Employment Cyclicality by Firm Size, Wage, and Productivity in Brazil

Túlio A. Cravo
Inter-American Development Bank, 1300 New York Ave NW, Washington, DC 20577, USA
tcravo@iadb.org

Paulo de Andrade Jacinto
Federal University of Paraná, Av. Prefeito Lothário Meissner, 632, Jardim Botânico - 80210-170 - Curitiba/PR Brazil
paulo.jacinto@ufpr.br

Caroline Schimanski [*]
UNU-WIDER, Katajanokanlaituri 6 B, 00160 Helsinki, Finland
Hanken School of Economics, Arkadiankatu 7, 00100 Helsinki, Finland
schimanski@wider.unu.edu

Version: November 9th, 2018

Abstract

We provide evidence on whether job flows reallocate workers from low productivity to high productivity firms using for the first time a direct productivity measure. We constructed a monthly linked employer-employee dataset for Brazil and argue for the use of a direct productivity measure to analyze the firm productivity job ladder as often used productivity proxies, such as employment size and wages, are weakly related to productivity. When total factor productivity is used to rank firms, results suggest that workers move up the productivity ladder by moving from young firms with low productivity to old firms with high productivity.

Keywords: Firm size, jobs flows, business cycles, market structure
JEL Classification: J2, J21, J3, J4, J6, E3

[*] Corresponding Author

1. Introduction

In recent years, a new wave of studies has reignited the discussion about the dynamics of employment creation and destruction in heterogeneous firms during business cycles. This discussion has direct implications for labor policies created to dampen employment fluctuations and is motivated by dynamic models of on-the-job-search that predict that workers move up the firm productivity job ladder, causing employment in large firms to be more sensitive to cycles than in small firms.[1] This contrasts with earlier studies motivated by literature on credit market frictions showing that small firms suffer more during cycles due to limited access to capital markets.[2] These two alternative views that suggest conflicting results are motivating new empirical studies analyzing the dynamics of employment creation and destruction in heterogeneous firms over the business cycle.

Data availability plays a vital role in this discussion. For instance, evidence by Moscarini and Postel Vinay (2009, 2012) is based on linked employer-employee data (LEED) for developed countries, which allows researchers to construct firm level longitudinal data that improves the quality of the analysis. This new wave of studies based on LEED, motivated by dynamic models of on-the-job-search, support the view that large firms are proportionately more sensitive than small firms to business cycles. However, subsequent studies (e.g., Fort et al., 2013; Haltiwanger et al., 2018b), also using LEED, indicate that aspects such as the *proxies* used for productivity, credit constraints, and firm age can affect this result and show that larger firms are not always more sensitive to business cycles.

Little is known about employment dynamics in different groups of firms over business cycles in developing countries. In developing countries such as Brazil, the labor market is characterized by complex and rigid labor laws that increase hiring costs in the formal sector and affect firm behavior.[3] The scant evidence available (e.g., Cravo 2011, 2017) indicates that small firms behave differently in Brazil in a developing country context when compared to more developed economies, but detailed evidence is needed to guide policies aimed at reducing employment fluctuations in recessions. As such, academics and policy-makers can benefit

---

[1] These models are suggested by Moscarini and Postel Vinay (2009, 2012, 2016) and tested using firm size as a proxy for productivity.

[2] Gertler and Gilchrist (1994) say that “practical considerations dictate using firm size to proxy for capital market access.”

[3] The hiring of a worker in the manufacturing sector requires at least 18 bureaucratic procedures that cost around 103% of the nominal minimum wage (Pastore, 2006).

greatly from deeper knowledge about the factors influencing employment dynamics in different groups of firms during business cycles in developing countries.

In this paper, we make three contributions to the literature. First, we contribute to this discussion by exploring the combination of monthly data from the Annual Social Information Report (RAIS), which is a LEED, with the Annual Manufacturing Survey (PIA) from January 2000 to December 2014 to provide comprehensive evidence of employment dynamics in a developing country. The use of this rich and newly constructed dataset, combined with macroeconomic indicators, provides new insights into employment dynamics over the cycle. To our knowledge, this study is the first to assess the existence of a job ladder using LEED in a developing country context. Evidence for developing countries is important for the development of adequate policy responses, as employment cyclicality is likely to respond differently to business cycles compared to developed countries.

Second, ours is the first study that tests whether workers move up the firm productivity jobladder, a prediction made by the dynamic on-the-job-search model, using Total Factor Productivity (TFP) as a direct proxy for productivity. Previous evidence on the job ladder have used weaker proxies for firm productivity.[4] Third, we provide further support to the view that employment size and wage are poor proxies for firm productivity, as the correlation between these variables and TFP is weak; this has clear implications for the interpretation of results in empirical work.

Our findings show a negative correlation between unemployment rate and differential employment growth rates (high productive minus low productive firms), suggesting that employment is more sensitive to cycles in more TFP productive firms, which lends support to the job ladder mechanism in a developing country context. These results are opposite when firms are classified by employment size and wages. The finding that results vary according to the measure used to classify firms is a clear warning that we cannot assume that the correlations among employment size, wages, and productivity are strong and positive as some studies suggest. Different measures might imbue different meanings and might be associated with different

[4] Moscarini and Postel-Vinay (2016) use employment size as a proxy for firm productivity and Haltiwanger (2018b) uses gross output per worker. Both are crude measure for productivity when compared with total factor productivity.

aspects influencing employment dynamics and whether workers move up the size, wage, or productivity ladder.[5]

The estimations of Vector Autoregressions (VARs) complements the analysis and allows us to examine the response of firms with different productivity levels to unemployment while controlling for macroeconomic factors such as monetary policy, inflation, and credit constraint. Using TFP to rank firms, we find that shocks to unemployment reduce the differential growth rate, given by the difference between employment growth rates in high productivity and low productivity firms. This result is in line with the job ladder, in which employment in highly productive firms is more sensitive to unemployment.

Furthermore, this paper contributes to the literature by analyzing the role of age and productivity in the employment reallocation of firms in a developing country. Haltiwanger et al. (2013) have already pointed to the importance of considering the age of firms in the analysis, as younger firms can be more sensitive to changes in credit conditions. The VARs that consider the age of firms support their findings regarding the importance of age in employment reallocation dynamics and suggest that workers move up the firm productivity job ladder by moving with greater intensity from young, low productivity firms to high productivity firms.

The discussion generated by the results presented in the paper is critical for the formulation of labor market policies, especially during recessions. A better understanding of the types of firm in which workers suffer most during recessions is crucial for the design of better theoretical models and policies to dampen employment fluctuations and reduce the economic and social costs of job losses. This line of research is important to the literature as the evidence produced can be used to devise a unified theory that explains employment dynamics over the cycle in developed and developing countries.

The remainder of the paper is structured as follows. Section 2 provides a more detailed background of the existing evidence on employment dynamics over the business cycle, in particular on the role of different productivity proxies and firm age. Section 3 presents the steps taken to construct a unique dataset based on linked employer-employee data. Section 4 presents the methodology used in this analysis and discusses the advantages of using microdata to avoid potential biases that might affect results. Section 5 presents the results of how firm size, wage,

[5] Haltiwanger et al. (2018b) show that job-to-job moves across firm size and firm wage ladders over the business cycle are different and suggest that firm size based on employment might be a more limited proxy for firm productivity, as it is less able to incorporate the influence of the role of age and credit constraints.

age, and productivity affect employment dynamics across business cycles. The VAR specifications that analyze the response of different groups of firms to unemployment is presented in Section 6. Section 7 concludes.

2. Background

The availability of linked employer-employee data (LEED) and wider options of analysis has revitalized and challenged the existing literature on the sensitivity of employment in small and large firms. Following Fort et al. (2013), we consider two lines of the literature that promote the ongoing debate about how different firms respond to the business cycle.

The first line of studies generated a consensus in the 1990s that small firms were proportionately more sensitive to business cycles due to credit constraints. Brock and Evans (1989) argue that the different behavior of small businesses during business cycles is likely related to their financial liquidity constraints. In an influential paper, Gertler and Gilchrist (1994) use firm size as a proxy for capital market access and find evidence that small firms are more sensitive to cyclical conditions. The authors use sales to define firm size and show that small businesses contract substantially more than larger enterprises after tight money episodes, accounting for a disproportionate amount of the resultant decline in manufacturing sales. However, this consensus was built based on evidence generated by repeated cross-sectional data that suffer from "reclassification bias," as researchers could not follow the same firms over time.

"Reclassification bias" occurs in datasets where firms and individuals cannot be tracked throughout the years, as firms can be reclassified into different "size" groups during economic cycles. For instance, during times of economic expansion, small firms might grow beyond a defined size threshold, thus being reclassified as another size. This issue has an impact on the assessment of employment cyclicality by firm size during business cycles (Moscarini and Postel-Vinay, 2012).

