Misallocation and Access to Subsidized Credit: How Sensible are the Wedges to a Credit Shock?*

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Abstract

This paper uses a reclassification of firms done by the Brazilian Development Bank in 2003 as a natural experiment to causally identify the impact of a shift in credit conditions on capital, labor and scale wedges measuring the misallocation of resources. We find that firms reclassified as small, coming from medium, suffered a shift of - 0.261 in their average log capital wedge 6 years after treatment. Firms reclassified as medium, coming from large, had its largest impact at - 0.123 log average capital wedge 2 years after treatment, but the gap was closed again 6 years after treatment. That change in the average distribution of log capital wedges, particularly when one starts to face the favored credit conditions from the small cohort, suggests that the BNDES size classification can potentially have noticeable impacts in resource allocation through this mechanism, particularly capital allocations, either positively or negatively, depending on the credit constraints of firms. We then use the difference-in-differences result with the assumption that the log capital wedge around zero is a good approximation of the efficient allocation of funds. We find that new small firms moved symmetrically from the under-invested position to the over-invested one, with potentially no impact on allocational efficiency. New medium firms went from around efficiency into over-investment territory. We also calculate that if not for favored BNDES credit policy, small firms would be far from the efficiency line. Results on the misallocation exercise are heavily dependent on stringent assumptions, and should be taken with caution.

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1 Introduction

The misallocation of resources is one of the possible explanations for the income disparity between high and low income countries. Although the notion of resource misallocation has existed since Alfred Marshall, Jules Dupuit and Arnold Harberger (Baqaee and Farhi, 2020), whose work in the field was done in the XIXth and early XXth centuries, only recently, since the works of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), the literature has been revisited with the help of modern mathematical modelling, access to microdata and cheap computational power.

Restuccia and Rogerson (2017) have suggested that there are two avenues of investigation on the matters of misallocation: the indirect approach and the direct approach. The indirect approach is the one related to Hsieh and Klenow (2009)'s seminal paper, where a model allows for the inference of input distortions, or wedges, preventing the optimal allocation of resources. By accounting for the dispersion in wedges, one can perform cross-country comparisons using a benchmark country as allocational reference. This method has yielded several papers identifying relevant misallocation of resources in the developing world, for agricultural, manufacturing and service sectors (Busso et al., 2013; Kalemli-Ozcan and Sørensen, 2016; Hsieh and Klenow, 2009; de Vries, 2014; Dias et al., 2016; Adamopoulos and Restuccia, 2014; Chen et al., forthcoming; Vasconcelos, 2017). Some caveats to this approach exist, though. One shortcoming is the fact that the indirect approach may capture the existence and magnitude of misallocation, but cannot account for the sources of misallocation. Another problem is that, even though the preferred models are fairly general in this literature, the assumptions are still somewhat restrictive. This has come to light with works from Haltiwanger et al. (2018) and Baqaee and Farhi (2020), which identify how demand and supply structures, and input-output networks might affect the implied misallocation measures. The work by Bils et al. (2021) shed light on the mismeasurement problem. As for the direct approach, the researcher establishes a structural model to capture explicitly the mechanism responsible for the possible misallocation.

The problem here is that one needs a good measure on the source of misallocation, which is generally not available. In our case at hand, one would need information about the lending interest rates available to specific firms (Restuccia and Rogerson, 2017).

Many papers have tried to connect specifically the financial sector with misallocation. Some papers have established that financial frictions are more relevant for technology adoption and the misallocation of entrepreneurial talent, instead of in the allocation of funds into already established firms. Firms with high productivity but facing financial frictions are able to avoid that constraint by accumulating funds and resorting to self-finance, but entrepreneurial talent in the traditional sector would face a high fixed cost to enter in the modern, technology-intensive sector. Such a shift might not be easily financed in developing countries (Buera et al., 2011; Midrigan and Xu, 2014; Buera and Shin, 2013; Gilchrist et al., 2013).

A recent paper by David and Venkateswaran (2019) attempted to impose more structure in the misallocation exercise and disentangle some of the sources of capital misallocation through the tracking of the moments in firm-level data. That made possible to identify the contribution of transitory factors, like adjustment costs and uncertainty, the contribution of markups and technological heterogeneity, and the size or productivity-dependent component. In the United States, the summation of transitory and technological/markup component is quite relevant (2/3rds of the dispersion in average revenue product of capital), but that is not true for China, where the unidentified size and productivity-dependent component is what accounts for 2/3rds of the dispersion in the average revenue product of capital. That may suggest that misallocation in advanced economies are largely due to demand and supply characteristics, whereas developing economies potentially face true distortions, or at least policy-relevant distortions, i.e. the ones that could be tackled by removing either government or market frictions. Wu (2018) is a paper that attempts to disentangle financial frictions arising from market imperfections and from other types of policies distorting capital allocation in China. Although the importance of financial frictions are much larger in relation to the developed world, policy distortions are still more relevant an explanation for the dispersion of marginal revenue product of capital.

Brazil is a country with high levels of general misallocation and capital misallocation (Vasconcelos, 2017), specifically. If China is a better reflection of Brazil's financial markets than the developed world, one would expect two things: (i) market failures could be responsible for a significant share of capital misallocation; and (ii) government policy distortions could be responsible for another large share of the dispersion in marginal revenue products of capital. In fact, policy aiming at solving market failures, if badly designed, could worsen misallocation. Just like India and China (Banerjee and Duflo, 2014; Hsieh and Klenow, 2009; Wu, 2018), Brazil also has channelled a significant share of its credit through the public sector. Since mid 2000's, the Brazilian Development Bank (BNDES) started to gain a larger and larger role on credit allocations. General reasons to implement this policy change are given in their documents, but information on specific goals and policy evaluation are scarce. One would like to know, in the best case scenario, how to measure the impact of this policy change on capital allocation. Full data on market interest rates are not easily available at the firm-level, so the indirect approach is the substitute available for measuring wedges preventing optimal capital allocation. Since the indirect approach is unable to disentangle the sources of capital misallocation, we need to couple the generic wedges' evolution with an identification strategy that provides an exogenous shift in credit conditions.

This paper attempts to infer the impact of improved conditions for subsidized credit on capital, labor and scale wedges, estimated through Hsieh and Klenow (2009)'s model using a natural experiment from Brazil, where a reclassification of firms' size by the Brazilian Development Bank [1] (BNDES) in 2003 allowed for a plausibly exogenous shock in credit conditions for firms reclassified to smaller categories. This shift provides an excellent opportunity for an identification by differences-in-differences, since both common trends

[1] *Banco Nacional de Desenvolvimento Econômico e Social* in Portuguese

and the exogeneity of the shock guarantees a clean identification. Under the assumption that mismeasurement arising from modelling and data constraints are not different in the treated and control groups at each time, I can follow the evolution of wedges after the shock to capture the impact of the change in credit conditions on them. By doing so, I can, as a first exercise, quantify the shift in wedges in relation to the overall distribution of wedges, gathering an idea of the impact an improvement in access to credit has in shifting targeted firms across the distribution. As a second exercise, I can observe how the position of targeted firms' wedges relate to the optimal allocation.

This paper is, then, in the spirit of both the direct and the indirect approach. Since the wedges are coming from a general model, I have generic measures of misallocation, like in the indirect approach. Still, the identification strategy allows me to infer changes in the generic measures through a specific channel, the credit condition, which is the objective of the direct approach. In doing so, we follow the lead of Bau and Matray (2023), which used a natural experiment on access to foreign credit to identify changes in wedges, although in their exercise they were able to compute a better measure of allocational change.

We find that the reclassification of firms, which had a quite large impact on the investment rate of firms in treated groups, especially for the new small firms, coming from the medium category (Cavalcanti and Vaz, 2017), had the expected negative impact in capital wedges, and that impact was larger than the impact on both the labor wedges and the scale wedges. New small firms shifted - 0.261 in average log capital wedge in the last year available after treatment. This is not a very large shift to the left, despite the apparent large increase in the investment rate for those firms, but it is still able to generate some fat tail in the overall distribution of capital and scale wedges depending on the original position of the distribution of wedges by cohorts, and that would match, at least partially, with the overall distribution of capital and scale wedge, suggesting the BNDES credit policy would be partially responsible for the larger misallocation present at small firms. A naive approach to compute misallocation against the capital wedge efficiency line, though, suggests the BNDES heavy handed credit policy towards the small group might have actually helped to compensate for financial frictions affecting that cohort. Results for the new medium firms, coming from the large group, are not as impactful. Average log capital wedges shifted - 0.123 2 years after treatment, but that result have not sustained itself through time.

This chapter is organized in the following manner: section 2 explains the policy environment of the reclassification of firms operated by the BNDES; section 3 describes the misallocation model used in the analysis, by Oberfield (2013); section 4 explains the data used in the exercise; section 5 produces some motivational results; section 6 explains the identification strategy used to capture the causal effects; section 7 presents results and discussion; section 8 concludes; and section 9 is an appendix with tables and graphs.

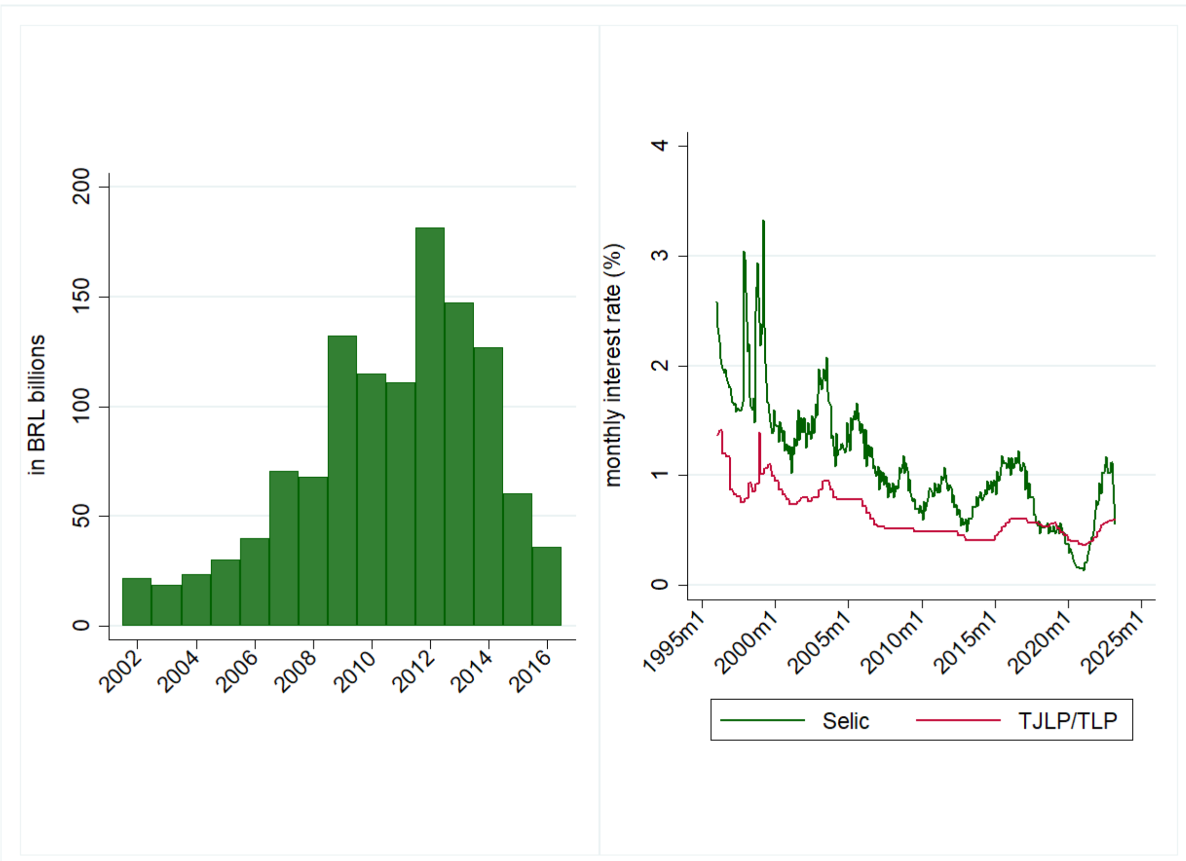
2 The Brazilian Development Bank and its Lending Conditions

