The Cleansing and Sullying Effects of Recessions in Heterogeneous Sectors

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Abstract

Using rich administrative data from Brazil, I study how worker reallocation in recessions impacts sorting, match quality, and aggregate productivity in heterogeneous sectors. My first finding is that the percentage of new hires who are high-type workers increases in all sectors except farming during recessions. Therefore, I find evidence for a cleansing effect of recessions: new hires are better. The second finding, however, is that the share of employment that accrues to high types decreases during recessions for all sectors as well. Thus, there is also a sullying effect of recessions: employers are worse. I then investigate the evolution of match quality and find that overall sorting improves for all sectors. In conclusion, I also examine how the reallocation of workers and jobs and changes in match quality affect aggregate productivity. A decomposition exercise shows that reallocation during recessions impacts sectors heterogeneously. A counterfactual analysis shows that the services sector, which relies more on labor, sees a higher adverse impact in recessions from the sullying effect, while the cleansing effect prevails in manufacturing.

Keywords: Job Ladder, Business Cycles, Firm Dynamics, Frictions, Poaching, On-the-Job Search, Unemployment, Vacancies, Worker Flows, Productivity Growth, Sector Heterogeneity.

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1 Introduction

Is the change in match quality over the cycle heterogeneous among different economic sectors? What are the implications of such change for productivity growth? If recessions are cleansing, in the sense that they wipe out less productive matches in the labor market[1], why do I see productivity growth decelerate or even fall for some sectors? The implications of the changes in quality of workers and firms and overall productivity growth over the business cycle are very important for policy-makers and have been the subject of an ongoing debate. However, there is still no consensus about these questions [2] and even less on how heterogeneous sectors are impacted differently. Understanding these dynamics better is important for many reasons, including identifying the sources of productivity growth (Bagger, Fontaine, Galenianos and Trapeznikova (2020)[1]).

According to Crane, Hyatt and Murray (2020)[13] (hereafter CHM), there are two competing channels through which economic downturns might affect job match quality. There is a traditional "cleansing effect"—that is, less productive matches are destroyed in recessions—and a possible "sullying effect" famously posited by Barlevy (2002)[4]—that is, good workers may find themselves stuck in worse matches in downturns since there are fewer job opportunities. However, little is known empirically about how economic cycles affect the quality of the distribution of workers and firms, especially in heterogeneous sectors.

In this paper, I contribute to this debate, using a rich Brazilian confidential administrative labor market dataset (RAIS), covering over 5.5 million establishments, and Valor Pro data on firm balance sheets. I consider 3 main GDP supply-side sectors: agriculture, manufacturing and services. I find that there is a sullying effect of recessions for firms that is similar across all sectors, along the lines of the impact elaborated by Barlevy (2002)[4], as the share of employment that accrues to high-type workers decreases during recessions. This contrasts with the cleansing effect that I observe on

[1]Following the idea first emphasized by Schumpeter (1939))

[2]See, for example, Foster, Grim and Haltiwanger, 2016 [17].)

the workers' side in all sectors except farming. Crane et al. (2021) [13] find similar cleansing and sullying effects of recessions, using US aggregate data. Next, I investigate the evolution of match quality and find that overall sorting improves in all sectors, as the correlation of firm and worker rank increases in recessions. This corroborates the evidence that the cleansing effect on the worker side is more pronounced within better firms.

The last part of my analysis links these cleansing and sullying effects of recessions to productivity growth. A decomposition exercise in the spirit of Haltiwanger et al. (2001) shows that reallocation during recessions impacts sectors heterogeneously. A counterfactual analysis shows that the services sector, which relies more than manufacturing and agriculture on labor, sees a more adverse impact from the sullying effect. Thus, I present new evidence that the movement of workers across firms during crises compromises productivity growth in this sector more than in others.

To show that recessions shift the distribution of employment toward high-rank workers, I rank workers into three terciles based on their average tenure in my sample period; this methodology is similar to that in CHM (2021). I find that a one percentage point decrease in Hodrick-Prescott (HP) detrended GDP is associated with a decline of 0.43 percentage points in the share of low-rank workers in the manufacturing sector, 0.14 in the services sector and 0.24 in the aggregate economy. Meanwhile, a downward deviation of GDP of the same percentage point magnitude from its HP trend brings up the share of high-rank workers by 0.37 percentage points in the manufacturing sector, 0.17 in the services sector and 0.024 in the aggregate economy. I also find that there is a cyclical increase in new hires of high-ranked workers from poaching and a decrease in low-ranked workers from nonemployment (in the formal market) in economic downturns.

To analyze firms, I also use a methodology common in the literature (see Crane et al., 2020 [13]) to rank firms and study the dynamics of the employment creation of heterogeneous firms through cycle. The idea of the rank in this case is to proxy a job ladder [3]. I find that better-ranked firms

[3]A job ladder is a way to rationalize the dynamics of the allocation of workers to jobs. The basic idea of the job

are more sensitive to economic cycles. Additionally, this effect is similar across sectors. For every percentage point decline in the GDP rate relative to its HP trend, the employment share of low-rank firms increases by 0.35 percentage points in the farming sector, by 0.29 in the manufacturing sector, by 0.23 in the services sector and by 0.25 in the aggregate economy. On the other hand, a decrease in GDP of the same percentage point magnitude is associated with an increase in the employment share of high-rank firms of 0.0266 in the farming sector, 0.355 in the manufacturing sector, 0.23 in the services sector and 0.26 in the aggregate economy. This is a consequence of the slowdown of the job-ladder mechanism during recessions. This part of the analysis leads to the conclusion that recessions are sullying for firms, as the pool of jobs available in this period shifts toward less productive firms confronting the cleansing effect within workers.

I then investigate the evolution of match quality and find that overall sorting improves for all sectors as the share of high-rank workers at high-rank firms increases. A one percentage point decrease in HP-detrended GDP is associated with a 0.07 percentage point decline in the manufacturing sector share of employment of low-rank workers at high-rank firms and a 0.092 decline in the services sector. In this episode, the total labor share of low-rank workers at high-rank firms declines by 0.075 percentage points. At the same time, the share of high-rank workers at high-rank firms increases by 0.04 percentage points in manufacturing, 0.06 in the services sector and 0.04 in the aggregate economy.

As important as understanding the reallocation of workers and firms is assessing the aggregate economic consequences of this reallocation throughout the cycle. I proceed by creating a measure of labor productivity. I merge the RAIS data with a database on firm balance sheets called Valor Pro, a privately owned firm database with yearly balance sheet information for over 7,000 medium and large Brazilian firms. I then propose a widely used methodology to decompose the aggregate labor productivity as suggested by Foster, Haltiwanger and Krizan (2001) [18], which is a modified

ladder is that workers are more productive in some jobs than in others, according to Moscarini and Postel-Vinay (2018).

version of the method used by Baily, Hulten, and Campbell (1992)[3]. I find that movements of workers within firms contribute positively to productivity growth in recessions, meaning that firms hire more productive workers during economic downturns. This movement is homogeneous among sectors. However, the sullying effect on the firm side compromises productivity growth, especially in the services sector, which is more labor intensive. In unreported analysis, I find that results are robust to permitting firms to change ranks over time.

I conclude that that there is a deterioration in firms' creation of new jobs in recessions as movements along the job ladder decelerate. Meanwhile, workers that remain employed in recessions are on average more productive, which counterbalances this cleansing effect of recessions. These movements are similar across different economic sectors but have a heterogeneous effect on productivity growth. The results presented here cannot be disregarded in the design of policies to help firms and workers recover from economic downturns.

CONTRIBUTION TO THE LITERATURE. This paper contributes to several strands of literature. First, it relies on rich microdata to explore match quality over the business cycle and cyclical reallocation of workers along the job ladder. The conclusions here challenge the Schumpeterian idea of creative destruction and previous work in the 1990s that formalizes the notion that recessions promote solely a more efficient allocation of resources by "cleansing" less efficient production, as articulated by Hall (1991,2000)[21][22], Mortensen and Pissarides (1994) [31], Caballero and Hammour (1994, 1996)[10] [11], Lee and Mukoyama (2007)[28], and Gomes et al. (2001)[20].

The results presented here reinforce that there is a sullying effect of recessions, a theory posited by Barlevy (2002)[4], by proving that reallocation during crises can shift the labor market to a worse equilibrium, as jobs created in recessions tend to be worse. Fewer workers are allocated to jobs where they are more productive. Other recent evidence on the sullying effect of recessions on the labor market appears in Baydur and Mukoyama (2019) [7] and Nakamura et al. (2019) [33]. Evidence at the micro level supports that jobs created during recessions are usually less productive, less well paid, and less likely to last (Bils (1985)[8], Bowlus (1995)[9] and Davis et al. (1996)[15]) and, more recently, Mongey and Violante (2020)[30]. Some work has been done that shows evidence of worse compensation paths for matches made during recessions. Davis and Wachter (2011)[14] show that there are significant losses in earnings associated with job displacement, concluding that there is an important role of labor market conditions at the time of displacement. Kahn (2010) [27] shows negative wage effects from graduating in a bad economy.

Moreover, my analysis complements recent work from Crane, Hyat and Murray (2021)[13], which shows that sullying and cleansing effects of recessions can coexist but does not explore sector heterogeneity. Additionally, with US data, Haltiwanger et al. (2018) [23] find strong evidence of a wage ladder. They find that net flows from low-wage to high-wage firms are highly procyclical, with movements from bottom to high rungs declining by 85% during the Great Recession. However, they do not find the same evidence for the firm size ladder. My results for Brazil are in line with their findings, and I contribute to this research stream by introducing an industry perspective and measuring the consequences for labor productivity growth.

On the firm dynamics side, the new facts presented here also show important features of a firm's cyclical hiring patterns by poaching rank. Moscarini and Postel-Vinay (2012)[32], analyzing empirical data, show that for many countries, large employers on net destroy proportionally more jobs than do small employers when unemployment is above trend (this holds for the US and other countries), which also proves to be true in the Brazilian data. Additionally, other job ladder models, such as those of Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013), suggest a tight link between productivity, firm size and wages. As Haltiwanger et al. (2018) [23] find for US data, I find evidence that wage job ladders slow down in recessions.

I also contribute to improving the empirical debate on productivity growth decomposition, studying the implications of reallocation for productivity dynamics. In this literature, some work for the US has been provided by Baily, Hulten, and Campbell (1992)[3], Olley and Pakes (1996)[34], Bartelsman and Dhrymes (1998) [6], Dwyer (1998, 1997)[16][5] and Haltiwanger (1997)[24]; much of it is based on creative destruction models following the idea of Schumpeter (1942, 1983). I add to this literature by showing that within and between components can vary over the cycle, and the between component can bring a sullying effect for aggregate productivity growth in recessions.

PAPER OVERVIEW. The remainder of this article is structured as follows. Section 2 describes the database and motivates the analysis by economic sector. Section 3 provides the empirical analysis on the quality of workers, firms and match quality over the cycle. Section 4 presents the contribution of within- and between-firm reallocation of resources to productivity growth and lays out a counterfactual exercise. Finally, Section 5 concludes.

2 Studying Heterogeneous Workers and Sectors

2.1 RAIS Administrative Employer-Employee Database

I use the Brazilian administrative labor database RAIS (Relação Anual de Informações Sociais), which contains annual data collected by the Brazilian Ministry of Labor. These data are not publicly available, as they include confidential employee information. RAIS provides a matched employer-employee dataset that covers all firms in the Brazilian formal sector and offers information on all their workers, including both admission and separation dates. This allows me to construct a quarterly database of total employment.

Since the database is constructed with employer-reported information and used for government administrative purposes, such as computing unemployment benefits, taxes and mandatory employer pension contributions, it is subject to low measurement error. Additionally, this dataset is very complete and has a rich collection of employer and employee data, such as demographic information of all workers (age, education, race, nationality, gender and tenure), information about establishments (sector, size, firm age and location) and information about the job (average wage earned, average number of hours worked, occupation, dates of hire and resignation, type of contract, contract wage, total earnings and causes for the termination of employment). As RAIS has information on total earnings and contract hours, I can construct a measure of earnings per hour, which is useful for part of this analysis.

