Energy and Misallocation: Evidence from Brazil

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Abstract

The paper explores detailed firm-level data from 2007 to 2015 to analyze energy efficiency and its relation to productivity in the Brazilian Industry. We describe the relationship between energy misallocation and resource misallocation and quantify the extent to which distortions affecting energy use result in output losses at the aggregate level. Data are taken from the Annual Survey of Industry and the final database is composed of about 30,000 firms per year covering 106 sectors. We show that misallocation increased from 2007 to 2015, and was the main reason preventing aggregate productivity and energy efficiency growth. During this period, more productive and energy efficient firms lost market shares. Resources were reallocated from the most efficient firms, in terms of productivity and energy use, towards firms with lower efficiency levels. We also find that energy and resource misallocation are positively related across industries, which suggests that there is no trade-off between productivity and environmental gains. Finally, we use the model developed by Hsieh & Klenow (2009) to quantify potential aggregate productivity gains taking into consideration the existence of energy distortions. We find that reallocating resources between firms would result in substantial aggregate output gains. However, capital distortions are relatively more important than energy distortions in generating resource misallocation and productivity losses. The combination of these findings suggests that industrial initiatives are more effective than firm-level ones to improve energy efficiency in the Brazilian industry. Moreover, it is important that policymakers design broader industrial policies to tackle distortions that are more binding than energy distortions. This, in turn, would make room for programs that target industrial energy efficiency. The existence of an energy misallocation implies that potential gains from improving the allocation of resources in the economy would not only increase aggregate productivity but also raise well-being by reducing emissions and energy use.

1 Introduction

Recent empirical evidence has revealed a high degree of heterogeneity in energy efficiency levels across firms, even in narrowly defined industries (Cherniwchan et al. 2017). From the environmental point of view, this evidence suggests that firms underinvest in energy efficient technologies. In this case, there is considerable room for improvement in

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energy efficiency levels, reducing aggregate energy consumption and emissions associated with energy generation and use (DeCanio 1993).

A related strand of literature argues, both empirically and theoretically, that dispersion in firm productivity levels within industries might reflect resource misallocation (Banerjee & Duflo 2005, Restuccia & Rogerson 2008, Hsieh & Klenow 2009). This process is characterized by the presence of distortions that simultaneously affect the allocation of resources in the economy and allow the survival of unproductive firms. Resource misallocation implies that aggregate productivity gains can be obtained by reallocating resources across firms, such that the final allocation reflects firms' relative productivity levels. Hence, the dispersion of energy efficiency levels has another important implication, since it potentially reflects an inefficient allocation of energy usage across firms. Moreover, it implies that resource reallocation within industries could lead to both environmental and economic aggregate gains.

The main goal of this chapter is to describe resource misallocation in Brazilian manufacturing, and to quantify the role of energy use among firms in generating misallocation. Quantifying the degree in energy misallocation is important because it is informative of the attainable environmental gains associated with improvements in resource allocation. We also evaluate how allocation efficiency contributed to the evolution of aggregate productivity and energy efficiency in Brazil, from 2007 to 2015. Finally, we quantify the extent to which distortions in firms' inputs, including energy use, result in manufacturing productivity losses at the aggregate level. We take advantage of detailed Brazilian firm-level data with information on firms' outputs and inputs, covering 106 manufacturing industries. We focus on electricity as our measure of energy, due to its importance in firms' activities (Allcott et al. 2016) and consistent, yearly information on firms' electricity costs in the data.

First, we use the decomposition proposed by Olley & Pakes (1996) to define a direct measure of energy and resource misallocation. From the decomposition, we describe how the evolution of aggregate energy efficiency and productivity in Brazil were driven by technological changes and by the allocation efficiency of resources across heterogeneous firms. Then, we explore the relationship between energy and resource misallocation, both at the aggregate and industry levels. Furthermore, we apply the model in Hsieh & Klenow (2009) including electricity as an input, and we compute potential aggregate productivity gains from reallocating inputs across firms within industries. In a related experiment, we assess the relative importance of each input in generating resource misallocation. We quantify potential gains implied by the model assuming that there are only either capital or electricity distortions affecting firms' input choices.

Our main contribution is to provide empirical evidence that energy misallocation and resource misallocation are positively related across industries. This result implies that there is no trade-off between energy and economic efficiency, so efforts to improve energy efficiency are closely related to policies directed at improving aggregate productivity. Moreover, resource reallocation across firms has the potential to increase not only aggregate productivity, but also improve aggregate energy efficiency levels. The Olley & Pakes (1996) decomposition reveals that resource misallocation increased from 2007 to 2015, and was the main reason preventing aggregate productivity and energy efficiency growth. During this period, resources were reallocated from the most efficient firms, in terms of productivity and energy use, towards firms with lower efficiency levels.

Empirical estimates from the Hsieh & Klenow (2009) model imply that reallocating resources across firms at the industry level would lead to aggregate productivity gains ranging from 78% to 96%. However, relative gains from capital reallocation are higher than gains from electricity reallocation. While efficient capital allocation would increase aggregate productivity by 30%, the increase from reaching an efficient electricity allocation would be only 2.5%.

Assunção & Schutze (2017) argue that, in Brazil, policies and financial incentives to promote energy efficiency are mainly focused on household consumption. These policies have mostly been responsive to negative supply shocks, instead of being a continuous effort to promote better energy use. As a result, firms have little incentive to invest in more efficient technologies, even if they account for the majority of the country's electricity consumption[1]. Understanding the allocation of energy efficiency across firms can have important policy implications, pointing to actions that improve aggregate energy efficiency, without necessarily increasing individual firms' technology levels.

Inefficient energy allocation across firms could arise due to market failures such as imperfect information (Anderson & Newell 2004, Bloom et al. 2013), assymetric information and principal-agent problem (Howarth et al. 2000, De Almeida 1998, Ostertag 2012), credit constraints (Rohdin et al. 2007, Allcott & Greenstone 2012) and even energy price uncertainty (Diederen et al. 2003, Löfgren et al. 2008). The existence of an energy misallocation implies that potential gains from improving the allocation of resources in the economy would not only increase aggregate productivity, but also raise well-being by reducing emissions and energy use.

Our model is different from that of other papers addressing firm-level energy efficiency such as Copeland & Taylor (2013) or Barrows & Ollivier (2018), since it introduces firm-specific wedges that affect the marginal cost of electricity and, consequently, firms' optimal input choices. The inclusion of wedges is essential in our context, resulting in output losses from inefficient resource allocation. However, one disadvantage from using the framework proposed by Hsieh & Klenow (2009) is that it relies on strong assumptions about the elasticity of supply and demand. Haltiwanger et al. (2018) show that, in the case where these assumptions do not hold, the distortions computed from the data could reflect demand shifts or movements along the marginal cost curve, which are not indicative of inefficiencies faced by the firm.

The rest of the chapter is organized as follows. Section 2 describes our data sources. We describe the evolution and the relationship between energy misallocation and resource misallocation at the industry level in Section 3. In Section 4, we apply the model in Hsieh & Klenow (2009) by including electricity as a production input. Section 5 quantifies the potential gains from efficiently allocating resources across firms, and evaluates the relative importance of each distortion in generating resource misallocation. Section 6 addresses how our estimates for potential aggregate gains are robust to changes in model hypotheses and parameter values. Section 7 concludes.

2 Data

Our primary source of data is the *Pesquisa Industrial Anual* (PIA), a restricted-access panel data gathered annually by the Brazilian National Bureau of Statistics (IBGE), from 2007 to 2015[2]. PIA contains information on formal firms' production and inputs. It consists

[1] In 2016, manufacturing firms accounted for 33% of electricity consumption in Brazil (Empresa de Pesquisa Energética 2017)

[2] These are confidential data and have been granted access by IBGE through the use of its restricted-

of a census of firms with at least 30 workers or with gross revenue above a certain limit[3], and a random sample of smaller firms which do not qualify for the census sample. We drop smaller firms belonging to the random sample, since information is limited for this group and does not contain, for example, electricity expenditure separately from other sources of energy and data on capital stock.

The variables used from PIA include firm's industry according to the three-digit CNAE 2.0 classification, the number of workers on December 31st, labor compensation, value added, electricity expenditures, and the book-value of capital. We measure labor compensation as the sum of wages, bonuses, benefits and social security contribution to paid employees[4]. The book-value of capital is obtained from information on depreciation, investment, leasing and capital rents via the perpetual inventory method. We deflate all monetary values using the IPA-OG deflator, from Fundação Getúlio Vargas, a three-digit CNAE deflator.

By restricting the analysis to the census sample of PIA, we use 76% of firm-level observations available in PIA. This sample of firms corresponds to 97% of Brazilian employment, but only 15% of the total number of firms operating in Brazil. One drawback from not including the random sample of firms in PIA is that our results could be biased if smaller firms are more subject to distortions which prevents them from adopting energy efficient technologies. Since smaller firms are probably more prone to restrictions such as credit constraints, we believe that by excluding the random sample from our analysis, our results will underestimate the true potential gains from eliminating distortions that generate energy misallocation[5].

We input data on firm age and municipality from the *Relação Anual de Informações Sociais* (RAIS) dataset, collected annually by the Brazilian Labor Ministry, from 2007 to 2013. Every year, all formally registered firms are required to report firm-level information, as well as individual characteristics of all its workers. Although RAIS does not contain any reported information on firms' entry year, we infer entry from the earliest hiring year reported in each firm for the whole sample period. Based on the estimated entry year, we calculate firm age accordingly[6].