The Brazilian Development Bank (BNDES) has been present in the discussions of targeted policy for a long time. During the 2000's, the BNDES gained increased importance in credit policy. Figure 1 shows the evolution of credit disbursements by BNDES from 2002-2016. It is clear that the government has opted for an increase in its portfolio during the 2000's, but that has been rolled back since 2015. A sample of their today products are described in the footnote.[2]. Many of their operations use the TJLP/TLP ("Long Run Rate"), which is more stable and lower than market interest rate. In Figure 1, one can see that the overnight

[2] *Cartão BNDES*, which finances the acquisition of machine, equipment, inputs and services up to BRL 2 millions; *BNDES Automático* targets the acquisition of machine, equipment, construction, installations, training and the acquisition/development of national software, all focused on a more long run necessity than *Cartão BNDES*; *BNDES crédito pequenas empresas* targets the maintenance or generation of employment by micro and small firms; *BNDES Finame* targets the acquisition of machines, equipments, IT and automation products, buses and trucks; *BNDES microcrédito* targets micro firms, both formal and informal, in need of cash flows; *BNDES MPME Inovadora* targets the innovation on products, processes, and improvements in the ability to innovate; *BNDES Exim* targets the production of goods to be exported. *source: https://www.bndes.gov.br/wps/portal/site/home*

Selic rate (which serves as base rate for monetary policy in Brazil) has a spread against the TJLP/TLP. Treasury operations on bonds follow closely the Selic rate. Risk lending to production activities are presumably done at even higher interest rates than government bonds. Lendings using TJLP/TLP could be seen as subsidies granted by the Brazilian government through the public banking system, mainly the BNDES.

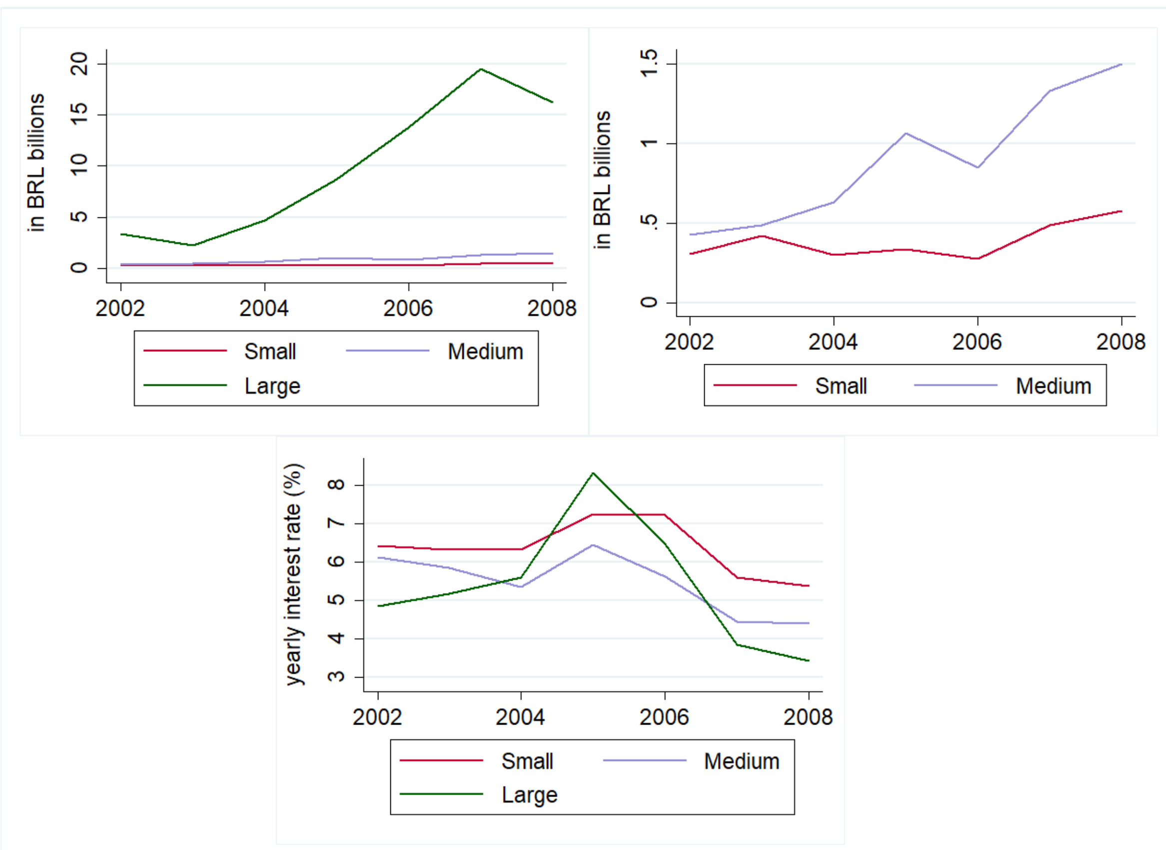
Figure 1: Credit Disbursements by BNDES from 2002-2016 (left), and Evolution of Key Interest Rates from 1996-2023 (right)



Source: The left graph is sourced from BNDES data for individual loan. The right graph is built with data from the Brazilian Central Bank.

Interest rates and the volume of credit granted by the BNDES through its size classification vary. Interest rates are mostly based on the TJLP/TLP, and are generally higher for smaller firms, followed by medium sized firms and then large firms, which most of the time are able to take credit at the lowest rate. The same is true for market interest rates, which tends to be much higher for smaller firms. Figure 2 plots the volume of credit granted for each category at the top left. At the top right, I zoom in for better visualization of small and medium. One can see that volume granted to the large category went through a very large shift. It was bellow *BRL 5 billions* in 2002, reaching almost *BRL 20 billions* in 2007, establishing a very large gap against the others. As for small and medium firms, the gap in volume is very narrow at the beginning, but begins to widen later in favor of medium sized firms. In terms of interest rates available, the years between 2004-2006 pushed higher interest rates to large firms. This reform is brought back to the traditional pattern in 2007.

Figure 2: Credit Disbursements by BNDES by Size Category from 2002-2008 (top), and Average Lending Interest Rates by Size Category from 2002-2008 (bottom)



Source: BNDES data for all individual loan: available by size classification.

3 Misallocation Framework

This section is concerned in explaining how we are going to measure the wedges. We choose to measure it based on Oberfield (2013). It differs from Hsieh and Klenow (2009) by assuming the capital intensity to differ from firm to firm, whereas in Hsieh and Klenow (2009) it is industry specific. In Hsieh and Klenow (2009)'s appendix they do a robustness check using different capital and labor intensities by firms.

We start by assuming a many industries environment. Within those industries, plants produce differentiated products that are combined to an industry aggregate. After that, industries aggregates are combined into a single aggregate good. Let Y_i be the output of plant i, and $Y_s \equiv (\sum_{i \in I_s} Y_i^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$, the quantity for the industry aggregate for industry s, and $Y \equiv \prod_{s \in S} Y_s^{\theta_s}$ is the quantity of manufacturing aggregate with $\sum s \in S\theta_s = 1$. industries shares evolve over time and price-taking consumers spend optimally. If P_i is the price of the good produced by plant i, than $P_s \equiv (\sum_{i \in I_s} P_i^{1-\sigma})^{\frac{1}{1-\sigma}}$, and $P \equiv \sum_{s \in S}(\frac{P_s}{\theta_s})^{\theta_s}$ are ideal price industries for the industry good and aggregate good, respectively.

Oberfield (2013) then constructs a frictionless economy, i.e., an economy where capital and labor are organized as to generate the optimum output.

$$\max_{[K_i, L_i]_{i \in I_s, s \in S}} \prod_{s \in S} [\sum_{i \in I_s} (A_i K_i^{\alpha_i} L_i^{1-\alpha_i})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}\theta_s}$$

subject to $\sum_{s \in S} \sum_{i \in I_s} K_i \leq K$ and $\sum_{s \in S} \sum_{i \in I_s} L_i \leq L$

The maximum attainable output is:

$$Y^{**} = \prod_{s \in S} (\sum_{i \in I_s} [A_i (\frac{\alpha_i}{\alpha^{**}} \theta_s K)^{\alpha_i} (\frac{1-\alpha_i}{1-\alpha^{**}} \theta_s L)^{1-\alpha_i}]^{\sigma-1})^{\frac{1}{\sigma-1}\theta_s} \tag{1}$$

where α_i is defined to satisfy:

$$\alpha^{**} = \sum_{s \in S} \theta_s \sum_{i \in I_s} \frac{[A_i (\frac{\alpha_i}{\alpha^{**}} \theta_s K)^{\alpha_i} (\frac{1-\alpha_i}{1-\alpha^{**}} \theta_s L)^{1-\alpha_i}]^{\sigma-1}}{\sum_{j \in I_s} [A_j (\frac{\alpha_j}{\alpha^{**}} \theta_s K)^{\alpha_j} (\frac{1-\alpha_j}{1-\alpha^{**}} \theta_s L)^{1-\alpha_j}]^{\sigma-1}} \alpha_i \tag{2}$$

Oberfield (2013) notes some features of the frictionless economy. First, $\frac{\partial lnY^{**}}{\partial lnK} = \alpha^{**}$ and $\frac{\partial lnY^{**}}{\partial lnL} = 1 - \alpha^{**}$, so that a first order approximation of the frictionless aggregate production function is a Cobb-Douglas production function with capital share α^{**}. This will be relevant when accounting for changes in output.

Second, the capital intensity of the frictionless economy, α^{**} is a weighted average of the capital intensities of individual plants, weighted by optimal size. As plants productivities change, the aggregate capital intensity shifts to better reflect the capital intensity of the lower-cost plants.

Third, α^{**} depends on the capital-labor ratio.

And lastly, with homogeneous capital intensities within industries, as in Hsieh and Klenow (2009), the frictionless factor share depends only on parameters: $\alpha^{**} = \sum_{s\in S} \theta_s \alpha_s$. In that case, α^{**} only changes because of the evolution of industry shares, θ_s.

