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A TALE OF TWO SECTORS: WHY IS MISALLOCATION HIGHER IN SERVICES THAN IN MANUFACTURING?

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Recent empirical studies document that the level of resource misallocation in the service sector is significantly higher than in the manufacturing sector. We quantify the importance of this difference and study its sources. Conservative estimates for Portugal in 2008 show that closing this gap, by reducing misallocation in the service sector to manufacturing levels, would boost aggregate gross output by around 12 percent and aggregate value added by around 31 percent. Differences in the effect and size of productivity shocks explain most of the gap in misallocation between manufacturing and services, while the remainder is explained by differences in firm productivity and age distributions. We interpret these results as stemming mainly from higher output-price rigidity, higher labor adjustment costs and higher informality in the service sector.

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1. Introduction

Recent empirical studies document that the level of resource misallocation in the service sector is significantly higher than in the manufacturing sector. In this paper, we quantify the implications for aggregate productivity and aggregate GDP of the "excess misallocation" in the service sector, and investigate to what extent this misallocation gap reflects structural differences between the two sectors.

A now well-accepted result in the growth literature is that differences in the degree of allocative efficiency are one reason why countries differ in terms of

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aggregate total factor productivity (TFP). Most of the empirical studies linking resource misallocation to differences in TFP have been based on data from the manufacturing or agricultural sectors (see, e.g., Hsieh and Klenow, 2009; Camacho and Conover, 2010; Machicado and Birbuet, 2012; Bellone and Mallen-Pisano, 2013; Ziebarth 2013; Adamopoulos and Restuccia, 2014; Calligaris, 2015; Chen and Irarrazabal, 2015; Gopinath *et al*., 2015). Despite services being the largest sector for most countries, either in terms of value added or in terms of total employment, it was only recently that estimates of misallocation for the service sector became available (see, e.g., Benkovskis, 2015; Garcia-Santana *et al*., 2015; Dias *et al*., 2016, for Portugal, Spain, and Latvia, respectively).

One new result, common to these economy-wide studies, is that the level of estimated efficiency gains in the service sector is significantly higher than in the manufacturing sector.[1] Estimates obtained in Dias *et al*. (2016) for Portugal, for the 2004–11 period, show that resource misallocation is, on average, 24 percentage points (p.p.) higher in services than in manufacturing, when evaluated in terms of gross output, or around 40 p.p. higher, when evaluated in terms of value added (see Dias *et al*., 2016, table 4). Similarly, estimates in Garcia-Santana *et al*. (2015) for Spain, for the 2001–7 period, suggest that efficiency gains are around 22 p.p. higher in services than in manufacturing (see Garcia-Santana *et al*., 2015, table 2), while estimates in Benkovskis (2015) for Latvia, for the 2007–13 period, allow us to compute an average misallocation gap of around 32 p.p. between the two sectors. Despite not being strictly comparable (methodologies and sectoral definitions vary across papers), these numbers show that the level of resource misallocation in the service sector is significantly higher than in the manufacturing sector.

In order to answer our questions regarding the sources of "excess misallocation" in the service sector and its aggregate implications, we use the theoretical framework developed in Hsieh and Klenow (2009), with the three-factor extension presented in Dias *et al*. (2016).

Using firm-level data for the Portuguese economy, we first show that the misallocation differences between the manufacturing and service sectors have important implications for aggregate TFP and aggregate GDP. We estimate that if the misallocation gap between services and manufacturing were closed (by making the level of misallocation in the service sector be the same as in manufacturing), aggregate gross output (or aggregate TFP) would increase by about 12 percent, while aggregate value added (GDP) would increase by around 31 percent. We next document that the significantly higher level of resource misallocation in the service sector is the result not of a small number of industries with abnormal levels of misallocation, but of a strong regularity: the majority of industries belonging to the manufacturing sector rank among the industries with the lowest misallocation.

Based on regression analysis, we find that the higher levels of allocative inefficiency in the service sector can be fully explained by structural differences between the two sectors. Idiosyncratic productivity shocks, which impact allocative efficiency in the presence of (capital/labor) adjustment costs and/or output-price

[1]Although not strictly correct, because there is a one-to-one mapping between efficiency (or TFP) gains from reallocation of resources and misallocation, we refer to both interchangeably throughout the paper.

rigidity, are the most important factor contributing to the misallocation differences between the two sectors. However, the contribution of productivity shocks stems more from the different impacts than from the difference in the magnitude of the shocks between the two sectors. In particular, the impact of productivity shocks on misallocation is significantly higher in the service sector than in the manufacturing sector. Further analysis of the different distortions suggests that higher output-price rigidity and higher labor adjustment costs may explain why the effect of productivity shocks on misallocation is larger in services than in manufacturing.

The sectoral firm-size structure, proxied by the skewness of the productivity distribution, emerges as the second most important factor to explain the difference in misallocation between the two sectors. Again, the bulk of the contribution of this regressor stems from its higher impact in the service sector. A higher proportion of low productivity firms in the service sector makes the productivity distribution more right skewed, contributing to a higher level of misallocation in the service sector stemming from size-dependent distortions. The higher level of informality in the service sector may explain why the sectoral structure has more of an impact on the level of misallocation in this sector.

Finally, our empirical model suggests that the proportion of young firms also has a bearing on misallocation differences between the two sectors. Young firms emerge as facing higher capital costs than older firms, which we link to the presence of credit constraints imposed by financial institutions on young firms due to a lack of credit history or because of insufficient guarantees. This regressor has two opposite effects on misallocation differences between the two sectors. On the one hand, the higher proportion of young firms in the service sector contributes to increasing the difference in misallocation between the two sectors but, on the other hand, the impact of this regressor is lower in the service sector, which contributes to reducing misallocation differences between the two sectors. Overall, its net contribution is negative. This means that in the absence of this effect, the difference in misallocation between the service and the manufacturing sectors would be even higher.

Our findings have important consequences for developing countries and economies undergoing structural transformation. Duarte and Restuccia (2010) demonstrate that differences in productivity in the service and agricultural sectors across countries are one of the main factors behind overall productivity differences between countries. In particular, low productivity in the service sector and lack of catch-up can explain the experiences of productivity slowdown, stagnation, and decline observed across economies. Hsieh and Klenow (2009) show that differences in misallocation in the manufacturing sector are important for understanding the differences of total factor productivity between developed and developing countries. Using data for the manufacturing sector in China and India, Hsieh and Klenow (2009) conclude that reducing the level of misallocation in these economies to the levels observed in the U.S. economy would increase productivity by 30–50 percent in China and 40–60 percent in India. However, if a significant difference of allocative efficiency between manufacturing and the service sector, similar to that documented for Portugal, Spain, or Latvia, is present in other countries, the importance of resource misallocation to explaining productivity differences between developed and developing countries may be even higher than what the empirical evidence based on data from the manufacturing sector alone would suggest.

By shedding light on the reasons behind the higher level of misallocation in the service sector relative to the manufacturing sector, this paper also contributes to the understanding of the policies that may contribute to increasing productivity growth. Boosting competition so as to reduce output price rigidity in the service sector, avoiding size-contingent laws that may contribute to the survival of unproductive firms, and reducing barriers to growth by eliminating credit constraints imposed by financial institutions on young firms can contribute to reducing within-industry misallocation, especially in the service sector, and thus to increase aggregate TFP and aggregate value added (GDP).

The rest of the paper is structured as follows. Section 2 provides a brief description of the theoretical framework. Section 3 describes the dataset used in the analysis. Section 4 computes misallocation in the manufacturing and service sectors and discusses the aggregate implications of excess misallocation in the service sector. Section 5 reviews the main potential sources of misallocation suggested in the literature, presents the empirical results and discusses their interpretation. Finally, Section 6 summarizes the main findings.

2. The Theoretical Framework

This section summarizes the methodology used to identify the linkage between aggregate productivity and resource misallocation that results from the existence of distortions and frictions affecting the optimal allocation of factors of production at the firm level. We adopt the framework developed in Hsieh and Klenow (2009, 2011), but extend their model to consider a production function with intermediate inputs, as a third factor of production. The model with three factors of production, as well as the derivation of the full set of results, is presented elsewhere (see Dias *et al*., 2016), so here we just briefly review the model and summarize the main results needed for our current purposes.

The model assumes an economy with a single final good Y, produced by a representative firm in a perfectly competitive market. This firm combines the output Y_s of S industries in the economy using a Cobb–Douglas production technology:

$$Y = \prod_{s=1}^{S} \left(Y_s \right)^{\theta_s}, \tag{1}$$

with $\sum_{s=1}^{S} \theta_s = 1$ and $\theta_s = (P_s Y_s)/(PY)$, where P_s is the price of industry gross output, Y_s, and P is the price of the final good. At the industry level, gross output Y_s is a CES aggregate of M_s differentiated products:

$$Y_s = \left[\sum_{i=1}^{M_s} \left(Y_{si} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where Y_{si} denotes the gross output of firm i and parameter σ measures the elasticity of substitution between varieties of differentiated goods. The assumptions of free entry and monopolistic competition at the industry level imply inverse demand equations for each individual variety equal to the following:

(3)
$$P_{si} = Y_s^{\frac{1}{\sigma}} P_s \left(Y_{si} \right)^{\frac{-1}{\sigma}}.$$

In equation (3), the term $Y_s^{\frac{1}{\sigma}} P_s$ is not observed, so we set it equal to 1 for each industry s. This assumption has no practical implications for the exercise. It does not affect relative productivities and hence reallocation gains, since we do not consider inter-industry reallocation.

At the firm level, the gross output for each differentiated product is given by a Cobb–Douglas production function:

(4)
$$Y_{si} = A_{si} K_{si}^{\alpha_s} H_{si}^{\beta_s} Q_{si}^{1-\alpha_s-\beta_s},$$

where A_{si}, K_{si}, H_{si}, and Q_{si} denote the firm $i's$ total factor productivity (TFP), capital stock, labor, and intermediate inputs, respectively.[2]

With three factors of production, it is possible to separately identify distortions that affect capital, labor, and intermediate input prices simultaneously from distortions that affect the marginal product of one of the factors relative to the others. Thus, we introduce three types of distortions, or wedges, in the model—an output distortion, denoted $\tau_{y_{si}}$, a capital distortion, $\tau_{k_{si}}$, and a labor distortion, $\tau_{h_{si}}$—that take the form of a tax (or subsidy) on revenues, on capital services, and on labor costs, respectively. Given these assumptions, profits are given by the following:

(5)
$$\pi_{si} = (1-\tau_{y_{si}}) P_{si} Y_{si} - (1+\tau_{k_{si}}) R_s K_{si} - \left(1+\tau_{h_{si}}\right) W_s H_{si} - Z_s Q_{si},$$

where R_s, W_s, and Z_s denote the user cost of capital, the labor wage, and the intermediate inputs price, respectively.[3]

Profit maximization yields the standard conditions that the firm's output price is a fixed markup over marginal cost:

(6)
$$P_{si} = \frac{\sigma}{\sigma-1} \Psi_s \frac{(1+\tau_{k_{si}})^{\alpha_s} (1+\tau_{h_{si}})^{\beta_s}}{A_{si}(1-\tau_{y_{si}})},$$

where

(7)
$$\Psi_s = \left[\left(\frac{R_s}{\alpha_s} \right)^{\alpha_s} \left(\frac{W_s}{\beta_s} \right)^{\beta_s} \left(\frac{Z_s}{1-\alpha_s-\beta_s} \right)^{1-\alpha_s-\beta_s} \right].$$

[2]In the data, we observe nominal output ($P_{si} Y_{si}$), but not firm-specific output prices. Thus, to calculate the firm's real gross output, we use the relationship between nominal and real output that is assumed by the model. From equation (3) and using the assumption $Y_s^{\frac{1}{\sigma}} P_s = 1$, we obtain $Y_{si} = \left(P_{si} Y_{si}\right)^{\frac{\sigma}{\sigma-1}}$. We use this identity to compute the firm's real gross output. That is, we infer price versus quantity from nominal gross output and an assumed elasticity of demand. From the estimates of real output and the production function given in equation (4), we can obtain estimates of the firm-level total factor productivity ($\text{TFP}_{si} = A_{si}$).

