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Resource misallocation and total factor productivity

Manufacturing firms in South Africa

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Abstract: Misallocation of labour and capital can greatly reduce aggregate productivity. In this study, we use tax administrative data to examine the extent of resource misallocation in the South African context. In addition, we zoom in on how different government incentives affect the allocation (or misallocation) of capital and labour across firms, and we quantify the extent to which alleviating these policy-induced distortions would improve productivity for the manufacturing sector in South Africa. We also analyse heterogeneity in the extent of misallocation along the firm size distribution and identify firm size categories where these policy distortions are having the biggest impact on productivity.

Keywords: marginal revenue product, resource misallocation, South Africa, total factor productivity
JEL classification: D24, O4

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1 Introduction

There is a large and persistent variation in living standards across countries. A large part of the variation can be explained by differences in productivity. One explanation for lower productivity in poorer countries is that they are less effective at efficiently allocating resources to their most productive use. While frictions preventing the efficient allocation of resources can also be present in developed economies, resource misallocation is more pronounced in developing countries where factor markets operate much less efficiently and frictions such as corruption and regulation play a more pervasive role (Restuccia and Rogerson 2017). A key question, therefore, for understanding why some countries have lower aggregate productivity than others is how to understand the underlying causes of resource misallocation. Are the causes of misallocation the same in developing countries as in developed countries, or are there channels that are specific to low-income settings? A key challenge to addressing these questions is the lack of detailed firm-level data for developing countries that would facilitate the measurement of the overall extent of misallocation and the identification of the underlying drivers.

In this paper, we address this challenge using tax administrative data from South Africa. We examine the extent of resource misallocation in the South African context and explore the extent to which specific identifiable distortions, including the inefficient allocation of credit and government incentives for the use of different inputs, affect the misallocation of capital and labour across firms. We also quantify the extent to which alleviating these distortions would improve productivity for the manufacturing sector and uncover whether heterogeneity along the firm size distribution exists, and we identify whether these policy distortions are having a bigger impact on productivity for smaller than for larger enterprises.

Our paper is motivated by the literature highlighting the impact that idiosyncratic distortions can have on aggregate productivity. In particular, the literature has shown significant heterogeneity across countries in the extent of misallocation and in the nature of such distortions. Hsieh and Klenow (2009), in their seminal work on this issue, calculate potential total factor productivity (TFP) gains of 30 to 50 per cent in China and 40 to 60 per cent in India if resources were reallocated to equalize marginal products to US levels. Bartelsman et al. (2013) show significant variation across countries in the extent of within-industry misallocation. Using a model of heterogeneous firms, they explain the variation in misallocation across countries by adjustment frictions and distortions, which in turn lead to differences in aggregate productivity performance. Similarly, Asker et al. (2014) investigate the extent to which the adjustment costs associated with dynamic production inputs lead to a misallocation of capital within industries and countries. They find that a very large proportion of the cross-industry and cross-country variation in the dispersion of the marginal revenue product of capital can be explained by volatility in productivity.

TFP changes over time within countries are generally much smaller than the differences in productivity observed across countries. This suggests that in specific country contexts, misallocation may be persistent and, as such, alleviating potential distortions to the efficient allocation of resources could have significant effects on productivity. Understanding the sources of misallocation, and how resources can be more efficiently allocated, can provide valuable lessons for policymakers. In particular, there is potentially a lot to be gained from studies which examine how misallocation changes in contexts where important policy shifts or regulatory changes occur. Restuccia and

Rogerson (2017) provide an overview of the literature to date on the causes and costs of misallocation. They classify potential sources of within-country resource misallocation into three categories. First, misallocation can be due to statutory provisions, such as regulation and taxes that vary with firm characteristics, such as the size of the firm or the sector of operation. Second, misallocation can result from discretionary provisions that favour or penalize specific firms. For example, distortions can arise from the granting of tax breaks or low interest loans for particular types of activities or types of firms. Distortions resulting from cronyism or other forms of corruption can also be classified in this group. Third, distortions can arise from market imperfections, such as monopoly power or poorly defined property rights, that in fact could be alleviated through appropriate corrective policy measures.

The wide-ranging nature of these sources of misallocation suggests that they can be specific to different contexts. There are, however, many general policy lessons that can be taken away from country-specific empirical studies of the kind we undertake in this paper. Indeed, a recent empirical literature has emerged which focuses on identifying the sources of misallocation within particular country contexts. For example, a number of recent papers highlight the role of credit constraints in creating distortions that lead to a misallocation of capital across firms (Brandt et al. 2013; Caballero et al. 2008; Caggese and Cuñat 2013; Gopinath et al. 2015; Midrigan and Xu 2014). Channels through which labour is misallocated have also been identified. For example, Hsieh et al. (2013) attribute part of the reduction in misallocation in the US since 1960 to better allocation of talent due to a reduction in gender and race discrimination. Labour may also be misallocated due to policies that affect the size distribution of firms (Guner et al. 2008). Most studies examine the extent and sources of misallocation in different developed-country contexts.[1] There is, however, a dearth of evidence on emerging markets, where distortions and frictions are potentially significantly larger.[2]

A further strand of this literature examines misallocation in the context of the size distribution of firms. Bento and Restuccia (2017) develop a model which connects distortions and frictions in the economy to firm-level productivity. They find that the greater the distortions, the smaller the size of firms, and the lower the firm-level productivity and aggregate productivity. This work supports that of Guner et al. (2008), who examine explicitly size-dependent distortions, such as regulations or taxes that apply to different-sized firms, but also extends it by showing that distortions impact on productivity for all firms along the size distribution. Similarly, Garicano et al. (2016) show the welfare effects of size-contingent labour regulations using the case of France, where regulations are in place to support small firms. They find that such regulations impose a welfare cost that is borne primarily by workers but also by large firms.

Our paper contributes to this literature in two key ways. First, we provide empirical evidence of the extent and sources of misallocation in an emerging market economy that has faced significant domestic policy challenges, which can provide valuable lessons for similar contexts globally. Second, we explore the extent to which policy distortions affect firms differently along the size distribution. This is important for two reasons. First, small firms are considered an important engine for growth and job creation in developing countries. Distortions in the economy that prevent the most efficient firms from accessing capital and labour within this size group could have detrimental effects for the

[1] See, for example, Calligaris et al. (2018) for evidence from Italy; and Fujii and Nozawa (2013) for evidence from Japan.

[2] Exceptions include Chen and Irarrazabal (2015), who find that misallocation decreased in Chile during the growth period following the crisis in the early 1980s, and that this was an important source of productivity growth.

growth and survival of these firms and the potential for this sector to contribute to growth in the future. Second, there is also a case for focusing the analysis on large firms. Restuccia and Rogerson (2008) find that for misallocation to have large effects on aggregate productivity, distortions and market imperfections must restrict inputs in high-productivity firms. Given that the largest firms contribute the most to productivity growth in the South African manufacturing sector, focusing on the extent of misallocation among large firms will provide insights into the extent to which misallocation depresses aggregate productivity growth.

We pay close attention to the measurement challenges present in studies of this kind and attempt to isolate the true impact of specific policy distortions by ruling out other confounding factors. How to measure and attribute distortions and frictions to misallocation has also been the subject of much debate in the literature. Two general approaches have been applied to date: a direct approach that focuses on specific sources of misallocation and examines their impact; and an indirect approach that measures the extent of misallocation without first identifying the source. The latter applies some underlying production structure to the behaviour of firms but does not require a full structural model. Given model assumptions, the efficient allocation of resources requires that the marginal products of labour and capital are equalized across firms. The estimation of misallocation therefore only requires basic balance sheet information on firms and so is an ideal approach when only tax administrative data are available. A key challenge with this approach is that misallocation could also capture other factors. Putting all variation in marginal products across firms down to misallocation, however, is extreme. This variation will embody measurement error, adjustment costs, and other dynamic decision-making processes of firms. We take account of these factors by considering how much of the misallocation we can actually explain through quantifiably measurable potentially distortionary measures.

We find evidence of significant misallocation of labour and capital in the South African manufacturing sector. Reallocation of resources could lead to a potential gain in aggregate TFP of between 16 and 22 per cent. We consider the impact of a number of policy measures on the distribution of TFP, including access to credit and other government measures, that may explain the misallocation across firms. These include: (1) a Research and Development (R&D) incentive which allows for a tax deduction of 150 per cent of expenditure incurred for R&D and an accelerated depreciation deduction for capital expenditure for R&D purposes; (2) a general depreciation allowance on movable capital equipment which can be deducted from profits for the purpose of computing tax owed; and (3) a learnership incentive scheme which provides employers with allowances for facilitating the engagement of their employees in learnership agreements which are essentially training and skills development programmes. Each of these schemes could incentivize firms to alter their allocations of labour and capital, and so could serve to either increase the extent of misallocation, thereby having a distortionary effect, or reduce the extent of misallocation, thereby serving to correct inefficiencies in the economy. We find that, combined, these policy measures explain 11.3 per cent of the measured misallocation, implying that if they were adjusted to facilitate a more efficient allocation of resources across firms, this could lead to productivity gains of approximately 2.2 per cent per annum. Given that year-on-year changes in TFP in South African manufacturing have been approximately 3 per cent per annum, this could meaningfully impact on aggregate productivity. We also find considerable heterogeneity across the size distribution, with most misallocation occurring among micro and small-sized firms. As such, any gains in productivity as a result of a readjustment of these policy measures would benefit the smaller end of the size distribution most.