Finally, electricity prices by municipality are calculated based on publicly available data from *Agência Nacional de Energia Elétrica* (ANEEL), the Brazilian Electricity Regulatory Agency. For each electricity distributor in Brazil, we calculate the annual average industrial tariff charged from 2007 to 2015. Although the average tariff does not perfectly reflect the true electricity cost faced by all firms, it is an excellent approximation. We then associate annual electricity prices to Brazilian municipalities based on the geographical coverage of each distributor, and attribute these prices to firms based on the municipality in which they are located. Since we do not have data on firms' municipalities for 2014 and 2015, we recover this information from firms' appearances in RAIS in previous years, whenever possible.

About 10% of firms in the data report zero or unreasonably low values of electricity expenditures. In Brazil, the government establishes a minimum charge on electricity bills of

access room. The results and conclusions expressed in this chapter are our own and do not necessarily present the views of IBGE. Our results do not constitute official IBGE statistics.

[3]This limit is established yearly. For example, this limit was equal to R$12.8 million in 2015.

[4]Our results are not altered by the exclusion of social security contributions in the measure of labor compensation.

[5]Our results are still comparable to those of Hsieh & Klenow (2009), since their data also includes only firms above certain size or revenue restrictions.

[6]Since we do not have access to RAIS for the years of 2014 and 2015, we did not consider any age measure for those years.

R\$30, even when there is no consumption at all[7]. Thus, we drop all observations reporting electricity expenditures lower than this minimum charge. We also drop five industries with the lowest number of observations, with consistently less than five observations per year.[8] The final database comprises 63,431 unique firms in 106 three-digit CNAE industries. A complete list of the industries included in our paper is presented in the Appendix, in Table 11. Table 1 details the number of firms and employment included in PIA for each year of the sample.

Our measure of energy efficiency used in section 3 consists on the ratio of value added to electricity expenditure. Ideally, we would like to identify electricity consumption by each firm. Electricity consumption is affected by the price of electricity available to firms in different geographical areas. The idea of this energy efficiency is capturing how much production can be attained with a given consumption of electricity. It is widely adopted in works such as Allcott & Greenstone (2012), Fisher-Vanden et al. (2004) and by the International Energy Agency. A similar definition considering emissions is common as well, as in Andersen (2017), Barrows & Ollivier (2018). One disadvantage from using this energy efficiency measure is that it relies on electricity costs, and so it does not capture auto-production of electricity by firms. We also measure electricity usage imperfectly for firms in industries where other sources of energy are especially relevant.

Table 1: Number of observations in PIA

Year	Firms	Employment
2007	27,604	5,158,598
2008	29,508	5,415,605
2009	29,943	5,415,981
2010	30,753	5,852,775
2011	32,520	6,085,518
2012	32,718	6,202,386
2013	32,139	6,258,764
2014	32,240	6,122,721
2015	29,765	5,660,443

Notes: Number of firms and total employment by year. Data from PIA.

3 Energy misallocation

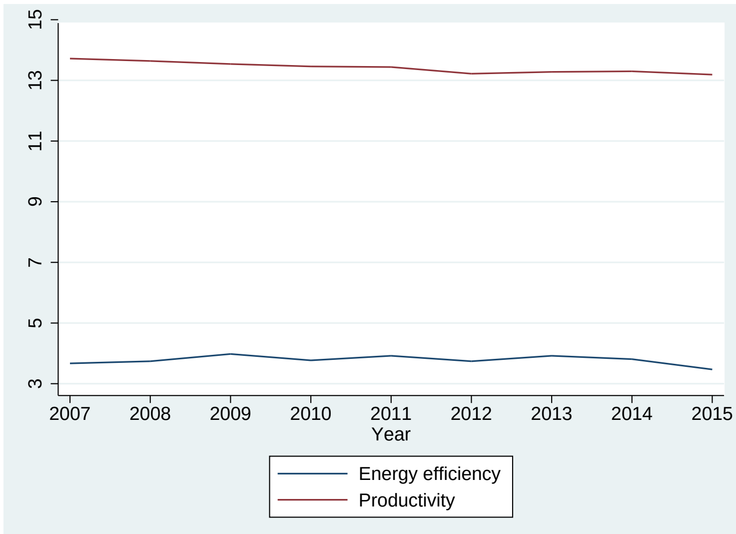
In this section, we define a measure of productivity and energy efficiency dispersion, and we use it to describe the relationship between energy misallocation and overall resource misallocation at the industry level. We also show how the allocation of resources has affected the evolution of aggregate productivity and energy efficiency levels in Brazil, from 2007 to 2015. We use the decomposition developed by Olley & Pakes (1996), which tracks how the evolution of aggregate productivity is affected by technological innovations and changes in the allocation efficiency of resources.

[7]Resolução Normativa 414/2010.

[8]These sectors are: Extraction of crude petroleum and natural gas; Support activities for other mining and quarrying; Manufacture of coke oven products; Manufacture of magnetic and optical media; Manufacture of military fighting vehicles.

Figure 1 illustrates that Brazilian aggregate productivity steadily decreases from 2007 to 2015. Aggregate energy efficiency does not change much during this period, although there seems to be a decline starting in 2013. We now decompose these aggregate measures of efficiency to better understand how they were affected by changes in technology and by changes in the allocation of resources across firms.

Figure 1: Aggregate energy efficiency and aggregate productivity



Notes: Aggregate productivity and aggregate energy efficiency by year. Data from PIA and RAIS, from 2007 and 2015.

We denote value added from firm i in industry s by $P_{si}Y_{si}$. The aggregate value added of industry s is given by $V_s = \sum_{i=1}^{M_s} P_{is}Y_{is}$, where M_s is the number of firms operating in industry s. Firm i's market share is calculated as $\varphi_{is} = \frac{P_{is}Y_{is}}{V_s}$.

We define firm-level energy efficiency as the ratio of value added to electricity expenditure, $e_{is} = P_{is}Y_{is}/E_{is}$, where E_{is} is electricity expenditure by firm i in industry s. The intuition of this measure is that higher energy efficiency levels e_{is} allow more output to be produced from a given consumption of electricity.

Using the decomposition proposed by Olley & Pakes (1996), we can write the aggregate energy efficiency of industry s as a weighted average of firms' individual energy efficiency levels, using market shares as weights. This term can then be expressed as a function of average energy efficiency and market shares, and deviations from this average value.

$$e_s = \sum_{i=1}^{Ms} \varphi_{is} e_{is} = \sum_{i=1}^{Ms} \left(\overline{\varphi}_s + \Delta\varphi_{is}\right)\left(\overline{e}_s + \Delta e_{is}\right) \tag{1}$$

where $\overline{\varphi}_s$ and $\overline{e}_s$ represent the unweighted industry averages of market shares and energy efficiency, respectively. $\Delta\varphi_{is}$ and Δe_{is} express deviations from the industry average, given by $\Delta\varphi_{is} = \varphi_{is} - \overline{\varphi}_s$ and $\Delta e_{is} = e_{is} - \overline{e}_s$.

From the decomposition, we obtain:

$$e_s = \sum_{i=1}^{Ms} \overline{\varphi}_s \overline{e}_s + \overline{\varphi}_s \sum_{i=1}^{Ms} \Delta e_{is} + \overline{e}_s \sum_{i=1}^{Ms} \Delta \varphi_{is} + \sum_{i=1}^{Ms} \Delta \varphi_{is} \Delta e_{is} \tag{2}$$

The industry sum of deviations from the mean must be zero, by definition, such that $\sum_{i=1}^{M_s} \Delta\varphi_{is} = \sum_{i=1}^{M_s} \Delta e_{is} = 0$. Moreover, $\sum_{i=1}^{M_s} \overline{\varphi}_s \overline{e}_s = M_s \overline{\varphi}_s \overline{e}_s = \overline{e}_s$, using the fact that $\sum_{i=1}^{M_s} \varphi_{is} = 1$. This leaves us with the following expression for aggregate energy efficiency:

$$e_s = \overline{e}_s + \sum_{i=1}^{Ms} \left(\varphi_{is} - \overline{\varphi}_s\right)\left(e_{is} - \overline{e}_s\right) \tag{3}$$

The idea of this decomposition is that aggregate energy efficiency is affected by a technical component, $\overline{e}_s$, measuring increases in average energy efficiency, and a composition component, $\sum_{i=1}^{Ms} \left(\varphi_{is} - \overline{\varphi}_s\right)\left(e_{is} - \overline{e}_s\right)$, which captures how the allocation of resources between firms of varying levels of energy efficiency affects the aggregate level of this variable.

The composition component of energy allocation in industry s, denoted by λ_s^e, is described in equation 4.

$$\lambda_s^e = \sum_{i=1}^{Ms} \left(\varphi_{is} - \overline{\varphi}_s\right)\left(e_{is} - \overline{e}_s\right) \tag{4}$$

The energy allocation λ_s^e is a measure of the covariance between firms' market shares and energy efficiency in industry s. It is negatively related to the degree of misallocation, since higher values of λ_s^e imply that electricity is being allocated to firms with high energy efficiency, which in turn increases aggregate energy efficiency in that industry.

We can use the Olley & Pakes (1996) decomposition to define a measure of resource allocation, λ_s^θ. The composition component of the resource allocation, λ_s^θ, is defined analogously to λ_s^e.

$$\lambda_s^\theta = \sum_{i=1}^{Ms} \left(\varphi_{is} - \overline{\varphi}_s\right)\left(\theta_{is} - \overline{\theta}_s\right) \tag{5}$$

Firm productivity, θ_{is}, is defined as value added per worker. Again, λ_s^θ a higher delta implies a more efficient allocation of resources, which in turn implies a lower level of misallocation.