[3]Equation (5) expresses the distortions in terms of output, capital, and labor relative to the intermediate inputs distortion. Thus, in the model, an intermediate input distortion will show up as a higher output distortion and as lower capital and labor market distortions. An observationally equivalent characterization would be in terms of distortions to the absolute levels of capital, labor, and intermediate input prices (and no output distortion).

In turn, from the first-order conditions for profit maximization, we obtain the following:

$$(8)\qquad \begin{aligned} \left(1+\tau_{k_{si}}\right) &= \frac{\alpha_s}{(1-\alpha_s-\beta_s)}\frac{Z_s Q_{si}}{R_s K_{si}}, \\ \left(1+\tau_{h_{si}}\right) &= \frac{\beta_s}{(1-\alpha_s-\beta_s)}\frac{Z_s Q_{si}}{W_s H_{si}}, \\ \left(1-\tau_{y_{si}}\right) &= \frac{\sigma}{\sigma-1}\frac{1}{(1-\alpha_s-\beta_s)}\frac{Z_s Q_{si}}{P_{si} Y_{si}}. \end{aligned}$$

Equation (8) allows us to estimate the three wedges from information on gross output, input costs, and the elasticities σ, α_s, and β_s.

Next, defining total factor revenue productivity (TFPR) as $\text{TFPR}_{si} = P_{si} A_{si}$, we obtain, from equation (6):

$$(9)\qquad \text{TFPR}_{si} = \frac{\sigma}{\sigma-1}\Psi_s \frac{(1+\tau_{k_{si}})^{\alpha_s}(1+\tau_{h_{si}})^{\beta_s}}{(1-\tau_{y_{si}})}.$$

Equation (9) shows that TFPR does not vary across firms within the same industry unless firms face some type of distortion. Intuitively, in the absence of distortions, more capital, labor, and intermediate inputs would be allocated to firms with higher TFP(A_{si}) to the point at which their higher output resulted in a lower price and the exact same TFPR as in firms with lower TFP. In contrast, in the presence of distortions, a high (low) TFPR is a sign that the firm confronts barriers (benefits from subsidies) that raise (reduce) the firm's marginal products of the different factors of production, rendering the firm smaller (larger) than optimal.

Denoting the levels of efficient real and nominal output as Y^*_{si} and $\left(P_{si} Y_{si}\right)^*$, it can be shown (see [Dias *et al*. (2016)]) that

$$(10)\qquad Y^*_{si} = \left(\frac{A_{si}}{\text{TFPR}^*_s}\right)^{\sigma} = Y_{si}\left(\frac{\text{TFPR}_{si}}{\text{TFPR}^*_s}\right)^{\sigma},$$

$$(11)\qquad \left(P_{si} Y_{si}\right)^* = \left(\frac{A_{si}}{\text{TFPR}^*_s}\right)^{\sigma-1} = P_{si} Y_{si}\left(\frac{\text{TFPR}_{si}}{\text{TFPR}^*_s}\right)^{\sigma-1},$$

where TFPR^*_s is the efficient level of total factor revenue productivity common to all firms in industry s that will prevail if idiosyncratic distortions are eliminated from the industry. TFPR^*_s is defined so that all firms face the same average wedges, and these are such that the demand for factors of production at the industry level is the same before and after the reallocation of resources.[4] The average wedges, denoted as $\left(1+\overline{\tau}_{k_s}\right)$, $\left(1+\overline{\tau}_{h_s}\right)$ and $\left(1-\overline{\tau}_{y_s}\right)$, are given by the following expressions:

$$(12)\qquad \begin{aligned} \left(1+\overline{\tau}_{k_s}\right) &= \frac{\alpha_s}{(1-\alpha_s-\beta_s)}\frac{Z_s Q_s}{R_s K_s}, \\ \left(1+\overline{\tau}_{h_s}\right) &= \frac{\beta_s}{(1-\alpha_s-\beta_s)}\frac{Z_s Q_s}{W_s H_s}, \\ \left(1-\overline{\tau}_{y_s}\right) &= \frac{\sigma}{\sigma-1}\frac{1}{(1-\alpha_s-\beta_s)}\frac{Z_s Q_s}{\left(P_s Y_s\right)^*}, \end{aligned}$$

[4]TFPR^*_s should not be confused with $\overline{\text{TFPR}}_s$ used in Hsieh and Klenow (2009). The latter is the average TFPR in industry s in the inefficient, or observed, allocation of resources. In contrast, TFPR^*_s is the average TFPR in industry s when all available factors of production are efficiently allocated.

where $\left(P_s Y_s\right)^* = \sum_{i=1}^{M_s} \left(P_{si} Y_{si}\right)^*$ is the industry efficient nominal output and $K_s = \sum_{i=1}^{M_s} K_{si}$, $H_s = \sum_{i=1}^{M_s} H_{si}$ and $Q_s = \sum_{i=1}^{M_s} Q_{si}$ are the actual industry levels of the capital stock, labor, and intermediate inputs, respectively.

Replacing the firm-specific wedges by the industry average wedges in equation (9), we have the following:

$$\text{TFPR}_s^* = \frac{\sigma}{\sigma-1}\Psi_s \frac{(1+\overline{\tau}_{k_s})^{\alpha_s}(1+\overline{\tau}_{h_s})^{\beta_s}}{(1-\overline{\tau}_{y_s})}, \tag{13}$$

so that we can decompose the (log) scaled TFPR ($\text{TFPR}_{si}/\text{TFPR}_s^*$) for each firm as a weighted sum of the (log) scaled capital, labor, and output wedges:

$$\ln\left(\frac{\text{TFPR}_{si}}{\text{TFPR}_s^*}\right) = \alpha_s \ln\left(\frac{1+\tau_{k_{si}}}{1+\overline{\tau}_{k_s}}\right) + \beta_s \ln\left(\frac{1+\tau_{h_{si}}}{1+\overline{\tau}_{h_s}}\right) - \ln\left(\frac{1-\tau_{y_{si}}}{1-\overline{\tau}_{y_s}}\right). \tag{14}$$

This equation allows us to see what happens to the output of the firm if distortions are eliminated from the economy, so that TFPR is equalized across firms in each industry. If scaled TFPR_{si} is above one, the firm is being "taxed," so that it will increase production if distortions are eliminated: in the absence of distortions, more resources are allocated to this firm to the point at which its higher output results in lower price and its TFPR equalizes TFPR_s^*. By looking at the right-hand side of this equation, we are able to see where the increase in production comes from. If, for instance, the scaled capital wedge $(1+\tau_{k_{si}})/(1+\overline{\tau}_{k_s})$ is larger than one, the firm is facing a capital tax, so that it will increase the capital stock if the distortion is eliminated. Similarly, for the scaled labor wedge. In contrast, firms for which the scaled output wedge, $(1-\tau_{y_{si}})/(1-\overline{\tau}_{y_s})$, is above one are benefiting from output subsidies, so that they would decrease production if those subsidies were eliminated.

Finally, by combining the various results presented above, it is straightforward to write the expression for the real gross-output gains at the industry level:

$$\frac{Y_s^*}{Y_s} = \frac{\left[\sum_{i=1}^{M_s}\left(Y_{si}^*\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s}\left(Y_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}} = \left[\frac{\sum_{i=1}^{M_s} A_{si}^{\sigma-1}}{\sum_{i=1}^{M_s}\left(A_{si}\frac{\text{TFPR}_s^*}{\text{TFPR}_{si}}\right)^{\sigma-1}}\right]^{\frac{\sigma}{\sigma-1}} = \left[\frac{1}{\sum_{i=1}^{M_s}\omega_{si}\cdot\left(\frac{1}{\text{TFPR}_{si}/\text{TFPR}_s^*}\right)^{\sigma-1}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{15}$$

where

$$\omega_{si} = \left(\frac{A_{si}}{\left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}}\right)^{\sigma-1} = \left(\frac{A_{si}}{\text{TFP}_s^*}\right)^{\sigma-1} = \frac{A_{si}^{\sigma-1}}{\sum_{i=1}^{M_s} A_{si}^{\sigma-1}}. \tag{16}$$

The interpretation of equation (15) is very intuitive, as it is simply the ratio of efficient output to observed output in industry s. Note that $\sum_{i=1}^{M_s}\omega_{si} = 1$ and that $\text{TFP}_s^* = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right)^{(1/(\sigma-1))}$ is the industry-level TFP in the absence of distortions (see Hsieh and Klenow, 2009). Thus, equation (15) shows that efficiency gains in industry s are a weighted sum of the inverse-scaled TFPR $(1/(\mathrm{TFPR}_{si}/\mathrm{TFPR}_s^*))$ across firms, where the weights are the contribution of each firm to the efficient industry TFP.[5] The smaller this weighted sum is, the larger are the efficiency gains obtained if distortions are eliminated from the industry. In particular, this sum will be small and, thus, efficiency gains will be large if there is a strong positive correlation between the weights ω_{si} and the scaled TFPR $(\mathrm{TFPR}_{si}/\mathrm{TFPR}_s^*)$. In other words, efficiency gains will be higher if, on average, more productive firms face higher distortions. From equation (15), we can also intuitively see that, everything else constant, efficiency gains will be higher the larger is the dispersion of scaled TFPR.[6]

Using the Cobb–Douglas aggregator given by equation (1), we obtain the economy-wide potential gross-output (or TFP) gains from resource reallocation:

$$\begin{aligned}\frac{Y^*}{Y} &= \prod_{s=1}^{S}\left\{\frac{Y_s^*}{Y_s}\right\}^{\theta_s} = \prod_{s=1}^{S}\left\{\left[\frac{\sum_{i=1}^{M_s} A_{si}^{\sigma-1}}{\sum_{i=1}^{M_s}\left(A_{si}\frac{\mathrm{TFPR}_s^*}{\mathrm{TFPR}_{si}}\right)^{\sigma-1}}\right]^{\frac{\sigma}{\sigma-1}}\right\}^{\theta_s} \\ &= \prod_{s=1}^{S}\left\{\left[\frac{1}{\sum_{i=1}^{M_s}\omega_{si}\cdot\left(\frac{1}{\mathrm{TFPR}_{si}^{**}}\right)^{\sigma-1}}\right]^{\frac{\sigma}{\sigma-1}}\right\}^{\theta_s}.\end{aligned} \tag{17}$$

Equations (15) and (17) will be used to compute industry and economy aggregate gross output reallocation gains, respectively. As the exercise fixes the total amount of inputs and calculates how much gross output could be increased by reallocating resources between firms within each industry, it follows that potential gross-output gains coincide with potential TFP gains, so that equation (17) gives us the potential efficiency gains both in terms of gross output and TFP. In the empirical section, we compute gross-output gains for two groupings of industries (manufacturing versus services) and for each case these formulas will be adjusted accordingly.

