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Is the Brazilian labor market granular?

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Abstract

This study explores the impact of large firms, often referred to as “big grains,” on hiring and firing cycles in the Brazilian labor market. We found strong support for the granular hypothesis. Our methodology involved analyzing the power-law distribution, granular residuals, and the granular size of the labor market. Key findings include the observation that firms exhibit a power-law distribution based on their workforce size, with large companies' idiosyncratic shocks significantly influencing hiring and firing cycles. In particular, the service sector plays a substantial role in explaining these cycles, while manufacturing has limited explanatory power. We determined that the granular size of the Brazilian labor market consists of 15 firms engaged in public services, and private companies have a relatively minor impact on hiring and firing cycles. The policy implication here is that addressing periods of high unemployment in Brazil may be more effectively achieved by investing in public services rather than providing fiscal stimulus for manufacturing. This study contributes to the global body of evidence on labor market granularity and is compared with the existing research focused on Germany. We find that the Brazilian labor market is less granular than the German one.

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1. Introduction

In 2023, the Brazilian federal government established a dedicated ministry to strengthen the role of micro and small businesses in job creation. These businesses, despite their size, are responsible for around 80% of job opportunities in Brazil. Do they, rather than large corporations, drive the hiring and firing cycles in the Brazilian labor market?

Following international evidence, the primary source of job turnover is in large, well-established companies (Davis *et al.*, 1996). This phenomenon, which contributes significantly to fluctuations in unemployment rates, can be explained by the concept of "granularity" (Kovalenko *et al.*, 2022).

Carlsson *et al.* (2021) highlighted the significant role of idiosyncratic shocks in labor market cycles. They analyzed how Swedish firms react to various shocks like technological advancements or market changes and their impact on workforce dynamics. Their findings indicate that companies often adjust their workforce through hiring and firing in response to these shocks. The extent of these adjustments depends on factors such as company size and shock persistence, with larger firms and enduring shocks leading to more substantial changes. However, their study did not delve into the granular hypothesis.

The granular hypothesis recognizes that a few major companies, or "grains," coexist with many smaller ones, challenging the belief that individual enterprise shocks are diluted by the law of large numbers (Gabaix, 2011). This idea aligns with skewed firm size distributions following a power law, where firm-level shocks from disproportionately large firms persist. The concept of "granular residual" is useful, as it aggregates idiosyncratic shocks to the largest firms, weighted by size. We can quantify its impact on aggregate quantities through regressions and R^2 statistics. Neglecting to calibrate for the appropriate number of firms can lead to underestimating or exaggerating the granular residual (Blanco-Arroyo et al., 2018). This study applies these ideas to the question, "Is the Brazilian labor market granular?"

We precisely explain how large companies' shocks contribute to the overall firing and hiring cycles in the labor market. In particular, we investigate whether specific sectors, such as industrial and service, have a more significant influence on hiring and firing cycles compared to the overall labor market. Furthermore, we analyze the role of the labor market in private enterprises separately from public companies.

Compared to a linear trend, the Brazilian labor market shows a cyclical pattern, as illustrated in Figure 1, which displays formal job growth in Brazil from 1996 to 2019. Do these cycles stem from overall economic shocks or from idiosyncratic shocks to major corporations?

The first possibility makes sense in a market with evenly-sized companies, where negative idiosyncratic shocks to some firms offset positive shocks in others. However, data indicates that Brazilian businesses follow a power-law distribution, where shocks to larger firms have a more significant impact on the business cycle (Da Silva *et al.*, 2018; Silva and Da Silva, 2020). This supports the third possibility, leading us to apply the granularity hypothesis to analyze hiring and firing cycles in the Brazilian labor market, following the pioneering approach of Kovalenko *et al.* (2022) in their study of the German labor market. Since Kovalenko *et al.* (2022) is the only study on labor market granularity, we compare our Brazilian labor market results with their German labor market analysis.