Table 2 illustrates the decomposition of aggregate energy efficiency and aggregate productivity for Brazil from 2007 to 2015. Aggregate energy efficiency decreased from 3.6 in 2007 to 3.47 in 2015, although there is not a clear negative trend in the data. Average firm energy efficiency consistently increases during this period, starting at 2.91 and reaching 3.41 in 2013, but it decreases abruptly to 3.12 in 2015. The energy allocation, on the other hand, worsened consistently during the whole period. In 2015, at 0.45, it falls to 60% of its initial level.

Table 2 expresses that, even with an overall improvement in the use of electricity within firms, reflected by average energy efficiency, we find that electricity inputs were reallocated from more energy efficient firms to less energy efficient firms. This fact helps to explain why there was no growth in aggregate energy efficiency during our sample period.

Table 2: Energy efficiency and productivity decomposition

	Energy Efficiency			Productivity		
Year	e	$\overline{e}$	λ^e	θ	$\overline{\theta}$	λ^θ
2007	3.67	2.91	0.77	13.72	11.61	2.11
2008	3.74	3.04	0.70	13.64	11.64	2.01
2009	3.98	3.07	0.91	13.54	11.59	1.95
2010	3.77	3.18	0.59	13.46	11.65	1.82
2011	3.92	3.23	0.69	13.44	11.65	1.79
2012	3.74	3.29	0.45	13.22	11.61	1.61
2013	3.92	3.41	0.51	13.28	11.65	1.63
2014	3.81	3.37	0.44	13.30	11.66	1.65
2015	3.47	3.02	0.45	13.19	11.63	1.56

Notes: Decomposition of aggregate energy efficiency and productivity into a technical component, $\overline{e}$ and $\overline{\theta}$, that measure average firm efficiency, and an allocation component, λ^e and λ^θ, that reflects how resources are allocated towards the most efficient firms. Data from PIA and RAIS.

The decomposition of aggregate productivity in Table 2 also indicates that the main factor hindering aggregate productivity growth in Brazil is the allocation of resources among heterogeneous firms. Brazilian aggregate productivity decreased from 13.72 in 2007 to 13.19 in 2015, but this evolution was not the result of a reduction in firms' average productivity. The main factor explaining the decrease of aggregate productivity is the composition component of resource allocation, revealing that resources were reallocated from more productive firms to less productive ones.

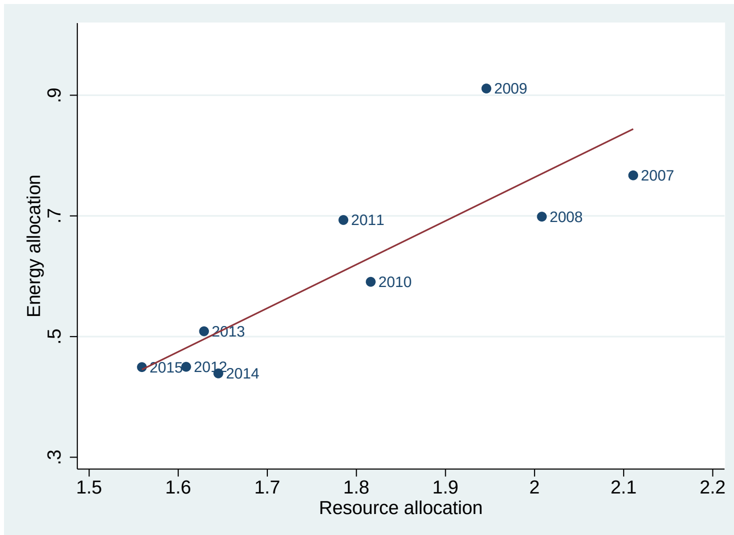
Figure 2 plots the relationship between the aggregate measures of the composition component, λ^e and λ^θ, for each year in our sample. It depicts that there is a positive correlation between the allocation efficiency of energy inputs and the overall allocation efficiency of resources. The Figure 2 also illustrates our result from Table 2 that this period was characterized by a decline in the allocation efficiency of resources and energy, as we can see from the falling levels of allocation efficiency over the years. During this period, more productive and energy efficient firms lost market shares, and resources were reallocated to less efficient firms, increasing misallocation.

At the aggregate level, however, dispersion in productivity and energy efficiency levels naturally arise due to differences in industry characteristics such as energy use intensity, production costs, and scale. To take these differences into consideration, we now turn to describe the allocation efficiency of resources and energy inputs at the industry level.

Figure 3 plots the relationship between the efficiency in energy allocation, λ_s^e, and in resource allocation, λ_s^θ, at the industry level. These measures are computed for each of the 106 mining and manufacturing industries in Brazil, by pooling observations from 2007 to 2015. In Section 6, we address if our results are robust to using alternative productivity measures.

Confirming our previous results, we find a positive cross-sectional relationship between λ_s^e and λ_s^θ, with a correlation coefficient of 0.40. This result implies that energy allocation and resource allocation are positively related across industries. In industries where electricity is allocated efficiently, to the most energy efficient firms, resources are generally also allocated to the most productive firms. Hence, we can directly infer that energy misallocation is

Figure 2: Aggregate misallocation



Notes: Composition component measures of energy allocation, λ^e, and resource allocation, λ^θ, plotted by year. Data from PIA and RAIS.

positively related to resource misallocation. This positive relationship is consistent with evidence that firm-level energy efficiency is one important component in the determination of productivity, since energy efficiency influences firms' optimal decision for other production inputs (Ryan 2015). Table 8 in the Appendix reports that these results are not altered when the allocation efficiency measures are computed for a specific year, 2015.

One important implication from these results is that there is no trade-off between energy allocation and resource allocation. In particular, it implies that public policy efforts to promote higher energy allocation efficiency should include actions that increase the market share of the most productive firms in each industry.

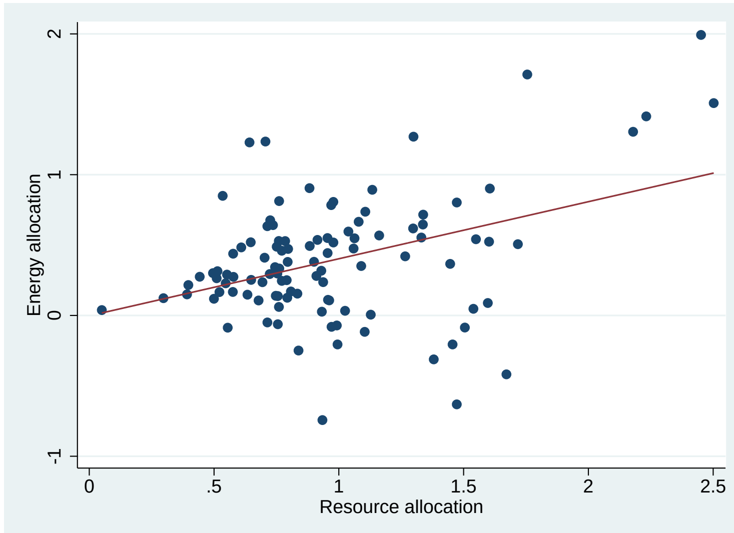
As a complementary exercise, to provide some evidence on the factors associated with firm performance, we explore the correlation between energy efficiency or productivity and firm characteristics. We run regressions of the form:

$$e_{ist} = \beta_1 log(Emp_{ist}) + \beta_2 Age_{ist} + \beta_3 X_{ist} + \beta_4 T_{ist} + \gamma_t + \gamma_s + \gamma_d + \epsilon_{ist} \tag{6}$$

$$\theta_{ist} = \beta_1 log(Emp_{ist}) + \beta_2 Age_{ist} + \beta_3 X_{ist} + \beta_4 T_{ist} + \gamma_t + \gamma_s + \gamma_d + \epsilon_{ist} \tag{7}$$

We consider both energy efficiency, e_{ist}, and productivity, θ_{ist}, as dependent variables. Subscripts represent firm i, operating in industry s, in year t. To provide some evidence on the behavior of our efficiency measures over the firm's life cycle, we include firm employment, $log(Emp_{ist})$, and age Age_{ist}, as independent variables. We also include electricity prices, T_{ist}. The vector X_{ist} is a set of firm characteristics possibly associated with energy efficiency and productivity levels. To test if firms more intensive in human capital are more efficient, on average, X_{ist} includes a measure of workers' skill level, the fraction of workers with at least a high school degree. We also include a measure of firm leverage, to explore if access

Figure 3: Resource and energy misallocation at the industry level



Notes: Measures of energy allocation, λ_s^e, and resource allocation, λ_s^θ, plotted for each of the 106 three-digit industries in our database. Data from PIA and RAIS.

to credit alter firm behavior. This measure is computed as the ratio of financial costs to value added. To consider the possibility that firm structure is related to performance, we also include as a control variable the fraction of family members working in the firm relative to total employment. This measure would capture, for example, differences in managerial practices adopted by family firms.

Additionally, we include year fixed effects, γ_t, to control for economic events that affect all firms simultaneously, and industry fixed effects, γ_s to control for differences in productivity and energy efficiency levels across activities. We also include electricity distributor fixed effects, γ_d, to control for differences in electricity price levels. The regressions are estimated pooling data from 2007 to 2013, the last year for which we have firm age information from RAIS. It is important to note that the goal of this exercise is to describe the relationship between energy efficiency, productivity and firm characteristics.

The results should not be interpreted as causality. The first two columns of Table 3 show that there is a positive relationship between firm employment and energy efficiency. This result could reflect the fact that larger firms invest more in energy efficiency due to capital availability or access to credit, or because this investments are profitable for firms operating at a larger scale. Age, on the other hand, is negatively related to energy efficiency. One possible explanation for this result is that firms adopt new technology available at the time they are born. However, as firms age, they do not update their production process as new technologies are made available.

