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Total factor productivity in South African manufacturing firms

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Abstract: The manufacturing sector is an important source of productivity growth and exports. Manufacturing firms are generally more productive than firms in the agricultural or services sectors and are an important source of job creation. Little is known about the productivity performance of the sector and its drivers in South Africa. The recent availability of firm-level tax administration data has made it possible to measure and analyse the productivity of manufacturing firms in South Africa for the first time. In this paper, we use firm-level data for the period 2010–13 to estimate total factor productivity in the South African manufacturing sector. We examine differences in the level and growth of productivity across manufacturing sub-sectors and examine the heterogeneity in productivity levels within sectors. Our analysis paves the way for future research into the factors driving productivity growth of manufacturing firms that will contribute to the evidence base of the reasons for the significant heterogeneity in measured firm performance, even within narrowly defined sectors and size groups.

Keywords: total factor productivity, South Africa, heterogeneity, tax administration data
JEL classification: D22, D24, O12

Figures and Tables: at the end of the paper.

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1 Introduction

The importance of manufacturing and industry in economic growth is well documented in the Kaldorian tradition.[1] Manufacturing firms are generally more productive than firms in the agricultural or services sectors and are an important source of job creation.[2] Several studies support the primacy of the manufacturing sector in determining output growth and employment creation (Li and Zhang 2008; Mahmood et al. 2014; Millin and Nichola 2005; Wells and Thirlwall 2003).[3]

The manufacturing sector in South Africa accounts for around 13 per cent of gross domestic product (GDP). This is similar to Brazil (14 per cent) but lower than Russia (16 per cent) and India (17 per cent), and significantly lower than China (30 per cent).[4] As evident from Figure 1, the contribution of the sector to GDP has been in decline over the last two decades. Although the contribution of the sector to output is also declining in the BRICS countries overall, the pace of decline has been faster in the case of South Africa. Growth in the sector has been slow relative to the rest of the economy and the sector was also hit especially hard by the recent global financial crisis. This decline is reflected in the employment and investment numbers, with the sector representing a decreasing proportion of the total numbers employed and the proportion of total fixed capital formation. Moreover, Aghion et al. (2008) highlight the poor productivity performance of the sector when compared to manufacturing internationally and show that higher mark-ups in the sector, due to low product market competition, has had a negative impact on productivity growth in manufacturing.

These trends are worrying if the manufacturing sector is an important source of employment and productivity growth. Indeed, Tregenna (2008) shows the importance of the South African manufacturing sector as a source of demand for the service sector and argues that declines in manufacturing growth may have had a negative impact on economic growth. This conclusion is supported by Rodrik (2008), who attributes South Africa's slow growth and slow employment growth to weakness in manufacturing exports.[5] To address these concerns, recent policy efforts in South Africa have focused on employment-intensive economic growth with particular emphasis on the role of exporters and the manufacturing sector in creating jobs, specifically for low-skilled workers (DTI 2010; DED 2011; NPC 2011).[6]

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[1] See Targetti (2005) for a discussion of Kaldor's (1967) contributions to development economics.

[2] Recent work by Newman et al. (2016) highlights the fact that other sectors of the economy, such as traded services and agri-business, also hold similar potential for output, employment, and productivity growth.

[3] Specifically, Millin and Nichola (2005) examine the role of the manufacturing sector in South Africa using data from 1946 to 1998. Their findings, however, do not relate to the post-Apartheid period.

[4] These figures are from the World Bank's World Development Indicators database (WDI 2016).

[5] There is some disagreement on the extent to which the decline in the manufacturing sector is of concern for economic growth. For example, Fedderke (2014) argues that the decline in employment in manufacturing in South Africa is partially due to high total factor productivity (TFP) growth in the sector and shows that TFP growth in manufacturing is high relative to the rest of the economy. Moreover, growth in South Africa has been more in the service and tertiary sectors, and so focusing on the manufacturing sector alone only gives a partial picture.

[6] This is evident in the Department of Trade and Industry's Industrial Policy Action Plan (DTI 2010), the Department of Economic Development's New Growth Path (DED 2011), and the National Planning Commission's National Development Plan (NPC 2011; see also Black and Gerwel 2014).

Given the importance of manufacturing in the South African context, understanding the productivity performance of the sector and its drivers is important in designing policies to promote the growth of the sector. The recent availability of firm-level tax administration data through collaboration between the South African National Treasury, United Nations University World Institute for Development Economics (UNU-WIDER), and South African Revenue Services (SARS) has made it possible to accurately measure and analyse the productivity of manufacturing firms in South Africa for the first time. Indeed, the scarcity of South African firm-level studies has thus far been primarily driven by a lack of data (Behar 2010; Bhorat and Lundall 2004). Providing accurate and robust measures of total factor productivity (TFP) at the firm level allows for a comparison of productivity distributions and trajectories across manufacturing sub-sectors. It also allows for a better understanding with respect to the heterogeneity in productivity levels within sectors and its relationship with government policies, local labour markets, and exposure to international markets, among others.

In this paper, we use the methodology of Ackerberg et al. (2006) on the South African administrative database to analyse the evolution of productivity in South Africa's manufacturing sector. We find that productivity grew on average between 2010 and 2013 but that there are some sectors that have seen productivity decline. We also find that productivity growth is largely driven by the firms that are most productive at the start of the period. We find significant heterogeneity in productivity within and between sectors. We find that TFP is increasing in the size category of the firm and that TFP growth is driven by the larger firms in terms of number of employees. We find that older firms are generally more productive as are firms that are engaged in international trade. We also consider the correlation between productivity and research and development (R&D) and find a positive relationship between R&D expenditure and TFP.

The rest of the paper is structured as follows. In Section 2, we describe in detail the data. In Section 3, we outline our approach to estimating productivity and present our core results. Section 4 presents a simple analysis of the factors related to productivity. Section 5 concludes.

2 Data

We use tax administrative data obtained from SARS for the 2010–13 period. The primary data source is the South African Corporate Income Tax (CIT) data. CIT data are collected by SARS annually with respect to the tax year that ends at the end of February each year. Firms are required to submit a corporate income tax return where they self-report items with respect to income, expenditures, equity and liabilities, capital items, and tax credits. Almost all reporting items are compulsory, although firms are allowed to submit a 'zero' where a specific field is not applicable to them. Firms are aware that they may be audited by SARS but do not know in any given year whether they will be selected for audit.

Compiling the CIT database from the raw data involves a number of steps. During the sample period in question, the format of CIT returns changed. Specifically, SARS changed the submission form from what was called the IT14 form to the ITR14 form. This change came into effect on 4 May 2013 (SARS 2016). The main difference between the IT14 and the ITR14 is the depth of data submission required of companies of different sizes. All firms, regardless of size, were required to submit the full IT14 form whereas for ITR14 the level of detail that firms are required to submit varies depending on firm size. This change in the way data are gathered affects the way in which the variables used for our analysis are constructed. This is discussed later in this section.

The CIT database does not include information on the number of persons employed in the firm. We use employee income tax certificates to construct a measure of labour employed by each firm. The IRP5 is a reconciliation form that includes details of the total amount paid to employees from different sources, the total amount of employer's tax that is paid, skills development levy payments, unemployment insurance fund payments, employment tax incentives deducted, as well as the periods worked in the year of assessment. An employer must issue an IRP5 certificate to each employee to whom remuneration is paid or has become payable and from which employees' tax for a given tax period has been deducted.[7] Where no employee tax has been deducted from remuneration, an IT3(a) form is submitted to an employee. Where an employee earns less than R2,000 in a given tax year and where no employee tax has been deducted from remuneration paid, the employee is not given an IRP5 or an IT3(a) form. The tax year runs from 1 March in a previous calendar to the last day of February in the tax year. The consequences for cleaning the data of the difference between a firm's tax year and financial year are discussed later in this section.

IRP5 data are aggregated for each Pay-As-You-Earn (PAYE) reference number. A table linking the PAYE reference numbers to the tax reference number of the firm in the CIT dataset is used to match employees to firms. Companies, identified by a unique tax reference number, may have multiple PAYE numbers. We match all employees with a matching PAYE reference number to their corresponding tax reference number.

In Table 1, the number of firms in the CIT dataset belonging to the manufacturing sector, classified using either the firm's profit code[8] or the firm's industry code from the IRP5 data, is reported. A core set of variables on firms is required to estimate productivity. Table 1 documents the loss of observations due to missing data on these core variables. Several observations are lost when restricting the firms to those with positive and non-missing sales, value added, and capital data. The availability of firms with labour data is indicative of an average matching rate of around 85 per cent of viable firms. A constraint of the procedure we use to estimate productivity is that it requires the use of lags. This means that firms must be present in at least two consecutive periods for it to be included for analysis. Moreover, they must not be missing lagged values for the variables of interest. Restricting the sample to those that satisfy these criteria leads to just less than half of viable firms falling out of the sample each year. Further, we cut the top and bottom 1 per cent of firms with respect to the value added to capital ratio in each year to eliminate outliers.

The IT14 and ITR14 forms are submitted by firms for a tax year determined by their financial year-end. That is, a firm with financial year-end on 31 January 2012 will submit financial statements for the financial year 1 February 2011 to 31 January 2012 for the tax year ending on 29 February 2012. Similarly, where a firm has a financial year from 1 January 2012 to 31 December 2012, the firm will be assessed for the tax year ending on 29 February 2012. IRP5 data, on the other hand, report on labour in the firm for the year from 1 March to 28 February the following year, regardless of the financial year-end. Although for most firms the financial year coincides with the SARS tax year, around 15 per cent of firms do not follow SARS conventions. To ensure that firms are reporting as close as possible in the same financial year, we move firms with financial year ending after 30 August to the next financial year. Thus, a firm

[7] Paragraph 13(1) of Schedule 4 of the Income Tax Act (Government of South Africa 1962).

[8] Note that the firm's profit code comes from the CIT data. This profit code is not used as a measure of industry in general as it is too inconsistent with other measures of the firm's industry. All results presented are robust to using the profit code as classifier, however.

with financial year ending on 31 September 2012 will be moved from tax year 2012 to tax year 2013. This also allows us to make sure that the firm's labour data capture most of the activity occurring during a specific year.[9]

We classify firms according to the industry code reported by their employees in IRP5. We use the IRP5 classification because the two main industry classifiers of IT14 and ITR14, the industry code and profit code of the firm, are noisy and often contradictory. We use the industry code recorded for most employees of the firm in the IRP5 data. We convert these codes to the 2-digit level of the fourth revision of the International Standard Industrial Classification of All Economic Activities (ISIC4) (United Nations 2008).

In calculating the total number of employees of the firm, each employee is weighted by the total number of periods they work at the firm. In Table 2, we compare the employment numbers based on our sample with those reported in the Quarterly Economic Survey (QES). As revealed, employment figures of manufacturing firms in our full sample is higher than the total employment figures reported in the QES. Once we restrict our sample to firms with sales and capital data, employment numbers in our sample drop to around 80 per cent of the QES. In our restricted sample, where we only use firms that have the necessary data to compute TFP, employment numbers are between 40 and 50 per cent of those reported in the QES data. It should be noted, however, that the QES data are computed on the basis of payroll data of value-added tax (VAT) registered firms only, which are, in general, larger (StatsSA 2015).

Fixed capital is reported differently in IT14 and ITR14. In IT14, all firms are asked to report their fixed property, their fixed assets, and their other fixed assets. In ITR14, firms of different types are asked different questions. Micro firms and small firms (as defined by their entry type in the online questionnaire) report fixed assets in a single item that combines property, plant, and equipment. Medium to large firms, on the other hand, are asked to submit three line items: fixed property, fixed assets, and other fixed assets. For ITR14, we construct fixed assets sum of these three line items where the missing entries are treated as zeros. We add the reported depreciation of the firm to the fixed asset value to get the value of fixed assets at the beginning of the year. We deflate this value using the manufacturing industry fixed capital investment deflators rebased to March 2012.[10] Lumpiness in fixed assets is controlled for using the two-year average of total assets.[11]

We compare our measures of fixed capital to the Quarterly Financial Statistics (QFS) collected by SARS and drawn from a sample of approximately 5000 VAT-paying enterprises. The sample is drawn each year from a population of enterprises that account for around 95 per cent of the total turnover per industry with adjustments made to account for the remainder (StatsSA 2010–15a). Comparing our total fixed assets measures with those in the QFS in Table 3 reveals that the sample covers between 19 and 24 per cent of fixed assets reported for manufacturing firms in the economy as a whole. Although these figures are substantially smaller than those reported in the QFS, the fact that the QFS only surveys VAT registered entities suggests that they may be over estimating total capital stock as these entities are, in general, larger than non-VAT registered entities (Pieterse et al. 2016).

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[9] Note that the IRP5 data actually contains information on the exact day a person is employed to the date employment ceases; however, data for 2009 and 2010 were not available.

[10] Gross fixed capital formation in manufacturing (SARB KBP6082; see SARB 2014).

[11] This is the approach adopted by Hsieh and Klenow (2009) in estimating productivity for the United States, China, and India.

Value added is computed as total sales minus the cost of sales. In the IT14 form, sales are reported as turnover in a single line item. In the ITR14 form, different firms submit different measures. Micro and small firms report sales or turnover in the same way as in the IT14 form, whereas medium to large firms submit foreign connected sales and other sales. Value added is deflated by the value added at basic prices deflator (SARB KBP6634; see SARB 2014). A comparison between the total value added of firms in our sample and those in the QFS is provided in Table 4. Similar to fixed assets, our sample covers around 24 per cent of the total value added reported in the QFS estimates.

In Table 5, the total number of firms in our sample by industry is provided. Motor vehicles, trailers, and semi-trailers, fabricated metal products, and other manufacturing are the largest manufacturing industries in terms of number of firms.[12] The smallest manufacturing industries, in terms of number of firms, include basic pharmaceutical products, beverages, leather and related products, and computer, electronic, and optical products.

We consider both weighted and unweighted estimates of productivity. In the weighted specification, for each industry *j*, we weight output (value added), capital, labour, and intermediates (cost of sales) by the proportion of sales that firm *i* in time *t* contributes to total sales of all firms in industry *j* for the entire period in question, as in Equation (1). This ensures that our TFP estimates give more weight to larger firms (in terms of sales) and so are a better representation of the manufacturing output of the sector.

$$weight_{ijt} = \frac{sales_{ijt}}{\sum_{i=1}^{n} sales_{ijt}}. \tag{1}$$

In Table 6, the mean log value added per firm in each industry and year is provided in its weighted and unweighted form. Firms producing pharmaceutical products, rubber and plastics products, and coke and refined petroleum products report the highest unweighted average value added per firm, whereas firms producing furniture, wearing apparel, or textiles report the lowest average value added per firm. Weighting the values as described change the rankings dramatically. The average value added per firm is still the highest among firms producing pharmaceutical products, whereas firms producing leather products and paper and paper products have the second and third highest weighted values, respectively. Firms producing food products, machinery and equipment not elsewhere classified, and other manufacturing products have the lowest weighted average value added per firm.

In Table 7, we report the sample statistics for our instrument, cost of sales. Firms in the production of coke and refined petroleum products, pharmaceuticals, and beverages report the highest unweighted cost of sales per firm on average, whereas firms in the production of printing and recorded media, furniture, and apparel report the lowest unweighted cost of sales per firm on average. We see dramatic shifts when weighting firms by sales contribution. Whereas firms in the production of coke and refined petroleum products and pharmaceuticals still have the highest average cost of sales per firm, those manufacturing leather products have higher average cost of sales than firms producing beverages. Interestingly, firms in the production of motor vehicles, other machinery, and printing have the lowest average cost of sales per firm.

[12] It should be noted that the motor vehicles sector also includes firms that manufacture parts and accessories for motor vehicles.

In terms of average capital stock (real values in logs), Table 8 reveals that firms in the production of beverages, pharmaceuticals, or rubber and plastics products have the highest capital stock on average, whereas firms manufacturing apparel, motor vehicles and other transport equipment, and leather products have the lowest values on average. In terms of weighted averages, firms producing pharmaceuticals, beverages, and paper products have the highest average capital stock, whereas firms producing motor vehicles, other manufacturing products, and other machinery have the lowest values.

In Table 9, the sample statistics of log labour per industry is given.[13] Firms in the production of pharmaceutical products, rubber and plastics products, and wood and products of wood have the highest average number of workers per firm. Firms manufacturing computer, electronic, and optical products, other machinery, and printing have the lowest number of workers per firm on average.

3 Productivity estimation

To measure productivity, we first estimate a production function for each 2-digit manufacturing sector and use the estimated parameters to back out a firm-specific measure of productivity. We also estimate the production function for each sector separately as the estimation assumes that all firms share a common technology; this is more realistic within 2-digit sub-sectors than for the manufacturing sector as a whole. Simultaneity between productivity shocks (observed by the firm but not the econometrician) and input choices leads to a bias in ordinary least square (OLS) estimates of the coefficients on these inputs in a standard production function. For example, firms that experience a negative productivity shock may decide to reduce their labour force or delay investment. This will lead to an upward bias in the coefficients on labour and capital. It is also possible that the employment decisions of firms are countercyclical, with higher productivity firms deciding to replace labour with more capital-intensive production processes. This would lead to a downward bias in OLS estimation of the coefficient on labour.

A common approach to estimating the production function parameters in the presence of such bias is to use a semi-parametric estimator that applies some structure to the underlying decision-making process of firms (Olley and Pakes 1996). In this paper, we use Ackerberg et al.'s (2006) modification of the Levinsohn and Petrin (2003) approach. Ackerberg et al.'s (2006) approach addresses multicollinearity issues that affect the identification of the parameters in the first stage of the estimation of the models of Olley and Pakes (1996) and Levinsohn and Petrin (2003). We estimate the model using a two-step generalized method of moments estimator (Wooldridge 2009). A brief description of the approach is provided in Appendix A, with a more detailed exposition available in Newman et al. (2015). In each case, tests for underidentification, weak identification, and first-stage *F*-tests confirm the validity of the instruments.[14] We use higher-order terms of the instruments or additional lags to test for overidentification. Details of the instrument used to test for the overidentifying restrictions in each sector are also provided in Table 10. For all sectors, we find the lag of labour to be a suitable instrument for current period

[13] Note that the negative weighted values are as expected because the number of employees is multiplied by the firm's weight before taking the natural logarithm.

[14] In Table 11, we present *P* values for each test. The underidentification test is based on the Kleibergen–Park Lagrange multiplier statistic, the weak identification test is based on the Kleibergen–Park Wald *F* statistic, the *F*-test is based on the Angrist–Pischke multivariate *F*-test of excluded instruments in the first stage, and the test for the overidentifying restrictions is based on Hansen's *J*-test.

labour. We use the parameter estimates from the exactly identified system to back productivity to avoid loss of data due to the inclusion of additional lags and to reduce the potential for weak instruments. The results do not change much when we use different combinations of valid overidentifying restrictions.

Table 10 presents the OLS and instrumental variables estimates for the production function parameters for each two-digit manufacturing sub-sector. We present the weighted estimates (preferred) as well as results for the unweighted and weighted balanced sample where we exclude all entrants and exits over the sample period for comparison.

The coefficient estimates on the labour and capital inputs are higher in the weighted sample than in the unweighted sample. This can be explained by the fact that in weighting the data before estimating the production function, we give more weight to larger firms (in terms of sales) who earn greater returns from their inputs than smaller firms. The capital coefficients in the balanced panel are larger than those in the restricted sample. This is in line with expectations given that the balanced panel captures survivors who, in general, are expected to have a higher capital stock.

Comparing our estimates to the OLS estimates, we find that in all cases the coefficient on labour is lower when the production function is estimated using the Ackerberg et al. (2006) approach. This makes sense if we believe that there is a positive correlation between labour and productivity shocks leading to an upward bias in the labour coefficient when using OLS. For the weighted sample OLS underestimates the capital coefficient, implying that the capital used by firms is negatively related to firm productivity leading to a downward bias.

We observe high capital elasticities (weighted estimates) ranging from 0.255 to 0.585. Firms manufacturing rubber and plastics products, wood products, basic metal products, transport equipment, beverages, and fabricated metal products all have a capital coefficient above 0.5. These sectors are among the smaller sectors in the sample when measured by total value added. Interestingly, firms manufacturing of coke, motor vehicles, and apparel have the lowest capital coefficient, below 0.3. Firms in the production of computer, electronic, and optical products, printing, motor vehicles, and transport equipment have labour elasticities above 0.5. Firms on the low end of the elasticity distribution include coke and refined petroleum products, pharmaceuticals, apparel, and leather products. We find evidence of constant returns to scale only for firms producing beverages, wood products, computer, electronic, and optical products, basic metals, and transport equipment, whereas all other industries are characterized by decreasing returns to scale.

4 TFP in South African manufacturing

We use the elasticity estimates presented in Table 10 to estimate productivity for each firm in each sector using Equation (2).

$$\hat{\omega}_{ijt} = y_{itj} - \hat{\beta}_{lj} l_{ijt} - \hat{\beta}_{kj} k_{ijt}, \tag{2}$$

where $\hat{\omega}_{ijt}$ is the estimated (log) of TFP for firm *i* in sector *j* in time *t*, *y* is log value added, *l* is the log of labour, *k* is the log of capital, $\hat{\beta}_{lj}$ is the estimated labour elasticity for sector *j*, and $\hat{\beta}_{kj}$ is the estimated capital elasticity for sector *j*. Given that firms in different sectors (by assumption) use different technologies, we cannot compare the level of productivity across sectors. We can, however, compare the growth trajectory. In Table 11, we present the growth in average TFP between 2010 and 2013 for each sector, where the level of TFP in each sector is indexed to the average value of TFP in 2010. The best performing sectors in terms of productivity growth are the chemicals, coke and refined petroleum, and non-metallic mineral products sectors.[15] The worst-performing sectors were firms in the production of leather products, pharmaceutical products, and wood products.

In Figures 2a and 2b, we provide scatter plots illustrating the differences across sectors in the TFP growth rate of firms in the top 25 per cent and bottom 25 per cent of the TFP distribution, respectively. The growth rate of the top and bottom 25 per cent of firms in each sector (relative to all other firms in the sector) is estimated using Equation (3).

$$TFP_{growth_i} = \alpha_0 + \alpha_1 Position_{i2010}, \tag{3}$$

where TFP_{growth_i} is the growth rate in TFP of firm *i* over the entire time period and $Position_{i2010}$ is an indicator for whether the firm was in the top or bottom 25 per cent of the TFP distribution in 2010. This estimate allows us to analyse the relative growth rates of the top and bottom performers in each industry. The size of the circles indicates the size of the industry in terms of contribution of that industry to total value added to the manufacturing sector.

In Figure 2a, we find a weak positive relationship between the growth rate of the top 25 per cent of firms in terms of productivity in each industry and the average growth rate for the industry as a whole. In Figure 2b, we see a very weak negative relationship between the growth rate of the bottom performing 25 per cent of firms and the growth of the industry as a whole. This suggests that the productivity growth of the industry is driven by the most productive firms in the industry. This is particularly the case for sectors that appear in the upper right quadrant of Figure 2a, namely, those producing chemicals and coke and refined petroleum products. The size of the industry does not appear to be related to the growth of the industry as a whole or the growth of the top and bottom performing 25 per cent of firms, although it does appear that a number of the smaller sectors have slower average growth in TFP.

A well-documented stylized fact relating to the manufacturing sector in both developed and developing country economies is that there is considerable heterogeneity in firm-level productivity, even within narrowly defined sectors (Syverson 2011; Tybout 2000). To examine the extent of heterogeneity in the South African context, we plot the distribution of productivity for each sub-sector and across different firm characteristics. To make meaningful comparisons across sub-groups of firms, we de-mean by the industry–year average to control for industry- and year-specific shifts.