The rest of the paper is organized as follows. In Section 2 we provide more details on the South African context. We present the methodological approach in Section 3. The data are described in Section 4. Section 5 presents the results and Section 6 concludes.

2 South African context

In this section we provide a background to the various government incentives that could potentially lead to a reallocation of labour and capital resources in South African manufacturing. We also describe the credit market incentives relevant to manufacturing firms.

2.1 Government incentives

A number of policy measures are in place in South Africa to encourage investment in capital, job creation, and entrepreneurship. We focus on three in this paper: an R&D incentive, a depreciation allowance, and a learnership incentive to encourage firms to train their workers. The size and extent of these measures can be quantified by considering what they cost the government in terms of forgone tax revenue, or tax expenditure. Tax expenditure as a portion of GDP has been around 3 per cent over the past few years in South Africa.

Table 1 shows the largest tax expenditure components in terms of corporate income tax which we focus on in this paper. The Income Tax Act Section 11D R&D incentive was introduced in 2006; its main objective is to encourage investment in scientific or technological research and development. The R&D incentive firstly allows for a tax deduction equal to 150 per cent of expenditure incurred directly for research and development. An accelerated depreciation deduction for capital expenditure incurred on machinery or plant used for R&D is also offered. It should be noted that large firms tend to benefit more from this type of incentive, given that smaller firms typically do not have the cash resources available to make large capital expenditures upfront. The Section 11D incentive replaced the R&D rule that was in place in terms of Section 11B. Given the favourable depreciation schedule and tax deduction for R&D expenditure, it is expected that, all other factors being equal, labour would be substituted for capital in the presence of this incentive. Moreover, it could lead to a reallocation of capital in the economy away from small firms towards larger firms. The extent to which this leads to a more efficient allocation of capital will depend on where along the size distribution the marginal product of capital is highest.

Table 1: Tax expenditure estimates for corporate incentives, 2010/11–2013/14

Corporate income tax				
R&D	1,216	1,131	360	745
Depreciation allowance	20	20	25	26
Learnership allowances	1,368	1,219	758	966

Source: Authors' construction based on National Treasury (2016).

The depreciation allowance falls under Section 12E of the Income Tax Act. It can be deducted on new and unused machinery used in manufacturing at a rate of 40 per cent in the first year of use and 20 per cent in the following three years. For machinery that is not new and unused, there is an allowance of 20 per cent per annum over a five-year period. This allowance favours the use of capital over labour but applies equally along the size distribution. This could have distortionary effects if it leads firms to employ capital when labour may well be more efficient. As for the R&D incentive, it again arguably benefits larger firms to a greater extent, given that they will have more resources available for investment in machinery.

The learnership allowance falls under Section 12H of the Income Tax Act and provides additional deductions to employers for qualifying learnership agreements. Two types of deductions are available: (1) an annual allowance and (2) a completion allowance. This serves as an incentive to employers to encourage training, skills development, and ultimately job creation. The number of firms that claimed under the annual allowance reached almost 1,800 in 2013, with a total amount claimed equal to R1.8 billion. This incentive will likely motivate firms to hire more workers (keeping all other factors constant), or at the very least encourage training opportunities among existing employees. If firms with higher marginal returns to labour are more likely to access the incentive, it has the possibility of being efficiency-enhancing, thus reducing the extent of misallocation. It could also work in the opposite direction.

2.2 Credit markets

The lending and financial services infrastructure of South Africa compares favourably with that of other upper middle-income countries, even when compared with the infrastructure of certain developed economies (Turner et al. 2008). However, a dichotomy exists between the larger and smaller firms in terms of gaining access to credit; larger firms enjoy easy access to credit financing, but this is not the case for businesses operating at a smaller scale.

Based on various surveys of lending to micro, small, and medium-sized enterprises in South Africa, it can be stated that small businesses in South Africa tend to struggle to obtain access to financing. The Global Entrepreneurship Monitor (GEM) (Herrington and Kew 2016) finds that over the period 2006–15, more than 25 per cent of businesses cited lack of finance as a reason for discontinuing their operations.

Several reasons have been given for the firm size heterogeneity in credit access. Small businesses are not always aware of all the avenues that exist to obtain finance, which could be partly attributed to a lack of information and high searching costs (Wellalage and Locke 2016). It is also the case taht young people in businesses are especially vulnerable as they often have a limited credit history and typically have insufficient savings to finance their business (Herrington and Kew 2016).In addition, the relatively poor levels of schooling may also especially disadvantage young entrepreneurs. Although government initiatives have been set in motion to make access to entrepreneurial finance easier, there seems to be an increasing divergence between entrepreneurs and financial service institutions, most likely due to: (1) insufficient collateral provided by the entrepreneur; (2) business plans that are considered to be of insufficient quality; (3) an inability of entrepreneurs to present a viable business idea; and (4) lack of market access.

However, it is not a given that allocating a larger share of loanable funds towards micro and small firms will reduce misallocation of capital in South Africa. Here, a rigorous analysis is needed of differences in marginal revenue product of capital (MRPK) across the firm size distribution.

3 Methodological approach

We use the indirect approach to measuring misallocation using the framework provided by Hsieh and Klenow (2009). This approach requires that we apply some structure to the behaviour of firms but does not require that we specify a full structural model. Misallocation is measured as the deviation of TFP from the level that could be obtained if all inputs were allocated efficiently across firms within a sector in a given time period. Unlike other direct approaches that examine specific causes of misallocation, we do not identify the sources of misallocation *a priori*, but rather measure the extent of misallocation and see how much of it we can attribute to specific identifiable sources using our data.

Hsieh and Klenow's (2009) approach is based on the idea that the optimal allocation of resources will occur in a situation where there are no frictions in factor markets or distortions that prevent labour and capital from being employed by the firms with the highest returns. This would result in the marginal product of labour and capital being equalized across firms within a sector in a given time period. By applying some structure to the underlying production technology and behaviour of firms, the optimal resource allocation can be determined and any deviation from the efficient allocative equilibrium can be attributed to distortions and frictions in labour and capital markets that affect heterogeneous firms differently.

In line with Hsieh and Klenow (2009), capital and labour shares are allowed to differ across industries, but not across firms within an industry. Hsieh and Klenow (2009) distinguish between two different types of distortions:

(1) those that affect the marginal products of labour and capital equally (such as, for example, subsidies for particular firms in a sector or firms that face high transport costs);
(2) those that affect the marginal product of one factor relative to another (such as, for example, credit constraints faced by certain firms or government incentives that favour the use of one factor over another).

Distortions that affect both capital and labour can be identified separately to distortions that change the marginal product of one of the factors relative to the other factor of production. Distortions that increase the marginal products of capital and labour by the same proportion are labelled output distortions (τ_Y), and these will be high for firms that face government restrictions on size or high transport costs and low for firms that benefit from subsidies. Distortions that raise the marginal product of capital relative to labour are denoted capital distortions (τ_K), and these will be high for firms that do not have access to credit but low for firms that have access to cheap credit.

The firm will choose capital (*K*) and labour (*L*) to maximize profits as follows:

$$\max_{L_{si},K_{si}}\left(1-\tau_{Y_{si}}\right)P_{si}Y_{si}-wL_{si}-\left(1+\tau_{K_{si}}\right)RK_{si}$$

where τ_Y and τ_K are wedges that are firm-specific distortions, either policy-induced or present due to market failure. It is assumed that a firm's produce output Y_{si} using a constant returns to scale production technology $Y_{si} = A_{si}K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}$, where A_{si} is physical productivity (TFPQ) and α_s is the capital–output elasticity. Maximization is done subject to a downward-sloping demand curve:

$$Y_s = \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where the elasticity of substitution σ is assumed to be greater than one. Optimization within this framework yields the following MRPK and MRPL:

$$MRPK_{si} \stackrel{\Delta}{=} \alpha_S \frac{\sigma-1}{\sigma} \frac{P_{si} Y_{si}}{K_{si}} = R \frac{1+\tau_{K_{si}}}{1-\tau_{Y_{si}}} \tag{1}$$

$$MRPL_{si} \stackrel{\Delta}{=} (1-\alpha_S) \frac{\sigma-1}{\sigma} \frac{P_{si} Y_{si}}{L_{si}} = w \frac{1}{1-\tau_{Y_{si}}} \tag{2}$$

where *R* is the interest rate and *w* wages. The after-tax marginal revenue products of capital and labour will be equalized across firms. The before-tax marginal revenue products will be higher in firms that face disincentives and lower in firms that benefit from subsidies and other incentives.

Firm-specific distortions can be measured by the firm's revenue productivity (Foster et al. 2008). We distinguish between revenue and physical productivity as follows, noting that firm-specific revenue productivity (TFPR) is just a firm's TFPQ multiplied by its output price:

$$TFPR_{si} \triangleq P_{si} A_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = \frac{\sigma}{\sigma-1} \left(\frac{MRPK_{si}}{\alpha_s} \right)^{\alpha_s} \left(\frac{MRPL_{si}}{1-\alpha_s} \right)^{1-\alpha_s} \tag{3}$$

$$TFPQ_{si} \stackrel{\Delta}{=} A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}{}^{1-\alpha_s}} \tag{4}$$

This implies that any variation in TFPR across plants within an industry is due to distortions. With no distortions, more capital and labour should be allocated to plants with higher TFPQ up to the point where their higher output results in a lower price and the exact same TFPR as in smaller plants. High plant TFPR is a sign that the plant confronts barriers that raise its marginal products of capital and labour, rendering the plant smaller than optimal. Industry TFP is aggregated as follows:

$$TFP_s = \frac{Y_s}{K_s^{\alpha_s} L_s{}^{1-\alpha_s}} = \left[\sum_{i=1}^{M} \left(A_{si} \cdot \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{5}$$

where

$$\overline{TFPR}_s \propto \left(\overline{MRPK}_s \right)^{\alpha_s} \left(\overline{MRPL}_s \right)^{1-\alpha_s}$$

is a geometric average of the average marginal revenue product of capital and labour in the sector. Without distortions, marginal products are equalized across plants and TFP will be:

$$\bar{A}_s = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}.$$

Assuming that TFPQ and TFPR are jointly log-normally distributed, the negative effect of distortions on aggregate TFP can be summarized by the variance of log TFPR. Therefore, the extent of misallocation is worsened the greater the dispersion of marginal products.