We also find that human capital is positively associated with energy efficiency, as measured by our skill proxy. Firm leverage is negatively associated with energy efficiency, while a high share of family employees is usually associated with higher levels of efficiency. In column two, we find a negative relationship between electricity prices and energy efficiency, which is not consistent with empirical findings (Barrows & Ollivier 2018). One

Table 3: Energy efficiency

	(1)	(2)	(3)	(4)
	e_{ist}	e_{ist}	e_{ist}	e_{ist}
log(Employment$_{ist}$)	0.0859***	0.0851***	0.154***	0.152***
	(0.00387)	(0.0038)	(0.0098)	(0.0098)
Age$_{ist}$	-0.0087***	-0.0087***	0.0584***	0.0336***
	(0.0003)	(0.0003)	(0.0014)	(0.0025)
Skill$_{ist}$	2.243***	2.240***	0.334***	0.323***
	(0.0529)	(0.0529)	(0.100)	(0.100)
Leverage$_{ist}$	-0.179***	-0.179***	-0.226***	-0.226***
	(0.0020)	(0.0020)	(0.0032)	(0.0032)
Frac(Family$_{ist}$)	0.328***	0.319***	0.236**	0.230**
	(0.0956)	(0.0961)	(0.101)	(0.102)
Tariff$_{ist}$		-0.0009***		-0.0010***
		(0.0001)		(0.00008)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Distributor fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
Observations	162,421	161,531	162,421	161,531
R-squared	0.314	0.314	0.828	0.828

Notes: This table presents firm-level regressions of energy efficiency on firm characteristics and the price of electricity. Firm characteristics include employment, age, workers' skill level, firm leverage and the ratio of family members to total employment. Data from PIA. Regressions cover data from 2007 to 2013. Robust standard errors in parenthesis. Significance levels: * 10%, ** 5%, *** 1%.

possible reason for this counterintuitive result is that our measure of energy efficiency is computed with electricity expenditure, while ideally we would like to measure consumption. If prices increase, then electricity expenditures will naturally rise.

In the last two columns of Table 3, we include firm fixed effects. These results use intra-firm variation over time to identify the effects of firm characteristics on energy efficiency. The relationship between energy efficiency and firm employment intensifies, meaning that firms improve their efficiency in the usage of electricity as they grow. In this specification, the effect of age on energy efficiency turns from negative to positive, which suggests firms invest in energy efficient technologies over their life cycle. The relationship between energy efficiency and the other variables considered are not altered with the inclusion of firm fixed effects.

Table 4 presents similar estimates to illustrate firm characteristics associated with high productivity. The first two columns include year, distributor and industry fixed effects. We find that both employment and age are positively associated with productivity, consistent with theoretical and empirical evidence (Hopenhayn 1992, Dunne et al. 1988). This result is consistent with theoretical predictions that firms' optimal employment is increasing in productivity. Human capital and the fraction of family members are positively related to productivity, while leverage is negatively related, similar to our findings for energy efficiency. We find no effect of electricity prices on productivity. Columns three and four additionally

Table 4: Productivity

	(1)	(2)	(3)	(4)
	θ_{ist}	θ_{ist}	θ_{ist}	θ_{ist}
log(Employment$_{\text{ist}}$)	0.107***	0.107***	-0.421***	-0.422***
	(0.0031)	(0.0032)	(0.0086)	(0.0086)
Age$_{\text{ist}}$	0.0091***	0.0091***	0.0488***	0.0470***
	(0.0002)	(0.0002)	(0.0010)	(0.0018)
Skill$_{\text{ist}}$	3.563***	3.561***	0.164**	0.163**
	(0.0423)	(0.0423)	(0.0768)	(0.0769)
Leverage$_{\text{ist}}$	-0.0856***	-0.0856***	-0.201***	-0.202***
	(0.0016)	(0.0016)	(0.0028)	(0.0028)
Frac(Family$_{\text{ist}}$)	2.376***	2.370***	0.968***	0.967***
	(0.0891)	(0.0895)	(0.0898)	(0.0901)
Tariff$_{\text{ist}}$		-0.00001		-0.00005
		(0.00008)		(0.00006)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Distributor fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
Observations	162,421	161,531	162,421	161,531
R-squared	0.341	0.340	0.821	0.821

Notes: This table presents firm-level regressions of productivity on firm characteristics and the price of electricity. Firm characteristics include employment, age, workers' skill level, firm leverage and the ratio of family members to total employment. Data from PIA. Regressions cover data from 2007 to 2013. Robust standard errors in parenthesis. Significance levels: * 10%, ** 5%, *** 1%.

include firm fixed effects to control for unobserved firm-specific characteristics that are constant over time. We find that the inclusion of firm fixed effects results in a negative relationship between productivity and employment. This, however, could be a reflection of our productivity measure, which declines linearly with employment.

In this section, we have shown that there is a positive relationship between the misallocation of energy and overall resource misallocation. Moreover, allocation efficiency in Brazil has not improved over the last decade, preventing aggregate productivity growth. This result suggests the presence of distortions which prevent the growth of the most productive firms. In the next section, we identify the prevalence of distortions affecting resource allocation and quantify the potential gains from reallocating resources across firms.

4 Theoretical framework

In this section, we introduce electricity into the model developed by Hsieh & Klenow (2009) to allow distortions affecting electricity allocation across firms. The model allows us to infer firm-specific distortions leading to non-optimal input choices. Based on these distortions, we can quantify potential aggregate productivity gains from reallocating resources across firms. Finally, the model also provides us with an intuitive productivity measure taking into consideration firms' electricity use.

The framework is a standard version of a monopolistic competition model with heterogeneous firms deriving from Melitz (2003). There is a single final good Y produced under perfect competition by combining inputs Y_s from S intermediate manufacturing industries.

$$Y = \prod_{s=1}^{S} Y_s^{\rho_s} \tag{8}$$

where ρ_s is the industry share of industry s and $\sum_{s=1}^{S} \rho_s = 1$. The first order condition from profit maximization implies that:

$$P_s Y_s = \rho_s P Y \tag{9}$$

Where P_s is the price of intermediate good Y_s, and P is the price of the final good Y, where $P \equiv \prod_{s=1}^{S} \left(\frac{P_s}{\rho_s}\right)^{\rho_s}$ is normalized to one.

In each industry s, there are M_s firms producing differentiated goods Y_{is} in a monopolistically competitive environment. The constant elasticity of substitution aggregation of these M_s goods results in the intermediate good Y_s.

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{is}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{10}$$

where σ is the elasticity of substitution between differentiated goods.

Each differentiated good Y_{is} in industry s is produced by a firm i according to a constant returns to scale Cobb-Douglas technology production function. Firms use capital, labor and electricity as inputs. Input shares α_s, β_s and $1 - \alpha_s - \beta_s$ are constant across firms within industry s, but are allowed to vary across industries. Firms are heterogeneous in their physical productivity θ_{is}, and thus production functions are given by:

$$Y_{is} = \theta_{is} K_{is}^{\alpha_s} L_{is}^{\beta_s} E_{is}^{1-\alpha_s-\beta_s} \tag{11}$$

There are firm-specific distortions which alter inputs' marginal costs, reflecting forces such as market failures or governmental policies that distort firms' optimal input choices. Output distortions τ_{Yis} affect the marginal product of all three inputs simultaneously, while distortions τ_{Kis} and τ_{Eis} affect the marginal revenue of capital and electricity relative to that of labor.

Hsieh & Klenow (2009) thinks of output distortions as reflecting government size restrictions, output subsidies or transportation costs, while capital distortions are likely the result of credit constraints or subsidized access to credit. In the context of electricity, distortions can be interpreted as the failure of prices to account for negative externalities resulting from energy use, or credit constraints that prevent firms from adopting energy efficient technologies. They could also reflect imperfect information which requires managers to incur in costs, either financial or opportunity costs, to learn about available energy efficiency investments.

Wages w, the rental price of capital R and electricity prices T are constant across firms and industries, so that profits are given by:

$$\pi_{is} = (1 - \tau_{Yis})\, P_{is} Y_{is} - w L_{is} - (1 + \tau_{Kis})\, R K_{is} - (1 + \tau_{Eis})\, T E_{is} \tag{12}$$

The profit maximization problem defines that the price chosen by each firm is a fixed markup over its marginal cost:

$$P_{is} = \left(\frac{\sigma}{\sigma - 1}\right) \left(\frac{R}{\alpha_s}\right)^{\alpha_s} \left(\frac{w}{\beta_s}\right)^{\beta_s} \left(\frac{T}{1 - \alpha_s - \beta_s}\right)^{1 - \alpha_s - \beta_s} \frac{1}{\theta_{is}} \frac{(1+\tau_{Kis})^{\alpha_s} (1+\tau_{Eis})^{1-\alpha_s-\beta_b}}{(1-\tau_{Yis})} \tag{13}$$

Distortions alter optimal input choices because marginal revenue is equated to the after-tax marginal cost of inputs. From firms' profit maximization problem, we can obtain expressions for the marginal revenue of labor (MRPL), capital (MRPK) and electricity (MRPE):

$$MRPL_{is} = w \frac{1}{(1 - \tau_{Yis})} \tag{14}$$

$$MRPK_{is} = R \frac{(1 + \tau_{Kis})}{(1 - \tau_{Yis})} \tag{15}$$

$$MRPE_{is} = T \frac{(1 + \tau_{Eis})}{(1 - \tau_{Yis})} \tag{16}$$

From first order conditions of the profit maximization problem, we can infer firm-specific distortions in a given year from relative input use and parameter values:

$$1 + \tau_{Kis} = \frac{\alpha_s}{\beta_s} \frac{w L_{is}}{R K_{is}} \tag{17}$$

$$1 + \tau_{Eis} = \frac{1 - \alpha_s - \beta s}{\beta_s} \frac{w L_{is}}{T E_{is}} \tag{18}$$

$$1 - \tau_{Yis} = \frac{\sigma}{\sigma - 1} \frac{w L_{is}}{\beta_s P_{is} Y_{is}} \tag{19}$$

The presence of distortions can also be inferred from the observed dispersion in revenue productivity (TFPR) across firms, which is defined as physical productivity (TFPQ) multiplied by the output price of firm i[9].

$$TFPQ_{is} = \theta_{is} = \frac{Y_{is}}{K_{is}^{\alpha_s} L_{is}^{\beta_s} E_{is}^{1-\alpha_s-\beta_s}} \tag{20}$$

$$TFPR_{is} = P_{is}\theta_{is} = \frac{P_{is} Y_{is}}{K_{is}^{\alpha_s} L_{is}^{\beta_s} E_{is}^{1-\alpha_s-\beta_s}} \tag{21}$$

[9]The definition of revenue productivity and its distinction from physical productivity is presented in Foster et al. (2008).