The recent increase in the availability of large LEED has opened an array of possibilities for more detailed, robust, and reliable analyses to test theoretical models on the issues of job-to-job moves, firm size, and cyclical conditions. The possibility of overcoming this data limitation is one factor that has contributed to the development of a new set of findings for developed countries, which contrasts with results of earlier studies that used typically aggregated data. New findings call the view that smaller firms are more sensitive to cycles into question. This second line of the literature is largely motivated by dynamic models of on-the-job-search that predict that workers move up the firm productivity job ladder.

A series of recent studies presents new empirical evidence for a set of developed countries that also circumvents the serious reclassification bias problem. Moscarini and Postel-Vinay (2010, 2012) present new evidence for the US, Canada, Denmark, the UK, and France, suggesting that employment in large firms is more sensitive to business cycle conditions than in small firms. This is in line with the predictions of the theoretical models of Moscarini and Postel-Vinay (2009, 2016) in which firm size is positively related to productivity and less productive (smaller and low-wage) firms hire proportionately more during recessions and periods of high unemployment due to a greater availability of workers willing to accept lower wages.[6] As the unemployment rate declines during economic expansion, more productive large firms increase wages and "poach" workers from smaller firms, restricting the employment growth of the latter during economic expansions. These two patterns are based on the idea that less productive (smaller) firms are more constrained in the wage level they can offer employees, whereas more productive (larger) firms can offer higher wages. During recessions, the available labor supply is greater, making it less necessary for firms to compete for a limited pool of workers. The dynamics related to poaching would thus indicate that larger firms are more sensitive to business cycles, as their hiring practices put a limit on smaller firms' ability to expand their workforce during economic booms. On the other hand, small firms' ability to hire low wage workers during recessions affords them a buffer during those periods.

The findings of the studies by Moscarini and Postel-Vinay (2009, 2010, 2012, 2016) have, in recent years, stimulated further research based on microdata focusing on employment cyclicality and particular firm classes measured by a variety of proxies (e.g., wage, size), as indicated in Cravo (2017). Importantly, in Haltiwanger et al. (2015; 2018b) not only the number of employees but also wage level is used as a *proxy* for firm productivity. Wage level is argued to be a better *proxy* for productivity, as wage captures the marginal products of labor units. Results provide evidence of a wage ladder whereby high wage firms poach workers from low wage firms. In contrast, little evidence for a size ladder is found, whereby large firms would be expected to poach from small firms. The different nature of productivity *proxies* results in firm

[6] These are dynamic versions of Burdett and Mortensen (1998) job ladder models.

rankings following different patterns. The authors suggest that the wage ladder is in line with the implications of search theory, in which workers look for higher wage paying firms, while a not evident firm size ladder suggests a possible role for age and credit constraints.[7]

While number of employees and wages are commonly used to define firm size under the assumption that those measures are positively related to TFP, Haltiwanger et al. (2018a) show that the relationship between size in terms of number of employees and productivity is weaker than expected for the US. To study the reallocation of workers between low productivity and high productivity firms, they use revenue labor productivity, which is a better but still gross *proxy* for productivity, as its correlation with TFP is argued to be about 0.6. Given the different setup of developing country economies and the potential different proportional use and importance of labor and capital, there is reason to expect a different correlation between labor productivity and TFP in a developing country context. The use of different productivity *proxies* in empirical studies and a discussion about their quality is paramount, and our paper contributes to this debate as it is the first empirical work that uses TFP to analyze employment reallocation and the existence of a firm productivity job ladder.

Furthermore, researchers addressing access to credit sometimes use employment size as a proxy for different levels of access to credit. Moreover, Fort et al. (2013) argue that when distinguishing between firm size, age is also important to consider in terms of its impact on the relationship between cyclical conditions and worker reallocation. They argue that younger firms have less access to credit markets and rely more heavily on personal sources of finance. Their results indicate that the greater sensitivity of large firms relative to small firms to cyclical conditions is mainly driven by firm maturity. In other words, the idea that larger firms are more cyclically sensitive receives greater support when the analysis is restricted to a subset of smaller and older firms, suggesting that smaller and younger firms may be more sensitive than previously thought. Further research on the relationship between size, age, and credit is important, considering that recent studies for the US indicate that the job ladder mechanism stopped working after the 2008 Great Recession (e.g., Haltiwanger et al., 2015; Haltiwanger et al., 2018; Hyatt and McEntafer, 2012; and Moscarini and Postel-Vinay, 2016). This seems to

[7] Haltiwanger et al. (2018b) suggest that firm size might be a poor proxy for productivity, as small, young firms might be highly productive and in the process of becoming large firms. Also, small businesses exhibit a greater decline in net job flows in contractions than large businesses, and this is driven by the responsiveness of net hires from nonemployment. This suggests a possible role for credit constraints across all small firms.

indicate that under conditions of extreme credit crunch, financial constraints are more binding on low wage and small firms, leading to a wave of layoffs that reverses the empirical results related to the job ladder mechanism. These results also send a message that theoretical models guiding public policy must include credit constraint as a major variable influencing employment dynamics during economic fluctuations. This is particularly true if one wants to understand what is happing in developing countries, which have less developed credit markets that might impose tighter credit constraints on smaller business.

Evidence for developing countries is important, as there are specificities beyond the less developed credit markets and potential differences in the correlation between productivity proxies and TFP compared to the US. The existing literature documents that business cycle fluctuations are more volatile in developing countries compared to developed countries (e.g., Neumeyer and Perri, 2005; Aguiar and Gopinath, 2007). Also, labor market adjustments have distinctive characteristics in developing countries; for instance, Haltiwanger et al. (2014) show that job reallocation rates are higher in Latin American than in OECD countries. Thus, worker reallocation and poaching are likely to vary across countries with different levels of development, meaning appropriate policy responses will also vary. Importantly, how age and productivity affect employment dynamics in developing countries, also a contribution of this paper, is fundamental for an adequate policy response in these countries.

3. Data

In this section, we describe the rich sources of microdata that allow us to construct a longitudinal database to produce robust results about how firm size, wage, and productivity influence job-to-job moves and the firm job ladder in a developing country. We use two main sources of data: the RAIS[8]—administrative employer and employee data produced by the Ministry of Labor—and the manufacturing sector survey PIA[9] produced by the Brazilian Institute of Geography and Statistics (IBGE).

3.1 Data Sources

[8] RAIS stands for Relação Anual de Informações Sociais, the Annual Social Information report.
[9] PIA (Pesquisa Industrial Anual)

RAIS

RAIS is administrative data collected annually by the Ministry of Labor. Every year, all formal businesses are required to by law to report on their business and employees to the Ministry of Labor. If an establishment fails to provide the annual RAIS declaration, it faces automatic fines proportional to the length of the delay and the number of declarations omitted. Severance payments are based on RAIS records, thus employers and workers have a strong incentive to submit the annual RAIS declaration. RAIS covered 3.9 million establishments and 49.5 million workers as of 31 December 2014, and the Ministry of Labor estimates that this coverage represents about 97% of the formal sector.[10]

The rich RAIS data provides us with an array of firm level information, such as sectoral classification, location, stock of employment, wages, and date of firm opening. This set of information allows for the calculation of the size class based on employment stock and wages as well as for the calculation of each firm's age. Importantly, RAIS is a linked employer-employee matched dataset that includes a unique firm identification number (CNPJ) and allows researchers to construct a longitudinal dataset tracking firms throughout the period of analysis. The possibility of constructing a longitudinal dataset is important for producing results that are not affected by size reclassification bias, which occurs as employers are reclassified into another size class as the economy grows or enters a recession. Using the RAIS firm identifier, we can rank firms by size and wage and fix this classification based on how firms are classified in the first period in January 2000. This way we can isolate and sidestep the reclassification bias effect, which, as shown in Moscarini and Postel-Vinay (2012), affects the results.

An interesting characteristic of RAIS is that it allows the construction of monthly data, as it indicates the month of hiring or separation of each individual worker within each year. For instance, if a worker had two jobs in a given year, the worker would appear twice in the RAIS records with the respective separation and hiring month related to each job. This allows us to calculate the monthly net job flows for the period of data availability, from January 2000 to December 2014. This is the first time such longitudinal monthly data based on continuing firms

[10] According to IBGE (2016), only 50% of workers in Brazil are formally registered; however, this aspect is not as pronounced in the manufacturing sector, which employs around 70% of the workers in the formal sector.

has been constructed based on matched employer-employee microdata in Brazil.[11] The data used in this paper is restricted to firms that continue to exist throughout the panel period to avoid reclassification bias. The resulting balanced longitudinal employment series with continuing firms encompasses 536,946 firms and 11,442,246 workers as of December 2014.