It is crucial to remember that this analysis captures correlations and does not imply causation. Therefore, although large firms appear to influence employment dynamics, we cannot conclude that they are the direct cause of these cycles.

The following is how the paper is organized. First, we provide the data and methodology that were used. Following that, we give descriptive statistics. The results are then reported. Then, we compare our findings to those of previous studies. The final part presents concluding comments.

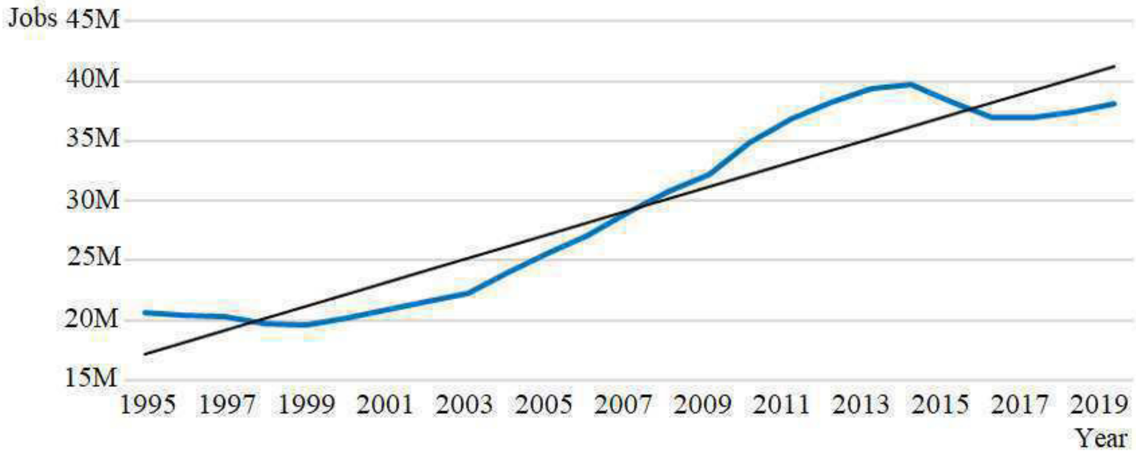

Figure 1. Formal job growth in Brazil from 1996 to 2019, where M stands for millions.

2. Data and methods

From 1996 to 2019, we obtained data on the total number of employees per company from the RAIS (Annual Social Information List) database and calculated the total number of formal occupations in Brazil using the CAGED (General Register of Employed and Unemployed) database, both provided by the Brazilian Ministry of Labor. Unlike Kovalenko *et al.* (2022), we do not have quarterly statistics, so we do not need to account for seasonality. Our data is aggregated by CNPJ, the National Register of Legal Businesses, an identity number for businesses of taxation relevance, including firms, partnerships, and foundations.

Our sample consists of the 1000 largest Brazilian companies listed in the RAIS database, with some companies entering or leaving the sample over time. About half of these companies are public, starting with an average of 7,000 employees, growing to just over 9,000 by the end, and averaging 8,900 employees during the entire period. The other half are private, smaller on average, beginning with around 3,000 employees, increasing to 5,000 by the end of the period, and maintaining an average of 4,100 employees throughout.

Because a power law determining firm distribution is required for granularity, we started by using the Gabaix and Ibragimov (2011) method to estimate coefficients and test if employee numbers follow a power law. We used ordinary least squares to derive estimates with this equation:

$$\ln\left(\text{rank}_i - \tfrac{1}{2}\right) = a + \alpha \ln \frac{\text{employees}_i}{\text{employees}_m}, \tag{1}$$

where rank_i represents the company's position in the ranking, sorted from largest to smallest based on employees_i (the number of employees at the company *i*) and employees_m (the smallest number of employees among the companies in the sample).

