour force into account and continue the emphasis on finding niche markets. Black et al. (2018) also state that until recently, government intervention was largely focused towards capital-intensive industries. The shift in policy is evident in the recent IPAP (2018/19–2020/21), where, for example, the clothing, textiles, leather, and footwear industry has been identified as a sectoral focus area with several targeted programmes (e.g. the development of a leather, leather goods, and footwear export cluster, called the fashion hub, and the regional cotton textiles development plan), which are aimed at boosting the industry and its employment creation (DTI 2018). Here, Rob Davies, then-Minister of Trade and Industry, emphasizes the need for firm-level interventions:

> At times industrial policy needs to drive focused firm-level interventions. For example, a key requirement of the labour-intensive clothing sector is the need to be able to rapidly respond to the retail demand for world class manufacturing principles including new designs and fast fashions, quick turn-around times and so forth. (DTI 2018: 5)

Davies emphasizes nuanced support for the sector across the entire value chain, as well as the importance of public–private partnerships. This supports our view of the need for a balanced policy approach that is further enlightened through firm-level research conducted under SA-TIED.

We recommend that further research should explore offshoring and (firm-level) policy interventions from the international business literature perspective by considering the manufacturing firms that are part of MNOs (especially in the automotive industry, which would be insightful given the Manufacturing Competitiveness Enhancement Programme, MCEP, and the Automotive Production and Development Programme, APDP), as well as from the literature perspective on GVCs in view of the countries where manufacturing imports originate and, in the case of narrow offshorers, the countries they export to.

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Appendix A

Table A1: IRP5 data-cleaning

Keep individual	From the IRP5 data, only workers/employees were used in this article, therefore from the variable 'nature of person' only 'Individuals' were kept.
Periods worked	Some of the data on the 'period employed from' and 'period employed to' have 'invalid periods' reported; this was corrected: 1. For instance 1910 instead of 2010 2. End date 27 February instead of 28 February 3. End date before start date 4. End date in the month before year end and then start again a few days after the start of the year.
Multiple job spells	There are individuals with 'multiple job spells', therefore one individual working multiple jobs at the same firm. When adding the number of days of each job spell 3% add up to more than 365 days (which is impossible). For this 3% of jobs the average of the worker's multiple job spells at the firm was taken.
Duplicate certificates	Each job is assigned a certificate number; duplicate certificates were dropped to avoid double counting.
Age 15–64	There were individuals found to be 90 years of age. This study kept to the South African labour force definition and kept workers of the age 15–64.
Income	There are various ways to calculate income; we used the gross remuneration (by adding three variables named: grossntaxableincomeamnt, grossretfundincomeamnt, and grossnretfundincomeamnt').

Source: Authors' construction.

Table A2: ISIC4 description

ISIC4	Description
1010	'Manufacture of food products'
1011	'Manufacture of beverages'
1012	'Manufacture of tobacco products'
1013	'Manufacture of textiles'
1014	'Manufacture of wearing apparel'
1015	'Manufacture of leather and related products'
1016	'Manufacture of wood and of products of wood and cork, except furniture'
1017	'Manufacture of paper and paper products'
1018	'Printing and reproduction of recorded media'
1019	'Manufacture of coke and refined petroleum products'
1020	'Manufacture of chemicals and chemical products'
1021	'Manufacture of pharmaceuticals, medicinal chemical and botanical products'
1022	'Manufacture of rubber and plastics products'
1023	'Manufacture of other non-metallic mineral products'
1024	'Manufacture of basic metals'
1025	'Manufacture of fabricated metal products, except machinery and equipment'
1026	'Manufacture of computer, electronic and optical products'
1027	'Manufacture of electrical equipment'
1028	'Manufacture of machinery and equipment n.e.c.'
1029	'Manufacture of motor vehicles, trailers and semi-trailers'
1030	'Manufacture of other transport equipment'
1031	'Manufacture of furniture'
1032	'Other manufacturing'
1033	'Repair and installation of machinery and equipment'

Source: Authors' construction based on United Nations (2008).

Table A3: Classification according to factor intensity

ISIC4	Description
	Capital-intensive
1011	‘Manufacture of beverages’
1017	‘Manufacture of paper and paper products’
1018	‘Printing and reproduction of recorded media’
1019	‘Manufacture of coke and refined petroleum products’
1020	‘Manufacture of chemicals and chemical products’
1024	‘Manufacture of basic metals’
	Labour-intensive
1013	‘Manufacture of textiles’
1022	‘Manufacture of rubber and plastics products’
1023	‘Manufacture of other non-metallic mineral products’
1025	‘Manufacture of fabricated metal products, except machinery and equipment’
1028	‘Manufacture of machinery and equipment n.e.c.’
	Ultra-labour-intensive
1014	‘Manufacture of wearing apparel’
1015	‘Manufacture of leather and related products’
1016	‘Manufacture of wood and of products of wood and cork, except furniture’
1031	‘Manufacture of furniture’

Source: Authors’ construction based on Edwards (2001).