The shortcoming is that RAIS does not provide information that allows for the construction of firm-level productivity. Thus, the job ladder mechanism that argues that job-to-job moves reallocate workers up the firm productivity ladder cannot be tested directly using RAIS data alone.

Manufacturing Sector Survey

To complement the RAIS data, we use the PIA microdata provided by IBGE, which is an annual survey covering the manufacturing sector that provides the information necessary for the calculation of firm level productivity measures. PIA is representative of the manufacturing sector at national level. The sample is constructed based on the General Registry of Enterprises (CEMPRE), which is based on administrative data provided by the Ministry of Labor (including RAIS) and IBGE surveys.

We calculate two productivity measures to rank firms using PIA data: labor productivity and total factor productivity (TFP). The labor productivity measure is a simpler and partial productivity proxy given by added value divided by workers. A more direct productivity measure is given by TFP, which indicates the efficiency at which the firm combines resources to generate output (see details in Annex A.1). After ranking firms by productivity, we define firms in the top quintile as high productivity firms and those in the bottom quintile of the distribution as low productivity firms.

The annual PIA data is combined with the constructed RAIS to provide the continuing monthly longitudinal panel with job flows. We cross the firm level ranking of productivity calculated using PIA with RAIS by using the unique firm identifier that is common to both datasets. This allows us to construct employment flows for the firms ranked by productivity. The result is a dataset that is a balanced longitudinal employment series with continuing firms that

[11] Annual longitudinal linked employer-employee series were constructed before; however, this paper overcomes the computational difficulties and constructs, for the first-time, monthly job flow longitudinal data to study employment dynamics. A simple exercise using part of this data can be seen in Cravo (2017).

appear both in RAIS and PIA in January 2000 and encompasses 4,988,557 workers as of December 2014.

Complementary Macroeconomic data

The paper relates net differential growth rates based on size, wage, and productivity with business cycles. The cyclical indicator used in this paper is the official monthly unemployment rate from IBGE, as in Moscarini and Postel Vinay (2012), the unemployment rate is an indicator of labor market tightness. The last part of the paper estimates VARs using aggregated monthly macroeconomic series to analyze the response of the differential growth rates and unemployment. The VARs also include reference interest rate (SELIC) and a credit constraint variable from the Brazilian Central Bank and official inflation (IPCA) from IBGE.[12]

3.2 Firm Ranking by Size, Wage and Productivity

Table 1 shows the employment stock and share by ranking firms by size, wage, and productivity. Firms are ranked using four measures. First, size is determined based on number of employees. Firms with fewer than 50 employees are considered small and those with more than 500 are considered large enterprises, following the definition used by Haltiwanger et al. (2015). Second, an alternative firm classification is determined over the distribution of total wage payments, whereby those firms in the first quantile of the wage distribution are considered "low-wage" and those in the last quintile "high-wage." Third, firm category is measured in terms of labor productivity and TFP, whereby low productivity firms are those in the first quintile of the productivity distribution and high productivity firms are those in the last quintile.

For each ranking, we create a subgroup based on the age of firm, an important factor to be considered in this paper. Young and old firms are those operating for less than 5 years and at least 5 years, respectively. The age of the firm is defined in 2000, the first year of our panel. The upper panel shows tabulations using absolute numbers, and the lower panel shows the relative numbers. Table 1 shows that the PIA/RAIS data includes 4,988,557 formal workers in 2014. The

[12] The credit constraint variable is the percentage of credit operations with non-earmarked funds in arrears from 15 to 90 days in financial institutions in Brazil. A similar credit constraint proxy is used in Aghion et al. (2008).

distribution of workers across classes and age differs according to the ranking criteria used. Most employment (34.5%) is in old and large firms when firms are ranked by employment. When firms are ranked by wage quintiles, the PIA/RAIS panel presents a substantial decrease in the share of workers in low ranked firms and an increase in high ranked firms. When using TFP as a productivity firm ranking measure, about one-quarter of all employees are employed in old high TFP productive firms and 10.7% of employees work in old low TFP productive firms. Differences in the distribution presented in Table 1 are a clear indication that the criteria used to classify firms might affect the results, particularly when employment is used as a proxy for productivity.[13]

Table 1 - Employment Stock and Share by Size Class and Age (2014)

Employment Stock by Size Class and Age (Young firm < 5 years, Old firm at least 5 years)												
	Employment			**Wage**			**Labor Productivity (LP)**			**Total Factor Productivity (TFP)**		
	Small	Medium	Large	Low wage	Medium	High wage	Low LP	Medium	High LP	Low TFP	Medium	High TFP
Young	447417	272518	260942	102012	462140	416725	78105	264572	180787	162003	256152	62967
Old	763799	1520733	1723148	208665	1555282	2243733	189105	1230391	1958693	399151	1950250	907823

Employment Share in by Size Class and Age (Young firm < 5 years, Old firm at least 5 years)												
	Employment			**Wage**			**Labor Productivity (LP)**			**Total Factor Productivity (TFP)**		
	Small	Medium	Large	Low wage	Medium	High wage	Low LP	Medium	High LP	Low TFP	Medium	High TFP
Young	9.0%	5.5%	5.2%	2.0%	9.3%	8.4%	2.0%	6.8%	4.6%	4.3%	6.9%	1.7%
Old	15.3%	30.5%	34.5%	4.2%	31.2%	45.0%	4.8%	31.5%	50.2%	10.7%	52.2%	24.3%

4. Methodology

In line with Fort et al. (2013), Haltiwanger et al. (2013) and Moscarini and Postel-Vinay (2012), this study calculates the net growth rates for firms of a respective firm category “s” and age “a” as follows:

$$g_{sat} = (E_{sat} - E_{sat-1})/X_{sat}$$

[13] Annex A.2 also shows that the average firm size changes within classes according to the criteria used to classify firms.

Where E_{sat} and E_{sat-1} stand for employment in year *t* and *t-1* in a firm of classification "s" and age "a."

The firm classification criteria "s" refers to any of the four firm ranking criteria used to classify firms. First, size is determined based on number of employees. Second, firms are ranked over the distribution of total wage payments. The conceptual advantage of using the ranking along the wage distribution is that the poaching mechanism is driven by wage differences and, as Svyerson (2011) points out, wages also account for the marginal product of labor.[14] Third, firms are ranked by productivity measures. We consider TFP our best productivity measure, which provides results that are more directly linked to the prediction of the dynamic on-the-job-search theory tested in this paper. We also use an alternative labor productivity measure given by value added by number of workers.

Age "a" refers to firms being young or old. The date at which the oldest establishment of the firm is created is used to calculate firm age and distinguish between young and old firms. Young and old firms are those operating for fewer than 5 years and at least 5 years, respectively.[15]

The term X_{sat} , which is defined as $X_{sat} = 0.5 * (E_{sat} + E_{sat-1})$ weights, employment in the two periods by 0.5, which is a common choice of weight in the literature as discussed in Davis et al. (1996). This weighting creates a growth rate bounded between (-2,2), that is, with entry and exit symmetric around zero.

The critical advantage of the availability of micro-level panel data is that it allows us to track each firm based on classification criteria "s" and age "a" between E_{sat} and E_{sat-1}, thereby avoiding reclassification bias. The growth rate can therefore be disaggregated and equivalently generated at the individual firm level. The weighted sum of growth rates (g_{sat}) of firms "f" in a given firm classification criteria and age and can be written as:

$$g_{sat} = \sum_{f \in sa} \frac{X_{fsat}}{X_{sat}} \left(\frac{E_{fsat} - E_{fsat-1}}{X_{fsat}} \right) = \sum_{f \in sa} \frac{X_{fsat}}{X_{sat}} g_{fsat}$$

[14] Wage is argued to be a better proxy to productivity compared to size based on employment. Considering that Brazil has a mandatory minimum wage for full-time employees, only those receiving at least minimum wage are included in the count.

[15] An alternative definition of young and old uses firms operating for fewer than 10 years and at least 10 years, respectively.

This allows the calculation of separate growth rates for employment size (large or small), wage, labor productivity and TFP level categories and age combinations (large, small, large/old, small/young, and so on).[16] The differential growth rates between large and old firms (LO) and small and young (SY) can be stated as:

$$\Delta g_{LO,SYt} = \sum_{f\in LO} \frac{X_{fLOt}}{X_{LOt}}\left(\frac{E_{fLOt} - E_{fLOt-1}}{X_{fLOt}}\right) - \sum_{f\in SY} \frac{X_{fSYt}}{X_{SYt}}\left(\frac{E_{fSYt} - E_{fSYt-1}}{X_{fSYt}}\right)$$

Our objective is to determine how the deviation from the trend of the differential growth rates, for instance, of LO firms and SY firms, correlates with unemployment rate.