To investigate the granular hypothesis regarding the influence of large companies *K* on hiring and firing cycles, we calculate the granular residual Γ_t as follows:

$$\Gamma_t = \sum_{i=1}^{K} \frac{\text{employees}_{it}}{\text{total employment}_t} \left(g_{it} - g_t \right). \tag{2}$$

Here, employees_{it} represents the number of employees at a specific firm *i* at time *t*, $\text{total employment}_t$ is the total population employment at time *t*, g_{it} refers to the growth rate of the number of employees at the largest firms in *t*, and g_t is the labor market's overall formal employment growth rate in *t*. We then use ordinary least squares regression to analyze the relationship between the growth rate of formal employment and the granular residual.

To adequately test the granular hypothesis, the required number of lags must first be determined. Without lags, the impact of large grains on hiring and firing cycles is temporary, limited to the current period, and may not always reflect reality. The Akaike information criterion provides a guideline for determining the number of lags (Kovalenko *et al.*, 2022).

Furthermore, using an inappropriate number of firms *K* in equation (2) can lead to an inaccurate estimation of a firm's contribution to hiring and firing cycles. Blanco-Arroyo *et al.* (2018) suggest a method for finding the granular size K^*. This involves comparing the explanatory power of a firm's granular residual by evaluating a weighted curve (the same equation (2)) against another curve with identical weights after making $g_{it} = g_t$ in equation (2). The function *C*(*L*)'s "granular curve" is

$$C(L) = \frac{1}{Q} \sum_{K=1}^{Q} \mathrm{R}^2(K, L). \tag{3}$$

Here, *Q* is an arbitrary number of firms. In the Appendix, we describe how equation (3) is used to calculate the granular size K^*.

The empirical model is defined as follows:

$$G_t = \beta_1 + \beta_2 \Gamma_t + \varepsilon_t. \tag{4}$$

Here, G_t is the growth rate of the formal jobs in time period *t*, β_1 and β_2 are parameters estimated using ordinary least squares, as described in Gabaix (2011), where β_1 represents the average value of the growth rate of the number of jobs relative to the granular residual, β_2 is the sensitivity of the growth rate to the granular residual, and ε_t is the estimated error. The adjusted R^2, calculated for this model, quantifies how well the granular residual explains hiring and firing cycles.

3. Descriptive statistics

Table 1 shows that as the sample size grows from 50 to 1000 firms, the average number of employees decreases over the period from 1996 to 2019. A positive asymmetry value suggests that the sample is skewed to the left, meaning that smaller enterprises are closer to the mean. Additionally, excess kurtosis values exceeding three indicate leptokurtosis.

Table 2 provides descriptive statistics for employee growth rates. The aggregate growth rates for the largest 50, 100, 200, and 500 enterprises are lower than that for the

1000 largest firms. This suggests that job growth during the period primarily occurred in smaller firms, as mentioned earlier.

We found no evidence to reject the hypothesis that growth rates follow a normal distribution at the 5% significance level when we look at the kurtosis values. This aligns with Dosi *et al.*'s (2019) assertion that while firm size distribution may follow a power law, the growth rates they experience should still conform to a normal distribution.

Table 1. Companies' descriptive statistics in relation to the number of employees.

Number of firms	*Average number of employees*	*Standard deviation*	*Asymmetry*	*Kurtosis*
50	50,298	66,881	4.80	27.42
100	31,105	51,053	6.30	48.78
200	19,236	38,007	8.43	89.46
500	10,387	25,106	12.62	205.63
1000	6,534	18,168	17.24	389.94

Table 2. Companies' descriptive statistics in relation to the growth rates in the number of employees.

Number of firms	*Growth average*	*Standard deviation*	*Asymmetry*	*Kurtosis*	*Jarque-Bera test*
50	–0.0033	0.0333	0.08	3.38	0.17
100	0.0001	0.0310	0.35	3.70	0.94
200	0.0039	0.0294	0.35	3.53	0.72
500	0.0093	0.0279	0.22	2.87	0.21
1000	0.0296	0.0403	0.61	4.00	2.38

4. Results

As we present the findings in this section, it is important to note that the relationships identified are based on correlations rather than causal inferences. This means that while we can observe significant associations between variables, we cannot definitively establish that changes in one variable directly cause changes in another. This limitation should be kept in mind when interpreting the results and their implications.