Based on the above, it is possible to quantify the magnitude of the output loss stemming from resource misallocation relative to the efficient allocation as follows:[3]

$$\frac{Y}{Y_{EFF}} = \prod_{s=1}^{S} \left(\frac{TFP_s}{\bar{A}_s}\right)^{\theta_s} = \left(\sum_{i=1}^{M_s} \left(\frac{A_{si}}{\bar{A}_s} \frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}} \quad (6)$$

With this structure in hand, our empirical investigation is composed of three steps. In the first step, we compute the dispersion in lnTFPR (log of Equation 3), lnMRPK (log of Equation 1), and lnMRPL (log of Equation 2) and examine how that dispersion has evolved over time in the case of South Africa. We decompose the variance in lnTFPR into the part attributable to lnMRPK and lnMRPL. We also examine heterogeneity in the dispersion of these distributions across sectors and across the size distribution.

In the second step, we quantify the magnitude of the loss associated with resource misallocation using Equation 6 and document how this has changed over time and the extent to which it is different across different-sized firms.

In the third and final step, we perform an ex-post empirical analysis of potential sources of misallocation. To achieve this, we estimate the empirical specification given in Equation 7:

$$lnTFPR_{sgt} = \boldsymbol{\beta}\mathbf{X}_{sgt} + \delta_s + \gamma_g + \tau_t + \epsilon_{sgt} \quad (7)$$

where the dependent variable is the standard deviation in lnTFPR in sector *s*, size group *g*, at time *t*, $\mathbf{X}_{sgt}$ is a set of policy variables that we consider potential sources of misallocation, δ_g are indicators for the size of the firm, δ_s are sector fixed effects, and τ_t are time dummies. The logic behind this approach is that once we control for size groups, sector effects, and time effects there should be no variation in lnTFPR across firms. Following Hsieh and Klenow (2009), this variation can be attributed to misallocation. Our aim is to see how much of the variation in lnTFPR we can attribute to specific sources, including access to credit and different policy measures.

A common critique of the direct approach to analysing misallocation is that observed deviations from a hypothetical optimal allocation of resources could be attributed to more than just distortions. Restuccia and Rogerson (2017) point out three possible alternative explanations for deviations from the optimum in resource allocations. First, the direct approach assumes that all producers within a particular sector in a given year use the same production technology. It may be that differences in the allocation of labour and capital inputs across firms reflect differences in the underlying production technologies in use. Second, there may be adjustment costs or transitory firm-specific shocks that cause deviations in optimal allocations in a particular period.[4] Third, deviations from the

[3] This is equivalent to equation 20 in Hsieh and Klenow (2009).

[4] David and Venkateswaran (2017) examine the extent to which capital misallocation can be attributed to adjustment costs or distortions. They find that adjustment costs play a modest role in China but are relatively important among large firms in the US. Given that we are using an indirect approach to measuring misallocation, this is beyond the scope of

optimal allocation may be due to measurement error, which is common in firm-level data sets, particularly in developing-country contexts (see Bils et al. 2017).

We attempt to address these concerns as follows. First, as a robustness check we examine heterogeneity across the size distribution in the extent of misallocation. While there are many possible firm characteristics that might lead firms in the same sector to use different technologies, we might expect this to be less so within particular size groups of firms. We treat each size group, in each sector, in each period, as having a separate production technology and examine the extent of misallocation evident within each group. Second, we exploit the panel structure of our data and consider lags of the policy variables to capture the extent to which the variation in lnTFPR is associated with adjustment costs. Third, to abstract from potential measurement error we focus on the proportion of the variation in lnTFPR that we can actually explain using the policy variables, and how much of the predicted loss in productivity due to misallocation could be alleviated in the absence of these distortions.

4 Data

We use tax administrative data collected by the South African Revenue Services (SARS) for the 2010–14 period.[5] The primary data source is the South African Corporate Income Tax (CIT) data, which are collected annually and are based on self-reported corporate income tax returns.[6] These data include information on sales, capital, wages, and other financial indicators, as well as information on access to government incentives.

Output is measured using value added, which is computed as total sales minus the cost of sales. Value added is deflated by the value added at basic prices deflator. Labour is measured as the total real wage bill of the firm also deflated by the basic price deflator. Capital is measured as the fixed assets of the firm deflated using the manufacturing industry fixed capital investment deflators rebased to March 2012.[7] To address lumpiness in fixed assets we use the two-year average of total assets, in line with Hsieh and Klenow's (2009) approach. Summary statistics by year for each of these variables are presented in Table 2.

Table 2: Summary statistics

'000 Rand	2010	2011	2012	2013	2014
Value added	8,798	11,800	14,200	15,200	18,100
Real wages	5,496	8,027	9,080	9,231	10,500
Fixed assets	3,428	4,517	5,412	5,688	5,984

Source: Authors' construction based on tax administrative data.

this paper. We do, however, control for the possibility that adjustment costs are driving misallocation empirically, as explained below.

[5] For a full description of the data set and how it is compiled, see Kreuser and Newman (2018).

[6] 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.

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

The database does not include information on the number of persons employed in the firm. We gather this information from the PAYE tax data records that are also collected by SARS and that can be matched to the firms in the CIT database. Employers must issue tax certificates to all employees who are paid by the firm. Firm size is measured as the total number of employees of the firm, where each employee is weighted by the total number of periods they work at the firm.

The core sources of misallocation that we consider in this paper are access to credit and the capital and learnership incentives described in Section 2. Access to credit is measured as total current liabilities less cash holdings. It is taken as a proportion of total fixed capital of the firm and is expressed in logs. Averages by year, and by size category and sector for 2014, are presented in Table 3.

Government incentives are largely accessed by the largest firms. Over 25 per cent of large firms have learnership incentives and almost 32 per cent have a depreciation allowance. Micro and small firms barely access these incentives. To the extent that such incentives could influence the allocation of labour and capital resources, it is likely that this occurs only among large firms. In terms of borrowing, micro firms are more indebted than large firms in that current borrowing makes up a greater proportion of their fixed capital. This could be due to the fact that they have a high level of borrowing or a low level of fixed capital. This will be teased out further in the empirical analysis that follows.

There is also some heterogeneity across sectors in the take-up rate of the different incentive schemes. On average in 2014, 2.2 per cent of firms availed themselves of learnership incentives. This ranged from as few as 0.4 per cent in the wood and furniture sectors to almost 7 per cent in pharmaceuticals. The take-up of the depreciation allowance was slightly higher, at 2.4 per cent, in 2014, with firms in the pharmaceuticals sector more likely to avail themselves of it. On average, very few firms take up the R&D allowance, and those that do are concentrated among large firms as mentioned. The lowest take-up rates for the R&D incentive are in pharmaceuticals and in chemicals.

Table 3: Take-up rate of government incentives across sectors

	Credit	Learnership	Depreciation	R&D
Year				
2010	3.3	1.1	1.8	0.6
2011	3.8	1.4	2.0	0.6
2012	4.3	1.8	2.3	0.6
2013	4.6	1.8	2.3	0.4
2014	4.6	2.2	2.4	0.3
Size 2014				
Micro	5.2	0.1	0.7	0.1
Small	4.4	1.0	1.5	0.2
Medium	3.9	6.6	5.9	0.7
Large	2.6	31.7	25.6	3.6
Sector 2014				
Food	2.8	1.5	2.9	0.2
Beverages	5.3	3.8	5.1	0.0
Textiles	7.1	1.7	1.5	0.3
Apparel	7.4	2.6	1.4	0.0
Leather	6.4	2.3	3.4	0.4
Wood	2.5	0.4	2.7	0.0
Paper	3.1	2.8	3.2	0.7
Printing	3.3	1.2	2.1	0.0
Coke & refined petrol	4.9	1.5	1.7	0.2
Chemical	6.0	1.9	3.0	0.5
Pharmaceuticals	5.5	6.8	4.8	1.0
Plastics	3.4	1.3	3.1	0.3
Other minerals	3.7	1.0	3.2	0.0
Basic metals	4.3	2.8	2.5	0.1
Other metals	3.4	2.3	2.0	0.4
Computer, electronic	5.7	1.2	2.2	1.0
Electrical machinery	4.7	2.2	2.0	0.7
Machinery n.e.c.	4.7	1.5	1.9	0.5
Motor vehicles	7.3	4.1	1.8	0.1
Transport equipment	4.2	2.9	4.4	0.2

Furniture	4.0	0.4	1.6	0.1
Other manufacturing	4.1	2.3	3.1	0.7
Total	172,427	2.07	1.50	1.72

Note: n.e.c. = not elsewhere classified.

Source: Authors' construction based on tax administrative data.