The choice of unemployment rate as a business cycle indicator is guided by the theory that assumes that labor market tightness determines the relative contributions of high and low productivity firms to job creation; highly productive firms poach employees from low productivity firms when unemployment is high in the dynamic job ladder model (e.g., Moscarini and Postel Vinay 2009, 2016). To extract cyclicality from the data, this study applies the band pass filter developed by Christiano and Fitzgerald (2003), abbreviated as the CF filter, that accounts for the common definition of cycle fluctuations lasting between 1.5 and 8 years and removes fluctuations of higher and lower occurrences (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003; Rua and Nunes, 2005).[17]

5. Evidence on Employment Cyclicality by Firm Size, Wage, Age, and Productivity

This section first presents figures with the patterns of the deviation of the differential employment growth rates between high-ranked (large) and low-ranked (small) firms based on employment, wage, labor productivity, and TFP in relation to the unemployment rate. Next, the correlations among the four measures included in this study and in the literature used as proxies

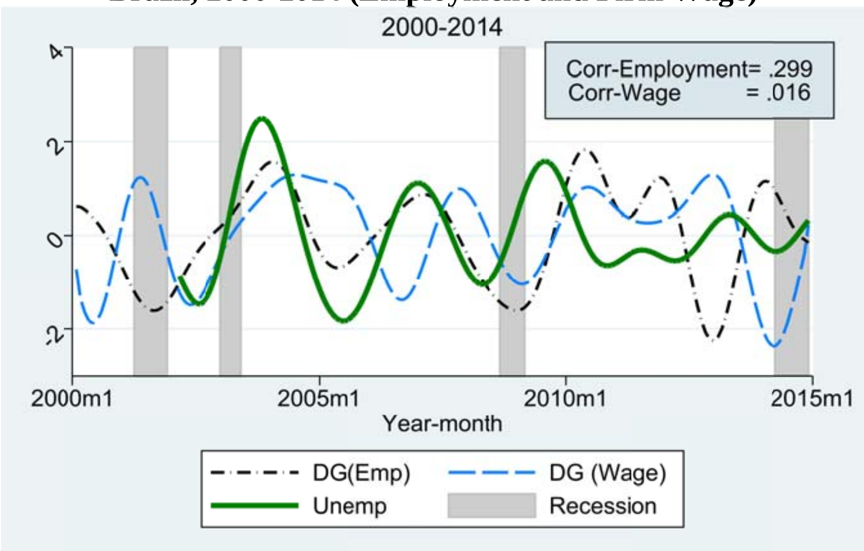
[16] Alternatively, an unweighted employment growth measure (shown in Annex A.4), proposed by Moscarini and Postel-Vinay (2012), is calculated as a robustness check. Results are similar and available upon request.

[17] Given the shortcomings of the alternative Hodrik-Prescott (HP) filter discussed by Baxter and King (1999), Christiano and Fitzgerald (2003), and Hamilton (2017), we use the band pass filter as the filtering method in this study. Hamilton (2017) provides a critical account of the use of the HP filter. Thus, results presented by Moscarini and Postel Vinal (2012) and Fort et al. (2013) that use the HP filter in the context of employment cyclicality must be interpreted with caution.

for productivity are discussed. Finally, the patterns of the deviation of the differential employment growth rates, further disaggregated by incorporating firm age, are shown. All rates are seasonally adjusted using the CF-filter, and the recession periods marked in grey are based on the classification of the Brazilian Business Cycle Dating Committee (CODACE) of the Brazilian Institute of Economics (IBRE).

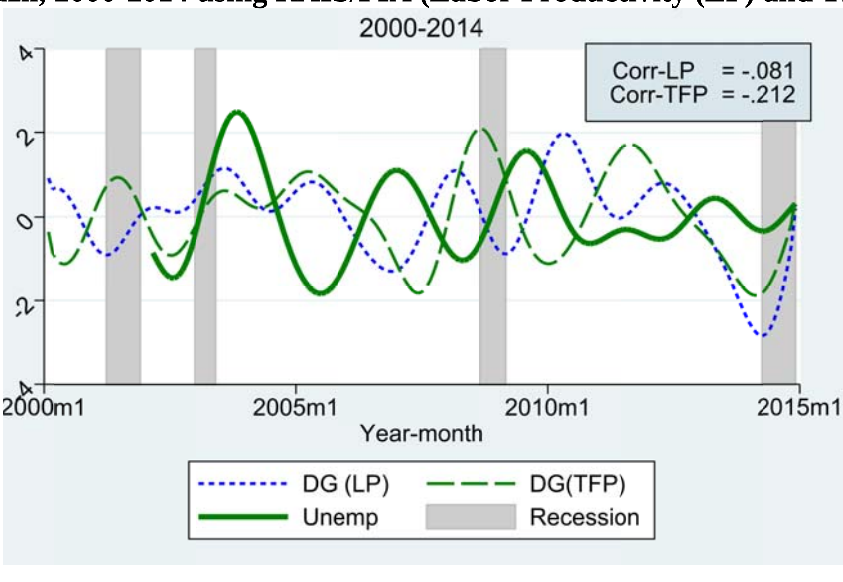
Figure 1 shows the correlation between the unemployment rate and the differential growth rates using firm size and wage distribution to rank firms. The unemployment rate increases over the marked recession periods and peaks shortly after. The differential employment growth rate, using firm size as firm ranking criteria, presents a strong positive correlation with unemployment, suggesting that employment in small firms is more cyclically sensitive to unemployment. The differential employment growth rate, using the wage distribution to rank firms, presents a slightly positive correlation with unemployment. These results are in line with available evidence for Brazil and suggest that employment in small and low-paying firms is more cyclically sensitive (Cravo, 2011; 2017). These results are based on proxies that are used in the literature based on the argument that they are positively related to productivity.

Figure 1- Differential Growth and Cycles
Brazil, 2000-2014 (Employment and Firm Wage)



Results ranking firms by productivity measures are presented in Figure 2 and show the opposite correlation from results presented in Figure 1. When firms are ranked by labor productivity or TFP, our most direct and preferred productivity measure, results indicate that high productivity firms are more sensitive to cycles. When unemployment rates rise, the differential employment growth rate decreases, meaning that highly productive firms face greater employment losses than low productivity firms. Thus, results indicate a negative correlation between unemployment and net differential growth, suggesting that employment is more sensitive to cycles in more productive firms. This result supports the job ladder mechanism suggested by Moscarini and Postel-Vinay (2009, 2012) in a developing country context. Nevertheless, the results shown in Figure 2 provide a clear warning that firm ranking cannot assume that the correlations among employment size, wages, and productivity are positive, as suggested in Moscarini and Postel-Vinay (2012).[18] The stylized facts about employment cyclicality are complex, and, as Cravo (2017) notes, recent studies are improving our understanding of employment cyclicality by indicating that other aspects such as the age of firms, credit constraints, and the use of direct productivity proxies are important.

Figure 2 –Differential Growth and Cycles
Brazil, 2000-2014 using RAIS/PIA (Labor Productivity (LP) and TFP)



[18] Table 2 shows that the correlations between TFP and employment, wages, and labor productivity are weak. Particularly, the correlation between TFP and employment size is zero for the manufacturing sector in Brazil. Results based on different proxies should be used with caution and might be used to inform different policy aspects. The non-existent size ladder but sizable wage ladder that Haltiwanger et al. (2018b) observe in the US are interesting results that might be related to different aspects of employment cyclicality.

The use of a direct productivity proxy is important in testing the existence of a firm productivity job ladder. Table 2 provides correlations between TFP, a direct productivity *proxy*, employment, wage, and labor productivity at firm level. The correlation between TFP and employment is non-existent, and correlations with wages and labor productivity are low, at 0.25 and 0.32 respectively. The low correlation between TFP and other *proxies* for productivity help explain the different patterns found in Figures 1 and 2. The weak correlation between TFP and proxies for productivity suggest that we should focus on more direct productivity measures when the objective is to analyze the firm productivity job ladder.

Table 2 – Correlations between TFP and other firm ranking measures: employment, wage, and labor productivity

	Labor Productivity	Wage	Employment Size
TFP	0.32	0.25	0.0

As our main objective is to provide evidence of employment dynamics and job ladder using TFP as a more direct proxy for productivity, we focus our discussion by including age as moderating factor on the result using the firm classification criteria TFP and, according to Table 2 the most correlated indirect productivity proxy, labor productivity. The results based on employment size and wages that are often used as a gross proxy for productivity are provided in the Annex.

