Banco de México

Working Papers

N° 2023-11

Misallocation of Resources, Firm Characteristics, and Structural Factors: Evidence from Mexico

Miguel Orozco Vázquez
Banco de México

October 2023

Documento de Investigación
2023-11

Working Paper
2023-11

Misallocation of Resources, Firm Characteristics, and Structural Factors: Evidence from Mexico*

Miguel Orozco Vázquez†
Banco de México

Abstract: This paper aims to measure the gross output loss due to misallocation of resources in Mexico during 2008-2018 and to study what determines this resource misallocation. To do so, I use an extension of Hsieh and Klenow (2009) and Mexican Economic Censuses. Alternatively, I estimate resource misallocation using data processed with a Bayesian model to correct for measurement error. I find that the misallocation in Mexico is mainly in the service sector, as a result of capital and labor misallocation. Furthermore, econometric results show that formal firms are more affected than informal firms by distortions to their capital and labor utilization. Similarly, firms with a bank account to operate their business were more affected than those firms without a bank account. Finally, insecurity and corruption faced by firms, especially in the service sector, are structural factors related to the misallocation of resources in Mexico.
Keywords: Misallocation of Resources, Productivity, Distortions, Mexico
JEL Classification: D24, O12, O47

Resumen: El paper analiza si la asignación de recursos es ineficiente para la economía mexicana durante 2008-2018 y estudia sus posibles determinantes. Para ello, se utiliza una extensión del modelo de Hsieh y Klenow (2009) y los Censos Económicos de México. Alternativamente, se calcula dicha asignación ineficiente usando datos provenientes de un modelo bayesiano que corrige por error de medición. Los resultados señalan que la asignación ineficiente de recursos proviene principalmente del sector de servicios, como resultado de distorsiones en las asignaciones de capital y trabajo. Asimismo, los resultados econométricos muestran que las empresas formales resultan más afectadas que las empresas informales por distorsiones que favorecen la mala asignación de capital y trabajo. Similarmente, las empresas que tienen una cuenta bancaria para operar su negocio se vieron más afectadas por dichas distorsiones que las empresas sin cuenta bancaria. Finalmente, la inseguridad y la corrupción que enfrentan las empresas, particularmente en el sector de servicios, son factores estructurales vinculados con la inadecuada asignación de recursos en México.
Palabras Clave: Asignación Ineficiente, Productividad, Distorsiones, México

*I am thankful to Sangeeta Pratap for her advice and support throughout this project. I also thank two anonymous referees for their valuable comments and suggestions.
† Dirección General de Investigación Económica. Email: morozco@banxico.org.mx.

1 Introduction

Differences in aggregate productivity across countries explain discrepancies in their living standards. Misallocation of resources at the micro level is one of the main drivers behind the low total factor productivity (Banerjee and Duflo, 2005; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Midrigan and Xu, 2014), which ultimately leads to a weak growth. An inefficient allocation of resources is when a low-productivity firm attracts a larger proportion of scarce resources such as labor or capital than its optimal level as opposed to a high-productivity firm in the same sector that fails to receive sufficient resources. According to Restuccia and Rogerson (2017), causes of misallocation can be grouped into three categories: i) statutory provisions, e.g. tax code and regulations that vary depending on the size or age of the firm; ii) discretionary provisions made by the government or other entities, e.g. subsidies, tax breaks, or low interest rate loans granted to specific firms; and iii) market imperfections, e.g. monopoly power, market frictions, and enforcement of property rights.

The misallocation literature is mainly focused on the manufacturing sector. However, studying resource misallocation in the service sector is paramount. The importance of this sector in terms of GDP has grown over time. Also, recent studies for these countries suggest the level of resource misallocation in the service sector is higher than in the manufacturing sector (Busso et al., 2013; Dias et al., 2016; Garcia-Santana et al., 2017; De Vries, 2014; Benkovskis, 2015). Therefore, focusing on the manufacturing sector only does not provide a full description of the level of distortion of the whole economy. However, one of the challenges of studying misallocation is possible measurement error in the data, in particular for the service sector, which might lead to mismeasurement of misallocation and a poor understanding of its main drivers.

The first objective of this paper is to quantify resource misallocation for Mexico. I follow Dias et al. (2016) to compute misallocation for manufacturing and service sectors, whose model is an extension of a three-factor production function of Hsieh and Klenow (2009, 2011). [1] In the literature, this method is known as the indirect approach, and it compares the actual output with respect to an efficient level. The data comes from the economic censuses (micro-data level) for 2008, 2013, and 2018 provided by the INEGI (Mexican Institute of Statistics). Furthermore, I recalculate misallocation using the same theoretical framework but using data processed through a Bayesian approach that assumes a possible measurement error in the data (Rotemberg and White, 2021).

As for the results, the resource misallocation in Mexico increased during 2008-2018. However, my two estimates of misallocation vary significantly. The results that correct for possible measurement error in the data indicate that the increasing misallocation over time is much lower than the baseline results using the original data. Indeed, the baseline results indicate that the gross-output gains have gone from 55.1% in 2008 to 80.5% in 2018, whereas after correcting for measurement error they would have gone from 49% in 2008 to 58.7% in 2018. The service sector is the most inefficient one, as a result of capital and labor misallocation. Although these numbers seem large, the output gains of getting rid of misallocation using the indirect approach are usually big numbers. In fact, my results are more conservative in levels than previous estimates for Mexico but they are aligned with the recent trend illustrated in the literature. For example, Levy (2018) highlights that Mexico has gone through a period of deteriorative misallocation from 1998 to 2013. He calculates that getting rid of distortions, Mexico's output gains would have increased from 63% in 1998 to 148% in 2013.

[1] Hsieh and Klenow (2009, 2011) is the seminal paper in resource misallocation literature. It uses a standard model of monopolistic competition with heterogeneous firms as Melitz (2003), but without international trade.

The second objective is to estimate econometric models to characterize the distortions or wedges as firm characteristics and structural factors responsible for this resource misallocation.

The findings indicate that formal firms are more affected than informal firms by distortions to their labor and capital utilization due to an environment that encourages the inefficient allocation of resources [2]. Likewise, firms that use a bank account to operate their business, face higher distortions to their labor and capital utilization than those firms that operate without a bank account. Also, using the latest economic census, evidence suggests that the problems that firms face such as government regulation, insecurity, and corruption are associated with firms with higher distortions to labor and capital utilization. In particular, corruption generates input distortions in the service sector. Other factors analyzed such as production process and institutional constrains have mixed results.

My paper has two main contributions. Firstly, in the misallocation literature related to addressing the measurement error. Indeed, one of the concerns of studies on resource misallocation is the use of data with measurement error, e.g. establishments misreporting their own characteristics and/or later data processing introducing new errors. Restuccia and Rogerson (2017) warn that output, particularly, in service sectors, such as education, health care, among others, is likely to be very poorly measured. Also, Rotemberg and White (2021) highlight that data reported by younger and smaller firms can be particularly affected by this type of measurement error and, as a result, altering the measured allocative efficiency. My paper is the first one that also quantifies the degree of misallocation in Mexico with an alternative data processed through a statistical model to correct for measurement error. This allows comparing these quantitative estimates with those of the baseline results under an unprocessed

[2]The formality level variable is measured through a continuous and positive index where higher numbers mean firms are more formal. In particular, I will use the definition of formality by Levy (2018), where **Formality index** = establishment's contributory social insurance payments/(wages of salaried workers + payments to non-salaried workers).

data set. Ultimately, this exercise quantifies the importance of measurement error in the data, differentiating manufacturing and service sector. Secondly, my paper contributes to the literature that explores the link between misallocation, total factor productivity, and structural factors in Mexico. Busso et al. (2012) provides new classifications of firms based on their formality and legal status. Using the approach of Hsieh and Klenow (2009) to compute resource misallocation, they show evidence that informal and illegal firms have been a drag on total factor productivity in Mexico. They claim a driver of this productivity loss was the excessive informality caused by the asymmetry in the regulation of salaried and non-salaried labor. Levy (2018) updates Busso et al. (2012) and argues that the combination of deficient institutions, social insurance, labor, and tax policies have affected the efficient use of physical and human capital which hurts productivity. Also, Misch and Saborowski (2018), using a similar methodology from previous studies, exploit a variation across Mexican industries and states. They find that misallocation increases when structural factors, such as labor informality, crime, corruption, market concentration, among others, are present. My paper has several improvements over those above-mentioned. On the one hand, Busso et al. (2012) and Levy (2018) use cross-sectional data to analyze the relationship between distortions and informality in specific years, but I run pooled regressions in order to take into account all the Economics Censuses together. On the other hand, unlike Misch and Saborowski (2018) that exploit variation in resource misallocation within industries and across states, I use more granular, firm-level data, which enable me to capture the heterogeneity existing within sectors and states, by characterizing the wedges as problems that the firm face such as corruption, insecurity, government regulation, among others. Although the nature of data, non-experimental, does not allow to infer a causal relationship, it offers potential research avenues to explore the economic mechanisms in which structural factors affect the efficient allocation of resources in Mexico.

The rest of this paper is structured as follows. Section 2 describes the theoretical framework to compute resource misallocation. Section 3 describes the data. Section 4 shows the baseline results on resource misallocation using the original data and results based on measurement-error corrected (MEC) data. Also, this section shows econometric exercises to determine the relationship between inputs wedges, firm characteristics, and structural factors in Mexico. Section 5 concludes.

2 Theory

This section describes the methodology to study the connection between misallocation of resources, total factor productivity, and growth. The approach is called indirect since it assumes generic individual distortions that cause firms to make inefficient decisions. It is worth mentioning that when the environment (social and economic context) that firms face when making decisions is not the optimal, those distortions appear in the economy. Although the indirect approach relies on strong assumptions, it helps to determine the relative misallocation of resources by industry. The objective is, once the distortions are eliminated, to compute output and value-added gains by industry. To pursue this, I follow closely Dias et al. (2016) using a third-factor production function with intermediate inputs of the original methodology devised by Hsieh and Klenow (2009, 2011). Since the intermediate input share of output is about half and its role along a production chain can amplify the misallocation of resources, its inclusion is key to study economic development (Jones, 2011, 2013).

My methodology has some caveats worth mentioning. The results in misallocation must be interpreted through the lens of this model. An efficient allocation requires in this case, as it will be shown later, the Total Factor Productivity Revenue (TFPR) to be the same across firms within a sector. However, in more general frameworks, an efficient allocation can be reached even if such a condition does not hold. Therefore, misallocation can be overestimated if differences of TFPR across firms reflect sources different from misallocation. There are at least three important sources to generate a higher dispersion of TFPR beyond misallocation. First, Hsieh and Klenow (2009, 2011), the cornerstone of my methodology, assume all firms within a sector use the same Cobb-Douglas production function, thus differences in capital-to-labor-ratios is interpreted as misallocation. However, producers within a sector might show differences in capital-to-labor ratios because of heterogeneity in producer-level production functions rather than misallocation. Although assuming the same production function in manufacturing is more plausible due to the similarities in their production processes, it is harder to claim the same for the service sector. Second, Asker et al. (2014) consider a variant of a standard dynamic investment model in which firms face costs when adjusting capital and get a firm-specific productivity shock in each period, thus a capital stock determined in some previous period may not longer appear to be optimal after the productivity shock. Therefore, higher dispersion in the marginal product of capital appears as misallocation in the static model by Hsieh and Klenow (2009, 2011), but it might be efficient in a dynamic setting under adjustment costs. Also, Bartelsman et al. (2013) investigate the sources of productivity differences between countries and how resource allocation and firm selection play a significant role in explaining these variations. In their model, TFPR exhibits dispersion and is correlated with firm-level productivity even without distortions. Overhead labor plays a role in influencing such a pattern. Finally, measurement error in firm-level data might lead to conclude that variation across producers is a result of misallocation when it might not be the case. Bils et al. (2021) use the datasets for India and the United States in Hsieh and Klenow (2009, 2011) to estimate measurement error in each country and infer the extent of differences in productivity due to misallocation after accounting for measurement error. They find that an assumed additive measurement error accounts for a substantial amount of the dispersion in marginal revenue products. All the factors above mentioned might overestimate misallocation. Although the direct approach is an alternative to study misallocation, identifying the underlying source of misallocation usually leads to small output efficiency gains (Leal-Ordóñez, 2014; Guner et al., 2008). A possible explanation is that the relatively simple models in the direct approach might not be able to capture the full extent of frictions in less-developed countries (Restuccia and Rogerson, 2017). Finally, Haltiwanger et al. (2018) warn about using differences across producers' measured revenue productivity (TFPR) levels to identify distortions that impact the allocation of resources. They claim that the assumptions made by Hsieh and Klenow (2009, 2011) that enable such identification, i.e. every producer must face isoelastic residual demand curve and producers must have flat marginal cost curves, do not hold using their data that contain prices and quantities separately. Therefore, the "wedges" recovered from the data using Hsieh and Klenow (2009, 2011) may not be signs of inefficiency, but they may reflect demand shifts or movements of the firm along its (nonconstant) marginal cost curve instead. They propose to test those assumptions made by Hsieh and Klenow (2009, 2011) as long as the data are feasible. However, as it will be clear later, the prices and quantities are not available in the Mexican Economic Censuses (it is only observed revenues and input expenses), thus it is not possible to test the assumptions made by Hsieh and Klenow (2009, 2011).

This framework 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:

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

with $\theta_s \geq 0$ and $\sum_{s=1}^{S} \theta_s = 1$.

At the industry level, gross output Y_s is a CES aggregate of M_s differentiated products:

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

where Y_{si} stands for the gross output of firm i in industry s and σ the elasticity of substitution between varieties of differentiated goods. Note that M_s is also the number of firms within industry s.

At the firm level, the gross output for each differentiated product within the industry s is given by a Cobb-Douglas production function with constant returns to scale:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} H_{si}^{\beta s} Q_{si}^{1-\alpha_s-\beta_s} \tag{3}$$

where A_{si}, K_{si}, H_{si}, and Q_{si} refers to the firm $i's$ total factor productivity, capital stock, labor, and intermediate inputs, respectively. I use A and $TFPQ$ interchangeably in the paper for total factor productivity. Note that factor shares (α_s, β_s) can vary across industries but not across firms within the same industry.

In this economy, there are three individual distortions (or wedges): distortion to output (τ_{ysi}), distortion to capital utilization (τ_{ksi}), and distortion to labor utilization (τ_{hsi}) which act like a tax on revenues, a tax on capital services, and a tax on labor costs, respectively. For example, Hsieh and Klenow (2009) mention that a distortion to output (τ_y) is high for firms that face government restrictions on size or low in firms that benefit from output subsidies if the firm's production is below a certain threshold. For instance, a sales tax rate that goes up with higher level of sales, it would discourage firms from expanding its production. Also, a distortion to capital utilization (τ_k) is high for those firms that have access to expensive credit, but low for firms with access to cheap credit. For instance, politically connected firms can get cheaper loans from state-owned banks, avoiding higher productive firms from accessing to more financial resources to invest in capital. Finally, a distortion to labor utilization (τ_h) can be seen as a higher tax on larger firms in terms of labor. For instance, regulations that only become effective beyond some employment threshold like a payroll tax that charges a higher tax rate for firms above a certain number of workers.