The previous thought experiment involved imagining a frictionless economy across sectors. We now focus on another thought experiment, which consists in imagining the reallocation of capital and labor within industries.

let $Y^* \equiv \prod_{s\in S} (Y_s^*)^{\theta_s}$, where Y_s^* is:

$$\max_{[K_i,L_i]_{i\in I_s}} [\sum_{i\in I_s} (A_i K_i^{\alpha_i} L_i^{1-\alpha_i})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$$

subject to $\sum_{i\in I_s} K_i \leq K_s$ and $\sum_{i\in I_s} L_i \leq L_s$. the maximum attainable industry aggregate is:

$$Y_s^* = (\sum_{i\in I_s} [A_i(\frac{\alpha_i}{\alpha_s^*} K_s)^{\alpha_i} (\frac{1-\alpha_i}{1-\alpha_s^*} L_s)^{1-\alpha_i}]^{\sigma-1})^{\frac{1}{\sigma-1}} \tag{3}$$

And α_s^* is defined as:

$$\alpha_s^* = \sum_{i\in I_s} \frac{[A_i(\frac{\alpha_i}{\alpha^*} K_s)^{\alpha_i} (\frac{1-\alpha_i}{1-\alpha_s^*} L_s)^{1-\alpha_i}]^{\sigma-1}}{\sum_{j\in I_s} [A_j(\frac{\alpha_j}{\alpha_s^*} K_s)^{\alpha_j} (\frac{1-\alpha_j}{1-\alpha_s^*} L_s)^{1-\alpha_j}]^{\sigma-1}} \alpha_i \tag{4}$$

Oberfield (2013) shows that a particular Solow residual can be decomposed into changes in ”technology” and changes in the extent of misallocation.

Measuring allocational efficiency between and within industries:

$$M_W \equiv \frac{Y}{Y^*}$$

$$M_B \equiv \frac{Y^*}{Y^{**}}$$

Where M_W measures within-industry misallocation, and M_B measures the additional contribution to output of allocational efficiency between industries.

Changes in the efficient level of output can be decomposed into changes in aggregate capital, changes in aggregate labor, and a residual that reflects change in technology, $dlnA^{**}$.

$$dlnY^{**} = dlnA^{**} + \alpha^{**}dlnK + (1-\alpha^{**})dlnL$$

changes in actual output can be decomposed as:

$$dlnY = dlnM_B + dlnM_W + dlnA^{**} + \alpha^{**}dlnK + (1-\alpha^{**}dlnL)$$

which can be rewritten as:

$$dlnY - \alpha^{**}dlnK - (1-\alpha^{**}dlnL) = dlnM_B + dlnM_W + dlnA^{**}$$

The equation above makes it possible to disentangle changes in allocational efficiency from changes in technology.

Now we need to focus on how the measures of allocational efficiency, M_W and M_B, and factor shares from efficient production, α^{**} and α_s^*, can be obtained from plant-level data.

Optimal spending by consumer requires $Y_i = Y_s(\frac{P_iY_i}{P_sY_s})^{\frac{\sigma}{\sigma-1}}$. Combining this with $Y_i = A_iK_i^{\alpha_i}L_i^{1-\alpha_i}$ gives:

$$A_i = Y_s \frac{\frac{P_i Y_i}{P_s Y_s}^{\frac{\sigma}{\sigma-1}}}{K_i^{\alpha_i} L_i^{1-\alpha_i}} \tag{5}$$

Plugging this in equations (2) and (4) and rearranging yields:

$$0 = \sum_{s \in S} \theta_s \sum_{i \in I_s} [(\frac{P_i Y_i}{P_s Y_s})^{\frac{\sigma}{\sigma-1}} (\frac{K/\alpha^{**}}{K_i/\alpha_i})^{\alpha_i} (\frac{L/(1-\alpha^{**})}{L_i/(1-\alpha_i)})^{1-\alpha_i}]^{\sigma-1} (\alpha_i - \alpha^{**}) \tag{6}$$

$$0 = \sum_{i \in I_s} [(\frac{P_i Y_i}{P_s Y_s})^{\frac{\sigma}{\sigma-1}} (\frac{K/\alpha_s^{*}}{K_i/\alpha_i})^{\alpha_i} (\frac{L/(1-\alpha_s^{*})}{L_i/(1-\alpha_i)})^{1-\alpha_i}]^{\sigma-1} (\alpha_i - \alpha_s^{*}) \tag{7}$$

Similarly, plugging (5) into equations (1) and (3) along with $Y = \prod_{s \in S} Y_s^{\theta_s}$ yields:

$$\frac{Y^{**}}{Y} = \frac{1}{M_W M_B} = \prod_{s \in S} (\sum_{i \in I_s} [(\frac{P_i Y_i}{P_s Y_s})^{\frac{\sigma}{\sigma-1}} (\frac{\theta_s K/\alpha^{**}}{K_i/\alpha_i})^{\alpha_i} (\frac{\theta_s L/(1-\alpha^{**})}{L_i/(1-\alpha_i)})^{1-\alpha_i}]^{\sigma-1})^{\frac{\theta_s}{\sigma-1}} \tag{8}$$

$$\frac{Y^{*}}{Y} = \frac{1}{M_W} = \prod_{s \in S} (\sum_{i \in I_s} [(\frac{P_i Y_i}{P_s Y_s})^{\frac{\sigma}{\sigma-1}} (\frac{K_s/\alpha_s^{*}}{K_i/\alpha_i})^{\alpha_i} (\frac{L_s/(1-\alpha_s^{*})}{L_i/(1-\alpha_i)})^{1-\alpha_i}]^{\sigma-1})^{\frac{\theta_s}{\sigma-1}} \tag{9}$$

Note that no assumptions are made regarding plant's choices of capital and labor. The only assumption used are (i): the functional forms of each plants production function; (ii) the functional form of the demand system; and (iii) price-taking consumers make optimal purchasing decisions. The framework takes no stand on how prices are set.

Now we need to define the terms that characterize allocational efficiency. If resources are allocated efficiently within industries, the ratio of value added for plant i satisfies $\frac{\alpha_i P_i^* Y_i^*}{K_i^*} = \frac{\alpha_s^* P_s Y_s}{K_s}$. Define the capital wedge of plant i to be the deviation of this ratio from its efficient (within-industry) level: $T_{K_i} \equiv \frac{P_i Y_i / K_i}{P_i^* Y_i^* / k_i^*}$. Similarly, define the labor wedge to be $T_{L_i} \equiv \frac{P_i Y_i / L_i}{P_i^* Y_i^* / L_i^*}$. Lastly, we define the scale wedge for plant i to be $T_i \equiv T_{K_i}^{\alpha_i} T_{L_i}^{1-\alpha_i}$ A plant scale wedge is related to its within-industry allocational efficiency. A scale wedge larger than one means that the plant is small relative to its size in the efficient allocation.

Those wedges are actually what we are interested in estimating and using it as our main outcome.

4 Data

Data comes from the Brazilian Institute of Geography and Statistics (IBGE), specifically, the PIA (Annual Industrial Survey). It reveals firm-level economic information about the manufacturing sector, such as employees, wages and salaries, revenues, costs and expenses, investment, depreciation, output and intermediate consumption. It covers about 40,000 firms that has more than 30 employees and a sample of firms below 30 employees.

There are no variables for the capital stock. It must be generated through the available data. The most popular method is the perpetual inventory model. In the exercise of section 5, we compute it through the traditional perpetual inventory method, where missing values on investment could implicate the existence of measurement error.

In the main exercise in Section 7, we use capital stock data available at IBGE's restricted room, where PIA is located. It was built as in Alves and Messa Silva (2008). An initial capital stock is constructed for 1996 using sectoral level data, at the lowest level available. The perpetual inventory method is then applied to capital formation statistics at the aggregate level, and then generated at the firm-level by assuming equal capital-to-labor ratios inside sectors. From then on, it is straightforward to compute the following years' capital stocks by taking account of the investment flows and the depreciation. Apart from that, the data also suffers from missing observations for the investment variables. Imputation is done by propensity score. The first years of the series could distort overall misallocation measures because of the way capital levels are computed for 1996, but this effect is already lowered by 1998. We choose to use this metric in our main estimation because the imputation helps with lowering additive measurement error. Our exercise starts mostly post 1998, and distortions from the methodology are unlikely to affect size cohorts differently.

Labor income is calculated as annual wages paid for blue and white collar professionals, corrected by the operation days of each firm. Wages were deflated by the Brazilian general price index.

The value added is calculated by the industrial gross value of output deducted by the industrial operational cost. Value added is also deflated by the Brazilian general price index.

We also reclassified firms, using the International Standard Industries Classification (ISIC) code system. The disaggregation occurred at the 4-digit level. We did not use sectors comprising of less than 4 firms, and excluded the top 1% and bottom 1% of firms as outliers. In addition, non-manufacturing firms were excluded from the sample.

Table 1: Descriptive Statistics ($\sigma = 3$)

	New Small			Always Small		
Variable	mean	median	Obs	mean	median	Obs
K	5,560,071	2,463,269	12,939	1,997,300	658,801.86	50,030
WL	500,630.91	376,321.66	12,939	260,804	173,573.25	50,030
Revenue	9,097,503.9	9,084,428.5	12,939	2,733,624.5	2,401,756	50,030
Capital Wedge	0.097	0.187	12,939	0.021	0.126	50,030
Labor Wedge	- 0.378	- 0.262	12,939	- 0.419	- 0.279	50,030
Scale Wedge	0.020	0.137	12,939	- 0.081	0.056	50,030
	New Medium			**Always Large**		
Variable	mean	median	Obs	mean	median	Obs
K	27,022,904	10,866,583	7,002	126,335,786	27,210,427	5,898
WL	1,980,462.8	1,459,063	7,002	7,483,984	3,331,247.5	5,898
Revenue	45,131,330	44,947,968	7,002	279,489,864	108,821,200	5,898
Capital Wedge	0.103	0.178	7,002	0.122	0.145	5,898
Labor Wedge	- 0.440	- 0.3390	7,002	- 0.550	- 0.469	5,898
Scale Wedge	0.03	0.124	7,002	0.042	0.087	5,898

Notes: Descriptive statistics generated with the database presented in the data section (PIA-IBGE) plus estimations of wedges using the model described in section 2.3.

5 Some Motivational Results

We first bring some results on both the evolution of misallocation around the period of the exercise and some indication that the BNDES might be able to target firms with a larger wedge.

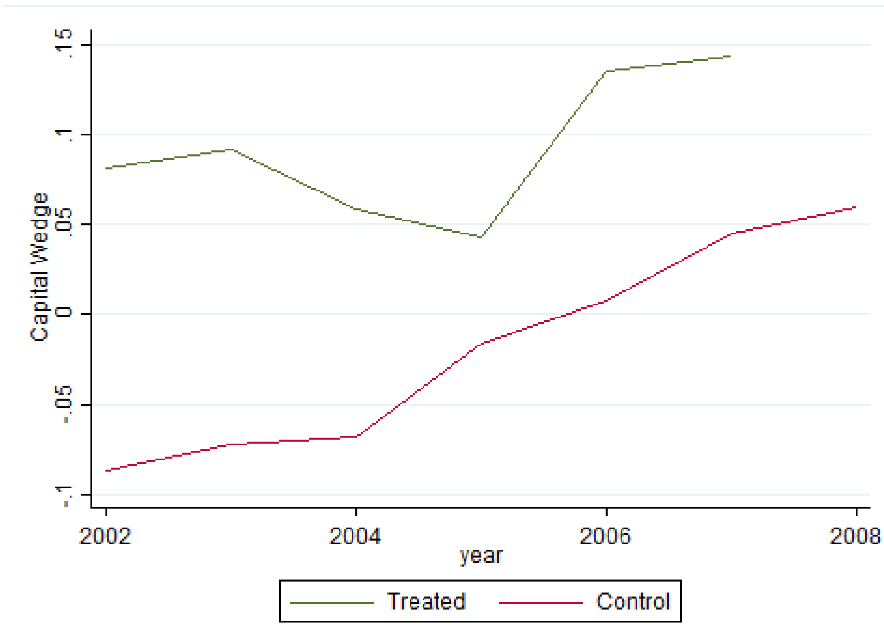
Figure 3 reports the evolution of misallocation between 1996-2012. Vasconcelos (2017) has already executed this exercise. I replicate it here inside the context of increased directed credit. Both within-sector misallocation and between-sector misallocation appear to coincide, on a casual correlational view, with the expansion of public credit. This serves as a motivation for the main exercise, where one could see the impact a change in credit conditions might have on the wedges used to create this measure.