Figure 3 presents the distribution of productivity across different sub-sectors of manufacturing, and the distribution of productivity in each sub-sector for each year of the sample is presented in Appendix B (Figure B1). In Figure 3a, the productivity distributions for food and beverages sectors are observed to have relatively high dispersions. The dispersion of TFP for the food sector appears to be widening over time (Appendix B) owing to increasing density in the left tail. Firms that manufacture beverages are very widely dispersed with a mode below the mean and a

[15] It should be noted that changes in productivity over time may be due to either real productivity changes or the entry and exit of firms given that we are working with an unbalanced panel. However, this effect is unlikely to be high, as our estimates are robust to including controls for exit.

concentrated right tail. This is due to an increasing dispersion in productivity in the industry over time, marked by an increasing density at the very top and bottom of the distribution.

In Figure 3b, the TFP distributions for textiles, apparel, and leather manufacturing firms are shown to be very wide relative to that of other industries. The dispersion in productivity in textiles changed very little over time whereas the productivity distribution for apparel seems tightened over the timeframe of our analysis. This appears to be due to decreasing tails whereas the density of firms below the mean is on the increase. The productivity distribution of leather firms did not change much over time.

In Figure 3c, firms in the production of wood products are shown to have a tight dispersion but this appears to be widening over time (Appendix B), with more firms forming part of the left tail of the distribution. Firms in the production of paper products, on the other hand, are evenly dispersed compared to other industries, with the distribution becoming bimodal over time. Printing products have a tight dispersion with an increasing density at the left tail.

In Figure 3d, firms in the production of coke and refined petroleum products are shown to be relatively widely dispersed with a mode above the mean. In Appendix B, the mean above the mode is shown to be a relatively new phenomenon. Firms in the production of chemical products are dispersed with a mode below the mean and a relatively large density above the mean. The increase in density appears to be due to firms close to the top of the distribution growing at a faster rate than other firms in the sector. The pharmaceutical products sector is the most widely dispersed. Interestingly, this sector is also the one with the fewest firms. In Appendix B, we observe that an increasing density of firms in the right tail drives the widening in the dispersion of the distribution over time.

In Figure 3e, firms in the production of rubber and plastics products are shown to be very tightly distributed with a mode above the mean. In Appendix B, we observe a rather dramatic widening of the distribution of the firms around the mean, with the sector appearing to be tending towards bimodality. The productivity of firms producing other non-metallic mineral products has a medium dispersion that appears to be tightening over time.

In Figure 3f, firms in the production of fabricated metals are shown to be very tightly distributed with a mode slightly below its mean. Although the industry has a mode at its mean in 2010, as shown in Appendix B, the mode has consistently shifted left since then. Firms in the production of basic metals, on the other hand, are relatively tightly dispersed with a mode slightly above the mean. The TFP dispersion of basic metals appears to be increasing over time.

In Figure 3g, firms in the production of computer, electronic, and optical products are tightly dispersed with a mean above the mode. The tight distribution is largely due to very short tails. In Appendix B, the industry can be seen to be tending towards bimodality and shorter tails. Firms that manufacture electrical equipment are tightly dispersed around the mean and the distribution appears to be tightening over time, although not consistently. Although firms that manufacture other machinery are also tightly dispersed, the distribution appears to be widening with more firms dispersed around the mean in later years.

In Figure 3h, firms in the production of transport equipment are shown to be very tightly dispersed and the distribution appears to be tightening over time. Firms in the production of motor vehicles, on the other hand, are relatively widely dispersed with increasing density in the left tail over time. Finally, in Figure 3i, furniture firms are shown to have a tighter than average dispersion in productivity with very short tails. There is no clear trend in the shape of the TFP distribution over time. Other manufacturing firms have an average dispersion that appears to be slowly widening.

Figure 4 illustrates the productivity distribution for firms in different size categories. We consider eight size categories in total: firms with 1–4 employees, 5–9 employees, 10–19 employees, 20–49 employees, 50–99 employees, 100–249 employees, 250–999 employees, and 1000+ employees. We find that average productivity increases with firm size and that the distribution is narrowest for firms with between 10 and 19 employees. The level and dispersion in productivity is very different at the two extremes of the size distribution. For micro firms, those with fewer than 5 employees, we find that average productivity is much lower than for firms with more than 1000 employees. Productivity is also widely dispersed among micro firms, suggesting that there is a lot of heterogeneity in productivity levels within this size category. The largest firms also appear to have a wide and bimodal distribution, suggesting that there are distortions at the top end of the size distribution that allow for large amounts of heterogeneity in the productivity of large firms.

Figure 5 illustrates the productivity distribution for firms in different age categories. We consider five age categories in total: firms in existence for less than 5 years, firms aged 5–10 years, 10–20 years, 20–40, and 40+ years. The youngest firms have the lowest productivity level and also exhibit a wide dispersion in the productivity distribution. The average productivity level appears to be increasing with firm age and the distribution of productivity narrowing as firms approach the 20–40-year category. Firms older than 40 years appear to be substantially more productive than younger firms on average but with a relatively wide distribution.

5 Productivity and its correlates

The construction of unbiased firm-specific productivity measures provides an important basis for analysing the determinants of manufacturing productivity in South Africa and paves the way for future research aimed at determining the causal drivers at work. To motivate future research in this area, Table 12 presents the results of simple OLS regressions of firm characteristics on weighted TFP. Industry dummies are included in both regressions to control for differences in average TFP in each sector, but are not reported.

Consistent with Figure 4 we find that larger firms, in terms of numbers employed, are more productive than smaller firms. The relationship between firm size and productivity has been explored extensively in the empirical literature, but the evidence is mixed. Using a similar approach to the one we use in this paper, Fernandes (2008) finds that smaller firms in Bangladesh manufacturing industries have higher TFP on average. Similarly, Söderbom and Teal (2004) find evidence of substantial allocative inefficiency in large manufacturing firms in Ghana due to higher labour costs than in smaller firms and more costly capital-intensive technology. In contrast, Van Biesebroeck (2005a) finds that larger firms are more productive in general (for Burundi, Ethiopia, Tanzania, Zambia, Kenya, Cote d'Ivoire, Ghana, Zimbabwe, and Cameroon). He also finds that larger firms grow larger and become more productive faster. This is further supported by Arnold et al. (2008) who find a productivity premium for larger manufacturing firms in Africa. The relationship between firm size and productivity in the South African context appears to be consistent with the latter findings on the basis of our estimates. We also find that older firms are generally more productive.

We find a positive and significant correlation between R&D expenditure and productivity. Similarly, R&D tax allowances are also shown to be positively correlated with TFP even after controlling for actual R&D expenditure. More capital-intensive firms (i.e. those with a higher capital–labour ratio) are more productive. We find significant productivity premiums for firms involved in international trade. Similar studies to ours also find a positive relationship between exporting and productivity (see Alvarez and Lopez 2005: for Chile manufacturing firms; Cruz et al. 2016: for Mozambique; Fernandes 2008: for Bangladesh; Newman et al. 2015: for Vietnam; and Van Biesebroeck 2005b: for Sub-Saharan Africa). Finally, we find that TFP increases relative to 2010 levels in 2011 and 2012 but experiences a statistically significant decline in 2013.

In Table 13, we show the relationship between firm characteristics and future TFP growth of the firm. The level of real value added of the firm is shown negatively correlated with TFP growth whereas the capital–labour ratio of the firm is significantly positively correlated. We find that firms in the bottom 25 per cent of the value added distribution in an industry in a given year grow faster than other firms. We do not find any statistically significant difference in the growth rate of firms in the top 25 per cent of the value added distribution.

We find substantial differences in the growth rates of firms of different sizes dependent on their position in the TFP distribution. Smaller firms in the top 25 per cent of the TFP distribution are expected to grow slower than firms of similar size lower in the TFP distribution. The negative relationship between ranking and firm size declines and eventually becomes positive for firms in the top 25 per cent who are also employing between 100 and 249 persons.

Firms in the bottom 25 per cent of the TFP distribution are expected to grow around 7 per cent faster than other firms, with most of the growth accruing to firms employing 1–4 persons, 50–99 persons, and 100–249 persons. Although firms in the top 25 per cent and bottom 25 per cent of the TFP distribution grow at rates different from those of their comparator firms, the high coefficients on firm size show that it remains the case that larger firms grow faster than smaller firms on average. In this context, it appears as though firm size in terms of number of employees plays a more important role in increasing productivity than value added.

Age has no impact on TFP growth. Table 12 shows that importing firms have higher TFP levels than exporting firms in general; however, exporting firms become more productive at a faster rate than non-exporting firms and importing firms. Although tax allowances for learnerships are positively correlated to TFP growth, the coefficient is extremely small in magnitude.

We find that after controlling for size, TFP distribution, export status, age, and other variables, large numbers of industries are growing at around the same rate as the food sector. Firms that manufacture textile and computer, electronic, and optical products are growing at a statistically significantly slower rate than the food sector. The general decline of productivity in the leather, pharmaceuticals, and apparel industries are shown to be insignificantly different to the growth of the food sector at the firm level after conditioning on size, age, export status, and other characteristics.

6 Conclusion

The recent availability of tax administration data for South Africa provides researchers and policymakers with a unique and invaluable opportunity to truly understand the dynamics of the private sector. In this paper, we present for the first time disaggregated TFP estimates across sectors, years, and firm characteristics, which provides some new insights into the nature and performance of the manufacturing sector in South Africa.

We find that productivity grew in most sectors between 2010 and 2013, and there is heterogeneity across sectors in the pace of growth. We also find significant heterogeneity in productivity within and between sectors. We find that firm size (in terms of number of employees) is positively correlated with TFP and its growth rate. We also consider the correlation between productivity and R&D and find a positive relationship between R&D expenditure and TFP. Moreover, similar to other studies, we find that there is a productivity premium associated with engaging in international trade.

Understanding the drivers of firm performance is crucial in designing policies aimed at promoting and expanding the private sector, arguably the key driver of productivity, job creation, and exports in the economy. Our analysis paves the way for future research into the factors driving productivity growth of manufacturing firms that can provide causal explanations for the significant heterogeneity in measured firm performance, even within narrowly defined sectors and size groups. This research will play an important role in shaping future industrial policy for the South African economy.

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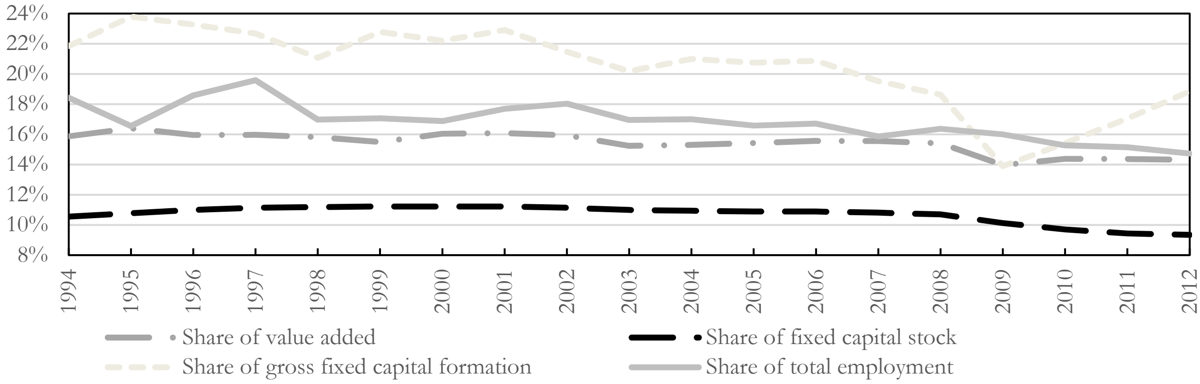
Figures

Figure 1: Manufacturing industry's share in gross value added, fixed capital stock, fixed capital stock formation, and total employment

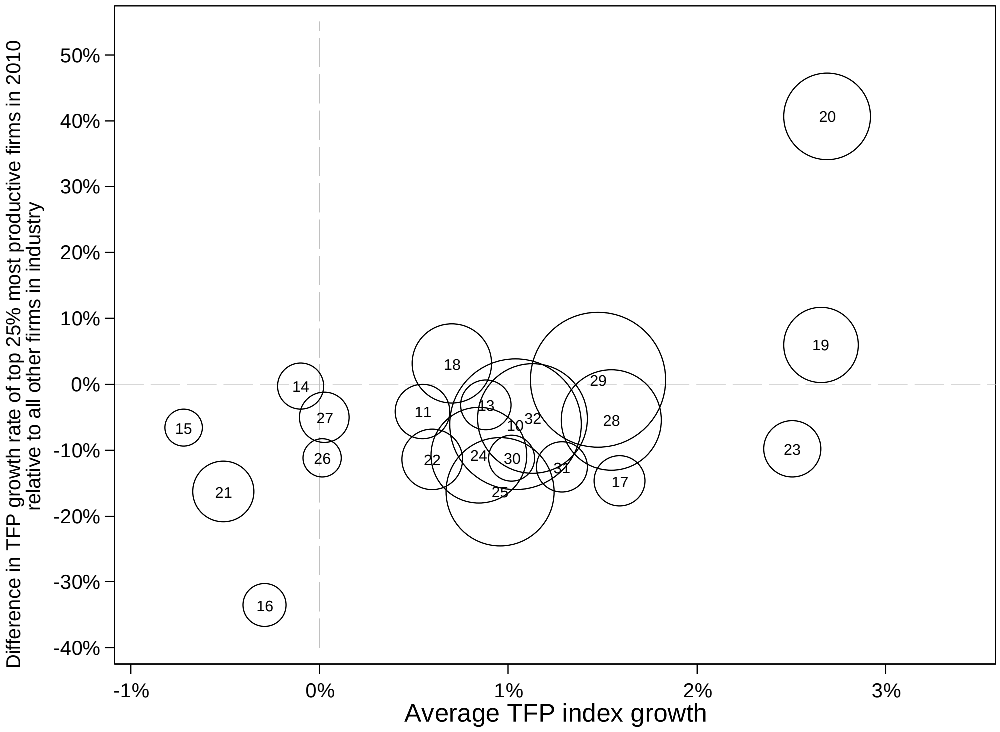


Note: All values are at constant 2010 prices. Note that the primary axis is on a logarithmic scale. Employment figures are obtained from the Post-Apartheid Labour Market Series (1994–2012) using cross-entropy weights.

Source: Authors' calculations based on DataFirst (1994–2012) and SARB (2014).

Figure 2: TFP growth and growth of top and bottom performing firms by industry share in total value added

(a)



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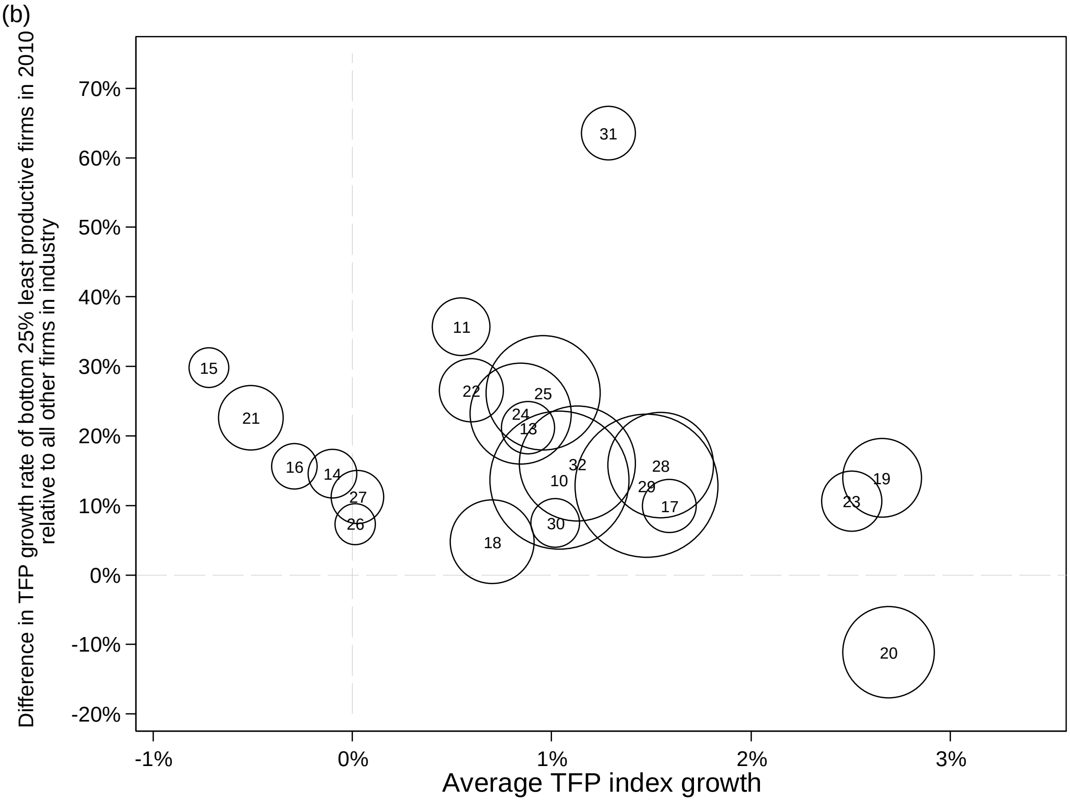
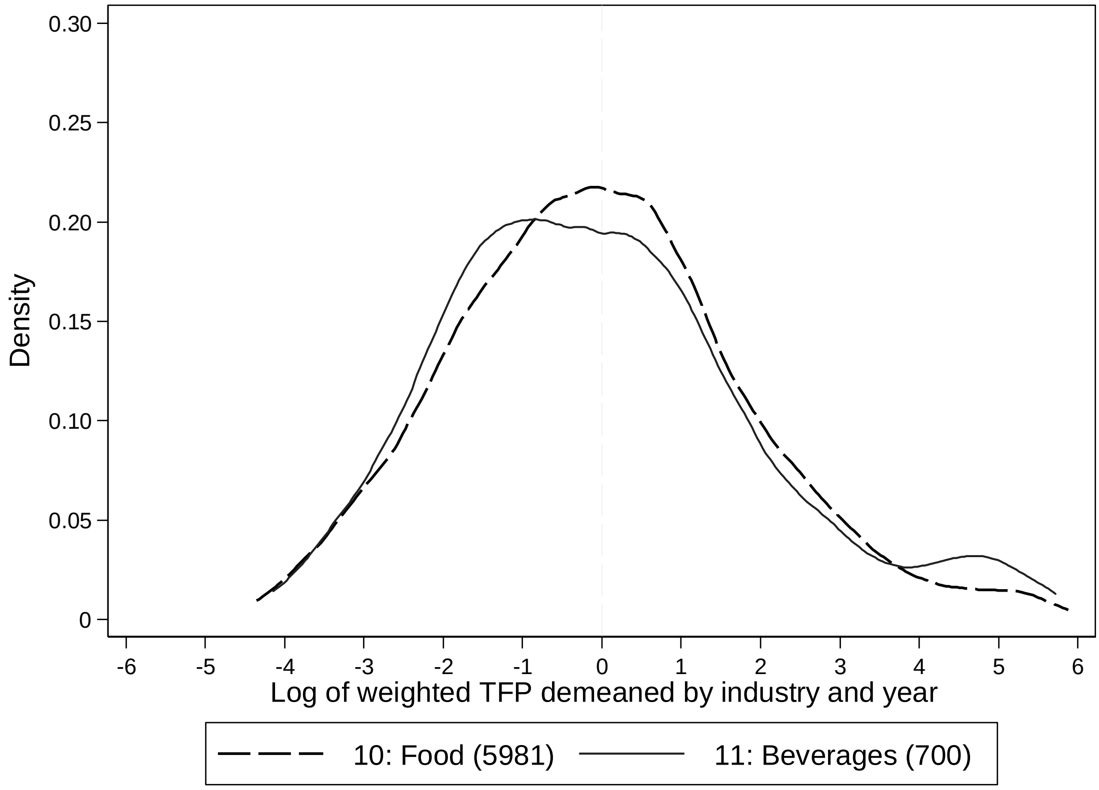


Note: Industry codes are as follows: 10 Food; 11 Beverages; 13 Textiles; 14 Apparel; 15 Leather; 16 Wood; 17 Paper; 18 Printing; 19 Coke and refined petroleum; 20 Chemicals; 21 Pharmaceuticals; 22 Rubber and plastics; 23 Non-metallic mineral products; 24 Basic metals; 25 Fabricated metals; 26 Computer, electronic, and optical products; 27 Electrical equipment; 28 Machinery not elsewhere classified (n.e.c.); 29 Motor vehicles; 30 Other transport equipment; 31 Furniture; 32 Other manufacturing. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors’ calculations based on results from TFP regressions on CIT–IRP5 data.

