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Tariffs, productivity, and resource misallocation

Michael Kilumelume,[1] Bruno Morando,[2] Carol Newman,[3] and John Rand[4]

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Abstract: An often-neglected potential negative consequence of tariffs is the impact they may have on the misallocation of factor inputs. Trade protection can provide space for domestic firms to increase prices and mark-ups, allowing low-productivity firms to survive, thereby leading to a sub-optimal allocation of resources. This paper explores the impact of tariffs on the allocation of capital using administrative data from South Africa. We find that tariffs are highly correlated with capital misallocation, leading to aggregate productivity losses of 5–10 per cent. In particular, tariffs are strongly related to distortions that are correlated with firm productivity. The main channel through which tariffs distort the allocation of capital is through the protection they offer to low-productivity firms, reducing their probability of exiting and increasing firm survival.

Key words: tariffs, productivity, misallocation, South Africa

JEL classification: D24, F14, O12

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[1] UNU-WIDER, Helsinki, Finland, and Stellenbosch University, Stellenbosch, South Africa; [2] Maynooth University, Maynooth, Ireland, and Trinity College Dublin, Dublin, Ireland; [3] Trinity College Dublin, Dublin, Ireland; [4] University of Copenhagen, Copenhagen, Denmark; corresponding author: cnewman@tcd.ie

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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1 Introduction

Tariffs have long been used as a mechanism to protect domestic producers against competition from imports. They are often justified by governments as an anti-dumping policy measure to stop importers from selling products below production costs in local markets. Their purpose is therefore to relieve domestic producers from 'unfair' international competitive pressure. However, levelling the playing field in this way may in fact worsen the productivity of firms affected by anti-competitive practices once tariffs are implemented.

First, firms that are protected from competition as a result of high tariffs on imports have less of an incentive to innovate or reduce slack in their production processes, and so may experience productivity losses or at least slower productivity growth than they would otherwise have achieved in the absence of the tariff (Amiti and Konings 2007; Jabbour et al. 2019; Konings and Vandenbussche 2008). Second, domestic firms that import inputs that are subject to higher tariffs will face higher input costs and a reduction in the foreign varieties at their disposal, which may lead to productivity losses (Amiti and Konings 2007; Halpern et al. 2015). Third, tariffs have been found to be beneficial to relatively less productive plants (Jabbour et al. 2019; Pierce 2011), so it is also possible that tariffs reduce aggregate productivity by leading to a misallocation of factors of production across firms. This latter mechanism is relatively under-explored in the literature.

In this paper, we examine the effect of import tariffs on the allocation of capital across manufacturing firms in South Africa. We consider import tariffs as a type of distortion that affects different sectors and firms in different ways. Their imposition can protect unproductive firms, allowing them to survive and preventing capital and labour from being used more productively elsewhere in the economy (Jabbour et al. 2019). Moreover, they can remove competitive pressures for more productive firms in a sector, allowing increases in prices and mark-ups, creating scope for inefficiencies and slack that would otherwise not be tolerated (Edmond et al. 2015; Pierce 2011). Import tariffs can thus be thought of as a source of distortions that could cause severe inefficiencies in the distribution of inputs. As such, aggregate productivity in the economy as a whole is likely to be negatively affected through a resource misallocation channel. If this is the case, then previous studies measuring the productivity impacts of tariffs have underestimated the true effect.

We use tax administrative data for South Africa (National Treasury and UNU-WIDER 2019a,b, 2021), which allows us to match company income tax (CIT) data to the customs data, which documents all import and export transactions by South African firms. To measure misallocation we use the methodology developed by David and Venkateswaran (2019), who provide a framework for measuring the contribution of a number of factors to misallocation (adjustment costs, uncertainty/informational frictions, correlated distortions, fixed distortions, and transitory distortions) and their consequential impact on productivity. We measure the extent of capital misallocation and its sources for 71 industries within the manufacturing sector for the period 2010–16. We then explore the relationship between tariffs and each of the sources of misallocation and quantify the impact on aggregate productivity. We consider a number of different mechanisms through which tariffs could lead to misallocation, including heterogeneity in mark-ups and technology and firm survival.

We find that tariffs are highly correlated with capital dispersion and, in particular, correlated distortions that are related to the underlying productivity of firms. We estimate that moving from the bottom to the top quartile of the tariff distribution leads to productivity losses of 5–10 per cent. In terms of the underlying mechanisms at work we do not find any evidence that heterogeneity in mark-ups drives misallocation, suggesting that they are not an important channel through which tariffs distort the distribution of capital. We do find evidence that tariffs reduce the probability of firm exit in the lower part of the productivity distribution. This is the most likely mechanism through which tariffs impact aggregate productivity through the capital misallocation channel.

We contribute to the literature in the following ways. First, we add to the broad literature which highlights heterogeneous impacts of trade protection measures on firms (Jabbour et al. 2019; Konings and Vandenbussche 2008, 2013; Melitz 2003). This literature shows that high tariffs and anti-dumping measures protect low-productivity firms and delay firm closures. We provide further empirical evidence for this and examine the implications of the allocation of capital within industries, a channel not previously considered. Second, we contribute to the recent empirical literature focused on identifying the sources of resource misallocation and its implications for productivity.[1] One recent example, and the paper closest in spirit to ours, is David et al. (2020), who examine the sources of capital misallocation across countries and find that distortions that are correlated with firm size and productivity make the largest contribution to capital misallocation. They also find that such distortions are negatively correlated with income per capita and the quality of the business environment.[2] To our knowledge no study has considered the relationship between trade distortions in the form of tariffs and the allocation of capital within industries. We add further to this literature by considering the likely channels through which tariffs distort the allocation of capital and explore the consequences for productivity. Third, we provide new empirical evidence of the impact of tariffs on the manufacturing sector through these channels in South Africa, an emerging economy that has faced significant policy challenges. This will provide valuable lessons for other countries at similar stages of development.

The rest of the paper is structured as follows. In Section 2 we describe the theoretical framework and empirical methodology. In Section 3 we describe the data and provide summary statistics. Our results are presented in Section 4. Section 5 concludes.

2 Theoretical framework and methodology

To measure capital misallocation we adopt the methodology developed by David and Venkateswaran (2019) (DV). Their model extends the theoretical framework proposed by Hsieh and Klenow (2009) to incorporate dynamic investment decisions of firms. This framework provides a set of moments that can be empirically targeted to simultaneously estimate the parameters that determine the contributions of various sources of dispersion to the dispersion in the revenue capital productivity (σ^2_{arpk}). More specifically, the sources considered are: adjustment costs, uncertainty/informational frictions, and other firm-specific distortions.

2.1 Model intuition

Hsieh and Klenow (2009) use a standard model of monopolistic competition with heterogeneous firms and show how distortions that drive wedges between the marginal products of capital and labour across firms will lower aggregate total factor productivity (TFP). The optimal allocation of resources would occur where there are no frictions in capital markets or distortions that prevent labour and capital from being employed by the most productive firms. The optimal allocation of resources would result in the marginal product of labour and capital being equalized across firms within an industry. As such, the

[1] Restuccia and Rogerson (2017) provide a comprehensive overview of the literature on the causes and costs of misallocation. Most notable are the contributions of Hsieh and Klenow (2009), Bartelsman et al. (2013), and David and Venkateswaran (2019). Examples of papers that examine in detail the potential sources of misallocation include Asker et al. (2014), who focus on the role of adjustment costs, and David et al. (2016), who examine the role of uncertainty.

[2] A number of recent papers have highlighted the role of financial frictions in creating distortions that lead to a misallocation of capital (Brandt et al. 2013; Caballero et al. 2008; Caggese and Cuñat 2013; Gopinath et al. 2017; Midrigan and Xu 2014).

dispersion in revenue productivity within an industry can be used to detect misallocation and quantify the contribution it makes to productivity loss. In this seminal work, the dispersion in marginal productivities is directly attributed to unspecified distortions, the magnitude of which is directly matched to the variance in capital and labour marginal products.

DV extend this framework to include the dynamic considerations in firms' investment decisions and crucially allow for 'efficient' sources of dispersion in capital marginal productivity, namely adjustment costs and informational frictions/uncertainty, as well as inefficient sources. The model disentangles five distinct forces that contribute to the ex-post dispersion in the average revenue product of capital, *arpk*.

First, the model assumes that there are capital adjustment costs $\hat{\xi}$, which enter the model through the cost of capital function. In particular, the investment costs Φ for a generic firm i are equal to:

$$\Phi(K_{it+1}, K_{it}) = \frac{\hat{\xi}}{2}\left(\frac{K_{it+1}}{K_{it}} - (1-\delta)\right)^2 K_{it} \tag{1}$$

where K is the firm's stock of capital and δ is the rate of depreciation.

This implies that firms do not fully adjust capital when they experience a productivity shock, as in the presence of convex adjustment costs it might be optimal to spread the investment over years rather than reacting immediately. This will increase the dispersion in capital productivity as firms do not immediately respond to productivity shocks.[3]

Second, capital accumulation will depend on the evolution of productivity. Uncertainty, captured by the parameter V, arises because productivity is a stochastic process and firms receive noisy signals about their future productivity. In particular, the model assumes that firms' TFP a follows an AR(1) process:

$$a_{it} = \rho a_{it-1} + \mu_{it}, \quad \mu_{it} \sim \mathcal{N}(0, \sigma_\mu^2) \tag{2}$$

where μ_{it} is a random shock term and the variance σ_μ^2 is the key parameter defining the typical magnitude of the productivity shocks experienced by firms.

The model allows for firms to be at least partly informed in advance of future productivity shocks. This is captured by a noisy signal s_{it}:

$$s_{it} = \mu_{it} + e_{it}, \quad e_{it} \sim \mathcal{N}(0, \sigma_e^2) \tag{3}$$

where the precision of the signal is inversely proportional to the variance of the noise σ_e^2.

Overall, uncertainty V is a function of both σ_μ^2 and σ_e^2. More specifically:

$$V = \left(\frac{1}{\sigma_\mu^2} + \frac{1}{\sigma_e^2}\right)^{-1} \tag{4}$$

Equation 4 shows that uncertainty is increasing in the variance of both the productivity shock and the noise of the signal, and it drops to zero whenever either is equal to zero (i.e. either productivity is fixed over time, or firms receive a perfect signal about future shocks).

This uncertainty, which can also be interpreted as an information constraint, causes a lag in the investment responsiveness of firms to price and production shocks. This will increase the variance in

[3] In the remainder of the paper, we will refer to adjustment costs using the parameter ξ, which is a re-scaled version of $\hat{\xi}$ in Equation 1.

capital dispersion across firms, especially when productivity shocks are large in magnitude and hard to predict.

Third, the model also incorporates institutional and firm-specific factors that affect the cost of capital, which can best be described as distortions. In the DV model, these distortions can be divided into three components: (1) correlated distortions, which are proportional to productivity; (2) fixed distortions, which are not correlated with firm characteristics and do not change over time; and (3) random distortions.