Recent studies have shown that employment dynamics are influenced not only by level of employment, wage, or productivity but also by the age of the firm (e.g., Haltiwanger et al. 2013; Fort et al. 2013). Distinguishing firm age is important, as younger firms might have less access to credit markets and rely more on personal sources of finance. Nevertheless, the literature for developing countries neglects firm age, which is paramount to better understanding the factors influencing employment fluctuations. This paper incorporates the discussion of the importance of firm age for employment fluctuations, and Figure 3 shows the net growth differentials for firms ranked by productivity and age. As indicated in the previous sections, young and old firms are those operating for less than 5 years and at least 5 years, respectively.

Figure 3 shows that there are different cyclical patterns across age groups, indicating that age is an important variable determining employment patterns across business cycles. Results for the manufacturing sector using total factor productivity, our preferred measure, always support the job ladder mechanism. “High-productivity/old” firms are more sensitive to cycles, regardless of the age classification of low-productivity firms. The correlation between high-productivity/old and low-productivity/young firms is more intense, suggesting that the job ladder (and poaching) affects low-productivity and new firms more. When firms are ranked by labor productivity, results indicate that the correlation between the difference in net growth rates between high-productivity/old and low-productivity/old firms and unemployment is slightly negative, in line with results found in Figure 2 and supporting the job ladder and poaching mechanism based on the assumption that high productivity firms are able to poach employees from low productivity firms. Yet, the employment differential between high-productivity/old and low-productivity/young firms and unemployment has the opposite sign, suggesting that employment in young low-productivity firms is more sensitive to business cycles. This result might indicate that firm age is more important only when we use gross proxies for productivity. Results suggest that even the use of a gross measure of productivity must be considered with caution, as it produces different results compared to our preferred TFP measure.

Figure 3 - Differential Growth and Cycles
Brazil, 2000-2014 using RAIS/PIA - Labor Productivity (LP) and TFP

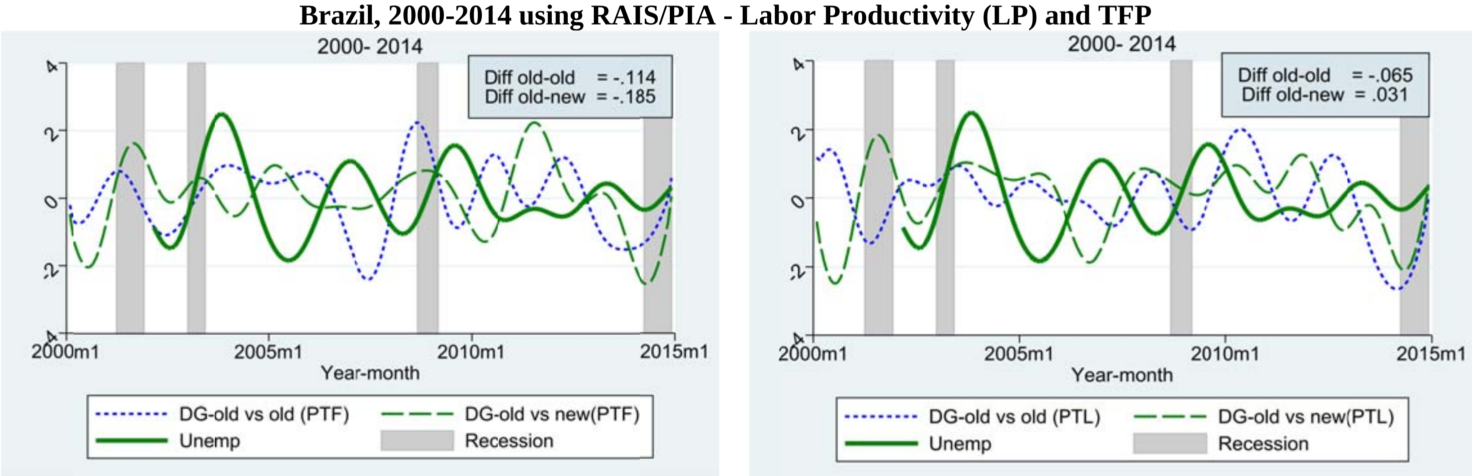


Table 3 summarizes the correlations between the net differentials of employment growth based on firm rankings, constructed based on productivity measures, and unemployment as shown in Figures 2 and 3. The correlations between the change in the unemployment rate and net differentials of employment growth rates are overall negative. These results are in line with the job ladder theory, in which employment in high-productivity firms is more sensitive than in low-productivity firms.

Table 3 - Correlations Between Unemployment and Net Differential Employment Growth Rates (2000-2014) – Productivity - Using PME, Balanced Panel, complete period

	PIA - TFP	PIA - LP
High Productivity- Low Productivity	-0.21	-0.08
High Productivity Old - Low Productivity Old	-0.11	-0.07
High Productivity Old - Low Productivity Young	-0.18	0.03

Note: Correlations between cyclical components of variables extracted by the CF filter

The results shown in Figure 3 and Table 3 are in stark contrast to the results presented in Figure 1, which shows a positive correlation between the net differentials of employment growth when the rankings of firms are based on firm size or wages. The use of different proxies to rank firms in a developing country leads to a dramatic change in the results, from opposing the job ladder to supporting it. For developed countries, Haltiwanger et al. (2018a, 2018b) has already shown that the relationship between employment size, wage, and (labor) productivity is weaker than expected for the US. However, as our results show, the correlation between the commonly used productivity proxies of employment size, wage, labor productivity, and TFP are even weaker than in the US in the developing country context of Brazil. Thus, a more direct use of productivity is paramount in studying the job ladder mechanism, particularly in a developing country context.

The new set of stylized facts presented in this section uncovers important aspects that are fundamental to public policy concerning employment during different stages of the business cycle. Our results show the importance of using a direct productivity measure in a developing country context as opposed to gross proxies for productivity. The stylized facts show, in a comprehensive manner, how net differential employment growth rates correlate with cyclical conditions. However, the results presented so far are correlations from which causal inferences cannot be made. The next section complements the evidence provided by the stylized facts and exploits variation across time to investigate, in a more structured manner, how business cycle shocks affect net differential employment growth rates and poaching.

6. The Response of Firms to Unemployment

To examine the relationship between differential growth rates and cycles, we follow Gertler and Gilchrist (1994), Moscarini and Postel-Vinay (2010) and Fort et al. (2013) and analyze the behavior of differential growth rates conditional to shocks to business cycle-related measures. By estimating VARs, we provide evidence of how shocks to unemployment affect the differential growth rates of firms with high and low productivity. We estimate the VARs using the unemployment rate, inflation rate (IPCA), credit constraint, net differential growth rate (DGR), and interest rate.[19] Two VARs are estimated for the manufacturing sector; we present the first VAR estimation using TFP to classify firms in this section and alternative results using labor productivity in Annex 6.

Figure 4 reports a set of selected impulse responses with their confidence band. The variables are ordered as indicated above, and the reference interest rate is placed last, as in Gertler and Gilchrist (1994), to capture the idea that monetary policy adjusts to current events but its effects operate only in the following month.

The first panel in the upper left corner shows the response of the differential growth rate to unemployment, the primary effect of interest, based on our preferred TFP measure. A shock to unemployment leads to a significant decline in the differential growth rate, a result in line with dynamic models of on-the-job-search that predict that workers move up the firm productivity job ladder. This result is in line with the stylized facts reported in Table 3, which shows that high productivity firms are more cyclically sensitive.[20]

[19] The VAR order was chosen based on the Final Prediction Error (FPE) and Hannan-Quinn (HQ) criteria.
[20] Annex 7 presents the same impulse response based on labor productivity. For this alternative and gross productivity measure, results show that shock to unemployment does not affect the differential growth rate.