In my main empirical work, I restrict the sample to individuals between 24 and 55 years old to ensure that the patterns that I want to analyze are not driven by schooling decisions at the young end or changes in retirement at the older end. I remove government-owned firms from my sample, as they have different employment dynamics; however, they represent a very small share of my sample. $oflessthan0, 05\%.$

When I divide individuals into sectors, I use the GDP division used by the Brazilian Statistics Bureau (IBGE), based on National Classification of Economic Activities (CNAE), which is the code that defines the productive activity of a company. The national accounts data released by the Brazilian IBGE groups activities into three main sectors: agriculture (farming); the manufacturing sector, which accounts for industries including construction and mining, and utilities; and services, which include retail, transportation, information services, financial services, real estate, education and public administration.

Because of potential measurement issues and the lack of some important variables, I perform my main analysis using data from 2003 to 2017. This period encompasses three recessions, one that started in 2003, another in 2008 (the Great Recession) and the longest one, particular to Brazil, which started at the end of 2014 and ended only in the last quarter of 2016, according to the Brazilian Committee of Economic Cycles (CODACE). As I have both the admission and separation dates for each contract, I am able to construct a quarterly database. The final sample by individuals has nearly 290 million observations. In terms of firms, this period spans almost 60 million firm-quarter observations for over 5.5 million establishments on my baseline firm sample. Summary statistics for new hires and incumbents are presented in Appendix A.

Throughout the paper, I define a firm based on the complete 14-digit CNPJ, which refers to each subsidiary (establishment). This allows me to benefit from the fact that I have data at the establishment level, where hiring decisions should be driven more frequently.

2.2 Sector Heterogeneity

Is there a reason to believe the composition of workers and firms changes over the cycle heterogeneously among sectors? Do different sectors follow different labor market paths throughout the cycle? As evidenced by Alves and Correa (2013), there is a strong reason to believe that the manufacturing and services sectors in Brazil and in other economies behave very differently. According to Alves (2016), any analysis of production, labor market and inflation using Brazilian data must consider the strong heterogeneity of the services and manufacturing sectors and both the intensive and the extensive margins of labor in both sectors.

Like the US and many other countries, Brazil has a services-based economy. Moreover, in recent decades, the share of the economy's output accounted for by goods-producing industries has fallen, while services-producing industries now account for almost 70% of Brazilian GDP and a comparable proportion of total employment (64% of the formally working population). Meanwhile, over the last three decades, the production share of the manufacturing sector decreased, accounting for approximately 25% of total output and 32% of total employment, and the agriculture sector accounted for only 6% and 4%, respectively (see Figure 8 in the Appendix). Since the farming sector represents only a very small share of GDP and labor and is very automatized in Brazil, the analysis here focuses more on manufacturing and services.

Additionally, the manufacturing sector is the one with the highest value added per worker and consequently the one that pays higher wages on average. The services sector encompasses a much more diverse range of industries, including various forms of transportation and communications, wholesale and retail trade, financial services, and business, personal, and professional services. Patterns of productivity change inside the manufacturing and services sector are diverse as well. However, the cyclical behavior of the two sectors looks very similar (Figure 8).

2.3 Ranking of Workers and Firms

To decide which firms and workers are better, I follow some ranking criteria commonly used in the literature. I use the Brazilian RAIS database and build time-invariant ranks for both firms and workers. Additionally, the ranks are constructed within sectors. In my main analysis, I rank workers by their average job duration throughout the sample period (2003-17). That is, those who spend more time on average on the same job should have a higher duration and, as a consequence, receive a better score. I rank firms according to their average poaching share of new hires, following Bagger and Lentz (2019)[2].[4] I define a job-to-job transition as when an employee changes from one firm to another within 3 months. The sample is restricted to formal employees aged between 16 and 65 and holding monthly contracts, not temporary contracts. Firms with 4 employees or less and public firms are also excluded.

I experiment with other ways of ranking workers and firms, which I use as a robustness test. I rank workers by their residual wages and firms by average real wages. The residual wages are computed by regressing the log of real wages on a series of worker characteristics alongside a firm fixed effect. This allows me to isolate from wages all possible effects related to workers' observable characteristics and firm effects.

[4] Similar specifications have been used to measure the cyclicality of job ladders in the labor market by, among others, Haltiwanger et al. (2018).

I try other ranks, such as the AKM FE, but according to Lopes de Melo (2008)[29], the AKM model has some shortcomings, as one standard—and very robust—result is that the correlation between these fixed effects is zero (or even negative). Taken at face value, this means that there is little sorting in labor markets. This author shows that this result can be misleading because of the nonmonotonicity of wages. [5] Since conducting a sorting analysis is one of my objectives with this study, I leave the AKM rank out of this exercise, although some of the results based on this ranking method are presented in the appendix.

3 Empirical Strategy: How Does Employment Evolve over Time?

Here, I describe how I express the change in employment over time. I adopt a methodology similar to that in CHM (2020). I let E^s_{ijt} denote the number of employees of rank tercile i working at firms of rank tercile j at time t and in sector s. Let us define the sum of employees in sector s of rank i across firms of any rank at time t as:

$$E^s_{i\bullet} = \sum_{j}^{J} E^s_{ij}$$

Analogously, let us define the sum of employees of sector s and rank j across all employee ranks at t as:

$$E^s_{\bullet j} = \sum_{i}^{I} E^s_{ij}$$

[5]To compute the AKM FE, I follow both the original Abowd, Kramarz. and Margolis (1999) methodology and include some suggestions from Card, Heining, and Kline (2013) [12]. I assume the following equation: $y_{it} = \alpha_i + \psi_{\mathbf{J}(i,t)} + x'_{it}\beta + r_{it}$, where y_{it} is the log wage of worker i at firm j, α_i is the individual fixed effect, and $\mathbf{J}(i,t)$ uniquely identifies the establishment that employs worker i in year t (firm FE). In x_{it}, I include a set of year dummies and simple and quadratic terms of age fully interacted with educational attainment.

The sum of employees of sector s across all employees and firms ranks at t is:

$$E^s_{\bullet\bullet} = \sum_i^I \sum_j^J E^s_{ij}$$

Then, the share of workers for each worker rank i is given by:

$$Share_{E^s_{i\bullet t}} = \frac{E^s_{i\bullet t}}{E^s_{\bullet\bullet t}} \tag{1}$$

At the same time, the shares of new hires from poaching ($N^{poach,s}_{i\bullet t}$) and nonemployment ($N^{nonempl,s}_{i\bullet t}$) for each worker rank i are given by:

$$Share_{E^s_{i\bullet t}} = \frac{N^{poach,s}_{i\bullet t}}{N^{poach,s}_{t}} \tag{2}$$

and

$$Share_{E^s_{i\bullet t}} = \frac{N^{nonempl,s}_{i\bullet t}}{N^{nonempl,s}_{\bullet\bullet t}} \tag{3}$$

The total employment share for each sector s and firm rank j changes according to:

$$\Delta_{share} E^s_{i\bullet t} = \frac{E^s_{i\bullet t}}{E^s_{\bullet\bullet t}} - \frac{E^s_{it-4}}{E^s_{\bullet\bullet t}} \tag{4}$$

3.1 Fact 1: Worker Composition Improves in Recessions in all Sectors

To motivate the analysis presented here, I begin with a puzzle. Figure 1 shows the densities in quarters of booms and recessions of hourly real wages for incumbents, that is, employees who did not enter or leave the firm in that particular quarter. I perform both Kolmogorov-Smirnov and Epps-Singleton tests of the equality of distributions, and both reject the null hypothesis that the distribution of wages in booms and recessions are the same. Therefore, I conclude that during recessions, the distribution of worker wages shifts to the right; in other words, there are more high-wage workers employed during recessions. I interpret this as a sign that the labor force improves in recession. Figure 2 shows that the wage changes that job changers should expect are not very different from the ones that I see in booms.

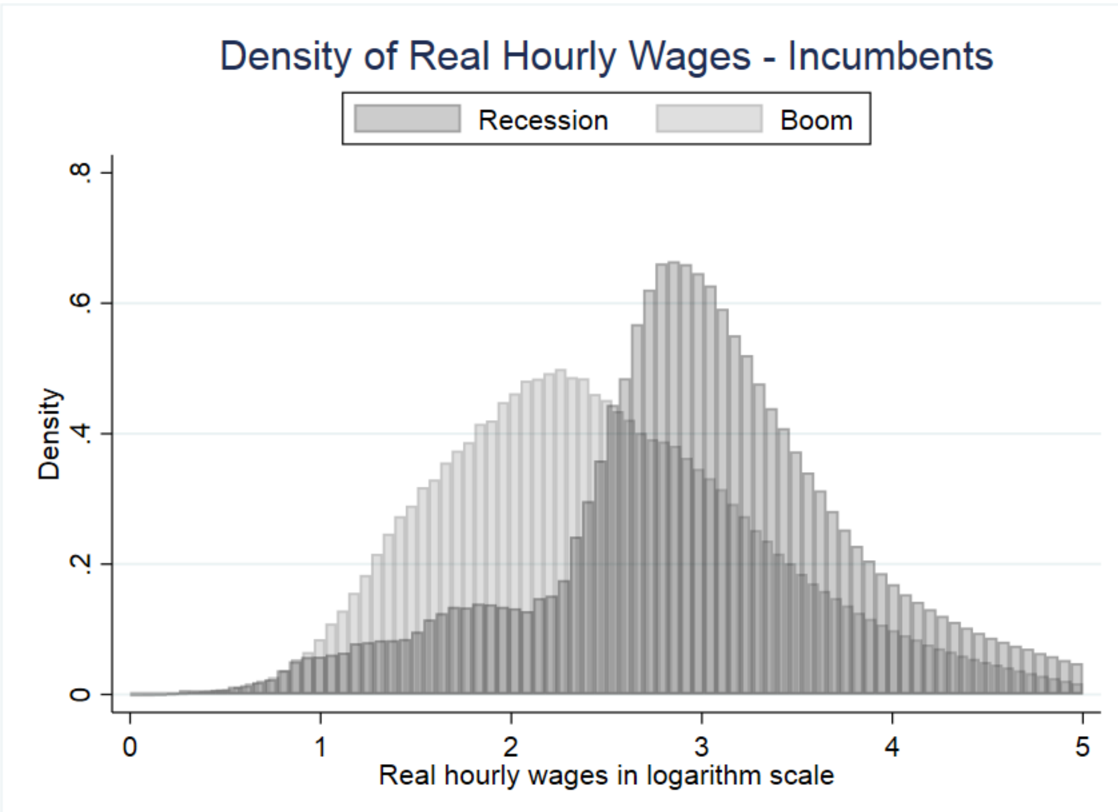


Figure 1: Incumbents' wage distribution shifts to the right. This figure shows the density of hourly real wages for incumbents, that is, employees who did not enter or leave their firm in that particular quarter. The p values values of the Kolmogorov-Smirnov and Epps-Singleton tests of the equality of distributions are shown at the bottom. The sample for all figures here is restricted to the state of São Paulo and male individuals aged between 24 and 55 and not working under temporary contracts. Government-owned firms are also excluded.