4.1 Power law

To support the granular hypothesis, firm size (in terms of employee count) must follow a power-law distribution rather than a normal distribution (Gabaix, 2011). In a power-law distribution, larger firms are more abundant, leading to a slower tail decay. This implies that idiosyncratic shocks to these large grains play a more substantial role in explaining hiring and firing cycles, challenging the conventional idea that only aggregate shocks influence these cycles observed under a normal distribution.

The Jarque-Bera test rejects the null hypothesis that the distribution of firms' number of employees is Gaussian. For all the number of firms in Table 1, the test yields much higher values than the critical value of 5.99, as it follows a chi-square distribution with two degrees of freedom. Meanwhile, the high R^2 value in Table 3 from equation (1) suggests that we cannot dismiss the possibility that firms follow a power-law distribution.

Table 3. The power law for the firm size distribution in terms of employee count.

Number of firms	R^2	*Intercept*	*Pareto exponent*
1000	0.99	6.92	–1.60
		(< 0.001)	(< 0.001)

Note: *p*-values are in brackets.

4.2 Granular residual

Following Kovalenko *et al.* (2022), we use the Akaike information criterion to identify the number of lags needed for testing the granular hypothesis, with a maximum lag duration of two years. This figure is derived from Kovalenko *et al.*'s selection of six lags, equivalent to a year and a half in their quarterly data. The results are presented in Table 4.

When we exclude lags in the model, values decrease, suggesting that the impact of large grains on hiring and firing cycles is short-lived within the current period. Consequently, we employed the lag-free model for data analysis.

Table 4. The number of lags selected according to the Akaike information criterion.

	Number of firms			
Lags	50	100	200	500
0	−6.73	−6.74	−6.76	−6.72
1	−6.37	−6.42	−6.46	−6.45
2	−6.29	−6.33	−6.38	−6.37

Since we employed annual data, we refrained from seasonally adjusting the quarterly results. Table 5 provides a summary of the results from equation (4), where only the granular residual was used as a regressor.

Table 5. Estimation of equation (4).

	All firms				*Manufactures*	*Services*
	Top 50	Top 100	Top 200	Top 500	Top 100	Top 100
Granular residual	−7.07	−6.29	−5.69	−5.03	2.64	−4.17
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.6984)	(0.0044)
Intercept	0.0090	0.0092	0.0098	0.0110	0.0289	0.0166
	(0.2566)	(0.2486)	(0.2231)	(0.1556)	(0.0129)	(0.0316)
F-statistic	22.14	21.48	20.44	22.18	0.05	10.20
Adj. R^2	0.50	0.49	0.48	0.50	−0.04	0.29
Labor market, %	8.53	10.55	13.05	17.61	1.53	10.29

Note: p-values are in brackets. When calculating the labor market percentage, the average from 1996 to 2019 is utilized.

The relatively high adjusted R^2 values cannot reject the granular hypothesis in the Brazilian labor market. In particular, the granular residual's explanatory power surpasses the labor market's firm representation percentage. This criterion (Gabaix, 2011) reveals the disproportionate impact large firms have on aggregate market dynamics, beyond their numerical representation in the labor market. Thus, this finding shows the significant influence of idiosyncratic shocks from large firms on hiring and firing cycles.

One intriguing finding is that manufacturing does not seem to be correlated with employment trends in the Brazilian labor market. This is indicated by the non-significant granular residual and a negative adjusted R^2. Several possible explanations include: 1) Manufacturing has a smaller share compared to other sectors; 2) The manufacturing workforce is shrinking (as shown in Figure 2); and 3) The largest employers in the Brazilian industrial sector are not big grains. For example, the top company that once ranked 20th in job creation in 1996 has now dropped to 68th place in 2019.