These distortions are captured by τ_i, which is a firm-specific factor that is an additional cost of capital. It is expressed as:

$$\tau_{it} = \gamma a_{it} + X_i + \varepsilon_{it}, \quad X_i \sim \mathcal{N}(0, \sigma_X^2) \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{5}$$

and consists of the three above-mentioned components. The magnitude of correlated distortions will be captured by γ, the absolute value of which determines the correlation between firm-specific productivity and the cost of capital. The contribution of fixed and random distortions to capital misallocation will be captured by σ_X^2 and σ_ε^2, respectively.

The model allows these five different sources of capital misallocation, as well as their contribution to the dispersion in the marginal productivity of capital σ_{arpk}^2, to be teased out by matching a small number of empirical moments describing the joint dynamic distribution of the accumulation of capital and productivity. The following section provides a more in-depth explanation of the intuition underlying the estimation of the model.

2.2 Model estimation

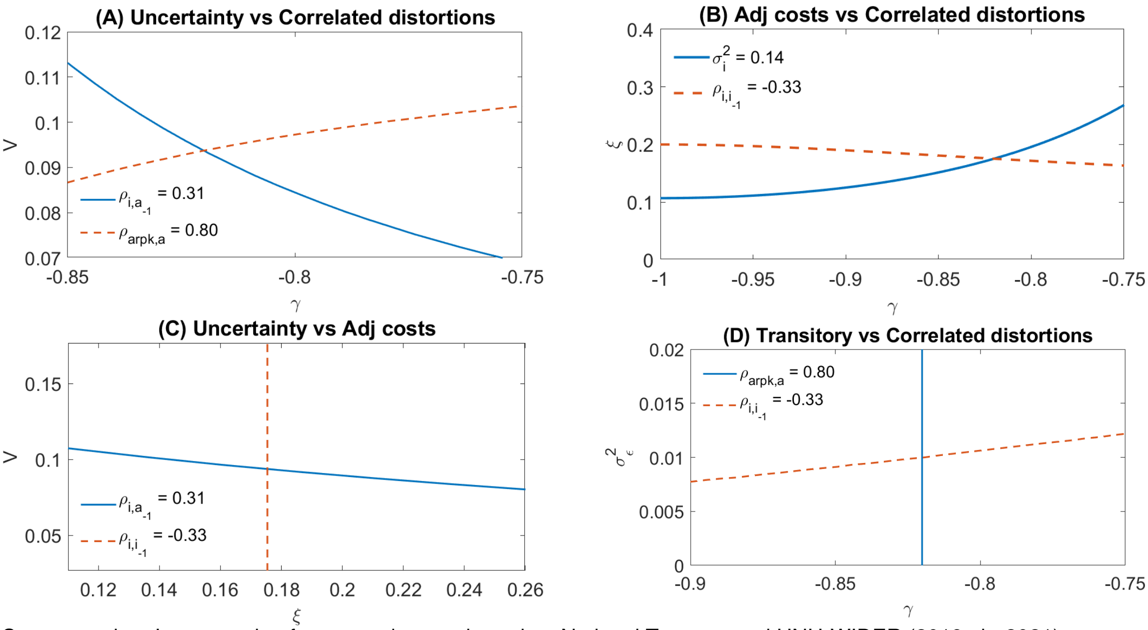
In practical terms, the methodology involves estimating the structural parameters that determine the severity of each of these sources of capital misallocation by matching a set of empirical moments that relate to the structural parameters in a non-linear way. Specifically, five different empirical moments are jointly targeted: (1) the correlation between investment and past productivity shocks $\rho_{i,a_{-1}}$; (2) the autocorrelation of investments $\rho_{i,i_{-1}}$; (3) the correlation between firm productivity and the *arpk* $\rho_{arpk,a}$; (4) the variance of investment σ_i^2; and (5) the dispersion of *arpk* σ_{arpk}^2. We follow DV in setting up the economy-wide parameters defining the within-industry elasticity of substitution θ to 6, the depreciation rate δ to 0.1, and the representative consumer's discount factor β to 0.95.[4] Unlike DV, rather than assuming a certain capital elasticity in the production function, we estimate it separately for each sector as the inverse of the share of labour expenditure in total expenditure.

For the exact mapping of the empirical moments to the structural parameters, we refer the reader to the original DV paper. In what follows, we explain the intuition behind this methodology by examining the moments in a pairwise manner, using an illustrative example of the furniture industry in South Africa.

Using our data (described in Section 3), we estimate the five empirical moments describing the joint capital and productivity distribution for the industry. They are: $\rho_{i,a_{-1}} = 0.31$; $\rho_{i,i_{-1}} = -0.33$; $\rho_{arpk,a} = 0.80$, $\sigma_i^2 = 0.14$, and $\sigma_{arpk}^2 = 1.15$. To estimate the five structural parameters that describe the extent of capital misallocation and its sources for this industry, we find the set of parameters that are consistent with these empirical moments that we find in the data. Figure 1 illustrates this method by plotting the pairwise isomoment curves and illustrating the resulting parameter estimates. Each isomoment represents the range of values for the corresponding parameters that is consistent with the empirical moment in focus.

[4] Changing these parameters only affects the mapping between observed capital productivity dispersion and productivity losses, leaving the main findings of the paper (i.e. the relative contribution of each of the five sources of misallocation and their relationship with tariffs) unaffected. Estimates obtained using different economy-wide parameters are available on request.

Figure 1: Example of method of moments (furniture industry)



Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

In quadrant A of Figure 1, the impact of uncertainty and correlated distortions is disentangled by examining $\rho_{arpk,a}$ and $\rho_{i,a_{-1}}$. Both of these components increase the correlation between *arpk* and productivity. Indeed, if there is a positive productivity shock, due to uncertainty firms will not fully react to that shock and will not invest optimally in capital. As such, firms will have a higher *arpk* than they would have in the absence of uncertainty, as well as higher productivity due to the positive shock. On the other hand, correlated distortions imply that capital is more expensive for more productive firms. As a result, more productive firms will operate on a lower than efficient level of capital and will display higher factor productivity *arpk* in equilibrium. This explains why the isomoment curve for $\rho_{arpk,a}$ is positively sloped: *ceteris paribus*, an increase in uncertainty must be offset by a reduction in the absolute value of γ to maintain the same value for $\rho_{arpk,a}$.

These two forces act in opposite directions in determining the correlation between investment and past productivity $\rho_{i,a_{-1}}$. Intuitively, higher uncertainty about the future (either due to higher variability in productivity shocks or to lower precision of the signals) will lead firms to rely more heavily on past productivity shocks when making investment decisions, thus increasing $\rho_{i,a_{-1}}$. On the other hand, at higher levels of correlated distortions the cost of capital is higher for more productive firms, reducing the sensitivity of investment to past productivity shocks, thus reducing $\rho_{i,a_{-1}}$. The two isomoment curves thus have opposite slopes and the pair of parameters consistent with the observed empirical moments can be found where the two lines cross.

In quadrant B, we relate correlated distortions γ and adjustment costs ξ. Both reduce the variance of investments σ_i^2. For a given variance in investment there are various combinations of ξ and γ that are possible, but they both move in the same direction. Intuitively, when correlated distortions are high, firms are less willing to invest following a positive productivity shock as capital has become more expensive as a result of the change in productivity and vice versa; this reduces firms' responsiveness to productivity shocks and in turn the dispersion of investment. High adjustment costs have the same impact as they increase the cost of adjusting the amount of capital operated. On the other hand, the two forces have an opposing impact on the autocorrelation of investment, $\rho_{i,i_{-1}}$, as higher (quadratic) adjustment costs encourage firms to smooth investments over successive periods (increasing $\rho_{i,i_{-1}}$). In the case of correlated distortions, past investments (following positive productivity shocks) make future capital more expensive, reducing $\rho_{i,i_{-1}}$. As such, for a given value of $\rho_{i,i_{-1}}$, there are combinations of

ξ and γ that move in opposite directions. The parameters are identified where the pair of isomoments intersect.

In quadrant C, uncertainty V and adjustment costs ξ can be separately identified considering that they both increase the correlation between current investment and past productivity shocks $\rho_{i,a_{-1}}$, but only adjustment costs affect $\rho_{i,i_{-1}}$. Uncertainty means that firms rely more on past productivity realizations to predict future outcomes, thus increasing $\rho_{i,a_{-1}}$. Higher adjustment costs means that investment following productivity shocks is smoothed over the years, leading to a higher $\rho_{i,a_{-1}}$ than would be the case in the absence of adjustment costs. Only adjustment costs affect $\rho_{i,i_{-1}}$ (see above), while uncertainty does not as it is related to productivity shocks. Matching the two isomoments allows us to identify V and ξ.

Finally, in quadrant D, the impact of correlated distortions γ and transitory distortions σ^2_ε can be disentangled by considering that while they both reduce the autocorrelation of investments $\rho_{i,i_{-1}}$ (transitory distortions create noise that reduces how informative past investments are), only correlated distortions affect $\rho_{arpk,a}$. Matching the two isomoments allows us to identify γ and σ^2_e.

We use the generalized method of moments to choose the values for the parameters that simultaneously match these functions of the parameters to the data. This involves minimizing the equally weighted distance between the model and the data for the five empirical moments of interest.

The estimation of the structural parameters allows us to determine the magnitude of the contribution of each source to capital misallocation and, in turn, productivity losses. In particular, the parameters allow us to estimate the shares of the dispersion in the marginal productivity of capital that can be attributed to each of the five sources.[5] In the following, we will refer to the amount of *arpk* dispersion attributed to adjustment costs, uncertainty, correlated, fixed, and random distortions as σ^2_ξ, σ^2_V, σ^2_γ, σ^2_X, and σ^2_ε.[6]

Although the model allows us to identify the contribution of the above-mentioned factors to the dispersion in capital productivity, the identification of the actual drivers of these distortions is an empirical matter. Our main interest lies in the role played by import tariffs. We will use a reduced-form analysis (similar to David et al. 2020) to examine the empirical link between the magnitude and sources of industry-specific misallocation and the import tariffs imposed on their production in South Africa.

2.3 Reduced-form analysis of tariffs

To explore the link between tariffs and capital misallocation and its components, we estimate a number of cross-industry-level reduced-form regressions of the form in Equation 6:

$$Y_{is} = \beta_0 + \beta_1 \text{Tariffs}_{is} + \nu_s + u_{is} \tag{6}$$

Y_{is} represents the measure of capital misallocation σ^2_{arpk} or the particular component of interest (σ^2_ξ, σ^2_V, σ^2_γ, σ^2_X, and σ^2_ε) for industry i and sector s. Tariffs_{is} is the level of import tariffs imposed in industry i (expressed as a percentage of the *ad valorem* taxes), ν_s are sector-level fixed effects and u_{is} is a random noise term. We estimate each regression both with and without sector-specific fixed effects ν_s and in their unweighted form or weighting every industry by their value added.