Appendix B

Table B1: Regression results with log number of workers as dependent variable—Equation 2

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.005662	0.0016295	0.0002058	0.0018305	−0.0012056
	0.0024178	0.0041687	0.0043397	0.0061525	0.0086261
	0.019%	69.6%	96.2%	76.6%	88.9%
log capout	0.0152719	0.0133016	0.0148438	0.0145629	0.0180777
	0.0021135	0.0033803	0.0064137	0.0057484	0.0040949
	0%	0%	2.1%	1.1%	0%
log sales	0.3809965	0.3752202	0.3796237	0.4115028	0.3126568
	0.014246	0.023464	0.0391013	0.0516834	0.0514565
	0%	0%	0.%	0%	0%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	44,167	14,770	7,293	3,383	7,618
R-squared	0.6326	0.6201	0.6093	0.5726	0.6168

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B2: Regression results with log number of workers as dependent variable—Equation 3

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0055084	0.0005658	0.0016222	0.0022595
	0.0024503	0.004238	0.0044355	0.0062673
	2.5%	89.4%	71.5%	71.9%
log imports*narrow	−0.0004608	0.0128294	−0.0150413	−0.003926
	0.0033662	0.0053623	0.00966	0.0089599
	89.1%	1.7%	12%	66.1%
dumnarrow	0.0305483	−0.1868504	0.238413	0.1155396
	0.0496512	0.0774592	0.1421562	0.1319302
	53.8%	1.6%	9.4%	38.1%
log capout	0.0152838	0.01325	0.0146262	0.0147769
	0.0021123	0.003377	0.0063827	0.005705
	0%	0%	2.2%	1.0%
log sales	0.3806579	0.3748742	0.3792799	0.4082591
	0.0142463	0.0234397	0.0390849	0.0517804
	0%	0%	0%	0.0%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	44,164	14,770	7,293	3,383
R-squared	0.6318	0.6193	0.6097	0.5712

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B3: Regression results with log number of workers as dependent variable—Equation 4

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**	**Narrow offshorers**
log imports	0.0010283	0.0016744	−0.004416	0.000416	−0.0139504
	0.0023636	0.0039522	0.0035798	0.0077038	0.0128292
	66.4%	67.2%	21.8%	95.7%	27.7%
log capout	0.0036557	0.0049527	0.0027577	−0.0033024	0.0132536
	0.0018118	0.0027202	0.0039558	0.0058562	0.0057614
	4.4%	6.9%	48.6%	57.3%	2.2%
log sales	0.1432409	0.1506718	0.1002111	0.1628756	0.1344593
	0.0156051	0.0304504	0.0609346	0.0729243	0.0307118
	0%	0%	10%	2.6%	0%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	31,417	10,626	5,238	2,155	5,881
R-squared	0.0722	0.0678	0.0060	0.0428	0.0469

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B4: Regression results with log number of workers as dependent variable—Equation 5

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**
log imports	0.0008905	0.0017722	−0.0045973	0.0009423
	0.0023671	0.003959	0.0036081	0.0076406
	70.7%	65.4%	20.3%	90.2%
log imports*narrow	0.0009229	0−.0000973	0.0014648	−0.0007707
	0.0006383	0.0010228	0.002066	0.0018428
	14.8%	92.4%	47.8%	67.6%
dumnarrow	−0.0149601	−0.0147451	−0.0108106	0.0721342
	0.0128739	0.0218181	0.0404905	0.0420344
	24.5%	49.9%	79.0%	8.7%
log capout	0.0036709	0.0049506	0.0027621	0−.0031134
	0.0018119	0.0027193	0.0039664	0.0058628
	4.3%	6.9%	48.6%	59.6%
log sales	0.1431956	0.1506302	0.0994765	0.1610974
	0.0156055	0.030465	0.0610237	0.0729787
	0%	0%	10.3%	2.8%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	31,417	10,626	5,238	2,155
R-squared	0.0725	0.0676	0.0059	0.0429

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B5: Regression results with log number of workers as dependent variable—Equation 4 without firm fixed effects