3. The Data

In this paper, we use firm-level balance-sheet data and industry-level factor shares. The firm-level data draw on annual information for Portuguese firms reported under the *Informação Empresarial Simplificada* (IES). IES data exist from 2006 onward and cover virtually the entire universe of Portuguese non-financial firms. The almost universal coverage of IES emerges from the fact that it is the system through which firms report mandatory information to the tax administration and the statistical authorities such as the *Instituto Nacional de*

[5]Using equation (11), it is straightforward to show that these weights also correspond to the firm's gross-output market share, when all resources are efficiently allocated across firms; that is, $\omega_{si} = \left(P_{si}Y_{si}\right)^* / \sum_{i=1}^{M_s}\left(P_{si}Y_{si}\right)^* = A_{si}^{\sigma-1}/\sum_{i=1}^{M_s}A_{si}^{\sigma-1}$.

[6]Note that efficiency gains are zero if scaled TFPR is equal to one for all firms; that is, if there are no distortions in the industry, which means that dispersion of $(\mathrm{TFPR}_{si}/\mathrm{TFPR}_s^*)$ is zero. The introduction of distortions implies, in practice, making the dispersion of $(\mathrm{TFPR}_{si}/\mathrm{TFPR}_s^*)$ differ from zero.

Estatística (INE) (the Portuguese Statistics Institute) and the *Banco de Portugal* (the Portuguese central bank). The data provide very detailed information on the firms' balance sheets and income statements. From this dataset, we obtain information on firms' gross output, value added, consumption of intermediate inputs, labor costs (wages and benefits including social security contributions), employment (average number of employees), gross investment (or gross fixed capital formation), annual and accumulated depreciations, and the book values of gross and net capital stock.[7]

Even though we report results only for 2008 and 2010, we also use data for 2007 and 2009, because we need consecutive years for the construction of some ancillary variables such as productivity shocks. Before using the data, we clean the dataset by dropping firms that do not report strictly positive figures for gross output, labor costs, employment, capital stock, intermediate consumption, and value added. After cleaning the data, we are left with 236,022 and 230,157 observations for 2008 and 2010, respectively.

Table 1 records the relative importance of agriculture, manufacturing, and services in our dataset in terms of employment, gross output, and value added. Note the small contribution of agriculture for total employment and value added (around 2 percent), while the service sector contributes around 75 percent. Manufacturing, which has been the focus of most empirical studies, contributes only 22–24 percent to total value added.[8]

The dataset also includes information on firms' main industry of operation, based on the European Classification of Economic Activities (NACE). For our purposes, industries are defined by three-digit NACE codes (Rev 2.1). This definition implies 213 different industries for 2008 (16 for agriculture, 101 for manufacturing, and 96 for services) and 215 industries for 2010 (16 for agriculture, 101 for manufacturing, and 98 for services).

For the industry-level factor shares, we use the average factor shares that are observed in the United States (U.S.) during the period 1998 to 2010, which are published by the BEA (Bureau of Economic Analysis).[9] An important remark to be made is that, as with the BEA data, our firm-level data on worker compensation include the salaries and other labor costs such as pension contributions or fringe

[7]Gross output and value added are computed using data from firms' balance sheets and applying the National Accounts identities. Gross output reflects the value of production at market prices, while value added is the difference between gross output and consumption of intermediate inputs. An important issue relates to the measurement of the capital stock, as the extent of misallocation may be overstated if capital is poorly measured. Here, we follow the most common approach (see, e.g., Hsieh and Klenow, 2009; Machicado and Birbuet, 2012; Ziebarth, 2013; Chen and Irarrazabal, 2015) and use the book value of the total capital stock net of depreciations (tangible and intangible assets), taken from firms' balance sheets.

[8]According to information from the National Accounts produced by INE, in 2008, agriculture, manufacturing, and services contribute 2.4, 14.1, and 83.5 percent for aggregate GDP, respectively. Thus, if anything, our dataset appears to be slightly skewed toward manufacturing and against the service sector. We note, however, that, in contrast to the National Accounts, services in our dataset do not include information on the government sector, the financial sector, and self-employment.

[9]In our model, it is not possible to separately identify the average input distortions (average wedges) and the input elasticities in each industry. Thus, the use of factor shares from the U.S. economy is a simple way to control for distortions that could affect the input shares in the Portuguese economy, while the U.S. is taken as a benchmark of a relatively undistorted economy.

TABLE 1
THE RELATIVE IMPORTANCE OF EACH SECTOR IN THE DATASET (IN PERCENT)

	2008			2010		
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
Employment	1.97	25.34	72.69	2.04	23.69	74.26
Gross output	2.42	34.46	63.12	1.92	32.71	65.36
Value added	2.35	23.57	74.08	1.76	22.24	76.00
Number of firms	6,069	34,257	195,696	6,351	32,096	191,710

Notes: Agriculture also includes forestry, fishing, mining, and quarrying; services also include construction and utilities (electricity, water, and gas services).

TABLE 2
Efficiency Gains under Alternative Assumptions

	2008				2010			
Assumptions	Total	M	S	S − M	Total	M	S	S − M
Baseline model	43.36	16.02	59.19	43.18	49.33	16.81	66.46	49.65
Final model	28.46	14.15	37.66	23.51	31.28	14.43	40.82	26.39

Notes: Efficiency gains in the baseline model are computed taking all the firms in the dataset, assuming $\sigma = 3.0$ and trimming the 1 percent tails of $\log(\mathrm{TFPR}_{si}/\mathrm{TFPR}_s^*)$ and $log(A_{si} M^{\frac{1}{\sigma-1}}/\mathrm{TFP}_s^*)$. Efficiency gains in the final model are computed taking only firms with more than ten employees, assuming $\sigma = 4.5$ and trimming the 2.5 percent tails of the scaled TFPR and TFP distributions. M, Manufacturing; S, Services; S − M, the difference between the service and the manufacturing sectors. The total also includes firms from agriculture.

benefits. Because industry classification is different in the two countries, we make an approximate concordance between the two classifications.[10]

4. Misallocation in the Manufacturing and Service Sectors

In order to take the model to the data, we must choose a value for the elasticity of substitution parameter (σ), decide how to treat outliers, and choose the group of firms included in the analysis. It is known that these assumptions impact the estimated levels of misallocation (see, e.g., Hsieh and Klenow, 2009; Dias *et al*., 2016). Table 2 shows the estimates of efficiency gains for 2008 and 2010, under two sets of assumptions.[11] The "baseline model" assumes $\sigma = 3.0$ (the number usually assumed in the literature), trims the 1 percent tails of the scaled TFPR and TFP distributions (also the usual trimming used in the literature), and includes all firms in the dataset. The "final model" assumes $\sigma = 4.5$ (the average sigma estimated for Portugal—see Amador and Soares, 2013), trims the 2.5 percent tails of the scaled TFPR and TFP distributions, and excludes very small firms (firms with ten or fewer employees).

Under the "baseline model" assumptions, we see from Table 2 that if distortions in the economy were eliminated (by equalizing TFPR across firms in each industry and keeping industry-level factor demand constant), gross output (or TFP) for the whole economy would be around 43 percent above actual gross output (or actual TFP) in 2008 and around 49 percent in 2010. Efficiency gains are also clearly higher in the service sector (around 59 percent in 2008 and 66 percent in 2010) than in the manufacturing sector (around 16 percent and 17 percent in 2008 and 2010, respectively). Thus, the service sector emerges as far more inefficient than the manufacturing sector, in line with the results in Dias *et al*. (2016). Under the "final model" assumptions, the estimated efficiency gains for the whole

[10]In the small number of cases for which we were not able to find a good match, we used the average for the whole economy in the U.S. Between 1998 and 2010, gross output was composed of 46 percent consumption of intermediate inputs, 33 percent labor compensation, and the remaining 21 percent was compensation to capital owners.

[11]In the Appendix (in the Online Supporting Information), we compute the efficiency gains under alternative assumptions and discuss the implications for the estimated level of misallocation and for the difference of allocative efficiency between the service and manufacturing sectors.

economy become smaller: about 28 percent in 2008 and 31 percent in 2010.[12] The difference between the service and the manufacturing sectors also becomes smaller, but remains very high: about 24 p.p. in 2008 and 26 p.p. in 2010. The decreasing misallocation differences between the two sectors reflect a higher presence of small firms and a higher frequency of outliers in the service sector. By dropping small firms from the dataset and increasing the trimming of the scaled TFP and TFPR distributions, the estimated efficiency gains in the service sector are affected disproportionately.

Figures 1 and 2 depict industries ordered by the level of efficiency gains for 2008 under the baseline and the final models, respectively. The striking message from these figures is that the significantly higher levels of efficiency gains in the service sector are not the result of a small number of industries with abnormal levels of efficiency gains, but of a strong regularity: the bulk of the manufacturing sector industries rank first, while the bulk of the service sector industries appear on the right-hand side of the charts. More specifically, among the 50 percent of the industries with the lowest TFP gains (77 industries), only 11 industries (14.7 percent) in Figure 1 and 13 industries (17.3 percent) in Figure 2 belong to the service sector. This result shows that the presence of higher levels of inefficiency is a widespread phenomenon in the service sector.

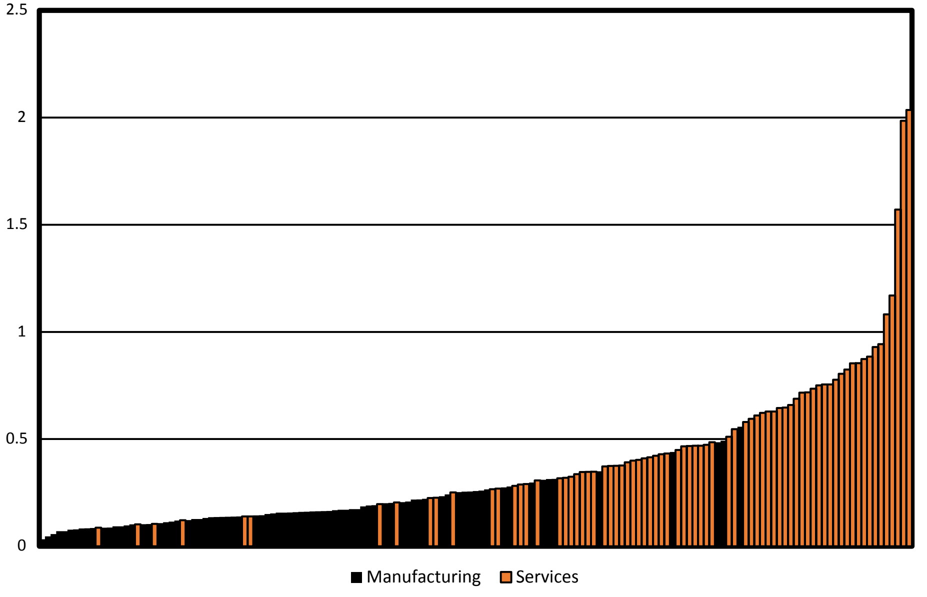

Figure 1. TFP Gains from Reallocation in 2008—Baseline Model
[Colour figure can be viewed at wileyonlinelibrary.com]

[12]Note that these are figures for gross output and that the efficiency gains evaluated in terms of value added (the type of estimates usually available in the literature) are significantly higher. For 2008, the corresponding value-added efficiency gains, under the "final model" assumptions, are 71.75 percent for the whole economy, 47.64 percent for manufacturing, and 84.05 percent for services.