Therefore, the static problem of a firm i in industry s is to maximize the following profit function:

$$\max_{P_{si},K_{si},H_{si},Q_{si}} \quad \pi_{si} = \left(1-\tau_{ysi}\right)P_{si}Y_{si} - (1+\tau_{ksi})R_sK_{si} - (1+\tau_{hsi})W_sH_{si} - Z_sQ_{si} \tag{4}$$

where R_s is the user cost of capital, W_s is the wage, and Z_s is the intermediate input price.

Assuming the demand equation for each differentiated product within the industry s is $Y_{si} = P_{si}^{-\sigma}$ [3] and plugging it into (4) the first order conditions are given by

$$[K_{si}]: \qquad \alpha_s \frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = \frac{1+\tau_{ksi}}{1-\tau_{ysi}}R_s$$

$$[H_{si}]: \qquad \beta_s \frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{H_{si}} = \frac{1+\tau_{hsi}}{1-\tau_{ysi}}W_s$$

$$[Q_{si}]: \quad (1-\alpha_s-\beta_s)\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{Q_{si}} = \frac{1}{1-\tau_{ysi}}Z_s$$

Given these equations, I can derive the input wedges as follows,

$$1+\tau_{ksi} = \frac{\alpha_s}{(1-\alpha_s-\beta_s)}\frac{Z_sQ_{si}}{R_sK_{si}}$$

$$1+\tau_{hsi} = \frac{\beta_s}{(1-\alpha_s-\beta_s)}\frac{Z_sQ_{si}}{W_sH_{si}}$$

[3]Since the demand function for firm i is $P_{si} = Y_s^{\frac{1}{\sigma}}P_s(Y_{si})^{-\frac{1}{\sigma}}$, I implicitly assume $P_sY_s^{\frac{1}{\sigma}} = 1$ for each industry s. Dias et al. (2016) proved that this is equivalent to $\kappa_s = \frac{(Y_sP_s)^{-\frac{1}{\sigma-1}}}{P_s} = 1$, which is the assumption made in Hsieh and Klenow (2009, 2011).

$$1-\tau_{ysi}=\frac{\sigma}{\sigma-1}\frac{1}{(1-\alpha_s-\beta_s)}\frac{Z_sQ_{si}}{P_{si}Y_{si}}$$

Notice how the three input distortions are expressed in terms of intermediate input expenditure. In particular, there is a distortion to capital(labor) utilization when the ratio of intermediate consumption to the capital(labor) costs is relatively high, given the level of the output elasticities with respect to capital(labor) and intermediate inputs. Also, the presence of the distortion to output is when the intermediate input share is relatively low, given the industry elasticity of output with respect to intermediate inputs. Intuitively, the wedges appear when input allocation deviate from the optimal conditions. The combination of these three indicators can be used to measure the distortion that a firm faces, which is defined as the total factor productivity revenue $TFPR_{si}(\equiv P_{si}A_{si})$. Substituting the above FOC into $TFPR_{si}$ yields:

$$\begin{aligned} TFPR_{si}=P_{si}A_{si}=P_{si}\frac{Y_{si}}{K_{si}^{\alpha_s}H_{si}^{\beta_s}Q_{si}^{1-\alpha_s-\beta_s}} &= \left(\frac{P_{si}Y_{si}}{K_{si}}\right)^{\alpha_s}\left(\frac{P_{si}Y_{si}}{H_{si}}\right)^{\beta_s}\left(\frac{P_{si}Y_{si}}{Q_{si}}\right)^{1-\alpha_s-\beta_s} \\ &= \frac{\sigma}{\sigma-1}\frac{(1+\tau_{ksi})^{\alpha_s}(1+\tau_{hsi})^{\beta_s}}{(1-\tau_{ysi})}\Psi_s \end{aligned} \tag{5}$$

where

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

According to expression (5), TFPR does not vary individually within the same sector unless there is some wedge or distortion. Intuitively, without distortions, more capital, labor and intermediate inputs would be allocated to higher productive firms to the point where the higher production would result in a lower price. Similarly, lower productive firms would produce less and their prices would go up. As a result, the TFPR would be the same across firms within the same industry. If the wedges (τ_{ksi},

τ_{hsi}, τ_{ysi}) were the same within industry, the TFPR would depend on industry-level parameters only, which could be computed as averages. Following Dias et al. (2016), I define an efficient allocation when all firms face the same average wedges - both terms are used interchangeably - rather than all wedges are equal to zero.[4] It can be shown to be equal to

$$(1+\bar{\tau}_{ks}) = \frac{\alpha_s}{1-\alpha_s-\beta_s)}\frac{Z_sQ_s}{R_sK_s}$$

$$(1+\bar{\tau}_{hs}) = \frac{\beta_s}{(1-\alpha_s-\beta_s)}\frac{Z_sQ_s}{W_sH_s}$$

$$(1-\bar{\tau}_{ys}) = \frac{\sigma}{\sigma-1}\frac{1}{(1-\alpha_s-\beta_s)}\frac{Z_sQ_s}{(P_sY_s)^*}$$

The capital, labor, and output wedges can be scaled by their efficient level, respectively, as follows

$$\frac{1+\tau_{ksi}}{1+\bar{\tau}_{ks}} = \frac{\frac{Q_{si}}{Q_s}}{\frac{K_{si}}{K_s}}$$

$$\frac{1+\tau_{hsi}}{1+\bar{\tau}_{hs}} = \frac{\frac{Q_{si}}{Q_s}}{\frac{H_{si}}{H_s}}$$

$$\frac{1-\tau_{ysi}}{1-\bar{\tau}_{ys}} = \frac{\frac{Q_{si}}{Q_s}}{\frac{P_{si}Y_{si}}{(P_sY_s)^*}}$$

Notice that the prices W_s, R_s, and Z_s affect the average wedges, but not the relative comparison between firms in a given industry. Indeed, the capital (labor) wedge now reflects a firm with relative low capital(labor) given its intermediate input level within the sector. Intuitively, the distortions (or wedges) are like specif-firm taxes that cause deviations from the optimal input mix needed for the firm to produce and

[4]Dias et al. (2016) argue that assuming all wedges are equal to zero does not guarantee that in equilibrium the industry-level demand for factors of production will be the same before and after the reallocation of resources. This implication would have general equilibrium effects which would lead to changes in the prices of factors of production.

reach its optimal level (distortion free economy). Following Dias et al. (2016), using the average wedges displayed above, it can be shown that the efficient level of TFPR for industry s is

$$TFPR_s^{\star} = \frac{\sigma}{\sigma-1}\frac{(1+\bar{\tau}_{ks})^{\alpha_s}(1+\bar{\tau}_{hs})^{\beta_s}}{(1-\bar{\tau}_{ys})}\Psi_s = \left(\frac{\sum_{i=1}^{M_s} A_{si}^{\sigma-1}}{K_s^{\alpha_s} H_s^{\beta s} Q_s^{1-\alpha_s-\beta_s}}\right)^{1/\sigma} \tag{6}$$

In order to compute the real gross-output gains for industry s, real and nominal output are expressed as follows:

$$Y_{si} = \left(\frac{1}{P_{si}}\right)^{\sigma} = \left(\frac{A_{si}}{P_{si}A_{si}}\right)^{\sigma} = \left(\frac{A_{si}}{TFPR_{si}}\right)^{\sigma}$$

$$P_{si}Y_{si} = \left(\frac{TFPR_{si}}{A_{si}}\right)\left(\frac{A_{si}}{TFPR_{si}}\right)^{\sigma} = \left(\frac{A_{si}}{TFPR_{si}}\right)^{\sigma-1}$$

And the corresponding levels of efficient real and nominal output (distortions eliminated) can also be expressed as:

$$Y_{si}^{\star} = \left(\frac{A_{si}}{TFPR_s^{\star}}\right)^{\sigma} = Y_{si}\left(\frac{TFPR_{si}}{TFPR_s^{*}}\right)^{\sigma}$$

$$P_{si}^{\star}Y_{si}^{\star} = \left(\frac{A_{si}}{TFPR_s^{\star}}\right)^{\sigma-1} = P_{si}Y_{si}\left(\frac{TFPR_{si}}{TFPR_s^{\star}}\right)^{\sigma-1}$$

Let Y_s^{*} be the efficient level of output in industry s. Using the above expressions, it can be shown that the real gross-output gain in industry s (ratio of efficient output to actual output) is given by:

$$\frac{Y_s^\star}{Y_s} = \frac{\left[\sum_{i=1}^{M_s}\left(y_{si}^\star\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s}\left(y_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}} = \frac{\left[\sum_{i=1}^{M_s}\left(A_{si}^{\sigma-1}\right)\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s}\left(A_{si}\frac{TFPR_s^\star}{TFPR_s}\right)^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}} = \left[\frac{1}{\sum_{i=1}^{M_s}\omega_{si}\left(\frac{1}{\frac{TFPR_{si}}{TFPR_s^\star}}\right)^{\sigma-1}}\right]^{\frac{\sigma}{\sigma-1}} \tag{7}$$

where $\omega_{si} = \left(\frac{A_{si}^{\sigma-1}}{\sum_{i=1}^{M_s}A_{si}^{\sigma-1}}\right) = \left(\frac{A_{si}^{\sigma-1}}{TFP_s^*}\right)$, and TFP_s^* is the efficient industry level of total factor productivity according to Hsieh and Klenow (2009).

Equation (7) is one of the key equations of this paper. Assuming no distortions, $TFPR_{si} = TFPR_s^*$, the whole expression would be equal to one since $\sum_{i=1}^{M_s}\omega_{si} = 1$,. That is, the actual industry-level output would be equal to my definition of efficiency, thus there is no resource misallocation. Note the smaller the denominator is, the greater the output efficiency gains are. In particular, what mainly increases the output gains is to have high productive firms (higher ω_{si}) that face a larger distortion (higher $\frac{TFPR_{si}}{TFPR_s^\star}$). In this case, removing the distortions of these higher productive firms would bring about output efficiency gains larger.

The Cobb-Douglas aggregator given by equation (1) implies the real gross output gain for the economy is:

$$\frac{Y^\star}{Y} = \prod_{s=1}^{S}\left(\frac{Y_s^\star}{Y_s}\right)^{\theta_s} = \prod_{s=1}^{S}\left(\left[\frac{1}{\sum_{i=1}^{M_s}\omega_{si}\left(\frac{1}{\frac{TFPR_{si}}{TFPR_s^\star}}\right)^{\sigma-1}}\right]^{\frac{\sigma}{\sigma-1}}\right)^{\theta_s} \tag{8}$$

Also, gross-output gains in terms of value-added are also computed since they will be more closely related to welfare gains (Dias et al., 2016). Using the equation from Dias et al. (2016), value-added efficiency gains are computed as the ratio of efficient value added (V_s^*) to actual value added (V_s) for industry s:

$$\frac{V_s^*}{V_s} = \frac{\frac{Y_s^*}{Y_s} - q_s}{1 - q_s} \tag{9}$$

where q_s is the share of industry-level intermediate inputs, while Y_s and Y_s^* refer to the actual and efficient gross output for industry s, respectively, as explained before. The value added efficiency gains are the output gains after taking into account the intermediate inputs within the sector.

In case of the whole economy, the value-added efficiency gains or the ratio of the total efficient value added (V^*) and the total actual value added (V) is as follows:

$$\frac{V^*}{V} = \frac{\frac{Y^*}{Y} - q}{1 - q} \tag{10}$$

Similarly, q is the share of intermediate inputs for the total economy, whereas Y and Y^* are the actual and efficient aggregate gross output, respectively.

Finally, I follow the appendix B of Dias et al. (2015) in order to determine the gross output gains by input of production. This exercise computes the output gains by eliminating variation in one wedge (or individual distortion) and fixing the quantity of the other two inputs. Intuitively, I try to measure how much the industry-level production would increase if I reallocated an input from lower to higher productive firms within the sector. Formally, let $\tilde{K}_{si}$, $\tilde{H}_{si}$, and $\tilde{Q}_{si}$ denote the reallocation referred for capital stock, labor, and intermediate inputs, respectively. It can be shown that (details can be checked in the appendix mentioned):

$$\tilde{K}_{si} = \frac{K_s}{Q_s} Q_{si} \tag{11}$$

$$\tilde{H}_{si} = \frac{H_s}{Q_s} Q_{si} \tag{12}$$

$$\tilde{Q}_{si} = Q_s \frac{\left[\left(A_{si} K_{si}^{\alpha_s} H_{si}^{\beta_s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-(1-\alpha_s-\beta_s)(\sigma-1)}}}{\sum_{i=1}^{M_s}\left[\left(A_{si} K_{si}^{\alpha_s} H_{si}^{\beta_s}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-(1-\alpha_s-\beta_s)(\sigma-1)}}} \tag{13}$$

where K_s, H_s, and Q_s denote the observed amounts of capital, labor and intermediate inputs used in industry s. After computing $\tilde{K}_{si}$, $\tilde{H}_{si}$ and $\tilde{Q}_{si}$, it can be proved that the firm-level output reallocated is as follows:

$$\tilde{Y}_{si}^{K} = Y_{si}\left(\frac{\tilde{K}_{si}}{K_{si}}\right)^{\alpha_s} \tag{14}$$

$$\tilde{Y}_{si}^{H} = Y_{si}\left(\frac{\tilde{H}_{si}}{H_{si}}\right)^{\beta_s} \tag{15}$$

$$\tilde{Y}_{si}^{Q} = Y_{si}\left(\frac{\tilde{Q}_{si}}{Q_{si}}\right)^{1-\alpha_s-\beta_s} \tag{16}$$

Finally, the aggregate output gains of allowing optimal reallocation of capital, labor, or intermediate input, respectively, are as follows:

$$\frac{\tilde{Y}^{K}}{Y} = \prod_{s=1}^{S}\left[\frac{\left[\sum_{i=1}^{M_s}\left(\tilde{Y}_{si}^{K}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s}\left(Y_{si}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}}\right]^{\theta_s} \tag{17}$$

$$\frac{\tilde{Y}^H}{Y} = \prod_{s=1}^{S} \left[\frac{\left[\sum_{i=1}^{M_s} \left(\tilde{Y}_{si}^H \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s} \left(Y_{si} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}} \right]^{\theta_s} \tag{18}$$

$$\frac{\tilde{Y}^Q}{Y} = \prod_{s=1}^{S} \left[\frac{\left[\sum_{i=1}^{M_s} \left(\tilde{Y}_{si}^Q \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s} \left(Y_{si} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}} \right]^{\theta_s} \tag{19}$$

3 Data

This paper uses firm-level balance sheet data for 2008, 2014, and 2018, as gathered by INEGI's Economic Censuses of 2009, 2014, and 2019, respectively. The census considers non-agricultural activity that takes place in private establishments with a fixed location in urban areas. Following Levy (2018), I drop energy, mining, transportation, construction, financial services, governmental activities, and those sectors with less than 10 firms. Furthermore, I also exclude the management of companies and enterprises sector since these companies do not demand labor and capital to produce a particular good or service, but they manage other firms instead.