Figure 3: TFP distribution by manufacturing sub-sector

(a)



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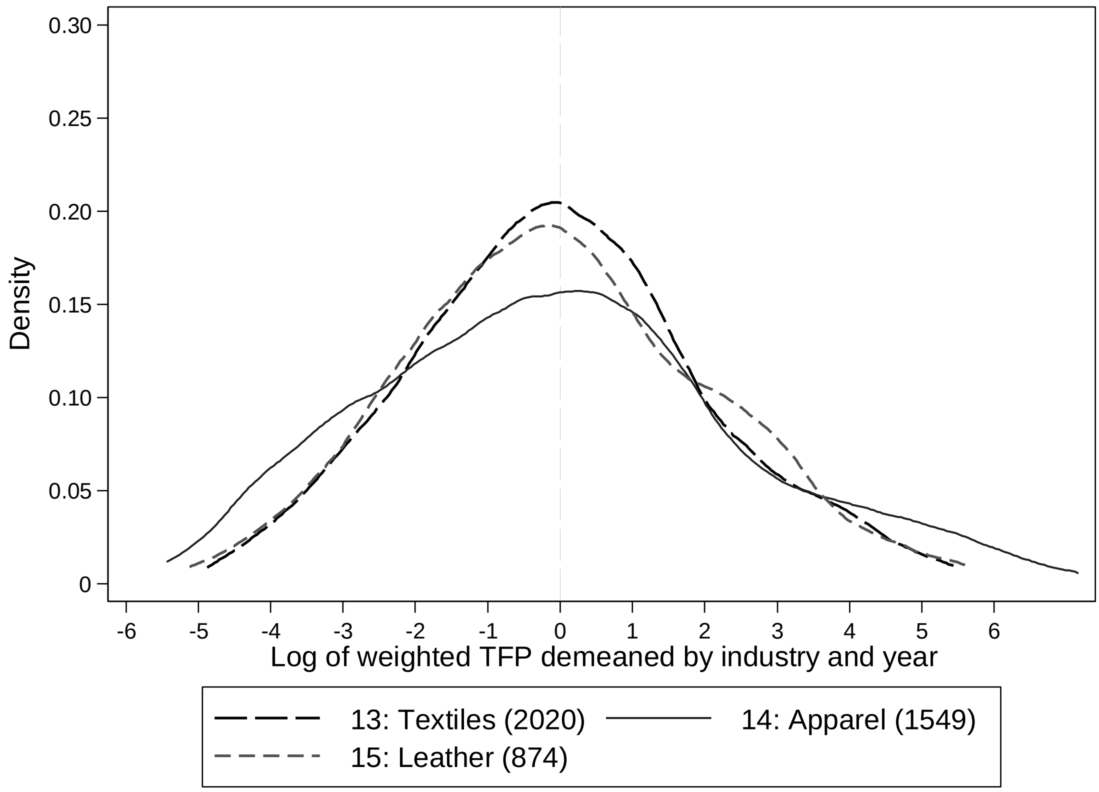

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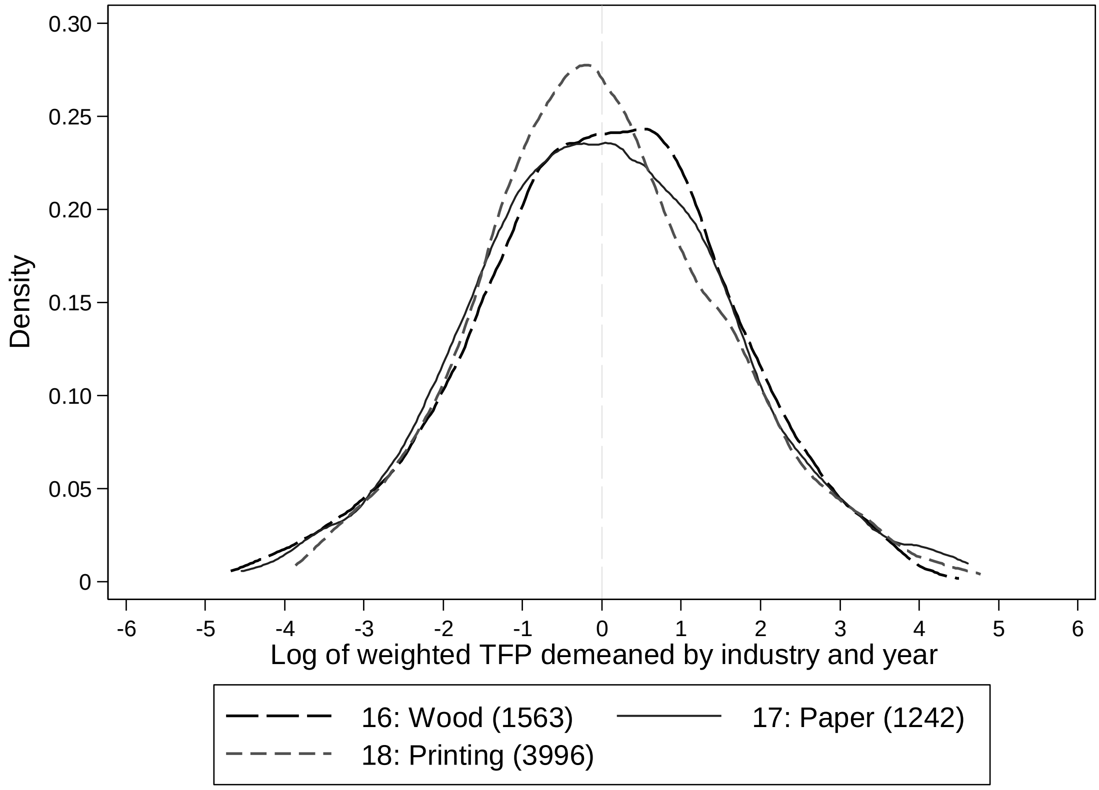

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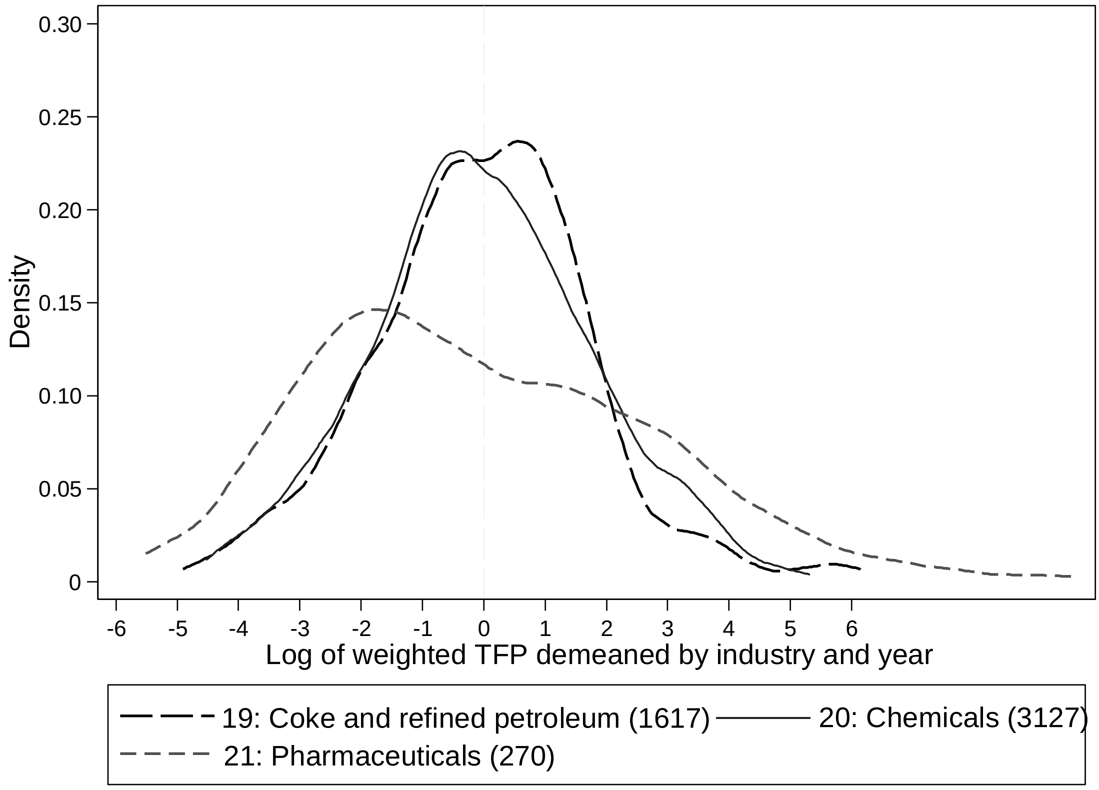
Log of weighted TFP demeaned by industry and year
16: Wood (1563)
17: Paper (1242)
18: Printing (3996)

(d)



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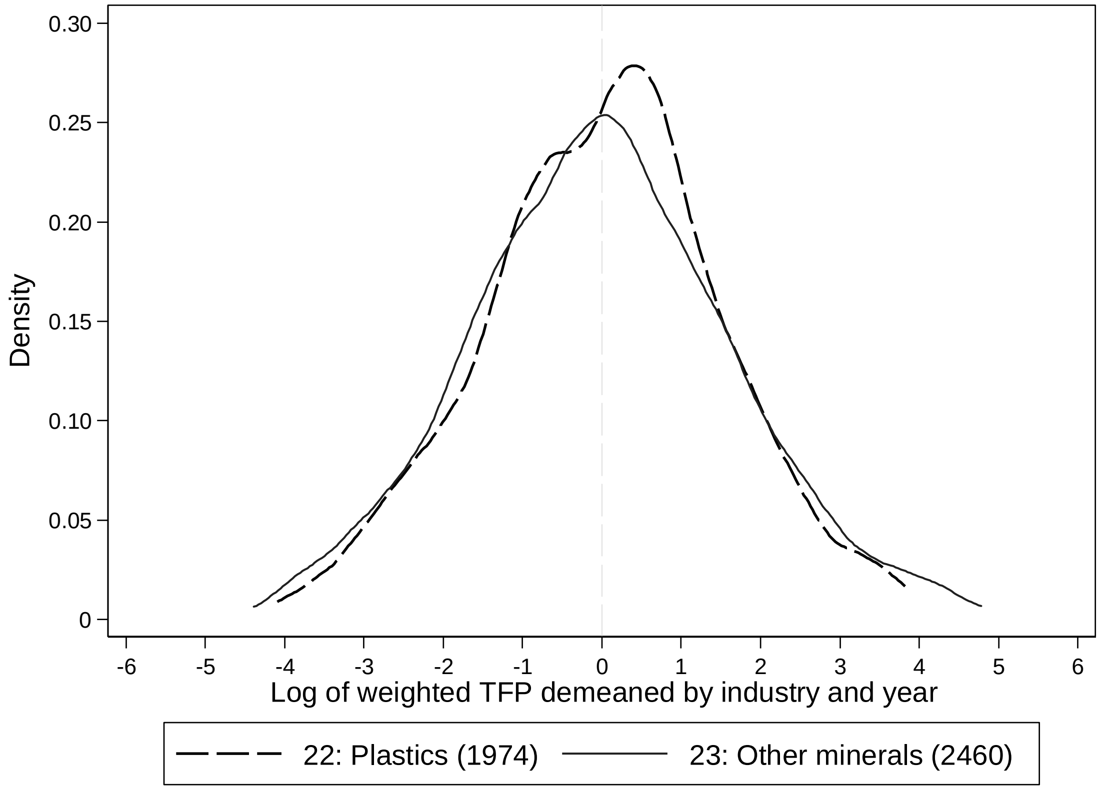
Log of weighted TFP demeaned by industry and year
19: Coke and refined petroleum (1617)
20: Chemicals (3127)
21: Pharmaceuticals (270)

(e)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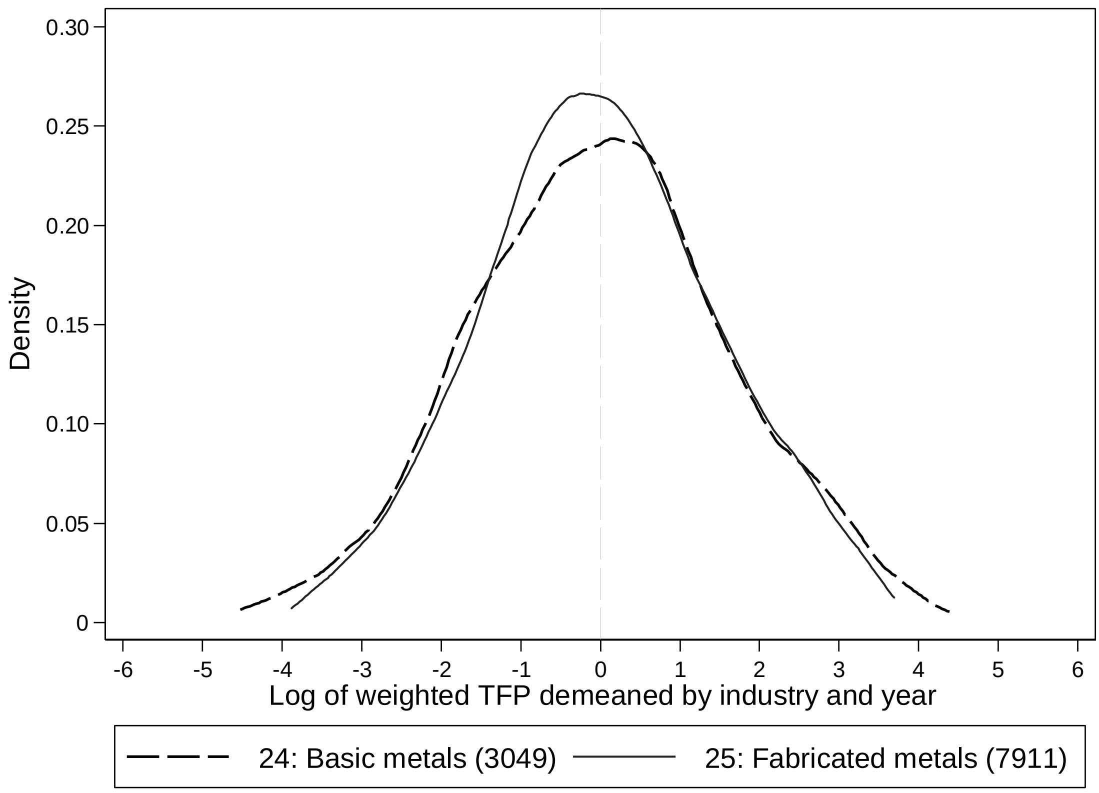
23: Other minerals (2460)

(f)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Log of weighted TFP demeaned by industry and year
24: Basic metals (3049)
25: Fabricated metals (7911)

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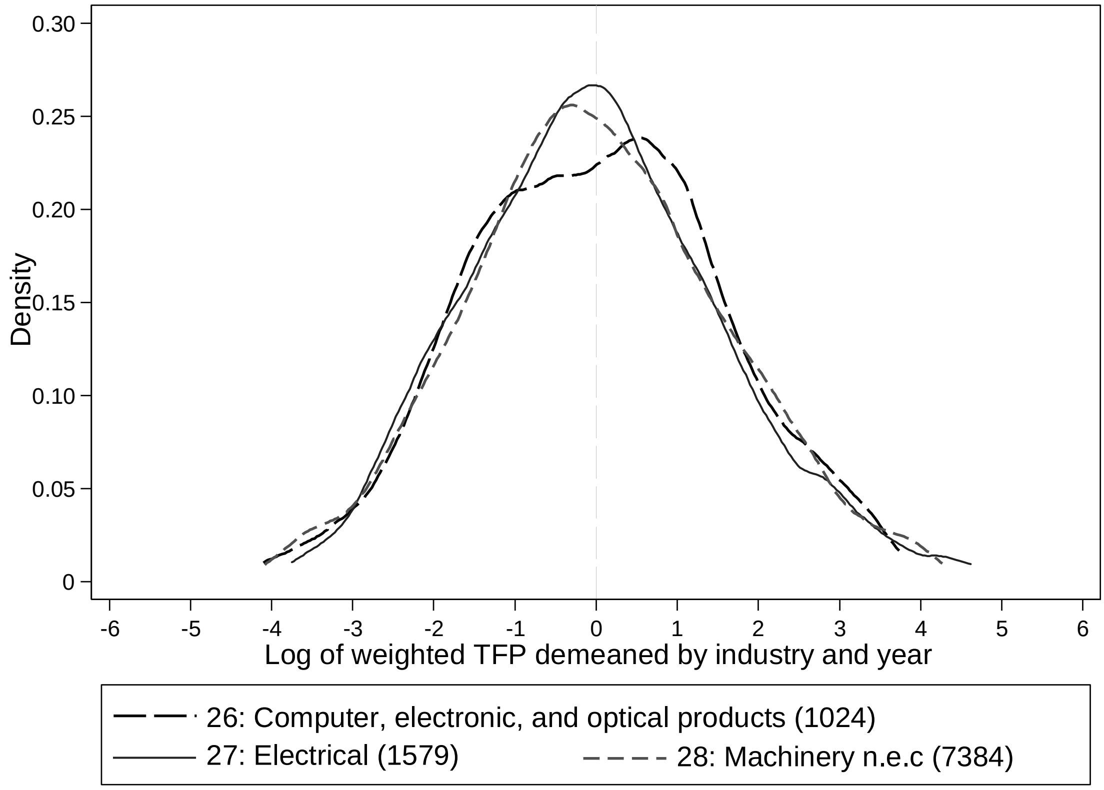
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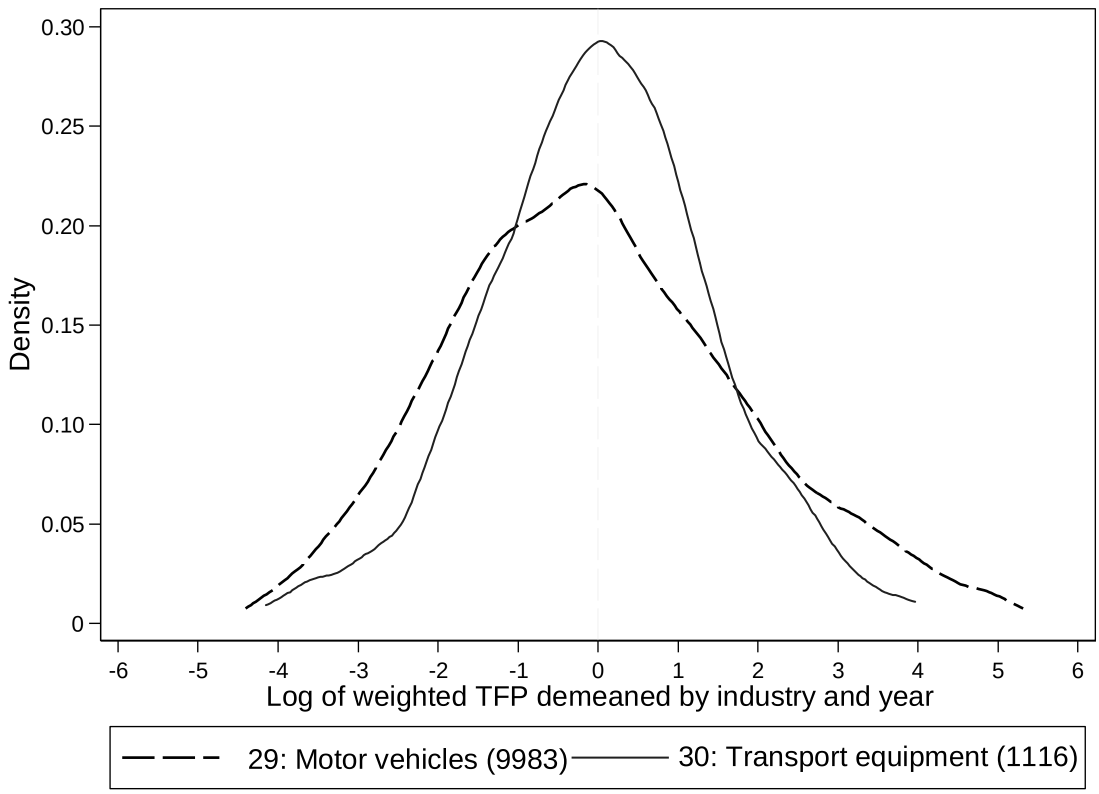
Log of weighted TFP demeaned by industry and year
26: Computer, electronic, and optical products (1024)
27: Electrical (1579)
28: Machinery n.e.c (7384)

(h)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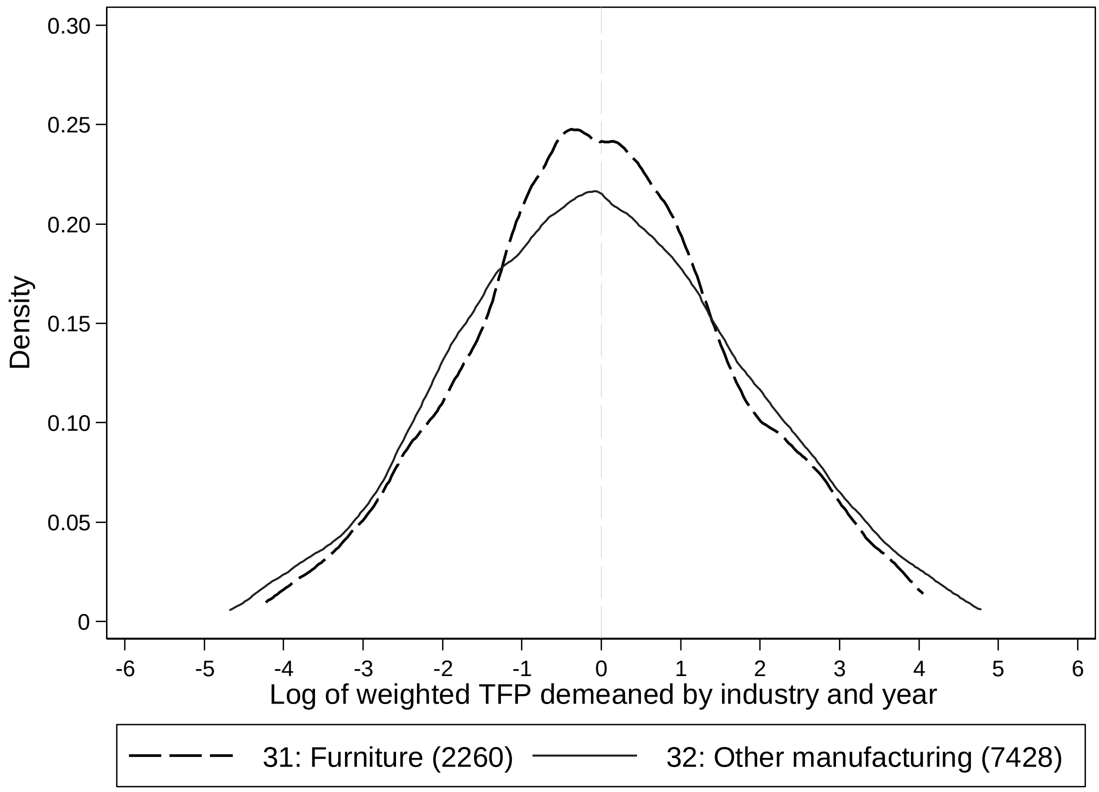
Log of weighted TFP demeaned by industry and year
29: Motor vehicles (9983)
30: Transport equipment (1116)

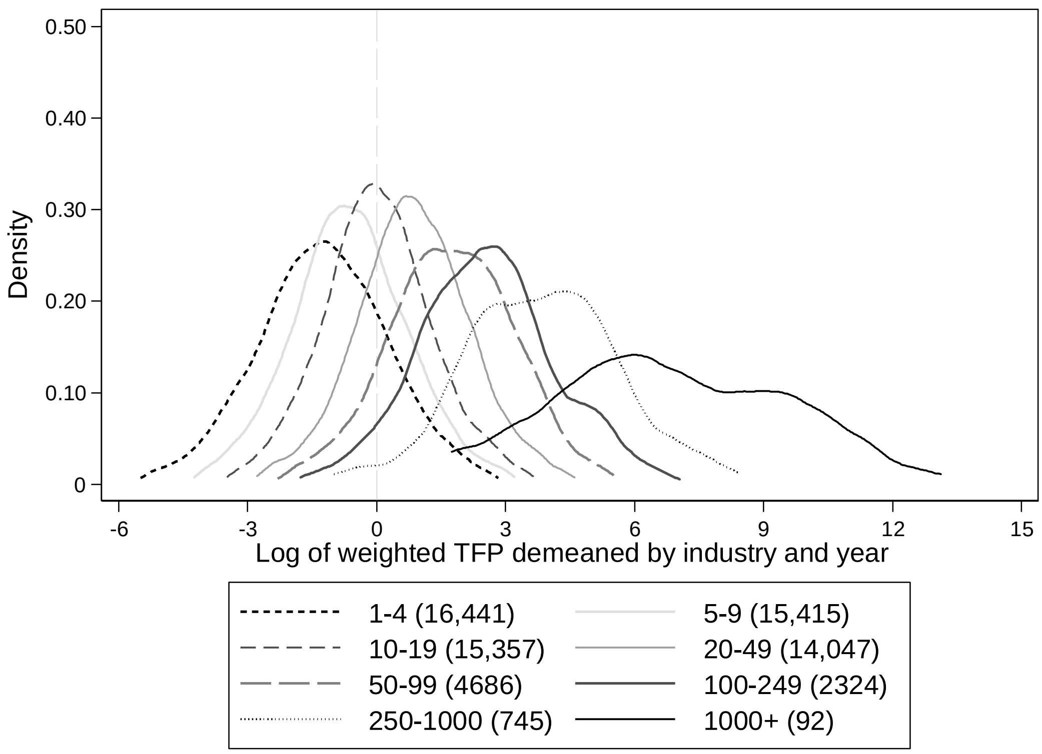
(i)



Note: Refer to United Nations (2008: 63–7) for the exact contents of each industry.