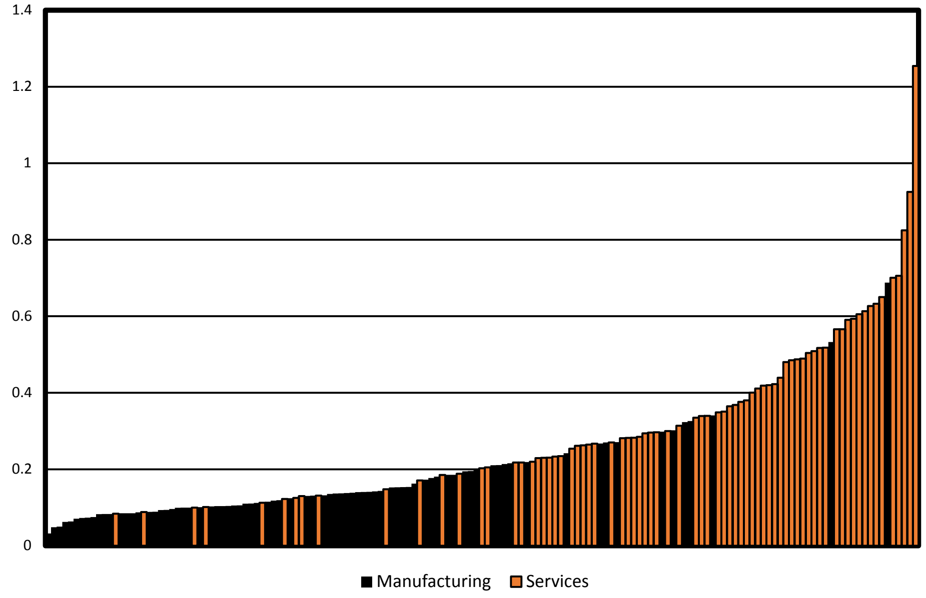

Figure 2. TFP Gains from Reallocation in 2008—Final Model
[Colour figure can be viewed at wileyonlinelibrary.com]

Hereafter, we focus on the "final model" assumptions, as these give rise to more conservative estimates of the differences of misallocation between the two sectors. Using the estimates recorded in Table 2, we conclude that closing the misallocation gap—that is, reducing misallocation in the service sector to the manufacturing levels in 2008 (from 37.66 percent to 14.15 percent)—would lead to a 12 percent boost in aggregate gross output (or aggregate TFP) and a 31 percent boost in aggregate value added (GDP).[13] These are large numbers, deserving a thorough investigation of the determinants underlying the misallocation gap between the two sectors.

Table 3 identifies the three industries with the lowest and the highest misallocation levels in the manufacturing and in the service sectors, as depicted in Figure 2. In the next section, we argue that adjustment costs, output-price rigidity, the relative importance of small and medium-sized firms, or the proportion of young firms are important characteristics that may give rise to significant differences in misallocation across industries. At this stage, however, without a model, we can only try to guess what the factors underlying the differences in misallocation in Table 3 can be.

Regarding the manufacturing sector, the six industries are all capital intensive, suggesting that this factor will probably not be a relevant characteristic in explaining different levels of misallocation, within the manufacturing sector. The three industries with the lowest misallocation appear to be highly competitive, with two

[13]The efficiency gains in terms of gross output are computed as $(1.3766/1.1415)^{\theta_s}$, where θ_S is the share of the service sector in aggregate gross output. The value-added efficiency gains are computed using equation (24) in [Dias et al.(2016)].

TABLE 3
Industries with the Lowest and the Highest Efficiency Gains, 2008

Industries	Efficiency gains
Manufacturing	
Lowest	
341: Manufacture of motor vehicles	3.21
202: Manufacture of veneer sheets, plywood/laminboard, particle board, fiber board, and other panels and boards	4.85
265: Manufacture of cement, lime, and plaster	5.01
Highest	
311: Manufacture of electric motors, generators, and transformers	34.07
322: Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy	53.26
272: Manufacture of cast iron or steel tubes	68.81
Services	
Lowest	
802: General secondary education	8.37
801: Primary and pre-primary education	8.80
455: Renting of construction and demolition equipment with operators	9.99
Highest	
744: Advertising agencies	82.47
702: Renting of real estate	92.53
741: Legal, accounting, bookkeeping and auditing activities; tax consultancy; market research and public opinion polling	125.44

Note: Industries with the lowest and the highest efficiency gains, as depicted in Figure 2 (Final model).

of them (industries 202 and 265) also displaying low levels of product differentiation, suggesting little price rigidity. Among the three industries with the highest efficiency gains, there is one where we can anticipate little output heterogeneity (industry 272) and two industries where significant product differentiation can be expected (industries 311 and 322). This evidence suggests that other factors, besides output market competition permitted by product differentiation, must play a role in explaining misallocation differences at the industry level.

Regarding the service sector, the three industries with the lowest efficiency gains (802, 801, and 455) are industries with little output differentiation. Industries 801 and 802 are also strongly regulated by the government (regarding, for example, teachers' wages, number of students per teacher, characteristics of the school premises, and materials used), so that the relative use of resources is expected to be similar across "firms," implying little misallocation. In contrast, the lack of competition stemming from the presence of local markets and output heterogeneity emerge as the likely factors underlying the high levels of misallocation displayed by the three remaining industries (especially so in the case of industries 702 and 741).

Although Table 3 provides some hints as to why misallocation is higher in the service than in the manufacturing sector, a more systematic analysis is needed. In the next section, we thoroughly examine the literature on misallocation and conduct regression analysis to identify the most relevant factors that could explain the differences in misallocation between the manufacturing and service sectors.

5. Explaining Differences in Misallocation Between the Service and Manufacturing Sectors

In this section, we use regression analysis and the Gelbach decomposition to identify which factors are most relevant for explaining the misallocation differences between the service and manufacturing sectors. We start by reviewing the main sources of misallocation suggested in the literature to guide our identification of the regressors required to complete the model specification. Next, we briefly present the Gelbach decomposition (see Gelbach, 2016) for our model and discuss the empirical results.

5.1. *Sources of Misallocation*

The list of potential sources of misallocation suggested by the literature is long and varied. For presentation purposes we group them in four categories: (a) adjustment costs and output-price rigidity; (b) distortions to input prices; (c) financial frictions; and (d) firm-specific markups.

(a) Adjustment costs and output-price rigidity

The Hsieh and Klenow (2009) model described above is static in the sense that it assumes that the adjustments are instantaneous, so that firms should always be in their long-run static equilibrium relationship no matter the frequency, size, or type of shocks that hit them. Thus, any short-term deviation from the static equilibrium relationship stemming from idiosyncratic shocks and the presence of adjustment costs will show up as misallocation in the model. In a recent paper, Asker *et al*. (2014) investigated the role of adjustment costs in shaping the dispersion of marginal product of inputs (see also Bartelsman *et al*., 2013; Song and Wu, 2013). In their model, firms acquire the inputs in a frictionless spot market, but are hit by idiosyncratic productivity shocks and face costs when adjusting their capital stock. In such a framework, dispersion in the marginal revenue product of capital arises naturally and the resource allocation, while appearing as inefficient in a static model, may be efficient in a dynamic sense. An important result for our paper is that, in the presence of adjustment costs, as the volatility of TFP shocks increase, so does the dispersion of the marginal product of the inputs. Thus, in the context of our model, we may expect volatility of TFP shocks to have a bearing on the dispersion of TFPR and, thus, on misallocation, especially through higher dispersion of the capital and/or labor wedges (see equation (14)).[14]

Another potential source of misallocation, stemming from the static nature of the Hsieh and Klenow (2009) model, is the implicit assumption of instantaneous price adjustment following productivity shocks. According to the model, there is a one-to-one contemporaneous negative relationship between productivity (A_{si}) and prices (P_{si}) (see equation (6)). That is, the model assumes that a 1 percent increase

[14]Imperfect information has also been suggested as a foundation for adjustment costs, giving rise to a sluggish response of inputs to fundamentals and thus to misallocation (see David *et al*., 2014). In our model, it is not possible, however, to distinguish between alternative sources of adjustment costs (technological versus informational frictions).

in productivity implies an instantaneous 1 percent decrease in prices. It is widely known, however, that price stickiness is a pervasive phenomenon in the economy and that firms may react differently to shocks (demand or cost shocks) and asymmetrically to positive and negative shocks.[15] Thus, similarly to what happens with capital or labor adjustment costs, we may expect firm-level productivity shocks in the presence of price rigidity to imply additional TFPR dispersion (through higher dispersion of the output wedge) and, thus, to give rise to increased misallocation.

We account for the possibility that productivity shocks might help to explain the differences in misallocation between the manufacturing and service sectors. As we will show, this will be the case if the average size of TFP shocks and/or the effect of these shocks differ across the two sectors. If the importance of adjustment costs or the degree of price rigidity varies across industries, we should expect the impact of productivity shocks on misallocation to also differ across industries. If, for instance, on average, price rigidity is higher in the service sector than in manufacturing, we might expect the impact of productivity shocks on misallocation to be higher in the former.

It should be noted that our framework does not allow for distinguishing productivity shocks from other type of shocks that may hit the economy. In what follows, we use the term "productivity shocks" to designate not only true productivity shocks, but also other shocks to production such as demand shocks, natural disasters, and so on.

(b) Distortions to input prices

A second potential source of misallocation is the presence of distortions on the prices of the production factors [for a discussion, see, e.g., Guner *et al*. (2008), Restuccia and Rogerson (2008), Hsieh and Klenow (2009)]. For instance, non-competitive banking systems may offer favorable interest rates on loans to some producers based on non-economic factors, leading to a misallocation of credit across firms. Governments may offer subsidies, special tax incentives, or lucrative contracts to specific producers. Various product and labor-market regulations may drive up the cost of labor in the formal *vis-à-vis* the informal sector, or in large versus small firms, or drive down the cost of capital in small firms through special lines of credit.

In the case of Portugal, there are many regulations that tend to benefit small and medium-sized firms, by granting these firms access to labor and investment subsidies that are not easily accessible or not accessible at all to large firms. These include (i) less bureaucratic processes for worker dismissals; (ii) less costly conditions regarding the provision of healthcare services; (iii) smaller fines for labor law breaches; (iv) better accessibility conditions (including reduction of social contributions) to subsidized employment creation, worker training, and professional internship programs; (v) better accessibility conditions to investment subsidies,

[15]Information costs and/or menu costs incurred by the firm to determine the optimal price and/or to change the price are usually suggested in the literature as the main sources of price rigidity. For empirical evidence on price rigidity at the firm level see, for instance, Fabiani *et al*. (2006) for the euro area and Dias *et al*. (2015) for Portugal.

including access to specific investment programs; and (vi) access to specific fiscal benefits (smaller taxes on profits).[16]

In practice, the impact of policies that favor smaller (or larger) firms through lower capital or labor costs is expected to vary across industries depending on the importance of smaller (or larger) firms in each industry. Below, we capture this phenomenon by looking at the skewness of the industry TFP distribution. We use this statistic as a summary measure to characterize the structure of each industry in terms of productivity. By looking at TFP rather than at other measures of size (employment or gross output) we avoid some additional endogeneity problems, as employment and gross output are distortion dependent.[17] By definition, skewness is high in industries with a high proportion of firms with low productivity and a few firms with very high productivity. Thus, we interpret the correlation between this statistic and misallocation, at the industry level, as measuring the importance of size-dependent distortions (if distortions were allocated purely randomly across firms, the covariance between misallocation and skewness should be zero). Further, by linking productivity to the individual wedges, we will be able to tell whether less productive firms are being taxed or subsidized, and the source of the tax or the subsidy.

(c) Financial frictions

A third potential source of misallocation is the presence of financial frictions. For instance, financial institutions may be unable or unwilling to provide credit to firms that are highly productive but that have no credit history or insufficient guarantees, preventing these firms from expanding their activities (for a discussion, see, e.g., Banerjee and Moll, 2010; Hosono and Takizawa, 2012; Gilchrist *et al*., 2013; Midrigan and Xu, 2014; Moll, 2014). But, financial frictions may instead affect larger firms with larger scales of operation and larger financing needs (see Buera *et al*., 2011).