To quantify resource misallocation, I get from these data sets information on gross output, consumption of intermediate inputs, paid employees, total remuneration for employees (wages and benefits including social security contributions), stock of fixed assets, and fixed assets depreciation. Physical capital is calculated as the difference between the stock of fixed assets and fixed assets depreciation. Intermediate input is defined as the consumption (expenditure) of intermediate inputs. Labor input is determined as the total remuneration for salaried and non-salaried employees. Earnings are used rather than employment because Hsieh and Klenow (2009) mention earnings per worker can better reflect hours worked and human capital per worker.

The computation of labor input requires a further explanation. Mexico is a special case in the sense that most of the firms reported in the Census, particularly in the service sector, either do not have employees (self-employed) or are a family business, thus they do not remunerate their workers. The exclusion of those firms in the analysis entails dropping over 50% of the total number of firms, affecting particularly the service sector. In order to include them, following Busso et al. (2012) and Levy (2018), I impute the remuneration for non-salaried workers as the average wage of the salaried employees of their corresponding 4-digit level sector and state, times the number of non-salaried employees. By doing so, I assume people face an opportunity cost by working for the family business since they can receive a wage from another firm in the same sector and state. There are some shortcomings of imputing the salaries in this way. People that work for a family business might be more productive - working harder - than in a non-family business. Since family businesses often achieve strong employee loyalty that reduces turnover and increases productivity, thus the measure of labor input for those non-salaried workers might be underestimated. However, in Appendix B, as a robustness check, I also consider alternatively the total employment and find that the main results hold.

The analysis in this paper uses industries defined at the 4-digit North-American Industry Classification System (NAICS). The sectors under study are manufacturing, including durable and nondurable goods; services, defined as wholesale trade, retail trade, and non-financial services[5]; and the rest is in other sectors, which includes forestry, fishing, and related activities.

Table 1 shows some summary statistics about the composition of the sectors in terms of output, value added, and employment. The final sample comprises of 2.43 million observations for 2008, 3.24 million observations for 2013, and 3.64 million observations for 2018. I include details on data filtering in Appendix D. In terms of gross

[5]The non-financial services encompasses real estate, professional services, educational services, health-care services, accommodation, food services, and other services.

output participation, the manufacturing sector has decreased from 57% in 2008 to 52.3% in 2018, whereas the service sector has expanded from 42.7% to 47.4%. It is worth mentioning that the relative importance of the manufacturing sector is due to the exclusion of subsectors in services and the data filtering detailed in Appendix D. However, the share of value added, number of establishments, and employment of the service sector have been consistently higher than that of the manufacturing sector during the period of study.

Table 1: Summary statistics

	2008			2013			2018		
	Man.	Serv.	Oth.	Man.	Serv.	Oth.	Man.	Serv.	Oth.
% Output	57.0	42.7	0.3	57.3	42.4	0.3	52.3	47.4	0.3
% Value added	41.8	57.8	0.3	40.5	59.1	0.3	34.3	65.4	0.3
% Employment	25.9	72.8	1.3	24.5	74.3	1.1	22.7	76.2	1.2
Establishments	298.5	2,123.0	18.0	386.0	2,836.9	17.4	383.6	3,233.6	23.3

Notes: Services includes wholesale trade, retail trade, and non-financial services. Other sectors include forestry, fishing, and related activities. Establishments are expressed in thousands.

The gross-output, consumption of intermediate inputs, total remuneration for employees, and physical capital are used to compute the TFPR, capital wedge, and the labor wedge. The TFPR and input wedges are scaled by their efficient industry levels and in logarithmic terms like in Section 2. Regarding firms' characteristics, I include number of workers, age, whether the firm has a bank account, formality level, and if the firms have received a formal or informal sector loan. The formality level variable is measured through a continuous and positive formality index where higher numbers mean firms are more formal.[6] Regarding loans, the formal sector includes commercial banks and saving banks, while the informal sector refers to suppliers, government, private lenders, family, and friends. In Appendix A, I include a detailed definition of all the variables. Larger firms, older firms, more formal firms, firms with a bank account, as well as those firms that have access to a loan have higher total

[6]Following Levy (2018), I use the definition of **Formality index** = establishment's contributory social insurance payments/(wages of salaried workers + payments to non-salaried workers).

factor productivities, but the service sector firms that receive informal sector loans only (see Table 24 in Appendix D).

Table 2 shows summary statistics of the TFPR, input wedges, and firm characteristics. Service sector firms possess mostly higher means (in absolute value) for TFPR and input wedges than the manufacturing sector. This implies that manufacturing firms, on average, operate closer to their efficient levels. Also, the dispersion measure indicates service sector firms have higher variability of TFPR and input wedges. As for firm characteristics, manufacturing firms are larger and older than those in the service sector. The formality index suggests that on average both manufacturing and service sector firms barely make social security payments (less than 2 % of the total remuneration for employees). Both manufacturing and service sector firms have similar share of bank account holders, showing an increase in the percentage of firms over time up to around 20%. Firms that only use formal sector loans are around 9% in recent years, which is higher than the 5% of firms that only have access to an informal sector loan. This implies that the majority of firms, approximately 85%, do not have access to either formal or informal sector loans.

4 Results

This section has two parts. The first one presents computations for gross-output efficiency gains, value added efficiency gains, and gross-output efficiency gains by individual distortion. To do this, I compute baseline results that use the original data and results based on measurement-error corrected (MEC) data. In the second part, using only MEC data, I analyze the relationship between input wedges and firm characteristics for manufacturing and service sector. Furthermore, using the latest economic census (2019), I analyze the importance of problems that firms face

Table 2: Summary statistics of key variables

	Manufacturing			Service Sector		
	2008	2013	2018	2008	2013	2018
TFPR						
Mean	-0.504	-0.733	-0.444	-1.324	-1.278	-2.210
Std. Dev	0.433	0.542	0.448	0.894	0.931	1.806
Capital wedge						
Mean	-0.022	0.101	-0.104	0.349	0.426	0.503
Std. Dev	1.519	1.579	1.489	1.851	1.844	1.825
Labor wedge						
Mean	-1.177	-1.417	-1.181	-0.920	-0.973	-0.938
Std. Dev	1.091	1.189	1.055	1.188	1.201	1.180
Number of workers						
Mean	10.374	9.171	10.295	4.079	3.672	4.060
Std. Dev	79.054	85.569	95.674	23.984	105.706	43.570
Age						
Mean	10.430	11.324	12.308	9.325	10.018	11.039
Std. Dev	11.841	11.670	12.020	11.146	11.006	11.293
Formality Index						
Mean	0.019	0.016	0.015	0.012	0.014	0.013
Std. Dev	0.049	0.048	0.043	0.039	0.047	0.044
Banking Account						
Mean	0.050	0.177	0.200	0.032	0.180	0.212
Std. Dev	0.219	0.382	0.400	0.176	0.384	0.409
Formal and Informal Loans						
Mean	0.004	0.007	0.006	0.002	0.007	0.006
Std. Dev	0.067	0.083	0.077	0.041	0.083	0.080
Formal Loans						
Mean	0.018	0.083	0.086	0.013	0.093	0.086
Std. Dev	0.134	0.276	0.280	0.112	0.290	0.280
Informal Loans						
Mean	0.013	0.048	0.045	0.012	0.063	0.049
Std. Dev	0.115	0.213	0.207	0.108	0.242	0.216

Notes: The TFPR, capital, and labor wedges are expressed in logs.

to predict their individual input wedges. [7]

4.1 Resource Misallocation

4.1.1 Baseline results

This section presents computations for gross-output efficiency gains, value added efficiency gains, and gross-output efficiency gains by individual distortion.

First, I describe the assumptions of the baseline parameters. Following Dias et al. (2016), the elasticity of substitution between firms' gross output, σ, is assumed to be equal to 3 as in the misallocation literature (Hsieh and Klenow, 2009; Dias et al., 2016).[8]The wage, W_s, is normalized to 1. The wage bill paid by firms, H_{si}, is the measure of labor input, which implies that $H_{si} = w_{si}L_{si}$, where L_{si} is the number of employees and w_{si} is the firm-specific average wage. So, it is implicitly assumed that the labor input reflects the number of workers as well as the firm-specific average wage, which is adjusted for differences in hours worked and worker skills. Also, the price of intermediate products, Z_s, is normalized to 1, so it is implicitly assumed, like in labor input, that the intermediate inputs' expenditure reflects the amount of these inputs and their attributes. I compute the parameters of the production function as the average of the U.S. industry-level factor shares with information from 2003 to 2016 published by the Bureau of Economic Analysis as in the misallocation literature (Dias et al., 2016; Misch and Saborowski, 2018). This implies that the U.S. is considered in this paper the benchmark of a relatively undistorted economy. Although the U.S. is the reference for an efficient economy, this does not mean the U.S is a distortion free economy. Indeed, the U.S. is a country with a minimum of distortions and certainly all the countries face distortions to their labor and capital

[7] For practical purposes, for the second part I only show the results using the MEC data set. The results with the original data set are similar and are available on request.

[8] In the Appendix, I compute the same misallocation indicators with an alternative value of $\sigma = 5$ (Hsieh and Klenow (2009)).

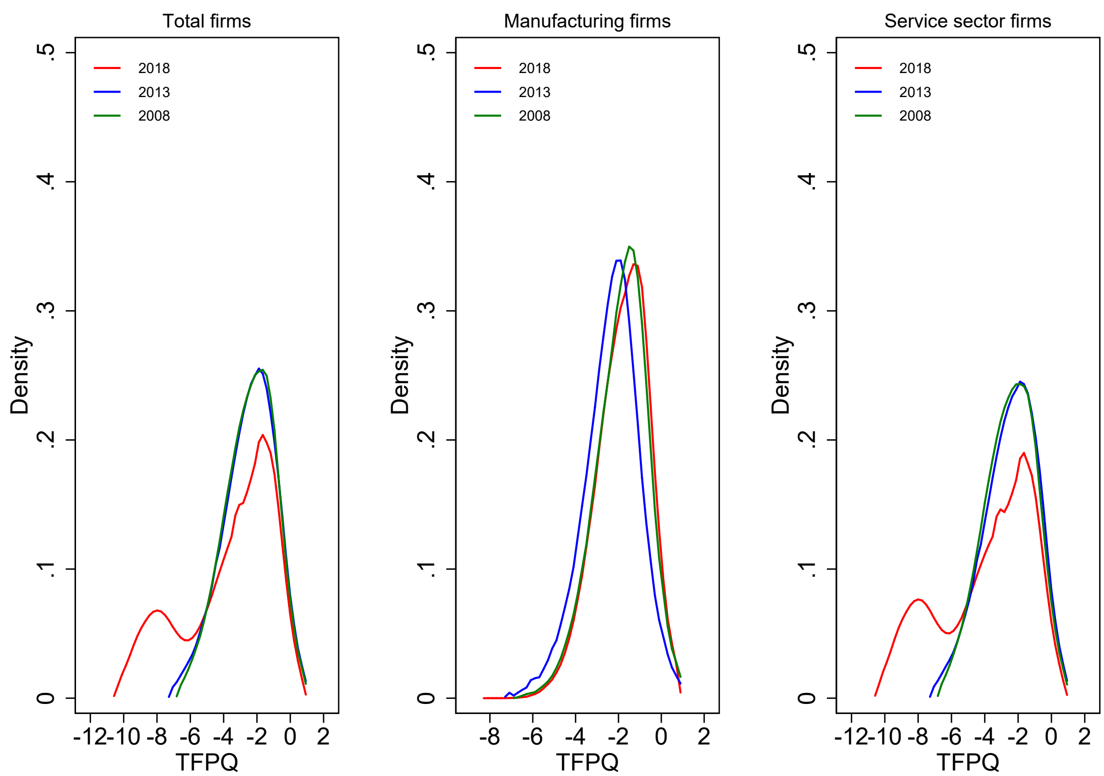
utilization to some extent.[9] An alternative approach to recover these parameters would be to estimate directly the production function using econometric techniques (e.g. Levinsohn and Petrin (2003); Ackerberg et al. (2015)). In this case, rather than being the U.S. the undistorted economy, the efficient allocation would be based on the Mexican production technology. However, there are some challenges of this option. The identification of parameters of a production function is a difficult task since the input choices are likely to be correlated with the producer's productivity, as well as a potential selection bias might arise due to more efficient producers are more likely to survive over time. Hence, it is noteworthy that the decision to obtain the elasticities of production function either using averages of the U.S. industry-level factor shares (or other benchmark economy) or estimating the production function is based on underlying assumptions, which ultimately can yield different results of TFPR and misallocation.

Before computing the aggregate level of distortions in the Mexican economy, I first look into total factor productivity (TFPQ) and total factor productivity revenue (TFPR) across firms for the years of study. Recall TFPQ is equivalent to A from the firm-level production function in equation (3), while TFPR is computed in equation (5). Similarly to the misallocation literature, I show those indicators in relative terms, i.e. scaled by their efficient industry levels and in logarithmic terms.

Figure 1 shows the Kernel distribution of log-scaled TFPQ for all the firms. The left tail of the total distribution gets thicker over time, particularly in 2018. This indicates that there are more unproductive firms surviving during this period, particularly service sector firms. Table 3 shows multiple measures of dispersion. The results confirm a higher TFPQ dispersion of service sector firms, particularly in 2018, unlike that of the manufacturing sector, which has not increased consistently over time.

[9] Regarding the value of the U.S. parameters of production function across all the sectors, the labor compensation is 31.1%, capital income is 21%, and consumption of intermediate inputs is 47.9%.

Figure 1: Density of TFPQ



Notes: TFPQ refers to total factor productivity and is calculated in logarithmic terms as $log(A_{si}M_s^{\frac{1}{\sigma-1}}/TFP_s^*)$, where M_s is the number of differentiated products in sector s and TFP_s^* is the efficient industry-level of total factor productivity. Firms around zero are those closer to their efficient levels.