Figure 3: Evolution of misallocation between 1996-2012

Source: Graph generated by the model presented in section 2.3. Larger values imply better allocative efficiency.

Figure 4 plots the evolution of capital wedges from 2002-2008, for both recipients (treated) and non-recipients (control). Treated observations were constructed as firms' capital wedges one year before their first credit taken from BNDES. Control observations were firms that did not take any credit from BNDES during the period. It does appear that BNDES is able to target firms with larger capital wedges on average. What is potentially troubling is the possibility that the difference between treated and control groups are not too large, so that once firms receive the subsidized credit they expand beyond what would be optimal.

Figure 4: Capital Wedges for BNDES recipients vs. non-recipients, pre concession



Source: Treated observations are the value of the average log capital wedge for 1 year before the firm first received a loan from BNDES. Control observations are firms that never received a loan in this period.

6 Identification Strategy

We build our identification strategy as in Cavalcanti and Vaz (2017). As already explained in the introduction, the BNDES operated a reclassification of firms in 2003. Some medium firms were suddenly classified as small, and some large firms were suddenly classified as medium, and then they became eligible to access different credit conditions. The natural experiment is built on this reclassification, as it creates the opportunity to assess the change in credit conditions against a counterfactual.

The quality of the natural experiment lies in the assumption that the reclassification was exogenous to firms, so they could not anticipate it and position themselves in a desired

Table 2: BNDES Firm Classification by Revenue Through Time (in BRL)

Year	Small		Medium		Large	
	Min	Max	Min	Max	Min	Max
2000	700,000	6,125,000	6,125,000	35,000,000	35,000,000	-
2001	700,000	6,125,000	6,125,000	35,000,000	35,000,000	-
2002	900,000	7,875,000	7,875,000	45,000,000	45,000,000	-
2003	1,200,000	10,500,000	10,500,000	60,000,000	60,000,000	-
2004	1,200,000	10,500,000	10,500,000	60,000,000	60,000,000	-
2005	1,200,000	10,500,000	10,500,000	60,000,000	60,000,000	-
2006	1,200,000	10,500,000	10,500,000	60,000,000	60,000,000	-
2007	1,200,000	10,500,000	10,500,000	60,000,000	60,000,000	-
2008	1,200,000	10,500,000	10,500,000	60,000,000	60,000,000	-

Source: BNDES. This table shows the classification of firms between small, medium and large, from 2000 to 2008.

spot. Checking for common trends ensure the quality of the identification. A possible concern would be the contamination of the control group by the treatment. If treated firms respond by further taking more or less credit from private credit markets, or if the possible expansion of public credit is done at the expense of private credit, the control group stops being a good counterfactual. We defend my identification on the basis that we are talking about a small fraction of the economy, i.e. the manufacturing sector. In addition, the treated groups are small in size in comparison to the rest of manufacturing. Therefore, it is unlikely that the control group becomes seriously contaminated by the treatment.

We build two new categories given the reclassification: *new small* and *new medium*. The *new small* group lies in between $BRL\ 7,875,000$ and $BRL\ 10,500,000$ in revenue. As one can see in Table 2, every firm falling in this bracket from 2000 onwards was classified as medium until 2002, and then they became small in 2003. The same happens with *new medium*, where firms in between $BRL\ 35,000,000$ and $BRL\ 60,000,000$ in revenue shift from large to medium. I construct the control groups as *always small*, with revenues from $BRL1,200,000$ and $BRL\ 6,125,000$ and *always large*, with revenues upwards of $BRL\ 60,000,000$.

We employ the following Differences-in-Differences model, then:

$$Y_{it} = \beta_1 New(category)_{it} + \beta_2 Post_t + \beta_3 Post_t \times New(category)_{it} + X_{it}\gamma + \epsilon_{it} \tag{10}$$

where Y_{it} are the capital and scale wedges, or respectively, T_{K_i} and T_i. X_{it} refers to the possible controls added to the model.

What interests us is the parameter β_3, which captures the conditional expected value of wedges before and after the shift.

$$\beta_3 = E[Y_{it}|\textit{new category} = 1, \textit{Post} = 1] - E[Y_{it}|\textit{new category} = 1, \textit{Post} = 0]$$

$$-E[Y_{it}|\textit{new category} = 0, \textit{Post} = 1] - E[Y_{it}|\textit{new category} = 0, \textit{Post} = 0]$$

For the case of the new small firms versus always small firms, we shift the treatment to 2002, instead of 2003. This anticipation is done because there is a small change in credit conditions in 2002 favoring medium firms, so new small firms started to have better conditions in 2002, and then got the treatment via the reclassification. Common trend would not be violated, though. Effects mount mostly after the reclassification, so one could take 2003 as treatment.

The two exercises in this paper are the comparison of new small firms against always small firms and new medium firms against always large firms after a reclassification took place in 2003. We do not have access to complete data on the periods prior to 2002, but strong common trends are established in the exercise, suggesting the pattern of changing volume and interest rates present post 2004 is not present in the pre-treatment years.

The first exercise interpretation is straightforward: if new small firms were in a trajectory with common trends with the always small firms, their trajectory post-treatment reflect the change in credit conditions. A first inspection of the data presented would suggest that the credit shock is negative, since interest rates are higher for the small firms and volume is lower, in comparison with medium firms. The correct interpretation would have to adjust credit volume as a proportion of the size of the capital stock in each category, though. Cavalcanti and Vaz (2017) conducted a differences-in-differences in the same new small versus always small category, but with the investment rate in mind (investment/capital stock). It grew by 33.9% after the reclassification on a full period differences-in-differences. Although there was no leads and lags analysis, a graph showing the unconditional evolution of the investment rate reaches around 75% larger investment rate in the last years in comparison with the pre-treatment investment rate, suggesting a large positive adjustment in the capital stock over the years. That would suggest falling capital wedges in this exercise. This finding would be just a mechanical one, but we are interested in the magnitude of wedge changes relative to the distribution, and also in the position of wedges relative to the efficiency line.

The second exercise is done by comparing new medium against always large firms. Since they were both large pre-treatment, they necessarily faced the same conditions up until treatment, even if it changed through time. But it then diverged for both groups since they were classified differently. The treated is compared against a group that suffers major shifts in their policy mix post-treatment, the large group. It still serves as an exercise on the impact of being medium against a counterfactual of a changing large.

Capturing common trends before treatment is important to establish that groups moved in tandem when facing similar trends in their credit conditions, suggesting post-treatment results are due to different credit conditions.

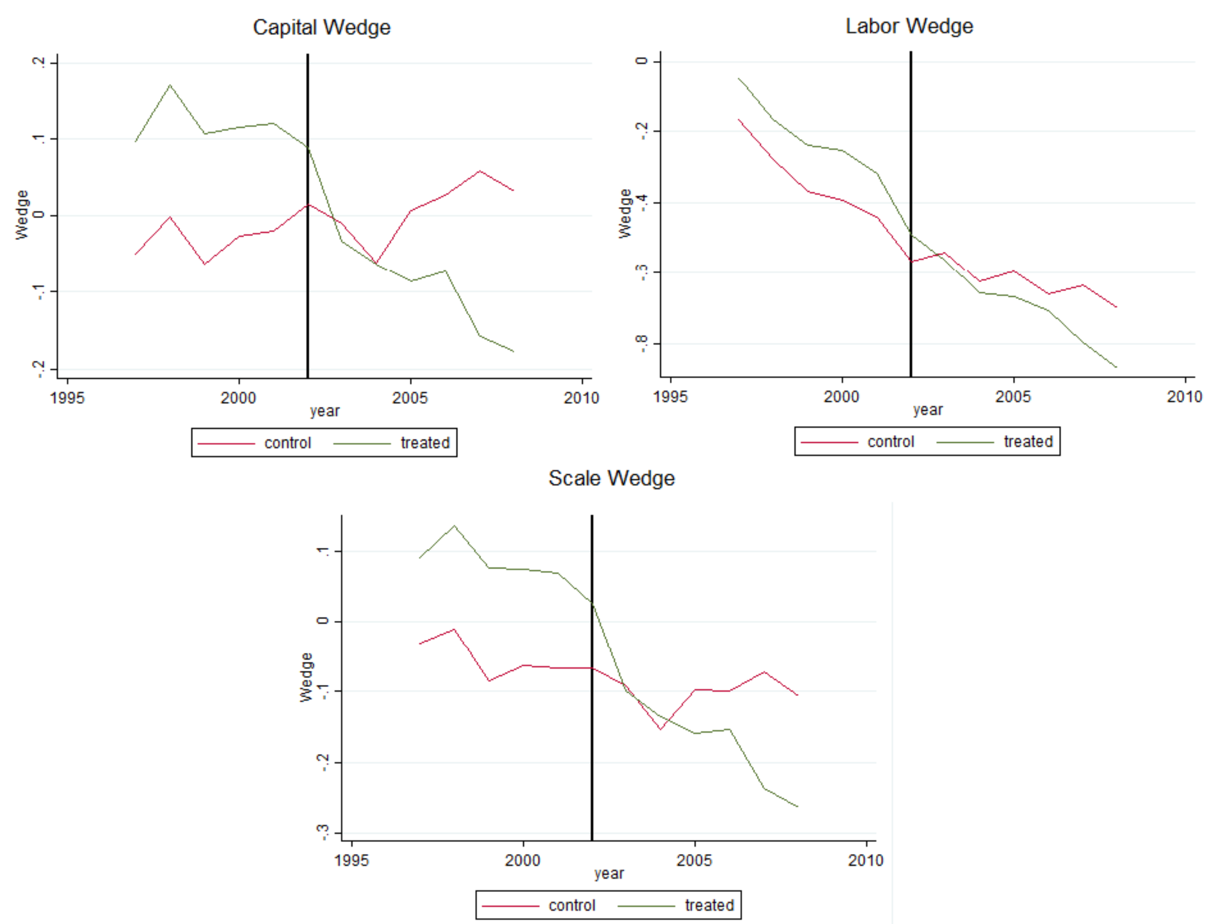
7 Results

We start by reporting the unconditional average for wedges during the study period in Figure 5. Results do not vary wildly by using different elasticities, so we report $\sigma = 3$ in the main text, while reporting results for $\sigma = 1.5$ and $\sigma = 5$ in the appendix tables, where one could also find the tables for these two sigmas that were produced for $\sigma = 3$ in the main text. It is already visible that the credit shock did affect the wedge dynamics. The response is more visible in the capital and scale wedges, and not so much on labor wedges. The stronger response on capital wedges are as expected. An expansion of the credit available for investment should mainly move the capital wedge, as firms take the opportunity to expand their capital stock and equalize marginal revenue with the new lower marginal cost. The less important dynamics on labor wedges are also expected, since the channel by which firms could use funds to adjust to their optimal labor hiring would be if they had serious cash flow constraints. That appears to be a smaller consideration. The scale wedge mimicked the evolution of the capital wedge.