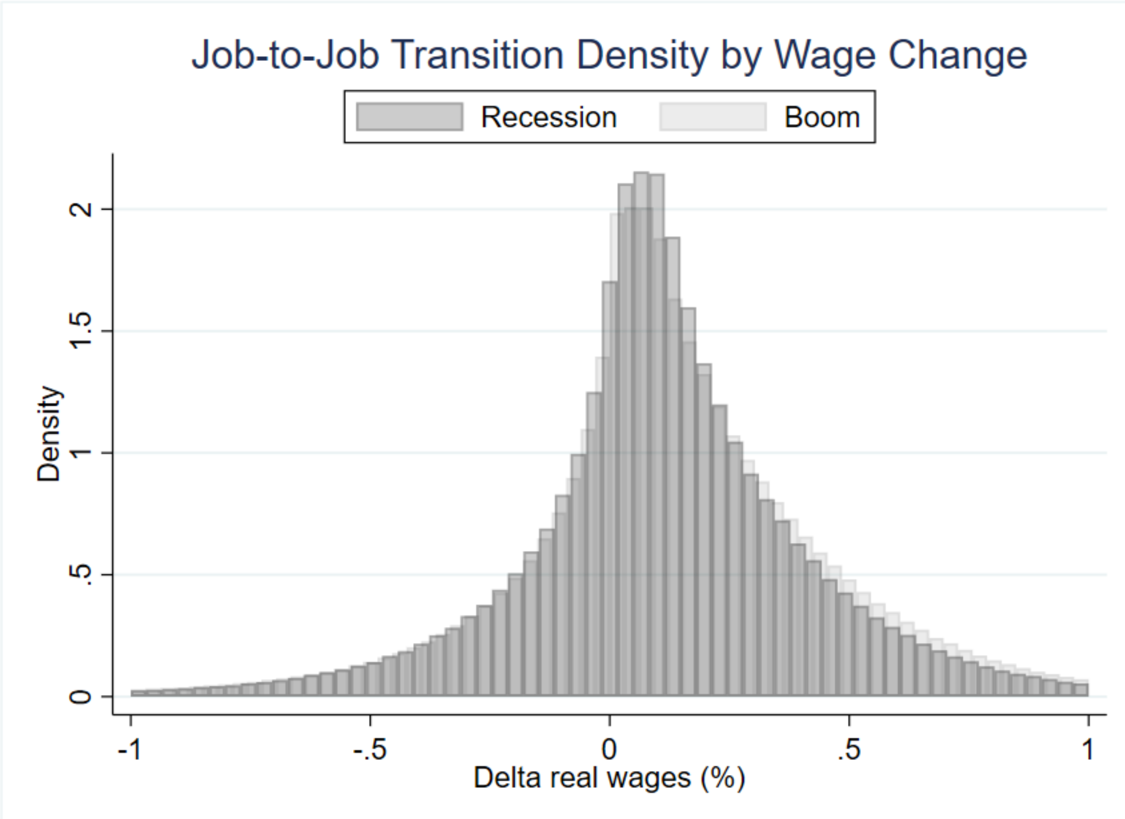


Figure 2: The graph shows the density of job-to-job transitions by real wage growth on a quarterly basis. The sample for all figures here is restricted to the state of São Paulo and male individuals aged between 24 and 55 and not working under temporary contracts. Government-owned firms are also excluded.

Source: Author's calculations from RAIS.

Thus, my goal in this section is to document how worker composition improves in recessions. As in CHM (2021), by construction of the worker terciles, low-, middle-, and high-rank workers on average each represent a one-third share. However, in any particular quarter, the shares of employment in these terciles can differ from one-third. Workers have a time-invariant rank and can leave and enter employment from one quarter to another. These transitions determine how the employment shares of these different groups evolve over time. For example, if more high-rank workers enter employment than other groups, their employment share increases in that period.

As Figure 3 shows, recessions are times when firms move away from low-rank workers. The graphs show the change in employment shares of high-, middle-, and low-rank firms over time, as defined by Equation 4. Individuals are ranked according to their average job duration, and the share of low-ranked individuals decreases in recessions for all sectors except agriculture. Shaded areas are recessions, and the series are seasonally adjusted and smoothed 4Q moving averages.

I then explore how the share of workers at high and low ranks changes in response to the cycle. Specifically, I regress the share of workers in sector s, firm i at t ($\frac{E^s_{i\bullet t}}{E^s_t}$) on the seasonally adjusted GDP deviation from the trend and seasonal dummies. The idea is to capture in a regression the cyclical movements of Figure 3. The results are presented on Table 1. I find that except for the farming sector, which is more intense in capital than in labor in Brazil, according to Alves (2016), recessions are cleansing, as they are periods when the share of high-rank workers increases. That is, the pool of workers shifts toward more productive workers. These results are in line with evidence found from US aggregate data, as in CHM. Since the farming sector represents only a small share of total employment, the aggregate result reinforces the cleansing effect of recessions on the worker side.

Quantitatively, Table 1 shows a negative sign for high-rank workers. This means that a one percentage point decrease in HP-detrended GDP is associated with a decline of 0.434 percentage points in the share of low-rank workers in the manufacturing sector, 0.14 in the services sector and 0.236 in the aggregate economy. Meanwhile, a downward deviation of GDP of the same percentage point magnitude from its HP trend brings up the share of high-rank workers by 0.369 percentage points in the manufacturing sector, 0.174 in the services sector and 0.0243 in the aggregate economy.

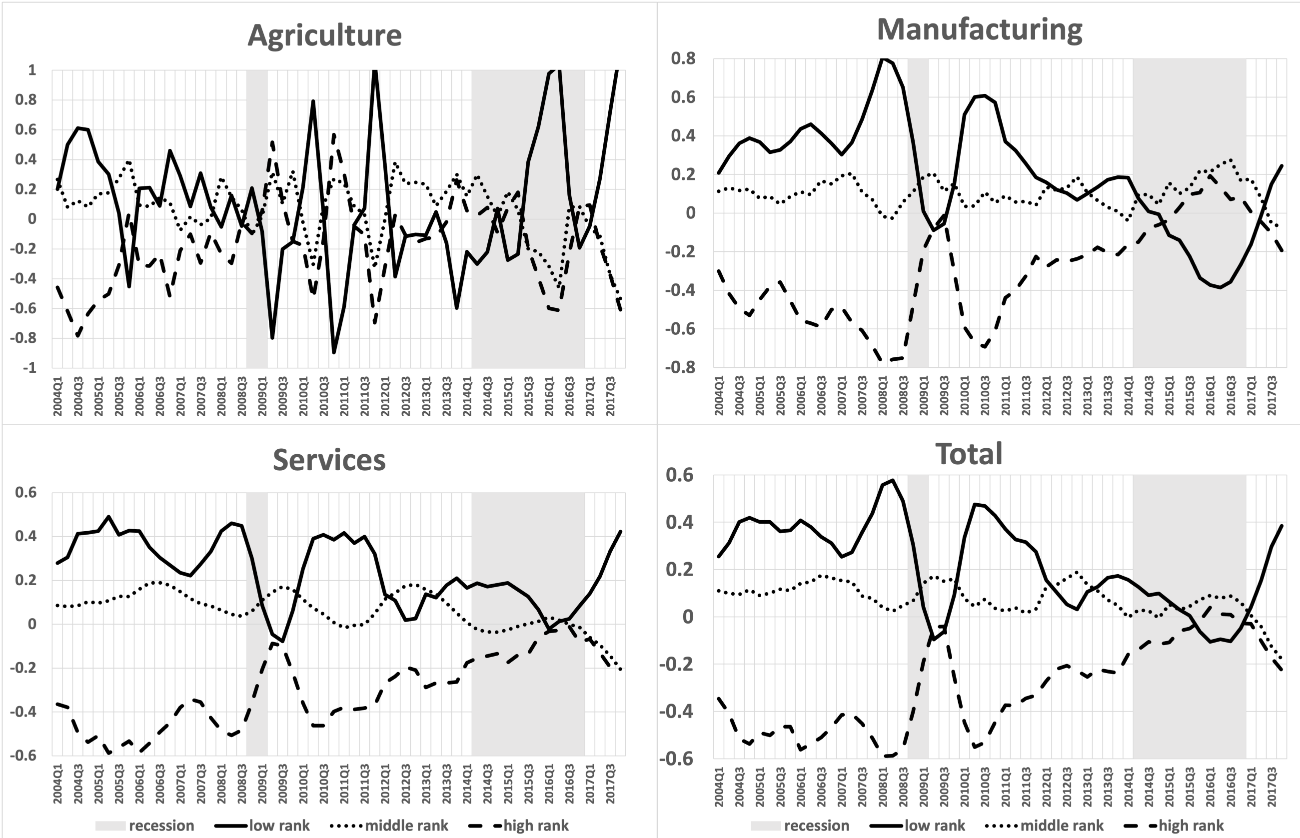


Figure 3: Recessions are times when firms move away from low-rank workers. The graphs show the change in employment shares of high-, middle-, and low-rank firms over time, as defined by Equation 4. Individuals are ranked according to their average job duration. Shaded areas are recessions. Seasonally adjusted, smoothed (4Q moving-average) series.

Worker Tercile	Agriculture	Manuf.	Services	Total
High	5.4	-36.9**	-17.4*	-2.4**
	(0.09)	(0.15)	(0.09)	(0.11)
Low	-14.8	43.4***	14.0**	0.2***
	(0.11)	(0.15)	(0.06)	(0.09)

Table 1: I regress the share of employment, characterized by Equation 1, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

To offer a sense of how much these employment changes in recessions come from new hires from other firms (poaching), Table 2 shows the results of the regression of the change in the share of new hires coming from other firms on the cyclical indicator. As I can see, the sensitivity in this case is only for high-type workers. A one percentage point decrease in HP-detrended GDP is associated with an increase of 0.165 percentage points in the share of high-rank workers in farming, a 0.262 percentage point increase in the manufacturing sector, a 0.35 percentage point increase in the services sector and a 0.331 percentage point increase in the aggregate economy. Meanwhile, a downward deviation of GDP of the same percentage point magnitude from its HP trend has no effect on low-type workers.

Worker Tercile	Agriculture	Manuf.	Services	Total
High	-16.5**	-26.2*	-35.0**	-33.1**
	(0.08)	(0.14)	(0.13)	(0.13)
Low	-24.5*	33.1	10.8	18.5
	(0.14)	(0.20)	(0.13)	(0.14)

Table 2: I regress the share of new hires poached from other firms, characterized by Equation 2, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

Finally, I also isolate the new hires coming from nonemployment or, in the Brazilian labor market case, employment in the informal sector [6]. Table 12 shows the results of the regression of the change in the share of new hires coming from nonemployment or employment in the informal sector on the cyclical indicator. As I can see, the sensitivity in this case is only for low-type workers. A one percentage point decrease in HP-detrended GDP is associated with a decrease of 0.653 percentage points in the share of low-rank workers in manufacturing, of 0.691 in the services sector and of 0.641 in the aggregate economy. Meanwhile, a downward deviation of GDP from its HP trend of the same percentage point magnitude has no effect on high-type workers coming from informal employment or nonemployment.

[6] In Brazil, approximately 35% of workers are employed in the informal sector. Most of these employees receive up to 2 minimum wages, according to data from PNAD Contínua, IBGE.

Worker Tercile	Agriculture	Manuf.	Services	Total
High	-0.1	-0.1	0.2	0.1
	(0.09)	(0.23)	(0.26)	(0.21)
Low	0.2	-0.7*	-0.7**	-0.6**
	(0.25)	(0.35)	(0.33)	(0.30)

Table 3: I regress the share of new hires from nonemployment or employment in the informal sector, characterized by Equation 3, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

3.1.1 Fact 2: In Recessions, Most Job Creation Happens at Bottom Ranked Firms in All Sectors

In this section, my main goal is to show that lower-ranked employers create proportionally more jobs in recessions, according to certain ranking criteria. That is, there is a firm composition change in job creation throughout the business cycle.

I rank firms following the methodology of CHM; that is, every quarter, I divide firms into three terciles according to my ranking criteria, which is the poaching rate in my main analysis, as in Bagger and Lentz (2019)[2]. This construction allows the share of workers, but not the share of firms, to vary in each tercile from one quarter to another. I define a job-to-job transition (poach) as when an employee changes from one firm to another within 3 months[7]. I show that firms that poach more workers from other firms pay higher wages on average, as expected. This ranking criterion should, therefore, approximate a firm's rank in the job ladder.

Table 4 shows the regression results for each sector. Specifically, similar to the worker analysis, I regress $\frac{E^s_{jt}}{E^s_t}$ on the GDP deviation from its HP trend or its first difference on a linear time trend and seasonal dummies. Labor market downturns are associated with an increase in the em-

[7]I use three months because Brazil has great unemployment insurance and a relatively large informal market, which allows workers to switch firms to delay their formal entrance in a new firm to benefit from this insurance (Van Doornik, Schoenherr and Skrastins, 2018).

ployment share of low-rank firms and a corresponding decline for high-rank firms. The change in employment composition by firm rank is qualitatively consistent across ranking methods when I use HP-detrended GDP as my cyclical indicator. For every percentage point decline in the GDP rate relative to its HP trend, the employment share of low-rank firms increases by 0.35 percentage points in the farming sector, by 0.289 in the manufacturing sector, by 0.228 in the services sector and by 0.249 in the aggregate economy. On the other hand, the same percentage point decrease in GDP is associated with an increase in the employment share of high-rank firms of 0.0266 in the farming sector, 0.355 in the manufacturing sector, 0.226 in the services sector and 0.259 in the aggregate economy.