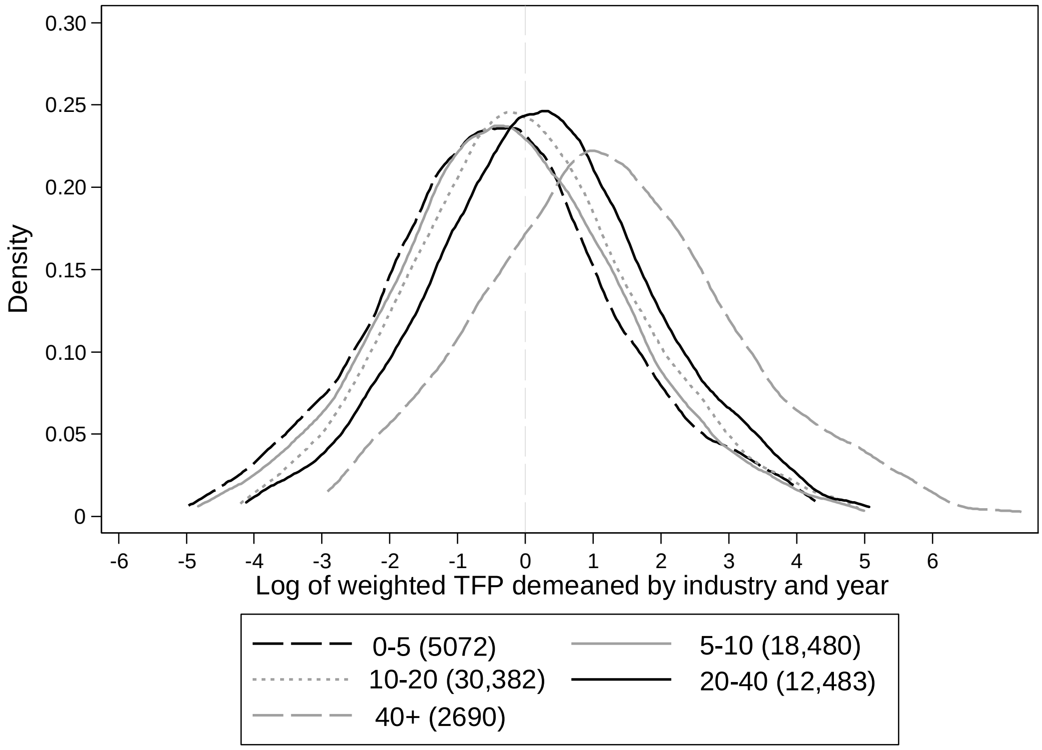
Source: Authors' calculations based on TFP results from regressions on the CIT–IRP5 data.

Figure 4: TFP demeaned by industry and year by employment category



Source: Authors' calculations based on TFP results from regressions on the CIT–IRP5 data.

Figure 5: TFP demeaned by industry and year by age category of firm



Source: Authors' calculations based on TFP results from regressions on the CIT–IRP5 data.

Tables

Table 1: Number of firms per year

	2010	2011	2012	2013
All firms	57,922	58,852	58,181	56,961
With sales	43,032	43,312	41,727	38,858
With value added	39,046	38,615	37,152	34,512
With capital	37,240	36,904	35,529	33,057
With labour	31,604	32,230	30,978	30,140
With lags	18,586	16,094	16,496	18,328
Sample	18,444	16,019	16,405	18,239

Source: Authors' calculations based on CIT–IRP5 data.

Table 2. Total employment in sample

Data availability	2010	2011	2012	2013
All firms	1,424,450	1,491,902	1,529,811	1,591,282
Non-missing	909,066	1,013,459	1,031,075	1,040,918
Sample[a]	487,922	462,788	496,694	566,185
% of non-missing data	53.67	45.66	48.17	54.39
% of QES labour	40.69	39.78	43.09	49.31
QES	1,199,000	1,163,250	1,152,750	1,148,250

Notes: Quarterly Economic Survey (QES) employment figure is the average for the period ending in March of a given year starting from June in the previous year. [a]The sample drops firms for which lags for any variable are not available at least one year prior to the year in question.

Source: Authors' calculations based on CIT–IRP5 and QES (StatsSA 2010–15b).

Table 3: Total fixed assets in millions of rands

	2010	2011	2012	2013
All firms	171,868	226,455	232,004	235,002
Non-missing	89,244	153,995	208,324	208,878
Sample[a]	73,387	70,124	77,523	89,236
% of non-missing data	82.23	45.54	37.21	42.72
% of QFS capital	23.42	19.86	20.97	23.85
QFS	313,372	353,134	369,648	374,212

Notes: The Quarterly Financial Statistics (QFS) book values are averages for the period ending in March in a given year and starting in June. [a]The CIT–IRP5 sample excludes firms that manufacture tobacco products.

Source: Authors' calculations based on CIT–IRP5 and QFS (StatsSA 2010–15a).

Table 4: Value added in millions of rands

	2010	2011	2012	2013
All firms: value added	355,313	512,092	549,837	490,419
Sales	1,251,389	1,896,772	2,098,981	2,135,804
Cost of sales[a]	896,076	1,384,681	1,549,145	1,645,385
Non-missing: value added	269,279	378,021	387,067	387,553
Sales	1,019,126	1,549,420	1,674,806	1,837,568
Cost of sales	749,847	1,171,399	1,287,739	1,450,015
Sample[b] value added	134,385	140,612	159,150	181,827
Sales	505,448	519,309	608,508	716,484
Cost of sales	371,063	378,696	449,358	534,657
% of non-missing data	49.91	37.20	41.12	46.92
% of QFS value added	23.99	24.63	25.49	27.40
QFS[c]	560,092	570,961	624,390	663,487
Sales	1,534,438	1,683,978	1,944,606	1,989,060
Cost of sales	974,346	1,113,017	1,320,216	1,325,573

Notes: [a]All 'Cost of sales' values are subtracted from 'Sales'. [b]The sample drops firms for which lags for any variable are not available at least one year prior to the year in question. [c]Turnover purchases.

Source: Authors' calculations based on CIT–IRP5 and QFS data (StatsSA 2010–15a).

Table 5: Number of firms by industry

Industry	2010	2011	2012	2013	Total
10: Food	1651	1340	1392	1598	5981
11: Beverages	191	159	161	189	700
13: Textiles	538	469	481	532	2020
14: Wearing apparel	449	352	354	394	1549
15: Leather	231	215	212	216	874
16: Wood	423	366	372	402	1563
17: Paper	317	295	299	331	1242
18: Printing	1037	935	967	1057	3996
19: Coke and refined petroleum	458	371	371	417	1617
20: Chemicals	806	735	763	823	3127
21: Pharmaceuticals	74	62	57	77	270
22: Rubber and plastics	482	463	494	535	1974
23: Other minerals	667	570	581	642	2460
24: Basic metals	805	705	741	798	3049
25: Fabricated metals	1947	1876	1935	2153	7911
26: Computer, electronic, and optical products	257	233	246	288	1024
27: Electrical equipment	398	376	370	435	1579
28: Machinery n.e.c.	2009	1704	1722	1949	7384
29: Motor vehicles	2679	2310	2370	2624	9983
30: Transport equipment	318	241	253	304	1116
31: Furniture	592	520	550	598	2260
32: Other manufacturing	2115	1722	1714	1877	7428
Total	18,444	16,019	16,405	18,239	69,107

Note: Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on CIT–IRP5 data.

Table 6: Sample statistics for value added

Industry	2010		2011		2012		2013	
	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
10: Food	4.11 (2.62)	14.78 (1.26)	4.41 (2.72)	14.94 (1.32)	4.5 (2.8)	14.97 (1.35)	4.48 (2.87)	14.96 (1.39)
11: Beverages	5.92 (3)	14.7 (1.52)	6.48 (3.1)	15.01 (1.6)	6.61 (3.23)	15.13 (1.65)	6.57 (3.21)	15.03 (1.65)
13: Textiles	5.31 (2.63)	14.47 (1.28)	5.66 (2.71)	14.65 (1.32)	5.75 (2.8)	14.69 (1.37)	5.74 (2.74)	14.67 (1.35)
14: Wearing apparel	5.34 (2.86)	14.43 (1.36)	5.58 (2.86)	14.56 (1.36)	5.61 (2.81)	14.58 (1.35)	5.57 (2.83)	14.56 (1.36)
15: Leather	6.51 (2.69)	14.73 (1.32)	6.82 (2.65)	14.9 (1.29)	6.95 (2.7)	14.94 (1.33)	6.89 (2.73)	14.92 (1.33)
16: Wood	5.75 (2.53)	14.56 (1.25)	5.9 (2.5)	14.64 (1.21)	5.97 (2.67)	14.67 (1.33)	5.96 (2.62)	14.68 (1.28)
17: Paper	6.16 (2.53)	14.9 (1.24)	6.54 (2.59)	15.09 (1.28)	6.7 (2.52)	15.16 (1.22)	6.68 (2.7)	15.13 (1.32)
18: Printing	4.59 (2.54)	14.52 (1.25)	4.87 (2.51)	14.67 (1.23)	4.97 (2.57)	14.71 (1.27)	4.9 (2.62)	14.68 (1.29)
19: Coke and refined petroleum	6.07 (2)	15.03 (0.94)	6.3 (2.06)	15.14 (0.96)	6.35 (2.14)	15.14 (0.98)	6.39 (2.21)	15.13 (1.03)
20: Chemicals	5.07 (2.76)	14.88 (1.33)	5.4 (2.7)	15.05 (1.32)	5.51 (2.76)	15.1 (1.33)	5.45 (2.83)	15.06 (1.38)
21: Pharmaceuticals	7.42 (3.21)	15.66 (1.63)	8.02 (3.38)	16 (1.75)	8.27 (3.32)	16.12 (1.72)	7.9 (3.43)	15.9 (1.76)
22: Rubber and plastics	6.07 (2.41)	15.03 (1.19)	6.32 (2.46)	15.17 (1.21)	6.47 (2.47)	15.24 (1.22)	6.41 (2.57)	15.21 (1.3)
23: Other minerals	5.34 (2.39)	14.66 (1.17)	5.52 (2.34)	14.75 (1.15)	5.59 (2.4)	14.77 (1.18)	5.7 (2.48)	14.84 (1.22)
24: Basic metals	4.82 (2.77)	14.94 (1.34)	5.01 (2.84)	15.03 (1.38)	5.28 (2.92)	15.16 (1.41)	5.4 (2.87)	15.22 (1.39)
25: Fabricated metals	4.46 (2.39)	14.84 (1.15)	4.72 (2.44)	14.99 (1.17)	4.86 (2.5)	15.05 (1.2)	4.91 (2.54)	15.07 (1.24)
26: Computer, electronic, and optical products	6.28 (2.4)	14.85 (1.18)	6.48 (2.41)	14.97 (1.18)	6.63 (2.4)	15.02 (1.15)	6.63 (2.5)	15.03 (1.19)
27: Electrical equipment	5.62 (2.48)	14.73 (1.17)	5.94 (2.38)	14.88 (1.15)	6.11 (2.39)	14.97 (1.15)	6.04 (2.41)	14.93 (1.16)
28: Machinery n.e.c.	4.18 (2.43)	14.66 (1.18)	4.49 (2.44)	14.81 (1.18)	4.63 (2.51)	14.88 (1.22)	4.69 (2.6)	14.9 (1.27)
29: Motor vehicles	2.99 (2.69)	14.53 (1.22)	3.29 (2.74)	14.68 (1.23)	3.44 (2.77)	14.74 (1.24)	3.42 (2.82)	14.72 (1.27)
30: Transport equipment	5.97 (2.5)	14.69 (1.29)	6.31 (2.68)	14.89 (1.36)	6.63 (2.77)	15.01 (1.38)	6.84 (2.73)	15.15 (1.36)
31: Furniture	5.14 (2.41)	14.36 (1.19)	5.43 (2.47)	14.52 (1.24)	5.34 (2.55)	14.48 (1.26)	5.44 (2.54)	14.54 (1.26)
32: Other manufacturing	4.26 (2.64)	14.77 (1.29)	4.55 (2.6)	14.93 (1.27)	4.66 (2.71)	14.97 (1.32)	4.69 (2.8)	14.98 (1.36)
Total average	4.58 (2.73)	14.71 (1.25)	4.88 (2.75)	14.86 (1.26)	5 (2.81)	14.91 (1.29)	5.01 (2.86)	14.92 (1.32)

Notes: Standard errors in parentheses. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on CIT–IRP5 data.

Table 7: Sample statistics for cost of sales

Industry	2010		2011		2012		2013	
	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
10: Food	4.88 (3.028)	15.55 (1.621)	5.156 (3.101)	15.686 (1.651)	5.309 (3.194)	15.771 (1.696)	5.26 (3.267)	15.741 (1.733)
11: Beverages	6.855 (3.276)	15.642 (1.732)	7.354 (3.305)	15.886 (1.731)	7.288 (3.522)	15.807 (1.882)	7.459 (3.51)	15.921 (1.869)
13: Textiles	5.737 (2.978)	14.899 (1.615)	6.05 (3.1)	15.043 (1.693)	6.145 (3.176)	15.09 (1.726)	6.173 (3.12)	15.102 (1.709)
14: Wearing apparel	5.735 (3.353)	14.824 (1.834)	5.934 (3.351)	14.915 (1.853)	5.938 (3.266)	14.913 (1.798)	5.895 (3.345)	14.877 (1.862)
15: Leather	6.996 (2.969)	15.216 (1.579)	7.23 (2.989)	15.316 (1.607)	7.442 (3.021)	15.433 (1.616)	7.292 (3.161)	15.325 (1.757)
16: Wood	6.148 (2.869)	14.956 (1.565)	6.291 (2.865)	15.033 (1.553)	6.355 (3.001)	15.052 (1.62)	6.306 (3.032)	15.02 (1.687)
17: Paper	6.777 (2.843)	15.515 (1.524)	7.145 (2.896)	15.696 (1.555)	7.352 (2.881)	15.808 (1.555)	7.373 (3.066)	15.819 (1.656)
18: Printing	4.516 (2.798)	14.447 (1.522)	4.799 (2.802)	14.592 (1.523)	4.864 (2.864)	14.611 (1.572)	4.772 (2.94)	14.559 (1.613)
19: Coke and refined petroleum	8.117 (2.45)	17.07 (1.318)	8.334 (2.578)	17.173 (1.391)	8.43 (2.729)	17.217 (1.487)	8.507 (2.757)	17.256 (1.487)
20: Chemicals	5.456 (3.214)	15.264 (1.766)	5.747 (3.164)	15.398 (1.757)	5.855 (3.239)	15.448 (1.796)	5.844 (3.3)	15.451 (1.826)
21: Pharmaceuticals	7.751 (3.35)	15.999 (1.756)	8.198 (3.39)	16.178 (1.774)	8.538 (3.283)	16.385 (1.675)	8.215 (3.606)	16.216 (1.914)
22: Rubber and plastics	6.567 (2.755)	15.532 (1.509)	6.796 (2.748)	15.642 (1.476)	6.956 (2.785)	15.723 (1.499)	6.847 (2.847)	15.65 (1.555)
23: Other minerals	5.743 (2.811)	15.057 (1.55)	5.914 (2.74)	15.144 (1.506)	6.016 (2.77)	15.203 (1.525)	6.09 (2.875)	15.23 (1.578)
24: Basic metals	5.368 (3.191)	15.491 (1.721)	5.565 (3.281)	15.588 (1.769)	5.85 (3.371)	15.73 (1.816)	5.946 (3.329)	15.775 (1.792)
25: Fabricated metals	4.716 (2.83)	15.098 (1.566)	4.925 (2.893)	15.189 (1.608)	5.086 (2.943)	15.273 (1.63)	5.112 (2.97)	15.278 (1.663)
26: Computer, electronic, and optical products	6.358 (2.832)	14.927 (1.595)	6.479 (2.827)	14.971 (1.595)	6.729 (2.907)	15.118 (1.645)	6.678 (3.01)	15.083 (1.688)
27: Electrical equipment	5.936 (2.959)	15.043 (1.634)	6.294 (2.753)	15.235 (1.505)	6.432 (2.765)	15.3 (1.504)	6.373 (2.819)	15.267 (1.544)
28: Machinery n.e.c.	4.369 (2.887)	14.849 (1.637)	4.7 (2.863)	15.026 (1.604)	4.87 (2.926)	15.115 (1.634)	4.925 (3.024)	15.14 (1.686)
29: Motor vehicles	3.69 (3.337)	15.23 (1.819)	3.996 (3.421)	15.382 (1.861)	4.162 (3.462)	15.467 (1.881)	4.161 (3.543)	15.464 (1.928)
30: Transport equipment	6.279 (2.883)	14.999 (1.658)	6.516 (3.131)	15.09 (1.804)	6.953 (3.224)	15.336 (1.835)	7.01 (3.241)	15.316 (1.919)
31: Furniture	5.542 (2.691)	14.769 (1.453)	5.789 (2.67)	14.883 (1.422)	5.696 (2.804)	14.836 (1.498)	5.765 (2.815)	14.862 (1.506)
32: Other manufacturing	4.519 (3.013)	15.033 (1.647)	4.777 (2.965)	15.155 (1.619)	4.918 (3.105)	15.229 (1.694)	4.941 (3.227)	15.235 (1.773)
Total average	5.029 (3.16)	15.156 (1.695)	5.299 (3.175)	15.282 (1.701)	5.441 (3.239)	15.354 (1.739)	5.45 (3.303)	15.354 (1.783)

Notes: Standard errors in parentheses. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on CIT–IRP5 data.

Table 8. Sample statistics for fixed capital.

Industry	2010		2011		2012		2013	
	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
10: Food	2.8 (2.91)	13.47 (1.72)	2.98 (3.04)	13.51 (1.8)	3.05 (3.15)	13.52 (1.87)	2.98 (3.29)	13.46 (1.98)
11: Beverages	5.24 (3.43)	14.02 (2.23)	5.71 (3.49)	14.24 (2.25)	5.83 (3.53)	14.35 (2.18)	5.75 (3.69)	14.21 (2.37)
13: Textiles	3.56 (3.06)	12.72 (1.94)	3.79 (3.21)	12.79 (2.05)	3.88 (3.36)	12.82 (2.16)	3.84 (3.34)	12.77 (2.18)
14: Wearing apparel	3.22 (3.29)	12.31 (2.1)	3.24 (3.3)	12.22 (2.15)	3.18 (3.39)	12.16 (2.27)	3.1 (3.6)	12.08 (2.46)
15: Leather	4.37 (3.26)	12.59 (2.13)	4.61 (3.06)	12.69 (1.91)	4.73 (3.22)	12.72 (2)	4.66 (3.14)	12.69 (1.91)
16: Wood	4.62 (2.69)	13.43 (1.57)	4.56 (2.7)	13.3 (1.59)	4.59 (2.83)	13.29 (1.67)	4.44 (3.01)	13.15 (1.87)
17: Paper	4.94 (3.01)	13.67 (1.89)	5.24 (3.07)	13.79 (1.91)	5.31 (3.11)	13.77 (1.97)	5.22 (3.3)	13.67 (2.1)
18: Printing	3.26 (2.9)	13.19 (1.8)	3.42 (2.96)	13.21 (1.87)	3.44 (3.08)	13.19 (1.96)	3.29 (3.19)	13.08 (2.07)
19: Coke and refined petroleum	3.99 (2.49)	12.94 (1.73)	4.16 (2.55)	13 (1.77)	4.2 (2.55)	12.99 (1.74)	4.24 (2.72)	12.98 (1.89)
20: Chemicals	3.49 (2.95)	13.3 (1.7)	3.7 (2.88)	13.35 (1.69)	3.77 (2.95)	13.36 (1.74)	3.7 (3.07)	13.31 (1.82)
21: Pharmaceuticals	5.43 (3.45)	13.68 (2.09)	5.92 (3.61)	13.9 (2.18)	6.18 (3.83)	14.03 (2.39)	6.14 (3.72)	14.14 (2.28)
22: Rubber and plastics	4.9 (2.65)	13.86 (1.58)	5.05 (2.76)	13.9 (1.65)	5.15 (2.86)	13.91 (1.73)	5.02 (2.94)	13.82 (1.81)
23: Other minerals	4.18 (2.8)	13.5 (1.78)	4.25 (2.8)	13.48 (1.77)	4.25 (2.89)	13.44 (1.85)	4.3 (2.99)	13.44 (1.93)
24: Basic metals	3.54 (2.97)	13.66 (1.71)	3.64 (3.02)	13.67 (1.71)	3.75 (3.09)	13.63 (1.76)	3.81 (3.15)	13.63 (1.83)
25: Fabricated metals	3.1 (2.58)	13.49 (1.54)	3.22 (2.67)	13.49 (1.6)	3.3 (2.8)	13.48 (1.7)	3.29 (2.86)	13.45 (1.77)
26: Computer, electronic, and optical products	4.26 (2.57)	12.83 (1.59)	4.42 (2.68)	12.91 (1.73)	4.45 (2.88)	12.84 (1.92)	4.54 (2.91)	12.95 (1.87)
27: Electrical equipment	3.85 (2.55)	12.96 (1.45)	4.08 (2.57)	13.02 (1.54)	4.17 (2.63)	13.04 (1.6)	4.17 (2.65)	13.06 (1.61)
28: Machinery n.e.c.	2.67 (2.63)	13.15 (1.62)	2.83 (2.67)	13.15 (1.67)	2.93 (2.76)	13.18 (1.72)	2.93 (2.9)	13.14 (1.83)
29: Motor vehicles	1.1 (2.96)	12.64 (1.81)	1.26 (3.02)	12.64 (1.86)	1.3 (3.16)	12.6 (2)	1.24 (3.36)	12.55 (2.19)
30: Transport equipment	4.68 (2.85)	13.4 (1.86)	4.92 (2.97)	13.5 (1.89)	5.11 (3.12)	13.49 (1.97)	5.33 (3.22)	13.64 (2.07)
31: Furniture	3.63 (2.64)	12.86 (1.62)	3.76 (2.73)	12.86 (1.67)	3.58 (2.93)	12.72 (1.86)	3.55 (2.95)	12.64 (1.88)
32: Other manufacturing	2.7 (2.94)	13.22 (1.8)	2.8 (2.99)	13.18 (1.87)	2.87 (3.13)	13.18 (1.95)	2.87 (3.26)	13.16 (2.05)
Total average	3.05 (3.03)	13.18 (1.78)	3.21 (3.08)	13.2 (1.82)	3.27 (3.19)	13.19 (1.91)	3.24 (3.31)	13.15 (2.02)

Notes: Standard errors in parentheses. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors’ calculations based on CIT–IRP5 data.