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**	**Narrow offshorers**
log imports	0.0018153	0.0014325	−0.0048212	−0.0018114	−0.0015585
	0.0021396	0.0034912	0.0032598	0.0063004	0.0074117
	39.6%	68.2%	13.9%	77.4%	83.3%
log capout	0.0069623	0.0089674	0.0068977	−0.0001538	0.0107334
	0.0017571	0.0029381	0.0039156	0.006152	0.0044399
	0%	0.2%	7.8%	98.0%	1.6%
log sales	0.2109208	0.2239703	0.2009447	0.2414287	0.2038464
	0.0144605	0.025048	0.049491	0.0599452	0.0305026
	0%	0%	0%	0.0%	0%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Instruments	No	No	No	No	No
Observations	31,417	10,626	5,238	2,155	5,881
R-squared	0.0878	0.0927	0.0826	0.0633	0.1199

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B6: Regression results with log number of workers as dependent variable—Equation 5 without firm fixed effects

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**
log imports	0.0016229	0.0015454	−0.0050035	−0.0018047
	0.0021436	0.0034999	0.0032798	0.0062848
	44.9%	65.9%	12.7%	77.4%
log imports*narrow	0.001353	−0.00056	0.0018589	0.0007736
	0.0004996	0.0008038	0.0015944	0.0017916
	0.7%	48.6%	24.4	66.6%
dumnarrow	−0.020391	0.0036512	−0.0326246	0.0363319
	0.0064219	0.0092826	0.0174881	0.0236058
	0.1%	69.4%	6.2%	12.4%
log capout	0.0070164	0.0089552	0.0070966	0.0001203
	0.0017575	0.0029361	0.0039288	0.006071
	0%	0.2%	7.1%	98.4%
log sales	0.2106811	0.2240805	0.2002549	0.2404576
	0.0144596	0.0250555	0.0495634	0.0600261
	0%	0%	0%	0.0%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Instruments	No	No	No	No
Observations	31,417	10,626	5,238	2,155
R-squared	0.0881	0.0928	0.0833	0.0650

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Author's estimation on SARS-NT panel data.

Table B7: Regression results with percentage of skilled workers as dependent variable—Equation 2

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**	**Narrow offshorers**
log imports	−0.0015884 0.0567063 97.8%	−0.0833326 0.0904721 35.7%	0.1996997 0.1770064 25.9%	0.1073866 0.164429 51.4%	0.2565919 0.2383063 28.2%
log capout	0.0059015 0.0648333 92.7%	0.0588453 0.1012133 56.1%	−0.2324844 0.1546603 13.3%	−0.2086189 0.1056657 4.9%	0.1787816 0.1491135 23.1%
log sales	0.4233692 0.2852389 13.8%	0.2445154 0.4288712 56.9%	1.831884 1.054066 8.2%	0.1529073 0.5272846 77.2%	−0.6454549 0.7273277 37.5%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	35,008	11,791	5,789	3,389	6,155
R-squared	0.0381	0.0309	0.0930	0.0202	0.0043

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B8: Regression results with percentage of skilled workers as dependent variable—Equation 3

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**
log imports	−0.0083336 0.0578038 88.5%	−0.0719141 0.0926788 43.8%	0.1926955 0.1769063 27.6%	0.1681255 0.1693407 32.1%
log imports*narrow	0.068886 0.0914342 45.1%	−0.1294066 0.1766754 46.4%	0.0681359 0.2354946 77.2%	−0.7521027 0.3042812 1.4%
dumnarrow	−1.085468 1.26662 39.1%	2.001447 2.419276 40.8	−1.411064 3.293218 66.8%	10.30014 4.181116 1.4%
log capout	0.0057701 0.0648258 92.9%	0.0591116 0.1012873 56.0%	−0.2296997 0.1545839 13.7%	−0.2106614 0.1060173 4.7%
log sales	0.4223141 0.2855638 13.9%	0.2483726 0.4292976 56.3%	1.837931 1.055814 82%	0.178323 0.5206273 73.2%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	35,008	11,791	5,789	3,389
R-squared	0.0388	0.0296	0.0926	0.0162

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B9: Regression results with percentage of skilled workers as dependent variable—Equation 4

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0166654	0.026381	0.0384032	0.2320681	−0.0522833
	0.0635087	0.0951132	0.1833563	0.1999902	0.2100417
	79.3%	78.2%	83.4%	24.6%	80.3%
log capout	0.1395614	0.3073367	0.1612514	0.1396786	0.1925611
	0.0772659	0.1597758	0.1619058	0.1041535	0.2807009
	7.1%	5.5%	31.9%	18.0%	49.3%
log sales	0.5103538	0.5370033	1.40062	0.4342948	−0.8414338
	0.317267	0.6297599	1.054788	0.9121904	0.9695717
	10.8%	39.4%	18.4%	63.4%	38.6%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	22,969	7,811	3,828	2,157	4,390
R-squared	0.0002	0.008	0.006	0.0023	0.0001

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B10: Regression results with percentage of skilled workers as dependent variable—equation 5