Firm Tercile	Agriculture	Manuf.	Services	Total
High	26.6***	35.5***	22.6***	25.9***
	(0.09)	(0.08)	(0.07)	(0.07)
Low	-35.0***	-28.9***	-22.8**	-24.9**
	(0.13)	(0.10)	(0.10)	(0.10)

Table 4: I regress the share of employment, characterized by Equation 4, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

These results are a consequence of the slowdown of the job-ladder mechanism during recessions and are in line with those found by CHM, Kahn and McEntarfer (2014) [26], and Haltiwanger, Hyatt and McEntarfer (2015) [25] based on US data. These authors investigate the cyclical properties of employment and employment growth for different firms. Their findings indicate that lower-paying firms are responsible for a higher share of employment and hires during downturns. The results reinforce recent discussion about the failure of the job ladder in recessions, proved both empirically (Haltiwanger et al. (2018)) and with a structural model (Moscarini and Postel-Vinay (2016)).

Specifically, Moscarini and Postel-Vinay (2016) rank firms on the job ladder using a structural model. They also find that high-rank firms curtailed their demand for new labor in the recession. As a result, the process of upgrading to better jobs through job-to-job quits from low-rank to high-rank firms slowed down considerably. That is, the job ladder fails in recessions, starting from the upper rungs.

According to CHM, during economic contractions, both the job ladder and hiring from nonemployment slow, but job ladder deceleration dominates in terms of cyclical employment composition at low- vs. high-rank firms. These authors find evidence that high-ranked firms in the US reduce their poaching margin in recessions, while low-ranked firms increase theirs. For Brazil, this adjustment looks similar. Figure 4 presents the 4-quarter moving-average growth rate of the poaching share for each poach-tercile group. High-ranked firms adjust their poaching rate faster when there is a recession than middle- or bottom-ranked firms; this was especially the case during the Great Recession.

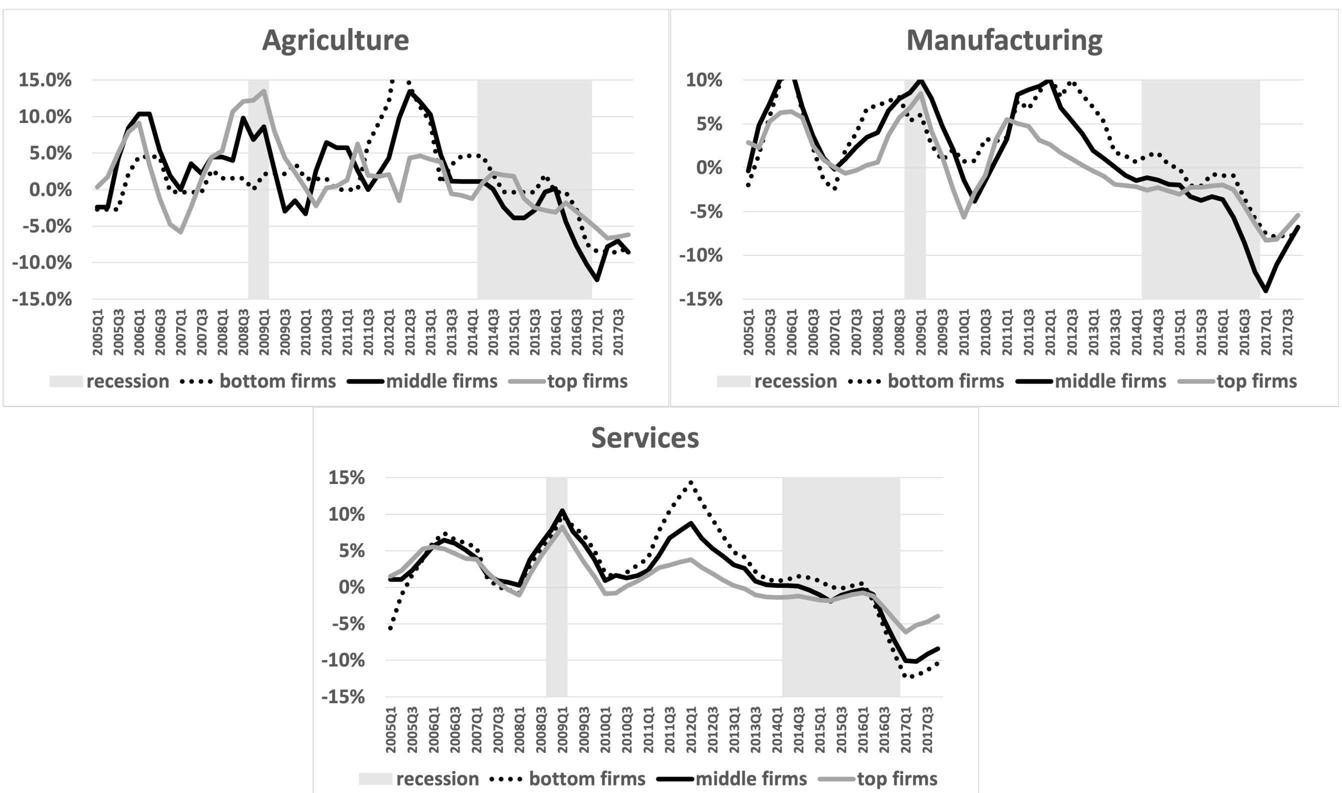


Figure 4: High-wage firms adjust their poaching rate faster. This graph shows the quarterly growth rate of the 4-quarter moving-average share of new hires from poaching for each sector and each poach rank (tercile) group.

3.1.2 Fact 3: Assortative Matching Increases in Recessions in All Sectors

The evidence presented here shows that I have a redistribution of workers and firms over the cycle that is very similar for heterogeneous sectors. Recessions are periods when job creation shifts to bottom-ranked firms and high-wage workers. However, what happens to sorting? Here, I briefly show that the same high-type worker, in recessions, goes to both high- and low-type firms. The overall result is an increase in positive assortative matching for all sectors.

In this part, I combine the firm and worker ranks and analyze them together to obtain a sense of sorting. That is, I trace what happens to high-rank workers within both high- and low-rank firms. Table 13 shows how sorting varies with GDP deviations from trend, my cyclical variable. The dependent variables in my regressions are the change in the share of i-rank workers at j-rank firms, $\frac{E^s_{ijt}}{E^s_t} - \frac{E^s_{ijt-1}}{E^s_t - 1}$, for each worker tercile i, firm tercile j and sector s. Again, I obtain negative coefficients for high-rank workers at both low- and high-rank firms. This means that in recessions, when GDP is below its HP trend, the employment share of low-rank workers at high-rank firms declines in both the manufacturing and services sectors. A one percentage point decrease in HP-detrended GDP is associated with a 0.067 percentage point decline in the manufacturing sector share of employment of low-rank workers at high-rank firms and a 0.092 decline in the services sector. In this episode, the total labor share of low-rank workers at high-rank firms declines by 0.075 percentage points.

At the same time, the share of high-rank workers at high-rank firms increases by 0.038 in the manufacturing sector, 0.059 in the services sector and 0.04 in the aggregate economy. I also see that the movement of high-type workers in low-type firms increases in recessions. A decrease of one percentage point in HP-detrended GDP is associated with an increase of 0.029 percentage points in the share of high-rank workers at low-rank firms in the manufacturing sector, a 0.025 percentage point increase in this type of match in the services sector and an increase of 0.028 in the aggregate economy. However, I see no significant cyclical change for movements of low-type workers at low-type firms.

	Agriculture	Manuf.	Services	Total
High-rank firms and...				
High-rank workers	6.0	-3.8***	-5.9**	-4.0**
	(0.04)	(0.01)	(0.02)	(0.02)
Low-rank workers	9.4	6.7***	9.2**	7.5**
	(0.08)	(0.02)	(0.05)	(0.03)
Low-rank firms and...				
High-rank workers	-0.9	-2.9***	-2.5**	-2.8***
	(0.03)	(0.01)	(0.01)	(0.01)
Low-rank workers	-5.6*	-2.2	0.00	-1.05
	(0.03)	(0.02)	(0.01)	(0.01)

Table 5: I regress the share of employment, characterized by Equation 4, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

Since the previous regressions indicate that there is a cyclical increase in the degree of sorting, my next task is to measure it. I now divide workers and firms into 50 time-invariant quintiles instead of 3, according to the poaching rank used previously for firms and the average tenure rank for workers. Then, I calculate the correlation between these two ranks over time and regress this correlation time series on my cyclical variable (GDP deviation from trend), with one regression for each sector. The results are presented on Table 7. The negative significant sign for all sectors confirms that the correlations increase during downturn periods (and decrease in booms). This means that sorting increases in recessions.

Table 6: Relationship between worker-firm correlations and the GDP gap

	Agriculture	Manufacturing	Services
GDP dev. from HP trend	-0.27*	-0.24*	-0.22*
	(0.001)	(0.001)	(0.001)

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

Table 7: I regress the correlation between worker and firm ranks on each quarter on the seasonally adjusted GDP deviation from its HP-trend, a time trend and seasonal dummies, seasonal dummies, and a linear time trend. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

4 Sullying and Cleansing vs. Labor Productivity over the Cycle

I have shown thus far that there is a change in the composition of workers and firms during recessions in Brazil. On the one hand, there is a better pool of workers as the share of high-rank workers increases. On the other hand, better-ranked firms are more sensitive to cycles, and their share of total employment falls during recessions. This cyclicality impacts the most important economic sectors in a nearly homogeneous way. Meanwhile, assortative matching improves. Here, I show that the impact of the redistribution of workers and firms in recessions on productivity growth can be heterogeneous among sectors.

Worker reallocation up the job ladder in advanced economies, such as the US, has been shown to be productivity enhancing (Haltiwanger et al. 2015; Restuccia and Rogerson 2008; Hsieh and Klenow 2009; Bartelsman, Haltiwanger, and Scarpetta 2013). In this context, it is reasonable to ask to what extent the deceleration of job creation in better firms impairs productivity growth. Here, I propose a methodology to decompose aggregate productivity growth into within- and between-firm components to provide an answer to this question. As I can see in Figure 5, labor productivity growth, as estimated by the total revenue divided by total employment, falls in manufacturing and services in recessions. The goal of this section is to understand how much of this fall might be attributed to changes in firms and worker characteristics, causing a misallocation of human capital.

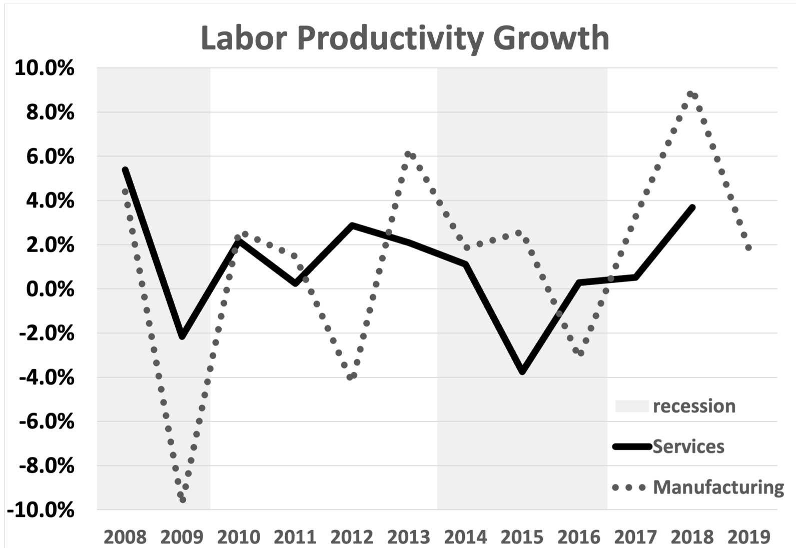


Figure 5: Labor productivity growth decelerates in years of recession. The figure shows the yearly growth rate for real labor productivity, measured in thousands of 2007 Brazilian R$ per worker.
Source: Brazilian Institute of Statistics (IBGE).

I propose a widely used methodology to decompose aggregate labor productivity. The objective is to understand how labor reallocation throughout the cycle can impact aggregate productivity. For this exercise, I merge firm balance sheet information from the Brazilian financial newspaper Valor Pro with firm employment data from RAIS. Valor Pro is a privately owned firm database with yearly balance sheet information. Despite some coverage limitations, especially among medium and small companies, Valor Pro contains balance sheet information for over 7,000 medium and large Brazilian firms at yearly frequency. According to data from IBGE's Annual Survey of Industry, in the last ten years, medium and large firms in this sector accounted, on average, for 40% of employment and approximately 69% of gross revenue. In the retail sector, according to IBGE's Annual Survey, medium and large firms are responsible for 24% of sector revenue and 27% of total employment.