We try to accommodate the possibility that young firms (irrespective of their size) face financial constraints by investigating how misallocation varies with the age of the firm. In practice, our model allows us to distinguish financial frictions that operate as quantity restrictions from size-dependent policies that operate through the price of inputs. The presence of size-dependent policies that affect the price of the inputs may be detected by looking at the relationship between the size of the firm and the individual scaled wedges. For instance, if distortions are due to firm-size contingent policies that favor smaller firms by reducing the cost of capital (through special lines of credit) or the cost of labor (through special labor regulations), returns to additional capital and labor would be expected to be lower in smaller firms. That is, we would expect a positive relationship between size and TFPR or size and the capital or labor wedge. In contrast, if misallocation is due to

[16]For a list of size-dependent polices passed by the Portuguese governments since the early 1990s, see Dias *et al*. (2016). Illustrations of size-dependent polices for Italy and France can be seen in Guner *et al*. (2008) and in Gourio and Roys (2014) and Garicano *et al*. (2013), respectively.

[17]Bartelsman *et al*. (2013) show that misallocation stemming from policy-induced distortions may affect the correlation between the distribution of productivity and the size of the firm. Recall also that, according to the discussion in Section 2, industry-level misallocation will be higher the stronger is the (positive) firm-level correlation between TFP and scaled TFPR.

financial market failures that constrain young firms, we would expect the presence of many of these firms that do not grow because they could not secure access to credit. In other words, we would expect a negative relationship between the age of the firm and the capital wedge. Of course, the two situations may coexist in practice: there may, at the same time, be small firms that benefit from lower capital costs (special lines of credit) and young firms (eventually small) that are facing capital constraints.

(d) Firm-specific markups

Imperfectly competitive product markets with firm-specific markups have also been suggested as a potential source of misallocation (see, e.g., Syverson, 2004a,b; Peters, 2013). In an environment with imperfectly competitive output markets, misallocation, as identified by the static model, occurs because firms have monopoly power and set firm-specific markups. While distortions on the prices of inputs imply that firms with relatively high TFPR are constrained (or "taxed"), imperfectly competitive output markets predict that high TFPR is indicative of market power (captures higher markups).[18] According to this type of model, industry-level misallocation is expected to be negatively correlated with the level of competition. For instance, barriers to substitution across producers, stemming from various forms of product differentiation (spatial, physical, or brand driven) may explain different levels of misallocation among industries.

To capture the impact of competition on misallocation, we need reliable measures of competition across industries. However, satisfactory measures of competition are very difficult to build, either because they are theoretically unsatisfactory or because appropriate data are not available. Statistics such as output concentration ratios, advertising intensity measures, price–cost margins, the Herfindahl index or the Ellison and Glaeser (1997) concentration index, or measures of sunk entry costs or of international exposure, do not capture the degree of competition in the relevant markets for all industries. For instance, for Portugal, the concentration ratio (the importance of sales of the largest four or eight firms in total industry sales) is higher in the manufacturing sector than in services. Taken at face value, this would mean that the manufacturing sector is less competitive than the service sector. However, the number of firms in the industry or its concentration ratio does not identify the degree of competition in the product market if a significant part of the industry output is exported. What matters is competition in the destination market. Similar comments can be made about most of the other statistics.[19]

Thus, our estimated model does not explicitly include any direct competition measure. However, it is important to note that competition affects the degree of price rigidity, as well as the characteristics of the productivity distribution. We may expect less price rigidity, and thus less misallocation, in industries where competition is higher. Similarly, in industries in which it is easy for customers to switch

[18]In the model suggested by Peters (2013), $TFPR_{si}$ is proportional to the firm-specific markup, which replaces the right-hand side of equation (9).

[19]For a thorough discussion on this issue, see Holmes and Schmitz (2010).

between competing suppliers, the productivity distributions should exhibit higher minima, less dispersion, and lower skewness. Thus, in our empirical model, the skewness of the productivity distribution may also be interpreted as an indirect measure of competition: higher skewness signals lower competition.

5.2. *Gelbach Decomposition*

To study the causes of misallocation differences between services and manufacturing, we use the methodology developed in Gelbach (2016). Let us denote the efficiency gains in industry s by $Z_s = Y_s^*/Y_s$, and let D be a dummy variable, which equals 1 if the industry belongs to the service sector and 0 if it belongs to the manufacturing sector.[20] In the simple cross-section regression

$$Z_s = a_0 + a_1 D_s + u_s, \tag{18}$$

the coefficient a_1 measures the difference between the efficiency gains in the service and manufacturing sectors. The D_s variable in the simple regression given in equation (18) may be thought of as a proxy for differences of certain factors (characteristics) between the manufacturing and service sectors.

The theories of misallocation, surveyed above, suggest that we should expect industry-level efficiency gains to be correlated with productivity shocks, skewness of the TFP distribution, and the proportion of young firms in each industry. Let us denote these three regressors by X_{1s}, X_{2s}, and X_{3s}, respectively. If we account for the possibility of each regressor having a different impact on the service and manufacturing sectors, the general model may be written as follows:

$$Z_s = a_0 + a_1 D_s + b_1 X_{1s} + c_1 D_s X_{1s} + b_2 X_{2s} + c_2 D_s X_{2s} + b_3 X_{3s} + c_3 D_s X_{3s} + v_s, \tag{19}$$

where the c_i coefficient measures the difference of the impact of the X_{is} regressor between the two sectors. From the estimates for the full model, given in equation (19), we can tell whether the regressors are able to fully explain the difference between the misallocation in the two sectors. This will be the case if coefficient a_1 is not statistically different from zero.

The Gelbach decomposition of omitted variable bias allows us to quantify the impact that each variable and/or factor has on the change in the estimate of a_1. Using the results in Gelbach (2016), we can write

$$\hat{a}_1^{\text{base}} = \hat{a}_1^{\text{full}} + \hat{\theta}_1 \hat{b}_1 + \hat{\mu}_1 \hat{c}_1 + \hat{\theta}_2 \hat{b}_2 + \hat{\mu}_2 \hat{c}_2 + \hat{\theta}_3 \hat{b}_3 + \hat{\mu}_3 \hat{c}_3, \tag{20}$$

where:

1. $\hat{a}_1^{\text{base}}$ and $\hat{a}_1^{\text{full}}$ are the ordinary least squares (OLS) estimates of a_1 in the base model given in equation (18) and the full model given in equation (19), respectively.
2. $\hat{b}_i$ and $\hat{c}_i$ (i = 1, 2, 3) are the OLS estimates of the b_i and c_i parameters in the full model given in equation (19).

[20]In the analysis that follows, we drop the agricultural sector, as we are only interested in explaining the differences between misallocation in the manufacturing and service sectors.

3. $\widehat{\theta}_i$ and $\widehat{\mu}_i$ are the OLS estimates of the θ_i and μ_i parameters in the simple regressions $X_{is} = b_{i0} + \theta_i D_s + \varepsilon_{is}$ and $D_s X_{is} = c_{i0} + \mu_i D_s + \varepsilon_{is}$, (i = 1, 2, 3), respectively.

In our case, the OLS estimates of the parameters in equation (20) lend themselves to a very intuitive interpretation:

1. $\widehat{a}_1^{\text{base}}$ is the difference between the efficiency gains in the service and the manufacturing sectors;
2. $\widehat{a}_1^{\text{full}}$ is the residual difference between the efficiency gains in the service and manufacturing sectors not accounted for by the model;
3. $\widehat{\theta}_i$ is the difference between the mean of X_{is} in the service and manufacturing sectors, and
4. $\widehat{\mu}_i$ is the mean of X_{is} in the service sector.

The total contribution of the X_{is} regressor is given by $\widehat{\theta}_i\widehat{b}_i + \widehat{\mu}_i\widehat{c}_i$. Thus, X_{is} accounts for the difference between the efficiency gains in the two sectors, if at least one of the following two conditions is met: (i) the mean of X_{is} differs across the two sectors ($\widehat{\theta}_i \neq 0$); or (ii) the impact of X_{is} differs between the two sectors ($\widehat{c}_i \neq 0$). We note that the Gelbach decomposition for our particular model is similar to the so-called Oaxaca–Blinder decomposition that has been used extensively in the literature to decompose mean wage differentials (see, e.g., Blinder, 1973; Oaxaca, 1973; Jann, 2008). One important difference, however, is that the methodology developed in Gelbach (2016) allows for statistical inference regarding the decomposition, while the Oaxaca–Blinder method does not.[21]

5.3. *Regression Analysis*

The results of decomposition given in equation (20) are presented in Table 4 for 2008 and 2010, with robust *t*-statistics in parentheses. The first row records the $\widehat{a}_1^{\text{base}}$ estimates; that is, the difference between efficiency gains in the service and manufacturing sectors.[22] The second row reports the explained difference; that is, the sum of contributions of the 3 regressors. The second row from the bottom records the unexplained difference; that is, $\widehat{a}_1^{\text{full}}$. For each regressor X_{is},

[21]To see the similarities between the two decompositions, consider the two linear models $Z_j = b_{0j} + X_j' B_j + \varepsilon_j$ for $j = k, r$ (k = services and r = manufacturing), where $X_j' = [X_{1j}, X_{2j}, X_{3j}]$ and $B_j' = [b_{1j}, b_{2j}, b_{3j}]$. Assume that the two models are separately estimated by OLS and let $\bar{X}_j' = [\bar{X}_{1j}, \bar{X}_{2j}, \bar{X}_{3j}]$ denote the sectoral means of the regressors. With this notation, the Oaxaca–Blinder decomposition reduces to

$$\begin{aligned} E[Z_k] - E[Z_r] = \bar{Z}_k - \bar{Z}_r &= (\hat{b}_{0k} - \hat{b}_{0r}) + \bar{X}_k'\hat{B}_k - \bar{X}_r'\hat{B}_r \\ &= (\hat{b}_{0k} - \hat{b}_{0r}) + (\bar{X}_k' - \bar{X}_r')\hat{B}_r + \bar{X}_k'(\hat{B}_k - \hat{B}_r), \end{aligned}$$

where $(\hat{b}_{0k} - \hat{b}_{0r})$ represents the unexplained difference between the two sectors. Now, bearing in mind that in equation (20) we have $\hat{\theta} = [\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_2]' = [\bar{X}_k - \bar{X}_r]$, $\hat{b} = [\hat{b}_1, \hat{b}_2, \hat{b}_3]' = \hat{B}_r$, and $\hat{\mu} = [\hat{\mu}_1, \hat{\mu}_2, \hat{\mu}_3]' = [\bar{X}_k]$, it is straightforward to show that the Gelbach decomposition may be written as follows:

$$\widehat{a}_1^{\text{base}} - \widehat{a}_1^{\text{full}} = (\bar{X}_k' - \bar{X}_r')\hat{B}_r + \bar{X}_k'(\hat{B}_k - \hat{B}_r),$$

which corresponds to the parameterization of the Oaxaca–Blinder decomposition shown above.

[22]Note that the difference in efficiency gains between the two sectors in Table 4 is a non-weighted average, which explains the difference *vis-à-vis* the figures reported in the last row of Table 2.