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0147701	0.0201231	0.0348838	0.2287153
	0.0635509	0.0946212	0.1835608	0.1986408
	81.6%	83.2%	84.9%	25.0%
log imports*narrow	−0.00245	0.0163357	0.0139613	−0.0674469
	0.0245362	0.0434777	0.0748641	0.0798073
	92.0%	70.7%	85.2%	39.8%
dumnarrow	0.5453509	0.4888704	0.7337143	0.2982385
	0.4822637	0.8336512	1.352813	1.602725
	25.8%	55.8%	58.8%	85.2%
log capout	0.1395461	0.3085049	0.1589557	0.1324402
	0.0772756	0.1598381	0.1614338	.1050698
	7.1%	5.4%	32.5%	020.8%
log sales	0.5060837	0.534098	1.387351	0.4628443
	0.3174646	0.6297162	1.056764	0.91896
	11.1%	39.6%	18.9%	61.5%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	22,969	7,811	3,828	2,157
R-squared	0.0002	0.008	0.007	0.0029

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B11: Regression results with percentage of skilled workers as dependent variable—Equation 4 without firm fixed effects

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.034638	−0.0073065	0.2301913	0.2123865	0.1212753
	0.0585242	0.0929727	0.1811245	0.183862	0.1395026
	55.4%	93.7%	20.4%	24.8%	38.5%
log capout	0.1142477	0.2974036	0.0852502	−0.0512965	0.1286352
	0.0608562	0.1273135	0.115655	0.0710496	0.1701762
	6.0%	1.9%	46.1%	47.0%	45.0%
log sales	0.1828132	0.4492006	1.229444	−0.0421227	−1.071625
	0.2563041	0.5253499	0.7282065	0.663849	0.7424632
	47.6%	39.3%	9.1%	94.9%	14.9%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Instruments	No	No	No	No	No
Observations	22,969	7,811	3,828	2,157	4,390
R-squared	0.0020	0.0038	0.0057	0.0038	0.0077

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Author’s estimation on SARS-NT panel data.

Table B12: Regression results with percentage of skilled workers as dependent variable—Equation 5 without firm fixed effects

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0320649	−0.0127198	0.2272877	0.2116449
	0.058649	0.0927037	0.181352	0.18444
	58.5%	89.1%	21.0%	25.1%
log imports*narrow	0.0121323	0.0248611	0.0324817	−0.0503081
	0.0174721	0.0309301	0.0492146	0.0559857
	48.7%	42.2%	50.9%	36.9%
dumnarrow	−0.034232	−0.1722103	−0.2419939	0.1479749
	0.1761999	0.3302441	0.5108702	0.5777369
	84.6%	60.2%	36.6%	79.8%
log capout	0.1143576	0.2974079	0.0878185	−0.0573968
	0.0608906	0.1273791	0.1154538	0.0723909
	6.0%	2.0%	44.7%	42.8%
log sales	0.1804136	0.4431579	1.215227	−0.0256211
	0.2563656	0.5262794	0.7298761	0.6620907
	48.2%	40.0%	9.6%	96.9%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Instruments	No	No	No	No
Observations	22,969	7,811	3,828	2,157
R-squared	0.0020	0.0039	0.0059	0.0043

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors’ estimation on SARS-NT panel data.

Table B13: Regression results with percentage of unskilled workers as dependent variable—Equation 2

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	−0.0632472	−0.1148732	−0.2181694	0.1517732	−0.1323532
	0.0911982	0.1582061	0.1922593	0.3114942	0.3341465
	48.8%	46.8%	25.7%	62.6%	69.2%
log capout	0.0278921	0.0266017	0.157173	0.1571348	−0.6299718
	0.0943354	0.1493978	0.264599	0.2011348	0.2297258
	76.7%	85.9%	55.3%	43.5%	0.6%
log sales	−0.5769552	−0.0354235	−0.4980497	1.483539	−1.925674
	0.4027889	0.8430601	0.8354397	1.237451	1.173243
	15.2%	96.6%	55.1%	23.1%	10.1%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	35,008	11,791	5,789	3,389	6,155
R-squared	0.0138	0.0257	0.0730	0.0027	0.0851

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B14: Regression results with percentage of unskilled workers as dependent variable—Equation 3