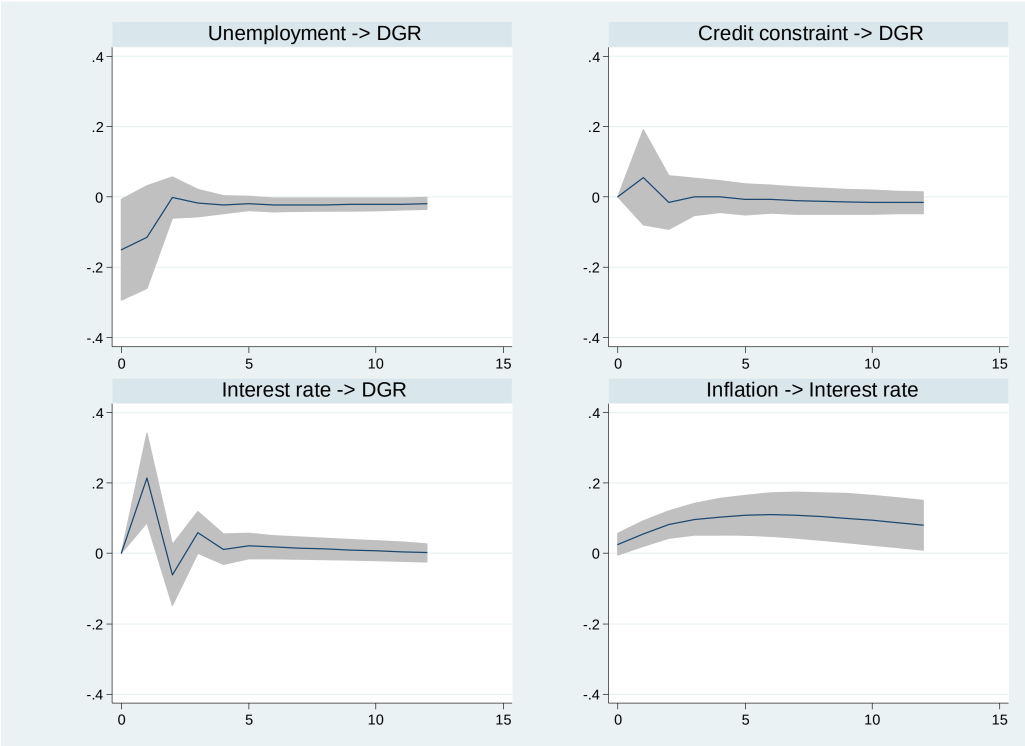
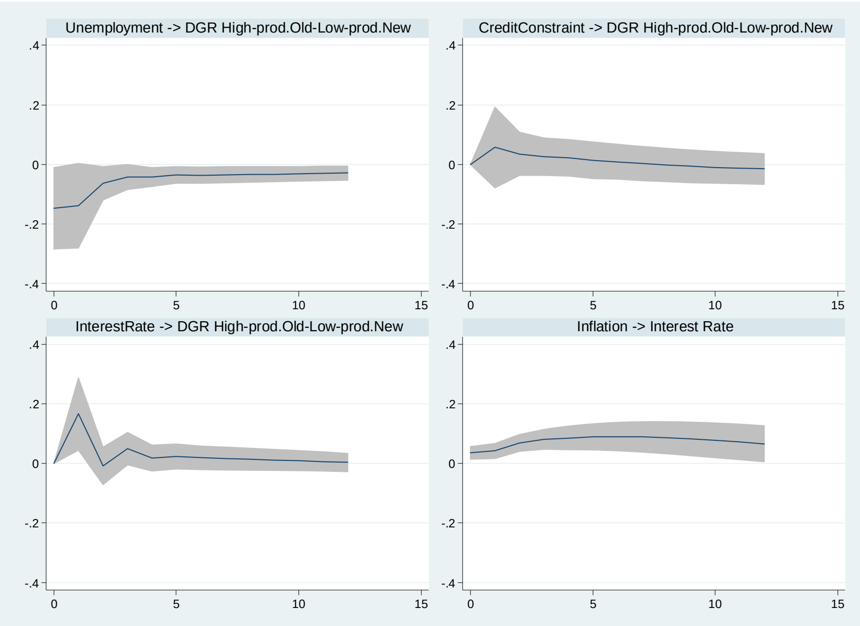


Figure 4: Selected Impulse response functions - DGR between High-productivity and Low-productivity (TFP firm ranking)

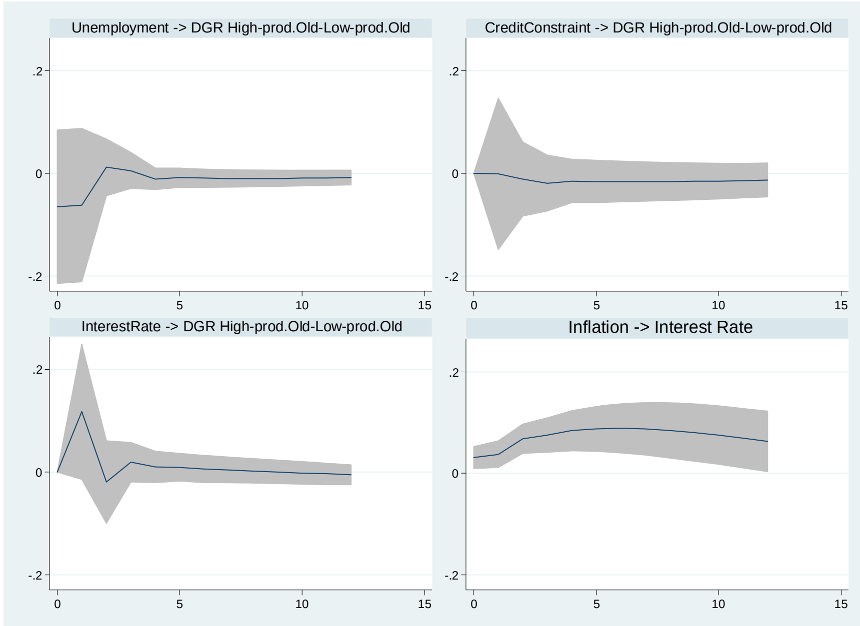
The results also show that interest rate increases during periods of expansion tend to constrain employment growth in low-productivity firms. The impulse response in the bottom left corner of Figure 4 shows that the DGR tends to increase when the SELIC increases, indicating that a higher interest rate prevents low-productivity employment growth—an argument in line with Moscarini and Postel-Vinay (2010). In the bottom right corner of Figure 4, the monetary policy responds to inflation in the expected direction, a shock to inflation leads to an increase in interest rates, suggesting that the Central Bank follows the Taylor rule and is concerned with the inflation target via monetary policy response as previously documented in the literature (e.g., Moura and Carvalho, 2010).

As discussed, Fort et al. (2013) argue that the age of firms is important to understanding the relationship between cyclical conditions and worker reallocation, as younger firms might have less access to credit markets and rely more heavily on personal sources of finance. Thus, the job ladder might work differently as a result of younger firms having less access to credit. To test this argument, we follow Fort et al. (2013) and show in Figure 5 the impulse responses for the VARs estimated using the age criteria. We show VAR impulse response functions using the differential growth rate between high-productivity/old and low-productivity/young firms (Panel A) and afterwards using the differential growth rate between high-productivity/old and low-productivity/old firms (Panel B).

In general, the impulse responses in Panel A of Figure 5 are similar to those shown in Figure 4. In the upper left corner, the impulse response shows that the differential growth rate related to low-productivity/young firms declines as a result of a shock to unemployment. This suggests that workers move up the firm productivity job ladder by moving from a low-productivity/young firm to a high-productivity/old firm in a period of expansion. On the other hand, the differential growth rate related to low-productivity/old firms does not respond to a shock to unemployment in panel B. This indicates that workers move up the firm productivity job ladder by moving from a low-productivity/young firm to a high-productivity/old firm in a period of expansion. The bottom left corner of panels A and B show that interest rate increases during periods of expansion tends to constrain employment growth only in low-productivity/young firms.



Panel A
DGR between high-productivity old and low-productivity new



Panel B
DGR between high-productivity old and low-productivity old

Figure 5: Selected Impulse response functions - DGR between High-productivity and Low-productivity by Firm´s Age - Manufacturing (PIA) Sector LO_SO (DG between High-productivity old and Low-productivity Old) and LO_SN (DG between High-productivity old and Low-productivity New) (TFP classification)

Our results support the argument that older firms might have more access to credit regardless of being high or low productivity firms, and this might weaken the job ladder mechanism. If age captures the ability of firms to get credit, a small but older firm can use credit to cushion the effect of a crisis and retain its employees. New firms might also have more difficulties in times of higher interest rates. Thus, the stylized facts in Figure 2 show that low productivity firms are proportionately less sensitive, and this seems to be driven by young low productivity firms that suffer more from poaching and interest rate increases.[21]

7. Conclusion

In this paper, we provide evidence of the dynamics of employment creation and destruction in heterogeneous firms during business cycles in a developing country context. To do so, we use linked employer-employee data and manufacturing sector surveys from Brazil between January 2000 and December 2014 to calculate monthly job creation. We use unemployment rate to test the dynamic job ladder model in a developing country and to estimate employment sensitivity to shocks using VARs.