Revenue productivity can be written as a function of the marginal revenue product of inputs:

$$TFPR_{is} = \frac{1}{\sigma - 1} \left(\frac{MRPK_{is}}{\alpha_s} \right)^{\alpha_s} \left(\frac{MRPL_{is}}{\beta_s} \right)^{\beta_s} \left(\frac{MRPE_{is}}{1 - \alpha_s - \beta_s} \right)^{1-\alpha_s-\beta_s} \tag{22}$$

Substituting the expressions for each marginal revenue product, we finally obtain the expression for TFPR which we take to the data:

$$TFPR_{is} = \frac{\sigma}{\sigma-1} \left(\frac{R}{\alpha_s} \right)^{\alpha_s} \left(\frac{w}{\beta_s} \right)^{\beta_s} \left(\frac{T}{1-\alpha_s-\beta_s} \right)^{1-\alpha_s-\beta_s} \frac{(1+\tau_{Kis})^{\alpha_s}(1+\tau_{Eis})^{1-\alpha_s-\beta_b}}{(1-\tau_{Yis})} \tag{23}$$

From equation 23, we see that if firm-specific distortions are zero, revenue productivity is constant and depends only on parameter values. Hence, TFPR dispersion across firms results exclusively from distortions τ_{Yis}, τ_{Kis} and τ_{Eis}. If resources were allocated based on firms' physical productivity, then the output of the most productive firms would increase, and their prices would decrease such that TFPR would be constant in equilibrium.

From the expression above, we can define industry TFP as a function of firms' TFP, weighted by their TFPR relative to the industry average.

$$TFP_s = \left[\sum_{i=1}^{Ms} \left(\theta_{is} \frac{\overline{TFPR}_s}{TFPR_{is}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{24}$$

Where the average revenue productivity, TFPR, in industry s is given by:

$$\overline{TFPR}_s = \frac{\sigma}{\sigma-1} \left(\frac{R}{\alpha_s \sum_{i=1}^{M_s} \frac{1-\tau_{Yis}}{1+\tau_{Kis}} \frac{P_{is}Y_{is}}{P_sY_s}} \right)^{\alpha_s} \left(\frac{w}{\beta_s \sum_{i=1}^{M_s} (1-\tau_{Yis}) \frac{P_{is}Y_{is}}{P_sY_s}} \right)^{\beta_s} \left(\frac{T}{1-\alpha_s-\beta \sum_{i=1}^{M_s} \frac{1-\tau_{Yis}}{1+\tau_{Eis}} \frac{P_{is}Y_{is}}{P_sY_s}} \right)^{1-\alpha_s-\beta_s} \tag{25}$$

We can now derive an expression that allows us to compute physical productivity from the data. We can infer firm output from revenue at a given elasticity of demand, since this elasticity σ implies a direct relationship between firms' revenues, quantities and prices.

$$\theta_{is} = \kappa_s \frac{(P_{is}Y_{is})^{\frac{\sigma}{\sigma-1}}}{K_{is}^{\alpha_s} L_{is}^{\beta_s} E_{is}^{1-\alpha_s-\beta_s}}, \text{ where } \kappa_s = w^{1-\alpha_s} \frac{(P_sY_s)^{-\frac{1}{\sigma-1}}}{P_s} \tag{26}$$

The scalar κ depends on the value of P_s, which is not observable in the data. Nevertheless, κ_s is constant across firms in industry s, and so does not affect relative productivities and potential reallocation gains. We will therefore set $\kappa = 1$.

In the absence of firm-specific distortions, marginal revenue products are equalized across firms and industry TFP is given by:

$$\overline{\theta}_s = \left(\sum_{i=1}^{Ms} \theta_{is}^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{27}$$

Finally we can define the relationship between actual and efficient levels of aggregate output. First we calculate the ratio of actual to efficient TFP for each industry, then aggregate this measure by considering industries' output shares.

$$\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S} \left[\sum_{i=1}^{Ms} \left(\frac{\theta_{is}}{\overline{\theta}_s} \frac{\overline{TFPR}_s}{TFPR_{is}} \right)^{\sigma-1} \right]^{\frac{\rho_s}{\sigma-1}} \tag{28}$$

This expression quantifies aggregate losses due to the inefficient use of resources between firms. It allows us to compute the potential aggregate output gains if resources were efficiently allocated within all industries.

5 Potential gains

So far, we have shown that there is considerable variation in the degree of energy misallocation at the industry level. We also provide evidence that energy misallocation is positively related to overall resource misallocation. In this section, our aim is to quantify resource misallocation in Brazil. We use the model developed by Hsieh & Klenow (2009) to quantify potential aggregate productivity gains taking into consideration the existence of distortions affecting firms' electricity use.

Empirical evidence reveals that the allocation of resources across firms is not only determined by their productivity levels, but also by other external factors affecting firm input choices, for example, labor market regulations, financial constraints, fiscal benefits or subsidized credit. Given industries' productivity distribution, the misallocation of resources across firms reduces potential industry and aggregate output (Restuccia & Rogerson 2008, Buera et al. 2011, Bartelsman et al. 2013, Hsieh & Klenow 2009). The theoretical framework presented in Section 4 provides a way of identifying distortions affecting firms' input choices and, consequently, enables us to compute how much aggregate productivity would increase in a hypothetical situation where all distortions are eliminated. Lastly, we provide additional evidence on the determinants of misallocation by computing potential aggregate gains in counterfactual scenarios, to identify the relative importance of distortions.

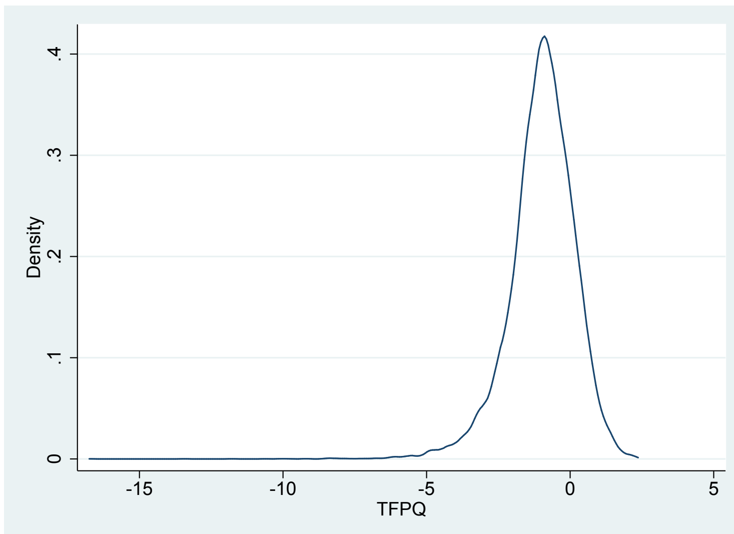
We take the model to the data by measuring labor inputs as labor compensation, to account for heterogeneity in human capital. We later show how results are robust to defining labor as firm employment. We set industry capital shares, α_s, and labor shares, β_s, to those observed in the data for each industry. Industry shares are calculated based on aggregate value added.

Following Hsieh & Klenow (2009), we set the rental price of capital to $R = 0.1$, considering a 0.05 interest rate and 0.05 depreciation rate. We also set the elasticity of substitution between differentiated goods as $\sigma = 3$, although we analyze the response of our results to a larger value of σ in our robustness checks in Section 6. We set electricity prices to 440 R$/kWh, the average electricity price in our sample of firms.

To avoid our results being driven by outlier firms, we compute TFPQ and TFPR for all firms in a given year, then drop the top and bottom 1% firms in the distribution of $log(TFPR_{is}/\overline{TFPR}_s)$ and $log(\theta_{is}/\overline{\theta}_s)$ across industries. Once we drop outlier firms, we compute once again industry measures L_s, K_s, E_s, P_sY_s, $\overline{TFPR}_s$ and $\overline{\theta}_s$, and industry shares ρ_s.

Figure 4 plots the distribution of physical productivity, $log(\theta_{is} M_s^{\frac{1}{\sigma-1}})$ for 2015, the latest year in our sample. There is considerable dispersion in physical productivity across firms. The heavy left tail of productivity distribution is consistent with theoretical and empirical evidence documenting that misallocation worsens selection and allows unproductive firms to artificially survive alongside productive ones.