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	−0.0601991	−0.1264177	−0.2010924	0.1251375
	0.0930418	0.1598911	0.1992507	0.3130429
	51.8%	42.9%	31.3%	68.9%
log imports*narrow	−0.0649769	0.1740912	−0.1637211	0.4059589
	0.128796	0.254946	0.361325	0.4042236
	61.4%	49.5%	65.1%	31.5%
dumnarrow	1.398591	−3.025406	3.246773	−2.149559
	1.937458	3.74347	5.664357	5.78798
	47.0%	41.9%	56.7%	71.0%
log capout	0.0280783	0.0263391	0.151294	0.1706062
	0.0943395	0.1493688	0.2647429	0.202475
	76.6%	86.0%	56.8%	40.0%
log sales	−0.5803003	−0.0388835	−0.5097468	1.284228
	0.4029767	0.8432079	0.8355921	1.228645
	15.1%	96.3%	54.2%	29.6%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	35,008	11,791	5,789	3,389
R-squared	0.0126	0.0266	0.0711	0.0035

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B15: Regression results with percentage of unskilled workers as dependent variable—Equation 4

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0240638	0.2512432	−0.0002767	−0.1747546	0.9060044
	0.1008722	0.1593451	0.1879001	0.3076343	0.4246286
	81.1%	11.5%	99.9%	57.0%	3.3%
log capout	0.1674484	−0.0056247	−0.4870103	0.1394623	−0.3593144
	0.1012936	0.1691118	0.2150004	0.1813667	0.2335722
	9.8%	97.3%	2.4%	44.2%	12.4%
log sales	−0.4273501	−0.5161783	−2.187448	2.020601	0.0443774
	0.5608143	0.9990705	1.470836	1.499196	1.285769
	44.6%	60.5%	13.7%	17.8%	97.2%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	22,969	7,811	3,828	2,157	4,390
R-squared	0.007	0.008	0.0033	0.0066	0.0011

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B16: Regression results with percentage of unskilled workers as dependent variable—Equation 5

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0155965	0.2526718	−0.0116012	−0.1730618
	0.1008378	0.1586955	0.1877621	0.3054464
	87.7%	11.1%	95.1%	57.1%
log imports*narrow	0.0471575	−0.0023846	0.1272428	0.2797307
	0.0328397	0.0626677	0.0866836	0.1205099
	15.1%	97.0%	14.2%	2.1%
dumnarrow	−0.5618276	−0.1878228	−2.543182	−2.723429
	0.6668807	1.277957	1.804599	2.747441
	40.0%	88.3%	15.9%	32.2%
log capout	0.1677173	−0.0060124	−0.480507	0.1636054
	0.1012189	0.1691163	0.2166863	0.1835201
	9.8%	97.2%	2.7%	37.3%
log sales	−0.4302132	−0.5158068	−2.229917	1.947713
	0.5612376	0.9997171	1.469214	1.498104
	44.3%	60.6%	12.9%	19.4%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	22,969	7,811	3,828	2,157
R-squared	0.0007	0.0008	0.0036	0.0080

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B17: Regression results with percentage of unskilled workers as dependent variable—Equation 4 without firm fixed effects

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0032846	0.1760808	−0.0316999	−0.1470728	0.2260318
	0.0898497	0.147327	0.1704295	0.252141	0.2608722
	97.1%	23.2%	85.2%	56.0%	38.6%
log capout	0.0825092	0.0379468	−0.1846119	0.1179298	−0.1801521
	0.0873021	0.1559966	0.1412607	0.1769526	0.1770672
	34.5%	80.8%	19.1%	50.5%	30.9%
log sales	−0.0428958	0.032164	−1.46508	1.925928	1.056506
	0.4790516	0.8842241	1.07125	1.241823	0.9774984
	92.9%	97.1%	17.1%	12.1%	28.0%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Instruments	No	No	No	No	No
Observations	22,969	7,811	3,828	2,157	4,390
R-squared	0.0041	0.0056	0.0074	0.0102	0.0093

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B18: Regression results with percentage of unskilled workers as dependent variable—Equation 5 without firm fixed effects

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	−0.0021222	0.1790255	−0.0374962	−0.1444835
	0.0898889	0.1472198	0.1699959	0.2516515
	98.1%	22.4%	82.5%	56.6%
log imports*narrow	0.024623	−0.0049025	0.0724827	0.1884496
	0.0243326	0.0434932	0.0608216	0.088093
	31.2%	91.0%	23.3%	3.2%
dumnarrow	−0.0327931	−0.2758574	−0.7274605	−0.6180592
	0.2599145	0.4864813	0.6665546	1.191353
	90.0%	57.1%	25.7%	60.4%
log capout	0.0826346	0381401	−0.1774845	0.1401903
	0.0873155	0.1560661	0.1419381	0.1798906
	34.4%	80.7%	21.1%	43.6%
log sales	−0.0474934	0.0322242	−1.49653	1.864519
	0.4793118	0.8847866	1.071975	1.239114
	92.1%	97.1%	16.3%	13.2%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Instruments	No	No	No	No
Observations	22,969	7,811	3,828	2,157
R-squared	0.0041	0.0057	0.0079	0.0129