Table 9: Sample statistics for employment

Industry	2010		2011		2012		2013	
	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
10: Food	–8.185 (2.491)	2.486 (1.326)	–7.808 (2.509)	2.722 (1.248)	–7.717 (2.582)	2.745 (1.266)	–7.738 (2.644)	2.743 (1.284)
11: Beverages	–6.604 (2.792)	2.182 (1.449)	–6.034 (2.761)	2.498 (1.378)	–5.965 (2.82)	2.554 (1.343)	–5.924 (2.858)	2.538 (1.397)
13: Textiles	–6.875 (2.5)	2.286 (1.333)	–6.513 (2.528)	2.48 (1.292)	–6.477 (2.605)	2.467 (1.318)	–6.438 (2.581)	2.491 (1.329)
14: Wearing apparel	–6.863 (2.882)	2.226 (1.557)	–6.648 (2.916)	2.332 (1.586)	–6.61 (2.855)	2.364 (1.569)	–6.589 (2.829)	2.393 (1.518)
15: Leather	–5.786 (2.619)	2.435 (1.434)	–5.499 (2.542)	2.587 (1.37)	–5.388 (2.597)	2.604 (1.397)	–5.392 (2.575)	2.642 (1.368)
16: Wood	–6.163 (2.461)	2.645 (1.317)	–5.999 (2.478)	2.742 (1.3)	–5.928 (2.575)	2.769 (1.32)	–5.95 (2.566)	2.764 (1.306)
17: Paper	–6.195 (2.479)	2.544 (1.313)	–5.802 (2.464)	2.748 (1.239)	–5.673 (2.412)	2.783 (1.2)	–5.72 (2.558)	2.726 (1.271)
18: Printing	–7.738 (2.42)	2.193 (1.216)	–7.503 (2.418)	2.29 (1.214)	–7.445 (2.481)	2.302 (1.248)	–7.508 (2.53)	2.278 (1.267)
19: Coke and refined petroleum	–6.574 (1.923)	2.379 (1.132)	–6.153 (1.955)	2.686 (1.018)	–6.113 (2.029)	2.675 (1.015)	–6.08 (2.067)	2.669 (1.04)
20: Chemicals	–7.58 (2.526)	2.227 (1.264)	–7.314 (2.478)	2.337 (1.233)	–7.234 (2.51)	2.359 (1.238)	–7.251 (2.592)	2.356 (1.291)
21: Pharmaceuticals	–5.391 (3.045)	2.858 (1.566)	–4.787 (3.136)	3.193 (1.608)	–4.542 (3.117)	3.305 (1.628)	–4.939 (3.214)	3.062 (1.637)
22: Rubber and plastics	–6.176 (2.259)	2.788 (1.159)	–5.962 (2.267)	2.885 (1.139)	–5.912 (2.302)	2.855 (1.168)	–5.998 (2.347)	2.805 (1.175)
23: Other minerals	–6.848 (2.296)	2.467 (1.256)	–6.638 (2.251)	2.592 (1.211)	–6.557 (2.254)	2.63 (1.182)	–6.506 (2.364)	2.634 (1.231)
24: Basic metals	–7.49 (2.595)	2.633 (1.301)	–7.337 (2.639)	2.686 (1.283)	–7.172 (2.669)	2.708 (1.282)	–7.046 (2.68)	2.783 (1.293)
25: Fabricated metals	–7.849 (2.284)	2.533 (1.149)	–7.648 (2.301)	2.616 (1.122)	–7.583 (2.357)	2.603 (1.15)	–7.556 (2.383)	2.61 (1.165)
26: Computer, electronic, and optical products	–6.506 (2.196)	2.063 (1.078)	–6.337 (2.191)	2.155 (1.052)	–6.23 (2.238)	2.158 (1.068)	–6.222 (2.271)	2.183 (1.046)
27: Electrical equipment	–6.835 (2.37)	2.272 (1.171)	–6.58 (2.215)	2.361 (1.096)	–6.468 (2.231)	2.401 (1.117)	–6.514 (2.264)	2.38 (1.112)
28: Machinery n.e.c.	–8.416 (2.254)	2.064 (1.116)	–8.191 (2.248)	2.135 (1.105)	–8.072 (2.316)	2.174 (1.123)	–8.013 (2.411)	2.202 (1.17)
29: Motor vehicles	–9.341 (2.522)	2.2 (1.156)	–9.092 (2.544)	2.295 (1.127)	–8.989 (2.571)	2.316 (1.135)	–8.991 (2.625)	2.313 (1.141)
30: Transport equipment	–6.525 (2.36)	2.194 (1.245)	–6.288 (2.49)	2.286 (1.278)	–6.057 (2.524)	2.326 (1.286)	–5.852 (2.597)	2.453 (1.325)
31: Furniture	–6.909 (2.305)	2.318 (1.227)	–6.647 (2.341)	2.447 (1.227)	–6.704 (2.398)	2.437 (1.218)	–6.651 (2.444)	2.447 (1.244)
32: Other manufacturing	–8.136 (2.452)	2.378 (1.234)	–7.872 (2.448)	2.506 (1.222)	–7.783 (2.529)	2.528 (1.24)	–7.749 (2.6)	2.545 (1.262)
Total average	–7.784 (2.601)	2.344 (1.242)	–7.515 (2.608)	2.468 (1.216)	–7.428 (2.649)	2.485 (1.226)	–7.412 (2.697)	2.492 (1.244)

Notes: Standard errors in parentheses. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on CIT–IRP5 data.

Table 10: Production function regression results

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
10: Food products						
Labour	0.353***	0.621***	0.319***	0.463***	0.317***	0.444***
	(0.0158)	(0.00828)	(0.0155)	(0.00922)	(0.0211)	(0.0102)
Capital	0.440***	0.366***	0.129***	0.353***	0.507***	0.548***
	(0.0250)	(0.00683)	(0.0201)	(0.00641)	(0.0335)	(0.00887)
N	5981	5981	5981	5981	3420	3420
N clusters	2226		2226		855	
R^2	0.986	0.929	0.999	0.726	0.993	0.953
R^2 centred	0.952		0.825		0.965	
OID variable	llab_lag2		k_lag4		llab_lag2	
Overidentification	0.178		0.752		0.542	
Underidentification	5.72e−103		0		0	
Weak identification	3352.8		3038.6		11,649.4	
Endogenous regressors	470.3		420.9		220.8	
Returns to scale	0.793	0.988	0.448	0.815	0.824	0.992
RT S.E.	(0.025)	(0.004)	(0.025)	(0.007)	(0.033)	(0.004)
RT=1, *P* value	0.0000	0.0012	0.0000	0.0000	0.0000	0.0584
11: Beverages						
Labour	0.421***	0.801***	0.375***	0.612***		
	(0.0780)	(0.0277)	(0.0763)	(0.0345)		
Capital	0.524***	0.230***	0.269***	0.261***		
	(0.0796)	(0.0220)	(0.0696)	(0.0213)		
	700	700	700	700		
N clusters	263		263			
R^2	0.989	0.921	0.998	0.707		
R^2 centred	0.946		0.811			
OID variable	llab_lag2		llab_lag2			
Overidentification	0.338		0.413			
Underidentification	0.0000103		0			
Weak identification	3785.4		456.7			
Endogenous regressors	28.34		24.03			
Returns to scale	0.946	1.031	0.643	0.873		
RT S.E.	(0.061)	(0.012)	(0.086)	(0.024)		
RT=1, *P* value	0.3738	0.0121	0.0000	0.0000		
13: Textiles						
Labour	0.385***	0.713***	0.319***	0.511***	0.289***	0.550***
	(0.0277)	(0.0147)	(0.0269)	(0.0167)	(0.0371)	(0.0191)
Capital	0.362***	0.261***	0.133***	0.253***	0.566***	0.429***
	(0.0375)	(0.0116)	(0.0317)	(0.0106)	(0.0550)	(0.0162)
N	2020	2020	2020	2020	1088	1088
N clusters	750		750		272	
R^2	0.989	0.909	0.998	0.671	0.994	0.922
R^2 centred	0.941		0.797		0.948	
OID variable	k_2lag2		llab_lag2		llab_lag2	
Overidentification	0.102		0.119		0.171	
Underidentification	1.84e−47		0		0	
Weak identification	1521.4		1392.5		652.6	
Endogenous regressors	159.2		126.7		54.41	
Returns to scale	0.747	0.973	0.452	0.764	0.855	0.979
RT S.E.	(0.04)	(0.007)	(0.04)	(0.013)	(0.062)	(0.009)
RT=1, *P* value	0.0000	0.0002	0.0000	0.0000	0.0192	0.0203

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
14: Wearing apparel						
Labour	0.274***	0.685***	0.235***	0.499***	0.267***	0.490***
	(0.0323)	(0.0140)	(0.0307)	(0.0155)	(0.0345)	(0.0206)
Capital	0.270***	0.245***	0.0789***	0.204***	0.468***	0.454***
	(0.0493)	(0.0118)	(0.0282)	(0.0107)	(0.0494)	(0.0186)
N	1549	1549	1549	1549	832	832
N clusters	602		602		208	
R^2	0.988	0.898	0.998	0.645	0.994	0.934
R^2 centred	0.941		0.807		0.964	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.726		0.482		0.278	
Underidentification	1.24e–25		0		0	
Weak identification	1018.0		1275.0		793.7	
Endogenous regressors	64.58		55.60		55.45	
Returns to scale	0.545	0.931	0.314	0.703	0.735	0.944
RT S.E.	(0.056)	(0.008)	(0.04)	(0.013)	(0.052)	(0.009)
RT=1, *P* value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
15: Leather and related products						
Labour	0.277***	0.603***	0.260***	0.427***	0.208***	0.419***
	(0.0415)	(0.0213)	(0.0412)	(0.0229)	(0.0593)	(0.0281)
Capital	0.418***	0.345***	0.0916***	0.304***	0.475***	0.556***
	(0.0647)	(0.0173)	(0.0353)	(0.0160)	(0.0761)	(0.0269)
N	874	874	874	874	516	516
N clusters	291		291		129	
R^2	0.992	0.901	0.998	0.655	0.995	0.922
R^2 centred	0.942		0.802		0.952	
OID variable	k_lag4		llab_lag2		k_lag4	
Overidentification	0.698		0.255		0.694	
Underidentification	5.78e–16		0		0	
Weak identification	1485.3		569.4		582.8	
Endogenous regressors	40.81		39.49		11.67	
Returns to scale	0.695	0.948	0.352	0.731	0.683	0.975
RT S.E.	(0.061)	(0.011)	(0.047)	(0.019)	(0.074)	(0.013)
RT=1, *P* value	0.0000	0.0000	0.0000	0.0000	0	0.0538
16: Wood and products of wood and cork, except furniture						
Labour	0.371***	0.662***	0.301***	0.522***	0.352***	0.526***
	(0.0366)	(0.0165)	(0.0363)	(0.0182)	(0.0482)	(0.0228)
Capital	0.557***	0.308***	0.199***	0.273***	0.641***	0.422***
	(0.0518)	(0.0148)	(0.0450)	(0.0142)	(0.0640)	(0.0213)
N	1563	1563	1563	1563	832	832
N clusters	569		569		208	
R^2	0.990	0.913	0.998	0.676	0.995	0.936
R^2 centred	0.936		0.771		0.955	
OID variable	k_2lag3		llab_lag2		llab_lag4	
Overidentification	0.344		0.132		0.137	
Underidentification	5.17e–28		0		0	
Weak identification	550.1		503.9		230.4	
Endogenous regressors	86.58		60.96		40.56	
Returns to scale	0.928	0.97	0.5	0.795	0.993	0.948
RT S.E.	(0.049)	(0.008)	(0.059)	(0.014)	(0.059)	(0.009)
RT=1, *P* value	0.1467	0.0001	0.0000	0.0000	0.8991	0.0000

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
17: Paper and paper products						
Labour	0.455***	0.753***	0.403***	0.582***	0.388***	0.538***
	(0.0403)	(0.0183)	(0.0371)	(0.0208)	(0.0430)	(0.0218)
Capital	0.376***	0.216***	0.110***	0.224***	0.376***	0.403***
	(0.0617)	(0.0145)	(0.0387)	(0.0132)	(0.0481)	(0.0194)
N	1242	1242	1242	1242	680	680
N clusters	438		438		170	
R^2	0.994	0.933	0.999	0.751	0.998	0.947
R^2 centred	0.953		0.830		0.966	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.777		0.112		0.169	
Underidentification	0.000784		0		0	
Weak identification	4919.4		434.0		332.2	
Endogenous regressors	88.57		86.23		58.76	
Returns to scale	0.831	0.969	0.513	0.806	0.764	0.941
RT S.E.	(0.058)	(0.008)	(0.045)	(0.013)	(0.048)	(0.009)
RT=1, *P* value	0.0038	0.0001	0.0000	0.0000	0.000	0.0000
18: Printing and reproduction of recorded media						
Labour	0.540***	0.808***	0.476***	0.671***	0.476***	0.717***
	(0.0239)	(0.00907)	(0.0239)	(0.0109)	(0.0296)	(0.0124)
Capital	0.356***	0.178***	0.124***	0.184***	0.435***	0.273***
	(0.0278)	(0.00736)	(0.0221)	(0.00697)	(0.0332)	(0.0109)
N	3996	3996	3996	3996	2464	2464
N clusters	1346		1346		616	
R^2	0.990	0.940	0.999	0.770	0.994	0.947
R^2 centred	0.952		0.829		0.960	
OID variable	llab_lag2		llab_lag2		llab_lag2	
Overidentification	0.432		0.556		0.386	
Underidentification	1.03e–64		0		0	
Weak identification	2403.4		2107.8		1280.0	
Endogenous regressors	419.9		348.8		206.6	
Returns to scale	0.896	0.986	0.6	0.855	0.911	0.989
RT S.E.	(0.028)	(0.004)	(0.031)	(0.008)	(0.032)	(0.005)
RT=1, *P* value	0.0002	0.0005	0.0000	0.0000	0.0060	0.0258
19: Coke and refined petroleum products						
Labour	0.281***	0.678***	0.244***	0.435***	0.230***	0.585***
	(0.0270)	(0.0136)	(0.0259)	(0.0167)	(0.0396)	(0.0189)
Capital	0.255***	0.292***	0.0738***	0.234***	0.287***	0.394***
	(0.0354)	(0.0105)	(0.0253)	(0.00991)	(0.0547)	(0.0164)
N	1617	1617	1617	1617	896	896
N clusters	614		614		224	
R^2	0.993	0.871	0.999	0.516	0.996	0.889
R^2 centred	0.930		0.738		0.939	
OID variable	llab_lag2		k_lag4		llab_lag2	
Overidentification	0.490		0.420		0.475	
Underidentification	0.00000117		0		0	
Weak identification	8774.0		1121.5		359.2	
Endogenous regressors	100.7		85.88		34.71	
Returns to scale	0.536	0.97	0.318	0.669	0.518	0.98
RT S.E.	(0.041)	(0.009)	(0.038)	(0.017)	(0.061)	(0.012)
RT=1, *P* value	0.0000	0.0014	0.0000	0.0000	0.0000	0.0831

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
20: Chemicals and chemical products						
Labour	0.407***	0.699***	0.362***	0.548***	0.366***	0.512***
	(0.0239)	(0.0118)	(0.0243)	(0.0136)	(0.0283)	(0.0148)
Capital	0.466***	0.323***	0.142***	0.314***	0.538***	0.515***
	(0.0330)	(0.0101)	(0.0296)	(0.00985)	(0.0403)	(0.0137)
N	3127	3127	3127	3127	1796	1796
N clusters	1086		1086		449	
R^2	0.989	0.926	0.999	0.702	0.995	0.953
R^2 centred	0.950		0.812		0.964	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.935		0.290		0.160	
Underidentification	1.06e−62		0		0	
Weak identification	3099.8		2820.8		1306.0	
Endogenous regressors	249.4		204.4		142.2	
Returns to scale	0.873	1.023	0.504	0.861	0.903	1.028
RT S.E.	(0.032)	(0.005)	(0.035)	(0.01)	(0.038)	(0.006)
RT=1, *P* value	0.0001	0.0000	0.0000	0.0000	0.0104	0.0000
21: Basic pharmaceutical products and pharmaceutical preparations						
Labour	0.254***	0.760***	0.235**	0.611***		
	(0.0872)	(0.0458)	(0.0915)	(0.0524)		
Capital	0.407***	0.244***	0.197***	0.263***		
	(0.0973)	(0.0393)	(0.0763)	(0.0378)		
N	270	270	270	270		
N clusters	104		104			
R^2	0.994	0.934	0.999	0.762		
R^2 centred	0.964		0.875			
OID variable	llab_lag2		llab_lag2			
Overidentification	0.496		0.755			
Underidentification	0.0000203		0			
Weak identification	2041.9		57.81			
Endogenous regressors	7.451		5.910			
Returns to scale	0.661	1.005	0.432	0.874		
RT S.E.	(0.109)	(0.017)	(0.109)	(0.032)		
RT=1, *P* value	0.0019	0.7890	0.0000	0.0001		
22: Rubber and plastics products						
Labour	0.352***	0.621***	0.305***	0.458***	0.297***	0.496***
	(0.0337)	(0.0158)	(0.0341)	(0.0177)	(0.0405)	(0.0206)
Capital	0.585***	0.360***	0.286***	0.349***	0.682***	0.501***
	(0.0362)	(0.0129)	(0.0420)	(0.0121)	(0.0533)	(0.0177)
N	1974	1974	1974	1974	1100	1100
N clusters	688		688		275	
R^2	0.992	0.917	0.999	0.693	0.995	0.935
R^2 centred	0.939		0.776		0.954	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.141		0.183		0.120	
Underidentification	1.81e−27		0		0	
Weak identification	1505.0		1311.4		1740.7	
Endogenous regressors	109.2		79.82		57.17	
Returns to scale	0.938	0.981	0.591	0.807	0.979	0.997
RT S.E.	(0.037)	(0.007)	(0.054)	(0.013)	(0.056)	(0.008)
RT=1, *P* value	0.0882	0.0077	0.0000	0.0000	0.7044	0.7165

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
23: Other non-metallic mineral products						
Labour	0.329***	0.618***	0.272***	0.408***	0.290***	0.459***
	(0.0282)	(0.0139)	(0.0285)	(0.0150)	(0.0339)	(0.0179)
Capital	0.478***	0.324***	0.170***	0.294***	0.549***	0.503***
	(0.0398)	(0.0111)	(0.0357)	(0.0100)	(0.0411)	(0.0152)
N	2460	2460	2460	2460	1432	1432
N clusters	885		885		358	
R^2	0.988	0.890	0.998	0.623	0.994	0.914
R^2 centred	0.925		0.736		0.942	
OID variable	llab_lag2		llab_lag2		llab_lag2	
Overidentification	0.216		0.388		0.973	
Underidentification	3.25e–49		0		0	
Weak identification	1535.4		1476.3		1052.7	
Endogenous regressors	124.4		86.70		67.48	
Returns to scale	0.807	0.943	0.442	0.702	0.839	0.962
RT S.E.	(0.039)	(0.007)	(0.043)	(0.012)	(0.042)	(0.008)
RT=1, *P* value	0.000	0.0000	0.0000	0.0000	0.0001	0.0000
24: Basic metals						
Labour	0.444***	0.679***	0.398***	0.549***	0.428***	0.585***
	(0.0274)	(0.0120)	(0.0267)	(0.0139)	(0.0373)	(0.0153)
Capital	0.547***	0.332***	0.195***	0.322***	0.618***	0.441***
	(0.0378)	(0.0104)	(0.0303)	(0.0102)	(0.0436)	(0.0140)
N	3049	3049	3049	3049	1592	1592
N clusters	1121		1121		398	
R^2	0.987	0.930	0.998	0.713	0.994	0.952
R^2 centred	0.944		0.785		0.960	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.283		0.148		0.108	
Underidentification	6.74e–48		0		0	
Weak identification	1714.6		1580.4		1048.0	
Endogenous regressors	236.0		220.1		118.7	
Returns to scale	0.991	1.011	0.593	0.871	1.046	1.026
RT S.E.	(0.037)	(0.005)	(0.038)	(0.01)	(0.035)	(0.006)
RT=1, *P* value	0.8085	0.0345	0.0000	0.0000	0.1839	0.0000
25: Fabricated metal products, except machinery and equipment						
Labour	0.443***	0.731***	0.377***	0.587***	0.395***	0.596***
	(0.0165)	(0.00697)	(0.0164)	(0.00831)	(0.0222)	(0.00929)
Capital	0.518***	0.268***	0.190***	0.254***	0.578***	0.408***
	(0.0194)	(0.00595)	(0.0184)	(0.00576)	(0.0246)	(0.00863)
N	7911	7911	7911	7911	4508	4508
N clusters	2731		2731		1127	
R^2	0.987	0.922	0.999	0.690	0.993	0.940
R^2 centred	0.938		0.766		0.950	
OID variable	k_lag4		llab_lag2		k_lag4	
Overidentification	0.610		0.530		0.643	
Underidentification	8.61e–121		0		0	
Weak identification	3299.1		3082.4		1248.1	
Endogenous regressors	587.4		478.7		264.7	
Returns to scale	0.961	0.998	0.566	0.841	0.973	1.003
RT S.E.	(0.019)	(0.003)	(0.024)	(0.007)	(0.022)	(0.004)
RT=1, *P* value	0.0449	0.5838	0.0000	0.0000	0.2294	0.4170

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
26: Computer, electronic, and optical products						
Labour	0.585***	0.878***	0.494***	0.721***	0.422***	0.773***
	(0.0497)	(0.0185)	(0.0486)	(0.0247)	(0.0707)	(0.0270)
Capital	0.356***	0.154***	0.108**	0.156***	0.471***	0.264***
	(0.0487)	(0.0149)	(0.0422)	(0.0147)	(0.0726)	(0.0228)
N	1024	1024	1024	1024	544	544
N clusters	387		387		136	
R^2	0.991	0.919	0.998	0.660	0.995	0.929
R^2 centred	0.929		0.730		0.941	
OID variable	llab_lag2		llab_lag2		llab_lag2	
Overidentification	0.426		0.657		0.713	
Underidentification	3.92e–24		0		0	
Weak identification	1324.7		1320.6		1253.4	
Endogenous regressors	112.8		92.50		31.76	
Returns to scale	0.942	1.032	0.602	0.877	0.893	1.037
RT S.E.	(0.042)	(0.01)	(0.053)	(0.02)	(0.069)	(0.013)
RT=1, *P* value	0.1623	0.001	0.0000	0.0000	0.1200	0.0035
27: Electrical equipment						
Labour	0.444***	0.751***	0.396***	0.620***	0.365***	0.611***
	(0.0348)	(0.0149)	(0.0347)	(0.0178)	(0.0431)	(0.0209)
Capital	0.452***	0.262***	0.0960***	0.241***	0.636***	0.423***
	(0.0415)	(0.0130)	(0.0341)	(0.0129)	(0.0554)	(0.0202)
N	1579	1579	1579	1579	896	896
N clusters	564		564		224	
R^2	0.992	0.926	0.999	0.696	0.996	0.941
R^2 centred	0.943		0.793		0.956	
OID variable	llab_lag2		llab_lag2		llab_lag2	
Overidentification	0.856		0.931		0.552	
Underidentification	4.18e–30		0		0	
Weak identification	586.9		548.3		216.0	
Endogenous regressors	124.5		109.4		53.73	
Returns to scale	0.896	1.012	0.492	0.862	1.001	1.034
RT S.E.	(0.042)	(0.007)	(0.046)	(0.015)	(0.049)	(0.009)
RT=1, *P* value	0.0135	0.0903	0.0000	0.0000	0.9790	0.0001
28: Machinery and equipment n.e.c.						
Labour	0.474***	0.817***	0.401***	0.661***	0.410***	0.670***
	(0.0179)	(0.00730)	(0.0185)	(0.00912)	(0.0268)	(0.0103)
Capital	0.464***	0.205***	0.152***	0.201***	0.597***	0.359***
	(0.0218)	(0.00615)	(0.0187)	(0.00602)	(0.0295)	(0.00940)
N	7384	7384	7384	7384	4072	4072
N clusters	2752		2752		1018	
R^2	0.985	0.919	0.998	0.672	0.992	0.938
R^2 centred	0.937		0.769		0.953	
OID variable	k_lag4		llab_lag2		llab_lag4	
Overidentification	0.427		0.335		0.104	
Underidentification	2.90e–146		0		0	
Weak identification	5127.3		5071.9		1936.7	
Endogenous regressors	584.2		432.8		214.7	
Returns to scale	0.938	1.022	0.553	0.862	1.007	1.029
RT S.E.	(0.02)	(0.004)	(0.025)	(0.007)	(0.025)	(0.004)
RT=1, *P* value	0.0021	0.0000	0.0000	0.0000	0.7682	0.0000