TABLE 4
Efficiency Gains: Gelbach Decompositions of the Difference Between Services and Manufacturing

	2008	2010
Difference in efficiency gains	0.202 (8.31)	0.205 (7.90)
Explained difference:	0.225 (2.36)	0.207 (2.45)
(a) Productivity shocks	0.175 (1.82)	0.123 (1.64)
(a_1) characteristics effect	0.027 (1.77)	0.023 (2.17)
(a_2) coefficients effect	0.148 (1.44)	0.099 (1.23)
(b) Sectoral firm-size structure	0.086 (2.60)	0.113 (3.07)
(b_1) characteristics effect	0.016 (2.15)	0.002 (0.33)
(b_2) coefficients effect	0.069 (2.00)	0.112 (2.85)
(c) Importance of young firms	−0.036 (−0.96)	−0.029 (-0.97)
(c_1) characteristics effect	0.021 (1.83)	0.014 (1.70)
(c_2) coefficients effect	−0.057 (−1.32)	−0.042 (−1.37)
Unexplained difference	−0.023 (−0.26)	−0.002 (−0.02)
Number of industries	154	154

Notes: Efficiency gains are obtained assuming the final model in Table 2. Productivity shocks are proxied by the industry-level standard deviation of firms' log TFP changes between year t and year $t-1$; the sectoral structure is proxied by the skewness of the productivity distribution and the importance of young firms is proxied by the proportion of firms with 3 years of age or less. The difference in efficiency gains is given by the coefficient of the industry dummy in the regression given by equation (18), while the unexplained difference is given by the coefficient of the industry dummy in the regression given by equation (19). Robust t-statistics in parentheses.

the total contribution is divided into two components: one stemming from the difference between the mean of the regressors in the two sectors (characteristics effect) and one stemming from the difference of the regressors impact in the two sectors (coefficients effect). To help in understanding the estimation results, Table 5 presents some descriptive statistics for the regressors (mean, standard deviation, and interquartile range), distinguishing between manufacturing and services and contrasting the top 10 percent of industries where misallocation is highest with the remaining industries.

An important result is that the model fully accounts for the difference between the efficiency gains in the two sectors. The unexplained difference—that is, $\widehat{a}_1^{\text{full}}$—is not significantly different from zero both in 2008 and 2010. Similar to Figures 1 and 2, if we now order industries by the level of unexplained efficiency gains in 2008, we conclude that among the 50 percent of the industries with the lowest TFP gains (77 industries), 43 industries (58.1 percent) belong to the service sector (compared to 17.3 percent in Figure 2). These numbers suggest that our model is able to explain the misallocation differences between industries of the two sectors to the point at which no systematic differences of TFP gains in the two sectors remain.[23]

(a) Productivity shocks

To identify the firm-level productivity shocks, we assume that TFP follows an AR(1) process:

[23]As a robustness test, we also performed the Gelbach decomposition excluding some outliers (the three industries with the highest and the three industries with the lowest levels of misallocation). We did not find qualitative differences in the contributions of the regressors, compared to the results in Table 4.

TABLE 5
Descriptive Statistics of the Regressors, 2008

	All industries			Top 10% misallocation industries		
	Mean	SD	IQ range	Mean	SD	IQ range
Productivity shocks						
Manufacturing	0.154	0.043	0.046	0.189	0.027	0.030
Services	0.199	0.052	0.054	0.251	0.083	0.108
Total	0.176	0.052	0.053	0.220	0.068	0.065
Sectoral structure						
Manufacturing	0.874	0.485	0.684	1.257	0.687	0.826
Services	1.180	0.726	0.818	1.949	0.717	0.987
Total	1.021	0.629	0.822	1.603	0.767	1.058
Share of young firms						
Manufacturing	0.049	0.043	0.038	0.102	0.062	0.096
Services	0.069	0.046	0.062	0.083	0.057	0.087
Total	0.059	0.045	0.051	0.092	0.059	0.078

Notes: Productivity shocks are proxied by the industry-level standard deviation of firms' log TFP changes between year t and year $t-1$; the sectoral structure is proxied by the skewness of the productivity distribution; and young firms are defined as firms with 3 years of age or less. The top 10 percent misallocation industries correspond to the eight industries in each sector with the highest misallocation.

$$a_{si,t} = \mu_s + \rho_s a_{si,t-1} + \phi_s \upsilon_{si,t},$$

where $a_{si,t}$ denotes the log of TFP of firm i, in industry s, in period t and $\upsilon_{si,t} \sim N(0,1)$ is an independent and identically distributed (i.i.d.) standard normal random variable. The ϕ_s term denotes the standard deviation of firm-level productivity shocks in industry s and corresponds to our measure of industry-level productivity shocks. To estimate ϕ_s, we use two years of consecutive data, but restrict the sample to firms that appear in both years. When estimated freely, ρ_s is close to unity for the great majority of industries. Thus, ultimately, we compute the productivity shocks as the industry-level standard deviation of $a_{si,t} - a_{si,t-1}$.[24] Productivity shocks emerge as the most important factor explaining misallocation differences between the two sectors. Importantly, the contribution of productivity shocks stems mostly from the difference of the impacts between the two sectors (the coefficients effect). In particular, from Table 4 we see that the impact of productivity shocks in the service sector is significantly higher than in the manufacturing sector. This is an interesting result that warrants some explanation. For reasons discussed above, we expect industry-level efficiency gains to be positively correlated with productivity shocks. In the presence of adjustment costs, a firm can only adjust capital or labor with some lag, as it takes time to install capital or to hire new employees. A similar process takes place in the presence of output-price rigidity. Thus, when hit by an idiosyncratic productivity shock, a firm responds with a lag and adjusts the input level or the output price sluggishly, which leads to variation of TFPR across firms. With this lagged response, greater idiosyncratic shocks lead to greater variation of TFPR across firms and, thus, to greater misallocation.[25] However, for the impact of productivity shocks on misallocation to differ across sectors, we need to assume that the importance of input adjustment costs (capital and/or labor) or the degree of price rigidity vary across industries. In order to investigate this issue further, we use equation (14) to look at the correlation between TFP shocks and the dispersion of individual wedges. This analysis allows us to tell whether the impact of TFP shocks on misallocation stems mainly from the presence of capital, labor, or output distortions. Table 6 reports these correlations for 2008.

An interesting result from Table 6 is that productivity shocks are not very correlated with the standard deviation of the capital wedge, especially in the service sector.[26] By contrast, productivity shocks appear more correlated with the labor-wedge and output-wedge dispersion in the service sector than in the manufacturing sector. This evidence is consistent with the idea of higher price rigidity and higher labor adjustment costs in the service sector. The empirical evidence in the literature has shown that price rigidity is higher in the service

[24]The correlation between the two measures of productivity shocks (the standard deviations of the residuals of the autoregressive model versus the standard deviations of TFP changes between t and $t-1$) is 0.97, which shows that the two variables are very close to each other. These correlations are 0.93 for manufacturing and 0.98 for services.

[25]Note from Table 5 that the mean and dispersion of TFP shocks are higher in services than manufacturing.

[26]This does not necessarily mean that capital adjustment costs are not present in the economy, as the adjustment costs are not the only source of dispersion of the marginal product of capital.

TABLE 6
THE CORRELATION BETWEEN THE REGRESSORS AND THE STANDARD DEVIATIONS OF SCALED TFPR AND SCALED WEDGES, 2008

	TFP shocks		Sectoral structure		Share of young firms	
	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services
SD(τ_k)	0.114	0.059	0.212	−0.089	0.302	0.225
SD(τ_h)	0.108	0.418	0.084	0.241	0.308	0.233
SD(τ_y)	0.342	0.393	0.299	0.163	0.398	0.160
SD(TFPR)	0.337	0.456	0.264	0.228	0.359	0.153

Notes: The entries are the correlations between the regressors and the industry-level standard deviations of scaled TFPR and scaled wedges; SD(x) denotes the industry-level standard deviation of ln (x); TFP shocks are proxied by the industry-level standard deviation of firms' log TFP changes between year t and year t−1; the sectoral structure is proxied by the skewness of the productivity distribution; and young firms are defined as firms with 3 years of age or less.

sector (see, e.g., Fabiani *et al.*, 2006 for the euro area; Dias *et al.*, 2015 for Portugal). It is also known that price rigidity is higher in less competitive markets (Martin, 1993; Gopinath and Itskhoki, 2010). Together, this evidence suggests that higher output-price rigidity in the service sector might stem from lower competition in this sector, as services are typically more differentiated than manufacturing (see ECB, 2006).[27] In turn, higher informational frictions (stemming from higher spatial dispersion of firms due to local markets) might explain why labor adjustment costs appear to be higher in the service sector. Thus, together, higher output-price rigidity and higher labor adjustment costs emerge as the explanation for the higher impact of productivity shocks on misallocation in the service sector.

(b) Sectoral firm-size structure

The sectoral firm-size structure, as proxied by the skewness of the productivity distribution, emerges as the second most important factor to explaining misallocation differences between the two sectors. As explained above, we use the skewness of the productivity distribution as a way of summarizing the industry-level characteristics that may affect the impact on misallocation of size-dependent distortions.[28] The aggregate impact of size-dependent policies varies across industries according to the characteristics of the size distribution of each industry. In an economy where special lines of credit (with subsidized interest rates) or employment subsidies are available to small and medium-sized firms, we would expect industries with higher skewness to exhibit higher misallocation.[29]

From Table 4, we see that the bulk of the contribution of the sectoral firm-size structure comes from the higher impact of this regressor in the service sector (the coefficients effect). According to the evidence presented in Table 7, which records the correlation coefficients between TFP, TFPR, and their components, the higher impact of skewness on misallocation in the service sector must reflect the higher positive correlation between productivity and TFPR in this sector (0.70 in the service sector compared to 0.43 in the manufacturing sector, in 2008). This higher positive correlation in the service sector means that there must be size-dependent

[27]Of course, besides competition, there might be other factors that contribute to higher price rigidity in the service sector, such as higher information or search costs due to higher geographic dispersion.

[28]Skewness of the productivity distribution is computed using the usual Fisher–Pearson formula:

$$sk_s = \sum_{i=1}^{Ms} \left(X_{si} - \overline{X_s} \right)^3 / \mathrm{SD}(X_s)^3,$$

where X_{si} denotes the scaled TFP_{si} and $\mathrm{SD}(X_s)$ is the standard deviation of X_s, with $X_{si} = (A_{si} M_s^{\frac{1}{\sigma-1}} / TFP_s^*)$ and TFP_s^* as defined above. We note that skewness is a measure of asymmetry of the distribution about its mean. Positive skewness indicates that the tail of the distribution on the right-hand side is longer or fatter than on the left-hand side. In a positively skewed distribution, the mean is usually greater than the mode, which means that there are a lot of firms with low productivity levels (below the mean) and a few firms with productivity far above the mean.

[29]Note from Table 5 that, similarly to TFP shocks, the mean and dispersion of skewness is also higher in services than in manufacturing.

TABLE 7
THE CORRELATION BETWEEN SCALED TFP, SCALED TFPR, AND THE SCALED WEDGES (AVERAGE OF INDUSTRY-LEVEL CORRELATIONS)

	2008		2010	
	Manufacturing	Services	Manufacturing	Services
corr(TFP,τ_k)	0.291	0.387	0.303	0.384
corr(TFP,τ_h)	0.407	0.314	0.442	0.297
corr(TFP,τ_y)	0.156	0.046	0.167	0.026
corr(TFP,TFPR)	0.431	0.696	0.448	0.693
corr(TFP,TFPR+τ_y)	0.437	0.424	0.462	0.419

Notes: Here, corr(TFP, x) denotes the correlation between log(scaled TFP) and log(x), where x represents scaled TFPR or one scaled wedge. The figures correspond to the (non-weighted) average of the industry-level correlations.

distortions in this sector that are not present, or are present to a lesser degree, in the manufacturing sector.