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B19: Regression results with log salary per worker as dependent variable—Equation 2

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0003402	0.001485	0.0053457	−0.0014046	−0.0121062
	0.0030528	0.0056366	0.005444	0.0079547	0.0102422
	91.1%	79.2%	32.6%	86.0%	23.7%
log capout	0.0021616	0.005264	−0.0029147	0.0044355	0.0043663
	0.0025941	0.0042847	0.0069487	0.0072845	0.0055527
	40.5%	21.9%	67.5%	54.3%	43.2%
log sales	0.0731502	0.0805566	0.074398	0.0537797	0.1606446
	0.0163454	0.0282184	0.0365981	0.0566606	0.052805
	0%	0.4%	4.2%	34.3%	0.2%
Industry FE	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	
Instruments	No	No	No	No	No
Observations	43,515	14,591	7,152	3,331	7,517
R-squared	0.0535	0.0240	0.0766	0.0153	0.0798

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B20: Regression results with log salary per worker as dependent variable—Equation 3

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0007613	0.0018113	0.004793	−0.004247
	0.0030925	0.0056896	0.0056163	0.0080607
	80.6%	75.0%	39.4%	59.8%
log imports*narrow	−0.0034386	−0.0059069	0.0051125	0.0344945
	0.0040897	0.0077468	0.0107761	0.0122891
	40.0%	44.6%	36.5%	0.5%
dumnarrow	0.0412003	0.1019322	−0.0632109	−0.5122286
	0.0583537	0.108426	0.1469008	0.1844905
	48.0%	34.7%	66.7%	0.6%
log capout	0.0021691	0.0052737	−0.0028843	0.0043662
	0.002594	0.0042826	0.0069357	0.0072992
	40.3%	21.8%	67.8%	55.0%
log sales	0.073361	0.0805222	0.0742569	0.0545181
	0.0163704	0.0282412	0.0367013	0.0567449
	0%	0.4%	4.3%	33.7%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	43,515	14,591	7,152	3,331
R-squared	0.0528	0.0241	0.0770	0.0159

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B21: Regression results with log salary per worker as dependent variable—Equation 4

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0038286	0.0062885	0.0037759	0.0106356	0.0000114
	0.0030652	0.0054318	0.0060565	0.0113202	0.0138621
	21.2%	24.7%	53.3%	34.8%	99.9%
log capout	0.0029613	0.0065794	−0.0004541	0.0032028	−0.0054869
	0.0023255	0.0038859	0.0056999	0.0085768	0.0076045
	20.3%	9.1%	93.7%	70.9%	47.1%
log sales	0.1534689	0.118498	0.2039605	0.1334734	0.1898012
	0.0234978	0.0324151	0.0896956	0.0660141	0.046849
	0%	0%	2.3%	4.4%	0%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Instruments	No	No	No	No	No
Observations	30,757	10,445	5,096	2,107	5,768
R-squared	0.0254	0.0205	0.0057	0.0119	0.0167

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B22: Regression results with log salary per worker as dependent variable—Equation 5

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0039767	0.0064157	0.0041038	0.0093303
	0.0030699	0.0054272	0.0060818	0.011109
	19.5%	23.7%	50%	40.1%
log imports*narrow	−0.0010283	0−.0010704	−0.0026549	0.0026851
	0.0008597	0.0015719	0.0022962	0.0033602
	23.2%	49.6%	24.8%	42.5%
dumnarrow	0.0181929	0.0274458	0.0296915	−0.1865009
	0.0190308	0.0369084	0.0474378	0.0710333
	33.9%	45.7%	53.1%	0.9%
log capout	0.0029451	0.0065617	−0.0004842	0.0027636
	0.0023259	0.0038891	0.0057239	0.0085218
	20.5%	9.2%	93.3%	74.6%
log sales	0.1534979	0.1187646	0.2052796	0.1382738
	0.0234941	0.0324225	0.089754	0.0666975
	0%	0%	2.2%	3.9%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Instruments	No	No	No	No
Observations	30,757	10,445	5,096	2,107
R-squared	0.0253	0.0200	0.0060	0.0125

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B23: Regression results with log salary per worker as dependent variable—Equation 4 without firm fixed effects

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0038286 0.0030652 21.2%	0.0030838 0.004765 51.8%	0.0063679 0.0049303 19.6%	0.0094152 0.0090673 29.9%	−0.001377 0.0086087 87.3%
log capout	0.0029613 0.0023255 20.3%	0.0049094 0.0034999 16.1%	−0.0019968 0.0048331 67.9%	0.0069988 0.0058222 22.9%	−0.0015913 0.0050581 75.3%
log sales	0.1534689 0.0234978 0%	0.1009394 0.0286463 0%	0.1348409 0.0638483 3.5%	0.1230653 0.0521626 1.8%	0.1267566 0.0452703 0.5%
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Instruments	No	No	No	No	No
Observations	30,757	10,445	5,096	2,107	5,768
R-squared	0.0254	0.0250	0.0346	0.0129	0.0420