Table 3: Dispersion of TFPQ

	2008			2013			2018		
	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
S.D.	1.50	1.21	1.52	1.57	1.29	1.59	2.71	1.19	2.77
75th-25th Perc.	2.14	1.61	2.20	2.17	1.65	2.25	3.82	1.65	4.24
90th-10th Perc.	3.93	3.08	4.01	4.08	3.25	4.16	7.40	3.06	7.50

Notes: TFPQ refers to total factor productivity and is calculated in logarithmic terms as $log(A_{si}M_s^{\frac{1}{\sigma-1}}/TFP_s^*)$, where M_s is the number of differentiated products in sector s and TFP_s^* is the efficient industry-level of total factor productivity. S.D.=standard deviation, 75-25= difference between percentiles 75 and 25, and 90-10=difference between percentiles 90 and 10.

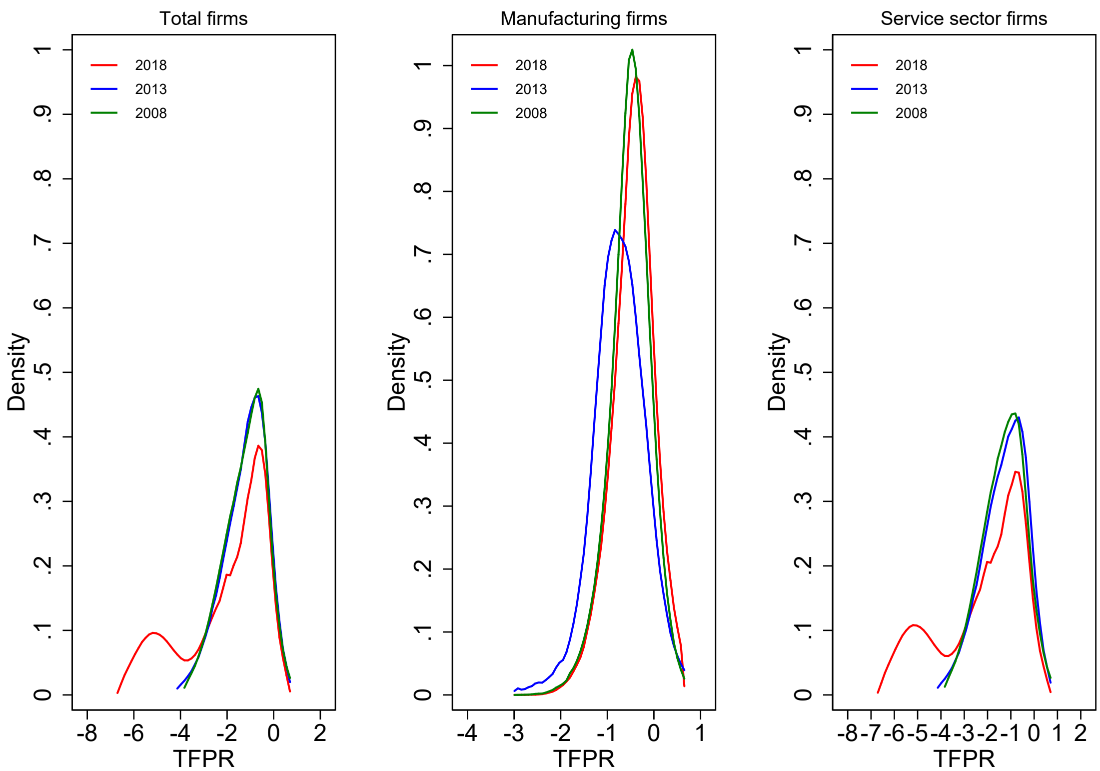
Similarly, Figure 2 illustrates the Kernel distribution of log-scaled TFPR for all the firms. The distribution of TFPR of total firms shifts to the left over time, as a result of a higher concentration of service sector firms with a TFPR away from their efficient level. Table 4 also corroborates that TFPR has a higher dispersion in the service sector than in the manufacturing sector. Table 5 shows a positive correlation between TFPQ and TFPR, especially for firms in the service sector. Indeed, more productive firms are subject to higher level of distortions to labor and capital utilization, which ultimately prevent those firms from making optimal decisions. In this sense, structural factors such as government regulation, corruption, and crime that favor lower productive firms over higher productive firms to access more capital and labor can be potential sources of misallocation. For instance, criminals extorting high-productive firms disincentivize them from producing goods and services, allowing lower productive firms obtain more inputs than they would have received based on their productivity level. This is a first indicator of a resource misallocation problem.

Table 4: Dispersion of TFPR

	2008			2013			2018		
	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
S.D.	0.90	0.45	0.90	0.92	0.56	0.94	1.79	0.45	1.80
75th-25th Perc.	1.28	0.54	1.28	1.27	0.72	1.33	2.35	0.57	2.57
90th-10th Perc.	2.34	1.11	2.36	2.38	1.37	2.44	4.87	1.15	4.88

Notes: S.D.=standard deviation, 75-25= difference between percentiles 75 and 25, and 90-10=difference between percentiles 90 and 10.

Figure 2: Density of TFPR



Notes: TFPR refers to total factor productivity revenue and is calculated in logarithmic terms as = $log(TFPR_{si}/TFPR_s^*)$, where $TFPR_s^*$ is the efficient industry level of distortion. Firms around zero are those closer to their efficient levels.

Table 5: Correlation between TFPQ and TFPR

	2008	2013	2018
Total	0.91	0.92	0.97
Manufacturing	0.76	0.74	0.75
Services	0.94	0.94	0.98

Notes: Total includes other sectors such as forestry, fishing, and related activities.

Table 6 shows the gross-output efficiency gains from equalizing TFPR across firms in each industry. To do so, all the sectors are consolidated and the 1% tails of scaled TFPQ and TFPR are trimmed. Then, I recalculate all industry-level variables (K_s, H_s, Q_s, $TFPR_s^*$,TFP_s^*). The gross output efficiency gains from getting rid of distortions are substantial, increasing from 55.1% in 2008 to 80.5% in 2018. In words, if the factors of production were reallocated to the most productive firms within the sector, the Mexican economy would be 80.5% larger than its actual value in 2018. Although this number seems large, as it was mentioned in the theory section, the output gains of getting rid of misallocation using the indirect approach are relatively big numbers. In fact, my results are more conservative in levels than previous estimates for Mexico but they are aligned with the recent trend illustrated in some papers. For example, Levy (2018) highlights that Mexico has gone through a period of deteriorative misallocation from 1998 to 2013. He calculates that if Mexico got rid of distortions, it would have increased from 63% in 1998 to 148% in 2013. Similarly, Misch and Saborowski (2018) compute output gains for Mexico on the order of 125% in 2013.

With regard to the output efficiency gains by sector, the results are heterogeneous. Misallocation estimates in manufacturing are relatively small, going from 23.9% in 2008 to 25.3% in 2018. These numbers are similar to the misallocation literature for Latin America. In particular, my results are close to those found by Levy (2018), whose output gains for manufacturing were 26% in 2013. Also, Busso et al. (2013) use micro-data from manufacturing firms in 10 Latin American countries [10] to measure the extent by which misallocation of resources can explain differences in productivity between Latin American countries mainly from the 1990s to mid-2000s. They find that for most Latin American countries the output gains would be around 50%-60%. On the other hand, the service sector has larger efficiency gains than those of manufacturing, increasing from 109.1% in 2008 to 169.9% in 2018. My results suggest that the sectors that mainly explain this deterioration are retail trade in

[10] The countries are Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Uruguay, and Venezuela.

self-service shops, wholesale trade of industrial raw materials, food and alcoholic and non-alcoholic beverage preparation services, retail trade of groceries and food, among others (see Tables 21- 23). These findings cannot be compared directly to those of Levy (2018) since he treats separately commerce, but they are moving in the same direction. Indeed, Levy (2018) shows that the output gains of getting rid of distortions in commerce would grow from 99% in 2008 to 193% in 2013, whereas in services the equivalent figures would go from 85% to 102%.

Table 6: Gross Output Efficiency Gains (%)

	2008	2013	2018
Total	55.1	64.4	80.5
Manufacturing	23.9	33.4	25.3
Services	109.1	117.5	169.9

Notes: $output_{eg} = 100 * (\frac{Y^*}{Y} - 1)$, where Y^* and Y are the efficient and actual output, respectively. Total includes other sectors.

The smaller output efficiency gains or lower input distortions in the manufacturing sector could reflect the fact that this industry, unlike the service sector, is exposed to international trade. This situation has forced Mexican manufacturing firms to become more productive, among other reasons, to integrate to the global value chains or compete with other exporting countries for U.S. market share.

The value added efficiency gains are also big. The valued added is the difference between output and intermediate inputs. Table 7 shows that value added efficiency gains are higher than those of gross output. Under this concept, the economy has efficiency gains from 129.6% in 2008 to 172% in 2018. Similar to gross output analysis, the service sector has the highest resource misallocation, increasing from 189.5% in 2008 to 263.5% in 2018. In contrast, the manufacturing sector grows from 76.6% in 2008 to 116.2% in 2013, followed by a reduction of 82.2% in 2018.

Table 7: Value Added Efficiency Gains (%)

	2008	2013	2018
Total	129.6	158.4	172.0
Manufacturing	76.6	116.2	82.2
Services	189.5	207.1	263.5

Notes: $va_{eg} = 100 * \left(\frac{\frac{Y^*}{Y} - q}{1-q} \right)$, where Y^* is the efficient output, Y is the actual output, and q is the total economy intermediate input share. Total includes other sectors.

Furthermore, Table 8 shows the gross output efficiency gains by individual distortion. To compute this, I fixed two factors of production, while the variation in the third wedge is removed. Then, I compute the efficiency gains associated with this reallocation. The results indicate that capital is the input most misallocated for the manufacturing and service sectors. Labor and output wedges, in general, show similar output efficiency gains for both sectors. However, the service sector shows the highest deterioration for all wedges during the period of study.

Table 8: Gross Output Efficiency Gains by Individual Distortion (%)

	2008			2013			2018		
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.6	7.3	20.1	16.7	12.2	23.1	16.3	7.2	27.3
Labor	8.2	5.3	12.1	9.4	7.4	12.1	10.2	6.3	14.7
Output	9.0	5.4	14.0	8.7	4.8	14.2	11.3	5.8	17.7

Notes: The formulas to compute the gross output efficiency gains by input are at the end of the theory section.

4.1.2 Measurement error

Measurement error in the data is one of the main challenges of studying misallocation since it might cause a higher dispersion of TFPR and bigger estimates of misallocation. In this section, I compute misallocation indicators with an alternative data set processed to correct for measurement error using a Bayesian approach. I refer to this information as measurement-error corrected (MEC) data. The measurement error in the data appears when records are mistaken because respondents do not answer correctly the question, or the interviewer records incorrectly the answer reported, thus differing the actual from the true responses. This is especially relevant for service sector data since, unlike manufacturing sector, it is more likely to be poorly measured (Restuccia and Rogerson, 2017). This is not the only method to address measurement error. An alternative is Bils et al. (2021), which assumes an additive measurement error in revenue and inputs but whose variance can scale up with the plant's true revenue and inputs. In any case, using either the Bayesian method or Bils et al. (2021), it is not possible to know what the true value is. Instead, a type of measurement error is assumed to recalculate resource misallocation, and together with the baseline results, determine a range of potential misallocation for Mexico.

The statistical procedure consists in using a Bayesian hierarchical model that edits and imputes data on the output and inputs of the firm-level production function needed to calculate the resource misallocation indicators. The methodology follows Rotemberg and White (2021), which builds on Kim et al. (2015). Although it is hard to determine which the true value (response) of the variable is, the intuition of this procedure is to assume the true value comes from a joint distribution, which, in turn, is generated by a statistical measurement error model. By using this distribution to replace the faulty values for new ones that make each firm's record plausible and data drawn from the same sector-level joint distribution, it is possible to generate values of the output and inputs (capital, total remuneration for employees, and intermediate input) consistent to a firm-level production function. This is an advantage over other statistical procedures such trimming outliers than do not take into consideration the plausibility of economic relationships, e.g. the production function in this case. Ultimately, the generated data is the one used to compute resource misallocation. The methodological details are in Appendix C.

Tables 9 and 10 show the gross output and value added efficiency gains using the MEC data. These numbers are much lower in levels than those of the baseline estimates, and the growth rates over time are more moderate. The manufacturing sector's efficiency gains show a similar trend as the original data. But they are, in general, lower and more stable. Regarding the service sector, the gross output and value added efficiency gains are also increasing, although less importantly in 2018 than those of the baseline results. Therefore, the quality of data plays a key role to the study of misallocation and it can be problematic for the service sector. The misallocation in the Mexican economy has gone from around 49% in 2008 to 58.7% in 2018. The results that correct for possible measurement error in the data indicate that the increasing misallocation over time is much lower than the baseline results using the original data. Finally, Table 11 indicates the gross output efficiency gains by individual distortion using MEC data. Similar to the baseline estimates, capital is the input that represents the highest misallocation of resources. Notice that after using the MEC data, the distortion to capital utilization shows a lower deterioration in 2018. This distortion is more relevant in the service sector. Labor and output wedges show deterioration for manufacturing and service sector.

Table 9: Gross Output Efficiency Gains with MEC data (%)

	2008	2013	2018
Total	49.0	57.5	58.7
Manufacturing	24.7	28.6	26.5
Services	90.5	104.6	119.0

Notes: $output_{eg} = 100 * (\frac{Y^*}{Y} - 1)$, where Y^* and Y are the efficient and actual output, respectively. Total includes other sectors.

Table 10: Value Added Efficiency Gains with MEC data (%)

	2008	2013	2018
Total	116.7	143.4	134.2
Manufacturing	79.1	100.8	85.5
Services	159.3	189.4	192.4

Notes: $va_{eg} = 100 * \left(\frac{\frac{Y^*}{Y} - q}{1 - q}\right)$, where Y^* is the efficient output, Y is the actual output, and q is the total economy intermediate input share. Total includes other sectors.

Table 11: Gross Output Efficiency Gains by Individual Distortion with MEC data (%)

	2008			2013			2018		
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.0	7.8	18.2	14.9	10.3	21.1	13.3	7.3	22.4
Labor	7.6	5.4	10.6	8.9	7.1	11.2	8.8	6.6	11.9
Output	7.9	5.0	12.2	8.1	4.6	12.8	9.9	6.3	15.3

Notes: The formulas to compute the gross output efficiency gains by input are at the end of the theory section.

4.2 Input distortions and firm characteristics

In this section, I investigate the link between firm characteristics, main problems faced by firms, and input wedges.[11] To do this, I run a pooled regression model, using the Mexican economic censuses, to analyze the relationship between input wedges and firm characteristics for manufacturing and service sector. Furthermore, I estimate a lasso regression to determine the importance of firm characteristics and problems that firms face to predict their input wedges.