I define labor productivity as gross revenue per worker in real terms, deflated by the IPCA inflation index. According to Haltiwanger (2021), measuring productivity as standard gross output per worker is common at the micro and macro levels but is relatively crude in comparison to using total factor productivity (TFP). However, in the empirical literature, this revenue-based labor productivity measure has been shown to be highly correlated with TFP-based measures of productivity across businesses within industries.

To study the components of labor productivity growth, I decompose it using a widely adopted decomposition suggested by Foster, Haltiwanger and Krizan (2001) [19], which is a modified version of that used by Baily, Hulten, and Campbell (1992) [3]; here, the decomposition is given by:

$$\begin{aligned} \Delta P_{it} = & \underbrace{\sum_{e \in C} \left(p_{et-1} - P_{it-1}\right) \Delta s_{et}}_{(i-between)} + \underbrace{\sum_{e \in C} s_{et-1} \Delta p_{et}}_{(ii-within)} + \underbrace{\sum_{e \in C} \Delta p_{et} \Delta s_{et}}_{(iii-crosscov)} \\ & + \underbrace{\sum_{e \in N} s_{et} \left(p_{et} - P_{it-1}\right)}_{(iv-entering)} - \underbrace{\sum_{e \in X} s_{et-1} \left(p_{et-1} - P_{it-1}\right)}_{(v-exiting)} \end{aligned} \tag{5}$$

where C denotes continuing plants, N denotes entering plants and X denotes exiting plants. e represents an establishment and i an industry. s_{et} denotes the initial share in the industry (sector). Additionally, (i) is the between-establishment component, reflecting the increase in the share of firms more (less) productive than the industry average; (ii) is the within-establishment component, which reflects the increase (decrease) in establishment productivity; (iii) reflects the increase in the share of firms more (less) productive than the industry average; (iv) is the contribution of entering plants; and (v) is the contribution of exiting plants. Thus, aggregate productivity growth (ΔP_{it}) is given by the sum of (i) through (v).

From the decomposition equation, it is clear that while many factors beyond the redistribution of the labor force (such as innovation) can affect firm productivity, the firm share in the industry (Δs_{et}), if defined as the labor force share, is affected directly and only by this redistribution. Therefore, this approach is the one that I take. I define Δs_{et} as the labor share of the firm in that particular industry.

I perform this decomposition with my establishment-level data on a quarterly basis. Figure 15 presents the empirical results for components (i) and (ii) of Equation 5 for all sectors (agriculture, manufacturing, and services) and for the aggregate economy. The values represent the average contribution of each component to productivity growth in periods of booms and recessions. As this database accounts for medium to large firms only, the contribution of entering and exiting firms is negligible, and the contribution of the cross-covariance term is left out of this exercise. Thus, the total annual growth for each period is the sum of the two components.

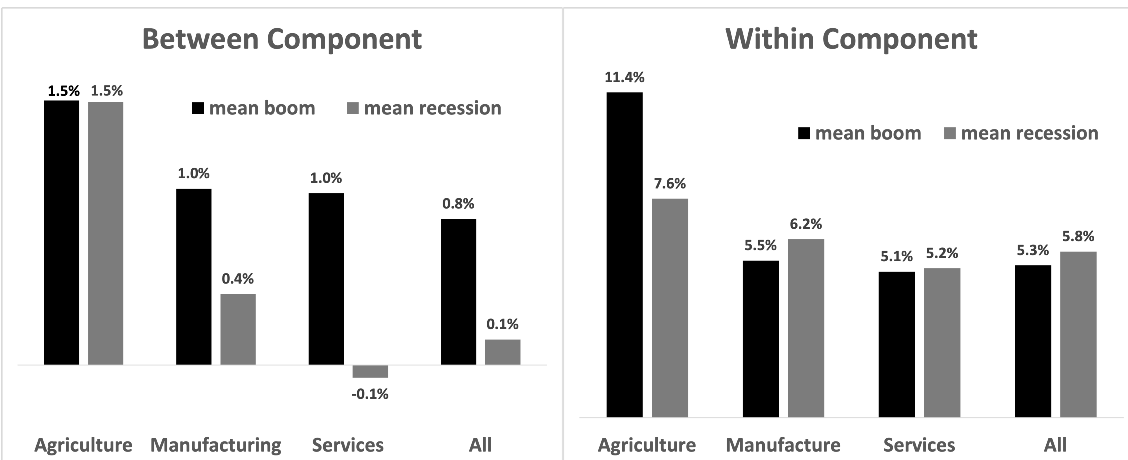


Figure 6: The within component is more important for productivity growth. The graphs present the empirical results for components (i) (between) and (ii) (within) from Equation 5 in booms and recessions for all economic sectors (agriculture, manufacturing, and services) and for the aggregate economy. The values represent the average contribution of each component to productivity growth in boom and recession quarters. Total yearly growth for each period is the sum of all components. As this database accounts for medium to large firms only, the contribution of entering and exiting firms, as well as the cross-covariance term, is negligible and left out of the analysis.

The main takeaways from this first exercise are that (i) the within-establishment contribution is more important for explaining productivity growth in both boom and recession periods, meaning that the increase in productivity inside firms is more important to productivity growth; (ii) the within-establishment component is always positive and increases in recessions in all sectors except farming, as the cleansing worker effect occurs; and (iii) the between component is always smaller in recessions and even negative for the services sector, as the sullying firm effect occurs. That is, in recessions, workers tend to reallocate to less productive firms, and this movement impairs productivity growth. Meanwhile, the movements of workers within firms contribute positively to productivity growth in these periods.

4.1 Fact 4: Reallocation of Workers Has a Heterogeneous Impact among Sectors on Productivity Growth

According to the results from the decomposition of productivity growth, reallocation of workers to less productive firms may be responsible for the sluggishness of the between-firm component in recessions. To further investigate the impact of worker reallocation among firms in recessions on overall productivity growth, I perform a counterfactual analysis. To do this, I keep the industry share of the firm (s), from Equation 5, at the average boom level and let firm productivity p and aggregate productivity P vary at their actual level. Since this database contains mainly medium and large firms, the number of entering and exiting firms is low; thus, terms (iv) and (v) are not relevant in this analysis. I also exclude term (iii), which has a very small impact. Thus, I compute:

$$\underbrace{\sum_{e \in C} \left(p_{et-1} - P_{it-1}\right) \Delta s_{et}^{boom}}_{\text{counterfactual between effect}} \tag{6}$$

Figures 7 presents the results for this counterfactual analysis for all sectors and the aggregate economy. The graph presents the empirical results for the between component both observed in the data on average in booms and recessions ((i) of Equation 5) and from the counterfactual analysis ((i) of Equation 6).

As I can see, the impact is heterogeneous among sectors. Only in the services sector, the most labor-intensive sector, would growth improve if firms had the same share of employees in their industries that they had in boom years. This indicates that in manufacturing[8], the cleansing effect, which increases firm productivity (p), is large enough to overcome the sullying effect from the redistribution of workers to less productive firms. Thus, even in recessions, I see a positive contribution from the between effect for productivity growth in this sector. Meanwhile, the services sector, which is more intense in labor, makes a slight negative contribution to growth from the between effect. My counterfactual analysis shows that this negative growth contribution could be reverted if the distribution of workers among firms followed boom shares.

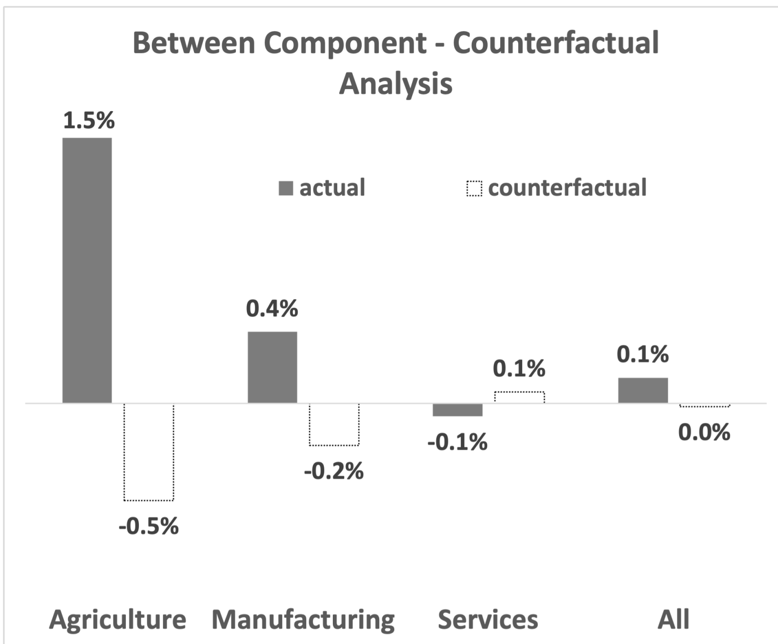


Figure 7: I conduct a counterfactual analysis of the between effect. This graph presents the empirical results for the within component both observed in the data ((i) of Equation 5) and from the counterfactual analysis ((i) of Equation 6) for all three main economic sectors (agriculture, manufacturing, and services). The values represent the contribution of each component to productivity growth. Total annual growth for each period is the sum of all components. As this database accounts for medium to large firms only, the contribution of entering and exiting firms is negligible and left out of the analysis.

[8] I leave the agriculture sector out of the analysis because it represents a very small share of labor in comparison to manufacturing and services and has a different dynamic related to international prices.

5 Conclusion

In this paper, I use large and comprehensive Brazilian administrative data to bring new evidence on how match quality evolves throughout the cycle for heterogeneous economic sectors. My first important finding is that recessions are periods when the pool of workers shifts toward higher-rank workers in all sectors. Later, I show that this movement is productivity enhancing. I thus conclude that recessions have a cleansing effect within workers. Furthermore, I show that most of this improvement comes from new hires from poaching.

My second important finding is that the pool of jobs available during recessions shifts toward worse-ranked firms in all sectors. I conclude this from an empirical exercise that analyzes whether there is a change in the composition of firms that create new jobs during recessions. Thus, I conclude that recessions are sullying for firms, along the lines posited by Barlevy (2002). Here, I follow some steps of CHM and rank firms according to their poaching rate of new hires. The results show that larger, top-ranked firms decelerate their job creation more than bottom-ranked firms during recessions. Those looking for new jobs in recessions have a smaller chance of finding one at better firms. These results are also in line with previous results from CHM and findings in the previous literature that large employers are more sensitive to business cycles, as job-to-job transitions are an important hiring channel for them. Later, using a counterfactual analysis, I show that this firm movement compromises productivity growth in recessions, especially in the services sector, which relies more on labor input.

When I combine workers and firms ranks, I find that this reshuffling of workers over the cycle also happens within firms, especially high-ranked firms, in all sectors except farming. This increases the share of high-rank workers at high-rank firms, improving assortative matching. This helps the economy overcome the adverse sullying effect previously found.

Building a structural model that incorporates heterogeneous sectors and both the cleansing and sullying effects of recessions, along with cyclical assortative matching, would allow us to assess further macroeconomic consequences of these labor market facts and offer a good path for future research.