We present stylized facts about the sensitivity of employment in firms ranked by employment size, wage, or productivity to business cycles. The first important result of the paper is that the correlation between employment size, wage, and productivity is not as strong as argued in other studies, and results differ according to the variable used. Thus, direct productivity measures should be used to analyze the productivity job ladder. Our study calls for caution in the use of employment and wages as productivity proxies and stresses that different interpretations should be given for the results based on less direct proxies than TFP. Second, we show that high productivity firms shed proportionally more jobs in recessions and gain more in booms when firms are ranked by the TFP distribution—a result that suggests that workers move up the firm productivity ladder in the manufacturing sector in Brazil. Third, our impulse response analysis indicates that shocks to unemployment hit high productivity employers harder, which is further evidence in favor of job ladder models. The impulse response analysis suggests that workers move up the productivity ladder by moving from young firms with low levels of

[21] Annex A.7.2 shows the results based on the alternative measure of labor productivity. Both graphs show that a shock to unemployment does not have a statistically significant effect on the differential related to low-productivity regardless of firm age.

productivity to old firms with high levels of productivity. Thus, the results of this study suggest that the productivity job ladder and the age of firms should be considered by policy-makers when designing policies aiming to reduce employment fluctuations during different stages of the business cycle.

Annex

A.1 – Productivity Measures (labor productivity and Total Factor Productivity)

Labor productivity

Labor productivity (LP) is a popular measure broadly used in the literature and characterized by easy calculation and interpretation. It is directly calculated without imposing a hypothesis and does not require the estimation of a production function or capital stock. The calculation of labor productivity uses an index that considers the added value divided by workers:

LP= AV/L

where LP is labor productivity, AV is added value, and L is the number of workers in a firm. Nevertheless, labor productivity presents some limitations. For instance, productivity increases occur only via capital accumulation.

Total Factor Productivity

A more direct productivity measure is given by the Total Factor Productivity (TFP), which is a measure that indicates the efficiency at which the firm combines resources to generate output. In this paper, we follow Petrin, Levinsohn and Poi (2003) to estimate the production function and compute the TFP. The choice of this method is twofold. First, it uses intermediary inputs to calculate TFP. Second, it corrects for selection bias. Data on occupied workers (L), capital stock (K), calculated based on perpetual inventory and intermediate inputs (net machinery investment), are the variables we use to calculate the production function.

Different from LP, TFP requires identification, measurement, and knowledge of how each resource is used in the production process. TFP is an efficiency measure that identifies efficiency gains and factor accumulation. Thus, it is regarded as a better productivity measure than LP, which is a partial productivity measure that does not account for efficiency gains from factor substitution. To calculate the TFP of firm i at year t , consider the following Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m}$$

where Y_{it} represents the product of firm i at year t; K_{it} , is the stock of capital; L_{it} , stock of occupied workers; M_{it} is intermediate input and A_{it}, a unobservable technology parameter to the researcher. We apply logs to generates a linearized version of this equation:

$$\ln Y_{it} = \beta_0 + \beta_k lnK_{it} + \beta_l lnL_{it} + \beta_m lnM_{it} + v_{it} + u_{it}$$

where $\ln(A_{it}) = \beta_0 + v_{it}$, β_0 represents the average level of efficiency among firms and u_{it} is an error term. The estimates for $\widehat{\beta_0}$, $\widehat{\beta_k}$, $\widehat{\beta_m}$ and $\widehat{\beta_l}$ allow us to compute TPF that is given by:

$$\widehat{w_{it}} = lnY_{it} - \hat{\beta}_k lnK_{it} - \hat{\beta}_l lnL_{it} - \hat{\beta}_m lnM_{it}$$

We estimate the TFP as suggested in Levinsohn and Petrin (2003) by following the two-stage strategy described in Petrin, Levinsohn and Poi (2003).

A.2 - Average Firm Size by ranking criteria and year

A.2.1 - Average Firm Size by ranking criteria and year

	Employment			Wage			Labor Productivity			Productivity (TFP)		
Year	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Low	Medium	High
2000	19.1	148.7	1617.6	26.6	54.1	211.9	73.9	111.6	315.7	99.8	167.0	234.7
2001	20.9	152.2	1623.6	28.8	56.9	212.8	78.0	112.5	317.2	103.1	168.9	230.9
2002	21.1	148.4	1550.3	31.7	56.5	200.2	77.0	109.0	304.3	107.0	164.0	213.7
2003	22.2	153.0	1616.0	33.7	59.2	206.3	78.3	112.1	315.1	116.2	168.7	217.7
2004	24.7	168.3	1769.2	36.1	66.7	223.3	86.0	123.3	343.0	133.8	183.7	235.4
2005	26.5	173.1	1811.6	36.9	68.6	233.1	87.3	123.7	357.1	140.1	186.9	241.5
2006	28.1	181.0	1872.7	39.0	71.1	244.4	92.5	125.9	375.5	150.0	192.2	252.1
2007	30.4	195.9	1976.6	40.2	75.0	266.6	100.0	131.7	409.3	167.4	204.6	268.1
2008	32.3	201.3	2003.2	41.0	76.0	278.3	100.9	131.5	424.5	167.1	207.7	278.2
2009	34.4	202.4	2007.1	42.2	77.3	282.2	101.7	132.4	425.1	171.5	209.0	275.6
2010	37.2	217.5	2171.1	43.8	83.0	307.8	105.2	143.1	459.7	191.8	224.9	294.6
2011	38.2	224.0	2221.3	44.2	84.3	319.1	109.9	143.9	476.5	199.8	227.8	306.7
2012	38.7	227.6	2225.7	43.3	85.0	323.7	109.1	144.9	480.9	203.4	229.4	308.3
2013	40.7	232.9	2246.2	42.8	86.4	335.1	110.1	146.4	489.1	210.6	232.7	309.4
2014	39.8	227.2	2214.4	41.9	85.1	326.9	106.0	143.9	479.9	210.9	227.0	304.2

Note: RAIS and PIA

A.2.2 - Average Firm Size by ranking criteria and year

	Employment			Wage			Labor Productivity			Productivity (TFP)		
Year	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Low	Medium	High
2000	13.0	144.3	1541.3	15.7	29.7	138.7	19.9	34.3	136.5	40.1	68.3	54.4
2001	12.8	141.8	1554.2	15.6	29.5	135.5	19.2	32.6	131.3	38.4	69.0	53.3
2002	11.9	128.8	1511.4	16.0	28.8	133.4	17.9	30.5	137.9	34.3	61.1	51.9
2003	12.0	130.7	1498.9	16.8	29.1	134.7	19.4	32.2	117.1	39.7	61.1	47.2
2004	12.2	127.3	1584.2	18.2	30.7	145.7	17.2	36.1	130.8	39.5	66.2	55.8
2005	12.4	126.4	1663.4	18.6	30.4	150.9	17.2	37.5	115.8	39.6	67.2	50.7
2006	12.3	126.0	1684.3	20.3	30.4	162.6	17.5	37.7	119.2	39.6	68.2	50.5
2007	9.0	126.0	1728.5	17.0	20.9	152.7	12.5	29.1	77.4	33.0	55.0	34.6
2008	9.0	124.4	1772.8	17.2	20.4	177.8	13.6	26.8	83.7	33.3	51.5	40.9
2009	9.3	124.0	1773.0	18.0	21.3	173.1	13.1	27.8	86.6	38.9	53.4	35.9
2010	9.4	124.8	1818.8	19.4	22.2	196.7	13.2	29.2	87.3	34.8	63.2	36.2
2011	9.3	125.1	1865.0	17.9	22.1	198.0	13.3	29.1	78.6	37.8	63.8	33.1
2012	9.0	126.2	1846.3	19.9	21.4	198.6	12.4	29.4	72.4	36.4	60.0	30.4
2013	9.0	127.9	1895.1	18.9	21.6	208.4	12.9	28.8	75.0	37.1	58.9	32.5
2014	9.2	127.3	1910.1	21.9	21.7	222.0	14.2	28.0	74.9	31.8	64.2	34.4

Note: RAIS and PIA

A.3 – Number of Firms

	Employment			Wage			Labor Productivity			Productivity (TFP)		
	Small	Medium	Large	Low	Medium	High	Low	Medium	High	Low	Medium	High
Young	9044	1074	65	2655	6055	1473	636	1474	490	529	1166	473
Old	21420	6820	831	4763	17643	6665	1885	8913	3968	2132	8553	2718

Note: RAIS and PIA. Young firm < 5 years and old firm >= 5 years.

A.4 – Unweighted employment growth

Alternatively, an unweighted employment growth ($g_{sat_{unweighted}}$) measure proposed by Moscarini and Postel-Vinay (2012) that will be calculated as a robustness check can be written as follows:

$$g_{sat_{unweighted}} = \sum_{f \in sa} \frac{\left(\frac{E_{fsat} - E_{fsat-1}}{X_{fsat}}\right)}{N_{sat}}$$

whereby N_{sat} stands for the number of enterprises of firm classification criteria “s” and age “a.”