In Kovalenko *et al.* (2022), manufacturing's explanatory power in the German labor market is weaker compared to other specifications, and the granular hypothesis was not disproven. However, a notable contrast arises: the top 100 German manufacturers account for 14.7% of jobs, whereas in Brazil, they represent only 1.5% of formal job positions. This indicates that German manufacturers are relatively larger grains than their

Brazilian counterparts. The largest German company employed approximately 62,000 individuals, whereas in Brazil, the largest company had 23,000 employees in 1997. It is important to note that our data are based on CNPJ registration, not establishments as in Kovalenko *et al.*, suggesting that the actual difference may be even more substantial.

It is worth mentioning that the observed association between sector-specific variables and employment trends reveals significant correlations in the above analyses. However, these findings should not be interpreted as evidence of a direct causal relationship, as the analyses are inherently correlational.

4.3 Granular size

Figure 3 shows that when $K^* = 15$, the weighted curve (equation (2)) crosses the equal-weight curve. The two curves move very near to each other after the crossing, indicating that the explanatory power owing to the differing weights becomes gradually irrelevant.

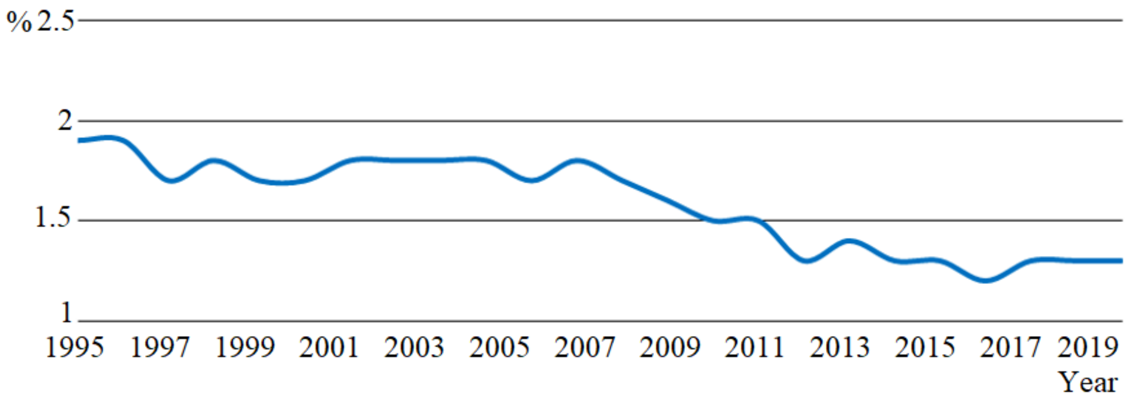

Figure 2. Manufacturing jobs as a percentage of total jobs.