Pooled regression model

I estimate a pooled regression model because panel data would limit the number of firms to those that appear at least twice over the economic censuses, biasing the sample to larger and older firms. [12]

The pooled regression has the following econometric specification:

$$\begin{aligned} ln(Y_{i,t}) = \beta_0 + \beta^{l} l_{i,t} + \beta^{form} formality_{i,t} + \beta^{banking} banking_{i,t} \\ + \beta_b^{borr} borr_{i,t}^{both} + \beta_f^{borr} borr_{i,t}^{f} + \beta_i^{borr} borr_{i,t}^{i} + \epsilon_{i,t} \end{aligned} \tag{20}$$

Here, i indexes the individual-level firm and t is the year of the economic census: 2008, 2013, or 2018. $ln(Y_{i,t})$ is the natural logarithm of the dependent variable capital wedge or labor wedge. The baseline specification above is in levels and $\epsilon_{i,t}$ is the individual disturbance term for year t, $l_{i,t}$ is the number of workers, $formality_{i,t}$ is the formality index, $banking_{i,t}$ equals 1 to indicate if the firm has a bank account to operate the business and 0 otherwise, $borr^{both}$ equals 1 if the firm receives formal and informal sector loans and 0 otherwise, $borr^{f}$ equals 1 if the firms has access to formal sector loans only and 0 otherwise, and $borr^{i}$ equals 1 if the firm gets informal sector loans only and 0 otherwise. Note that when all the borrowing variables are equal to

[11] The input wedges used in this section are derived from the MEC data.

[12] More specifically, there are 6.1 million firms considered in the analysis, in which 12.5% survive from 2008-2018, 9.2% from 2008-2013, 14.9% from 2013-2018, 17.2% in 2008 only, 17.7% in 2013 only, and 28.4% in 2018 only.

0, the firm does not receive any formal or informal sector loans, so this is the base category. The regression also includes controls for year, state, and sector.

Table 12 shows the pooled regression for the two main outcome variables on firm characteristics for the manufacturing sector. The main results indicate that more formal firms are generally subject to a higher capital wedge. Firms with a bank account have a lower distortion to capital utilization, and firms with either a formal or informal sector loan are subject to a lower distortion to capital utilization with respect to those that do not have any loan. As for the labor wedge, more formal firms, and firms with a bank account have a higher distortion to labor utilization. Also, firms with a formal or informal sector loan have a higher labor wedge compared to firms that do not.

Table 13 presents the pooled OLS regression for the two outcome variables on firm characteristics for the service sector. The main results indicate that more formal firms face a higher distortion to capital utilization. Also, firms with a bank account experience a higher capital wedge. Regarding the borrowing variables, only firms that received both a formal and informal sector loan are positively related to have a higher distortion to capital, as opposed to firms that were granted either a formal or informal sector loan only. Finally, regarding the labor wedge, more formal firms have a higher labor wedge. Establishments with a bank account have a higher labor wedge as well, and firms that receive either a formal or informal sector loan have a higher labor wedge compared to firms that do not.

Table 12: Pooled Regression on Input Distortion and Firm Characteristics for the Manufacturing Sector with MEC data

Dependent variable:	Capital wedge	Labor wedge
number of workers ($x10^{-3}$)	0.014	-0.022
	(0.017)	(0.015)
formality index	0.753***	3.025***
	(0.033)	(0.022)
banking account	-0.017***	0.503***
	(0.005)	(0.003)
formal and informal loans	-0.058***	0.349***
	(0.017)	(0.012)
formal loans	-0.113***	0.144***
	(0.006)	(0.004)
informal loans	-0.174***	0.060***
	(0.007)	(0.005)
Constant	-0.309***	-1.410***
	(0.046)	(0.038)
Observations (million)	1.04	1.04
R-squared	0.048	0.15
Adjusted R-squared	0.048	0.15

Notes: Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Pooled Regression on Input Distortion and Firm Characteristics for the Service Sector with MEC data

Dependent variable:	Capital wedge	Labor wedge
number of workers ($x10^{-3}$)	0.125***	-0.112***
	(0.037)	(0.023)
formality index	0.867***	2.218***
	(0.015)	(0.009)
banking account	0.182***	0.622***
	(0.002)	(0.001)
formal and informal loans	0.116***	0.359***
	(0.008)	(0.005)
formal loans	-0.085***	0.129***
	(0.002)	(0.002)
informal loans	-0.017***	0.047***
	(0.003)	(0.002)
Constant	0.174***	-0.887***
	(0.012)	(0.007)
Observations (million)	7.9	7.9
R-squared	0.04	0.10
Adjusted R-squared	0.04	0.10

Notes: Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lasso regressions

I complement the analysis of the previous section by estimating lasso regressions. I do so because I want to know which firm characteristics and structural factors in Mexico can help to predict firms that would face higher input wedges or distortions. There are at least three reasons to use lasso rather than a more traditional econometric approach: i) Model selection. The standard approach for model selection in econometrics is hypothesis testing, including the general-to-specific approach, which ultimately might lead the researcher to report only what worked. Instead, lasso does automatic variable selection to decide which variables should be included in the model and setting the coefficients for features it does not consider relevant to zero. ii) Reduced overfitting. OLS leads to overfitting, i.e. good-in sample fit but bad out-of-sample prediction. In contrast, lasso by adding the penalty to the model helps the model to prevent from overfitting. iii) Prediction. OLS estimator has zero bias, but not necessarily the best out-of-sample predictive accuracy. Lasso performs better than OLS in making out-of-sample predictions. In addition to the reasons above mentioned, lasso tries to retain the good features of both subset selection and ridge regression, and it helps to identify the importance of the predictors through the lasso coefficient path. A disadvantage of lasso is when the are several correlated explanatory variables, which lead to select arbitrarily some predictor variables. However, as I will explain below, I will group these correlated variables into categories and focus on a smaller set of explanatory variables in the analysis.

Following the notation of Tibshirani (1996), suppose the data is $\left(\mathbf{x}^i, y_i\right)$, where $i = 1, 2, ..N$ is the number of observations; $\mathbf{x}^i = (x_{i1}, x_{i2}, .., x_{ip})$ are the p predictor variables, where x_{ij} is standardized (zero mean and unit variance); and y_i are the responses. Let $\hat{\boldsymbol{\beta}} = (\hat{\beta}_1, \hat{\beta}_2, ..., \hat{\beta}_p)$, then the lasso estimator, $\hat{\boldsymbol{\beta}}^{lasso}$, solves the following problem:

$\hat{\beta}^{lasso} = \arg\min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} \beta_j x_{ij}\right)^2$ s.t. $\sum_{j=1}^{p} \left|\beta_j\right| < \lambda$, where λ is a tuning parameter.

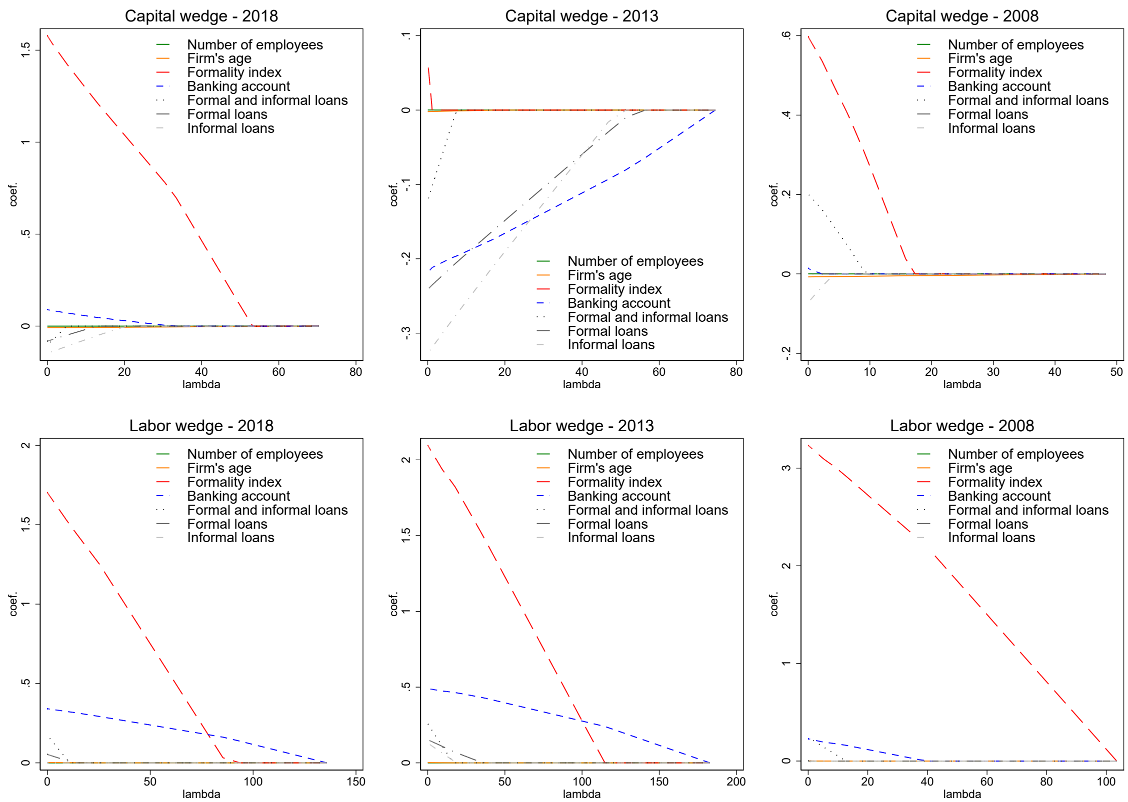
The lasso coefficient path (cp) shows the coefficients that solve the lasso problem for different values of the tuning parameter, lambda. A positive (negative) coefficient implies the independent variable can predict higher (lower) values of the dependent variable. Furthermore, the larger the penalty parameter is, the more shrinkage applied to the estimates, i.e. less variables must be included in the model. This implies that the predictors that survive for a higher range of lambdas are the most robust to predict the dependent variable. In the typical lasso analysis, the cp includes the optimal lambda that optimizes out of sample prediction of K-groups (folds) of equal size, known as K-fold cross-validation. However, given the small number of variables in my study, my objective is not to find the right model of prediction, but rather evaluate the individual importance of each predictor. That is why I exclude the optimal lambdas in the lasso cp.

In the next set of graphs, I show the lasso regression coefficient path for input wedges on firm characteristics. Figure 3 shows the coefficient path for the manufacturing sector. The first row shows the lasso cp for the capital wedge, while the second row is for the labor wedge. Formality status is the best predictor of firms that have higher capital wedges. That is, more formal firms tend to have a higher distortion to capital utilization. The bank account variable does not consistently predict distortions to capital utilization in the same direction. Having a bank account can predict firms with a higher capital wedge for 2018, but it entails firms with a lower distortion to capital utilization for 2013. The effect is not relevant for 2008. The borrowing variables (formal and informal loans, formal loans only, and informal loans only) show that, in general, having access to any type of lending implies a lower distortion to capital utilization for most of the censuses. As for the labor wedge, the formality index and bank account variable are the best predictors of those firms that face a higher distortion to labor utilization. This means that more formal firms, or firms with a bank account, tend to have a higher labor wedge. The borrowing variables can help to predict firms that have a higher labor wedge more consistently across the censuses, although the magnitude of the effect is more moderate. Firm's age is not statistically important.

Figure 4 shows the lasso regression coefficient path for input wedges, and firm characteristics for the service sector. It is more clear that, unlike the manufacturing sector, more formal firms, as well as firms with a bank account, have both higher capital and labor wedges. This can be interpreted as the fact that more formal firms or firms with a bank account, which are typically more productive firms, do not have access to more capital and labor as they should. The firms with any type of access to lending (borrowing variables), in general, tend to have a lower capital wedge, particularly in 2013. Likewise, firm's age is not relevant either.

Taking advantage of the information available from the last economic census (2019), I also estimate the lasso coefficient path for input wedges, and the problems that firms face. In the census, the firms are asked about sixteen specific problems in operating their business. One of the weaknesses of the lasso regression is when predictors are highly correlated with each other, which can lead to randomly select among the correlated predictors. In fact, some of the firm's problems are highly and positively correlated to each other (Tables 25 and 26), making it difficult to select the proper predictors. Thus, in order to get around this problem, I group the individual problems based on their similarities into three classifications: institutional constraints,

Figure 3: Coefficient Path of Input Wedges and Firm Characteristics for the Manufacturing Sector with MEC data

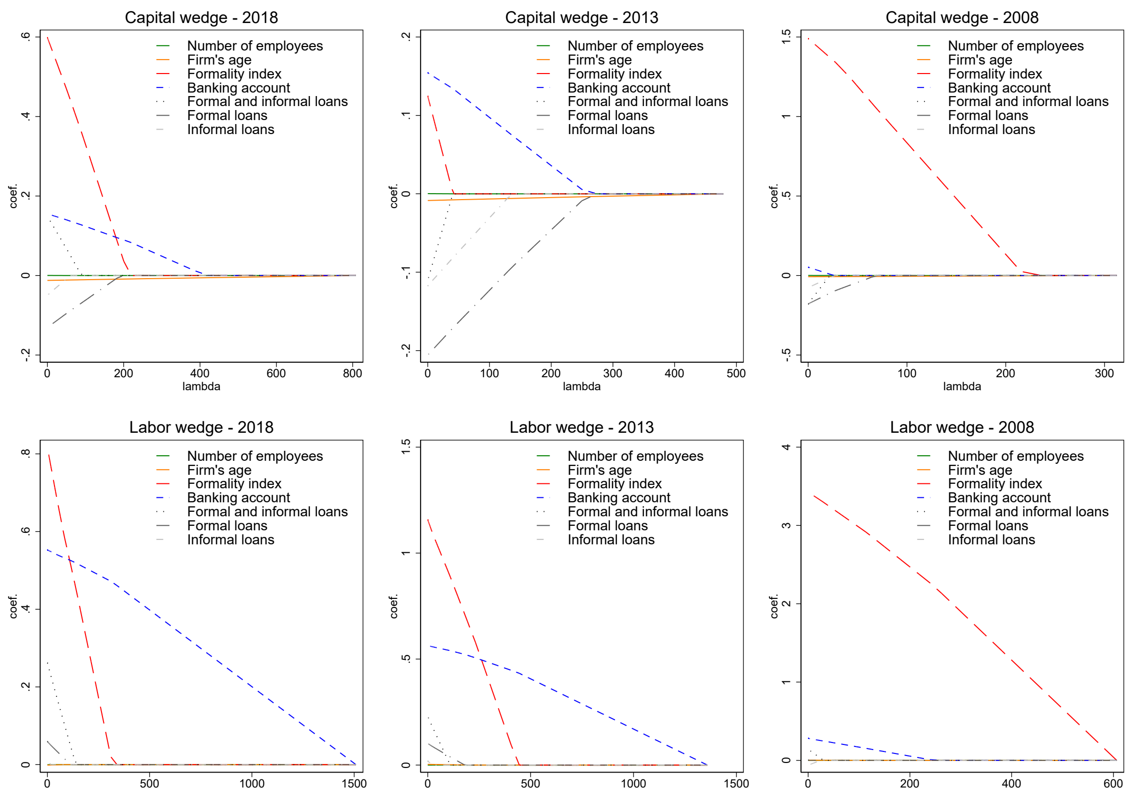


Notes: Coefficient path of the lasso regression. The coefficients are standardized and the penalty parameter, lambda, is in thousands.

general regulation, and production process.