5 Results

To measure the extent of misallocation and its drivers, the key parameters of the underlying TFP model presented in Section 2 first need to be determined. In line with Hsieh and Klenow (2009), we set the rental price of capital to 0.1, which is the sum of the real interest rate and the depreciation rate. The elasticity of substitution is set at 3 to simplify the analysis; this is a lower bound in terms of the typical values found in empirical studies examining the substitutability of manufacturing goods.[8] The elasticity of labour is allowed to vary across sectors and is computed as the sector average ratio of real wages in real value added. The average across all sectors is 0.44. As indicated in Section 3, the elasticity of capital is simply 1 minus this share. Using these parameters and the data, we estimate MRPK, MPRL, and TFPR using Equations 1, 2, and 3, respectively. We trim the top and bottom 1 per cent of the distribution of TFPR to eliminate outliers.

In Table 4 we document the extent of misallocation by examining the dispersion in TFPR, MRPK, and MRPL (in logs) in each year. We compute the variance within sector-time by weighting each firm by its contribution to total value added in that sector and time period. We aggregate the sector-time variance measures to an annual measure for the manufacturing sector by weighting each sector by its contribution to total value added of the manufacturing sector in that time period. We apply this method of aggregation to all measures in our analysis. In Table 4 we also present the distance between the 25th and 75th percentiles of the distribution, and the distance between the 10th and 90th percentiles of the distribution. The density functions for each measure are presented in the Appendix.

[8] As a robustness check, we set sigma equal to 5. The results are not qualitatively different and are available on request.

Table 4: Dispersion of TFPR, MRPK, and MRPL

	2010	**2011**	**2012**	**2013**	**2014**
lnTFPR					
Std Dev.	0.745	0.775	0.803	0.944	0.858
75–25	0.876	0.939	0.965	0.995	1.023
90–10	1.794	1.873	1.929	2.048	2.067
Number of firms	29,734	30,366	29,254	28,635	24,607
	2010	2011	2012	2013	2014
lnMRPK					
Std dev.	1.324	1.566	1.513	1.651	1.630
75–25	1.538	1.670	1.697	1.729	1.747
90–10	3.114	3.302	3.350	3.497	3.528
Number of firms	29,734	30,366	29,254	28,635	24,607
	2010	2011	2012	2013	2014
lnMRPL					
Std dev.	0.575	0.748	0.658	0.649	0.693
75–25	0.550	0.521	0.556	0.633	0.626
90–10	1.151	1.119	1.163	1.350	1.335
Number of firms	29,734	30,366	29,254	28,635	24,607

Source: Authors' construction based on tax administrative data.

The dispersion in the distribution of TFPR widened between 2010 and 2013, dipping slightly in 2014. The widening distribution is also reflected in the increase in the inter-quartile range and the distance between the 10th and 90th percentiles of the distribution. The density functions presented in the Appendix also illustrate the widening of the distribution of TFPR over time. It should be noted, however, that the level of TFPR increased over the period, as illustrated by the shift to the right in the mean of the distribution. This suggests that while productivity has increased during the period under study, it has not increased by as much as it could have if resources had been more efficiently allocated across firms.

It is also clear from Table 4, and the density functions presented in the Appendix, that the distribution of the marginal products of both capital and labour across firms is also widening over time, but to a much greater extent for capital. Table 5 presents a decomposition of the variance of TFPR into three components: the component attributable to the variance in MRPK, the component attributable to the variance in MRPL, and the component attributable to the covariance between MRPK and MRPL.[9] It is clear that the majority of the variance in TFPR is attributable to capital misallocation. The dispersion in the distribution of MRPL is much tighter.[10] This suggests that the main distortions impacting the misallocation of resources in South Africa are capital-specific rather than aggregate distortions affecting the allocation of both capital and labour. Also of note is the fact

[9] The decomposition is given by:

$$var(TFPR) = \alpha_s^2 var(MRPK) + (1-\alpha_s)^2 var(MRPL) + 2\alpha_s(1-\alpha_s)cov(MRPK, MRPL)$$

[10] This is consistent with findings from other countries. See, for example, Gopinath et al. (2015), who show a widening dispersion in productivity in Southern European countries that is associated with a widening dispersion in the returns to capital between 1999 and 2012, and a stable distribution in the returns to labour.

that the covariance between MRPL and MRPK is negative, indicating that the returns to these factors move in opposite directions. The magnitude is, however, small.

Table 5: Variance decomposition of TFPR

	2010	2011	2012	2013	2014
Variance lnTFPR	0.555	0.601	0.644	0.891	0.736
Contribution of:					
lnMRPK	0.553	0.773	0.717	0.863	0.839
lnMRPL	0.061	0.107	0.081	0.079	0.091
Covariance	−0.059	−0.279	−0.154	−0.051	−0.194

Source: Authors' construction based on tax administrative data.

To place this in context we consider other studies that have used a similar approach to determine the extent of misallocation. In Table 6 we compare the standard deviation in lnMRPK and lnMRPL for a selection of European countries for the 1996–2013 period. These are taken from Larrain and Stumpner (2017).

Despite the much longer time period considered in Larrain and Stumpner's (2017) study, the dispersion in MRPK is much greater in South Africa than in Europe. It is not surprising that the dispersion is higher relative to more-developed European countries, but it is notable that the dispersion is so much greater than that of the collection of Eastern European countries considered in their study. Also of note is the relatively low level of MRPL relative to that of the other countries, suggesting that labour resource may in fact be more efficiently allocated in South Africa compared with other country contexts.

Table 6: Measures of misallocation across countries

	Std dev. lnMRPK	Std dev. ln MRPL
South Africa (2010–14)	1.537	0.665
Austria (1996–2013)	1.087	1.031
Belgium (1996–2013)	1.153	1.094
France (1996–2013)	1.001	0.950
Germany (1996–2013)	1.076	1.021
Netherlands (1996–2013)	1.142	1.083
Eastern Europe (1996–2013)	1.306	1.282

Note: The ten Eastern European countries are Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Ukraine.

Source: Authors' construction based on tax administrative data.

We also explore heterogeneity in the extent of misallocation across subsectors of manufacturing. The model assumes that firms within sectors in a particular time period use the same technology, and so it is the dispersion within sector-time in TFPR that we are interpreting as misallocation. This means that we can easily compare differences in the dispersion of TFPR across sectors. The standard deviation in TFPR by sector is presented in Table 7.[11] While all sectors experience a widening in the distribution of TFPR, there are some differences across sectors in the extent of misallocation. The sectors where resources are most misallocated include the manufacture of paper, and of coke and refined petroleum. Higher levels of misallocation are also evident in textiles and the manufacture of motor vehicles. Resources are more efficiently allocated in more-traditional sectors such as furniture, beverages, food, and wood.

A key focus in this paper is the extent to which misallocation differs along the size distribution of firms. We consider two approaches to examining heterogeneity in misallocation along the size distribution. The first approach is to assume that firms of all sizes within a sector and a particular time period use the same technology. We compute TFPR, MRPK, and MRPL, as above for each firm, but in computing the variances we weight each firm in a sector-year by their contribution to total value added within their size category. To compute an annual average for all of manufacturing for each size group in a particular year, we aggregate by weighting each sector size group average by the contribution of that sector size group to total value added in that size group in all of manufacturing.

Table 7: Heterogeneity across sectors in standard deviation of lnTFPR

	2010	2011	2012	2013	2014
10: Food	0.670	0.671	0.679	0.694	0.739
11: Beverages	0.569	0.571	0.514	0.672	0.634
13: Textiles	0.801	0.744	0.801	0.926	0.848
14: Wearing apparel	0.890	0.605	0.607	0.724	0.706
15: Leather	0.899	0.952	0.935	0.794	0.871
16: Wood	0.624	0.586	0.675	0.649	0.768
17: Paper	0.708	1.054	1.041	1.044	1.163
18: Printing	0.658	0.723	0.737	0.805	0.725
19: Coke and refined petroleum	0.905	0.913	0.840	1.376	0.977
20: Chemicals	0.672	0.702	0.735	0.776	0.763
21: Pharmaceuticals	0.474	0.657	0.647	1.202	0.892
22: Rubber and plastics	0.643	0.713	0.664	0.712	0.812
23: Other minerals	0.949	0.815	0.814	0.853	0.838
24: Basic metals	0.659	0.792	1.022	0.933	0.882
25: Fabricated metals	0.596	0.628	0.644	0.754	0.745
26: Computer, electronic, optical products	0.563	0.751	0.851	0.810	0.942
27: Electrical equipment	0.667	0.712	0.725	0.652	0.719
28: Machinery n.e.c.	0.610	0.822	0.811	0.911	0.860
29: Motor vehicles	0.928	0.773	0.903	0.791	0.873
30: Transport equipment	0.722	0.693	0.695	0.730	0.783
31: Furniture	0.584	0.609	0.635	0.590	0.688
32: Other manufacturing	0.647	0.701	0.680	0.736	0.776

Source: Authors' construction based on tax administrative data.

[11] For all sectors, the dispersion in MRPK is the driving factor behind the wide, and widening, dispersion in TFPR. Results not presented but available on request.

A key focus in this paper is the extent to which misallocation differs along the size distribution of firms. We consider two approaches to examining heterogeneity in misallocation along the size distribution. The first approach is to assume that firms of all sizes within a sector and a particular time period use the same technology. We compute TFPR, MRPK, and MRPL, as above for each firm, but in computing the variances we weight each firm in a sector-year by their contribution to total value added within their size category. To compute an annual average for all of manufacturing for each size group in a particular year, we aggregate by weighting each sector size group average by the contribution of that sector size group to total value added in that size group in all of manufacturing.