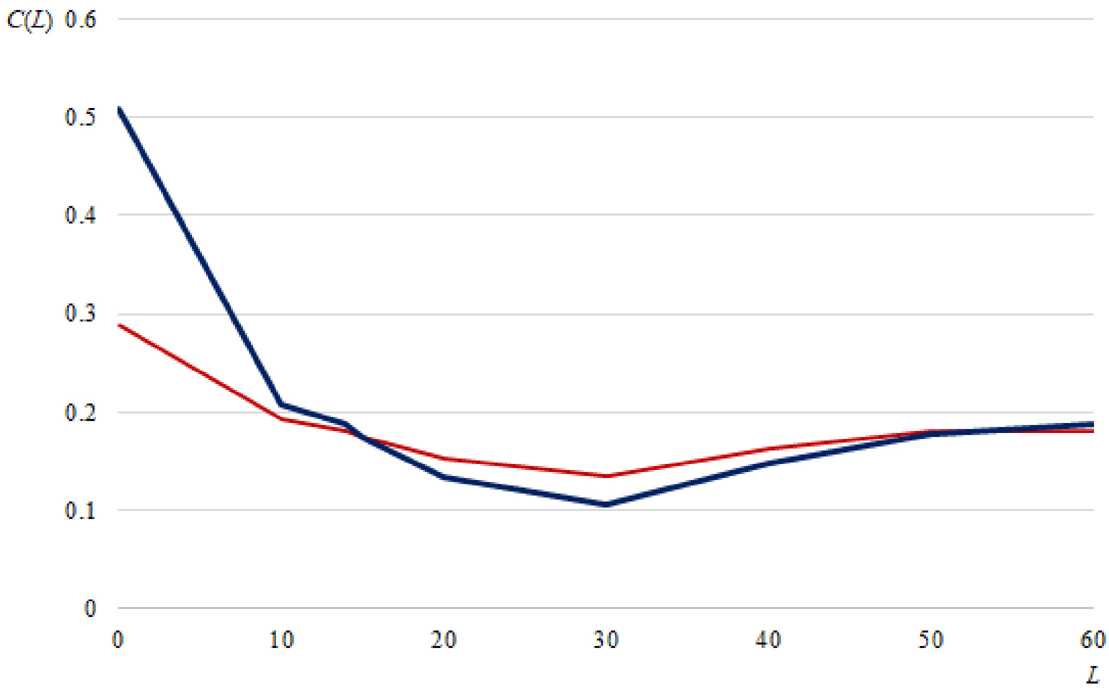

Figure 3. The granular size of the Brazilian labor market.
Note: The weighted curve (equation (2)) is represented by the blue line, and the equal-weight curve is the red line.

These 15 companies that define the granular size of the Brazilian job market are linked to the government. When we reestimate equation (4) using only private companies, the results are shown in Table 6.

Table 6. Estimation of equation (4) using only private companies.

	Number of firms			
	Top 50	Top 100	Top 200	Top 300
Granular residual	19.43	18.55	12.62	8.17
	(0.0631)	(0.0468)	(0.1034)	(0.1829)
Intercept	0.04	0.04	0.04	0.03
	(0.0002)	(0.0002)	(0.0004)	(0.0006)
F-statistic	3.85	4.46	2.90	1.90
Adj. R^2	0.11	0.14	0.08	0.04
Labor market, %	2	3	4	5

Note: *p*-values are in brackets. When calculating the labor market percentage, the average from 1996 to 2019 is utilized.

The coefficient for the granular residual is only statistically significant when the number of firms equals 100. Furthermore, the explanatory power is significantly lower compared to using all companies (as shown in Table 5). This suggests that the hiring and firing cycles in the Brazilian labor market are minimally influenced by idiosyncratic shocks from Brazilian private companies. This directly relates to our earlier finding that private firm manufacturing does not impact employment trends in Brazil's labor market.

This important result may be hypothesized to stem from two factors. First, the private businesses in our sample are smaller in size compared to the public companies. The top CNPJ among public companies has over 400,000 employees, while among private enterprises, the leading CNPJ has approximately 20,000 employees. This difference is partially due to private corporations having multiple CNPJs for various activities or regions.

Second, a theoretical interpretation could be offered for the observed discrepancy in the Pareto exponents between the distribution of private firms and the entire sample. The absolute value of the Pareto exponent for the distribution of private enterprises (2.4; Table 7) is notably higher than the exponent for the entire sample (1.6; Table 3). This is due to the smaller workforce in large private companies compared to the overall sample, resulting in larger grains being relatively smaller, a faster tail decay, and consequently, a decrease in explanatory power. These two hypotheses, albeit based on observed patterns and logical deduction, require additional empirical validation to determine their conclusive impact on the labor market dynamics under consideration.

Table 7. The power law for the firm size distribution in terms of employee count when only private companies are considered.

Number of firms	R^2	*Intercept*	*Pareto exponent*
100	0.98	4.71	–2.96
		(< 0.0001)	(< 0.001)
400	0.98	6.15	–2.38
		(< 0.0001)	(< 0.001)

Note: *p*-values are in brackets.

5. Discussion and conclusion

Job turnover is predominantly attributed to large corporations, also known as big grains. This phenomenon can be measured in terms of granularity. The present study shows that the granular hypothesis regarding the Brazilian labor market cannot be rejected.