Institutional constraints are composed of lack of access to credit, unfair competition, and informal section competition. *General regulation* consists of burdensome regulation, high taxes, and expensive government procedures. *Production process* is the lack of access to information technology, poor quality inputs, expensive utilities, inexperienced employees, and expensive inputs. I also include separately from these groups, problems of *corruption* and *insecurity*, given their particular importance in Mexico. Since the individual problems are reported like dummy variables, it equals 1 if the firm experiences the specific problem and 0 if it does not, the category varia-

Figure 4: Coefficient Path of Input Wedges and Firm Characteristics for the Service Sector with MEC data



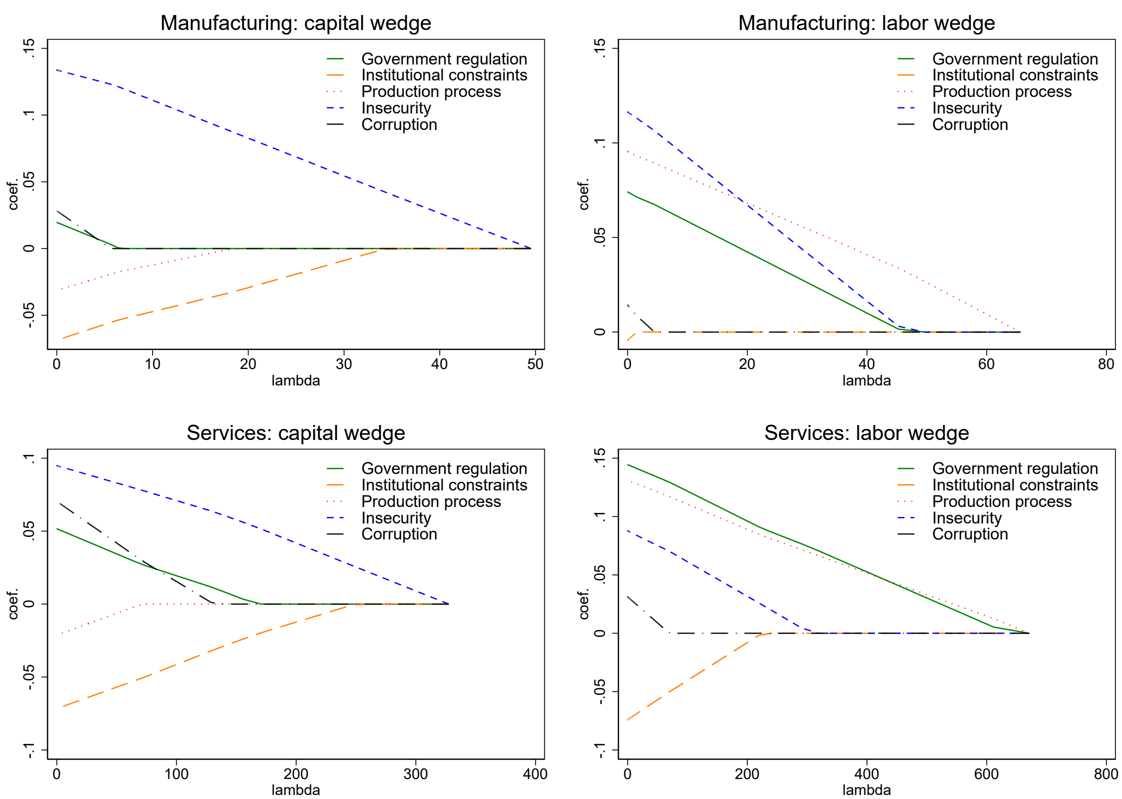
Notes: Coefficient path of the lasso regression. The coefficients are standardized and the penalty parameter, lambda, is in thousands.

ble equals 0 to the number of variables in the category. For instance, the general regulation variable can equal 0 if the firm reports not to be affected by burdensome regulation, high taxes, nor expensive government procedures, and it could be equal to 3 if firms reports to be affected by all these problems.

Figure 5 shows the coefficient path of the lasso regression of input wedges on the categories mentioned above. The first row of this figure is for manufacturing and the second row is for the service sector. For the manufacturing sector, firms affected by insecurity and government regulation have higher input wedges. Corruption can also predict a firm with higher capital and labor wedges, but less significantly. Production process can also help to predict a lower capital wedge but a higher labor wedge. Lastly, institutional constraints variable can predict those firms that face a lower distortion to capital utilization.

For the service sector, government regulation is a predictor of firms that face higher input wedges as well. Unlike manufacturing sector, both corruption and insecurity predict strongly firms that are affected by higher capital and labor wedges. Institutional constraints are more associated to firms with lower input wedges. Since misallocation could also be affected by sector and state where the firm is located, e.g., hotels might have a capital misallocation due to land restrictions they could have. I do the same exercises controlling for sector and state. The results corroborate the baseline findings (Figures 6, 7, and 8) .

Figure 5: Coefficient Path of Input Wedges and Firm Problems with MEC data



Notes: Coefficient path of the lasso regression. The coefficients are standardized and the penalty parameter, lambda, is in thousands.

5 Discussion

This section is divided into two set of results. One that relates distortions with firm characteristics, and the other one that relates the former with structural factors.

Regarding the firm characteristics, the main result is that more formal firms face higher capital and labor wedges. Since my formality variable is measured as a continuous variable, not a categorical one, this means that the more formal the firm is - the firm contributes more to social insurance payments with respect to its wage bill- the distortion to capital (labor) utilization is higher. Busso et al. (2012) and Levy (2018) suggest that, in addition to monopolistic behaviour by banks that results in low levels of credit to firms regardless of size and type in Mexico, credit is also misallocated because banks lend to firms that have higher net worth, which are not necessarily the more productive firms. These two factors make it difficult for more formal and productive firms to grow. Since less formal firms do not have to cover as many expenses (e.g social insurance) as more formal firms, they may have more liquidity and use self-financing as a form of insurance against incomplete access to credit markets (Moll, 2014). Also, firms with a bank account, in general, face higher input wedges than those without a bank account, especially in the service sector. And since firms with a bank account are more productive than those without a bank account, the gross-output efficiency gains from removing distortions to firms with a bank account would be larger.

Among the structural factors of the resource misallocation in Mexico, insecurity is the problem mainly associated to firms with higher input distortions. It could reflect the fact that insecurity is discouraging higher productive firms to produce, as a result of crime and extortion, which ultimately lead to less productive firms to obtain more capital and labor of what they should.

Also, corruption and government regulation create labor and capital misallocation mainly in the service sector. A possible explanation could be that commerce is more prone to be negatively affected by corruption and government regulation than manufacturing firms because the latter group of firms are normally larger, more formal, and more likely to meet the rules.

The relationship between distortions and the rest of the structural factors is less clear. On the one hand, firms that complain about their production processes (lack of access to information technology, poor quality inputs, expensive utilities, inexperienced employees, and expensive inputs) show higher labor wedges, but lower capital wedges. A possible explanation for this discrepancy might be that there are some labor-related factors such as inexperienced employees that cause labor misallocation, overcoming the effect of the rest of factors. Finally, institutional constraints show a negative association with input wedges. That is, those firms that complain about lack of access to credit, unfair competition, and informal sector competition, are associated with lower input wedges. This last result is puzzling. However, these are just correlations, and a more structural model is needed to account for these economic forces more accurately.

6 Conclusion

The first objective of this paper is to quantify resource misallocation for the Mexican economy. It is based on an extension of Hsieh and Klenow (2009) and Mexican Economic Censuses, using both original and processed data by a statistical procedure that addresses the measurement error problem. The second objective is to characterize these input distortions or wedges as firm characteristics as well as structural factors responsible for this resource misallocation.

As for the results, the resource misallocation in Mexico increased during 2008-2018. However, misallocation varies significantly depending on the data set used. The results that correct for possible measurement error in the data indicate that the increasing misallocation over time is much lower than the baseline results using the original data. Indeed, the baseline results indicate that the gross-output gains have gone from 55.1% in 2008 to 80.5% in 2018, whereas after correcting for measurement error they would have gone from 49% in 2008 to 58.7% in 2018. The service sector is the most inefficient one, as a result of capital and labor misallocation. The use of measurement error corrected data suggests that the service sector misallocation also reflects poorer quality data, which is something that should be taken into account when studying misallocation in this sector. Although these numbers seem large, the output gains of getting rid of misallocation using the indirect approach are relatively big numbers in the misallocation literature. In fact, my results are more conservative in levels than previous estimates for Mexico but they are aligned with the recent trend shown in the literature. For example, Levy (2018) highlights that Mexico has gone through a period of deteriorative misallocation from 1998 to 2013. He calculates that if Mexico got rid of distortions, it would have increased its output from 63% in 1998 to 148% in 2013.

Furthermore, I determine which firm characteristics and structural factors are associated to the resource misallocation in Mexico. The findings indicate that formal firms are more affected than informal firms by distortions to their labor and capital utilization due to an environment that encourages the inefficient allocation of resources. Likewise, firms that use a bank account to operate their business face higher distortions to their labor and capital utilization than those firms that operate without a bank account. These results are ultimately associated with government regulations and other structural problems that discourage the efficient allocation of resources. In particular, using the latest economic census, firms that report problems such as insecurity and corruption to operate are associated with higher distortions to labor and capital utilization, especially in the service sector. Thus, structural problems of developing countries, such as corruption and insecurity, could be other economic mechanisms behind the inefficient use of resources in the Mexican economy.

Some caveats to mention. The results must be interpreted through the lens of this model. An efficient allocation requires the TFPR to be the same across firms within a sector. However, in more general frameworks, an efficient allocation can be reached even if such a condition does not hold, e.g. when firms have more heterogeneous production processes, capital adjustment costs (Asker et al., 2014), or overhead labor (Bartelsman et al., 2013), which ultimately can overestimate misallocation.

References

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Asker, J., Collard-Wexler, A., and Loecker, J. D. (2014). Dynamic inputs and resource (mis)allocation. *Journal of Political Economy*, 122(5):1013–1063.

Banerjee, A. and Duflo, E. (2005). *Handbook of Economic Growth*. North Holland.

Bartelsman, E., Haltiwanger, J., and Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *The American Economic Review*, 103(1):305–334.

Benkovskis, K. (2015). Misallocation of resources in latvia: did anything change after the crisis? Technical report, Latvijas Banka.

Bils, M., Klenow, P., and Ruane, C. (2021). Misallocation or mismeasurement. *Journal of Monetary Economics*, 124(S):S39–S56.

Busso, M., Fazio, M. V., and Levy, S. (2012). (in)formal and (un)productive: The productivity costs of excessive informality in mexico. Technical report, Inter-American Development Bank.

Busso, M., Madrigal, L., and Pagés, C. (2013). Productivity and resource misallocation in latin america. *The B.E. Journal of Macroeconomics*, 13(1):903–932.

De Vries, G. J. (2014). Productivity in a distorted market: The case of brazil's retail sector. *Review of Income and Wealth*, 60(3):499–524.

Dias, D., Robalo, C., and Richmond, C. (2015). Misallocation and productivity in the lead up to the eurozone crisis. Technical report, Board of Governors of the Federal Reserve System.

Dias, D., Robalo, C., and Richmond, C. (2016). Misallocation and productivity in the lead up to the eurozone crisis. *Journal of Macroeconomics*, 49:46–70.

Garcia-Santana, M., Moral-Benito, E., Pijoan-Mas, J., and Ramos, R. (2017). Growing like spain: 1995-2007. Technical report, Banco de España.

Guner, N., Ventura, G., and Xu, Y. (2008). Macroeconomic implications of size-dependent policies. *Review of Economic Dynamics*, 11(4):721–744.

Haltiwanger, J., Kulick, R., and Syverson, C. (2018). Misallocation measures: the distortion that ate the residual. Technical report, National Bureau of Economic Research.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics*, 124(4):1403–1448.

Hsieh, C.-T. and Klenow, P. J. (2011). Misallocation and manufacturing tfp in china and india: Correction appendix. Technical report, Stanford University.

Jones, C. (2011). Intermediate goods and weak links in the theory of economic development. *American Economic Journal: Macroeconomics*, 3(2):1–28.

Jones, C. (2013). *Advances in Economics and Econometrics - Misallocation, economic growth and input-output economics*. Cambridge University Press.

Kim, H. J., Cox, L. H., Karr, A. F., Reiter, J. P., and Wang, Q. (2015). Simultaneous edit-imputation for continuous microdata. *Journal of the American Statistical Association*, 110(511):987–999.

Leal-Ordóñez, J. C. (2014). Tax collection, the informal sector, and productivity. *Review of Economic Dynamics*, 17(2):262–286.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2):317–341.

Levy, S. (2018). *Under-Rewarded Efforts: The elusive quest for prosperity in Mexico*. Inter-American Development Bank.

Melitz, M. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

Midrigan, V. and Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *The American Economic Review*, 104(2):422–458.

Misch, F. and Saborowski, C. (2018). Resource misallocation and productivity: evidence from mexico. Technical report, International Monetary Fund.

Moll, B. (2014). Productivity losses from financial frictions: Can self-financing undo capital misallocation? *American Economic Review*, 104(10):3186–3221.

Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous plants. *Review of Economic Dynamics*, 11(4):707–720.

Restuccia, D. and Rogerson, R. (2017). The causes and costs of misallocation. *Journal of Economic Perspectives*, 31(3):151–174.

Rotemberg, M. and White, K. (2021). Plant-to-tables(s and figures): Processed manufacturing data and measured misallocation. Technical report, New York University.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society*, 58(1):267–288.

Appendix

A. Data definitions

TFPQ = $\log(A_{si} M_s^{\frac{1}{\sigma-1}} / TFP_s^*))$, where M_s is the number of differentiated products in sector s and TFP_s is the efficient industry-level of total factor productivity.

TFPR = $log(TFPR_{si}/TFPR_s^*)$, where $TFPR_{si} = P_{si}A_{si}$ and $TFPR_s^*$ is the efficient industry level of distortion.