We use the World Bank definition of micro, small, medium, and large firms.[12] Firms in the largest size group contribute the most to output, at 49 per cent. Medium-sized firms account for 27 per cent of output, small firms 19 per cent, and micro firms 8 per cent. The standard deviations in TFPR, MRPK, and MRPL for each size group in 2010 and 2014 are presented in Table 8.

Table 8: Dispersion in distribution of TFPR, MRPK, and MRPL for different size groups

	2010	2011	2012	2013	2014
Micro firms					
lnTFPR	0.594	0.619	0.779	0.910	0.913
lnMRPK	1.698	1.830	2.036	2.218	2.399
lnMRPL	0.397	0.511	0.593	0.831	0.675
Small firms					
lnTFPR	0.469	0.495	0.566	0.614	0.619
lnMRPK	1.371	2.147	1.581	2.680	2.944
lnMRPL	0.369	1.047	0.387	0.966	1.168
Medium firms					
lnTFPR	0.363	0.412	0.415	0.479	0.468
lnMRPK	1.906	1.259	1.267	1.430	1.344
lnMRPL	0.319	0.379	0.376	0.352	0.424
Large firms					
lnTFPR	0.317	0.248	0.284	0.290	0.246
lnMRPK	0.785	0.761	0.729	0.699	0.672
lnMRPL	0.227	0.318	0.237	0.285	0.245

Source: Authors' construction based on tax administrative data.

The dispersion in the distribution of productivity is negatively correlated with firm size, suggesting that resources are misallocated to a greater degree among smaller firms, in particular the micro firms. We find that the dispersion in productivity among micro firms widens considerably between 2009 and 2014. This is due to a widening in the dispersion of both MRPK and MRPL. Small and medium-sized firms also experience a widening in the dispersion of the distribution of TFPR, but to a lesser extent. The largest firms experience a narrowing in the dispersion of TFPR, which can be attributed to a more efficient allocation of capital over time. This suggests that the distortions leading to resource misallocation disproportionately affect smaller firms. Resource misallocation may have negative consequences beyond productivity growth if small and medium-sized enterprises

[12] Micro firms are those with 1–9 employees, small firms have 10–49 employees, medium firms 50–299 employees, and large firms 300+ employees.

(SMEs) in South Africa are expected to be an engine for private sector development, job creation, and social inclusion.

The second approach we use to examine differences in the dispersion of revenue productivity and the marginal revenue products across size categories is to relax the assumption of a common technology across different-sized firms within sectors in a particular year. We assume that firms in different size categories have different elasticities of capital and labour, and estimate lnTFPR, lnMRPK, and lnMRPL separately for each size group. Table 9 presents the variance in lnTFPR over time for different size groups, along with its decomposition into the contribution of the variance of lnMRPK and lnMRPL and the covariance between the two, where the assumption of a common technology across size groups is relaxed.

As suggested by the analysis presented in Table 8, resources are most misallocated among micro firms, with capital misallocation being the main contributing factor. The extent of misallocation is increasing over time for this group. In the case of micro firms, the covariance between lnMRPK and lnMRPL is positive in the later time period, indicating that as lnMRPK increases, so too does lnMRPL, and suggesting that there are distortions restricting both labour and capital inputs for micro firms.

As observed in Table 8, the extent of misallocation decreases with firm size. Large firms have the narrowest dispersions in lnTFPR and its components. This suggests that firms in the largest size group are the least likely to be affected by distortions, and that the allocation of labour and capital between firms in this group is more efficient. Moreover, it appears that misallocation is declining over time for large firms, in contrast to micro, small, and medium firms.

Table 9: Decomposition in distribution of TFPR for different size groups, relaxing the common technology assumption

	2010	2011	2012	2013	2014
Micro firms					
Variance lnTFPR	0.601	0.761	1.057	0.971	1.185
Contribution of:					
lnMRPK	0.562	0.650	0.796	0.778	0.884
lnMRPL	0.066	0.108	0.132	0.148	0.199
Covariance	−0.027	0.003	0.130	0.045	0.102
Small firms					
Variance lnTFPR	0.443	0.456	0.520	0.524	0.503
Contribution of:					
lnMRPK	0.400	0.641	0.457	0.769	0.816
lnMRPL	0.077	0.210	0.079	0.196	0.235
Covariance	−0.034	−0.394	−0.016	−0.442	−0.548
Medium firms					
Variance lnTFPR	0.393	0.418	0.494	0.514	0.468
Contribution of:					
lnMRPK	0.374	0.402	0.433	0.458	0.416
lnMRPL	0.060	0.074	0.082	0.074	0.080
Covariance	−0.041	−0.059	−0.021	−0.018	−0.028
Large firms					
Variance lnTFPR	0.381	0.335	0.333	0.352	0.280
Contribution of:					
lnMRPK	0.310	0.287	0.270	0.268	0.241
lnMRPL	0.045	0.065	0.047	0.042	0.042
Covariance	0.026	−0.017	0.016	0.042	−0.002

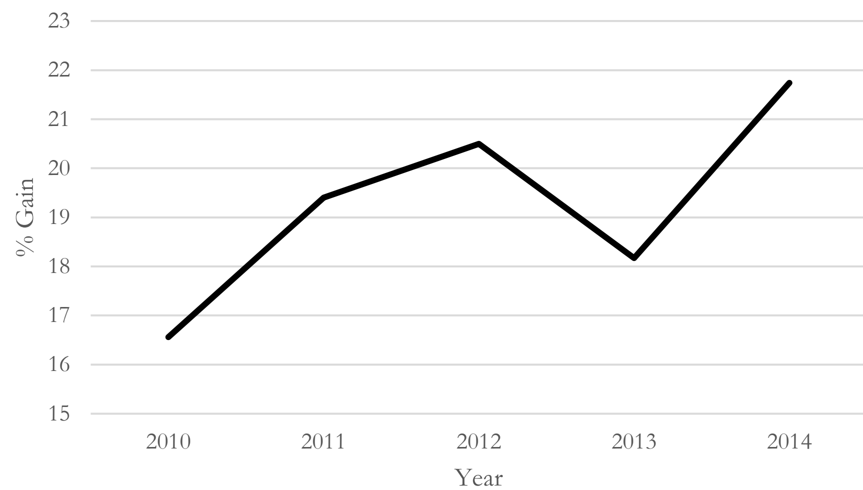
Source: Authors' construction based on tax administrative data.

The pattern of misallocation across size groups presented in Tables 8 and 9 suggests that misallocation is driven by the inefficient allocation of inputs among micro, small, and medium firms. While there is some misallocation evident among large firms, it is of a much smaller magnitude and declines over the time frame of the analysis. This will have implications for the overall impact of misallocation on productivity, given that firms in the largest size group, where misallocation is less of a concern, account for almost half of total output.

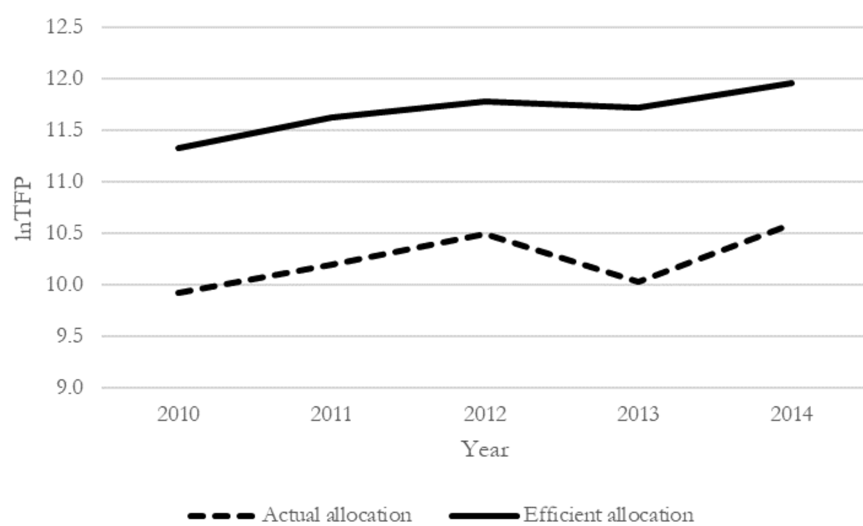
We now turn to the second stage of our analysis, where we quantify empirically the impact of misallocation on aggregate productivity for the economy. Using Equation 6 we compute how much of a productivity gain would result from reallocating capital and labour resources within sectors in a particular time period to their most efficient use. As graph A in Figure 1 illustrates, the annual potential gain in aggregate TFP is between 16 and 22 per cent. Given that year-on-year changes in TFP in South African manufacturing have been small (see Kreuser and Newman 2018), changes in the extent of resource misallocation can have a meaningful aggregate effect. In graph B in Figure 1, the change in the efficient level of productivity is compared with the actual level of productivity. There was some convergence between 2010 and 2012 but a divergence was observed thereafter.