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B24: Regression results with log salary per worker as dependent variable—Equation 5 without firm fixed effects

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0039055 0.0027927 16.2%	0.0030378 0.0047706 52.4%	0.0065872 0.0049494 18.3%	0.0094363 0.008987 29.4%
log imports*narrow	−0.0009896 0.0006443 12.5%	0.0006547 0.0011306 56.3%	−0.0020935 0.001749 23.1%	0.0002664 0.0028708 92.6%
dumnarrow	0.0088445 0.0078872 26.2%	−0.0172051 0.0129348 18.3%	0.025213 0.0181197 16.4%	−0.0827098 0.029693 0.5%
log capout	0.0026533 0.0020557 19.7%	0.0049202 0.003499 16.0%	−0.0021888 0.004852 65.2%	0.0068002 0.0057865 24.0%
log sales	0.1104293 0.0194583 0%	0.1007292 0.028691 0%	0.1357405 0.0639361 3.4%	0.1248588 0.0522075 1.7%
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Instruments	No	No	No	No
Observations	30,757	10,445	5,096	2,107
R-squared	0.0286	0.0251	0.0350	0.0157

Note: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format.

Source: Authors' estimation on SARS-NT panel data.

Table B25: Regression results with log monthly earnings per worker as dependent variable—Equation 2 (firm fixed)

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour	Narrow offshorers
log imports	0.0125342	0.0059475	0.0090873	0.0030847	0.022933
	0.0062927	0.0055868	0.005829	0.0111244	0.011394
	4.6%	28.7%	11.9%	78.2%	4.4%
log capout	−0.0018047	0.0091038	−0.0028854	−0.0360363	0.0215713
	0.0043087	0.0053987	0.0070976	0.0077183	0.0075857
	67.5%	9.2%	68.4%	0.0%	0.5%
log sales	0.0234942	0.0292688	0.0501711	0.0128604	0.1090687
	0.0267334	0.0525515	0.0321019	0.0357557	0.0361006
	38.0%	57.8%	11.8%	71.9%	0.3%
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Job FE	No	No	No	No	No
Observations	586,896	146,630	127,974	53,821	118,121
R-squared	0.1623	0.1069	0.1823	0.1137	0.2533

Notes: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format; all regressions include control variables for age, age^2, tenure, and tenure^2.

Source: Authors' estimation on SARS-NT panel data.

Table B26: Regression results with log monthly earnings per worker as dependent variable—Equation 3 (firm fixed)

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0118368	0.0060672	0.0080467	0.0046157
	0.0064988	0.0058195	0.0056591	0.0109022
	6.9%	29.7%	15.5%	67.2%
log imports*narrow	0.0043781	−0.0015106	0.0061836	−0.0078916
	0.0044943	0.0056188	0.0056107	0.0099274
	33.0%	78.8%	27.1%	42.7%
dumnarrow	−0.0597055	0.030178	−0.103345	0.1823616
	0.067935	0.0794342	0.0881491	0.1586586
	38.0%	70.4%	24.1%	25.1%
log capout	−0.0018694	0.0091229	−0.0031009	0−.035762
	0.0043012	0.0053752	0.0072517	0.0076495
	66.4%	9.0%	66.9%	0.0%
log sales	0.024118	0.0294387	0.0503413	0.0097485
	0.0264359	0.0526081	0.0324218	0.0352004
	36.2%	57.6%	12.1%	78.2%
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Job FE	No	No	No	No
Observations	586,896	146,630	127,974	53,821
R-squared	0.1639	0.1075	0.1809	0.1117

Notes: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format; all regressions include control variables for age, age^2, tenure, and tenure^2.

Source: Authors' estimation on SARS-NT panel data.

Table B27: Regression results with log monthly earnings per worker as dependent variable—Equation 2 (job fixed)

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**	**Narrow offshorers**
log imports	0.0058101	0.0096454	0.0027945	−0.0085568	0.0031058
	0.0006419	0.0013309	0.0010699	0.0026806	0.0016004
	0.0%	0.0%	0.9%	0.1%	5.2%
log capout	0.0028277	0.0022908	0.011775	−0.0308369	0.0054295
	0.0008971	0.0015057	0.0015899	0.002548	0.0021907
	0.2%	12.8%	0.0%	0.0%	1.3%
log sales	0.0513147	0.0497888	0.04808	0.014444	0.0745151
	0.0041135	0.0069618	0.0103057	0.0102486	0.0081248
	0.0%	0.0%	0.0%	15.9%	0.0%
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Job FE	Yes	Yes	Yes	Yes	Yes
Observations	586,896	146,630	127,974	53,821	118,121
R-squared	0.1970	0.1228	0.1768	0.1439	0.2131

Notes: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format; all regressions include control variables for age, age^2, tenure, and tenure^2.