[5] In order to achieve this, for each of the five sources of misallocation, we estimate the counterfactual productivity dispersion that would be observed where the corresponding parameter (ξ for adjustment costs, V for uncertainty and informational frictions, γ for correlated distortions, σ^2_X for fixed distortions, and σ^2_ε for random distortions) is set equal to our estimate and all the others are set to zero. In the case of our estimation, the sum of these five components matches virtually perfectly the total observed capital dispersion, indicating that interaction effects are trivial and as such they are not presented but are available on request.

[6] Note that the contribution of fixed and random distortions to the dispersion in *arpk* dispersion is exactly equal to their dispersion σ^2_X and σ^2_ε. Thus, the use of the same notation is not problematic.

This approach is similar to that used by David et al. (2020), who use country-level reduced-form regressions to establish a link between the ease of doing business and the magnitude of capital misallocation. In our case, our interest lies in understanding the correlation between industry-specific tariffs, targeted at protecting domestic firms from competitors, and capital misallocation. In line with recent findings in the literature that protection measures, such as anti-dumping, have heterogeneous effects on firms, typically favouring less productive establishments while damaging more productive firms (Jabbour et al. 2019; Pierce 2011), we expect tariffs to be correlated with the magnitude of capital misallocation. Moreover, we expect import tariffs to be correlated with firm-specific distortions (correlated distortions). As discussed above, tariffs have also been shown to increase prices and mark-ups (Pierce 2011). As such, we would also expect tariffs to be correlated with fixed distortions that capture industry mark-ups. On the other hand, we have no reason to believe that tariffs impact on adjustment costs since they are purely driven by technical features governing investment costs such as the administrative/legal costs faced when scaling up production or expanding production capacity, and so they should not have a systematic link with this source of capital misallocation. In addition to examining the relationship between tariffs and each of the sources of misallocation, we also estimate the proportion of misallocation that could be attributed to mark-ups and technology heterogeneity (as in DV) and explore how these components relate to tariffs. We also consider the impact of tariffs on firms' survival across the productivity distribution.

We do not claim to identify a causal relationship between import tariffs and misallocation, but rather aim to show the extent of correlation between tariffs and capital misallocation and its components. It is worth noting, however, that our measure of tariffs is the level of tariffs in 2010, while our measures of misallocation and its components are based on data from 2011–16. Moreover, as an additional robustness check we also include a number of industry-level control variables. These include the industry-level measure of concentration in 2010, the size of the industry in 2010 measured as value added, the average level of (log) capital of the firms in the industry in 2010, and the percentage of exporters.[7]

3 Data

The primary data source is the South African CIT data (National Treasury and UNU-WIDER 2019a, 2021), which are collected annually and are based on self-reported CIT returns. We focus on manufacturing firms operating between 2010 and 2016. Our data include 195,543 observations on 60,041 firms. The main variables required for the estimation of the DV model are total capital (based on initial values of fixed assets imputed across the time series using the perpetual inventory method),[8] the wage bill, and value added, computed as the difference between the value of total output less the costs of sales. Descriptive statistics are presented in Table 1.

We identify 71 different industries (including a residual generic category) containing enough observations for a consistent estimation of the empirical moments. Our categorization is similar to the four-digit ISIC classification. The industries are spread across 23 manufacturing sectors, which are similar to the two-digit ISIC code categorization. Table A2 in Appendix A presents the breakdown of our sample by industry.

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[7] Industry concentration is based on the Herfindahl–Hirschman index, computed based on the value added of the firms.

[8] The perpetual inventory methodology follows Gal (2013). For details see Kreuser and Brink (2021). We assume a capital depreciation rate of 10 per cent (also used to parameterize the model). For missing and negative capital values we use a straight-line imputation with a maximum length of two years.

Table 1: Descriptive statistics

	Wages	Capital	Value added	Value added/wages	Value added/capital
2010	35.2	78	98.6	2.52	3.31
	(440.0)	(2,258.9)	(1,593.1)	(1.32)	(2.28)
2011	41.1	90.9	117.45	2.63	3.86
	(520.9)	(2,534.1)	(1,823.9)	(1.36)	(2.20)
2012	44.5	89.7	123.0	2.50	4.03
	(535.0)	(2,586.1)	(2,205.9)	(1.33)	(2.41)
2013	44.6	68.5	114.1	2.35	4.38
	(504.2)	(1,486.9)	(2,268.2)	(1.3)	(2.84)
2014	48.1	67.2	106.3	2.14	4.44
	(532.9)	(1,360.5)	(1,642.5)	(1.23)	(1.74)
2015	49.8	62.9	105.1	2.03	4.49
	(525.3)	(1,283.9)	(1,630.5)	(1.21)	(1.71)
2016	53.6	60.3	106.0	1.88	4.64
	(529.1)	(1,150.7)	(1,510.0)	(1.20)	(1.72)

Note: the table presents the average and standard deviation of labour costs (wages), capital, value added, and relative productivities (value added per wage cost and capital) for the firms in our sample. Wages, capital, and value added are expressed in 100,000 South African rands and are computed using industry-wide deflators.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

In order to measure the level of tariff protection, we rely on the customs data (National Treasury and UNU-WIDER 2019b) that are part of the SARS-NT panel (Ebrahim et al. 2021).[9] The data set includes detailed information on each transaction that took place between local firms and foreign countries. In particular, for each good (HS6) and destination/origin country (depending on whether the local firm is an exporter or an importer) the customs data set includes information on the value of the transaction and the duties paid. We use this information to compute the tariffs imposed on the import of a very wide range of goods. We define the duty imposed on a given good (identified by its HS6 code) imported from a specific country in a year as the median percentage tariff paid by the local importers.

While this approach will give us a reasonably accurate representation of the system of tariffs enforced by South African authorities on foreign imports, it also presents some challenges. First, we only have data on transactions that actually happened, so we only have information on tariffs for good/country combinations where at least one transaction took place in the time frame under analysis. This implies that we are not able to capture the impact of (potentially high) duties that do not enter our data due to the lack of corresponding transactions. In order to partially address this concern, we 'fill' the gaps in the data by using interpolation where possible or by replacing missing values with the most recent observation or the closest in time. This implies that we only fail to detect item- and country-specific tariffs when no transaction took place during the seven years under analysis rather than assuming that no duty was imposed in years where such transactions were not observed. Admittedly, this artificially reduces the variation in tariffs over time, but this is preferable to ignoring potentially relevant tariffs.[10]

This provides us with a list of good–country–year observations where each tariff is expressed as a percentage of the value of the good. In order to aggregate the estimates to the good–year level, we weight country-specific tariffs on the basis of the overall trade flow of that country with South Africa. As the

[9] An alternative source of data that could be used for this purpose is the UN Comtrade data set; however, only 33 items are listed as receiving anti-dumping protection in this data set. This largely understates the import tariffs imposed by South Africa according to our data based on actual transactions from the customs data, where we could identify more than 5,280 different items subject to import tariffs.

[10] Overall, out of the 1,310,036 of the good/country/year observations, 523,406 needed to be imputed (about 40 per cent of the total). However, these observations are predominantly from countries whose trade with South Africa is negligible and, as such, due to the weighting applied when aggregating tariffs, they have a very limited impact on the computation of the tariffs. More specifically, tariffs imposed on items coming from the top quintile of countries in the trade intensity distribution contribute to over 90 per cent of the aggregate tariffs, and only 5 per cent of the observations for such countries needed to be imputed.

total value of imports is likely to be endogenous to the level of tariffs imposed, we use the total value of exports (computed using the customs data) from South Africa to the given country over the 2010–16 period to compute the weights.[11] Our approach allows us to estimate tariffs on 5,280 different goods for each year between 2010 and 2016.

The last step requires that we aggregate tariffs to the industry level in order to match this information to the classification available in the CIT data. We rely on the transaction-level customs data to infer the industry-specific output shares. The customs data records the total value and type (HS6) of goods that are exported or purchased from abroad. Thus, for each industry represented in the customs data we generate input and output shares based on this information for the 2010–16 period. There are two potential caveats to this approach. First, exporters may not be representative of all firms in the South African manufacturing sector. Second, at the firm level, the products exported are not necessarily representative of all the outputs produced. In order to partially correct for these issues, when computing output shares, firms are given different weights depending on their likelihood of being an exporter given their observable characteristics, and the share of revenue that is accounted for by exports.[12] The resulting output shares are used to aggregate product-specific tariffs to the industry level.

Table A1 presents the distribution of tariffs (in percentage points) across the years. It is clear that the distribution has not changed in any meaningful way over the years considered; indeed, there is very little variation in industry-level tariffs over time and most of the variation is observed across industries.[13] For this reason, in the remainder of the paper we use the 2010 level of tariffs and ignore the marginal changes over time.

Table A1 shows that while the bottom quartile of the industries receive very little to null protection from foreign exporters (with *ad valorem* duties lower than 5 per cent), the top quartile receive significant protection in the form of *ad valorem* duties higher than 10 per cent.[14]

Figure 2 shows the distribution of tariffs across the 23 different sectors in the sample. Interestingly, although there is some non-negligible variation in the levels of within-sector tariffs, it is clear that industries in food/beverages production and the textile and motor vehicles sectors receive significantly more protection than firms in the pharmaceutical, computers and electronic devices, and machinery and equipment sectors.[15]

[11] There is a strong (0.77) correlation between the export weights and the ones that would be obtained if we were to base them on the total value of inputs.

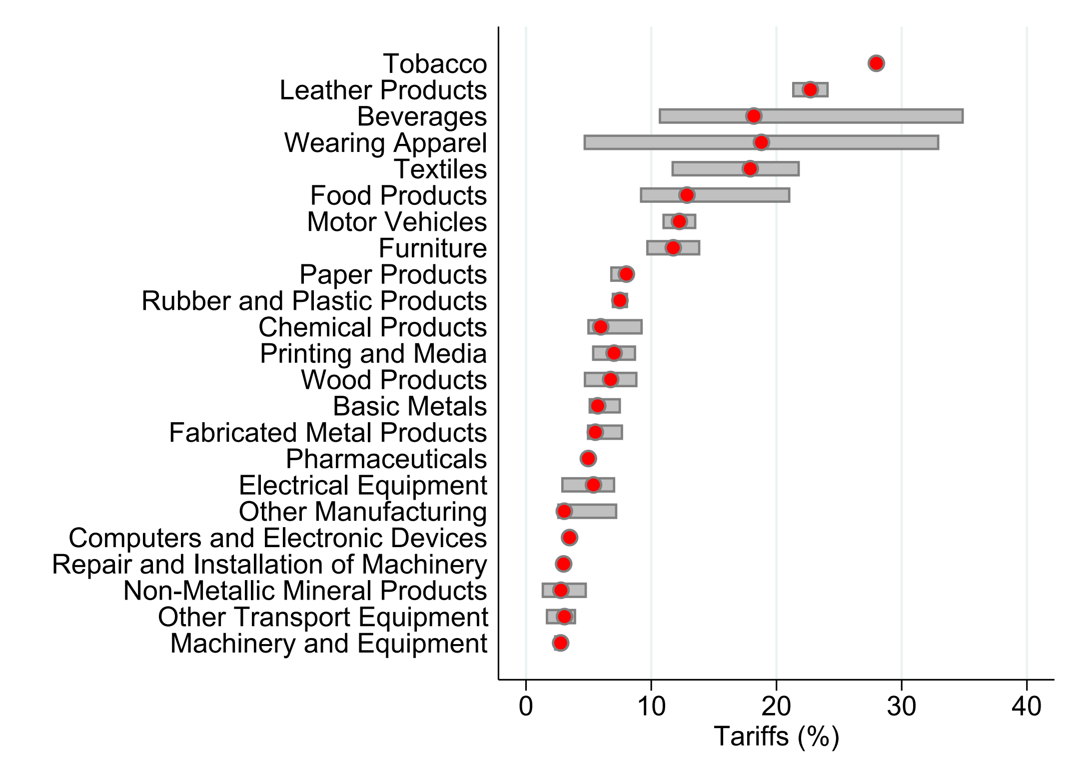
[12] The variables we used to estimate the probability of exporting were the total amount of capital, labour, and the firm's productivity.