Figure 1: Potential gain in aggregate TFP if resources were efficiently allocated

A: Gain in TFP: Efficient vs actual allocation of resources



B: lnTFP: Efficient vs actual allocation of resources

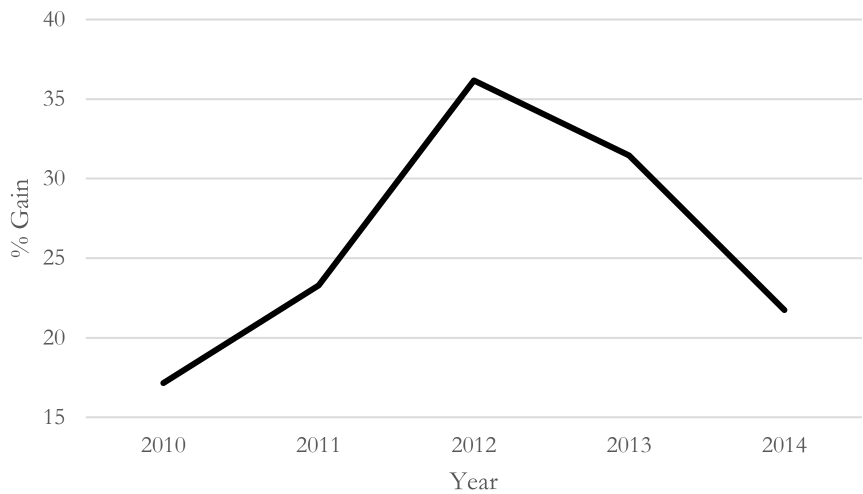


Source: Authors' construction based on tax administrative data.

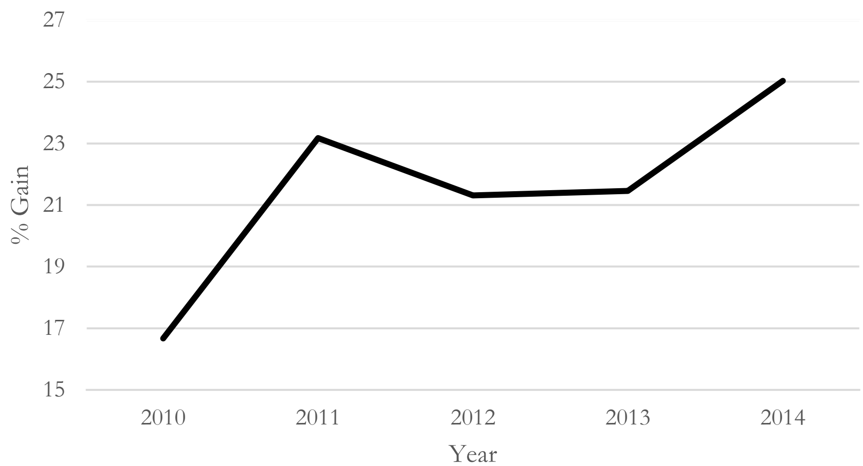
Given the differences in the extent of misallocation across different-sized firms, we estimate the impact of misallocation on TFP separately for different size groups using the assumption that they use different technologies (i.e. based on the dispersions presented in Table 9). Figure 2 illustrates the differences across time for each size group. For all groups the potential gains in productivity are large. The gains are greatest, however, for the largest firms. This is despite the fact that the extent of misallocation for this size group is lower than for the other size groups and reflects the fact that productivity and productivity growth are highest for large firms. We estimate that in 2009, if resources were efficiently allocated, productivity would have been 60 per cent higher. As the extent of misallocation fell between 2009 and 2014, so too do the potential gains, but they are still high. In 2014, addressing the misallocation of labour and capital resources among large firms could have increased productivity by 44 per cent. This could have had significant effects on aggregate productivity given that these firms account for over half of the output in the manufacturing sector.

Figure 2: Potential gain in aggregate TFP if resources were efficiently allocated for different size groups

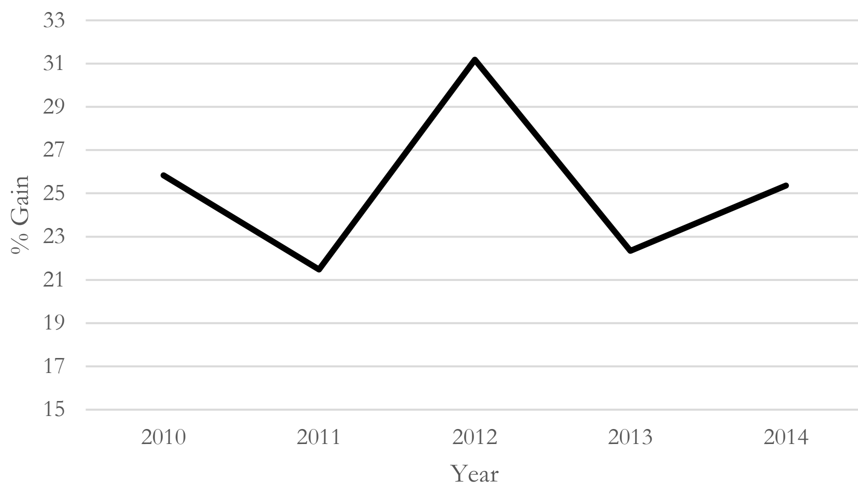
A: Micro firms



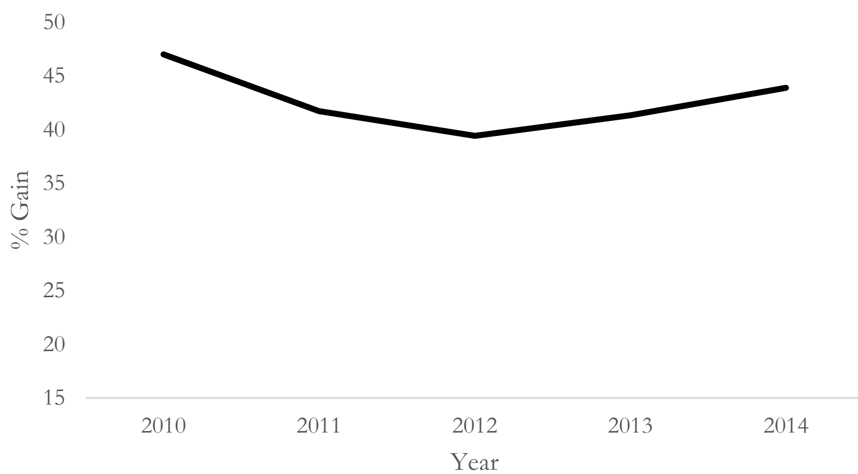
B: Small firms



C: Medium firms



D: Large firms



Source: Authors' construction based on tax administrative data.

Productivity gains due to a reallocation of resources, although more modest, are also possible among other size groups. For micro firms, in 2014, productivity gains of 40 per cent could have been achieved, while for small and medium-sized firms there would have been potential for productivity gains of around 25 per cent in 2014 due to a reallocation of resources.

Our analysis suggests that, as in other contexts, the misallocation of resources in South Africa is leading to aggregate productivity losses. It further suggests that this is primarily due to capital misallocation, but may also be related to a misallocation of labour among micro firms. The next question we ask is to what extent we can attribute the measured misallocation to observable distortions. We examine the correlation between the standard deviation within sector-size-time of lnTFPR, lnMRPK, and lnMRPL and specific policy measures put in place by the South African government (see Section 2 for details and Table 2 in Section 4) that could potentially distort the allocation of resources. For each sub-grouping of firms (sector-size-year) we compute the proportion of firms in that sector that has benefited from one of the policy measures (depreciation allowance, R&D allowance, and learnership allowance). We also examine the role of credit, given the evidence to date on how credit constraints can distort the distribution of returns to capital found in other contexts (Brandt et al. 2013; Caballero et al. 2008; Caggese and Cuñat 2013; Gopinath et al. 2015; Midrigan and Xu 2014) and the fact that the main driver of misallocation in our context is the misallocation of capital. Our measure of credit or borrowing is current liabilities less cash as a proportion of total capital (as in Gopinath et al. 2015). For the sector-size-year-specific measure we take the average across all firms.

We estimate Equation 7, which includes dummy variables for the size category, the sector, and the year. The results are presented in Table 10. Access to long-term credit is positively correlated with the dispersion in lnTFPR and lnMRPK. It is also correlated with the dispersion in MRPL but not when lags are included. This suggests that a key reason for the misallocation is access to credit. Other markers of relevance include the depreciation allowance. In sector size groups where there is greater access to the depreciation allowance the dispersion of MRPL is lower, suggesting that it is associated with a more efficient allocation of labour. While the R&D and learnership allowances also appear to narrow the dispersion in productivity, once adjustment costs are controlled for we find that this is only the case for lnMRPL.

We perform a number of other robustness checks on our results to account for the various critiques in the literature of the indirect approach to detecting misallocation and its drivers that we adopt in this paper. First, as seen above, we detect heterogeneity across the size distribution in the extent of misallocation. Part of this may be due to different technologies being used by different-sized firms, meaning that a comparison of marginal products across these firms will pick up differences in underlying production processes and not misallocation as we have defined it here. Moreover, as illustrated by the descriptive statistics presented in Section 3, the various government incentive schemes considered here are mainly accessed by large firms. We perform a similar exercise for each size category considering how the standard deviation in lnTFPR, lnMRPK, and lnMRPL within sectors in each size group varies with borrowing and the policy measures. The results are presented in Table 11.