Taking a first look at the wedge levels visible in the graphs, it appears that the shift in credit conditions sent both new small and new medium firms across the efficiency line at 0. In the case of new small firms, they start at a higher capital wedge level than both the counterfactual and the efficiency line, suggesting potential improvements with more access to capital. But the improvement in capital conditions actually sent new small firms below the efficiency line, from an under-investment position to an over-investment one, suggesting the improvement was actually more than needed from the economy perspective, if one takes the efficiency line as the correct metric for the evaluation of the misallocation of funds. Not only that, equal credit access as always small firms did not put new small firms in the same trajectory as always small firms afterwards. New small firms crossed the counterfactual line (the always small wedges), potentially because they are now the largest members of the small category, with better market interest rates available, making their mix of public and private credit interest rate lower than the smaller members of the small group.

As for the new medium comparison with the always large, their levels were already close to the efficiency line at pre-treatment. The shift in credit conditions to the new medium puts them in a lower level than the counterfactual (always large), even if the always large group also experienced a decrease in capital efficiency due to the large volume received after 2004.

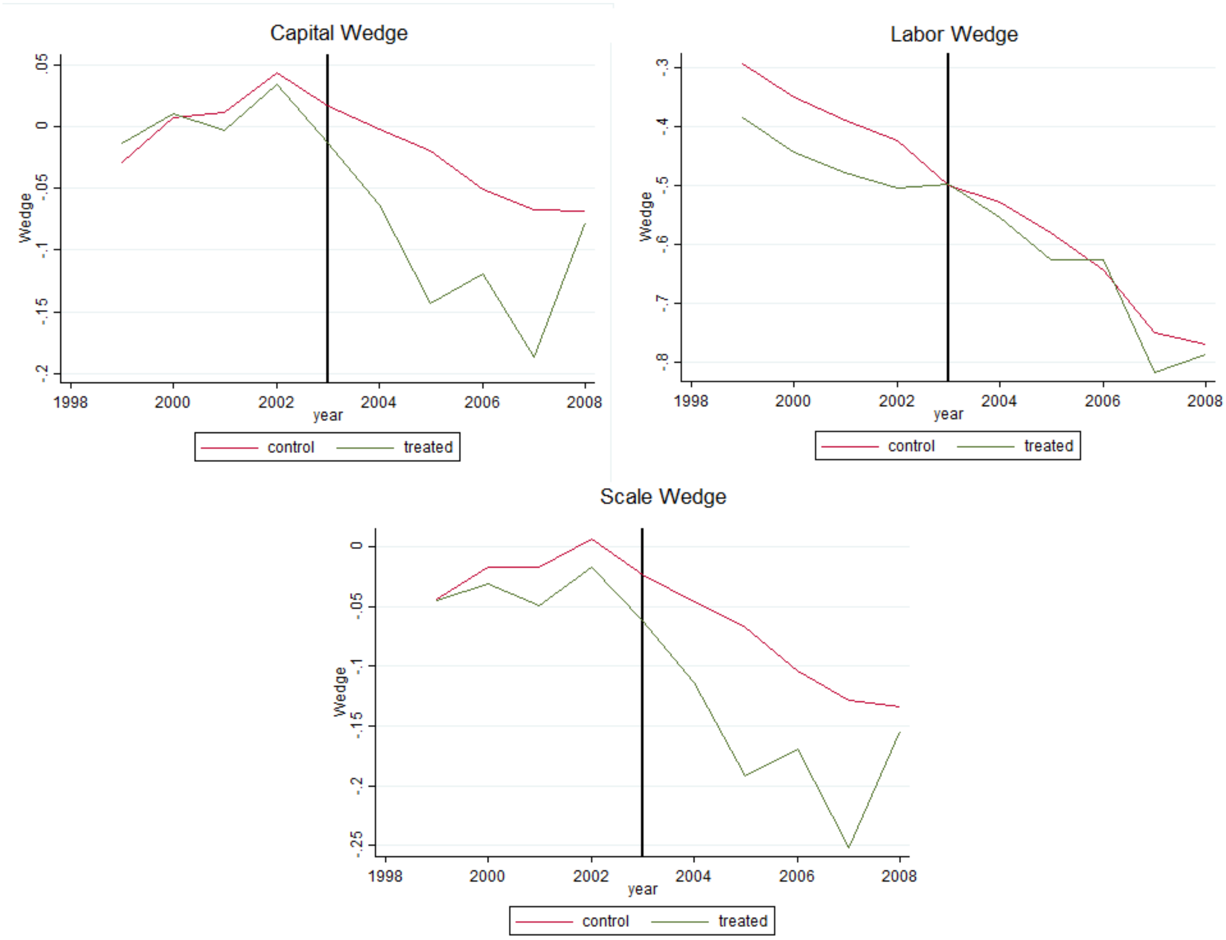
Figure 5: Unconditional Averages for Capital, Labor and Scale Wedges (New Small x Always Small)



Source: Graphs generated by plotting the unconditional means of the log capital wedge, log labor wedge and log scale wedge, for the size classifications of new small and always small

Table 3 reports differences-in-differences results for capital, labor and scale wedges, in both new small versus always small and new medium versus always large categories. As expected, results for the capital wedge are the most noticeable. Taking the specification

Figure 6: Unconditional Averages for Capital, Labor and Scale Wedges (New Medium x Always Large)



Source: Graphs generated by plotting the unconditional means of the log capital wedge, log labor wedge and log scale wedge, for the size classifications of new medium and always medium

with industry fixed effects and controls as the main result, a shift from medium to small generate a negative shift on average log capital wedges of - 0.157, significant at 99% confidence levels. Using results from Cavalcanti and Vaz (2017), the shift in the investment rate of 33.9% for new small firms during the treatment period caused the reduction of -0.157 in average log capital wedges. We report the 2008 wedge distribution in the Appendix Figure 11. We do not hold the standard deviation to calculate the shift relative to the standard deviation. Although it does appear to be a somewhat small move around the distribution, it is enough to make new small firms to cross the efficiency line, locating them at the over-invested side of the distribution.

Results for the labor wedge were significant, but smaller in magnitude, suggesting that access to better credit conditions facilitated hiring. The shift from medium to small reduced the average log labor wedge in - 0.087, significant at 90% confidence levels. Labor wedges were already trending downwards on the over-invested side of the distribution. Increased access to cheap credit pushed it down even further.

As for the scale wedges, one must remember that they are given by $Ti = Tki^{\alpha_{si}} Tli^{1-\alpha_{si}}$. Since the shift in labor wedges were smaller than capital wedges, and manufacturing plants are quite capital-intensive in comparison to the typical 2/3rds labor share and 1/3rd capital share for the whole of the economy, the average log scale wedge effect is in between, of - 0.112, significant at 95% confidence levels. The scale wedge also crosses the efficiency line into over-scale territory.

Moving to the comparison between new medium versus always large, effects are much less pronounced. Only the average log capital wedge returns a significant result. It is of - 0.070 in our preferred estimation. Starting from around efficiency levels, the capital wedge falls faster for new medium firms than for always large firms. Perhaps more interestingly, even the shift in volume favoring the large group with close to 4x more capital available during the treatment period, versus 3x more capital for medium firms, was not enough to compensate against being in a lower category, with presumably more credit per capital stock available for lending. One must also bear in mind that interest rate grew for the large group during mid treatment, which could also have had some effect. If one could use the proportional shift in capital wedges of new medium relative to the shift from capital wedges of new small, of 0.446, one could use the 33.9% change in the investment rate for the new small in Cavalcanti and Vaz (2017), and return a 15.11% change in the investment rate of the new medium category.

We shift to the more interesting dynamics reflected in the event studies. Figure 7 plots event studies for new small versus always small. The shift in the investment rate in Cavalcanti and Vaz (2017) also happens during a period of adjustment, with the investment rate for new small firms adjusting to always small levels close to 2008. That is why the capital wedge keeps falling during the treatment period. The investment rate for new small firms increase around 75% by 2008 (Appendix Figure 10). The event study reported in Figure 7 is also reported in the second column of Table 4. After 6 years, the shock in estimated average log capital wedge is of - 0.261, significant at 95% confidence levels, which is noticeably stronger than the results for the overall differences-in-differences (- 0.157). One should take the estimates for the last period seriously,

Table 3: Treatment Effects on Capital, Labor and Scale Wedges

	New Small x Always Small								
	Capital Wedge			Labor Wedge			Scale Wedge		
Eligible*Post	- 0.174***	- 0.163***	- 0.157***	- 0.086*	- 0.083*	- 0.087*	- 0.124**	- 0.115**	- 0.112**
	(0.062)	(0.061)	(0.059)	(0.051)	(0.049)	(0.048)	(0.057)	(0.056)	(0.0548)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**
Controls	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**
Obs	45,464	45,460	45,460	45,464	45,460	45,460	45,464	45,460	45,460
R^2	0.430	0.443	0.447	0.523	0.532	0.533	0.428	0.440	0.444
	New Medium x Always Large								
	Capital Wedge			Labor Wedge			Scale Wedge		
Eligible*Post	- 0.072*	- 0.075*	- 0.070*	0.059	0.055	0.057	- 0.061	- 0.064*	- 0.059
	(0.040)	(0.040)	(0.040)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.039)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**
Controls	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**
Obs	17,133	17,128	17,128	17,133	17,128	17,128	17,133	17,128	17,128
R^2	0.511	0.532	0.533	0.589	0.605	0.605	0.508	0.529	0.31

Notes: .

since it takes time for the investment rate and the capital stock to adjust to the new steady state. Those estimates reflect better the endpoints for wedges after the shock in credit conditions.

The same is true for labor wedges, which 6 years after the shock in credit conditions reach - 0.166, significant at 90% confidence levels. Results are not significant for scale wedges in any given year, despite being significant for the overall differences-in-differences. I still report here the effects for the last year, which is of - 0.195.

The new medium dynamics are different, and are reported in Figure 2.8 and Table 2.5 (the Figure 6 dynamics is shown in column 2). It actually reaches its largest results after 2 years. Credit conditions for medium and large groups did not change dramatically in the first periods, so this effect reflect better the difference in credit conditions in favor of medium firms against a stable counterfactual. The shift in volume and interest rates for the large group starts to appear more after that, and treatment reflect improvements for new medium firms in relation to an improving condition in volume and a temporary increase in interest rates for the large group.