[13] This is also true when we look at the variation in the item-specific tariffs, where more than 99 per cent of the variation is observed across goods and only in less than 5 per cent of the item–year pairs do we observe a yearly change in tariffs greater than 1 per cent.

[14] The fact that there are virtually no industries with zero protection is attributable to our methodology used to compute tariffs. Indeed, for our approach to record positive tariffs for an industry it is sufficient that one good once exported by a firm belonging to the industry was subjected to duties when imported by any South African company from any country.

[15] Table A2 shows all the industry-specific tariffs computed using our methodology.

Figure 2: Tariffs distribution by sector



Note: the bars show the interquartile range in each sector, while the red dots represent the median.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

4 Results

In this section we first report the results of the DV model, estimated separately for each of the 71 industries in the South African SARS-NT/CIT-IRP5 panel (National Treasury and UNU-WIDER 2019a,b, 2021). This allows us to obtain an industry-specific measure of capital misallocation along with an industry-specific decomposition of its sources. In that way we can empirically test to what extent capital misallocation is driven by industry-specific tariffs and explore the link between such tariffs and the different components of capital misallocation. As indicated above, in line with the recent findings in the literature showing that protection measures typically favour less productive establishments while damaging more productive firms (Jabbour et al. 2019; Pierce 2011), we expect tariffs to be especially linked with correlated, as well as firm-specific, distortions. We do not expect tariffs to have a systematic link with adjustment costs. The literature also suggests that tariffs allow higher mark-ups and prevent the least efficient firms from exiting. We also explore these mechanisms later in this section.

4.1 The DV model

We begin by computing empirical moments. To do this we follow the same data trimming process used by DV (dropping the 3 per cent tails in each empirical moment of interest as well as the observations with missing values). The resulting sample distribution is shown in Table A2. These moments are then estimated separately for each of the 71 industries. We then aggregate them by weighting each industry according to their value added to obtain moments describing the whole of the South African manufacturing sector.

The resulting estimates are shown in Table 2. These are compared to those found by DV in their original paper for China and the United States for the period 1998–2009. Our approach is almost identical to that of DV, with the exception that we estimate a different elasticity of capital for each industry based on the inverse of the average share of labour expenditure in total expenditure, whereas DV set this equal for all industries in their benchmark analysis.

Table 2: Empirical moments

	ρ	σ^2_μ	$\rho_{i,a_{-1}}$	$\rho_{i,i_{-1}}$	$\rho_{a,arpk}$	σ^2_i	σ^2_{arpk}
ARG	0.89	0.05	0.19	–0.36	0.58	0.06	0.54
BRA	0.90	0.08	0.13	–0.39	0.60	0.09	0.65
CHN	0.91	0.14	0.04	–0.36	0.68	0.14	0.92
COL	0.95	0.09	0.13	–0.35	0.61	0.07	0.98
MEX	0.93	0.07	0.17	–0.39	0.69	0.02	0.79
MYS	0.95	0.06	0.31	–0.29	0.86	0.03	0.73
TWN	0.96	0.04	0.34	–0.36	0.66	0.04	0.57
THA	0.95	0.07	0.26	–0.32	0.57	0.08	0.88
TUR	0.89	0.08	0.11	–0.38	0.57	0.09	0.56
JPN	0.98	0.03	0.13	–0.40	0.48	0.03	0.43
USA	0.93	0.08	0.25	–0.30	0.55	0.06	0.45
ZAF	**0.93**	**0.11**	**0.31**	**–0.34**	**0.75**	**0.11**	**1.19**

Note: the moments for South Africa are obtained by aggregating the industry-specific figures using industry value added as weights.

Source: authors' computation based on own data set built from National Treasury and UNU-WIDER (2019a,b, 2021) for South Africa, David and Venkateswaran (2019) for China and the United States, and David et al. (2020) for the remaining countries.

It is clear that capital dispersion is more pronounced in South Africa than in China and the United States. The higher dispersion than the United States does not come as a surprise since, as shown by Bartelsman et al. (2013) and more recently by David et al. (2020), there is a negative relationship between a country's GDP per capita and the dispersion in the marginal productivity of firms. However, the magnitude of the dispersion is larger than any country examined by David et al. (2020) (the highest value was 0.98 for Colombia). This might capture an actual higher dispersion observed among South African manufacturing firms or could be due to the fact that the data we use come from administrative sources rather than firm-level surveys.[16]

The other empirical moments are in line with the numbers observed for China. In particular, the investment dynamics are characterized by a strong correlation between past productivity shocks and investments, low autocorrelation of investments, and very high correlation between a firm's productivity and marginal capital product. This last empirical moment suggests a big role for correlated distortions in the South African case.

The estimated parameters governing capital accumulation and distribution across firms and their percentage contribution to capital misallocation are shown in Table 3. These are obtained following the procedure outlined in Section 2 and illustrated in Figure 1. Distortions account for the lion's share of capital dispersion in South Africa, even more so than in China and the United States. Altogether, uncertainty and adjustment costs account for less than 7 per cent of the dispersion in marginal productivity and the remainder can be attributed entirely to other distortions. Similar to the case of China, random distortions play a negligible role while fixed and correlated distortions have a very similar impact on capital misallocation in South Africa as in China.

[16] For the sake of comparability, we have applied the same trimming strategy as DV, although operating with a rather different data set.

Table 3: Estimated parameters

	Adjustment	Uncertainty	Correlated	Fixed	Random
Parameters	ξ	V	γ	σ_X^2	σ^2
ARG	0.19	0.03	–0.79	0.36	0.00
BRA	0.12	0.06	–0.67	0.42	0.00
CHN	0.16	0.09	–0.63	0.51	0.00
COL	0.54	0.05	–0.55	0.60	0.01
MEX	0.13	0.04	–0.82	0.42	0.00
MYS	0.83	0.03	–0.94	0.18	0.00
TWN	0.20	0.02	–0.65	0.32	0.00
THA	0.29	0.04	–0.58	0.59	0.00
TUR	0.15	0.06	–0.61	0.37	0.00
JPN	2.05	0.01	–0.35	0.32	0.06
USA	1.38	0.03	–0.33	0.29	0.03
ZFA	**0.14**	**0.07**	**–0.79**	**0.6**	**0.01**
Percentage contribution					
ARG	1	6	29	67	0
BRA	1	8	29	64	0
CHN	1	9	36	0.55	0
COL	3	6	31	61	0
MEX	1	5	45	53	0
MYS	3	4	73	25	0
TWN	1	4	40	56	0
THA	1	5	28	67	0
TUR	1	10	25	67	0
JPN	5	3	16	73	0
USA	11	7	14	65	6
ZFA	**1**	**6**	**44**	**49**	**0**

Note: the moments for South Africa are obtained by aggregating the industry-specific parameters using industry value added as weights.

Source: authors' computation based on own data set built from National Treasury and UNU-WIDER (2019a,b, 2021) for South Africa, David and Venkateswaran (2019) for China and the United States, and David et al. (2020) for the remaining countries.

4.2 Tariffs and regression analysis

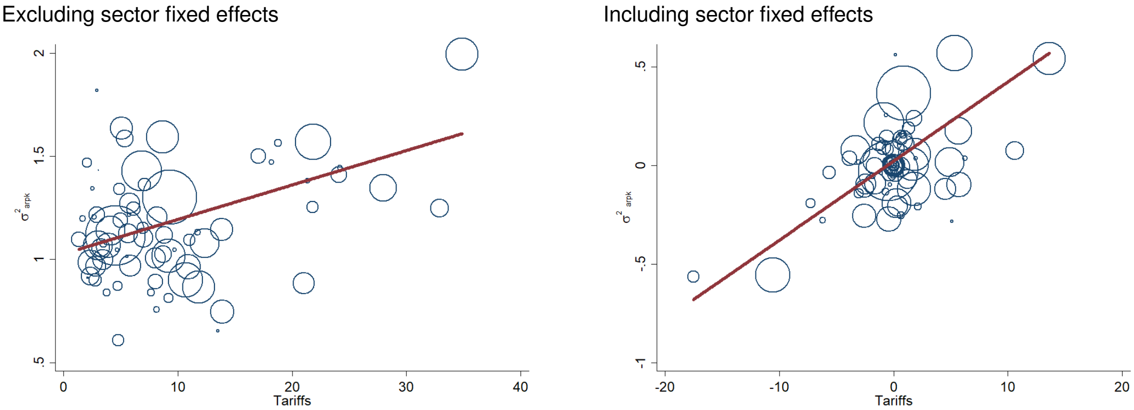
In this section, we run a number of reduced-form regressions (Equation 6) to establish whether there is any correlation between the industry-level import tariffs and total capital misallocation (captured by dispersion in the marginal productivity of capital) as well as the different components.[17]

We consider six different dependent variables: the industry-level variance in *arpk*; the contribution of adjustment costs; uncertainty; correlated distortion; fixed distortions; and random distortions. The explanatory variable of interest is the level of tariffs (expressed as a percentage of the *ad valorem* taxes) imposed on imports into that industry in 2010. We estimate such regressions both with and without sector-specific fixed effects and in their unweighted form or weighting by industry-specific value added.

In Figure 3 we illustrate the correlation between tariffs and the dispersion in capital productivity measured by the total variance in *arpk* computed by weighting each industry by its value added. The left-hand panel shows the results obtained excluding sector fixed effects, while the right-hand panel shows the results when including sector-specific fixed effects. In both specifications (as well as in the unweighted regressions presented in Figure A1), we find a positive and significant relationship. This indicates that the more protected an industry is, the higher is the dispersion in the marginal productivity of capital among its firms. This correlation is statistically significant at the 5 per cent significance level at least in all specifications.

[17] This exercise resonates with the study by David et al. (2020), who estimated similar regressions at the country level to examine whether cross-country differences in capital misallocation could be accounted for by differences in the ease of doing business.