Source: Authors' estimation on SARS-NT panel data.

Table B28: Regression results with log monthly earnings per worker as dependent variable—Equation 3 (job fixed)

	All manufacturing	**Labour-intensive**	**Capital-intensive**	**Ultra-labour-intensive**
log imports	0.0057989	0.0096923	0.0030812	−0.0080964
	0.0006558	0.0013761	0.0010808	0.0026593
	0.0%	0.0%	0.4%	0.2%
log imports*narrow	0.0000895	−0.0003784	−0.0018645	0.0096716
	0.0007091	0.001757	0.0013433	0.0034923
	90.0%	82.9%	16.5%	0.6%
dumnarrow	−0.0015952	0.0061084	0.0121797	−0.0715241
	0.0115133	0.0267471	0.0202878	0.0533742
	89.0%	81.9%	54.8%	18.1%
log capout	0.0028282	0.0022993	0.0124617	−0.029457
	0.0008976	0.0015104	0.0016085	0.0025093
	0.2%	12.8%	0.0%	0.0%
log sales	0.0513181	0.049808	0.0494236	0.0116602
	0.0041108	0.0069631	0.0103683	0.010211
	0.0%	0.0%	0.0%	25.3%
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Job FE	Yes	Yes	Yes	Yes
Observations	586,896	146,630	127,974	53,821
R-squared	0.1970	0.1228	0.1780	0.1427

Notes: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format; all regressions include control variables for age, age^2, tenure, and tenure^2.

Source: Authors' estimation on SARS-NT panel data.

Table B29: Regression results with log monthly earnings per worker as dependent variable—Equation 4 (job fixed)

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive	Narrow offshorers
log imports	0.0048222	0.0089341	0.0048801	−0.0061351	−0.0070469
	0.0007626	0.0015528	0.001278	0.0031156	0.0024522
	0.0%	0.0%	0.0%	4.9%	0.4%
log capout	−0.0059388	0.0009924	0.0031522	−0.0207287	0.0047293
	0.0010221	0.0018937	0.0021388	0.0028872	0.002203
	0.0%	60.0%	14.1%	0.0%	3.2%
log sales	0.0390392	0.0797753	0.0579953	−0.0285388	0.0375813
	0.0050108	0.0093136	0.0112081	0.0138808	0.0103883
	0.0%	0.0%	0.0%	4.0%	0.0%
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Job FE	Yes	Yes	Yes	Yes	Yes
Observations	323,690	80,493	64,333	29,328	66,653
R-squared	0.0003	0.0015	0.0008	0.0034	0.0009

Notes: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format; all regressions include control variables for age, age^2, tenure, and tenure^2.

Source: Authors' estimation on SARS-NT panel data.

Table B30: Regression results with log monthly earnings per worker as dependent variable—Equation 5 (job fixed)

	All manufacturing	Labour-intensive	Capital-intensive	Ultra-labour-intensive
log imports	0.0047744	0.0094975	0.0044398	−0.0064439
	0.0007614	0.0015663	0.001251	0.003132
	0.0%	0.0%	0.0%	4.0%
log imports*narrow	−0.0011848	−0.0023221	−0.000168	−0.0008953
	0.0001676	0.0004271	0.00037	0.0005729
	0.0%	0.0%	65.0%	11.8%
dumnarrow	0.0226091	0.052898	−0.0126087	0.0539152
	0.0041795	0.0092411	0.0099914	0.0151811
	0.0%	0.0%	20.7%	0.0%
log capout	−0.0060377	0.0012845	0.0038032	−0.0200613
	0.0010227	0.0018952	0.0021783	0.0028871
	0.0%	49.8%	8.1%	0.0%
log sales	0.0385592	0.0799396	0.0575322	−0.0281275
	0.0050139	0.0093138	0.0112119	0.0139022
	0.0%	0.0%	0.0%	4.3%
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Job FE	Yes	Yes	Yes	Yes
Observations	323,690	80,493	64,333	29,328
R-squared	0.0003	0.0016	0.0008	0.0035

Notes: Each cell contains the estimated coefficient, followed by the robust standard error and the probability in percentage format; all regressions include control variables for age, age^2, tenure, and tenure^2.

Source: Authors' estimation on SARS-NT panel data.