Appendices

A Summary Statistics

A.1 Industry Heterogeneity

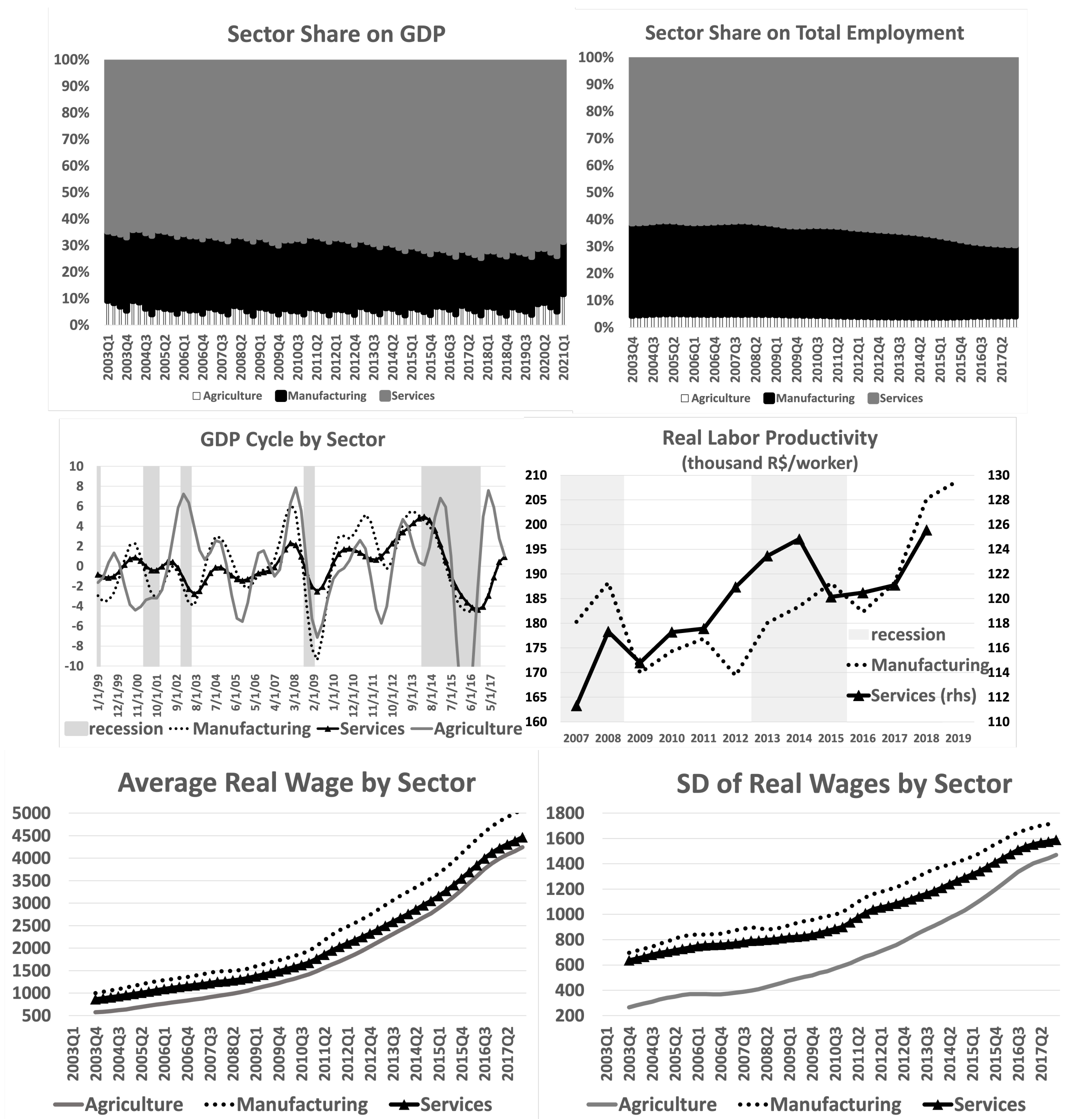


Figure 8: Compared to the manufacturing sector, the services sector has a greater share in GDP and employment and lower labor productivity but similar cyclical behavior. The upper left figure shows the share of each sector in Brazil's total GDP value (in nominal terms). The upper right figure shows the share of employment from each sector. The middle left figure shows the cyclical behavior of the GDP cycle extracted with the Christiano-Fitzgerald filter. The middle right figure shows real labor productivity. The bottom left figure shows the real monthly wage by sector, and the bottom right figure shows its standard deviation. Source: RAIS and National Accounts from IBGE.

A.2 Sample Statistics

Table 8: Mean tests for firm characteristics suggest that employees in each group are consistently different: covariate t-test for firm variables – new hires vs stayers (2003-17).

	Mean New Hires	Mean Incumbents
Size	4.3	10.4
Wage	938.4	973.7
Age	30.5	34.6
Potential Experience	13.6	18.1
Hours	43.0	43.0
Undergrad	0.1	0.1
High School	0.5	0.5
Elementary School	0.39	0.44
Male Employees	0.58	0.57
White Employees	0.60	0.64
Brazilian	1.0	1.0
Low-Skill Occup.	0.67	0.65
Middle-Skill Occup.	0.26	0.26
High-Skill Occup.	0.04	0.04

A.2.1 Worker Analysis Using Residual Wage Rank

Worker Tercile	Agriculture	Manuf.	Services	Total
High	-8.68	0.58	-13.30*	-8.79**
	(0.06)	(0.03)	(0.08)	(0.04)
Low	4.08	2.19	15.1**	10.3***
	(0.08)	(0.04)	(0.06)	(0.03)

Table 9: I regress the share of new hires from nonemployment or employment in the informal sector, characterized by Equation 3, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

A.2.2 Worker Analysis Using Worker AKM FE Rank

Worker Tercile	Agriculture	Manuf.	Services	Total
High	0.05	-0.37**	-0.17*	-0.24**
	(0.10)	(0.15)	(0.09)	(0.11)
Low	-0.13	0.45***	0.14**	0.25***
	(0.13)	(0.15)	(0.06)	(0.09)

Table 10: I regress the share of new hires from nonemployment or employment in the informal sector, characterized by Equation 3, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

A.2.3 Firm Analysis Using Average Wage Rank

Firm Tercile	Agriculture	Manuf.	Services	Total
High	31.1	34.3	5.92	14.5
	(0.33)	(0.28)	(0.31)	(0.30)
Low	-72.5***	-52.0*	-42.3	-45.3
	(0.25)	(0.28)	(0.28)	(0.27)

Table 11: I regress the share of new hires from nonemployment or employment in the informal sector, characterized by Equation 3, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

A.2.4 Firm Analysis Using Firm AKM Rank

Firm Tercile	Agriculture	Manuf.	Services	Total
High	0.59***	-0.05	0.06	0.01
	(0.18)	(0.17)	(0.08)	(0.12)
Low	-0.587**	0.00995	-0.104	-0.0673
	(0.22)	(0.10)	(0.077)	(0.09)

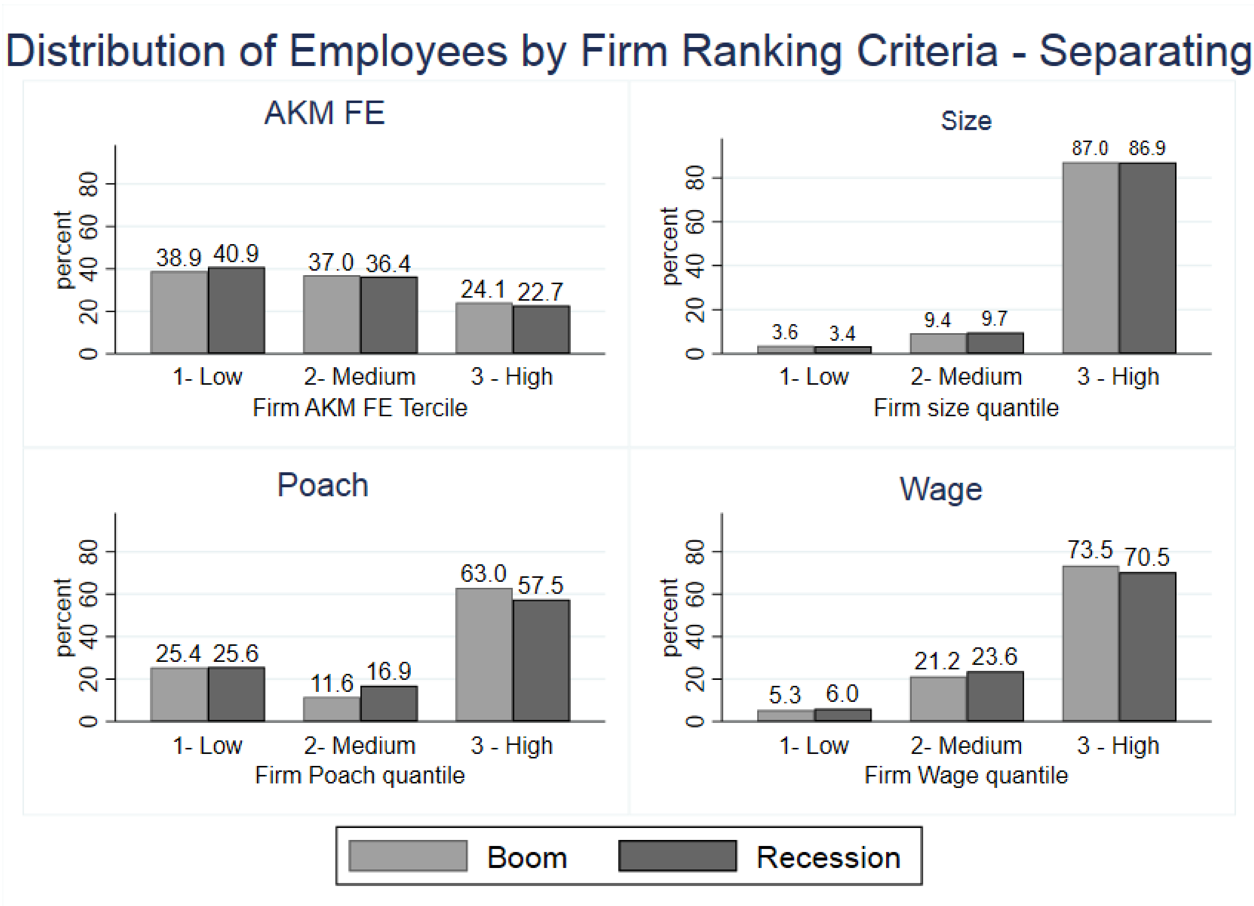
Table 12: I regress the share of new hires from nonemployment or employment in the informal sector, characterized by Equation 3, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

A.2.5 Sorting Analysis Using Firm and Worker AKM Rank

	Agriculture	Manuf.	Services	Total
High-rank firms and...				
High-rank workers	-3.23	1.54	-0.053	
	(2.86)	(1.96)	(2.22)	
Low-rank workers	6.30**	9.77***	-0.74	
	(3.11)	(2.92)	(2.65)	
Low-rank firms and...				
High-rank workers	3.02	-6.78*	10.80***	
	(3.727)	(3.530)	(3.552)	
Low-rank workers	2.59	3.39	-4.87	
	(2.73)	(3.26)	(3.20)	

Table 13: I regress the share of employment, characterized by Equation 4, on the seasonally adjusted GDP difference from its long-term HP trend, seasonal dummies, and a time trend. *, **, and *** indicate statistical significance at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

B BetIen-Firm Analysis



Better firms decelerate separations in recessions relative to worse firms. The tables present the share of total separations in each firm rank group in both booms and recessions. The construction of the rank follows the methodology of CHM; that is, every quarter, firms are divided into three terciles according to each ranking criterion (size, AKM FE, wage and poaching). The share of firms is constant in each tercile, but the share of separations may vary. The sample for all figures here is restricted to the state of São Paulo and male individuals aged between 24 and 55 and not working under temporary contracts. Government-owned firms are also excluded.

Source: Author's calculations from RAIS.

C Wage Distribution

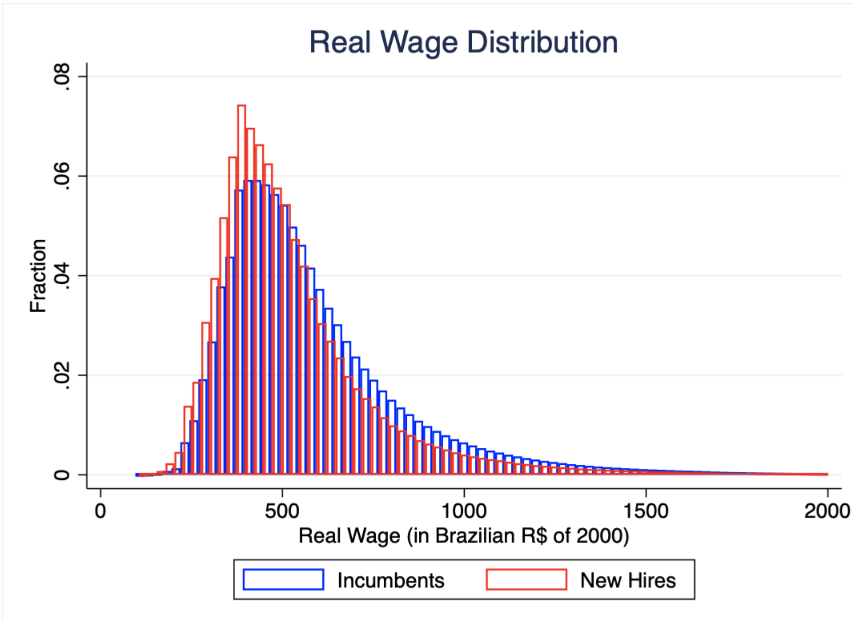


Figure 9: These three graphs show the distribution of real wages for new hires and incumbent workers over the period of 2003-2017. The sample used is restricted to formal employees aged between 16 and 65 and holding monthly contracts, not temporary contracts. Public firms are excluded.