Capital wedge = $\left(\frac{1+\lambda_{ksi}}{1+\bar{\tau}_{ks}}\right) = \frac{\frac{Q_{si}}{Q_s}}{\frac{K_{si}}{K_s}}$, where Q_{si} is the firm-level intermediate input, Q_s is the sector-level intermediate input, K_{si} is the firm-level capital, and K_s is the sector-level capital as defined in Chapter 1.

Labor wedge = $\left(\frac{1+\lambda_{hsi}}{1+\bar{\tau}_{hs}}\right) = \frac{\frac{Q_{si}}{Q_s}}{\frac{H_{si}}{H_s}}$, where Q_{si} is the firm-level intermediate input, Q_s is the sector-level intermediate input, H_{si} is the firm-level labor input, and H_s is the sector-level labor input as defined in Chapter 1.

Number of workers are salaried workers + non-salaried workers (imputed) who work during the corresponding year of the Census.

Firm age is computed as the difference between the year the firm started to operate and the corresponding year of the Census.

Formality index = establishment's contributory social insurance payments/(wages of salaried workers + payments to non-salaried workers) like Levy (2018).

Banking account equals 1 if the firm uses a bank (checking) account and 0 otherwise.

Formal and informal sector loans equals 1 if the firm gets both formal and informal sector loans and 0 otherwise.

Formal sector loans equals 1 if the firm gets only formal sector loans and 0 otherwise.

Informal sector loans equals 1 if the firm gets informal sector loans only and 0 otherwise.

Regarding the loans, **formal sector** refers to commercial banks and saving banks, while **informal sector** is composed by suppliers, government, private lenders, family, friends, or any other different source mentioned by the firm.

B. Robustness checks

In this section, I illustrate how the resource misallocation baseline indicators, using the original data set, would change with some critical assumptions. In particular, with a higher elasticity of substitution, using number of employees as the labor input, and excluding the self-employment for the analysis.

Elasticity of substitution

The elasticity of substitution reflects the degree of substitutability of goods within the industry. The baseline results is $\sigma = 3$. In the literature, some papers compare the benchmark results with a $\sigma = 5$, particularly when there is a more granular information of the sector. Table 14 shows that if I use this value, gross output and value added efficiency gains would almost double. Table 15 indicates that the gross output efficiency gains would increase, in general, for all the individual distortions. Capital would still be the most misallocated input. A higher value of σ or a higher flexibility to substitute less-distorted for distorted goods would result in distortions having a larger impact on aggregate productivity. This suggests that $\sigma = 3$ must be seen as a conservative estimate of misallocation in this paper.

Table 14: Efficiency Gains (%) for values of σ

Gross output

	Baseline			$\sigma = 5$		
	2008	2013	2018	2008	2013	2018
Total	55.1	64.4	80.5	115.7	128.0	164.8
Manufacturing	23.9	33.4	25.3	35.8	65.9	32.6
Services	109.1	117.5	169.9	222.8	267.4	378.4

Value-added

	Baseline			$\sigma = 5$		
	2008	2013	2018	2008	2013	2018
Total	129.6	158.4	172.0	249.3	327.7	345.9
Manufacturing	76.6	116.2	82.2	108.6	248.3	110.3
Services	189.5	207.1	263.5	383.3	461.8	599.7

Notes: Baseline is $\sigma = 3$.

Table 15: Gross Output Efficiency Gains by Individual Distortion (%) for values of σ

Baseline									
	2008			2013			2018		
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.6	7.3	20.1	16.7	12.2	23.1	16.3	7.2	27.3
Labor	8.2	5.3	12.1	9.4	7.4	12.1	10.2	6.3	14.7
Output	9.0	5.4	14.0	8.7	4.8	14.2	11.3	5.8	17.7
$\sigma = 5$									
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	15.7	7.7	23.1	17.6	11.7	27.1	18.4	6.8	29.3
Labor	11.2	6.3	15.6	12.5	7.3	20.7	13.0	6.4	18.9
Output	12.5	8.5	16.1	12.5	9.6	17.1	14.2	6.4	21.4

Notes: Baseline is $\sigma = 3$.

Number of Employees as the labor input

In the baseline results, I use the remuneration for employees as the labor input. Tables 16 and 17 show that if I use the number of employees as the labor input rather than remuneration for employees, gross output, value added, and gross output by individual distortion efficiency gains would not change significantly compared to the baseline results.

Table 16: Efficiency Gains (%) for different Labor Input

Gross output						
	Baseline			Number of employees		
	2008	2013	2018	2008	2013	2018
Total	55.1	64.4	80.5	56.0	63.6	76.4
Manufacturing	23.9	33.4	25.3	24.2	31.8	22.9
Services	109.1	117.5	169.9	117.2	118.2	172.3
Value-added						
	Baseline			Number of employees		
	2008	2013	2018	2008	2013	2018
Total	129.6	158.4	172.0	135.2	157.9	167.7
Manufacturing	76.6	116.2	82.2	78.8	110.5	76.1
Services	189.5	207.1	263.5	205.9	212.2	268.5

Notes: Baseline uses total remuneration for employees.

Self-employment

Hsieh and Klenow (2009) framework implicitly excludes self-employment since its behaviour is not represented properly by monopolistic competition. Including self-employment is critical to study misallocation in Mexico since those businesses are too many (over 1 million) to ignore. However, Tables 18 and 19 suggest that if we leave out self-employment, the results would change modestly, preserving the results derived from the baseline outcomes.

Table 17: Gross Output Efficiency Gains by Individual Distortion (%) for different Labor Input

	Baseline								
	2008			2013			2018		
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.6	7.3	20.1	16.7	12.2	23.1	16.3	7.2	27.3
Labor	8.2	5.3	12.1	9.4	7.4	12.1	10.2	6.3	14.7
Output	9.0	5.4	14.0	8.7	4.8	14.2	11.3	5.8	17.7
	Number of employees								
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.7	7.5	20.6	16.3	11.5	23.2	15.8	7.1	27.2
Labor	10.2	5.9	16.6	10.5	7.3	14.6	11.0	5.1	18.4
Output	8.7	5.2	14.1	8.9	5.1	14.1	10.6	5.4	17.2

Notes: Baseline uses total remuneration for employees.

Table 18: Efficiency Gains (%) with/without Self-Employment

Gross output						
	Baseline			Excluding self-employment		
	2008	2013	2018	2008	2013	2018
Total	55.1	64.4	80.5	54.0	63.8	77.4
Manufacturing	23.9	33.4	25.3	24.0	33.9	25.9
Services	109.1	117.5	169.9	107.6	117.7	166.1
Value-added						
	Baseline			Excluding self-employment		
	2008	2013	2018	2008	2013	2018
Total	129.6	158.4	172.0	127.9	158.1	167.8
Manufacturing	76.6	116.2	82.2	76.8	117.3	84.1
Services	189.5	207.1	263.5	187.8	208.0	258.6

Notes: Baseline includes self-employment.

Table 19: Gross Output Efficiency Gains by Individual Distortion (%) with/without Self-Employment

Baseline

	2008			2013			2018		
Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.6	7.3	20.1	16.7	12.2	23.1	16.3	7.2	27.3
Labor	8.2	5.3	12.1	9.4	7.4	12.1	10.2	6.3	14.7
Output	9.0	5.4	14.0	8.7	4.8	14.2	11.3	5.8	17.7

Excluding self-employment

Wedge	Total	Man.	Serv.	Total	Man.	Serv.	Total	Man.	Serv.
Capital	12.4	7.3	19.9	16.4	12.0	22.9	15.9	7.3	27.1
Labor	8.2	5.4	12.2	9.4	7.5	12.0	10.1	6.5	14.5
Output	8.8	5.3	13.7	8.7	4.9	14.3	11.0	6.0	17.3

Notes: Baseline includes self-employment.

C. Measurement error: methodology

In this section, I follow the notation used by Kim et al. (2015) and Rotemberg and White (2021). Before explaining the Bayesian editing model used to do so, we need to define some variables and concepts.

Let n be the number of establishments. For each establishment $i = 1,...,n$, assume a vector of true values $x_i = (x_{i1},...,x_{ip})$ with p variables, and a vector of reported values $y_i = (y_{i1},...,y_{ip})$ following the same logic. A discrepancy between x_i and y_i, $x_i \neq y_i$, is what we define as measurement error. Let $s_i = (s_{i1},...,s_{ip})$ be a vector that identifies for each establishment $i = 1,...,n$ if any of the variables $j = 1,...,p$ contains some source of measurement error. In particular, $s_{ij} = 0$ if $y_{ij} = x_{ij}$, i.e. no error in the data, and $s_{ij} = 1$, otherwise (including missing information).

The reported values are not considered true if they are not in a feasible region D that includes the combination of ratio edits and range restrictions that the data must satisfy. To choose the ratio edits, I follow Rotemberg and White (2021). So, for each 4-

digit sector and any pair of variables y_j and y_k, I compute the log ratio $r_{jk} = ln(\frac{y_j}{y_k})$ and its corresponding 25th (q_{jk}^{25}) percentile, 75th (q_{jk}^{75}) percentile, and interquartile range IQR_{jk}. I then flag all ratios smaller than $q_{jk}^{25} - C \times IQR_{jk}$ or larger than $q_{jk}^{75} + C \times IQR_{jk}$ in which C=3. The range restriction is defined as $max(0.1min(X), 1e-5)$ for the lower bound and $10max(x)$ for the upper bound, for all x. A_i indexes the failed ratio edit rules.

The model used to clean the data is a Bayesian hierarchical model with three levels, which includes a model for the underlying data x_i, a model for error indicators (s_i, A_i) given x_i, and a model for reporting error y_i given (x_i, s_i, A_i).

After using the Bayesian Editing Model, we want a distribution of the data that depends only on the observed data:

$f(x_i, s_i | y_i, A_i) \propto f(y_i | x_i, s_i, A_i) f(s_i, A_i | x_i) f(x_i)$

In the case of the model for reporting error, $f(y_i | x_i, s_i, A_i)$, the distribution is uniform over the support of feasible values if $y_{ij} \neq x_{ij}$.

As for the errors model, $f(s_i, A_i | x_i)$, the probability distribution assumed is a uniform as well. This means that there is no distinction among those variables that are more likely to be reported with error. Therefore, all draws s_i that belong to D have the same probability.

With regard to the underlying data, a flexible underlying model for x is chosen, in particular a finite mixture of multivariate normal distributions. It assumes that each establishment belongs to one of the K mixture components (z). Given a number for the K mixture components, the probability of being in each component (π) must be estimated, as well as the mean vector (μ) and covariance matrix (Σ) within each mixture. Additionally, to guarantee the draws pass the ratio edits, the distribution of x_i is

$$f(x_i|\theta_i) = N(x_{i,NT}|\mu_{zi}, \Sigma_{zi})\Pi_{l=1}^{q} 1(x_i \epsilon D)$$

where $N(\cdot)$ is a multivariate normal distribution of the set of reported values $X_{i,NT}$ and $1(\cdot)$ is a variable that takes the value of 1 if the statement inside the parenthesis is true.

The process consists of running a chain of Markov Monte Carlo for 400 iterations in the original data on the variables of the production function: output, capital, total remuneration for employees, and intermediate input at four-level digit sector. As Rotemberg and White (2021) mention, each iteration proposes s_i consistent to A_i, and then y_i is edited based on the draw of s_i and the underlying probability distributions for responses with no error. Ultimately, the generated data is the one used to compute resource misallocation. I also repeat the process for 200 and 1,000 iterations and the main results of this paper do not change significantly. Prof. Martin Rotemberg (NYU) kindly provided the R program that generates the measurement-error corrected data.

D. Additional Tables and Figures

Table 20: Data filtering of Mexican Economic Census

Filter	Number of observations		
	2019	2014	2009
Raw data	4,800,157	4,230,745	3,724,019
Dropping mining, energy, construction, transportation, financial and insurance services, management of companies and enterprises, and government activities	4,727,124	4,167,323	3,665,662
Keeping only positive values of gross output, intermediate input, value added, total remuneration, and capital	3,743,194	3,331,890	2,507,751
Dropping 1% tails of TFPR and TFPQ	3,640,429	3,240,350	2,439,537
Dropping sectors with less than 10 observations	3,640,422	3,240,331	2,439,524

Table 21: Output Efficieny Gains by Sector for 2008

Sector	Part. (%)	Output gains (%)
Manufacturing		
Automobiles and trucks manufacturing	19.0	5.2
Motor vehicle parts manufacturing	13.9	31.5
Plastic products manufacturing	4.5	24.1
Basic chemical products manufacturing	4.1	47.9
Pharmaceutical products manufacturing	3.6	30.6
Other food manufacturing	2.1	33.8
Bakery products and tortilla manufacturing	2.0	37.7
Synthetic resins and rubbers, and chemical fibers manufacturing	1.7	40.4
Cut and sew apparel manufacturing	1.5	45.5
Electric power generation and distribution equipment manufacturing	1.3	45.3
Service Sector		
Retail trade in self-service shops	6.4	32.0
Wholesale trade of industrial raw materials	5.3	124.4
Limited-Service Eating Places	5.0	68.8
Retail trade of groceries and food	4.5	239.0
Wholesale trade of groceries and food	4.5	351.3
Employment services	2.6	99.5
Retail trade of automobiles and pickup trucks	2.3	99.5
Retail trade of fuels, lubricating oils and greases	2.2	146.6
Real estate agencies and brokers	1.9	709.6
Retail trade of hardware and glass	1.9	133.1

Notes: $output_{eg} = 100 * (\frac{Y_s^*}{Y_s} - 1)$, where Y_s^* and Y_s are the sectoral efficient and actual output, respectively.

Table 22: Output Efficiency Gains by sector for 2013

Sector	Part. (%)	Output gains (%)
Manufacturing		
Automobiles and trucks manufacturing	23.6	20.6
Motor vehicle parts manufacturing	14.8	40.8
Basic chemical products manufacturing	8.0	35.8
Pharmaceutical products manufacturing	3.5	40.0
Plastic products manufacturing	3.5	28.5
Soaps, cleaners and toilet preparations manufacturing	3.2	84.6
Iron and steel basic industry	3.1	27.6
Bakery products and tortilla manufacturing	2.0	54.9
Cement and concrete products manufacturing	1.2	63.7
Electronic components manufacturing	1.2	65.5
Service Sector		
Wired telecommunications carriers	6.9	48.7
Retail trade in self-service shops	6.8	66.2
Wholesale trade of groceries and food	6.5	156.5
Food and alcoholic and non alcoholic beverages preparation services	5.7	54.6
Wholesale trade of industrial raw materials	4.4	200.0
Employment services	4.1	215.8
Retail trade of groceries and food	4.0	219.2
Wholesale of beverages, ice and tobacco	3.2	101.0
Retail trade of fuels, lubricating oils and greases	2.8	357.3
Retail trade in department stores	2.4	143.4

Notes: $output_{eg} = 100 * (\frac{Y_s^*}{Y_s} - 1)$, where Y_s^* and Y_s are the sectoral efficient and actual output, respectively.