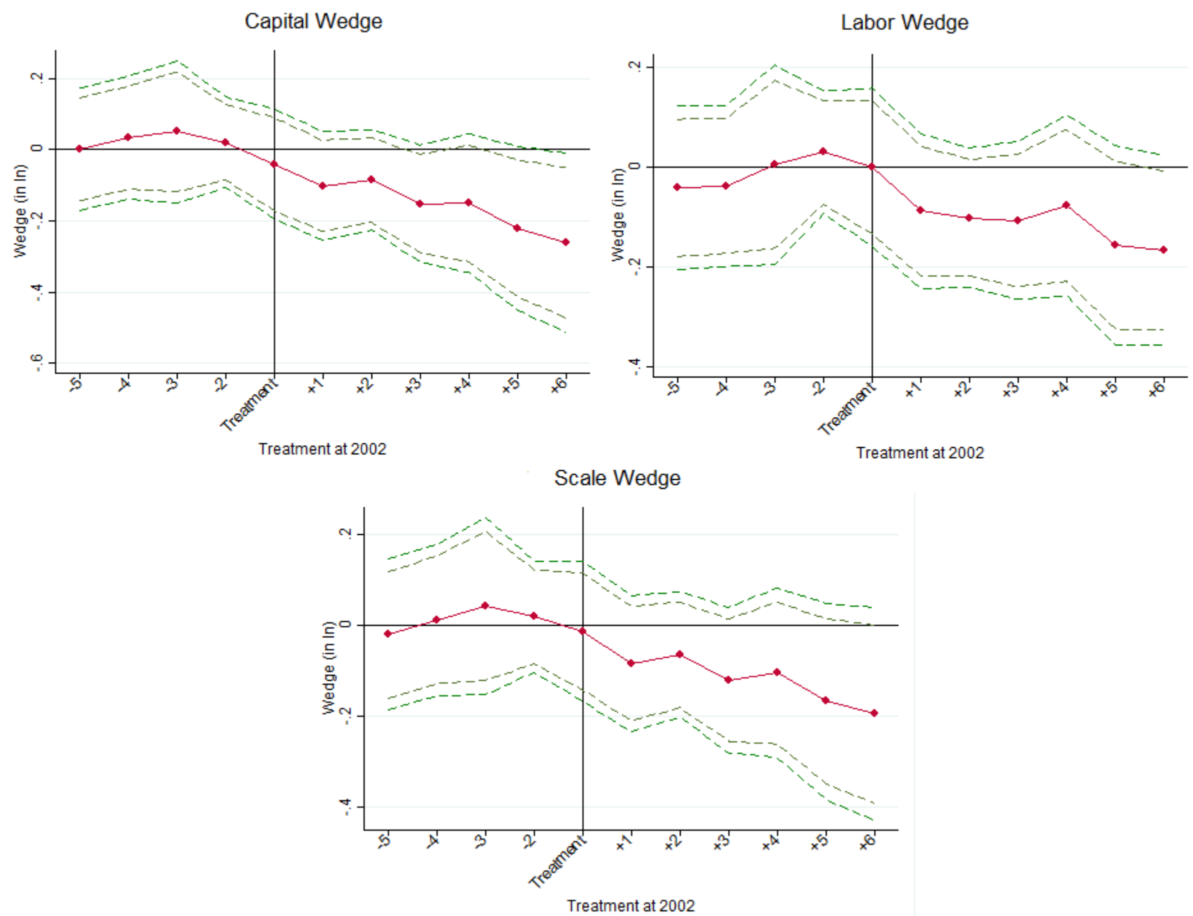
The impact in average log capital wedges were of - 0.123, significant at 95% confidence levels, a much lower impact than the top impact of moving from medium to small. Using Cavalcanti and Vaz (2017) results for the investment rate, we estimate that the investment rate peaked at 26.55% increase for the new medium category after two years of treatment.

The average log labor wedge has an unexpected trajectory, which is felt mostly in the treatment year and 3 years after treatment, with 0.102, significant at 90% confidence levels. Results were not significant for the overall differences-in-differences, though. It does not appear that new medium firms had any cash flow problems affecting hiring.

As for scale wedge, it reaches maximum results 2 years after the treatment. The average log scale wedge falls - 0.110, significant at 95% confidence levels.

Our results suggest that shifting to better credit conditions has an impact on the measured wedges. This result is expected and mechanical. The more interesting result comes

Figure 7: Event Study for New Small vs. Always Small

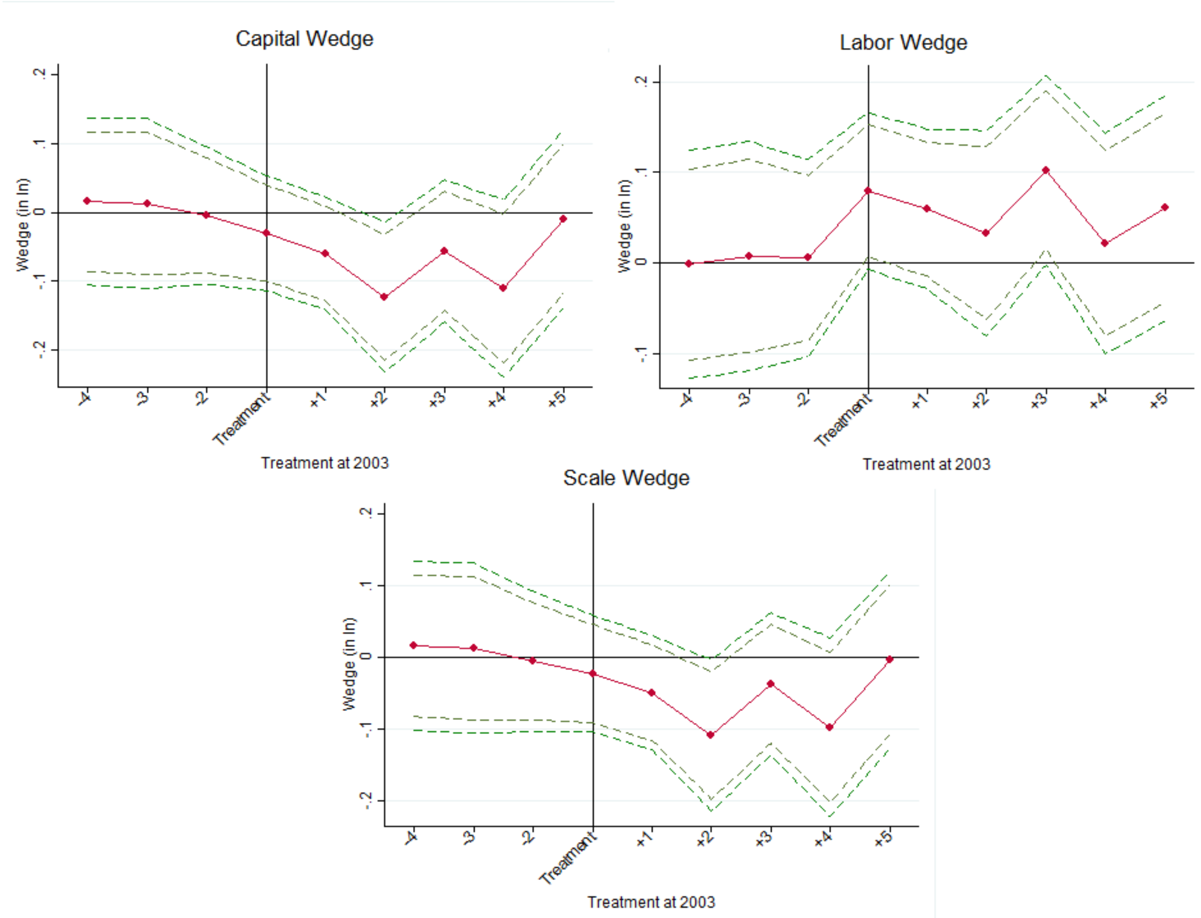


Source: Graphs generated by plotting the results of Table 4, column 2, for the treatment effects on the log capital wedge, log labor wedge and log scale wedge, for the new small vs. always small exercise. Confidence intervals of 90% and 95% are also reported.

from estimating the magnitude of the shift in wedges given a certain change in credit conditions. Shifting to the small category appears to bring the most notable shift. As showed above, in the most extreme case, when one waits for the capital stock to adjust the most, the average capital wedge shifted - 0.261. By looking at Appendix Figure 11, the shift in the average might look relatively small, but a shift of - 0.261 in the average distribution of a cohort could potentially produce a fatter tail on the negative side of Appendix Figure 11. To better visualize it with the distribution of wedges by revenues, Figure 9 below reveals that most of the concentration of negative capital wedges are present in the small category.

Since the estimate is the causal effect of access to better credit conditions from the BN-

Figure 8: Event Study for New Medium vs. Always Large



Source: Graphs generated by plotting the results of Table 5, column 2, for the treatment effects on the log capital wedge, log labor wedge and log scale wedge, for the new medium vs. always large exercise. Confidence intervals of 90% and 95% are also reported.

DES, one can be sure that better credit condition was making small firms to operate at least 0.261 average log capital wedge below what they would operate if their conditions were similar to medium firms around treatment time. And medium firms operated at most 0.123 average log capital wedge below large firms during one treatment year. So we have established that the BNDES definitely affected wedges differently depending on the size cohort defined by the institution. The average capital wedge gap for the small group versus the medium group appears to have been 2.12 times larger than the gap between the medium group vs. the large group around treatment time. This is our main and most trustworthy result. It suggests that the BNDES should be sure if their targets, specially

Table 4: Treatment Effects on Capital, Labor and Scale Wedges (Event Study)

	New Small x Always Small					
	Capital Wedge		Labor Wedge		Scale Wedge	
5 years before	- 0.018	0.001	- 0.047	- 0.042	- 0.039	- 0.0198
	(0.088)	(0.088)	(0.082)	(0.083)	(0.084)	(0.085)
4 years before	0.019	0.034	- 0.031	- 0.038	0.000	0.012
	(0.087)	(0.088)	(0.081)	(0.082)	(0.084)	(0.085)
3 years before	0.036	0.051	- 0.000	0.005	0.029	0.043
	(0.101)	(0.102)	(0.101)	(0.102)	(0.098)	(0.099)
2 years before	0.015	0.021	0.022	0.029	0.013	0.019
	(0.065)	(0.064)	(0.062)	(0.062)	(0.063)	(0.063)
1 year before	0	0	0	0		
Year of treat.	- 0.040	- 0.040	- 0.000	- 0.001	- 0.012	- 0.013
	(0.079)	(0.079)	(0.081)	(0.081)	(0.078)	(0.078)
1 year after	- 0.136*	- 0.101	- 0.095	- 0.089	- 0.112	- 0.084
	(0.079)	(0.078)	(0.080)	(0.079)	(0.077)	(0.076)
2 years after	- 0.114	- 0.085	- 0.105	- 0.102	- 0.087	- 0.065
	(0.073)	(0.072)	(0.073)	(0.071)	(0.071)	(0.070)
3 years after	- 0.180**	- 0.151*	- 0.101	- 0.107	- 0.140	- 0.120
	(0.089)	(0.084)	(0.087)	(0.080)	(0.087)	(0.082)
4 years after	- 0.190*	- 0.150	- 0.086	- 0.077	- 0.136	- 0.105
	(0.104)	(0.099)	(0.098)	(0.092)	(0.099)	(0.095)
5 years after	- 0.270**	- 0.221*	- 0.160	- 0.157	- 0.208*	- 0.167
	(0.123)	(0.117)	(0.107)	(0.101)	(0.115)	(0.110)
6 years after	- 0.258*	- 0.261**	- 0.147	- 0.166*	- 0.194	- 0.195
	(0.136)	(0.128)	(0.104)	(0.097)	(0.126)	(0.119)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Obs	45,464	45,460	45,464	45,460	45,464	45,460
R^2	0.430	0.448	0.523	0.533	0.428	0.444

Notes:

in the small group, are indeed credit constrained, otherwise it could give an important contribution to capital misallocation.