Figure 3, which depicts the relationship between firm-level scaled productivity and scaled wedges, allows us to further characterize the size-dependent distortions prevailing in the two sectors.[30] From the figure, we conclude that less productive firms are being subsidized, on average, both in the manufacturing and service sectors (the log of the scaled TFPR is negative for less productive firms in the bottom panel of Figure 3), and that these subsidies come from relatively lower capital and lower labor costs in these firms. Despite being obtained from firm-level data, the implicit correlations (a steeper slope for the capital wedge in the service sector and a steeper slope for the labor wedge in the manufacturing sector) appear fully consistent with the sector-level correlations in Table 7. But, what distinguishes the two sectors, in qualitative terms, is the output wedge. On average, in the manufacturing sector firms appear to face output "taxes" (negative figures of the log scaled output wedge) for a large range of scaled productivity levels, which offset to some extent the capital and labor "subsidies" in terms of scaled TFPR. However, in the service sector, firms appear to benefit from output "subsidies," on average, which add to capital and labor "subsidies" in the case of less productive firms. This evidence in Figure 3 translates into the significantly lower correlation between productivity and the output wedge in the service sector (0.046), compared to the manufacturing sector (0.156), seen in Table 7.[31] In order to evaluate the impact of the output distortions for the correlation between TFP and TFPR, we also computed the correlation between TFP and TFPR excluding the output-wedge component (see equation (14)). The numbers reported in the last row of Table 7 show that if we exclude the impact of the output wedge, the correlation between TFP and TFPR changes significantly in the service sector, and becomes about the same in the two sectors.

To sum up, the capital and labor wedges have correlations with productivity that differ across sectors but that tend to offset each other, so that ultimately it is the difference between the output wedges in the two sectors that is responsible for

[30]Figures 3 and 4 are obtained by fitting a kernel-weighted local polynomial smoothing to the data, with kernel = Epanechnikov and degree = 1.

[31]Note that, according to equation (14), the lower the correlation between productivity and the output wedge, the higher is the correlation between productivity and TFPR.

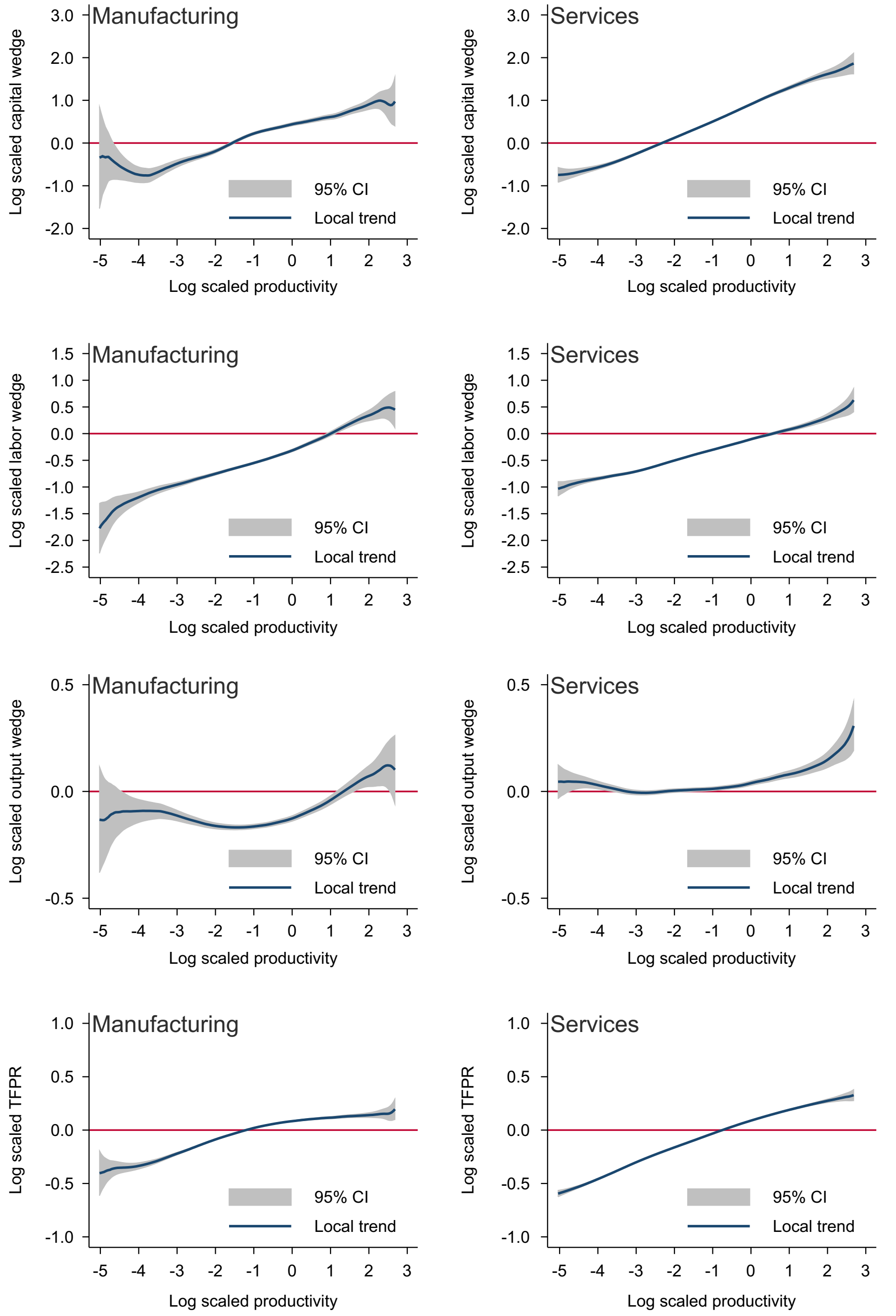

Figure 3. Wedges and Productivity, 2008
[Colour figure can be viewed at wileyonlinelibrary.com]

the higher correlation between TFP and TFPR in the service sector. At first sight, it is not clear why the output wedge should be so different in the two sectors. If

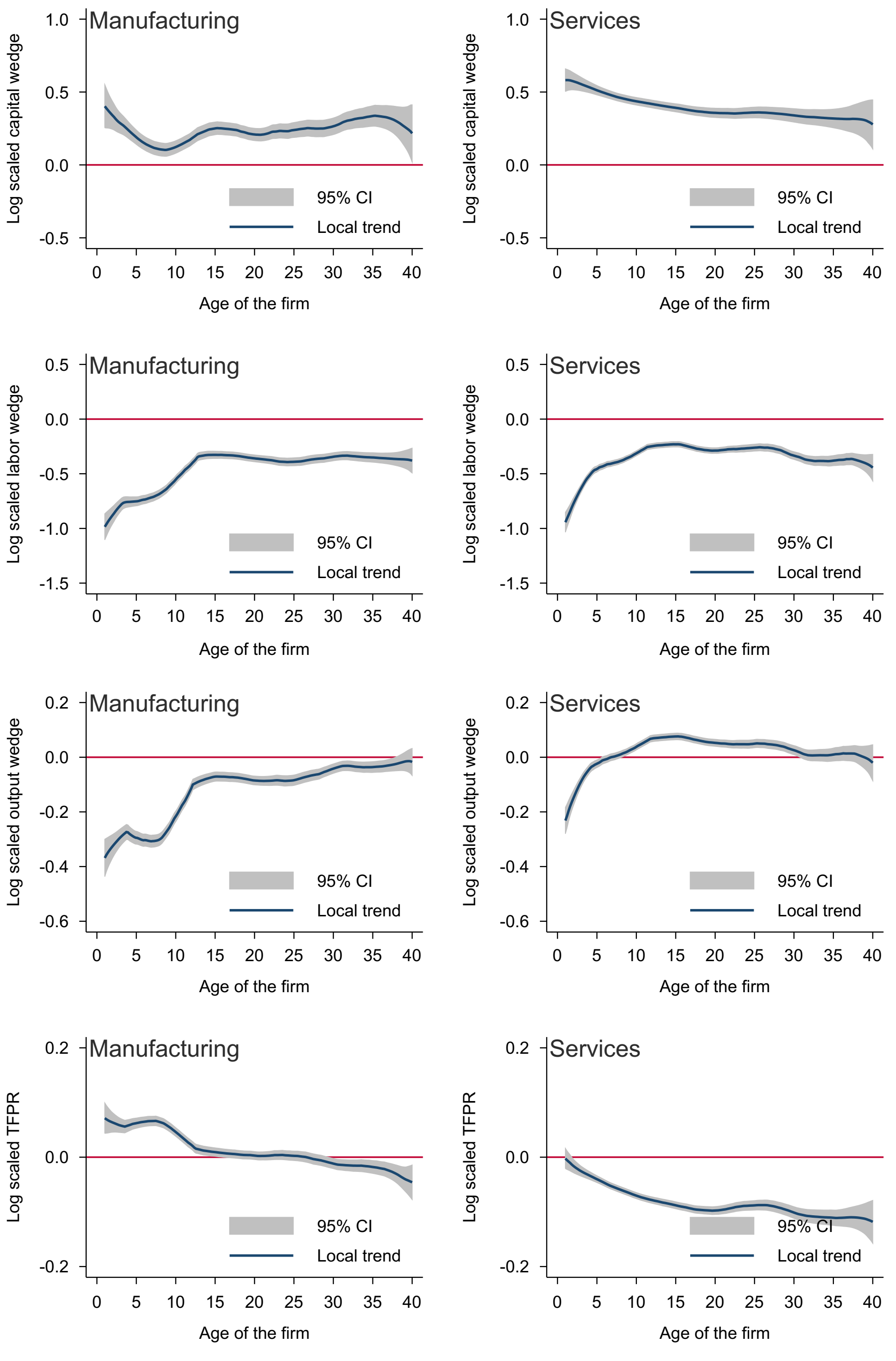

Figure 4. Wedges and Age of the Firm, 2008
[Colour figure can be viewed at wileyonlinelibrary.com]

we look at equations (8) and (12), which define the scaled output wedge, we can see that firms misreporting sales (for tax reasons, for instance) will tend to show up in the model as less productive firms, both in terms of TFP and of TFPR and so, as benefiting from output subsidies (they appear as producing more than what they should, given their TFP levels). Evidence suggests that informality is higher in the service sector, partly stemming from characteristics of the sector that make enforcement of tax collection much more difficult than in the manufacturing sector. We believe that this might be part of the story behind the documented difference between the two sectors, and this is an issue that deserves further investigation.

(c) The importance of young firms

To evaluate the importance of young firms, we use as regressor the ratio of the number of firms aged 3 years or less to the total number of firms in each industry. According to our model, the proportion of young firms also has a bearing on the difference in misallocation between the two sectors.[32] From Table 4, we conclude that this regressor contributes with two opposite effects to the difference in misallocation between the manufacturing and the service sectors. While the impact of the difference in the mean of this regressor between the manufacturing and service sectors (the characteristics effect) contributes to increasing the difference in misallocation between the two sectors (2.1 p.p. in 2008), the difference in the impact of the regressor between the two sectors (the coefficients effect) has the opposite effect (−5.7 p.p.), so that the total impact of this regressor is negative (−3.6 p.p.).[33] This means that the impact on misallocation from the proportion of young firms is lower in the service sector, and that, in the absence of this effect, the difference in misallocation between the service and manufacturing sectors would be even higher.

Figure 4, which depicts the relationship between firms' age and scaled wedges, shows that despite benefiting from lower labor costs (a lower-scaled labor wedge), young firms, on average, face higher distortions (a higher TFPR) than older firms, stemming from higher capital costs and higher output distortions. We link the higher capital costs to the presence of credit constraints imposed by financial institutions on young firms because of a lack of credit history or insufficient guarantees.[34] From Table 6, we see that the correlation between the proportion of young firms and the standard deviation of the individual wedges is lower in the service sector for all three wedges, suggesting that all distortions contribute to the lower impact of this regressor in the service sector (the negative coefficients effect). Nevertheless, as in the case of the skewness regressor, the output wedge appears to be mainly responsible for the differences in the impact of this regressor between the two sectors: output distortions in young firms are much less important in the service sector than in manufacturing, contributing significantly to the lesser contrast between younger and older firms in the former.