D Wage Distribution by Firm Type

To confirm whether the baseline result holds even within firms, I first check whether it holds within firm groups according to the CHM ranks that I constructed previously. Figures 10, 13, 12 and 11 show that the redistribution of workers in recessions holds for all firm ranking criteria.

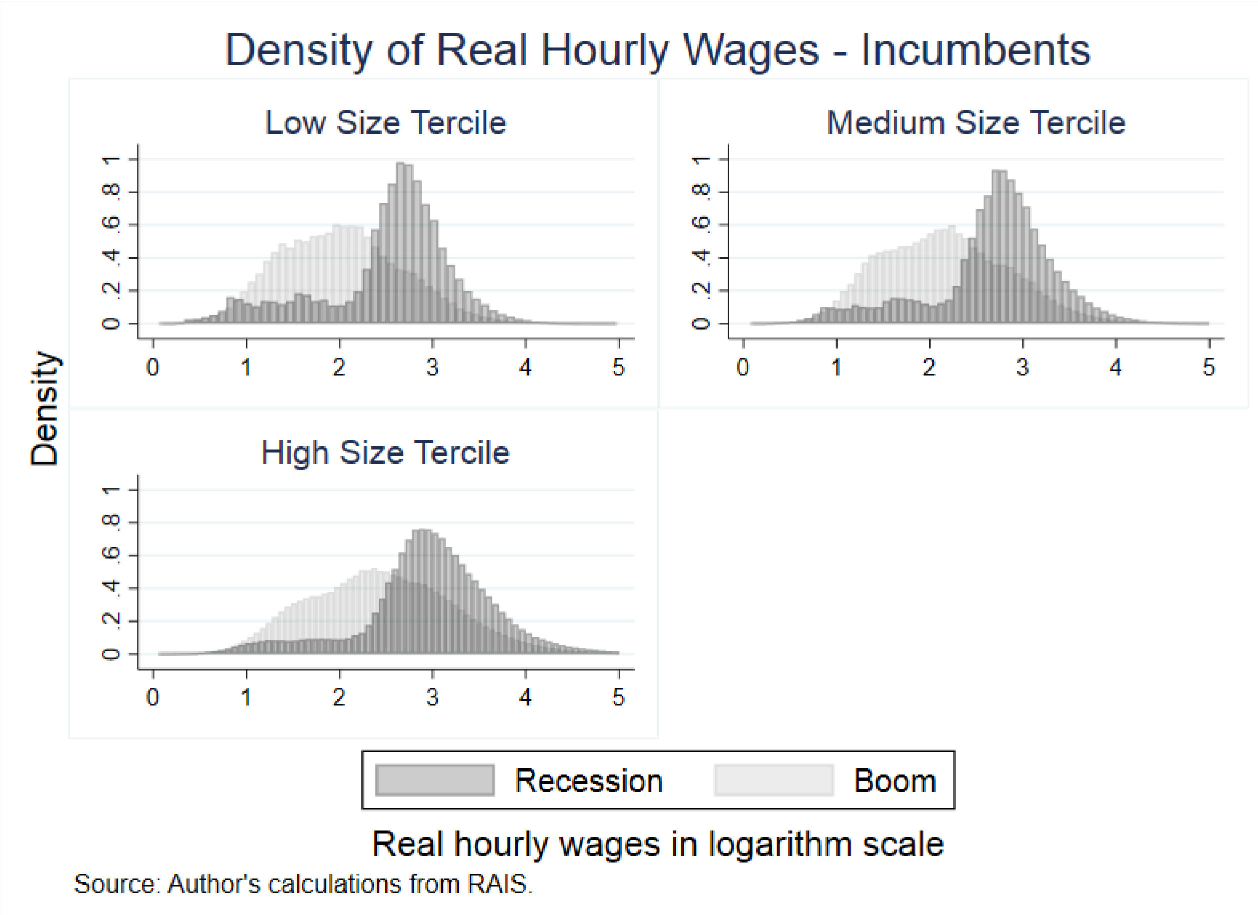


Figure 10: These three graphs show the distribution of real wages for incumbent workers over the period 2003-2017. The sample used is restricted to formal employees aged between 24 and 55 and holding monthly contracts, not temporary contracts. Public firms are excluded.

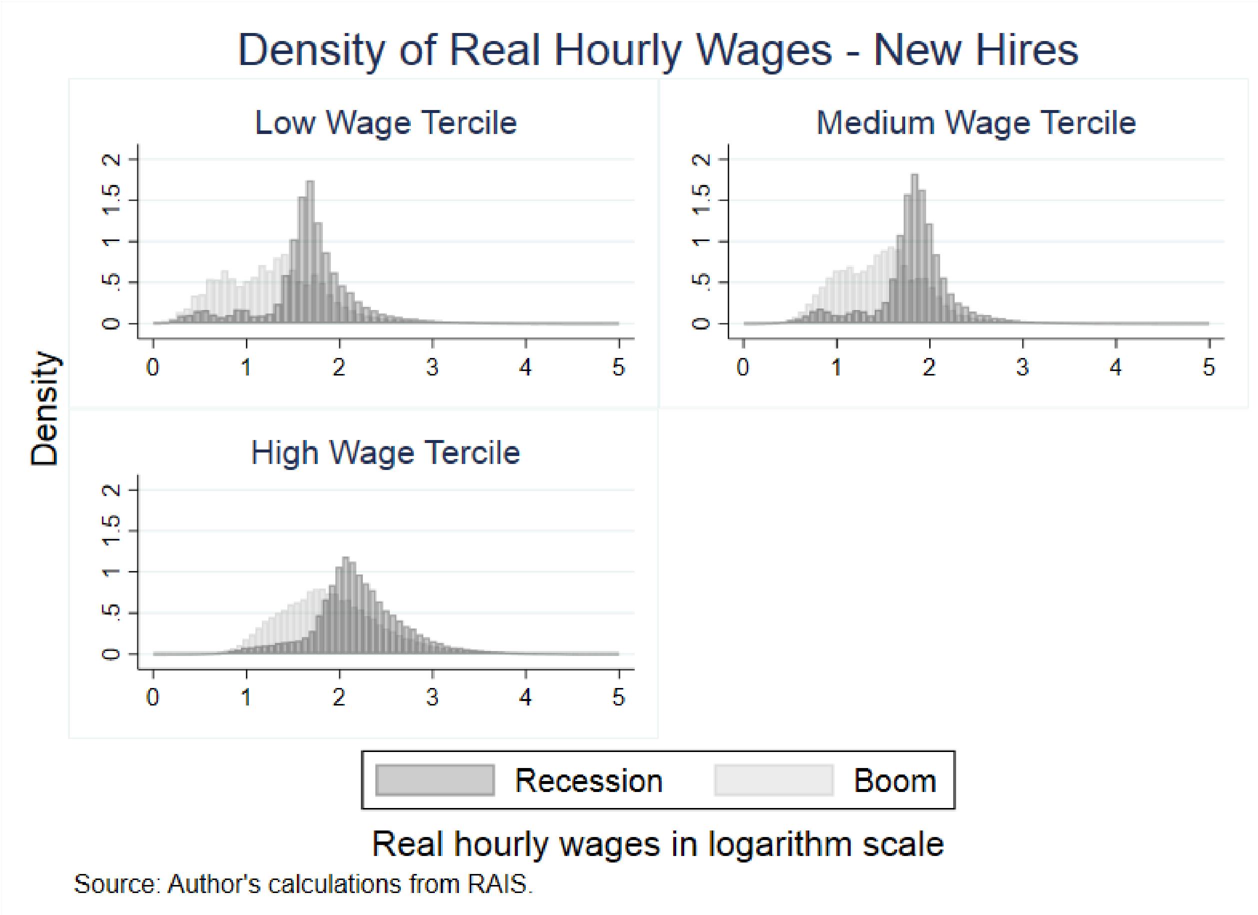


Figure 11: These three graphs show the distribution of real wages for new hires and incumbent workers over the period 2003-2017. The sample used is restricted to formal employees aged between 24 and 55 and holding monthly contracts, not temporary contracts. Public firms are excluded.

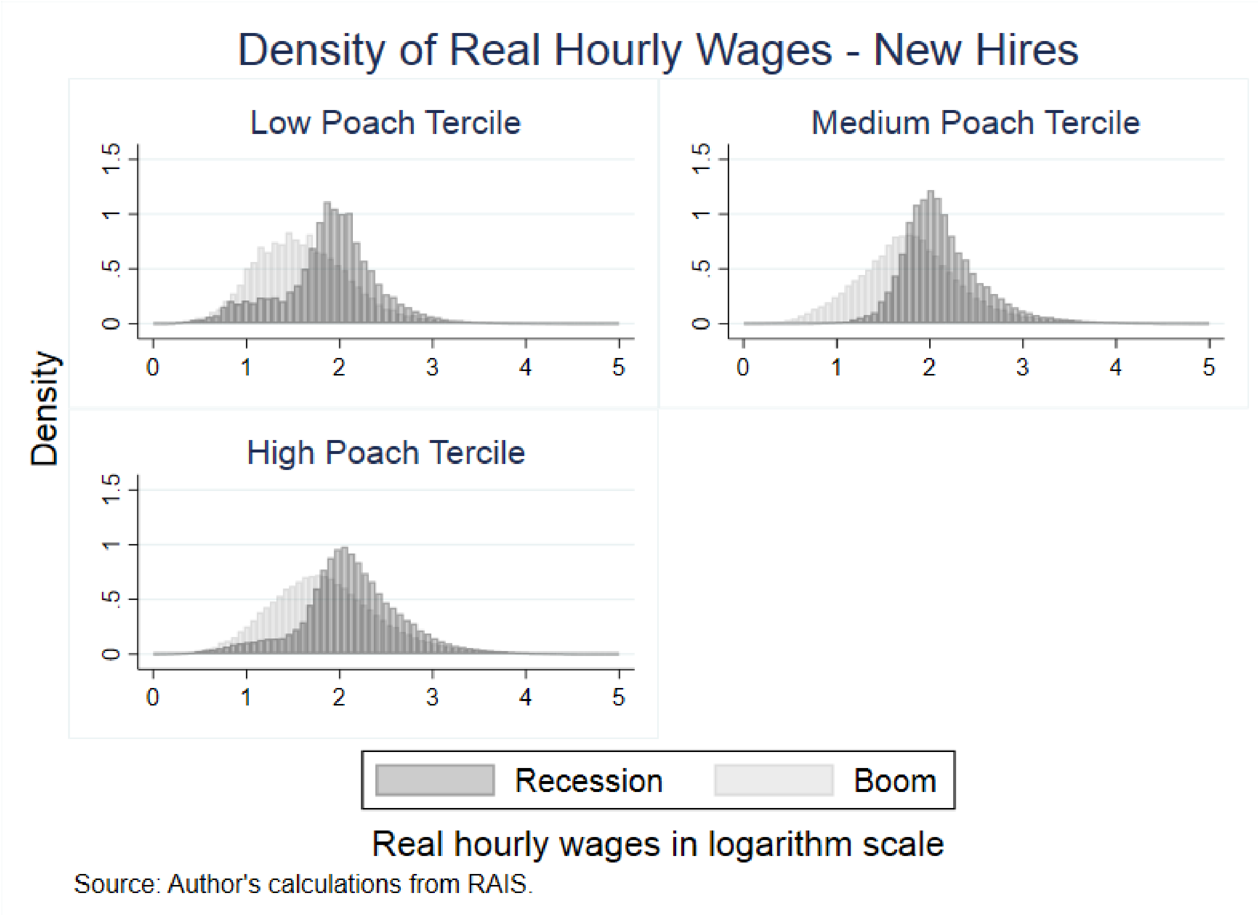


Figure 12: These three graphs show the distribution of real wages for new hires and incumbent workers over the period 2003-2017. The sample used is restricted to formal employees aged between 24 and 55 and holding monthly contracts, not temporary contracts. Public firms are excluded.