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
29: Motor vehicles, trailers, and semi-trailers						
Labour	0.519***	0.893***	0.468***	0.763***	0.482***	0.783***
	(0.0143)	(0.00486)	(0.0139)	(0.00685)	(0.0178)	(0.00702)
Capital	0.259***	0.141***	0.0935***	0.144***	0.366***	0.255***
	(0.0162)	(0.00399)	(0.0112)	(0.00396)	(0.0253)	(0.00641)
N	9983	9983	9983	9983	6096	6096
N clusters	3482		3482		1524	
R^2	0.984	0.946	0.999	0.735	0.991	0.961
R^2 centred	0.961		0.831		0.971	
OID variable	llab_lag2		llab_lag3		llab_lag2	
Overidentification	0.189		0.162		0.199	
Underidentification	3.85e–159		0		0	
Weak identification	4880.8		4714.7		2418.1	
Endogenous regressors	976.9		945.1		601.8	
Returns to scale	0.778	1.034	0.562	0.908	0.847	1.038
RT S.E.	(0.018)	(0.003)	(0.016)	(0.006)	(0.025)	(0.003)
RT=1, *P* value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30: Other transport equipment						
Labour	0.504***	0.709***	0.442***	0.572***	0.366***	0.606***
	(0.0348)	(0.0172)	(0.0338)	(0.0209)	(0.0450)	(0.0255)
Capital	0.533***	0.288***	0.295***	0.274***	0.646***	0.376***
	(0.0548)	(0.0141)	(0.0838)	(0.0137)	(0.0748)	(0.0226)
N	1116	1116	1116	1116	520	520
N clusters	476		476		130	
R^2	0.990	0.919	0.998	0.705	0.996	0.927
R^2 centred	0.933		0.759		0.948	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.316		0.457		0.447	
Underidentification	4.02e–31		0		0	
Weak identification	2371.7		2477.5		1547.4	
Endogenous regressors	182.8		158.4		60.89	
Returns to scale	1.037	0.997	0.738	0.847	1.011	0.982
RT S.E.	(0.058)	(0.009)	(0.098)	(0.017)	(0.079)	(0.012)
RT=1, *P* value	0.5206	0.7719	0.0073	0.0000	0.8870	0.1448
31: Furniture						
Labour	0.390***	0.715***	0.354***	0.566***	0.339***	0.546***
	(0.0267)	(0.0128)	(0.0259)	(0.0148)	(0.0367)	(0.0192)
Capital	0.482***	0.271***	0.153***	0.256***	0.594***	0.448***
	(0.0302)	(0.0108)	(0.0350)	(0.0103)	(0.0397)	(0.0177)
N	2260	2260	2260	2260	1288	1288
N clusters	804		804		322	
R^2	0.990	0.921	0.999	0.711	0.994	0.939
R^2 centred	0.944		0.809		0.956	
OID variable	k_lag4		llab_lag2		llab_lag2	
Overidentification	0.500		0.270		0.181	
Underidentification	8.94e–44		0		0	
Weak identification	1516.7		1672.3		5125.5	
Endogenous regressors	179.2		177.7		84.00	
Returns to scale	0.872	0.986	0.507	0.821	0.934	0.993
RT S.E.	(0.032)	(0.006)	(0.043)	(0.011)	(0.035)	(0.007)
RT=1, *P* value	0.0001	0.0212	0.0000	0.0000	0.0610	0.3566

	Weighted		Unweighted		Balanced	
	IV	OLS	IV	OLS	IV	OLS
32: Other manufacturing						
Labour	0.408***	0.751***	0.340***	0.589***	0.371***	0.598***
	(0.0168)	(0.00727)	(0.0165)	(0.00875)	(0.0219)	(0.0104)
Capital	0.439***	0.248***	0.123***	0.242***	0.561***	0.412***
	(0.0233)	(0.00592)	(0.0175)	(0.00566)	(0.0262)	(0.00925)
N	7428	7428	7428	7428	3912	3912
N clusters	2872		2872		978	
R^2	0.984	0.919	0.998	0.685	0.991	0.937
R^2 centred	0.938		0.777		0.950	
OID variable	k_lag4		llab_lag2		k_lag4	
Overidentification	0.262		0.116		0.606	
Underidentification	2.51e−148		0		0	
Weak identification	3991.4		3710.5		2123.2	
Endogenous regressors	525.3		408.3		252.7	
Returns to scale	0.847	0.999	0.463	0.831	0.932	1.01
RT S.E.	(0.025)	(0.004)	(0.023)	(0.007)	(0.027)	(0.004)
RT=1, *P* value	0.0000	0.8015	0.0000	0.0000	0.0112	0.0258

Note: OID, overidentification; RT, returns to scale. Production functions for the balanced panel for sector 11 (beverages) and sector 21 (pharmaceuticals) could not be estimated because of too few observations. Standard errors in parentheses. *P<0.10, **P<0.05, ***P<0.01. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on CIT–IRP5 data.

Table 11: TFP index per year

Industry	2010	2011	2012	2013
10: Food	100	104.380	106.471	103.739
11: Beverages	100	101.619	102.112	102.295
13: Textiles	100	101.274	104.762	102.443
14: Wearing apparel	100	102.849	102.279	100.406
15: Leather	100	96.550	97.585	97.614
16: Wood	100	99.825	103.487	99.093
17: Paper	100	99.895	100.141	104.643
18: Printing	100	97.110	101.910	102.193
19: Coke and refined petroleum	100	110.258	111.425	109.374
20: Chemicals	100	99.815	111.569	108.080
21: Pharmaceuticals	100	103.170	98.251	98.322
22: Rubber and plastics	100	101.128	101.142	101.684
23: Other minerals	100	104.123	105.372	109.326
24: Basic metals	100	101.518	102.244	101.451
25: Fabricated metals	100	100.878	101.626	102.496
26: Computer, electronic, and optical products	100	100.430	100.686	100.032
27: Electrical equipment	100	100.774	101.859	100.121
28: Machinery n.e.c.	100	102.378	103.352	104.457
29: Motor vehicles	100	102.828	103.340	104.460
30: Transport equipment	100	102.646	103.795	102.425
31: Furniture	100	103.505	103.219	103.890
32: Other manufacturing	100	100.969	102.784	103.059

Note: Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on results from TFP regressions on CIT–IRP5 data.

Table 12: OLS regressions of TFP on firm characteristics

Variables	Log weighted TFP	
	Estimated coefficient	Standard error
Firm size (base category: 1–4)		
5–9	0.611***	(0.0166)
10–19	1.211***	(0.0168)
20–49	1.973***	(0.0175)
50–99	2.687***	(0.0253)
100–249	3.351***	(0.0341)
250–1000	4.396***	(0.0576)
1000+	6.895***	(0.159)
Firm age (base category: 0–4)		
5–10	0.100***	(0.0235)
10–20	0.159***	(0.0227)
20–40	0.113***	(0.0251)
40+	0.200***	(0.0362)
Policy variables		
Log R&D expenditure	0.0299***	(0.00439)
Log R&D tax incentive	0.0485***	(0.00652)
Log amount of learnership agreements	0.0456***	(0.00427)
Log capital–labour ratio	0.0413***	(0.00391)
Trade variables (base category: no trade)		
Firm exports	0.520***	(0.0216)
Firm imports	0.580***	(0.0216)
Firm imports and exports	1.076***	(0.0165)
Year (base year: 2010)		
2011	0.121***	(0.0159)
2012	0.0603***	(0.0159)
2013	−0.0629***	(0.0156)
Model statistics		
N	69 107	
R^2	0.513	
Adjusted R^2	0.513	

Note: **P*<0.10, ***P*<0.05, ****P*<0.01.

Source: Authors' calculations based on TFP results from regressions on CIT–IRP5 data.

Table 13. OLS regressions of TFP growth rate on firm characteristics

Variables	TFP growth	
	Estimated coefficient	Standard error
Log real value added	−0.0891***	(0.00506)
Log capital–labour ratio	0.00510**	(0.00191)
Labour category (base category: 1–4 employees)		
5–9	0.113***	(0.00854)
10–19	0.172***	(0.00948)
20–49	0.231***	(0.0112)
50–99	0.285***	(0.0159)
100–249	0.305***	(0.0210)
250–1000	0.407***	(0.0351)
1000+	0.654***	(0.120)
Top 25% of value added distribution in industry and year	−0.00228	(0.00758)
Bottom 25% of value added distribution in industry and year	0.0272***	(0.00723)
Position in TFP distribution in industry and year with firm size interactions		
Top 25% and 1–4 employees	−0.0619***	(0.0104)
Top 25% and 5–9 employees	−0.0286**	(0.0108)
Top 25% and 10–19 employees	−0.0266**	(0.0106)
Top 25% and 20–49 employees	−0.0167*	(0.0101)
Top 25% and 50–99 employees	0.00599	(0.0159)
Top 25% and 100–249 employees	0.0515**	(0.0220)
Top 25% and 250–1000 employees	−0.0177	(0.0384)
Top 25% and 1000+ employees	−0.0558	(0.131)
Bottom 25% and 1–4 employees	0.0728***	(0.00980)
Bottom 25% and 5–9 employees	0.0361***	(0.00984)

Bottom 25% and 10–19 employees	0.0376***	(0.0100)
Bottom 25% and 20–49 employees	0.0317**	(0.0114)
Bottom 25% and 50–99 employees	0.0482**	(0.0199)
Bottom 25% and 100–249 employees	0.0649**	(0.0284)
Bottom 25% and 249–1000 employees	–0.0307	(0.0652)
Bottom 25% and 1000+ employees	–0.120	(0.196)
Age of firm (base category: 1–4)		
5–10	0.00429	(0.00721)
10–20	0.00334	(0.00690)
20–40	0.000437	(0.00775)
40+	0.0102	(0.0114)
Trade variables (base category: no trade)		
Firm exports	0.0302***	(0.00706)
Firm imports	0.0273***	(0.00706)
Firm imports and exports	0.0450***	(0.00556)
Policy variables		
Log R&D expenditure	0.00126	(0.00134)
Log R&D tax incentive	0.00209	(0.00200)
Log tax incentive amount for learnership agreements	0.00422**	(0.00139)
Industry (base category: food)		
11: Beverages	0.00490	(0.0196)
13: Textiles	–0.0416**	(0.0127)
14: Wearing apparel	–0.00351	(0.0143)
15: Leather	–0.0223	(0.0173)
16: Wood	0.0362**	(0.0138)
17: Paper	–0.00251	(0.0149)
18: Printing	–0.00329	(0.00992)
19: Coke and refined petroleum	0.0609***	(0.0139)
20: Chemicals	0.0167	(0.0108)
21: Pharmaceuticals	0.0257	(0.0305)
22: Rubber and plastics	0.0485***	(0.0125)
23: Other minerals	0.0151	(0.0117)
24: Basic metals	0.0403***	(0.0108)
25: Fabricated metals	0.0297***	(0.00839)
26: Computer, electronic, and optical products	–0.0476	(0.0167)
27: Electrical equipment	0.00149	(0.0137)
28: Machinery n.e.c.	0.0163*	(0.00869)
29: Motor vehicles	0.00197	(0.00814)
30: Transport equipment	0.0333**	(0.0164)
31: Furniture	–0.00134	(0.0120)
32: Other manufacturing	0.0132	(0.00865)
Current year of firm (base category: 2010)		
2011	–0.0384***	(0.00454)
2012	–0.0738***	(0.00455)
Constant	1.180***	(0.0637)
Model statistics		
Observations	44,652	
R^2	0.0625	
Adjusted R^2	0.0613	

Notes: *P<0.10, **P<0.05, ***P<0.01. Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors' calculations based on TFP results from regressions on CIT–IRP5 data.

Appendix A Productivity estimation

We assume a Cobb–Douglas production function written in the following form for the purpose of empirical estimation:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + e_{it}, \tag{A1}$$

where y_{it} is the log of value added, l_{it} is the log of the labour input, k_{it} is the log of the capital input, ω_{it} is unobserved productivity, and e_{it} is an unanticipated shock or random error term.

The theory underlying the Levinsohn and Petrin (2003) approach to estimating productivity is that for some function $f(.)$

$$\omega_{it} = f\left(k_{it}, m_{it}\right), \tag{A2}$$

where m_{it} are intermediate inputs.[16]

As in the Olley and Pakes (1996) approach, we assume that productivity evolves according to a first-order Markov process. So:

$$E\left(\omega_{it} \middle| \omega_{it-1}, \omega_{it-2}, \ldots, \omega_{i1}\right) = E\left(\omega_{it} \middle| I_{it-1}\right) = E\left(\omega_{it} \middle| \omega_{it-1}\right), \tag{A3}$$

where I_{it-1} is the information set at time $t-1$ and all past realizations of productivity are assumed to be part of that information set. In other words, the firm expectations about future productivity depend only on the productivity in the previous period.

We assume that labour is chosen at the same time that productivity is realized but that intermediate inputs and capital stock k_{it} are determined at time $t-1$.

Assuming that $E(e_{it} | k_{it}, m_{it})=0$, and substituting for ω_{it}, the production function in Equation (A1) can be written as:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + f\left(k_{it}, m_{it}\right) + e_{it}, \quad t = 1, 2, \ldots, T. \tag{A4}$$

The parameters β_l and β_k will not be separately identified, the former owing to collinearity between labour and productivity (Ackerberg et al. 2006) and the latter owing to the inclusion of k_{it} in $f(.)$.

Returning to the process assumed to underlie the evolution of productivity described in Equation (A3), we define innovation as follows:

$$\xi_{it} = \omega_{it} - E\left(\omega_{it} \middle| \omega_{it-1}\right). \tag{A5}$$

Combined with Equation (A2), which implies that $\omega_{it-1}=g(k_{i-1}, m_{it-1})$, and after some rearranging, Equation (A5) can be rewritten as:

[16] In the Olley and Pakes (1996) approach, investment is used in place of intermediate inputs.

$$\omega_{it} = f\left[g\left(k_{i=1} m_{it-1}\right)\right] + \xi_{it}. \tag{A6}$$

Substituting into Equation (A1) provides us with a second equation that can be used to identify the two parameters of interest, β_l and β_k:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + f\left[g\left(k_{it-1}, m_{it-1}\right)\right] + v_{it}, \quad t = 2, 3, \ldots, T, \tag{A7}$$

where $v_{it}=\xi_{it}+e_{it}$. A set of suitable moment restrictions emerges from the assumptions underlying the evolution of productivity and the timing of the choice of inputs. Equation (A5) implies that innovation will be independent of the information set at time $t-1$ (i.e. ω_{t-1}). As k_{it} is determined at period $t-1$, it will be uncorrelated with unobserved innovation ξ_{it}. In other words:

$$E\left(\xi_{it} \middle| k_{it}\right) = 0. \tag{A8}$$

Innovation will, however, be correlated with any production decisions that are made between period $t-1$ and t. As such, the labour input, determined at period t, will be correlated with ξ_{it}. The lag of labour, l_{it-1}, however, will not, given that it is part of the information set at time $t-1$. As such:

$$E\left(\xi_{it} \middle| l_{it-1}\right) = 0. \tag{A9}$$

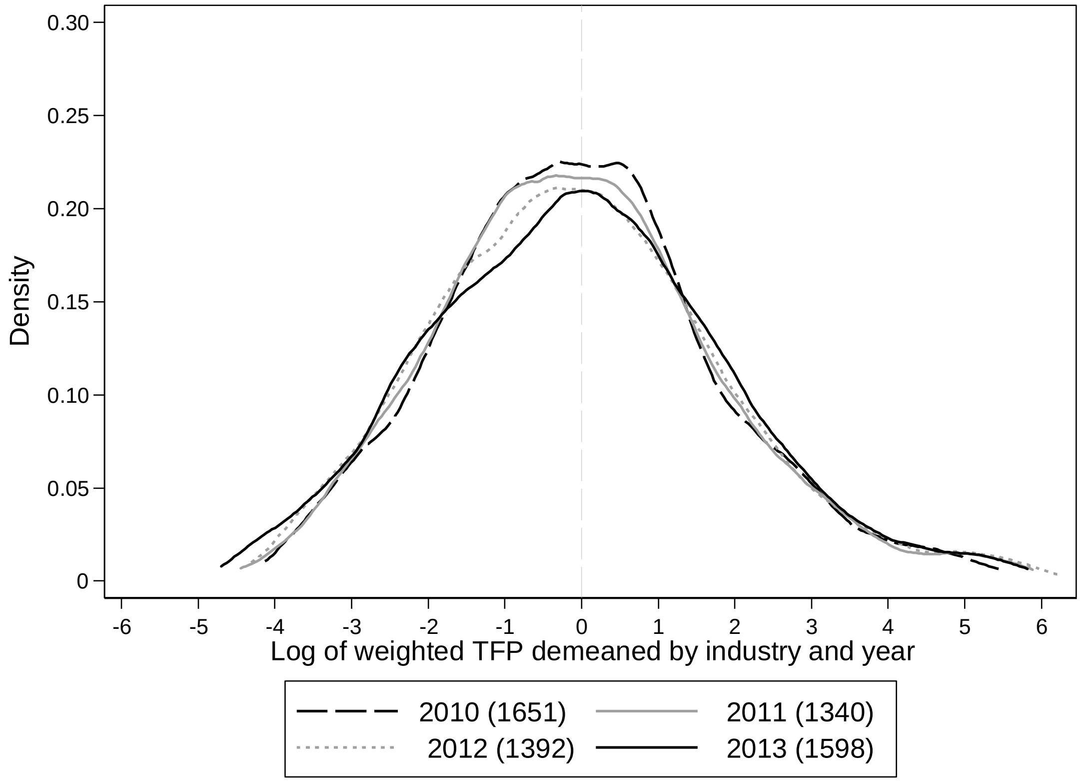
The full set of moment conditions is therefore given by $E(v_{it} | k_{it}, l_{it-1}, k_{it-1}, m_{it-1})=0$. The unknown functions $f(.)$ and $g(.)$ are approximated by third-degree polynomials. Equation (A7) can be estimated using pooled instrumental variables estimation with the instrument set $z_{it}=(k_{it}, l_{it-1}, k_{it-1}, m_{it-1}, \ldots)$, where all higher-order terms and their interactions in the polynomials act as their own instruments and all lags can also be used as instruments in testing overidentifying restrictions. In the estimation of Equation (A7), a full set of time dummies is included to control for heterogeneity over time in the production function and productivity. Once we have consistent estimators for β_l and β_k, productivity can be estimated using Equation (A10):

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}. \tag{A10}$$

Appendix B Distribution of total factor productivity (TFP)

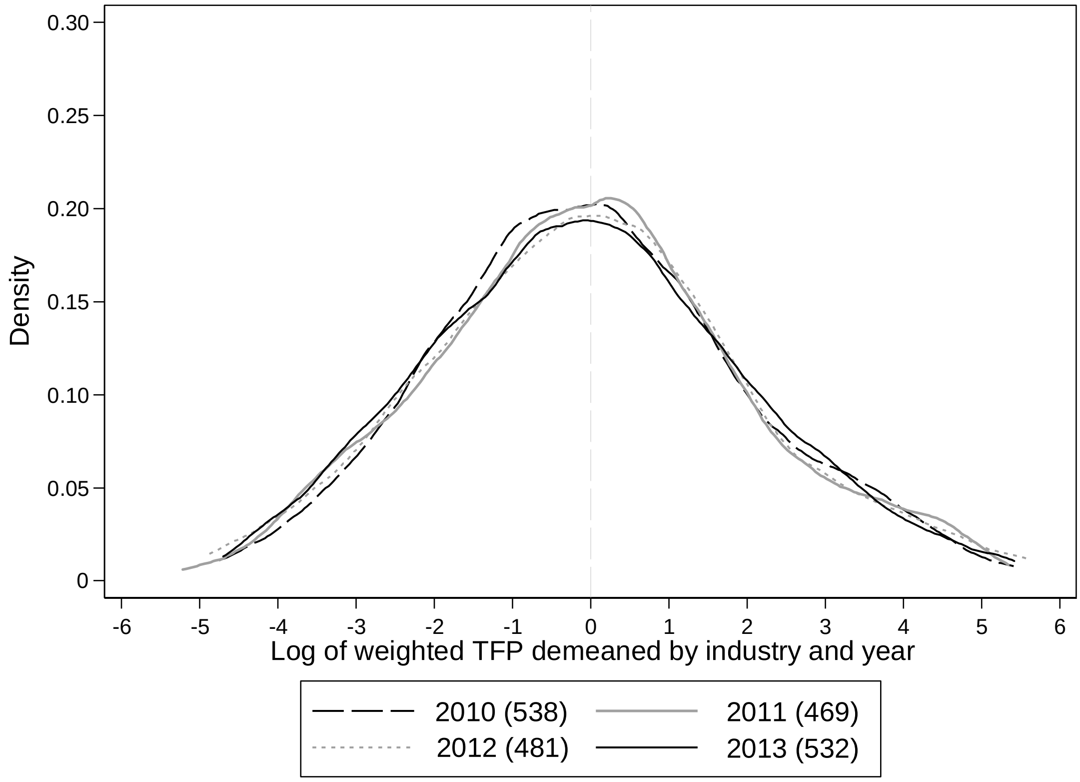
Figure B1: TFP distribution per industry per year