[32]We also estimated the model using the ratio of firms aged 5 years or less and the results did not qualitatively change.

[33]We see from Table 5 that the proportion of young firms is, on average, higher in the service sector, but that this relationship is inverted for the top 10 percent misallocation industries, suggesting a stronger correlation between this regressor and misallocation in the manufacturing sector.

[34]Note the qualitative differences *vis-à-vis* the evidence in Figure 3, where small firms appear as benefiting from capital subsidies, on average.

6. Conclusions

The empirical literature on misallocation has recently documented that the level of allocative efficiency in the service sector is significantly lower than that of the manufacturing sector. Because services are, by far, the most important sector of activity in most economies nowadays, significantly higher levels of misallocation in this sector have important implications for aggregate TFP and aggregate GDP.

Using firm-level data for the Portuguese economy, we document that the significantly higher levels of allocative inefficiency in the service sector are not the result of a small number of industries with abnormal levels of inefficiency but, rather, the outcome of a strong regularity. The great majority of the industries belonging to the manufacturing sector rank among the industries with the lowest misallocation. Conservative estimates for Portugal suggest that resource misallocation in 2008 was around 24 p.p. higher in the service than in the manufacturing sector. Closing this misallocation gap—that is, reducing misallocation in the service sector to the manufacturing levels—would lead to a 12 percent boost in aggregate gross output (or aggregate TFP) and a 31 percent boost in aggregate value added (GDP).

Using regression analysis, we are able to fully explain the difference between efficiency gains in the two sectors. Productivity shocks, which capture the impact of (capital/labor) adjustment costs and/or output-price rigidity on misallocation, emerge as the most important factor contributing to the differences in misallocation between the two sectors. This contribution stems more from differences in the impacts of productivity shocks on misallocation than from differences in these shocks between the two sectors. The bulk of the difference in misallocation due to productivity shocks is likely to originate from the presence of higher output-price rigidity and higher labor adjustment costs in the service sector.

The sectoral firm-size structure, which captures the impact of size-dependent distortions on misallocation, and is proxied by the skewness of the productivity distribution, emerges as the second most important factor in explaining the difference in misallocation between the two sectors. Also in this case, the bulk of the contribution comes from differences in the impact and not from differences in the mean of the regressor between the two sectors. The higher impact of this regressor on the service sector stems mainly from a higher level of informality, which makes enforcement of tax collection more difficult than in the manufacturing sector.

Finally, the empirical model suggests that the proportion of young firms also has a bearing on the misallocation differences between the two sectors, but its impact in the service sector is lower. We link this regressor to the presence of barriers to growth, stemming, for instance, from credit constraints imposed by financial institutions on young firms because they have no credit history or insufficient guarantees.

The fact that we are able to fully explain the differences of allocative efficiency between the manufacturing and service sectors suggests that such differences originate from identifiable theoretical sources of misallocation and not from higher unexplainable heterogeneity in the service sector that would make the Hsieh and Klenow (2009, 2011) methodology inapplicable to the service sector.

Our findings have important implications for economic policy. A significant part of the difference of allocative efficiency between the two sectors may be attributed to higher output-price rigidity in the service sector. To the extent that such higher price rigidity stems from lower competition, measures aimed at increasing product market competition in the service sector will contribute to increasing allocative efficiency in the sector and, thus, will boost aggregate productivity.

Less productive firms appear as benefiting from capital and labor subsidies, which suggests that there might be a trade-off between employment creation and aggregate productivity. Therefore, to the extent that they contribute to the survival of unproductive firms, especially in the service sector, where competition is weaker, size-contingent laws passed by governments and aimed at boosting employment creation in small or medium-sized firms (special lines of credit with subsidized interest rates and/or labor subsidies) will increase misallocation and have a strong negative impact on aggregate productivity. Finally, eliminating or minimizing the impact of financial constraints on young firms would also contribute to increasing aggregate productivity.

References

Adamopoulos, T. and D. Restuccia, "The Size Distribution of Farms and International Productivity Differences," *American Economic Review*, 104(6), 1667–97, 2014.

Amador, J. and A. C. Soares, "Competition in the Portuguese Economy: Estimated Price–Cost Margins under Imperfect Labour Markets," Working Paper 8, Banco de Portugal, Lisbon, 2013.

Asker, J., A. Collard-Wexler, and J. De Loecker, "Dynamic Inputs and Resource (Mis)Allocation," *Journal of Political Economy*, 122(5), 1013–63, 2014.

Banerjee, A. V. and B. Moll, "Why Does Misallocation Persist?," *American Economic Journal: Macroeconomics*, 2(1), 189–206, 2010.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta, "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, 103(1), 305–34, 2013.

Bellone, F. and J. Mallen-Pisano, "Is Misallocation Higher in France than in the United States?" GREDEG Working Papers 2013-38, Groupe de Récherche en Droit, Économie, Gestion (GREDEG CNRS), University of Nice – Sophia Antipolis, 2013.

Benkovskis, K., "Misallocation of Resources in Latvia: Did Anything Change after the Crisis?" Working Paper 5, Bank of Latvia, Riga, 2015.

Blinder, A. S., "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of Human Resources*, 8(4), 436–55, 1973.

Buera, F. J., J. Kaboski, and Y. Shin, "Finance and Development: A Tale of Two Sectors," *American Economic Review*, 101(5), 1964–2002, 2011.

Calligaris, S., "Misallocation and Total Factor Productivity in Italy: Evidence from Firm-Level Data," Research Paper Series 357, Centre for Economic and International Studies, Rome, 2015.

Camacho, A. and E. Conover, "Misallocation and Productivity in Colombia's Manufacturing Industries," Working Paper IDB-WP-123, Inter-American Development Bank, Washington, DC, 2010.

Chen, K. and A. Irarrazabal, "The Role of Allocative Efficiency in a Decade of Recovery," *Review of Economic Dynamics*, 18(3), 523–50, 2015.

David, J. M., H. A. Hopenhayn, and V. Venkateswaran, "Information, Misallocation and Aggregate Productivity," NBER Working Paper 20340, National Bureau of Economic Research (NBER), Cambridge, MA, 2014.

Dias, D. A., C. R. Marques, and C. Richmond, "Misallocation and Productivity in the Lead up to the Eurozone Crisis," *Journal of Macroeconomics*, 49, 46–70, 2016.

Dias, D. A., C. R. Marques, F. Martins, and J. M. C. Santos Silva, "Understanding Price Stickiness: Firm Level Evidence on Price Adjustment Lags and Their Asymmetries," *Oxford Bulletin of Economics and Statistics*, 77(5), 701–18, 2015.

Duarte, M. and D. Restuccia, "The role of the Structural Transformation in Aggregate Productivity," *The Quarterly Journal of Economics*, 125(1), 129–73, 2010.
ECB (European Central Bank), "Competition, Productivity and Prices in the Euro Area Services Sector," Working Paper Series 44, European Central Bank, Frankfurt, 2006.
Ellison, G. and E. L. Glaeser, "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach," *Journal of Political Economy*, 105(5), 889–927, 1997.
Fabiani, S., M. Druant, I. Hernando, C. Kwapil, B. Landau, C. Loupias, F. Martins, T. Mathä, R. Sabbatini, H, Stahl, and A. Stokman, "What Firms' Surveys Tell Us about Price-Setting Behavior in the Euro Area," *International Journal of Central Banking*, 2(3), 2006.
Garcia-Santana, M., E. Moral-Benito, J. Pijoan-Mas, and R. Ramos, "Growing Like Spain: 1995–2007," mimeo, 2015.
Garicano, L., C. LeLarge, and J. Van Reenen, "Firm Size Distortions and the Productivity Distribution: Evidence from France," Working Paper 18841, National Bureau of Economic Research (NBER), Cambridge, MA, 2013.
Gelbach, J. B., "When Do Covariates Matter? And Which Ones, and How Much?" *Journal of Labor Economics*, 34(2), 509–43, 2016.
Gilchrist, S., J. W. Sim, and E. Zakrajsek, "Misallocation and Financial Market Frictions: Some Direct Evidence from the Dispersion in Borrowing Costs," *Review of Economic Dynamics*, 16, 159–76, 2013.
Gopinath, G. and O. Itskhoki, "Frequency of Price Adjustment and Pass-Through," *The Quarterly Journal of Economics*, 125(2), 675–727, 2010.
Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez, "Capital Allocation and Productivity in South Europe," Working Paper 21453, National Bureau of Economic Research (NBER), 2015.
Gourio, F. and N. Roys, "Size-Dependent Regulations, Firm Size Distribution, and Reallocation," *Quantitative Economics*, 5, 377–416, 2014.
Guner, N., G. Ventura, and X. Yi, "Macroeconomic Implications of Size-Dependent Policies," *Review of Economic Dynamics*, 11(4), 721–44, 2008.
Holmes, T. J. and J. A. Schmitz, "Competition and Productivity: A Review of Evidence," Research Department Staff Report 439, Federal Reserve Bank of Minneapolis, 2010.
Hosono, K. and M. Takizawa, "Do Financial Frictions Matter as a Source of Misallocation? Evidence from Japan," PRI Discussion Paper Series 12A-17, Policy Research Institute, Tokyo, 2012.
Hsieh, C.-T. and P. J. Klenow, "Misallocation and Manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 124(4), 1403–48, 2009.
______, "Misallocation and Manufacturing TFP in China and India: Correction Appendix," Stanford University, CA, unpublished, 2011.
Jann, B., "The Blinder–Oaxaca Decomposition for Linear Regression Models," *The Stata Journal*, 8(4), 453–79, 2008.
Machicado, C. G. and J. C. Birbuet, "Misallocation and Manufacturing TFP in Bolivia During the Market Liberalization Period," *The B.E. Journal of Macroeconomics*, 12(1), 1–45, 2012.
Martin, C., "Price Adjustment and Market Structure," *Economics Letters*, 41(2), 139–43, 1993.
Midrigan, V. and D. Xu, "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, 104(2), 422–58, 2014.
Moll, B., "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?" *American Economic Review*, 104(10), 3186–221, 2014.
Oaxaca, R., "Male–Female Wage Differentials in Urban Labor Markets," *International Economic Review*, 14(3), 693–709, 1973.
Peters, M., "Heterogeneous Mark-Ups, Growth and Endogenous Misallocation," mimeo, London School of Economics, London, 2013.
Restuccia, D. and R. Rogerson, "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments," *Review of Economic Dynamics*, 11, 707–20, 2008.
Song, Z. and G. Wu, "A Structural Estimation on Capital Market Distortions in Chinese Manufacturing," Economic Growth Center Working Paper Series 1306, Nanyang Technological University, School of Humanities and Social Sciences, Economic Growth Center, Singapore, 2013.
Syverson, C., "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112(6), 1181–222, 2004a.
______, "Product Substitutability and Productivity Dispersion," *The Review of Economics and Statistics*, 86(2), 534–50, 2004b.
Ziebarth, N., "Are China and India Backwards? Evidence from the 19th Century U.S. Census of Manufactures," *Review of Economic Dynamics*, 16(1), 86–99, 2013.

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Appendix: Misallocation under Alternative Assumptions
Table A.1: Efficiency Gains under Alternative Assumptions
Table A.2: Efficiency Gains for Different Employment Cut-Offs (Baseline Assumptions)