Table 10: Markers of misallocation

	(1)	(2)	(3)	(4)	(5)	(6)
	lnTFPR	**lnTFPR**	**lnMRPK**	**lnMRPK**	**lnMRPL**	**lnMRPL**
Credit /K	2.308***	1.309***	3.671***	2.184***	0.730*	0.442
	(0.270)	(0.285)	(0.463)	(0.537)	(0.387)	(0.491)
Dep allow	−0.164	−0.178	−0.224	−0.330	−0.317**	−0.664***
	(0.103)	(0.111)	(0.177)	(0.209)	(0.148)	(0.191)
R&D allow	−0.269**	0.110	−0.600***	0.278	−0.257	0.025
	(0.130)	(0.150)	(0.223)	(0.282)	(0.186)	(0.258)
Learnership	−0.284***	0.136	−0.556***	−0.029	−0.187	−0.323*
	(0.090)	(0.111)	(0.155)	(0.209)	(0.129)	(0.191)
L. Credit /K		−0.103		−0.126		−0.070
		(0.253)		(0.476)		(0.436)
L.Dep allow		−0.031		−0.214		0.048
		(0.108)		(0.204)		(0.186)
L.R&D allow		−0.135		−0.322		−0.093
		(0.166)		(0.312)		(0.285)
L.Learnership		−0.059		−0.357*		−0.230
		(0.103)		(0.193)		(0.177)
Constant	0.645***	0.774***	1.102***	1.103***	0.649***	0.646***
	(0.014)	(0.034)	(0.024)	(0.063)	(0.020)	(0.058)
Observations	440	364	440	364	440	364
R-squared	0.328	0.637	0.328	0.574	0.136	0.344

Notes: Standard errors clustered at the sector-time level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' construction based on tax administrative data.

Once adjustment costs are accounted for, we find that the main driver of misallocation among micro firms is borrowing. We also find some evidence of misallocation associated with borrowing for medium and large firms. The policy variables appear to have, in general, very little relation to the dispersion in TFPR and MRPK. There are some exceptions. First, among medium and large firms, in sectors where a higher proportion of firms have learnerships, the dispersion in productivity is greater. This cannot be attributed directly to either lnMRPK or lnMRPL. Second, for medium-sized firms, we find that in sectors where a larger proportion of firms have access to the R&D allowance, the dispersion in productivity is narrower. A small number of firms in general access this allowance, so this is a surprising result. While not statistically significant, the relationship seems to be driven by the dispersion in lnMRPL, which is narrower (i.e. labour resources are applied more efficiently) in these sectors. We also find some evidence that among micro firms, in sectors where a greater proportion of firms access the depreciation allowance, the dispersion in lnMRPL is narrower, suggesting that labour is allocated more efficiently in those sectors.

Table 11: Markers of misallocation by size group

	(1) lnTFPR	(2) lnMRPK	(3) lnMRPL	(4) lnTFPR	(5) lnMRPK	(6) lnMRPL	(7) lnTFPR	(8) lnMRPK	(9) lnMRPL	(10) lnTFPR	(11) lnMRPK	(12) lnMRPL
		Micro			*Small*			*Medium*			*Large*	
Credit /K	5.342***	3.830***	4.001*	1.213	3.152	1.621	−1.186	0.155***	0.120	1.535*	2.489*	−0.080
	(1.136)	(1.303)	(2.070)	(1.104)	(3.067)	(4.213)	(1.512)	(0.022)	(2.806)	(0.790)	(1.398)	(1.266)
Dep allow	−5.162	−0.346	−27.857***	0.808	0.104	1.089	0.191	−0.006	−0.601	−0.147	0.193	−0.403
	(4.403)	(5.054)	(8.028)	(1.416)	(3.933)	(5.402)	(0.397)	(0.018)	(0.738)	(0.216)	(0.382)	(0.346)
R&D allow	5.484	3.429	37.536	−3.597	−0.602	−8.346	−1.614**	0.081	−0.439	−0.081	−0.634	0.106
	(13.518)	(15.515)	(24.643)	(3.128)	(8.690)	(11.937)	(0.689)	(0.052)	(1.278)	(0.251)	(0.444)	(0.402)
Learnership	−13.046	−21.809	−12.809	−1.024	4.998	12.680	1.810***	0.031	−0.301	0.800***	0.639	0.116
	(17.526)	(20.115)	(31.951)	(3.176)	(8.822)	(12.119)	(0.576)	(0.026)	(1.070)	(0.240)	(0.425)	(0.385)
L. Credit /K	3.404***	1.648	3.564*	0.860	0.172	1.740	0.364	0.075***	0.874	0.038	−0.878	0.800
	(1.097)	(1.259)	(2.000)	(1.161)	(3.226)	(4.431)	(1.223)	(0.012)	(2.269)	(0.744)	(1.317)	(1.193)
L.Dep allow	−1.522	0.270	−18.104**	2.346*	−1.254	0.936	0.348	−0.015	0.949	0.034	0.575	−0.075
	(4.186)	(4.804)	(7.631)	(1.209)	(3.359)	(4.613)	(0.341)	(0.018)	(0.632)	(0.197)	(0.349)	(0.316)
L.R&D allow	−24.261***	−1.284	−47.947***	1.055	5.026	0.847	1.423***	0.035	1.026	0.004	−0.058	0.192
	(8.266)	(9.487)	(15.070)	(1.921)	(5.336)	(7.329)	(0.448)	(0.055)	(0.831)	(0.251)	(0.444)	(0.402)
L.Learnership	−17.197	−11.654	−27.496	−0.455	−1.073	1.212	0.690	0.038	−0.603	0.164	−0.157	0.081
	(27.919)	(32.044)	(50.898)	(2.388)	(6.635)	(9.114)	(0.564)	(0.024)	(1.046)	(0.188)	(0.332)	(0.301)
Constant	0.587***	1.097***	0.755***	0.647***	1.083***	0.551***	0.462***	0.092	0.461***	0.468***	0.423**	0.725***
	(0.130)	(0.149)	(0.237)	(0.045)	(0.126)	(0.173)	(0.058)	(0.105)	(0.108)	(0.117)	(0.207)	(0.187)
Observations	79	79	79	77	77	77	76	15,949	76	78	78	78
R^2	0.785	0.730	0.686	0.750	0.777	0.592	0.898	0.102	0.646	0.717	0.756	0.660

Notes: Standard errors clustered at the sector-time level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' construction based on tax administrative data.

The analysis presented here is quite aggregate, and no causal interpretation should be placed on the correlations that are observed. It is nevertheless useful to consider the proportion of the variation in revenue productivity and marginal returns that these observable markers are actually explaining. To do this we turn to a firm-level regression analysis where we consider the proportion of the overall variation in lnTFPR, lnMRPK, and lnMRPL that we can actually explain with these markers. In Table 12, we present the R^2 from a series of such firm-level regressions for the purpose of comparing the R^2 from a baseline model, which controls for time, sector, and sector–time interactions, and specifications that include various combinations of the policy variables. We also consider a specification where we include lags of the policy variables to capture frictions or adjustment costs that cause a delay in any resulting resource reallocation, and disaggregate the results by size group.

Table 12: Reduced form analysis of dispersion in lnTFPR, lnMRPK, and lnMRPL

	(1) lnTFPR	(2) lnMRPK	(3) lnMRPL
Baseline R^2	0.074	0.060	0.045
Baseline + credit R^2	0.186	0.199	0.049
Baseline + credit + policy R^2	0.187	0.200	0.050
Baseline + credit + policy + lags R^2	0.202	0.214	0.053
Micro firms			
Baseline R^2	0.055	0.033	0.077
Baseline + credit R^2	0.185	0.189	0.079
Baseline + credit + policy R^2	0.185	0.189	0.079
Baseline + credit + policy + lags R^2	0.202	0.203	0.094
Small firms			
Baseline R^2	0.055	0.048	0.024
Baseline + credit R^2	0.167	0.189	0.030
Baseline + credit + policy R^2	0.168	0.190	0.031
Baseline + credit + policy + lags R^2	0.178	0.196	0.035
Medium firms			
Baseline R^2	0.078	0.085	0.009
Baseline + credit R^2	0.173	0.216	0.017
Baseline + credit + policy R^2	0.175	0.218	0.019
Baseline + credit + policy + lags R^2	0.211	0.257	0.023
Large firms			
Baseline R^2	0.112	0.124	0.030
Baseline + credit R^2	0.177	0.224	0.035
Baseline + credit + policy R^2	0.190	0.240	0.038
Baseline + credit + policy + lags R^2	0.231	0.282	0.048

Source: Authors' construction based on tax administrative data.

In each case, the baseline specification explains very little of the observed misallocation. For lnTFPR, only 7.4 per cent of the variation is explained through the baseline controls, for lnMRKP ony 6 per cent, and for lnMRPL only 4.5 per cent. The first policy variable we consider is our measure of a firm's access to credit. We find that including this variable significantly increases the explanatory power of the model in explaining the variation in lnTFPR. The R^2 increases from 7.4 per cent in the baseline specification to 18.6 per cent. This suggests that 11.2 per cent of the variation in the dispersion of lnTFPR can be explained by whether or not a firm has access to credit.

Including the credit variable in the regression of lnMRPK increases the R^2 from 6 per cent in the baseline to 19.9 per cent, suggesting that 13.9 per cent of the variation in lnMRPK can be explained by access to credit. In the case of lnMRPL, the inclusion of credit improves explanatory power but only by a very small magnitude (an increase from 4.5 per cent in the baseline specification to 4.9 per cent) Adding the policy variables barely increases the R^2, suggesting that they are not major contributing factors to misallocation.

To account for the possibility that there are adjustment costs associated with the policy variables themselves we also include the lag of each policy variable. The additional explanatory power is less than 2 per cent in each specification. This implies that a very large proportion of the variation in lnTFPR, lnMRPK, and lnMRPL remains unexplained, even after we have controlled for the policy variables and adjustment costs. The key driver is access to credit.