Figure 3: Tariffs and capital dispersion: σ^2_{arpk}



Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

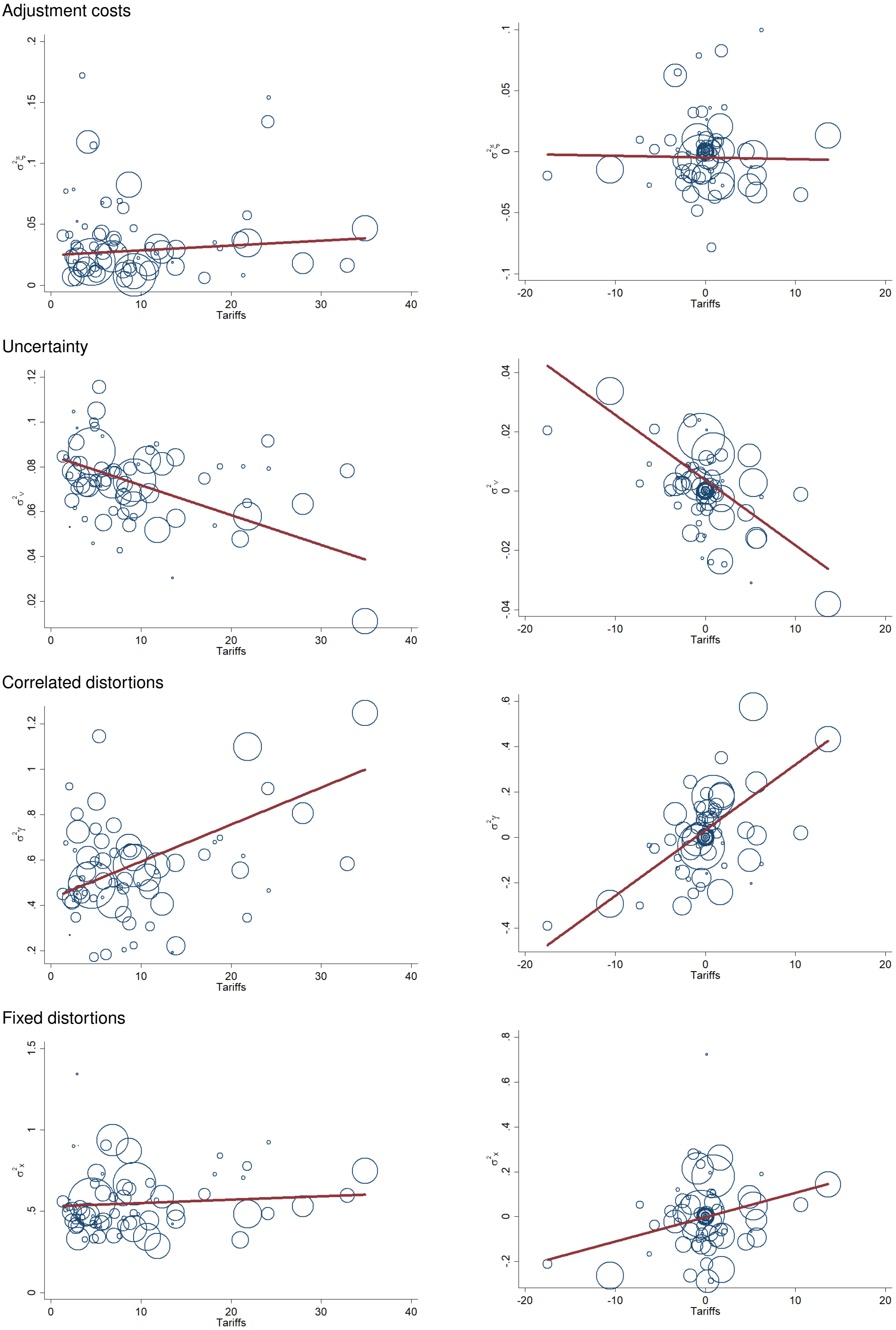
In Figure 4 we illustrate the correlation between tariffs and each of the different components of capital productivity dispersion computed using industry-specific weights.[18] As in Figure 3, the figures on the left-hand side present the results for the specification excluding fixed effects, while the figures on the right-hand side present the results including fixed effects. In the first panel, and in line with our expectations, we find no systematic relationship between the magnitude of the capital dispersion due to adjustment costs and tariffs at the industry level. Indeed, there is no rationale justifying a correlation between tariffs that protect local firms from competition and the magnitude of capital misallocation driven by adjustment costs which are likely to be orthogonal to protection policies.

The second panel shows the correlation between tariffs and the other 'efficient' source of capital dispersion, namely uncertainty or informational frictions. As mentioned above, this source captures two different components: the year-on-year productivity shocks experienced by firms and the precision of the signals firms receive on future levels of productivity. We find a strong and negative correlation between the capital productivity dispersion explained by such factors and the level of industry protection through import tariffs. A plausible explanation for this is that tariffs, by reducing exposure to foreign competition, reduce the uncertainty in the environment in which firms operate and in particular in their price and (relative) productivity shocks. This would contribute to reducing the share of the dispersion in capital productivity attributed to the lack of responsiveness of firms to productivity shocks in these industries. Thus, in this instance, tariffs may improve the allocation of capital within industries. It is important to point out, however, that only a small fraction (see Table 3) of the total capital dispersion can be attributed to uncertainty and informational frictions, and therefore the magnitude of this effect is rather negligible.

The correlation between tariffs and the magnitude of correlated distortions is illustrated in the third panel of Figure 4. We find a large positive and statistically significant relationship. The coefficient is positive in all specifications and is statistically significant at every confidence level. As discussed above, correlated distortions are time-varying firm-specific factors that are related to firm productivity. The positive correlation between tariffs and this component of misallocation suggests that tariffs affect firms in heterogeneous ways. This corroborates the work by Jabbour et al. (2019) and Pierce (2011), who found that tariffs advantage the less productive establishments while being detrimental to more competitive firms.

[18] The corresponding results for the unweighted specifications are shown in Figure A3.

Figure 4: Tariffs and sources of *arpk* dispersion



Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

The correlation between tariffs and fixed distortions, illustrated in the fourth panel, is only significant when sector fixed effects are included, although the point estimates are always positive. Fixed distortions capture distortionary factors that impact all firms within an industry in the same way. The positive correlation observed here suggests that tariffs also increase the extent to which these distortions contribute to misallocation. In what follows, we provide some suggestive evidence that tariffs increase the level of dispersion in mark-ups, which contributes to this component of capital misallocation.[19] The point estimates for each specification can be found in Table A3.

While we cannot rule out the possibility that there are confounding factors jointly affecting the protection an industry receives from external competitors and the dispersion in capital productivity, we run a robustness check by re-estimating Equation 6 including some industry-specific control variables: namely the (log) average capital used by firms, the industry concentration, the percentage of exporters, and the share of total value added of the industry in the whole manufacturing sector (all of these variables are computed for 2010). The results are very similar to those of our main specification (see Table A4).

Overall, there is a positive correlation at the industry level between tariffs and σ^2_{arpk}. This is driven by a strong positive relationship between the contribution of distortions (primarily correlated) and tariffs, and is only partially offset by a negative relationship between the impact of efficient sources (uncertainty) and tariffs.

To measure the impact of tariffs on aggregate productivity through the misallocation channel, we use the coefficients estimated in the previous regressions and the capital elasticities to estimate the impact of a change in tariffs on aggregate productivity. In particular, we consider an increase in tariffs that would move an industry from the bottom to the top quartile of the tariffs distribution (either across or within sector). The results are presented in Table 4.[20]

Table 4: Aggregate productivity impact of tariffs

	No FE, no weights (%)	No FE, weights (%)	FE, no weights (%)	FE, weights (%)
Adjustment costs	0.0	0.0	0.0	0.0
Uncertainty	0.5	1.0	0.0	0.5
Correlated	–6.3	–11.7	–3.5	–6.7
Fixed	0.0	0.0	–1.3	–3.0
Random	0.0	0.0	0.0	0.0
Total	–5.7	–10.8	–4.8	–9.2

Note: this table shows the productivity losses associated with an increase in the level of import tariffs sufficient to move an industry from the bottom to the top quartile of the distribution (an 8 and 3 per cent increase in *ad valorem* taxes across and within sectors, respectively). Whenever the point estimates from the associated regressions are not significant at least at the 90 per cent level, their impact is assumed to be zero.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Overall, tariffs have a strong and negative impact on productivity through the misallocation channel. A move from the bottom to the top quartile of the distribution leads to a reduction in aggregate productivity of between 4.8 and 10.8 per cent, depending on the specification used. In the case of the cross-sector specification, this is entirely driven by correlated distortions, while fixed distortions play a more important role in the within-sector specification. As mentioned above, tariffs also reduce the level of uncertainty faced by firms who, as a result, are better able to predict and adjust to future productivity shocks. However, this positive effect is very small in magnitude.

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[19] We also explore the relationship between tariffs and random distortions. We find no evidence of a statistically significant relationship. Moreover, the contribution of random distortions to overall productivity loss is less than 0 per cent. The plot can be found in Figure A2.

[20] The impact of capital dispersion on aggregate TFP, a, depends on the elasticity of substitution across goods within the same industry, θ, and the capital and labour shares $\hat{\alpha_1}$ and $\hat{\alpha_2}$. It is estimated as: $\frac{\partial a}{\partial \sigma^2_{arpk}} = -\frac{(\theta\hat{\alpha_1} + al\hat{pha_2})\hat{\alpha_1}}{2}$.

Additionally, our model suggests that misallocation represents a very serious issue in the manufacturing sector in South Africa. In particular, the very high dispersion in σ^2_{arpk} indicates that a redistribution of capital across firms within industries could improve aggregate productivity in a significant way. In particular, we estimate that aggregate production could be nearly doubled (increase by 97 per cent) if all sources of misallocation were eliminated.[21]

Crucially, the near totality of these productivity losses can be attributed to distortions affecting the firm-specific costs of acquiring capital, as opposed to 'efficient' sources like adjustment costs and informational frictions, which only account for 1 and 6 per cent of the observed misallocation. We find that in the case of South Africa, tariffs are one source of such distortions that account for a reasonably large component of misallocation and resulting productivity losses.

4.3 Mark-ups

The model assumes homogeneous mark-ups among firms operating in the same industry. However, some of the *arpk* dispersion observed in the data might be the result of differences in the mark-ups charged by firms, which would not be captured by the benchmark specification of the model. DV show that the impact of heterogeneous mark-ups on *arpk* dispersion can be captured using the methodology developed by De Loecker and Warzynski (2012), who find that there is a one-to-one mapping between the variance in the material shares of expenditures and the variance in mark-ups. Computing this variance therefore allows estimation of the proportion of marginal productivity dispersion that could be attributed to this source.