(a) 10: Food products

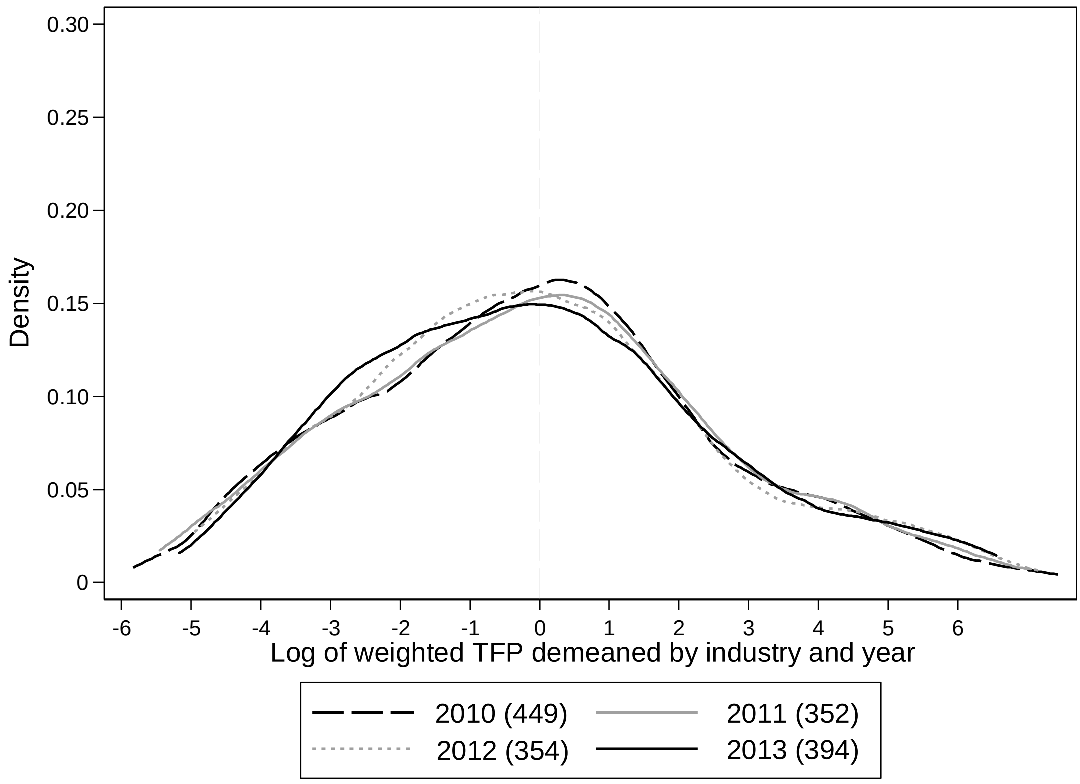


(b) 11: Beverages

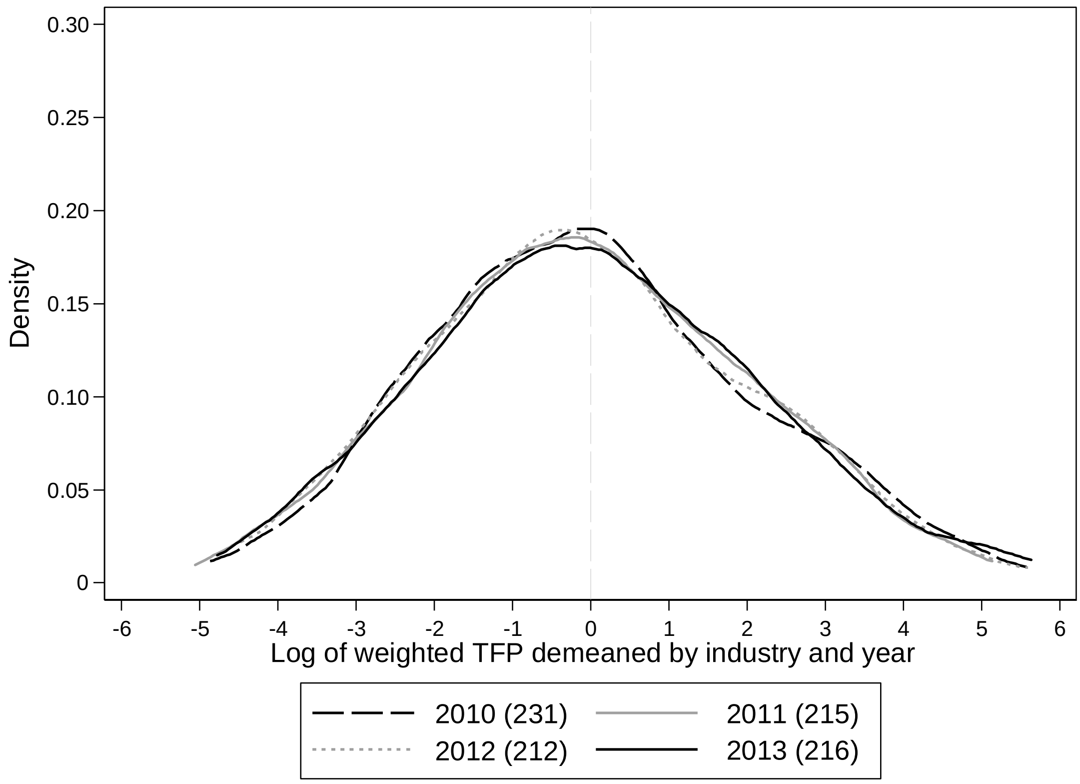
(c) 13: Textiles



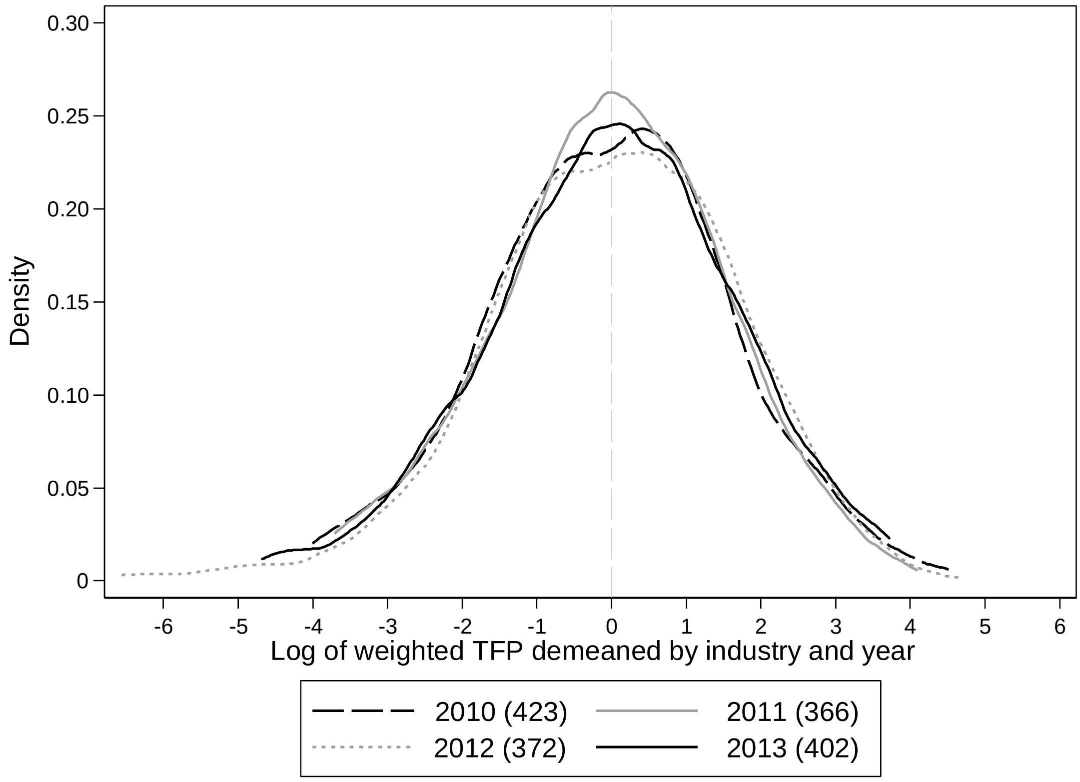
(d) 14: Wearing apparel



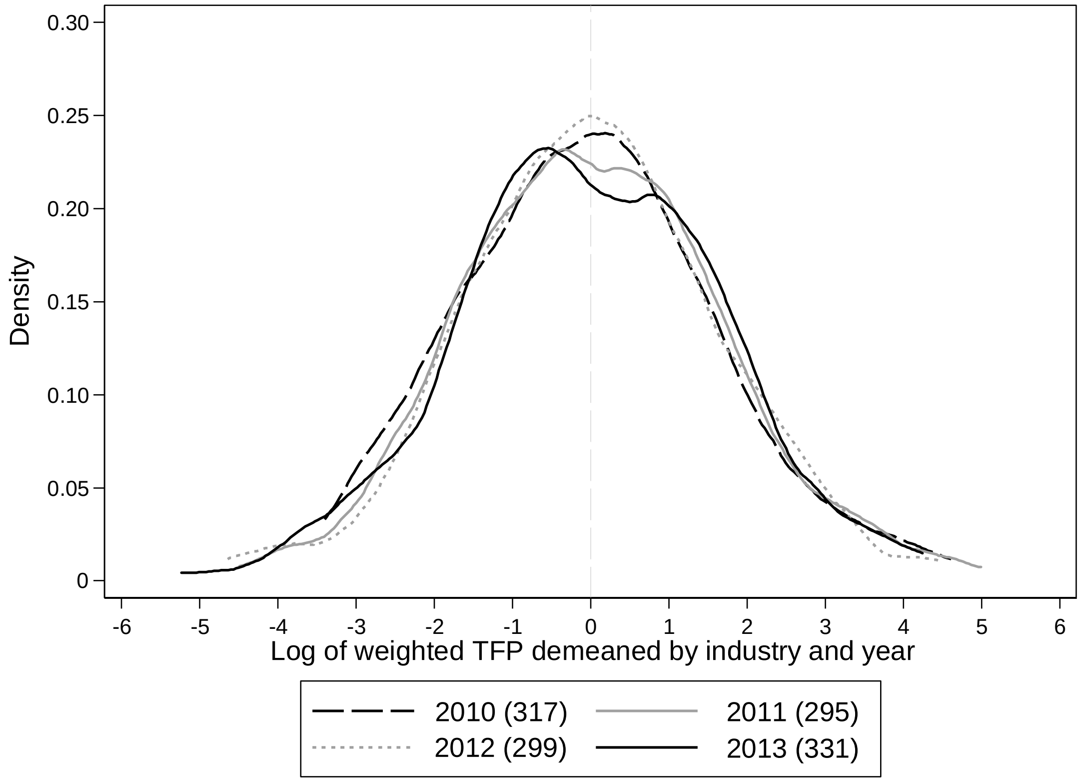
(e) 15: Leather and related products



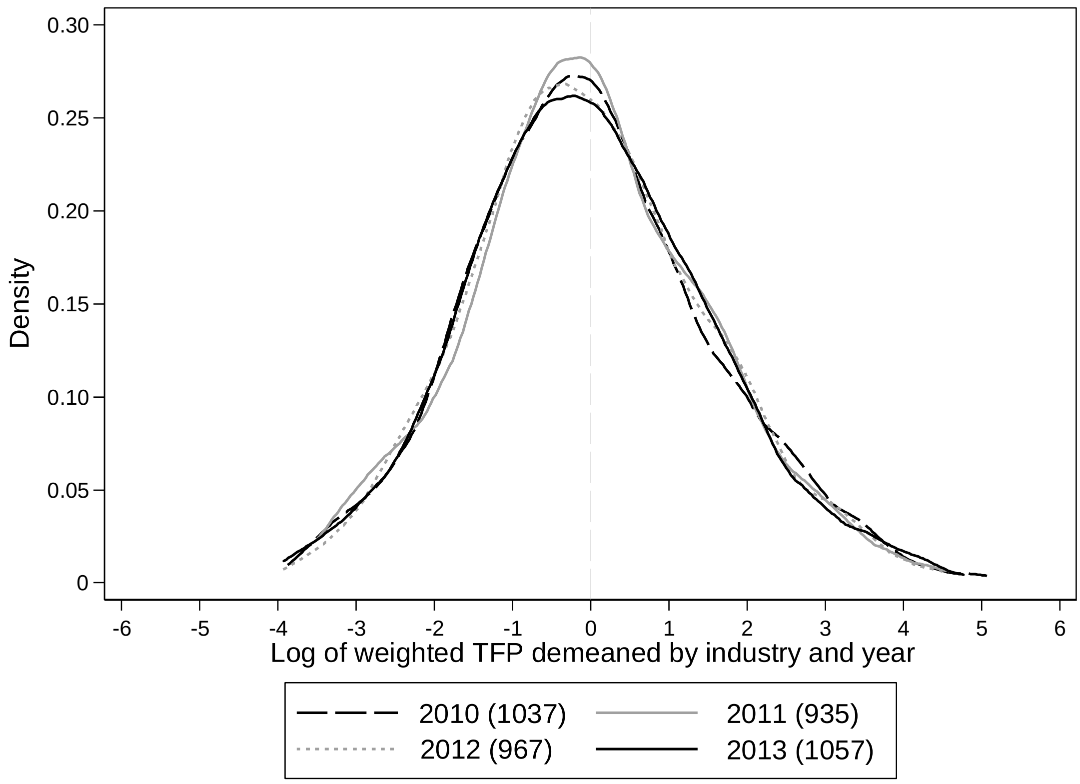
(f) 16: Wood and products of wood and cork, except furniture



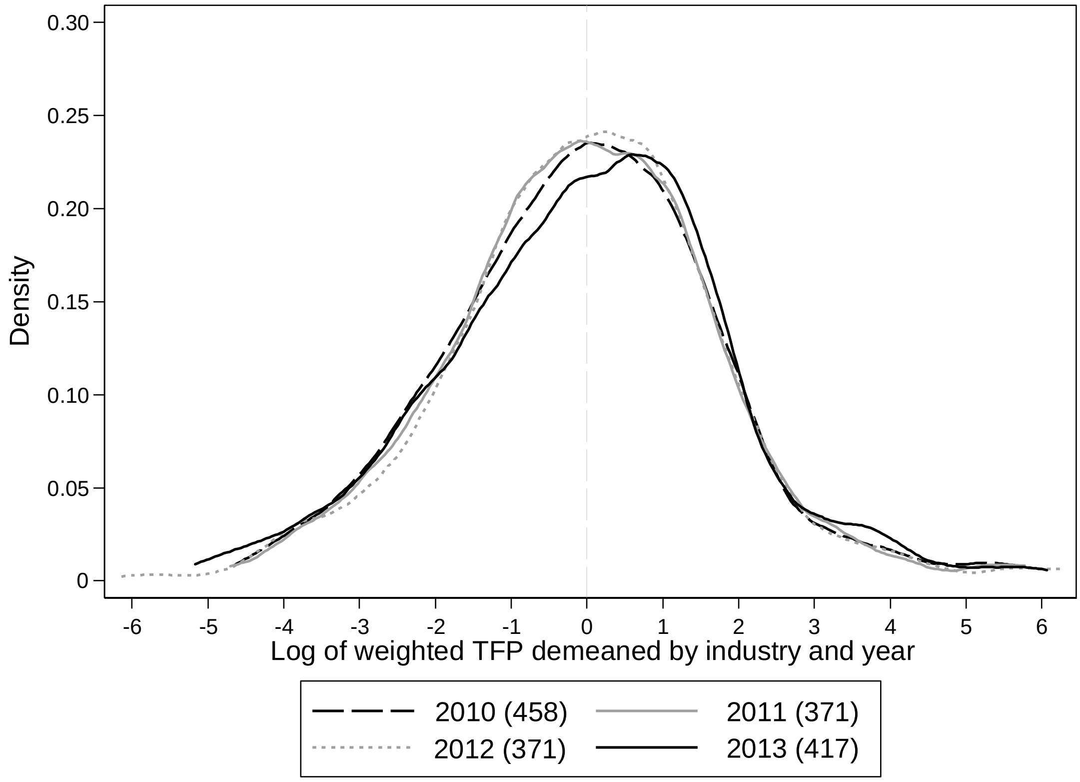
(g) 17: Paper and paper products



(h) 18: Printing and reproduction of recorded media

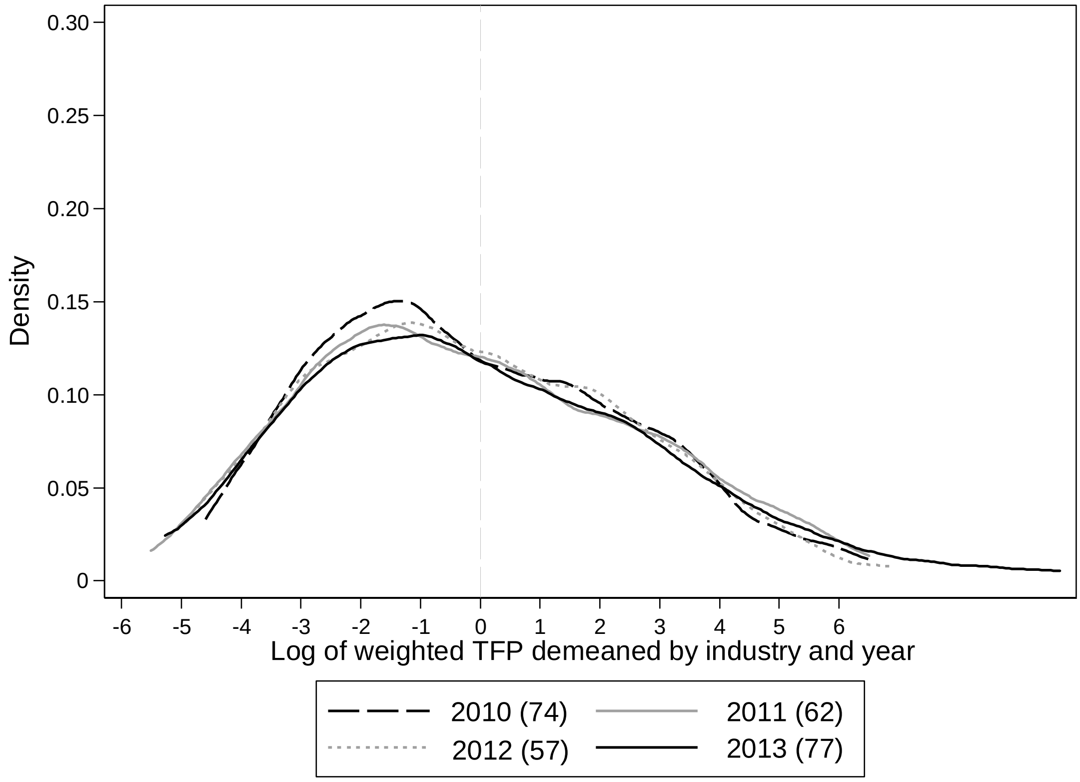


(i) 19: Coke and refined petroleum products

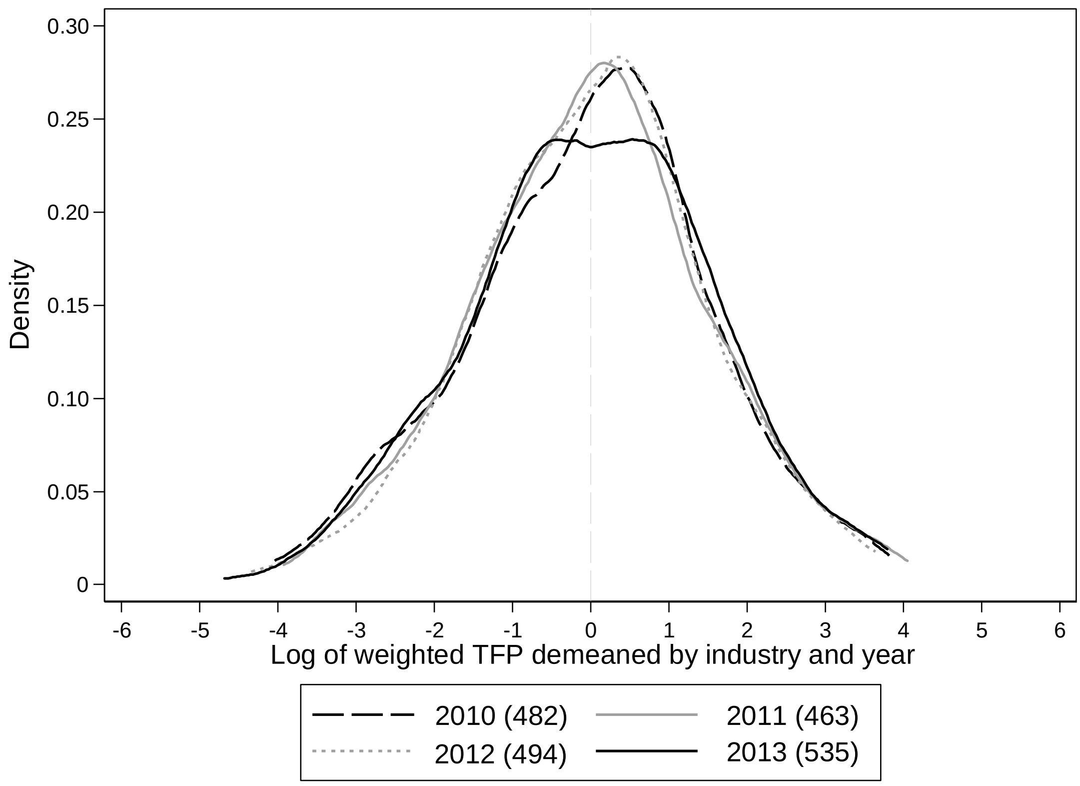


(j) 20: Chemicals and chemical products

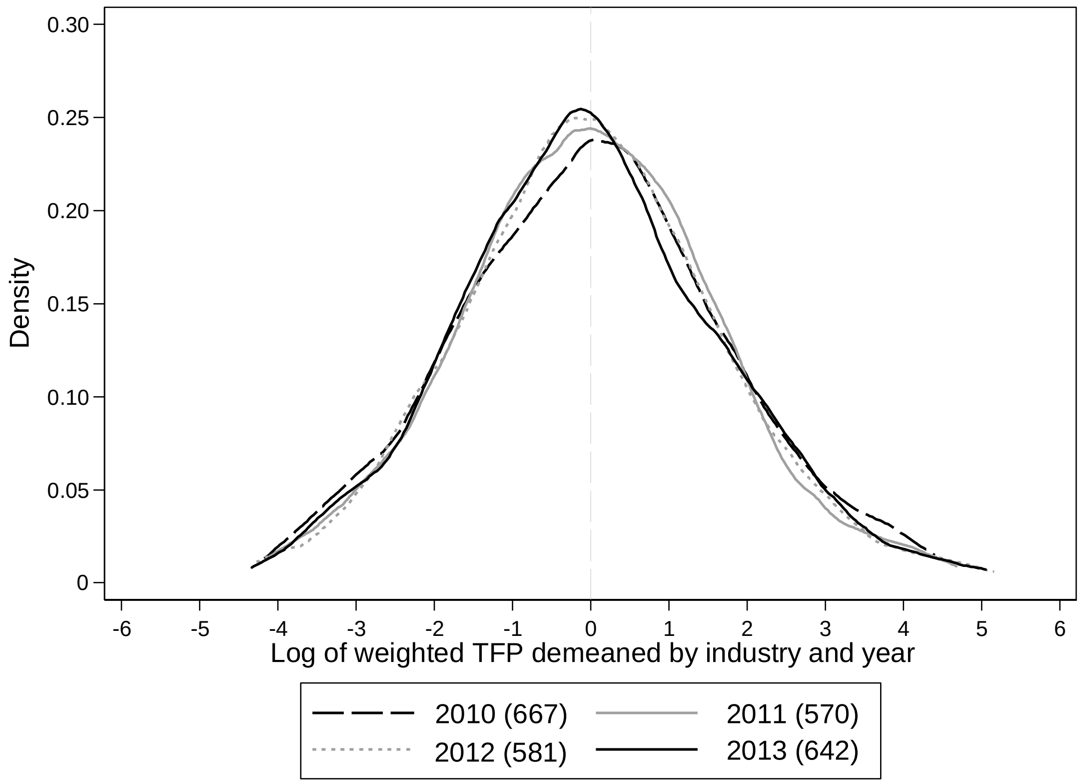
(k) 21: Basic pharmaceutical products and pharmaceutical preparations