Our findings in the Brazilian labor market align with Kovalenko *et al.*'s (2022) results in the German labor market, supporting the granular hypothesis. We also observe that the granular hypothesis' explanatory power diminishes when we focus solely on companies in manufacturing or services. In particular, when we isolate manufacturing, the granular residual loses its statistical significance, implying that manufacturing does not account for hiring and firing cycles in Brazil. This may be due to the absence of big grains within the Brazilian manufacturing sector.

One disparity in our results compared to Kovalenko *et al.* pertains to the extent of explanatory power. In all specifications, we observed lower adjusted R^2 values for Brazil, indicating that the Brazilian labor market is less granular than the German one. Furthermore, our consideration of companies by CNPJ, as opposed to Kovalenko *et al.*'s focus on establishments, may further accentuate the differences between the labor markets of the two countries.

We found that manufacturing had a minimal impact on hiring and firing cycles in the Brazilian labor market. This suggests that job-protection policies should not focus on manufacturing. A study by Geracy *et al.* (2019) supports our findings. Since 2007, tax policies have been used to stimulate the economy and create jobs, including taxing industrialized goods. However, Geracy *et al.* found that this strategy had little influence on the labor market from 2007 to 2012.

In our study, we discovered that the major players in the Brazilian job market are government-affiliated companies, highlighting the market's dependence on government employment. This suggests a lower degree of labor market "fluidity" (Davis and Haltiwanger, 2014) compared to more private-sector-driven economies, which can hinder overall productivity growth and economic development. Furthermore, the presence of numerous small and low-productivity firms can pose another obstacle to Brazilian economic growth (Firpo and Pieri, 2017).

To summarize, our study yielded five key findings: 1) Companies follow a power-law distribution based on their number of employees. 2) The hiring and firing cycles in the Brazilian labor market are significantly influenced by idiosyncratic shocks in large companies, supporting the granular hypothesis. 3) Manufacturing has limited explanatory power, while the service sector plays a significant role in these cycles. 4) The Brazilian labor market's granular size is 15 firms connected to public service provision. 5) Private companies have a minimal impact on hiring and firing cycles in the Brazilian labor market. Therefore, the findings strongly suggest that addressing high unemployment rates in Brazil can be accomplished more efficiently by investing in public services rather than providing fiscal stimulus to manufacturing.

Our study highlights significant correlations between large firms and employment cycles in the Brazilian labor market. However, these findings are based on correlational analysis, and caution should be exercised in interpreting them as causal relationships. Future research should aim to explore these relationships further to establish causality more definitively.

Appendix

In this Appendix, we describe how to compute the granular size K^* using equation (3). Our aim is to assess how R^2 reacts to the gradual exclusion of the largest firms by increasing *L*. We want to see how the granular curve performs as we replace the top *L* firms in the sample with the $Q + 1, \ldots, Q + L$ following firms. For each *L* value, we run *Q* regressions using the granular residual (the curve with weights) as the explanatory variable. $C(L)$ represents the average R^2 for these *Q* regressions.

Furthermore, the equal-weight curve estimates the impact of shocks from equally-sized firms, expected to be minor. We anticipate observing a shift from the granular curve $C(L)$ towards the equal-weight curve as we remove the *L* largest firms from the granular residual. The granular size K^* corresponds to the *L* value where the curve $C(L)$ intersects the equal-weight curve for the first time.

To streamline the computation process and reduce the number of regressions to under 1000, we start by assuming $Q = 40$. Then, we run regressions for the subset of firms *L* at intervals of ten ($L = 0$, 10, 20, and so on) until we observe the intersection of curves with and without weights. For each *L* value, we run regressions with variable *K*, incrementing by twenty up to 160 (i.e., $K = 20, 40, ..., 160$). When we identify a value of *K* where $C(L)$ falls below the R^2 value obtained without weights, we calculate $C(L)$ and run regressions for intermediate *L* values to pinpoint the granular size.

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