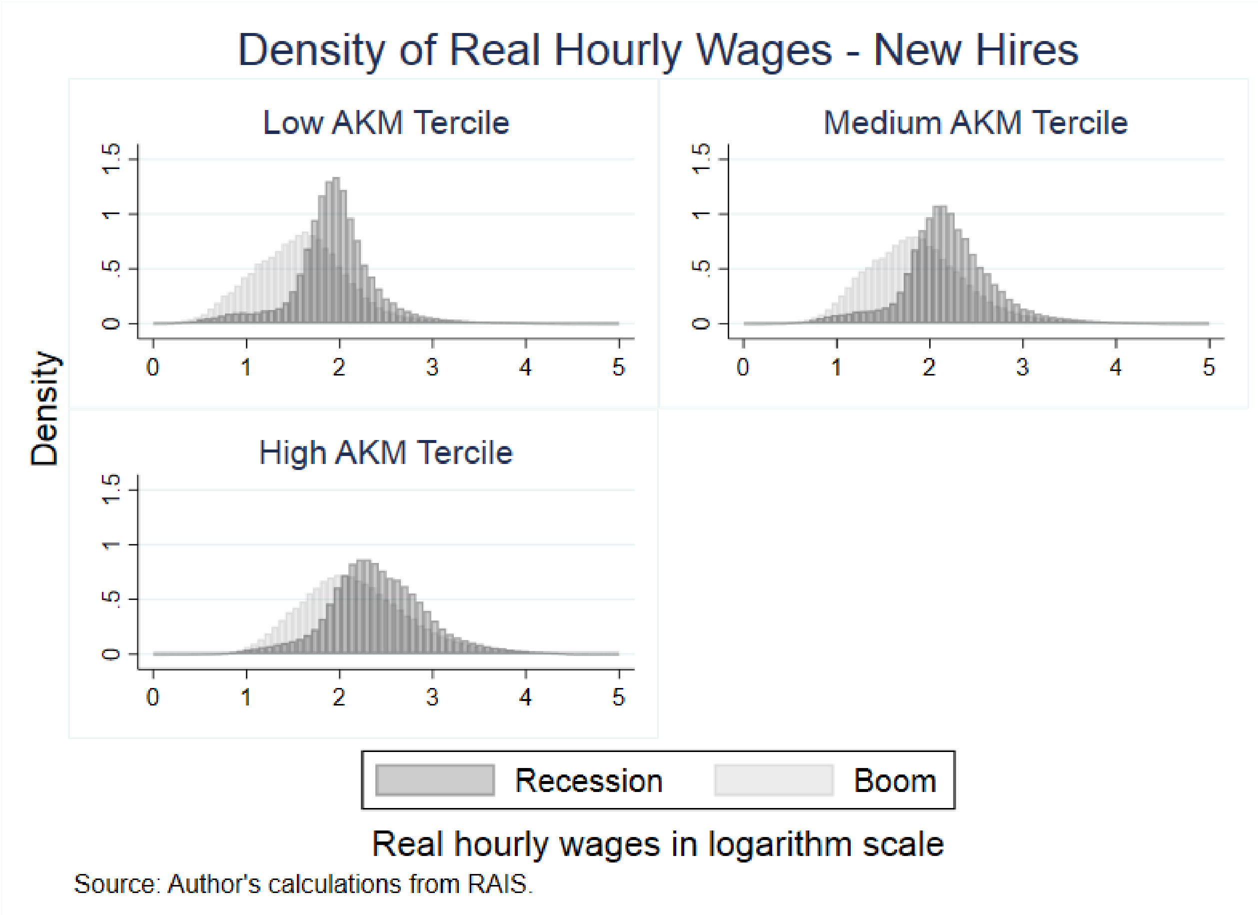


Figure 13: These three graphs show the distribution of real wages for new hires and incumbent workers over the period 2003-2017. The sample used is restricted to formal employees aged between 24 and 55 and holding monthly contracts, not temporary contracts. Public firms are excluded.

If I take a look at the job-to-job transition rate in Figure 14, I see that in the Brazilian labor market, the share of hires coming from job-to-job transitions decelerates. The procyclicality of job-to-job transitions has already been documented recently (Davis, Faberman, and Haltiwanger 2012; Hyatt and McEntarfer 2012b; Lazear and Spletzer 2012;Moscarini and Postel-Vinay (2009, 2013)). Here, I consider a job-to-job transition when an employee changes from one firm to another within 3 months; however, the results are not significantly changed if I consider a maximum of 1 or 2 months for the transition.

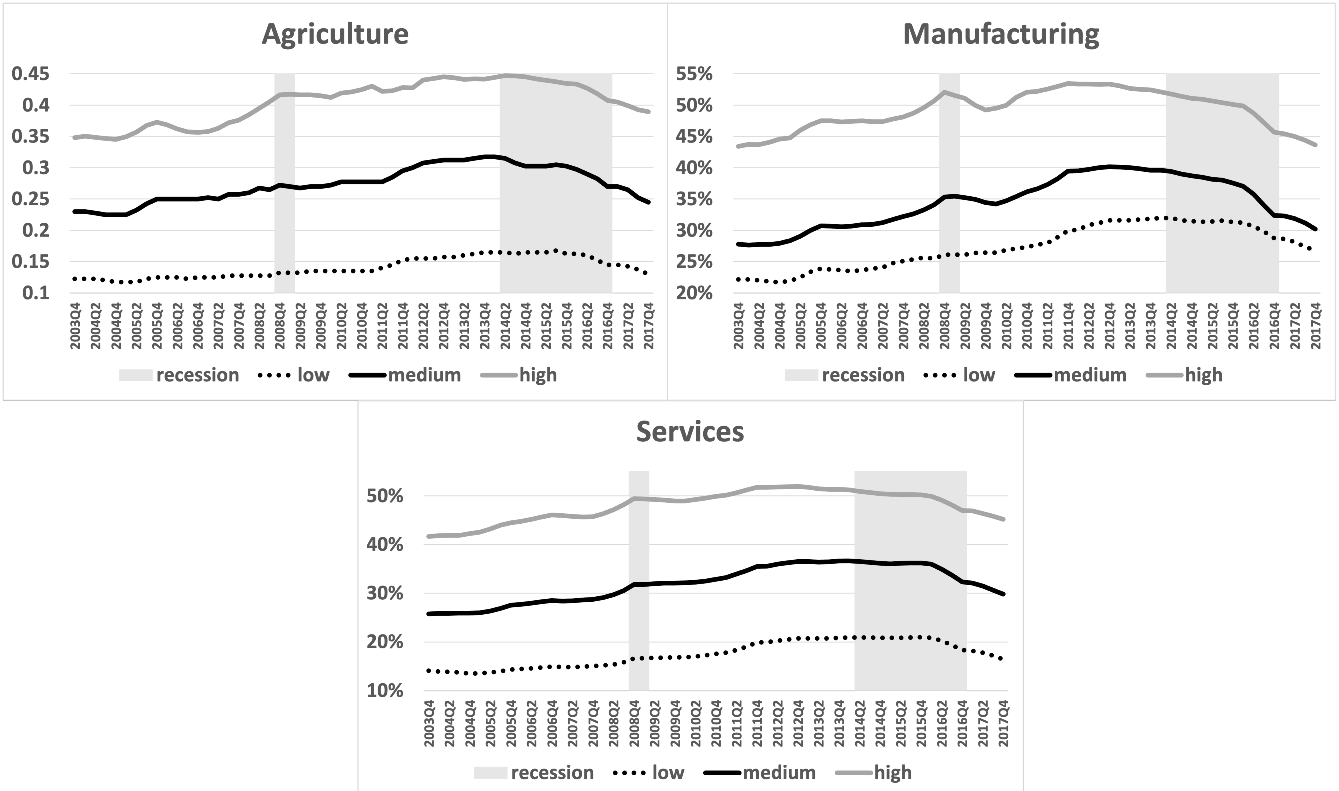


Figure 14: The graph shows the average job-to-job transitions as a share of total hires by sector for each poaching rank. I define a job-to-job transition as when an employee changes from one firm to another within 3 months. The sample used is restricted to formal employees aged between 16 and 65 and holding monthly contracts, not working under temporary contracts. Firms with 4 employees or less and public firms are also excluded.

E Within and Between Components over Time

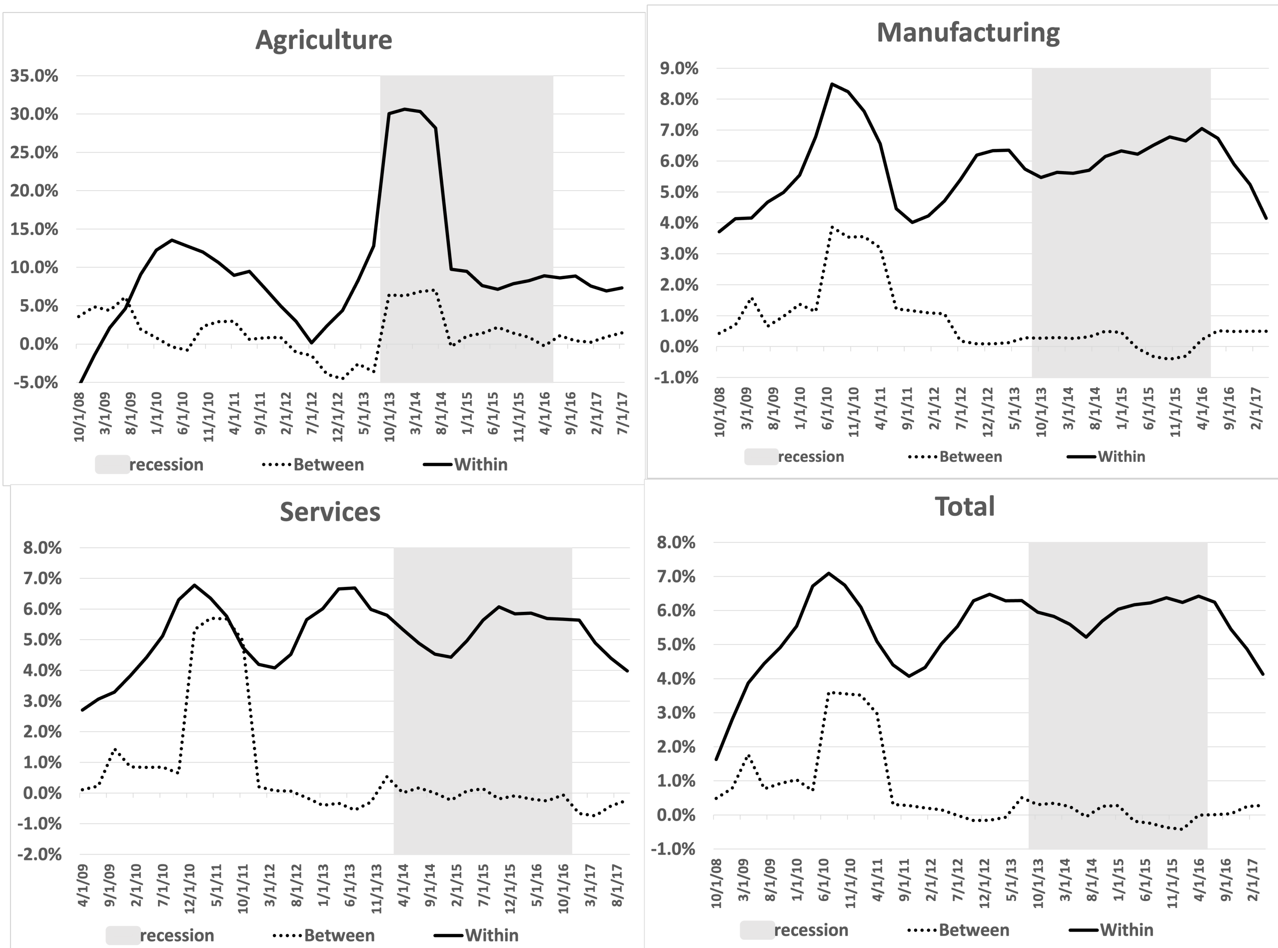


Figure 15: The within component is more important for productivity growth. The graphs present the empirical results for components (i) (between) and (ii) (within) from Equation 5 over time for all economic sectors (agriculture, manufacturing, and services) and for the aggregate economy. The values represent the contribution of each component to productivity growth. The total yearly growth for each period is the sum of all components. As this database accounts for medium to large firms only, the contribution of entering and exiting firms is negligible and presented in the Appendix.

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