In particular, the empirical moment of interest is:

$$\sigma^2 \log\left(\frac{P_{it}Y_{it}}{P_i^M M_{it}}\right) \tag{7}$$

that is, the variance in the (log) ratio of the total value of production and expenditure on intermediary goods. We estimate this value for each firm in our sample using the cost of sales as a proxy for the cost of intermediates and compute the variance for each industry. We find that the value-added weighted average of this variance across all industries is 0.04, which is comparable to the case of China (0.05) and the United States (0.06). This value can be directly used to compute the contribution of mark-up dispersion to the variance in *arpk* (see Table 2): $0.037/1.19 \approx 3$ per cent. This indicates that only a very small share of the capital dispersion observed in the sample can be attributed to mark-up heterogeneity.

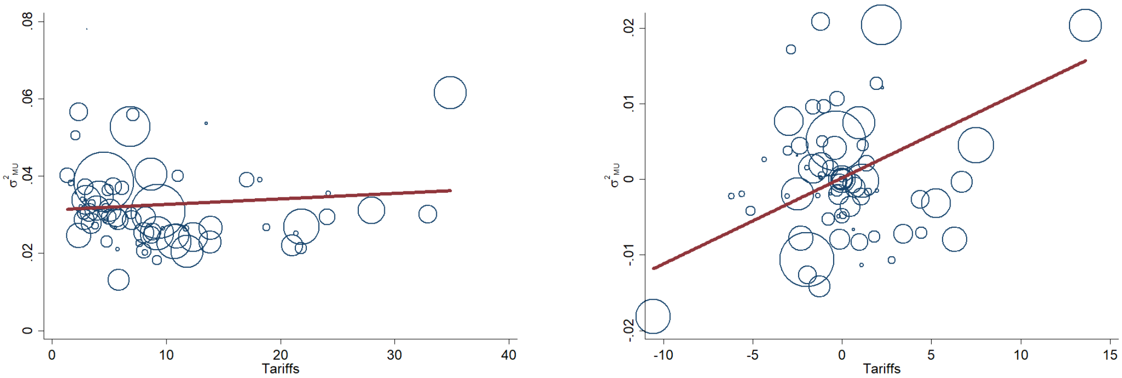
According to some models of monopolistic competition (Edmond et al. 2015), barriers to international trade can create dispersion in mark-ups across domestic firms. In light of this, even though mark-ups contribute very little to capital misallocation in our case, it is still interesting to study whether the magnitude of capital dispersion due to mark-up heterogeneity correlates with industry-specific import tariffs. In order to do so, we perform a similar reduced-form analysis to Equation 6, and regress the industry-specific magnitude of capital dispersion due to mark-ups on import tariffs in the same sector. For consistency we estimate the same four specifications as above: with and without sector-specific fixed effects and with and without weighting by the industry-specific value added.

The results from the weighted regressions with and without sector-specific fixed effects are shown in Figure 5 and Table A5. Overall, we find only a tenuous relationship the dispersion in mark-ups and tariffs, which is only statistically significant at the 10 per cent level in the case of the weighted regression with sector-specific fixed effects. In short, there is little evidence that differences in mark-ups explain

[21] This estimate is obtained applying the formula linking aggregate productivity and capital dispersion in DV: $\frac{\partial a}{\partial \sigma^2_{arpk}} = -\frac{(\theta\hat{\alpha_1} + al\hat{p}ha_2)\hat{\alpha_1}}{2}$.

a large share of *arpk* dispersion and little evidence that mark-up heterogeneity is an important channel through which tariffs distort the allocation of capital.

Figure 5: Tariffs and mark-ups dispersion



Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

4.4 Heterogeneous technology

Another potential source of productivity dispersion not captured by the model is heterogeneity in the technology used by firms in their production process. This would naturally lead firms within the same industry to optimally operate different shares of labour and capital. This would result in apparent differences in marginal productivities when they are computed under the assumption that all firms operate a common Cobb–Douglas production function.

Following DV, we can obtain an upper bound for this variance as:

$$\sigma^2\left(\log \hat{\alpha}_{it}\right) \leq \frac{\sigma^2_{\widetilde{arpk}}\sigma^2_{\widetilde{arpn}} - cov\left(\widetilde{arpk}, \widetilde{arpn}\right)^2}{2\frac{\bar{\alpha}}{\zeta-\bar{\alpha}} cov\left(\widetilde{arpk}, \widetilde{arpn}\right) + \left(\frac{\bar{\alpha}}{\zeta-\bar{\alpha}}\right)^2 \sigma^2_{\widetilde{arpk}} + \sigma^2_{\widetilde{arpn}}} \tag{8}$$

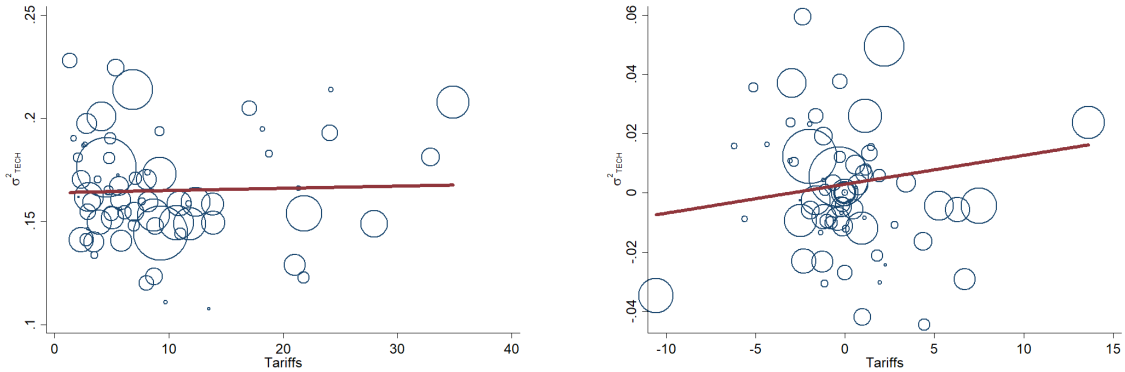
where ζ is the average revenue share of materials and $\bar{\alpha}$ is the average capital elasticity (that is empirically equal to the elasticity $\hat{\alpha}_1$ computed for the previous analysis) and $\widetilde{arpk}$ and $\widetilde{arpn}$ are the average revenue product of capital and labour, respectively, adjusted for the mark-ups.[22]

Intuitively, if the marginal revenue product of capital and labour tend not to move together, it means that firms are operating with different levels of capital and labour intensities, possibly indicating heterogeneity in their production processes. This can of course also be the result of some capital- or labour-specific distortions affecting the input mix of firms; the upper bound in Equation 8 is computed assuming that labour and capital distortions are perfectly correlated and as such all the existing variation in the input mix is due to differences in technology only.

We estimate this upper bound separately for each industry in our sample, and aggregate it for the whole manufacturing sector using weights based on industry-specific value added. We find that on aggregate this upper bound is equal to 0.215. In short, around one-fifth of the total capital productivity dispersion ($0.215/1.19 \approx 0.18$) at most could be attributed to heterogeneity in production technologies. This is lower than the upper bound found by DV for China (23.1 per cent) and the United States (44.4 per cent). We conclude from this that heterogeneous technologies could only explain part of the dispersion in *arpk* that we observe. Moreover, as shown in Figure 6 and Table A6, there does not appear to be any correlation between the upper bound of the heterogeneity in technology and industry-level tariffs.

[22] More specifically, they are computed as the difference between the (log) revenue productivity of capital/labour and the (log) mark-up obtained as the inverse of the firm-specific materials share of revenue.

Figure 6: Tariffs and technology dispersion



Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

4.5 Firm exit

A final potential channel through which tariffs can impact misallocation that we consider is the impact on the dynamic entry and exit of firms. In order to study this, we examine the likelihood of firms in different quartiles of the within-industry productivity distribution exiting the sample in any given year and how this is related to industry-specific import tariffs.

We perform a set of firm-specific linear regressions where the dependent variable is the average likelihood of a firm in industry i, sector s, and quartile of the productivity distribution q (1 being the lowest) in year y exiting the sample. The specification is given in Equation 9:

$$P(\text{Exit})_{isqy} = \beta_0 + \sum_j^4 \beta_j \text{quartile}_{isqy} + \sum_k^4 \gamma_k \text{quartile}_{isqy} \times \text{Protection}_{is} + \tau_y + \nu_s \tag{9}$$

where 'Protection' is a dummy variable taking a value of 1 whenever the industry has import tariffs higher than 7 percentage points (this splits the sample into two nearly equal parts). The likelihood of a firm exiting the sample therefore depends (after controlling for year and sector-specific fixed effects) both on its position in the probability distribution and on whether the industry is highly protected or not. The resulting estimates are shown in Table 5.

The results indicate that firms in the bottom quartile of the productivity distribution are the most likely to stop production (the exact probability in 2010 was 14.8 per cent). Moving up in the productivity distribution beyond the first quartile, however, does not have a significant effect on the likelihood of exiting production.

In sum, tariffs have an impact on the probability of firms continuing production. Specifically, they seem to play a role in keeping the least productive firms in business, reducing their likelihood of exiting the sample by between 2 and 2.5 percentage points. This finding corroborates the hypothesis that tariffs are disproportionately beneficial to less productive establishments and is in line with the strong correlation we identify between tariffs and correlated distortions.

Table 5: Tariffs and probability of exit

Dependent variable:	Average probability of exit			
Production quartile (1 = Lowest)				
2	–0.031***	–0.039***	–0.031***	–0.039***
	(0.01)	(0.01)	(0.01)	(0.01)
3	–0.046***	–0.053***	–0.046***	–0.053***
	(0.00)	(0.01)	(0.00)	(0.01)
4	–0.047***	–0.055***	–0.047***	–0.055***
	(0.00)	(0.01)	(0.00)	(0.01)
Interaction terms				
1 × Protection		–0.025**		–0.019*
		(0.01)		(0.01)
2 × Protection		–0.007		–0.002
		(0.01)		(0.01)
3 × Protection		–0.009		–0.003
		(0.01)		(0.01)
4 × Protection		–0.007		–0.002
		(0.01)		(0.01)
R-squared	0.208	0.062	0.331	0.179
N	1,988	1,988	1,988	1,988
Sector FE	No	No	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, robust standard errors in parentheses.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

5 Conclusion

This paper studies the impact of tariffs on the productivity of manufacturing firms through the capital misallocation channel. Utilizing an administrative census of South African firms we estimate the extent of capital misallocation evident in the manufacturing sector and the contribution of different sources of misallocation to associated aggregate productivity losses. The focus of our analysis is on the relationship between tariffs and misallocation. Using customs data on duties collected on imported goods, we compute the level of tariffs on inputs at the sub-industry level and study their impact on capital misallocation and its components.

We find that tariffs have a sizeable and detrimental effect on firm productivity through the capital misallocation channel. We estimate that moving from the bottom to the top quartile of the tariff distribution leads to productivity losses of 5–10 per cent. Tariffs are primarily associated with correlated distortions indicating that they affect firms differently along the productivity distribution of firms. While mark-ups play a small role, we do not find compelling evidence that they are the driving factor. The most likely mechanism is the protection that tariffs offer to low-productivity firms, reducing their probability of exit.