The second interesting exercise would be to determine if those shifts in wedges generated by the shift in credit conditions are actually improving or reducing allocational

Table 5: Treatment Effects on Capital, Labor and Scale Wedges (Event Study)

	New Medium x Always Large					
	Capital Wedge		Labor Wedge		Scale Wedge	
4 years before	0.020	0.015	- 0.007	- 0.002	0.019	0.015
	(0.060)	(0.062)	(0.063)	(0.064)	(0.059)	(0.060)
3 years before	0.0204	0.013	0.005	0.007	0.018	0.012
	(0.061)	(0.063)	(0.063)	(0.064)	(0.059)	(0.060)
2 years before	0.000	- 0.004	- 0.002	0.005	- 0.002	- 0.006
	(0.050)	(0.051)	(0.055)	(0.055)	(0.049)	(0.049)
1 year before	0	0	0	0	0	0
Year of treat.	- 0.021	- 0.030	0.083*	0.079*	- 0.015	- 0.023
	(0.041)	(0.042)	(0.044)	(0.044)	(0.040)	(0.041)
1 year after	- 0.052	- 0.059	0.053	0.059	- 0.044	- 0.049
	(0.040)	(0.042)	(0.043)	(0.045)	(0.039)	(0.040)
2 years after	- 0.110**	- 0.123**	0.041	0.033	- 0.099*	- 0.110**
	(0.055)	(0.055)	(0.057)	(0.058)	(0.054)	(0.054)
3 years after	- 0.055	- 0.056	0.099*	0.102*	- 0.038	- 0.037
	(0.052)	(0.0525)	(0.052)	(0.053)	(0.050)	(0.050)
4 years after	- 0.113*	- 0.110*	0.017	0.021	- 0.103	- 0.098
	(0.067)	(0.066)	(0.062)	(0.062)	(0.065)	(0.064)
5 years after	- 0.024	- 0.010	0.045	0.060	- 0.020	- 0.004
	(0.065)	(0.066)	(0.061)	(0.063)	(0.063)	(0.063)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Obs	17,133	17,128	17,133	17,128	17,133	17,128
R^2	0.511	0.534	0.589	0.605	0.508	0.531

Notes:

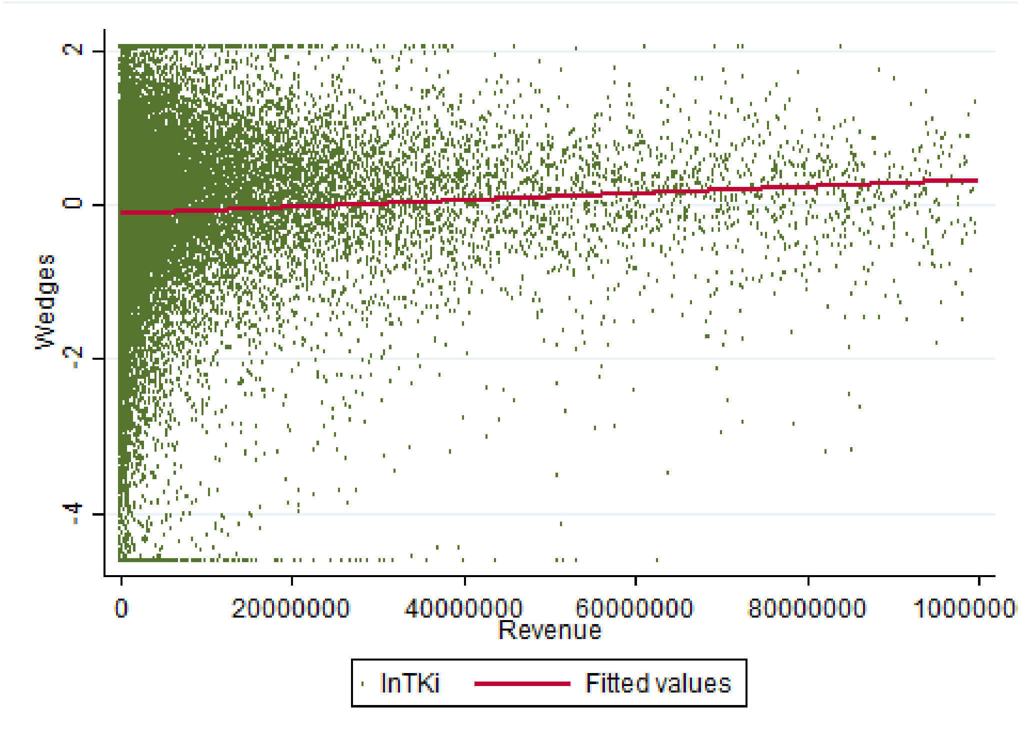
efficiency. If one takes the efficiency line at 0, this implies the assumption that all types of wedges affecting capital allocation act symmetrical on the distribution, so shifts in credit conditions improving or reducing optimal allocation could be approximated by the position of wedges relative to the overall efficiency line. Under this assumption, the new small group experienced a run into over-investment, after starting in under-investment position. Using estimates from the event study, we find that the reduction of 0.261 average log wedges 6 years after treatment against the counterfactual implies an average capital wedge of - 0.106, starting from 0.115 pre-treatment, which is basically a symmetric shift that would not have changed overall misallocation. In the case of the new medium group it shifted to - 0.138 because of changing credit conditions, coming from 0.03, which is an increase in misallocation due to the shock. If one could use estimates of the new small comparison against the always small in the reverse way, since the always small group is always close to the efficiency line, giving them the same condition of new small firms prior to treatment would send them to under-investment territory. Adding 0.261 to the first year pre-treatment average log capital wedge of - 0.01 would give us 0.260. That would suggest that the BNDES was actually giving the right amount of subsidies to the small group, and that handing them the same condition given to medium firms would increase misallocation.

The best way to use the indirect method coupled with an exogenous shock to capture misallocation is as in Bau and Matray (2023), a very recent paper pioneering this combination. Their shock is at the industry-level, through an event study. So any shrinkage of the distance between wedges above the median and the wedges below the median is enough to capture improved misallocation, which is what they report for their exercise on access to improved foreign credit. A next step would be to use similar intuition to this exercise to achieve better measures of misallocation.

8 Conclusion

Summarizing our results. First and foremost, an improvement in credit conditions for some medium firms that were reclassified as small, made their average log capital wedge and average log scale wedge shift significantly to the left of the distribution of their respective wedges. In terms of magnitude, it would be enough to generate a visible fat tail if we start by assuming that different cohorts starts with an equal distribution. That makes the BNDES credit policy of granting noticeable better conditions to the small firms a good

Figure 9: Capital wedges by revenue in 2004



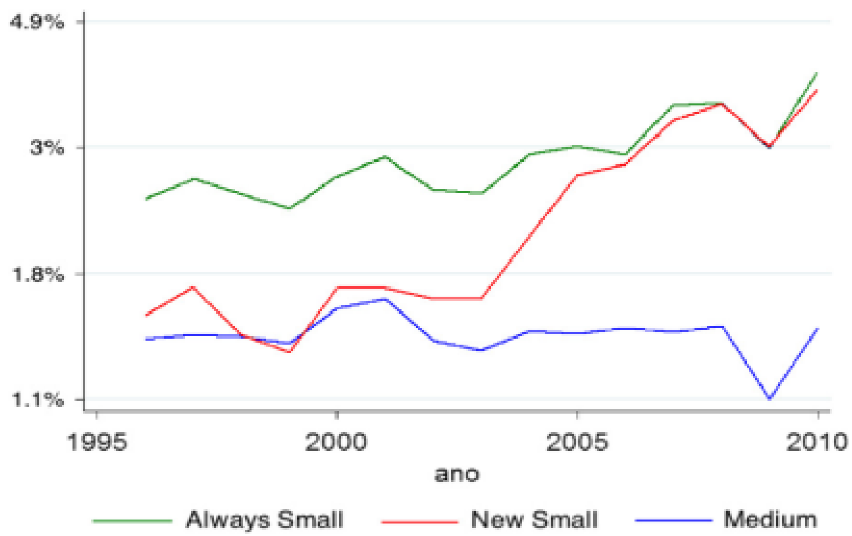
Source: Distribution of log capital wedges by revenue in 2004, showing the existence of a fat tail on the negative side of the smaller revenues

candidate to explain part of the fat tail concentrated at negative wedges of small firms. A first approximation using the efficiency line as a guide to interpreting the misallocation of funds actually suggest that the BNDES credit policy is helping the achievement of allocational efficiency, although this interpretation relies on a stringent assumption of the efficiency line being a useful guide to interpret the misallocation of funds.

The improvement in credit conditions for the new medium firms relative to the always large firms is much smaller and temporary. The contribution of the BNDES policy to the misallocation of funds in the large and medium category could be related to the dynamics of wedges inside the cohort, and not across those cohorts, which is perhaps an even more interesting question, which also apply to the inside of the small cohort, but which we cannot answer without applying the recent developments by Bau and Matray (2023).

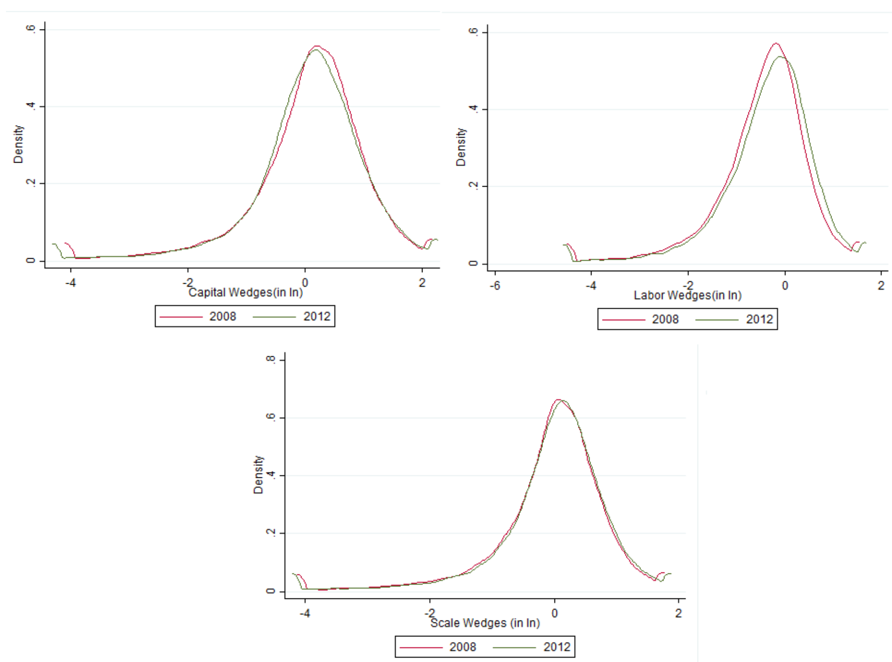
9 Appendix

Figure 10: log[investment/capital stock] new small vs. always small vs. always medium



Source: graph taken from Cavalcanti and Vaz (2017), page 24.

Figure 11: Capital, labor and scale wedges for the years 2008 and 2012



Source: Distribution of log capital, labor and scale wedges for the years 2008 and 2012, generated through the model in section 2.3.