Figure 4: Distribution of TFPQ



Notes: Distribution of physical productivity, $log(TFPQ_{is} M_s^{\frac{1}{\sigma-1}})$, where $TFPQ_{is} \equiv \frac{Y_{is}}{K_{is}^{\alpha} L_{is}^{\beta} E_{is}^{1-\alpha-\beta}}$.

Table 5 plots some concrete measures of dispersion for physical productivity, $log(TFPQ)$, in 2007, 2011 and 2015: the standard deviation, the difference between the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles and between the 90$^{\text{th}}$ and 10$^{\text{th}}$ percentiles. In 2015, the ratio of physical productivity between the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles in Brazil was 3.85, while the ratio between the 90$^{\text{th}}$ and 10$^{\text{th}}$ percentiles was equal to 15.48. To provide an idea for the magnitude of this dispersion, we can compare this result to the one in Hsieh & Klenow (2009). They report that, for the latest year in each sample, the ratio between the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles is equal to 5.0 in India, 3.6 in China and 3.2 in the United States[10].

Figure 5 plots the distribution of revenue productivity $TFPR$, $log(TFPR_{is}/\overline{TFPR}_s)$, for Brazilian manufacturing firms in 2015. Table 6 presents dispersion statistics for three years of the sample, 2007, 2011 and 2015. Our model implies that, in the absence of distortions, revenue productivity is constant across firms. Hence, the dispersion of $TFPR$ depicted in Figure 5 and Table 6 illustrates the degree of misallocation in the Brazilian economy. The dispersion of $TFPR$ is increasing from 2007 to 2011, implying a reallocation of resources towards unproductive firms. From 2011 to 2015, the dispersion of $TFPR$ remains roughly constant. Overall, there is a deterioration in resource allocation efficiency from 2007 to 2015, but the magnitude of this change is small. In 2007, the ratio of revenue

[10]When comparing our results to those of Hsieh & Klenow (2009) and other studies, we should take into consideration that the sampling frame and period are different for each country. Comparisons between countries should be made with caution.

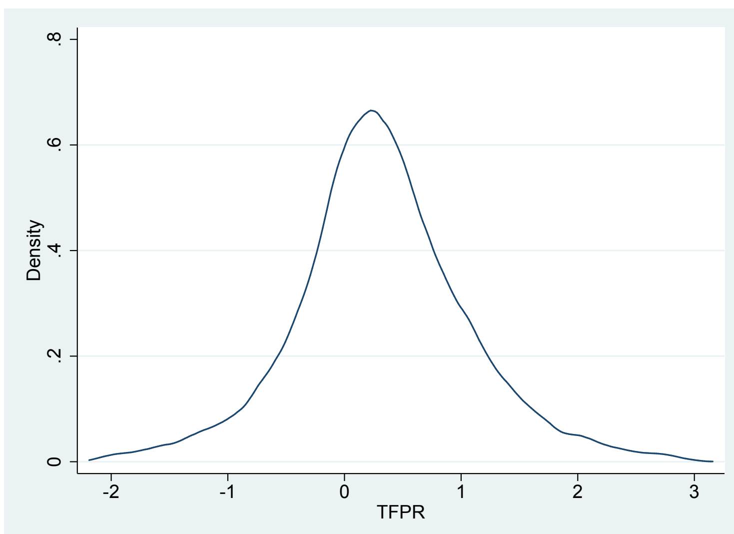
Table 5: Dispersion of TFPQ

	2007	2011	2015
S.D.	1.07	1.09	1.16
75 - 25	1.22	1.29	1.35
90 - 10	2.49	2.59	2.74
N	25,334	30,386	25,135

Notes: This table plots dispersion measures of physical productivity, log(TFPQ). For plant i in industry s, $\text{TFPQ}_{\text{is}} \equiv \frac{Y_{is}}{K_{is}^{\alpha} L_{is}^{\beta} E_{is}^{1-\alpha-\beta}}$. S.D. = standard deviation, 75-25 = difference between 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles, 90-10 = difference between 90$^{\text{th}}$ and 10$^{\text{th}}$ percentiles. N = number of observations. Data from PIA and RAIS.

productivity between the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles was equal to 2.36, and by 2015 it had decreased to 2.38. Hsieh & Klenow (2009) reports ratios of 2.2 in India, 2.3 in China and 1.7 in the United States, suggesting a higher degree of misallocation of resources in Brazil relative to the U.S.

Figure 5: Distribution of TFPR



Notes: Distribution of revenue productivity, $log(TFPR_{is}/\overline{TFPR}_s)$, where $TFPR_{is} \equiv \frac{P_{is}Y_{is}}{K_{is}^{\alpha} L_{is}^{\beta} E_{is}^{1-\alpha-\beta}}$.

We now calculate the potential gains in aggregate manufacturing productivity from equalizing the marginal product of inputs within each three-digit industry. Unlike Hsieh & Klenow (2009), we do not use the United States as a benchmark for the minimum dispersion in marginal products that can be achieved in practice. A full equalization of TFPR across firms might not be feasible due to the presence of measurement error in the data, adjustment costs or markup variation, for example, which are omitted from the model. Thus, our results should be interpreted as an upper bound for potential output gains in mining and manufacturing, given our sample of firms.

The ratio of actual aggregate output to efficient output is computed for each industry

Table 6: Dispersion of TFPR

	2007	2011	2015
S.D.	0.73	0.76	0.76
75 - 25	0.86	0.88	0.87
90 - 10	1.78	1.85	1.85
N	25,334	30,386	25,135

Notes: This table plots dispersion measures of revenue productivity, log(TFPR). For plant i in industry s, $\text{TFPR}_{\text{is}} \equiv \frac{P_{is}Y_{is}}{K_{is}^{\alpha}L_{is}^{\beta}E_{is}^{1-\alpha-\beta}}$. S.D. = standard deviation, 75-25 = difference between 75^{th} and 25^{th} percentiles, 90-10 = difference between 90^{th} and 10^{th} percentiles. N = number of observations. Data from PIA and RAIS.

according to:

$$\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S} \left[\sum_{i=1}^{Ms} \left(\frac{\theta_{is}}{\overline{\theta}_s} \frac{\overline{TFPR}_s}{TFPR_{is}} \right)^{\sigma-1} \right]^{\frac{\rho_s}{\sigma-1}} \tag{29}$$

From equation 29, we compute potential aggregate output gains as $(Y_{efficient}/Y) - 1$. Table 7 presents the potential aggregate output gains in Brazil for 2007 to 2015. Our estimates imply that reallocating resources to the point of fully equalizing TFPR within industries would lead to output gains ranging from 77.9% to 96.2%. These results are comparable to the 86% gains estimated for China by Hsieh & Klenow (2009), and 85% gains reported for South Korea by Kim et al. (2017). Busso et al. (2013) perform similar estimates for the Brazilian manufacturing sector, for years from 2000 to 2005. Their results imply aggregate productivity gains that are lower than ours, ranging from 41 to 49%.

The potential gains from eliminating misallocation reported in Table 7 fluctuate from 2007 to 2012, and are falling from 2012 onwards. Overall, there was an increase in potential gains during the whole period, from 81.7% in 2007 to 83.2% in 2015. This result is consistent with increasing TFPR dispersion over the sample period, indicating a rise in the misallocation of resources.

The results derived from the model are consistent with our findings in Section 3, that resource allocation efficiency has deteriorated from 2007 to 2015. Nevertheless, this relationship is not very clear from the estimated potential gains from reallocation, and there are some years for which gains increase significantly. One possibility for these inconsistent results is that the potential gains computed from the model are being affected by changes in the composition of firms, or by changes in the level of available technology.

As described in Section 2, our data does not include firms with less than 30 workers. We expect our estimated potential gains to underestimate the true potential gains from resource reallocation, since there is a negative relationship between size and overproduction (Kim et al. 2017). This evidence supports the fact that distortions and misallocation allow the survival of small, unproductive firms.

From equation 29, we are able to compute not only aggregate output gains, but also gains for each manufacturing industry separately. It is important to note that, due to confidentiality reasons, we cannot provide any statistics that were computed with less than 4 observations. So although all industries were considered for the computation of aggregate gains reported above, we cannot report individual gains for 3 specific industries[11]. Taking

[11] These industries are: Mining of coal and lignite; Reproduction of recorded media; Manufacture of

Table 7: Potential TFP gains (%)

Year	TFP Gains (%)
2007	81.72
2008	77.96
2009	96.26
2010	85.19
2011	92.58
2012	93.78
2013	90.30
2014	88.52
2015	83.26

Notes: Potential productivity gains from equalizing TFPR within industries, computed as $100(\frac{Y_{efficient}}{Y} - 1)$, where $\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S}[\sum_{i=1}^{Ms}\left(\frac{\theta_{is}}{\overline{\theta}_s}\frac{\overline{TFPR_s}}{TFPR_{is}}\right)^{\sigma-1}]^{\frac{\rho_s}{\sigma-1}}$ and $\mathrm{TFPR_{is}} \equiv \frac{P_{is}Y_{is}}{K_{is}^{\alpha}L_{is}^{\beta}E_{is}^{1-\alpha-\beta}}$.

this restriction into consideration, Table 8 presents the top 10 industries with the highest and the lowest potential gains from fully equalizing marginal products across firms in 2015.