We perform a similar exercise for different size groups. Focusing on credit, we find that for micro firms, access to credit explains 13 per cent of the variation in lnTFPR, for small firms 11.2 per cent, for medium firms 9.5 per cent, and for large firms 6.5 per cent. This reinforces our finding that credit is an important driver of misallocation, and disproportionately so for the smallest firms. We find that the policy variables themselves have little explanatory power.

The final challenge in interpreting these findings is to quantify the loss in productivity due to the misallocation that we can actually explain through the policy variables. As discussed above, a critique of the indirect approach is that some misallocation may in fact be due to measurement error. As shown in Table 12, the policy variables and the baseline controls explain 18.7 per cent of the variation in lnTFPR. With a baseline R^2 of only 0.074, this suggests that we manage to explain 11.3 per cent of the dispersion in lnTFPR with the policy variables. Figure 1 illustrates the potential gain in TFP if resources were reallocated to achieve allocative efficiency. We reproduce these gains in Table 13. If we are conservative and assume that only 11.3 per cent of this gain can actually be achieved through reallocations resulting from government policy, the average annual gain in productivity would be approximately 2 per cent. These gains, although modest relative to the overall potential gains, are qualitatively significant in the context of a country where TFP growth in manufacturing was around 3 per for the entire 2010–13 period (Kreuser and Newman 2018).

Table 13: Potential gains in productivity attributable to policy variables

	2010	2011	2012	2013	2014
All firms					
Aggregate gains	16.6	19.4	20.5	18.2	21.7
Gains through policy	1.9	2.2	2.3	2.1	2.5
Micro firms					
Aggregate gains	17.1	23.3	36.2	31.4	40.8
Gains through policy	2.2	3.0	4.7	4.1	5.3
Small firms					
Aggregate gains	16.7	23.2	21.3	21.5	25.0
Gains through policy	1.9	2.6	2.4	2.4	2.8
Medium firms					
Aggregate gains	25.8	21.4	31.1	22.3	25.4
Gains through policy	2.5	2.1	3.0	2.2	2.5
Large firms					
Aggregate gains	47.0	41.7	39.4	41.3	43.9
Gains through policy	3.7	3.3	3.1	3.2	3.4

Source: Authors' construction based on tax administrative data.

We perform a similar exercise across the size distribution. We consider the proportion of the aggregate potential gains in productivity for each size category of firms presented in Figure 2 that can be influenced through the policy variables as determined by the proportion of the variation in lnTFPR that can be explained by the policy variables within each size category as presented in Table 12. The largest gains would be for micro firms, with an average annual productivity gain of 3.9 per cent, while gains for small and medium firms would amount to around 2.4 per cent per annum. The largest firms would experience productivity gains of 3.3 per cent per annum on average, even though a greater proportion of the variation in lnTFPR among these firms is unexplained.

Overall, our results suggest that misallocation leads to lower-than-optimal aggregate productivity levels for South African manufacturing. The key driver is capital misallocation, and this is associated with heterogeneity in access to borrowing. The policy variables we consider do not appear to be causing distortions in the allocation of inputs.

6 Conclusion

Misallocation of labour and capital has been shown to reduce aggregate productivity in many different country contexts, but there is little empirical evidence of its impact on productivity or its drivers in developing-country contexts. In this paper, we explore the extent of resource misallocation in South African manufacturing, utilizing tax administrative data for the 2010–14 period.

We find evidence of resource misallocation in South African manufacturing which depresses aggregate productivity by between 16 and 22 per cent. This is driven primarily by capital misallocation that is associated with heterogeneity in access to borrowing across firms both within sectors and along the size distribution. We consider also specific policies that could distort the allocation of labour and capital and find no evidence that they have any additional misallocating effect. Our analysis suggests that removing the identifiable distortions could lead to productivity gains of approximately 2.2 per cent per annum. Relative to estimated annual in growth in actual TFP in the sector of 3 per cent per annum, this could meaningfully impact on aggregate productivity. We find considerable heterogeneity across the size distribution, with most misallocation occurring among micro and small firms. As such, any gains in productivity as a result of a readjustment of these policy measures would benefit the smaller end of the size distribution most.

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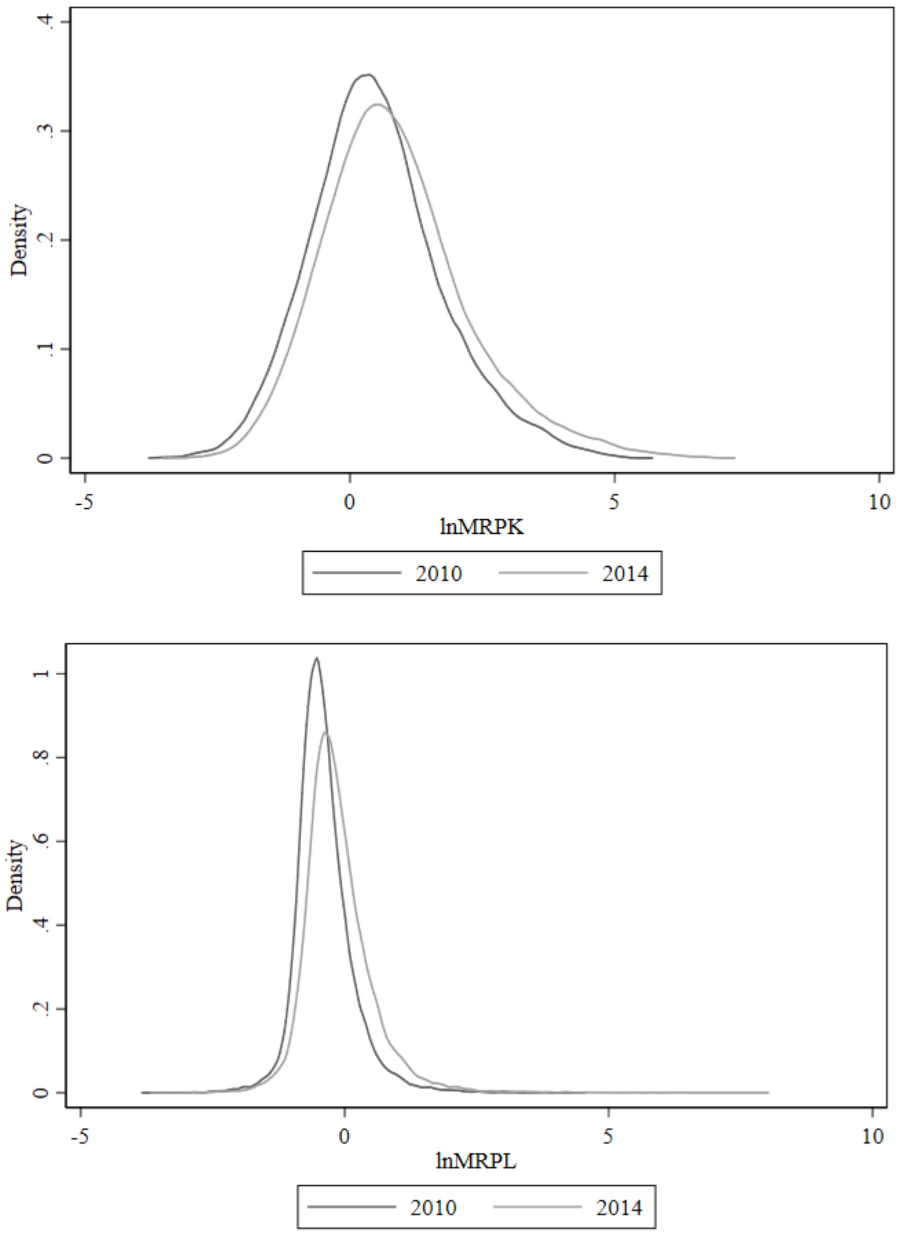
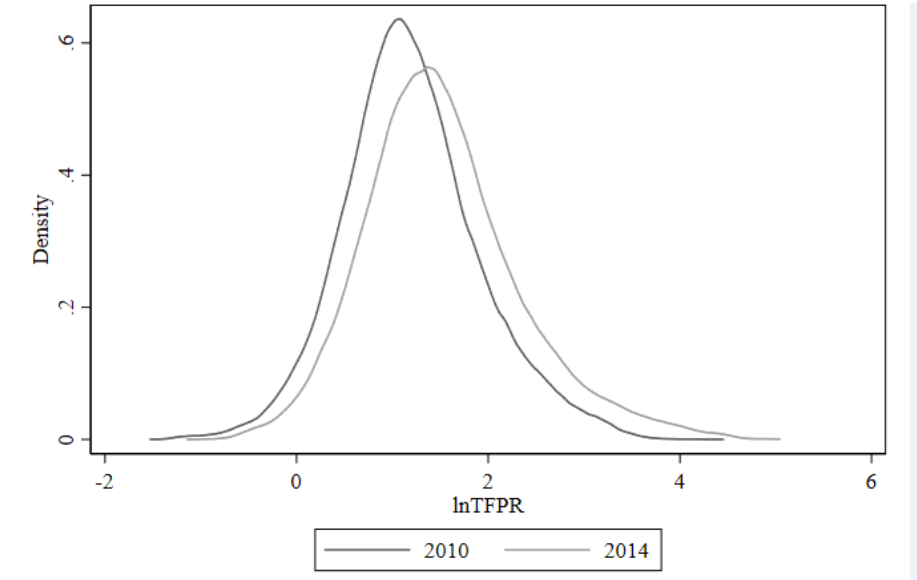
Appendix

Figure A1: Dispersion in MRPK and MRPL, 2010 vs 2014





Source: Authors' construction based on tax administrative data.