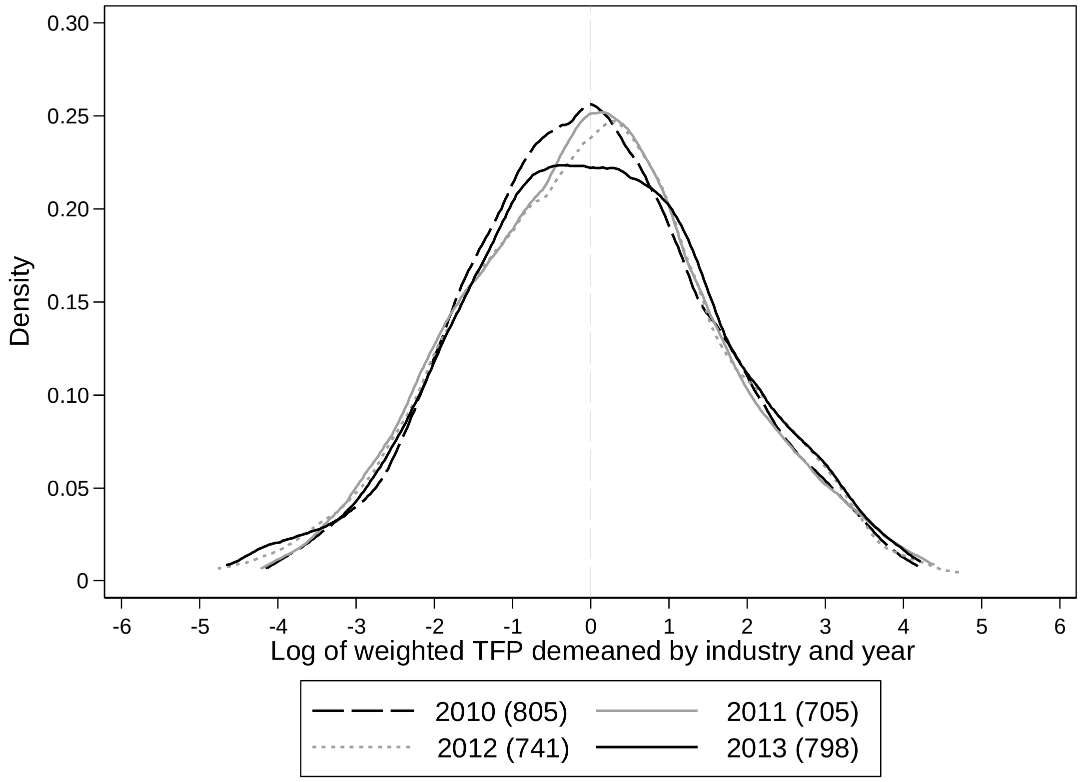
(l) 22: Rubber and plastics



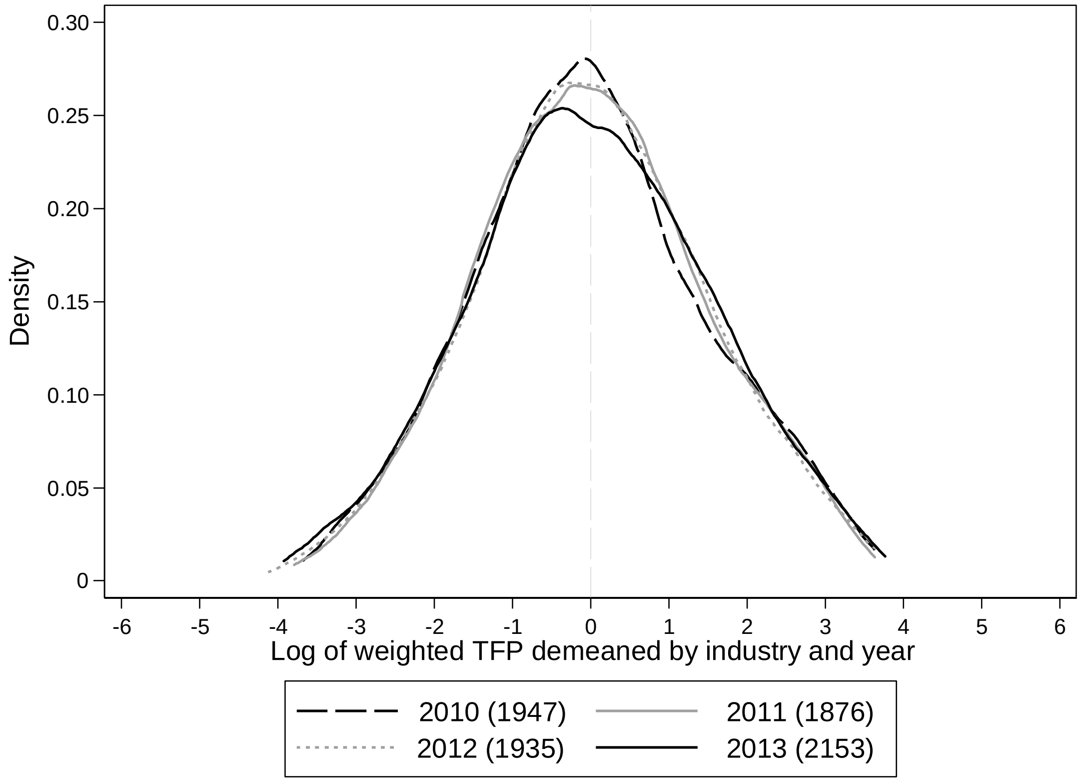
(m) 23: Other non-metallic mineral products



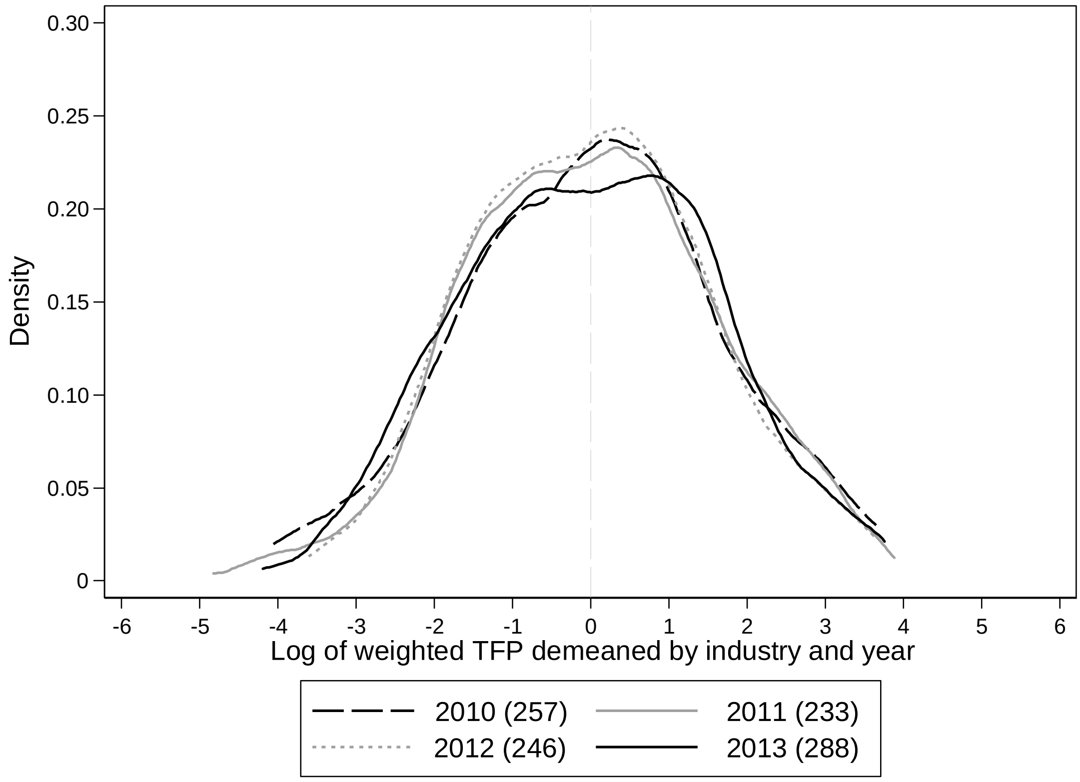
(n) 24: Basic metals



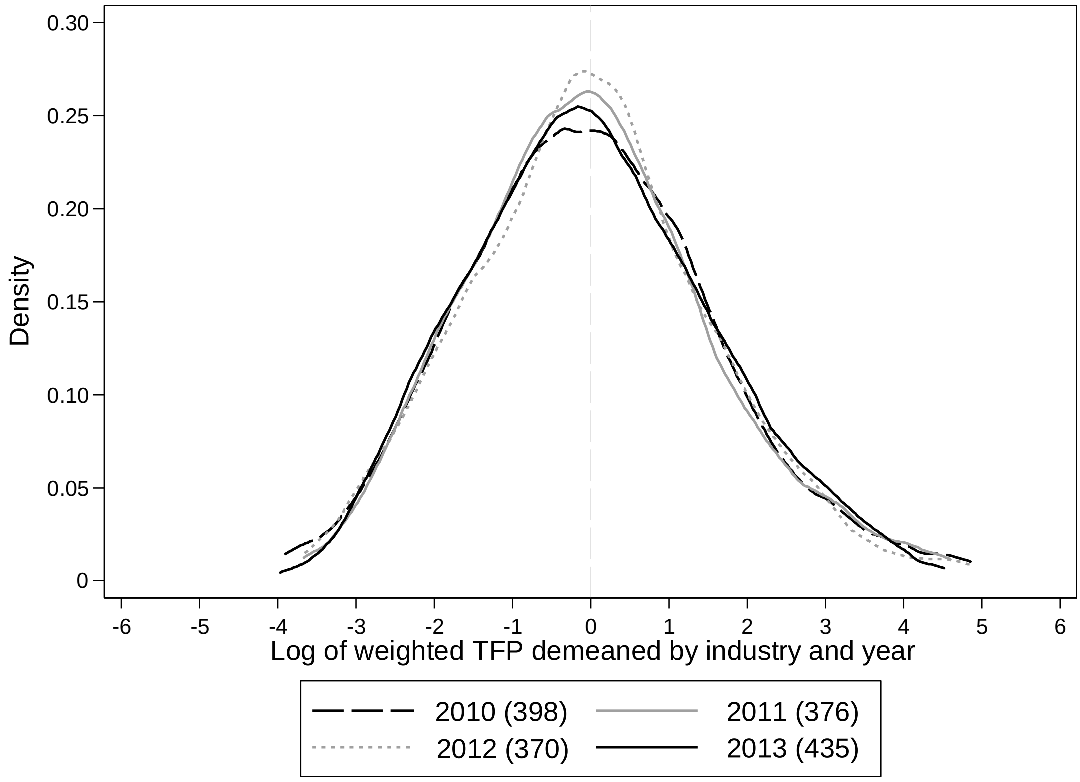
(o) 25: Fabricated metal products, except machinery and equipment



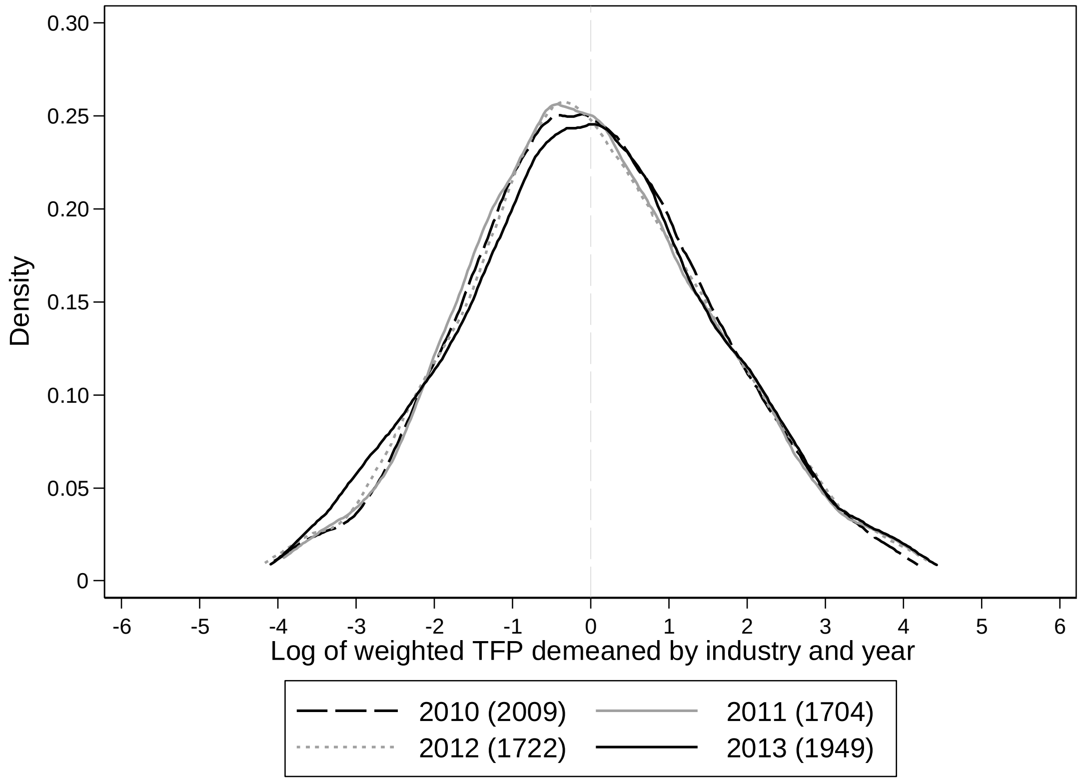
(p) 26: Computer, electronic, and optical products



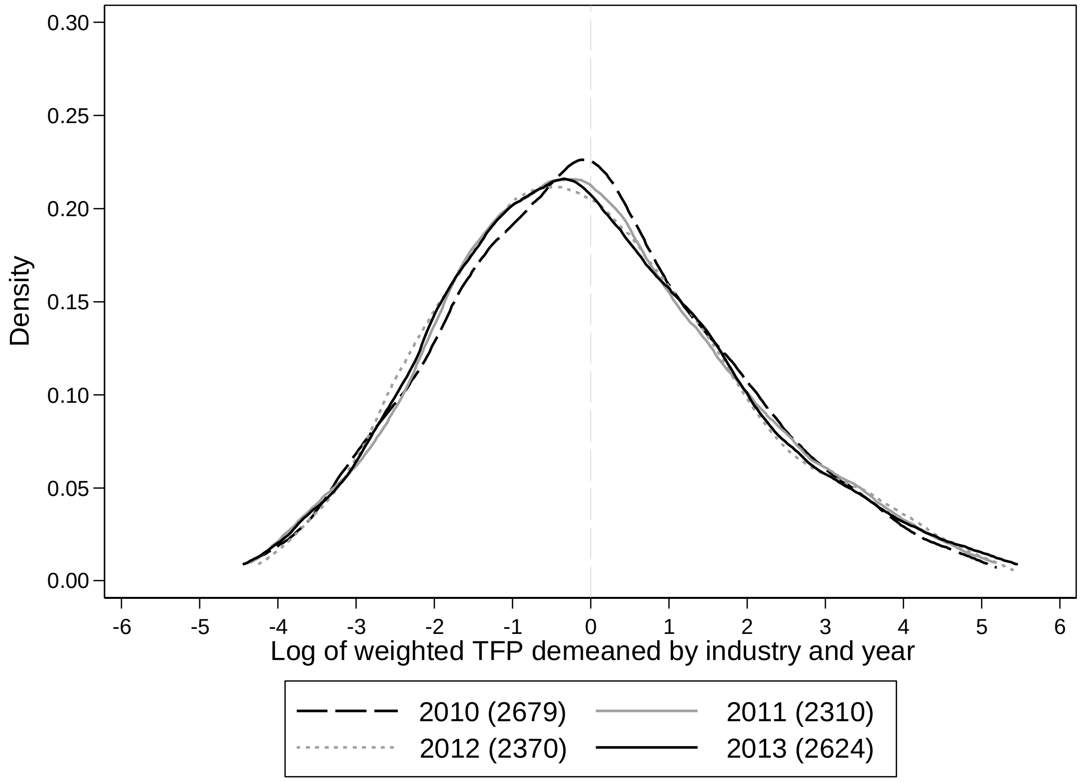
(q) 27: Electrical equipment



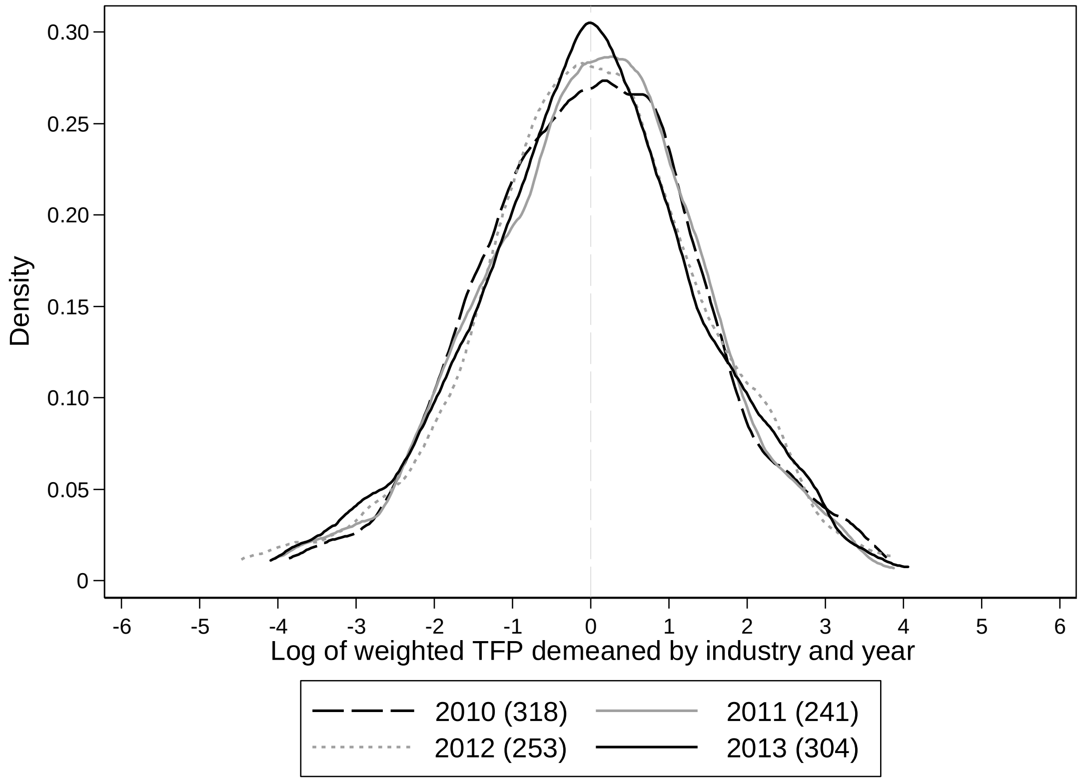
(r) 28: Machinery and equipment not elsewhere classified



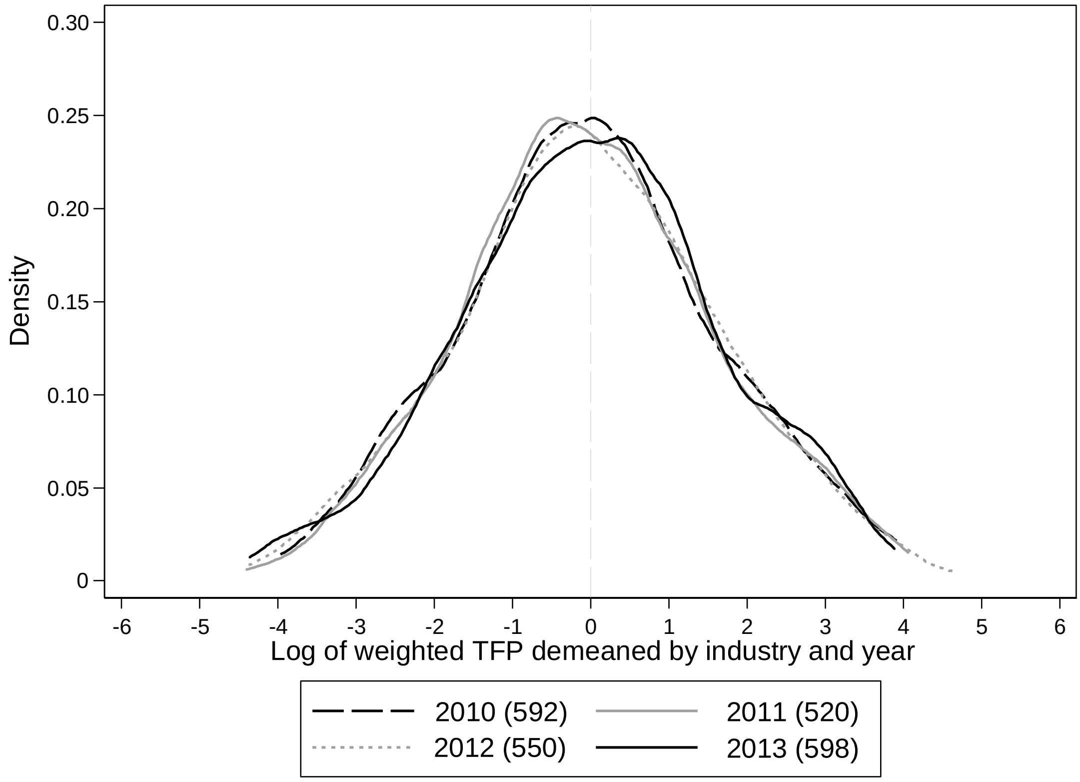
(s) 29: Motor vehicles, trailers, and semi-trailers



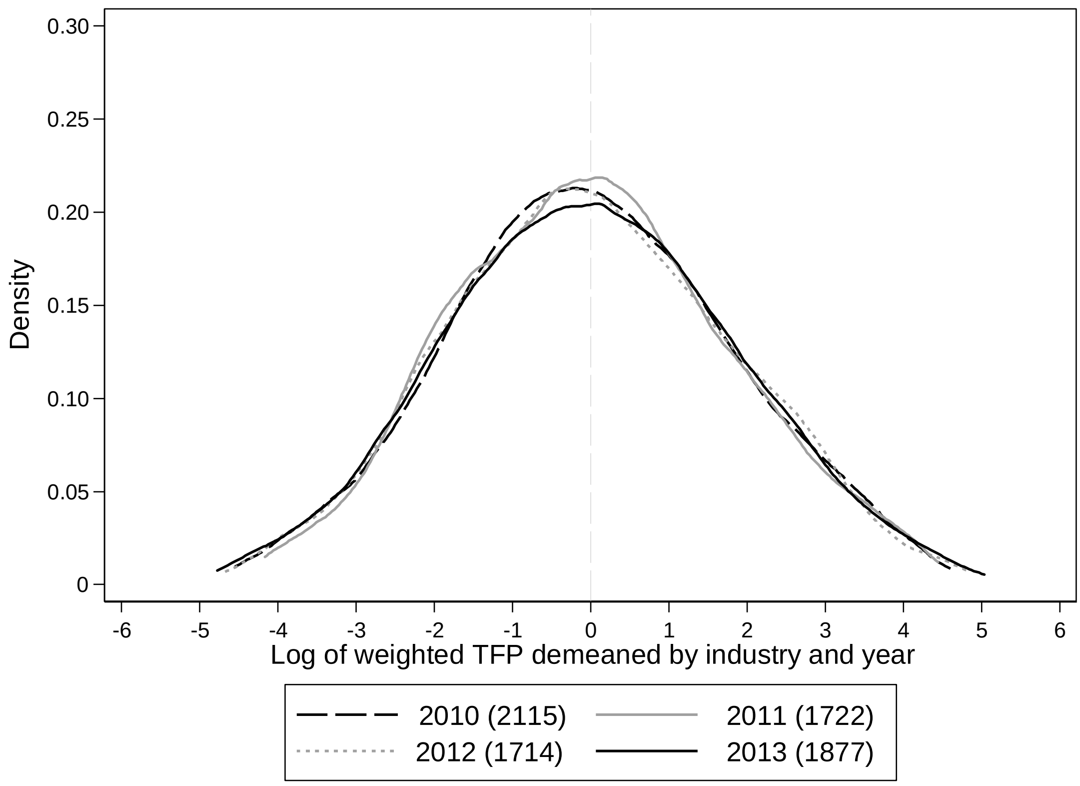
(t) 30: Other transport equipment



(u) 31: Furniture



(v) 32: Other manufacturing



Note: Refer to United Nations (2008: 63–7) for the exact contents of each industry.

Source: Authors’ calculations based on TFP results from regressions on CIT–IRP5 data.