Table 23: Output Efficiency Gains by sector for 2018

Sector	Part. (%)	Output gains (%)
Manufacturing		
Automobiles and trucks manufacturing	30.2	10.9
Motor vehicle parts manufacturing	19.2	28.1
Plastic products manufacturing	3.9	23.9
Pharmaceutical products manufacturing	3.9	67.6
Livestock, poultry and other edible animals	2.2	26.6
Basic chemical products manufacturing	2.2	41.2
Synthetic resins and rubbers, and chemical fibers manufacturing	1.6	34.5
Electronic components manufacturing	1.4	46.6
Other electrical equipment and accessories manufacturing	1.3	51.5
Soaps, cleaners and toilet preparations manufacturing	1.1	53.3
Service sector		
Retail trade in self-service shops	10.4	93.3
Wholesale trade of industrial raw materials	7.9	339.4
Food and alcoholic and non alcoholic beverages preparation services	6.8	53.5
Employment services	5.2	162.3
Retail trade of groceries and food	4.7	706.3
Wholesale trade of groceries and food	4.4	243.6
Retail trade of fuels, lubricating oils and greases	3.4	448.0
Wholesale of beverages, ice and tobacco	2.5	127.2
Retail trade of household furniture and other household goods	1.7	526.4
Real estate agencies and brokers	1.2	716.1

Notes: $output_{eg} = 100 * (\frac{Y_s^*}{Y_s} - 1)$, where Y_s^* and Y_s are the sectoral efficient and actual output, respectively.

Table 24: Correlations of firm characteristics to total factor productivity

	Manufacturing			Service Sector		
	2009	2014	2019	2009	2014	2019
Number of workers	0.141*	0.127*	0.112*	0.090*	0.018*	0.046*
age	0.078*	0.083*	0.078*	0.104*	0.083*	-0.010*
informaliy index	0.284*	0.281*	0.253*	0.170*	0.152*	0.162*
banking account	0.166*	0.288*	0.233*	0.068*	0.162*	0.223*
formal and informal funding	0.081*	0.065*	0.047*	0.020*	0.015*	0.025*
formal funding	0.049*	0.088*	0.052*	0.004*	-0.001	0.003*
informal funding	0.019*	0.004*	0.004*	-0.011*	-0.035*	-0.033*

Notes: *5% significance level

Table 25: Correlation of firm problems for the manufacturing sector

	IC Lack of access to credit	GR Burdensome regulation	GR High taxes	IC Unfair competition	IC Informal sector competition	PP Lack of access to information technology	PP Expensive utilities	GR Expensive government procedures	PP Inexperienced employees	INSEC Insecurity	CORR Corruption	PP Expensive inputs
Lack of access to credit	1											
Burdensome regulation	0.107*	1										
High taxes	0.087*	0.274*	1									
Unfair competition	0.026*	0.061*	0.079*	1								
Informal sector competition	0.047*	0.126*	0.126*	0.206*	1							
Lack of access to information technology	0.099*	0.147*	0.114*	0.068*	0.116*	1						
Expensive utilities	0.040*	0.129*	0.172*	0.054*	0.100*	0.067*	1					
Expensive government procedures	0.053*	0.342*	0.238*	0.055*	0.119*	0.128*	0.156*	1				
Inexperienced employees	0.038*	0.111*	0.105*	0.038*	0.085*	0.120*	0.062*	0.119*	1			
Insecurity	-0.016*	0.083*	0.087*	0.005*	0.051*	0.045*	0.027*	0.082*	0.043*	1		
Corruption	0.072*	0.203*	0.194*	0.096*	0.143*	0.134*	0.114*	0.199*	0.125*	0.233*	1	
Expensive inputs	0.039*	0.056*	0.060*	0.045*	0.067*	0.063*	0.139*	0.063*	0.036*	-0.051*	0.060*	1

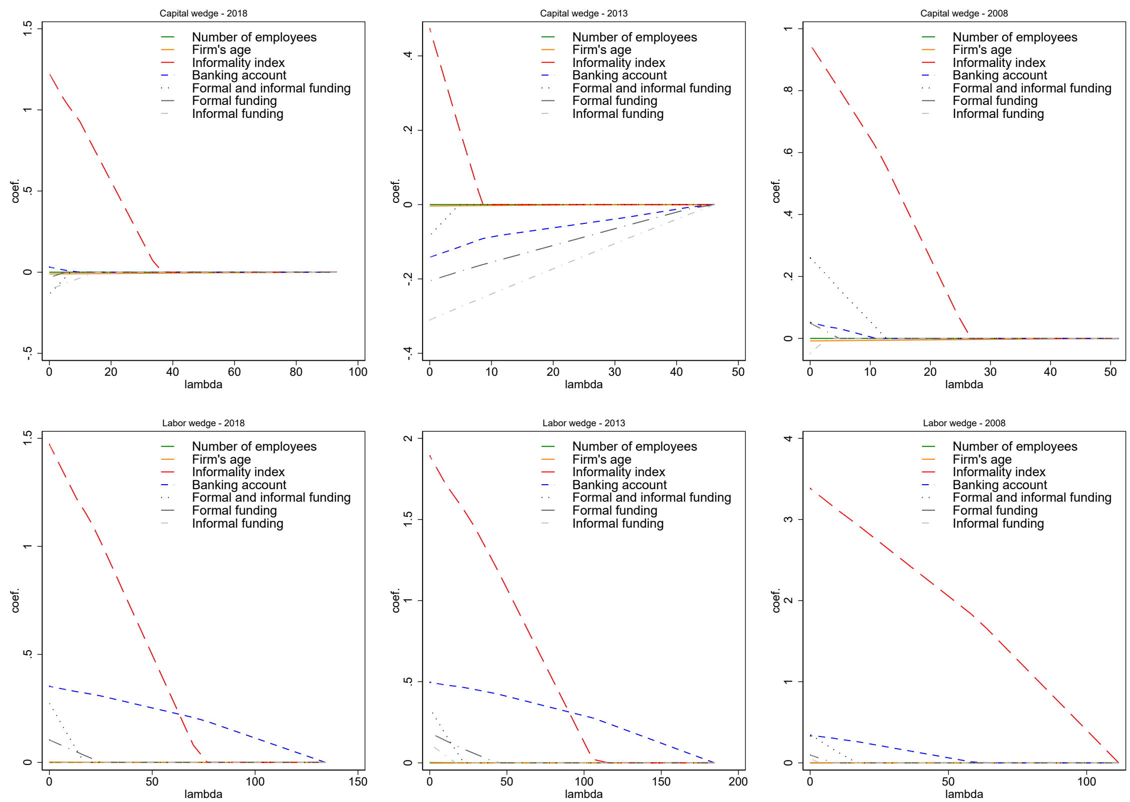
Notes: *5% significance level

Table 26: Correlation of firm problems for the service sector

	IC Lack of access to credit	GR Burdensome regulation	GR High taxes	IC Unfair competition	IC Informal sector competition	PP Lack of access to information technology	PP Expensive utilities	GR Expensive government procedures	PP Inexperienced employees	INSEC Insecurity	CORR Corruption	PP Expensive inputs
Lack of access to credit	1											
Burdensome regulation	0.093*	1										
High taxes	0.080*	0.269*	1									
Unfair competition	0.031*	0.058*	0.086*	1								
Informal sector competition	0.040*	0.110*	0.115*	0.215*	1							
Lack of access to information technology	0.090*	0.122*	0.101*	0.060*	0.098*	1						
Expensive utilities	0.049*	0.130*	0.168*	0.021*	0.077*	0.058*	1					
Expensive government procedures	0.047*	0.379*	0.245*	0.052*	0.111*	0.111*	0.168*	1				
Inexperienced employees	0.030*	0.110*	0.105*	0.040*	0.083*	0.107*	0.056*	0.123*	1			
Insecurity	-0.017*	0.071*	0.061*	-0.012*	0.038*	0.035*	0.023*	0.068*	0.029*	1		
Corruption	0.059*	0.206*	0.181*	0.093*	0.145*	0.113*	0.104*	0.199*	0.108*	0.215*	1	
Expensive inputs	0.053*	0.053*	0.057*	0.047*	0.061*	0.064*	0.152*	0.062*	0.033*	-0.016*	0.066*	1

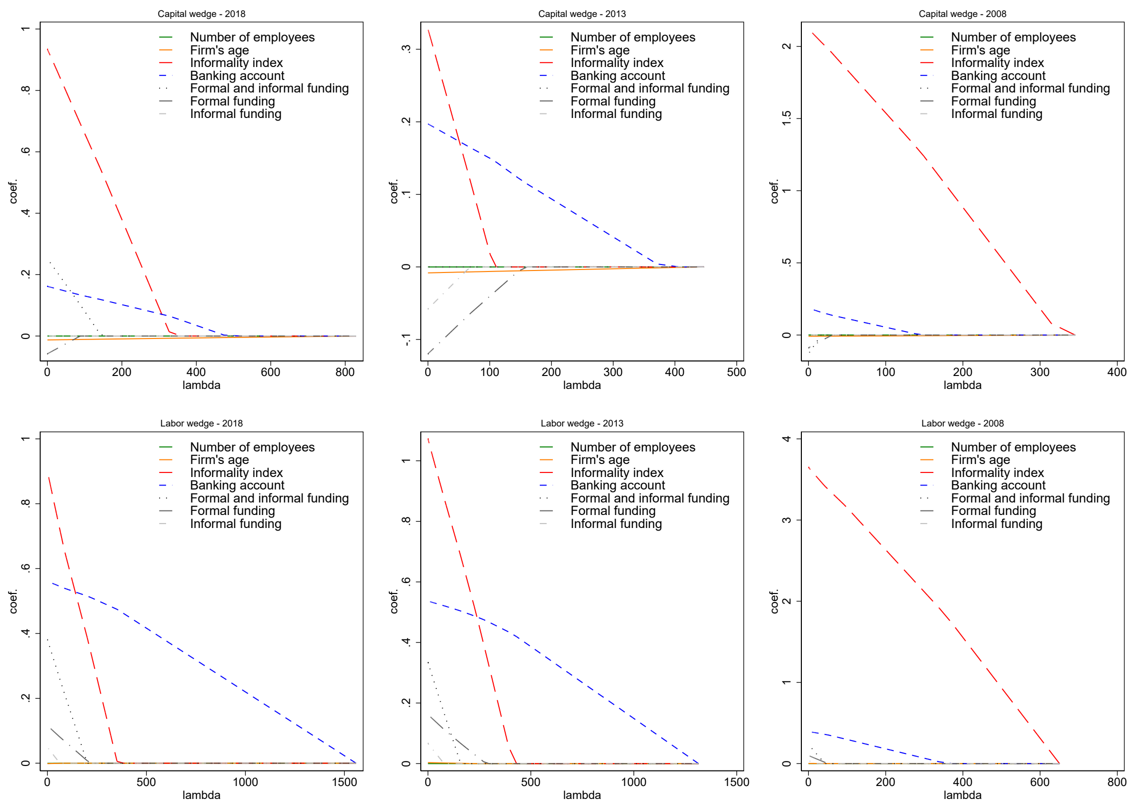
Notes: *5% significance level

Figure 6: Coefficient Path of Residual of Input Wedges and Firm Characteristics for the Manufacturing Sector



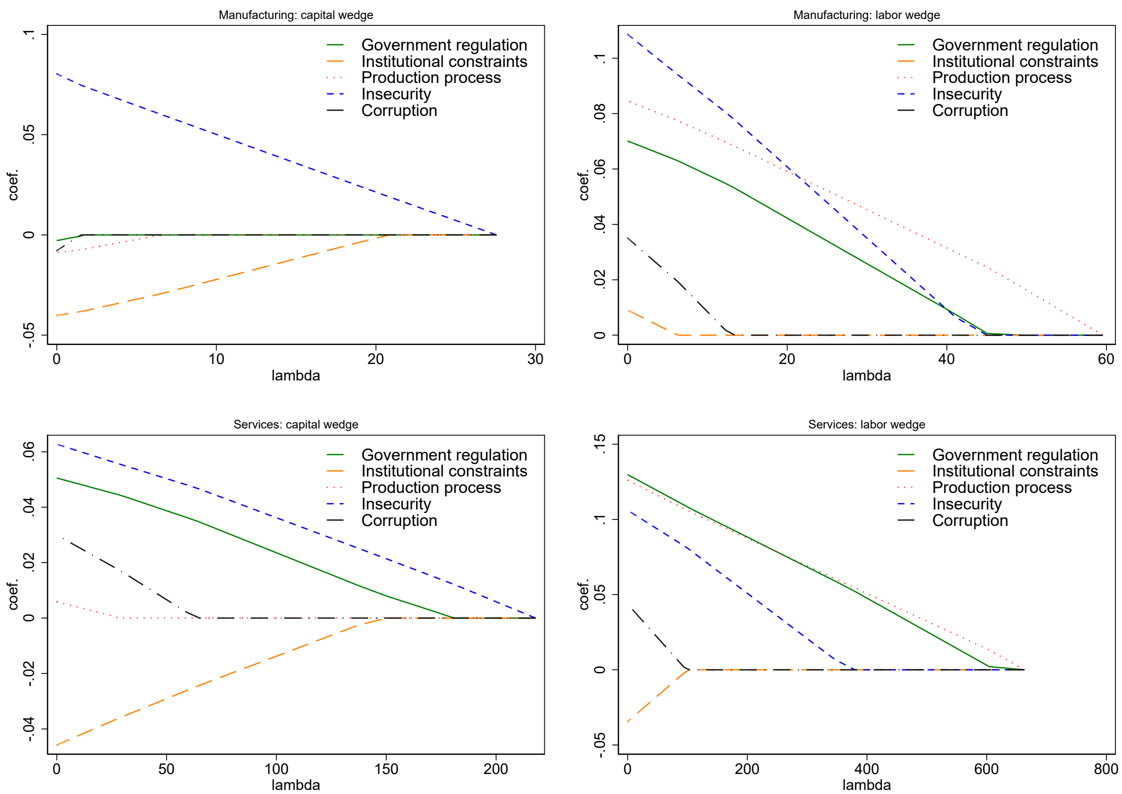
Notes: Coefficient path of the lasso regression. The coefficients are standardized and the penalty parameter, lambda, is in thousands.

Figure 7: Coefficient Path of Residual Input Wedges and Firm Characteristics for the Service Sector



Notes: Coefficient path of the lasso regression. The coefficients are standardized and the penalty parameter, lambda, is in thousands.

Figure 8: Coefficient Path of Residual of Input Wedges and Firm Problems



Notes: Coefficient path of the lasso regression. The coefficients are standardized and the penalty parameter, lambda, is in thousands.