Overall, these findings suggest that tariffs cause efficiency losses in the form of a sub-optimal distribution of capital across firms, a mechanism not previously given much attention in the literature. Future studies on the impact of trade tariffs should also consider this second component when evaluating the aggregate effect of protectionist measures.

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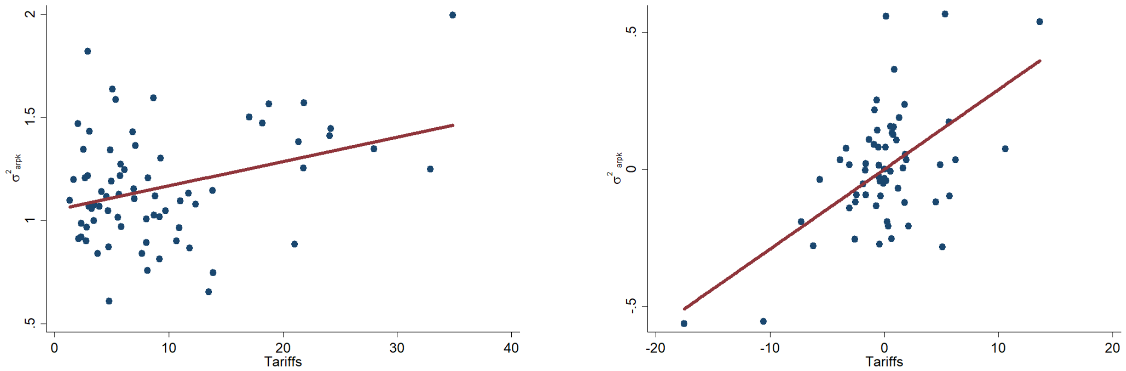
Appendix A: extra figures and tables

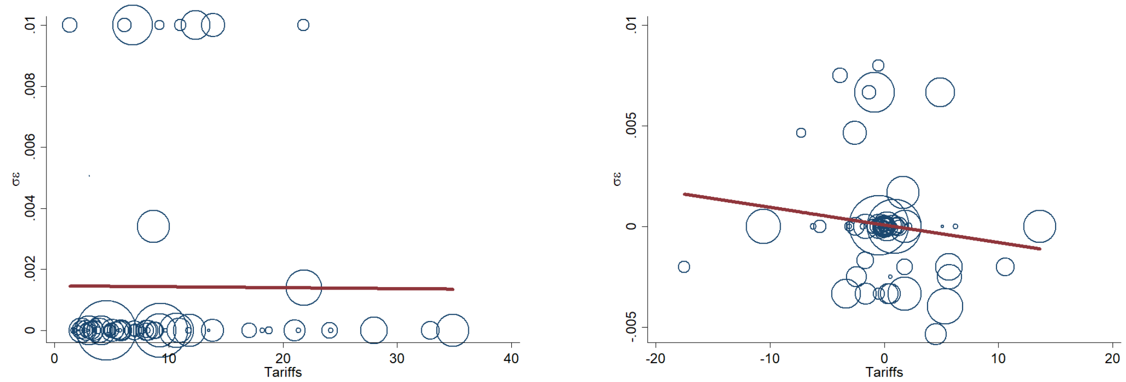
Figure A1: Tariffs and capital dispersion (unweighted specification): σ^2_{arpk}

Excluding sector fixed effects | Including sector fixed effects



Source: authors' compilation.

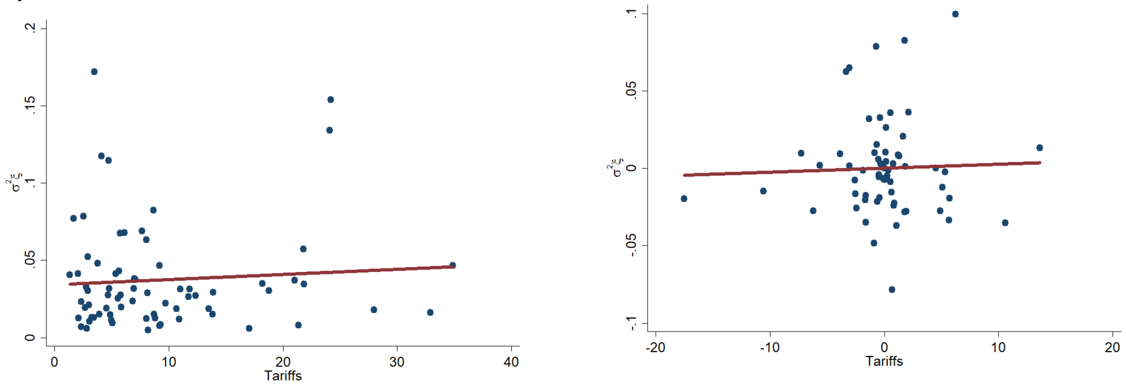
Figure A2: σ^2_e and tariffs



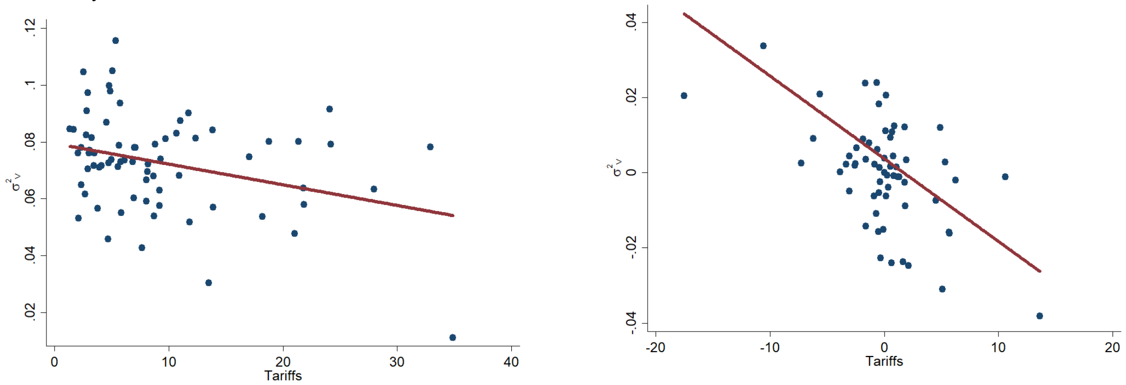
Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Figure A3: Tariffs and sources of *arpk* dispersion (unweighted specifications)

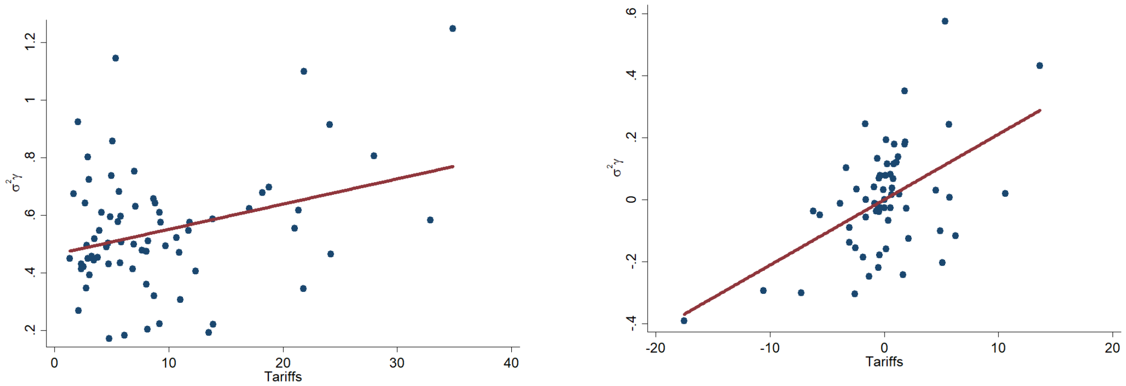
Adjustment costs



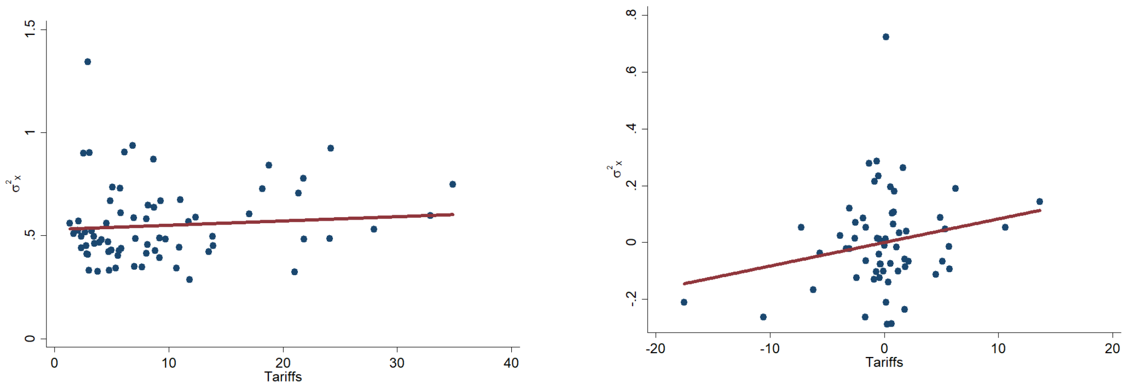
Uncertainty



Correlated distortions



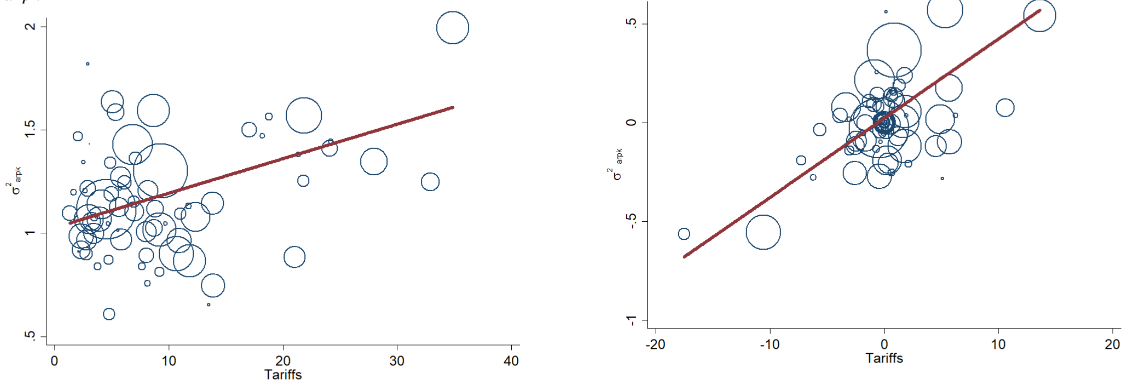
Fixed distortions



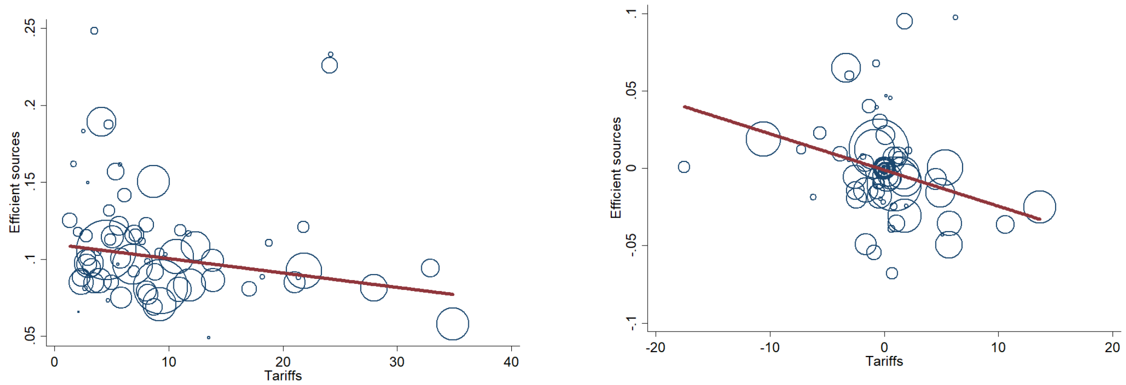
Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Figure A4: Tariffs and capital dispersion