The activity with highest potential gains from resource reallocation is manufacturing of refined petroleum products, where efficient allocation would lead to an increase in output of 290.4%. We can infer that in industries with the highest potential gains, distortions are more relevant in affecting firms' sizes, resulting in misallocation and the coexistence of productive and unproductive firms. The most efficient industry in our sample is the manufacture of musical instruments, where reallocating resources across firms would increase output in 15.7%. In this industry, firms' input use closely reflects their physical productivity levels. One interesting fact from Table 8 is that the dispersion in potential gains from industries with highest misallocation (highest potential gains) is much higher than the dispersion observed for the most efficient industries.

Finally, we focus on understanding the role of distortions in generating resource misallocation. Table 9 provides estimates of aggregate potential gains from eliminating a subset of, but not all, distortions simultaneously. We consider only the last year in our sample, 2015. The first line of Table 9 tells us that by eliminating distortions affecting the allocation of capital relative to labor, τ_{Kis}, aggregate productivity would increase by 30.3%. However, eliminating electricity distortions, τ_{Eis}, would lead to a productivity level only 2.4% higher.

If we compute hypothetical gains from eliminating misallocation generated by output distortions, τ_{Yis}, in addition to capital or electricity distortions, productivity gains would be 83.5% and 5.9%, respectively. Lastly, simultaneously eliminating capital and electricity distortions would result in productivity gains of 33.0%. This experiment reveals that although all distortions, τ_{Yis}, τ_{Kis} and τ_{Eis}, play a part in generating overall misallocation, distortions that affect the cost of capital relative to labor, along with output distortions, account for most of the resource misallocation observed in Brazil.

weapons and ammunition.

Table 8: Highest and lowest gains from equalizing TFPR (%)

CNAE	Industry description	TFP gains
Panel A: Industries with highest potential gains		
CNAE	Industry description	TFP gains
192	Manufacture of refined petroleum products	290.44
182	Service activities related to printing	171.10
221	Manufacture of rubber products	154,82
161	Sawmilling and planing of wood	146.31
241	Manufacture of pig iron and iron alloys	139.78
202	Manufacture of inorganic chemicals	139.16
285	Manufacture of machinery for mining, quarrying and construction	139.07
105	Manufacture of dairy products	138.85
232	Manufacture of cement	138.84
309	Manufacture of other transport equipment n.e.c.	137.66
Panel B: Industries with lowest potential gains		
CNAE	Industry description	TFP gains
272	Manufacture of batteries and accumulators	25.30
291	Manufacture of cars	25.10
303	Manufacture of railway locomotives and rolling stock	25.07
072	Mining of non-ferrous metal ores	24.56
263	Manufacture of communication equipment	24.55
122	Manufacture of tobacco products	23.77
171	Manufacture of pulp	21.92
121	Processing of tobacco	19.99
295	Engine restoration and rebuilding for motor vehicles	17.65
322	Manufacture of musical instruments	15.81

Notes: This table presents the top 10 industries with highest potential gains from reallocating resources resulting in constant TFPR within industries (Panel A), and the top 10 industries with the lowest potential gains (Panel B). Gains are computed as $100(\frac{Y_{efficient}}{Y} - 1)$, where $\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S}[\sum_{i=1}^{Ms}\left(\frac{\theta_{is}}{\overline{\theta}_s}\frac{\overline{TFPR}_s}{TFPR_{is}}\right)^{\sigma-1}]^{\frac{\rho_s}{\sigma-1}}$ and $\mathrm{TFPR_{is}} \equiv \frac{P_{is}Y_{is}}{K_{is}^{\alpha}L_{is}^{\beta}E_{is}^{1-\alpha-\beta}}$.

Table 9: TFP gains from equalizing TFPR within industries (%)

Distortions	Gains in 2015 (%)
τ_K	30.30
τ_E	2.47
τ_K, τ_E	33.08
τ_Y, τ_K	83.54
τ_Y, τ_E	5.96

Notes: Potential productivity gains assuming the presence of different combinations of distortions, depicted in the first column. Gains are computed as $100(\frac{Y_{efficient}}{Y} - 1)$, where $\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S}[\sum_{i=1}^{Ms}\left(\frac{\theta_{is}}{\overline{\theta}_s}\frac{\overline{TFPR}_s}{TFPR_{is}}\right)^{\sigma-1}]^{\frac{\rho_s}{\sigma-1}}$ and $\mathrm{TFPR_{is}} \equiv \frac{P_{is}Y_{is}}{K_{is}^{\alpha}L_{is}^{\beta}E_{is}^{1-\alpha-\beta}}$.

6 Robustness checks

In this section, we provide robustness checks to understand how our results are affected by slight modifications in our assumptions and parameter values.

First, we test how the relationship between energy and resource misallocation from Figure 3 is altered when we use different productivity measures to compute the degree of resource misallocation.

In Figure 6, we plot this relationship using a TFP productivity measure considering labor, capital and electricity as inputs. We also compute the physical productivity, TFPQ, defined in Section 4, and plot the results in Figure 7. As we can see, the positive relationship between resource and energy misallocation measures across industries is not affected by these alternative productivity measures. Figure 8 shows that the positive relationship between energy and resource allocation efficiency is not altered by our decision to calculate these measures for 2015, instead of pooling observations from all year.

Next, we analyze how our baseline results from quantifying potential reallocation gains in Table 7 are robust to measuring firm size as the number of employees, instead of labor compensation. In our baseline estimation, we measure labor inputs as labor compensation to control for differences in skills and hours worked across firms. However, Hsieh & Klenow (2009) argue that it is possible that wages are determined by other factors, such as rent sharing between firms and workers. The first line in Table 10 shows that, when measuring labor as the number of employees, potential reallocation gains in 2015 are equal to 92.78%, compared to 83.26% from our baseline estimates. Hsieh & Klenow (2009) find that measuring labor inputs with employment decreases potential gains, and they interpret these findings as evidence that wages amplify TFPR differences. For Brazil, wages reduce TFPR differences.

As a final robustness check, we examine how a larger elasticity of substitution between differentiated products, σ, affect our results. By setting σ to 5, potential gains from resource reallocation increase from 83.26% in our baseline estimates to 172.31%, as presented in the second line of Table 10. This illustrates how our baseline results should be interpreted as a lower bound to potential gains.

Table 10: TFP gains from equalizing TFPR within industries (%)

Distortions	2007	2011	2015
L_{is}	86.69	98.23	92.78
$\sigma = 5$	157.12	171.99	172.31

Notes: Robustness checks for potential productivity gains from equalizing TFPR within industries. L_{is}: firm labor is measured as number of workers. $\sigma = 5$: elasticity of substitution between differentiated goods is set as 5. Gains are computed as $100(\frac{Y_{efficient}}{Y} - 1)$, where $\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S} [\sum_{i=1}^{Ms} \left(\frac{\theta_{is}}{\overline{\theta}_s} \frac{\overline{TFPR}_s}{TFPR_{is}} \right)^{\sigma-1}]^{\frac{\rho_s}{\sigma-1}}$ and $\mathrm{TFPR_{is}} \equiv \frac{P_{is} Y_{is}}{K_{is}^{\alpha} L_{is}^{\beta} E_{is}^{1-\alpha-\beta}}$.

7 Conclusions

We use detailed firm-level data with information on electricity expenditures for Brazil, and we find that the degree of resource and energy misallocation are positively related, both at the industry and aggregate levels. This result has important policy implications, since it indicates that there is no trade-off between productive efficiency and environmental gains. Policies promoting the growth of the most productive firms in every industry will lead not only to better resource allocation and higher aggregate productivity, but also improve aggregate energy efficiency and reduce negative externalities associated with energy generation and consumption.

We also find that, since 2007, resources were reallocated towards unproductive firms, increasing resource and energy misallocation. Our results suggest that this was the main factor limiting aggregate productivity and energy efficiency growth in Brazil during this period. Our finding suggest that it is more effective to focus on industrial initiatives than on firm-level ones to improve aggregate energy efficiency in Brazilian industry. Efficiency in energy allocation provides a potential source of improvement in aggregate energy efficiency without the need for technological innovation.

In order to quantify aggregate gains from resource reallocation we apply the model in Hsieh & Klenow (2009) taking into consideration distortions that affect firms' energy use. Although our estimates reveal substantial gains from resource reallocation, capital distortions are relatively more important than energy distortions in generating resource misallocation and productivity losses.

This implies that it is crucial that policymakers design broader industrial policies to tackle distortions that are more binding than energy efficiency distortions. This would make room for programs that target industrial energy efficiency. Still, the existence of energy misallocation implies that potential gains from improving the allocation of overall resources in the economy would not only increase aggregate productivity but also raise well-being by reducing emissions and energy use.

One limitation from our work is that we consider only one energy source: electricity. Other energy sources could be particularly important for some industries, resulting in imprecision of our energy efficiency estimates. In the near future, it will be very important to evaluate how our results regarding allocation of energy and resources change when we use electricity priced to recover electricity consumption. Our next steps also include evaluating how electricity distortions identified by our theoretical framework are related to energy efficiency levels. This analysis would illustrate the role of resource reallocation in improving aggregate energy efficiency.