Table 6: Treatment Effects on Capital, Labor and Scale Wedges ($\sigma = 1.5$)

	New Small x Always Small								
	Capital Wedge			Labor Wedge			Scale Wedge		
Eligible*Post	- 0.176***	- 0.165***	- 0.160***	- 0.075	- 0.071	- 0.076	- 0.130**	- 0.121**	- 0.117**
	(0.061)	(0.061)	(0.059)	(0.050)	(0.048)	(0.047)	(0.057)	(0.056)	(0.055)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**
Controls	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**
Obs	45,464	45,460	45,460	45,464	45,460	45,460	45,464	45,460	45,460
R^2	0.428	0.441	0.446	0.528	0.539	0.539	0.437	0.449	0.453
	New Medium x Always Large								
	Capital Wedge			Labor Wedge			Scale Wedge		
Eligible*Post	- 0.066*	- 0.069*	- 0.064	0.020	0.017	0.019	- 0.058	- 0.060	- 0.056
	(0.040)	(0.040)	(0.040)	(0.036)	(0.037)	(0.037)	(0.039)	(0.039)	(0.039)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**
Controls	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**
Obs	17,133	17,128	17,128	17,133	17,128	17,128	17,133	17,128	17,128
R^2	0.510	0.532	0.534	0.596	0.611	0.612	0.512	0.533	0.535

Notes: Results from estimations of New small vs. always small and new medium vs. always large. The first column presents results with firm id and year fixed effects. The second column adds industry fixed-effects. The third column add controls: number of employees and state fixed effects.
*p*0.10 p**0.05 p***0.01*

Table 7: Treatment Effects on Capital, Labor and Scale Wedges ($\sigma = 1.5$) (Event Study)

	New Small x Always Small					
	Capital Wedge		Labor Wedge		Scale Wedge	
5 years before	- 0.015	0.002	- 0.066	- 0.052	- 0.039	- 0.021
	(0.088)	(0.088)	(0.081)	(0.081)	(0.084)	(0.084)
4 years before	0.022	0.033	- 0.043	- 0.041	- 0.000	0.008
	(0.087)	(0.088)	(0.077)	(0.079)	(0.084)	(0.0853)
3 years before	0.036	0.049	0.009	0.022	0.027	0.039
	(0.101)	(0.102)	(0.098)	(0.099)	(0.098)	(0.099)
2 years before	0.019	0.024	0.008	0.020	0.012	0.017
	(0.065)	(0.064)	(0.060)	(0.060)	(0.0629)	(0.063)
1 year before	0	0	0	0	0	0
year of treatment	- 0.039	-0.040	0.006	0.006	- 0.020	- 0.021
	(0.078)	(0.078)	(0.080)	-0.020	(0.078)	(0.080)
1 year after	- 0.133*	- 0.099	- 0.105	- 0.094	-0.114	-0.086
	(0.078)	(0.077)	(0.075)	(0.074)	(0.077)	(0.076)
2 years after	-0.112	-0.0857	- 0.099	- 0.088	-0.091	-0.070
	(0.072)	(0.071)	(0.071)	(0.069)	(0.071)	(0.070)
3 years after	- 0.177**	-0.152*	- 0.098	- 0.096	- 0.145*	- 0.126
	(0.089)	(0.084)	(0.085)	(0.078)	(0.087)	(0.081)
4 years after	- 0.188*	- 0.149	- 0.096	- 0.080	- 0.143	- 0.111
	(0.103)	(0.099)	(0.096)	(0.090)	(0.099)	(0.094)
5 years after	- 0.279**	- 0.232**	- 0.149	- 0.133	- 0.222*	- 0.182*
	(0.122)	(0.116)	(0.105)	(0.098)	(0.115)	(0.110)
6 years after	- 0.264**	- 0.269**	- 0.117	- 0.129	- 0.203	- 0.205*
	(0.135)	(0.127)	(0.103)	(0.096)	(0.126)	(0.119)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Obs	45,464	45,460	45,464	45,460	45,464	45,460
R^2	0.429	0.446	0.528	0.539	0.437	0.453

Notes: Results for estimations in the event study format for new small vs always small. The first column indicate results using firm id and year fixed effects. The second column indicate results adding controls: number of employees and state fixed effects.
*p*0.10 p**0.05 p***0.01*

Table 8: Treatment Effects on Capital, Labor and Scale Wedges ($\sigma = 1.5$) (Event Study)

	New Medium x Always Large					
	Capital Wedge		Labor Wedge		Scale Wedge	
4 years before	0.023	0.019	- 0.020	- 0.015	0.021	0.018
	((0.060))	(0.061)	(0.062)	(0.063)	(0.058)	(0.060)
3 years before	0.017	0.009	0.015	0.021	0.019	0.012
	(0.061)	(0.062)	(0.060)	(0.062)	(0.059)	(0.060)
2 years before	0.002	- 0.002	- 0.026	- 0.022	- 0.001	- 0.005
	(0.049)	(0.050)	(0.0524)	(0.053)	(0.049)	(0.049)
1 year before	0	0	0	0	0	0
Year of treat.	- 0.019	- 0.027	0.045	0.040	- 0.015	-0.022
	(0.041)	(0.042)	(0.040)	(0.040)	(0.040)	(0.041)
1 year after	- 0.046	- 0.052	- 0.003	- 0.000	- 0.042	- 0.047
	(0.039)	(0.041)	(0.038)	(0.039)	(0.039)	(0.040)
2 years after	- 0.109**	- 0.122**	- 0.000	- 0.007	- 0.097*	- 0.108**
	(0.055)	(0.055)	(0.054)	(0.055)	(0.053)	(0.053)
3 years after	- 0.048	- 0.048	0.049	0.050	- 0.035	- 0.035
	(0.052)	(0.052)	(0.049)	(0.0503)	(0.050)	(0.050)
4 years after	- 0.095	- 0.091	- 0.043	- 0.035	- 0.090	- 0.085
	(0.066)	(0.065)	(0.061)	(0.0605)	(0.065)	(0.063)
5 years after	- 0.017	- 0.003	0.020	0.032	- 0.012	0.002
	(0.065)	(0.066)	(0.059)	(0.061)	(0.063)	(0.063)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Obs	17,133	17,128	17,133	17,128	17,133	17,128
R^2	0.511	0.534	0.596	0.612	0.512	0.535

Notes: Results for estimations in the event study format for new medium vs always large. The first column indicate results using firm id and year fixed effects. The second column indicate results adding controls: number of employees and state fixed effects.
*p*0.10 p**0.05 p***0.01*

Table 9: Treatment Effects on Capital, Labor and Scale Wedges ($sigma = 5$)

	New Small x Always Small								
	Capital Wedge			Labor Wedge			Scale Wedge		
Eligible*Post	- 0.173***	- 0.163***	- 0.158***	- 0.077	- 0.075	- 0.078	- 0.120**	- 0.112**	- 0.109**
	(0.063)	(0.062)	(0.060)	(0.053)	(0.051)	(0.050)	(0.057)	(0.056)	(0.055)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**
Controls	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**
Obs	45,464	45,460	45,460	45,464	45,460	45,460	45,464	45,460	45,460
R^2	0.428	0.441	0.446	0.523	0.532	0.533	0.420	0.432	0.435
	New Medium x Always Large								
	Capital Wedge			Labor Wedge			Scale Wedge		
Eligible*Post	- 0.076*	- 0.080**	- 0.075*	0.080**	0.076*	0.078*	- 0.063*	- 0.067*	- 0.062
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.038)	(0.038)	(0.039)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**
Controls	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**
Obs	17,133	17,128	17,128	17,133	17,128	17,128	17,133	17,128	17,128
R^2	0.507	0.528	0.530	0.563	0.580	0.581	0.502	0.523	0.524

Notes: Results from estimations of New small vs. always small and new medium vs. always large. The first column presents results with firm id and year fixed effects. The second column adds industry fixed-effects. The third column add controls: number of employees and state fixed effects.
*p*0.10 p**0.05 p***0.01*

Table 10: Treatment Effects on Capital, Labor and Scale Wedges ($\sigma = 5$) (Event Study)

	New Small x Always Small					
	Capital Wedge		Labor Wedge		Scale Wedge	
5 years before	- 0.016	0.007	- 0.061	- 0.065	- 0.039	- 0.017
	(0.088)	(0.087)	(0.091)	(0.092)	(0.084)	(0.084)
4 years before	0.013	0.032	- 0.008	- 0.025	-0.002	0.012
	(0.087)	(0.088)	(0.091)	(0.091)	(0.084)	(0.085)
3 years before	0.031	0.050	0.011	0.008	0.028	0.044
	(0.100)	(0.102)	(0.110)	(0.110)	(0.097)	(0.098)
2 years before	0.010	0.018	0.010	0.017	0.013	0.019
	(0.065)	(0.065)	(0.063)	(0.063)	(0.063)	(0.063)
1 year before	0	0	0	0	0	0
Year of treat.	- 0.048	- 0.047	0.015	0.011	- 0.011	- 0.012
	(0.080)	(0.080)	(0.086)	(0.087)	(0.078)	(0.078)
1 year after	- 0.134*	- 0.095	- 0.092	- 0.096	- 0.112	- 0.082
	(0.080)	(0.079)	(0.092)	(0.092)	(0.077)	(0.076)
2 years after	- 0.118	- 0.085	- 0.089	- 0.094	- 0.088	- 0.064
	(0.074)	(0.073)	(0.078)	(0.077)	(0.072)	(0.071)
3 years after	- 0.188**	- 0.156*	- 0.088	- 0.097	- 0.138	- 0.117
	(0.090)	(0.084)	(0.095)	(0.090)	(0.087)	(0.082)
4 years after	- 0.190*	- 0.148	- 0.073	- 0.068	- 0.133	- 0.101
	(0.106)	(0.101)	(0.102)	(0.098)	(0.101)	(0.096)
5 years after	- 0.267**	- 0.217*	- 0.119	- 0.122	- 0.200*	- 0.159
	(0.126)	(0.120)	(0.112)	(0.109)	(0.117)	(0.112)
6 years after	- 0.255*	- 0.259**	- 0.147	- 0.164	- 0.190	- 0.189
	(0.136)	(0.129)	(0.108)	(0.103)	(0.126)	(0.119)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Obs	45,464	45,460	45,464	45,460	45,464	45,460
R^2	0.428	0.446	0.503	0.514	0.420	0.420

Notes: Results for estimations in the event study format for new small vs always small. The first column indicate results using firm id and year fixed effects. The second column indicate results adding controls: number of employees and state fixed effects.
*p*0.10 p**0.05 p***0.01*

Table 11: Treatment Effects on Capital, Labor and Scale Wedges ($\sigma = 3$) (Event Study)

	New Medium x Always Large					
	Capital Wedge		Labor Wedge		Scale Wedge	
4 years before	0.013	0.007	0.034	0.042	0.015	0.010
	(0.061)	(0.062)	(0.068)	(0.069)	(0.059	(0.060)
3 years before	0.019	0.011	0.024	0.027	0.016	0.009
	(0.061)	(0.062)	(0.068)	(0.069)	(0.059)	(0.0608)
2 years before	0.001	- 0.004	0.013	0.023	- 0.001	- 0.005
	(0.050)	(0.051)	(0.059)	(0.060)	(0.049)	(0.050)
1 year before	0	0	0	0	0	0
Year of treat.	- 0.021	- 0.032	0.114**	0.114**	- 0.014	- 0.024
	(0.042)	(0.042)	(0.054)	(0.054)	(0.040)	(0.041)
1 year after	- 0.059	- 0.069	0.098*	0.106**	- 0.049	- 0.056
	(0.041)	(0.042)	(0.051)	(0.052)	(0.039)	(0.041)
2 years after	- 0.111**	- 0.124**	0.062	0.054	- 0.099*	- 0.111**
	(0.055)	(0.055)	(0.061)	(0.062)	(0.054)	(0.054)
3 years after	- 0.065	- 0.068	0.142**	0.145**	- 0.044	- 0.045
	(0.052)	(0.053)	(0.057)	(0.058)	(0.050)	(0.050)
4 years after	- 0.130*	- 0.127*	0.080	0.084	- 0.114*	- 0.110*
	(0.068)	(0.066)	(0.067)	(0.067)	(0.065)	(0.064)
5 years after	- 0.023	- 0.009	0.083	0.095	- 0.019	- 0.004
	(0.066)	(0.066)	(0.066)	(0.067)	(0.062)	(0.063)
Unit FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Year FE	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Industry FE	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Controls	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Obs	17,133	17,128	17,133	17,128	17,133	17,128
R^2	0.507	0.530	0.563	0.581	0.502	0.525

Notes: Results for estimations in the event study format for new medium vs always large. The first column indicate results using firm id and year fixed effects. The second column indicate results adding controls: number of employees and state fixed effects.
*p*0.10 p**0.05 p***0.01*

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