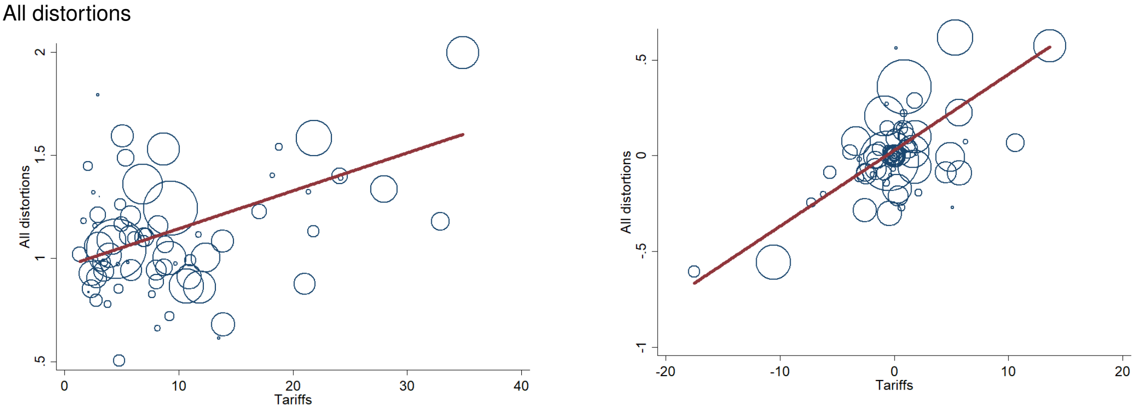
σ^2_{arpk}



'Efficient' sources



All distortions



Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A1: Industry-level tariffs over time

Year	Bottom decile (%)	Bottom quartile (%)	Mean (%)	Top quartile (%)	Top decile (%)
2010	1.3	3.4	8.6	11.4	18.5
2011	1.3	3.3	8.5	11.2	17.6
2012	1.2	3.3	8.5	11.3	18.9
2013	1.2	3.2	8.3	10.7	18.1
2014	1.2	3.2	8.4	10.8	18.2
2015	1.2	3.2	8.3	10.9	18.2
2016	1.2	3.2	8.4	11.0	18.1

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A2: Sectors, industries, and tariffs

Sector	Industry	Observations	Tariffs (%)
Food products	Chocolate and sweets	700	21.8
	Dairy products	1,145	13.9
	Bakery products	3,321	11.8
	Processing and preserving of fish	273	8.1
	Animal feeds	459	9.2
	Meat products	2,688	21.0
Beverages	Beer and malt	488	18.2
	Soft drinks and mineral waters	1,653	10.7
	Spirits	1,522	34.9
Tobacco	Tobacco	424	28.0
Textiles	Parts and accessories for motor vehicles	21,766	9.3
	Knitted fabrics	309	24.2
	Other textiles	3,220	17.0
	Cordage and ropes	293	11.7
	Made-up textile articles	1,925	18.8
	Carpets rugs and mats	680	21.8
Wearing apparel	Casting of iron and steel	452	4.7
	Wearing apparel (no fur)	9,172	32.9
Leather and related products	Footwear	1,679	24.1
	Luggage and handbags	919	21.3
Wood products	Planing of wood	960	4.7
	Other wood products	3,189	8.8
Paper products	Other paper and paperboard items	1,506	8.0
	Corrugated paperboards and paper containers	2,207	8.2
	Pulp, paper, and paperboards	779	6.8
Printing and media	Paints and printing	6,788	8.7
	Books and brochures	1,047	5.4
Chemical products	Primary plastics and rubber	1,030	6.1
	Soap and detergents	2,505	12.4
	Disinfectant and detergents	1,480	5.8
	Basic chemicals excluding fertilizers	2,838	4.1
Pharmaceuticals	Medical and surgical equipment	1,128	4.9
	Pharmaceutical and medical products	786	5.1
Rubber and plastic products	Other rubber products	1,195	6.9
	Rubber tyres and tubes	885	8.1
Non-metallic mineral products	Ceramic products	3,355	2.8
	Non-metallic	772	4.8
	Cement and plasters	1,101	1.3
Basic metals	Precious and non-ferrous metals	1,824	5.8
	Plastic products	5,444	9.2
	Basic iron and steel	6,986	4.5
	Forging, stamping, and roll-forming of metal	2,967	5.6
Fabricated metal products	Other fabricated products	2,218	5.0
	Cutlery, hand tools, and general hardware	1,155	7.7
	Structural metal products	346	5.5
	Optical instruments	606	3.5
Electrical equipment	Televisions and radio appliances	425	3.8
	Household appliances	1,214	7.0
	Insulated wires and cables	338	7.1
	Office and accounting appliances	2,938	2.0

Sector	Industry	Observations	Tariffs (%)
Machinery and equipment	Lifting and handling equipment	2,403	2.9
	Machinery for mining and quarrying	3,114	2.3
	Special motor vehicles parts	2,101	2.8
	Pumps, compressors, and valves	4,105	2.3
	Other general-purpose machinery	5,765	3.4
Motor vehicles	Motor vehicles	1,314	13.5
	Coachwork for motor vehicles	1,116	11.0
Transport equipment	Railway and locomotive	211	3.1
	Coating of metals and general mechanical engineering	10,598	3.9
	Aircraft and spacecraft	634	1.7
Furniture	Wooden containers	396	9.7
	Furniture	8,710	13.8
Other manufacturing	Machinery for textile and leather production	263	2.9
	Newspapers, periodicals, and magazines	3,331	8.7
	Sound or video recording	269	2.5
	Services related to printing	235	2.1
	Sport goods	446	5.7
	Other manufacturing	4,112	10.9
	Machine tools	686	2.6
	Other electrical equipment	2,552	3.2
Repair and installation of machinery	Special-purpose machinery	7,972	3.0

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A3: Tariffs and sources of capital misallocation

Dependent variable:		σ^2_ξ		
Tariffs	0.000	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.005	0.014	0.403	0.487
Dependent variable:		σ^2_V		
Tariffs	–0.001*	–0.001***	–0.001	–0.002***
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.104	0.390	0.450	0.700
Dependent variable:		σ^2_γ		
Tariffs	0.009**	0.016***	0.013**	0.025***
	(0.00)	(0.00)	(0.00)	(0.01)
R-squared	0.098	0.339	0.416	0.572
Dependent variable:		σ^2_X		
Tariffs	0.004	0.002	0.005*	0.011***
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.021	0.009	0.452	0.646
Dependent variable:		σ^2_ε		
Tariffs	0.000	–0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.002	0.000	0.284	0.412
N	71	71	71	71
Sector FE	No	No	Yes	Yes
Weights	No	Yes	No	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, robust standard errors in parentheses.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A4: Tariffs and sources of capital misallocation (with controls)

Dependent variable:		σ^2_{ξ}		
Tariffs	0.000	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.054	0.071	0.424	0.494
Dependent variable:		σ^2_{V}		
Tariffs	–0.001**	–0.001***	–0.001	–0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.163	0.469	0.453	0.612
Dependent variable:		σ^2_{γ}		
Tariffs	0.008**	0.014***	0.011**	0.009**
	(0.00)	(0.00)	(0.00)	(0.01)
R-squared	0.133	0.412	0.465	0.650
Dependent variable:		σ^2_{X}		
Tariffs	0.002	–0.000	0.002	0.006**
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.049	0.153	0.515	0.736
Dependent variable:		σ^2_{ε}		
Tariffs	0.000	–0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.003	0.003	0.346	0.531
N	71	71	71	71
Sector FE	No	No	Yes	Yes
Weights	No	Yes	No	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, robust standard errors in parentheses. The controls included are average of (log) capital, Herfindahl–Hirschman Index of concentration, percentage of exporters, and the relative importance of the industry (computed as the share of the industry in the total manufacturing value added).

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A5: Tariffs and dispersion in mark-ups

Dependent variable:		$\sigma^2_{Markups}$		
Tariffs	–0.000	0.000	0.000	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.002	0.012	0.383	0.420
N	71	71	71	71
Sector FE	No	No	Yes	Yes
Weights	No	Yes	No	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, robust standard errors in parentheses.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A6: Tariffs and dispersion in technology

Dependent variable:	$\sigma^2_{Technology}$			
Tariffs	0.000	0.000	0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.003	0.001	0.374	0.520
N	71	71	71	71
Sector FE	No	No	Yes	Yes
Weights	No	Yes	No	Yes

Note: $p<0.01$, ** $p<0.05$, * $p<0.1$, robust standard errors in parentheses.

Source: authors' computation from own data set based on National Treasury and UNU-WIDER (2019a,b, 2021).

Table A7: Dataset variables

Variable name	Variable type	Variable definition
g_sales	float	Sales revenue
g_cos2	float	Cost of sales
x_labcost	float	Labour cost
pi_iv_fixed_pd_10	double	Capital
x_control	float	Total costs
defl_grossvaladd	float	Gross value-added deflator
defl_grosscapform	float	Gross capital formation deflator
defl_cpi_economywide	float	Consumer price index
cust_import	float	Customs Derived-Total Value of Imports
cust_export	float	Customs Derived-Total Value of Exports
cust_customsvalue	long	Customs- 5.15 Customs Value. Indicated in Rands
hs6[1]		Customs- harmonized 6-digit system classification
imp_mic_sic7_2d	byte	Imputed Main Industry Code 2-digit level (SIC 7)
imp_mic_sic7_2d	byte	Imputed Main Industry Code 2-digit level (SIC 7)
comp_prof_sic5_4d	int	Composite Profit Code 4-digit level (SIC 5)

Source: authors' computation from SARS-NT/CIT-IRP5 panel.

[1]The hs6 variable is available in the custom transaction level datasets