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A Appendix

Table 11: Three-digit CNAE industries

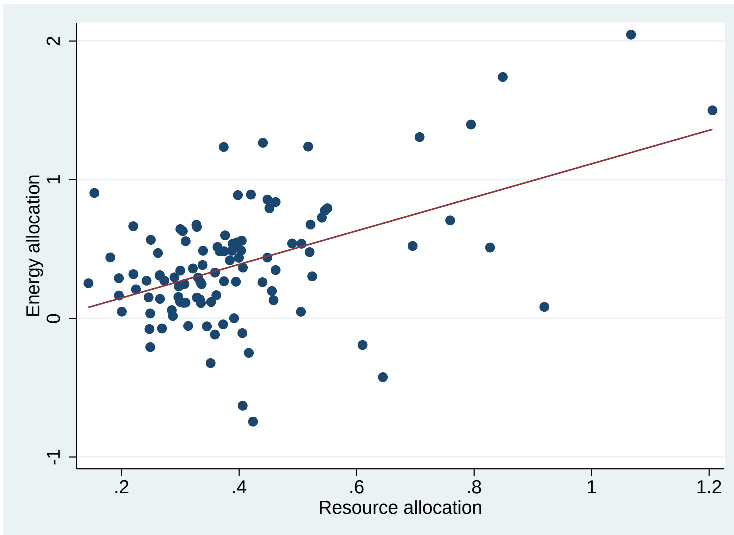
CNAE	Activity description
05.0	Mining of coal and lignite
06.0	Extraction of crude petroleum and natural gas
07.1	Mining of iron ores
07.2	Mining of non-ferrous metal ores
08.1	Quarrying of stone, sand and clay
08.9	Mining and quarrying n.e.c.
09.1	Support activities for petroleum and natural gas extraction
09.9	Support activities for other mining and quarrying
10.1	Processing and preserving of meat
10.2	Processing and preserving of fish, crustaceans and molluscs
10.3	Processing and preserving of fruit and vegetables
10.4	Manufacture of vegetable and animal oils and fats
10.5	Manufacture of dairy products
10.6	Manufacture of grain mill products, starches and starch products
10.7	Manufacture of sugar
10.8	Manufacture of coffee products
10.9	Manufacture of other food products
11.1	Manufacture of alcoholic beverages
11.2	Manufacture of non-alcoholic beverages
12.1	Processing of tobacco
12.2	Manufacture of tobacco products
13.1	Spinning, weaving of textiles
13.2	Manufacture of other textiles, except crocheted and knitted
13.3	Manufacture of knitted and crocheted textiles
13.4	Finishing of textiles
13.5	Manufacture of made-up textile articles, except apparel
14.1	Manufacture of wearing apparel
14.2	Manufacture of knitted and crocheted apparel
15.1	Tanning and dressing of leather
15.2	Manufacture of leather luggage, handbags, saddlery and harness
15.3	Manufacture of footwear
15.4	Manufacture of footwear parts
16.1	Sawmilling and planing of wood
16.2	Manufacture of products of wood, cork, straw and plaiting materials
17.1	Manufacture of pulp
17.2	Manufacture of paper and paperboard
17.3	Manufacture of containers of paper and paperboard
17.4	Manufacture of other articles of paper and paperboard
18.1	Printing
18.2	Service activities related to printing
18.3	Reproduction of recorded media
19.1	Manufacture of coke oven products
19.2	Manufacture of refined petroleum products
19.3	Manufacture of biofuels
20.1	Manufacture of organic chemicals
20.2	Manufacture of inorganic chemicals
20.3	Manufacture of plastics and synthetic rubber in primary forms
20.4	Manufacture of man-made fibres
20.5	Manufacture of pesticides and other agrochemical products
20.6	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
20.7	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
20.9	Manufacture of other chemical products
21.1	Manufacture of medicinal chemical products
21.2	Manufacture of pharmaceuticals
22.1	Manufacture of rubber products
22.2	Manufacture of plastics products
23.1	Manufacture of glass and glass products
23.2	Manufacture of cement
23.3	Manufacture of articles of concrete, cement and plaster
23.4	Manufacture of ceramic products

Continued on next page

Table 11 – *Continued from previous page*

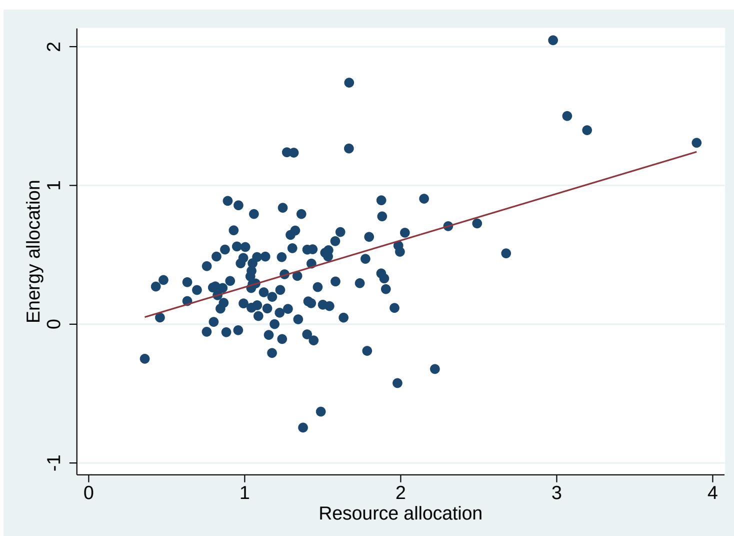
CNAE	Activity description
23.9	Manufacture of other non-metallic mineral products n.e.c
24.1	Manufacture of pig iron and iron alloys
24.2	Manufacture of steel
24.3	Manufacture of steel tubes
24.4	Manufacture of basic precious and other non-ferrous metals
24.5	Casting of metals
25.1	Manufacture of structural metal products
25.2	Manufacture of tanks, reservoirs and containers of metal
25.3	Forging, pressing, stamping and roll-forming of metal; powder metallurgy
25.4	Manufacture of cutlery, hand tools and general hardware
25.5	Manufacture of weapons and ammunition
25.9	Manufacture of other fabricated metal products n.e.c.
26.1	Manufacture of electronic components and boards
26.2	Manufacture of computers and peripheral equipment
26.3	Manufacture of communication equipment
26.4	Manufacture of equipment for reproducing, recording and amplifying audio and video
26.5	Manufacture of measuring, testing, navigating and control equipment; watches and clocks
26.6	Manufacture of irradiation, electromedical and electrotherapeutic equipment
26.7	Manufacture of optical instruments and photographic equipment
26.8	Manufacture of magnetic and optical media
27.1	Manufacture of electric motors, generators, transformers and
27.2	Manufacture of batteries and accumulators
27.3	Manufacture of electricity distribution and control apparatus
27.4	Manufacture of electric lighting equipment
27.5	Manufacture of domestic appliances
27.9	Manufacture of other electrical equipment
28.1	Manufacture of engines, pumps, compressors, gears, taps and valves
28.2	Manufacture of general-purpose machinery
28.3	Manufacture of agricultural and forestry machinery
28.4	Manufacture of machine tools
28.5	Manufacture of machinery for mining, quarrying and construction
28.6	Manufacture of special-purpose machinery
29.1	Manufacture of cars
29.2	Manufacture of trucks and buses
29.3	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
29.4	Manufacture of parts and accessories for motor vehicles
29.5	Engine restauration and rebuilding for motor vehicles
30.1	Building of ships and boats
30.3	Manufacture of railway locomotives and rolling stock
30.4	Manufacture of aircrafts
30.5	Manufacture of military fighting vehicles
30.9	Manufacture of other transport equipment n.e.c.
31.0	Manufacture of furniture
32.1	Manufacture of jewellery, bijouterie and related articles
32.2	Manufacture of musical instruments
32.3	Manufacture of sports goods
32.4	Manufacture of games and toys
32.5	Manufacture of medical and dental instruments and supplies
32.9	Other manufacturing n.e.c.
33.1	Repair of fabricated metal products, machinery and equipment
33.2	Installation of industrial machinery and equipment

Figure 6: Resource and energy misallocation (TFP)



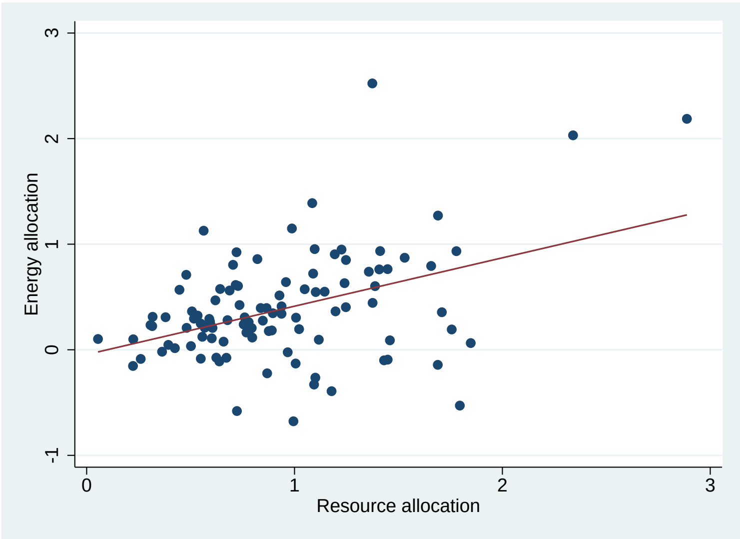
Notes: Measures of energy allocation, λ_s^e, and resource allocation, λ_s^θ, plotted for each of the 106 three-digit industries in our database. Productivity of firm i in sector s, θ_{si}, is total factor productivity estimates assuming a production function with capital, labor and electricity inputs. Data from PIA and RAIS.

Figure 7: Resource and energy misallocation (TFPQ)



Notes: Measures of energy allocation, λ_s^e, and resource allocation, λ_s^θ, plotted for each of the 106 three-digit industries in our database. Productivity of firm i in sector s, θ_{si}, is computed as value added per worker. Data from PIA and RAIS.

Figure 8: Resource and energy misallocation (2015)



Notes: Measures of energy allocation, λ_s^e, and resource allocation, λ_s^θ, plotted for each of the 106 three-digit industries in our database. Data from PIA and RAIS.