Table A.5 - Correlations between Unemployment and Net Differential Employment Growth Rates (2000-2014) – Wage and Employment - Using RAIS/PME, Balanced Panel, complete period

Net Differential Employment Growth Rates	Correlation
Wage	
Large - Small	0.16
Large Old - Small Old	0.01
Large Old - Small Young	0.04
Employment	
Large - Small	0.30
Large Old - Small Old	0.68
Large Old - Small Young	0.01

A.6 – Alternative VAR results using labor productivity

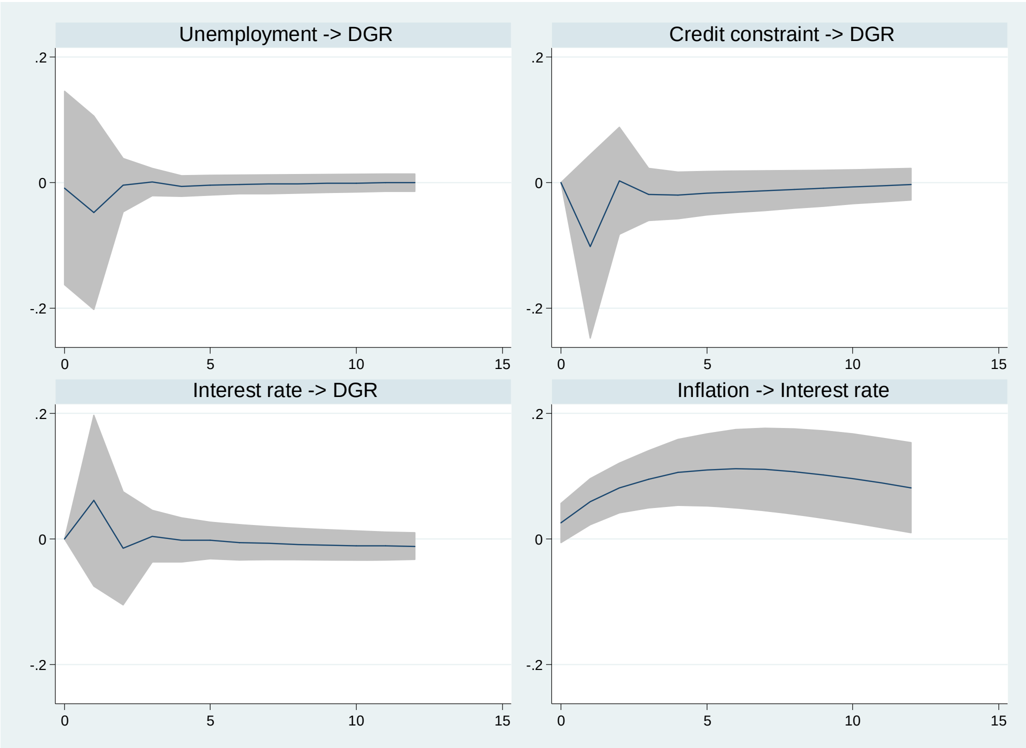


Figure A.6.1: Selected Impulse response functions
Selected Impulse response functions - DGR between high-productivity and low-productivity (Labor productivity firm ranking)

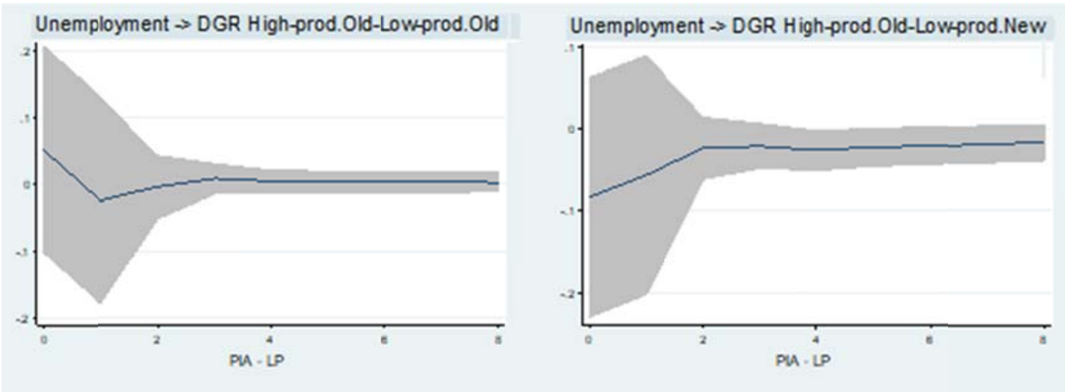


Figure A.6.2: Response of Net Differential Employment Growth to Unemployment by Firm's Age - Manufacturing (PIA) Sector
LO_SO (DG between high-productivity old and low-productivity old) and LO_SN (DG between high-productivity old and low-productivity young) - labor productivity classification

References

Aguiar, M., & Gopinath, G. (2007). Emerging market business cycles: The cycle is the trend. Journal of political Economy, 115(1), 69-102.

Baxter, M., & King, R. G. (1999). Measuring business cycles: approximate band-pass filters for economic time series. Review of economics and statistics, 81(4), 575-593.

Beaudry, P., & Pages, C. (2001). The cost of business cycles and the stabilization value of unemployment insurance. European Economic Review, 45(8), 1545-1572.

Brock, W. A., & Evans, D. S. (1989). Small business economics. Small business economics, 1(1), 7-20.

Cravo, T. A. (2011). Are small employers more cyclically sensitive? Evidence from Brazil. Journal of Macroeconomics, 33(4), 754-769

Cravo, T. A. (2017). Firm size and business cycles. IZA World of Labor, 371-371

Christiano, L. J., & Fitzgerald, T. J. (2003). The band pass filter. International Economic Review, 44(2), 435-465.

Davis, S. J., Haltiwanger, J., & Schuh, S. (1996). Small business and job creation: Dissecting the myth and reassessing the facts. Small business economics, 8(4), 297-315.

De Santis, M. (2007). Individual consumption risk and the welfare cost of business cycles. American Economic Review, 97(4), 1488-1506.

Fort, T. C., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). How firms respond to business cycles: The role of firm age and firm size. IMF Economic Review, 61(3), 520-559.

Gertler, M., & Gilchrist, S. (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. The Quarterly Journal of Economics, 109(2), 309-340.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. Review of Economics and Statistics, 95(2), 347-361.

Haltiwanger, J., Scarpetta, S., Schweiger, H. (2014). Cross country differences in job reallocation: The role of industry, firm size and regulations, Labour Economics, 26, 11-25.

Haltiwanger, J., Hyatt, H., & McEntarfer, E. (2015). Cyclical reallocation of workers across employers by firm size and firm wage. National Bureau of Economic Research Working Paper (No. w21235).

Haltiwanger, J., Hyatt, H., & McEntarfer, E. (2018a). Who moves up the job ladder? Journal of Labor Economics, 36, S1.

Haltiwanger, J. C., Hyatt, H. R., Kahn, L. B., & McEntarfer, E.(2018b). Cyclical Job Ladders by Firm Size and Firm Wage. American Economic Journal: Macroeconomics, 10(2): 52-85.

Hamilton, J. D. (2017). Why you should never use the Hodrick-Prescott filter. Review of Economics and Statistics (Forthcoming).

Harrison, A., & Leamer, E. (1997). Labor markets in developing countries: An agenda for research. Journal of Labor Economics, 15(S3), S1-S9.

IBGE (2016). Indicadores IBGE - Pesquisa Mensal de Emprego Fevereiro 2016.

IPEA (2015). Análise do Mercado de Trabalho Mercado de Trabalho, 59 (October).

Krebs, T. (2007). Job displacement risk and the cost of business cycles. American Economic Review, 97(3), 664-686.

Levinsohn, J.; Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. Review of Economics Studies, 70(2), 317-341.

Moscarini, G., & Postel-Vinay, F. (2009). The timing of labor market expansions: New facts and a new hypothesis. NBER Macroeconomics Annual, 23(1), 1-52.

Moscarini, G., & Postel-Vinay, F. (2009). Large employers are more cyclically sensitive. National Bureau of Economic Research Working Paper (No. w14740).

Moscarini, G., & Postel-Vinay, F. (2010). Unemployment and small cap returns: The nexus. American Economic Review, 100(2), 333-37.

Moscarini, G., & Postel-Vinay, F. (2012). The contribution of large and small employers to job creation in times of high and low unemployment. The American Economic Review, 102(6), 2509-2539

Moscarini, G., & Postel-Vinay, F. (2016). Did the job ladder fail after the Great Recession?. Journal of Labor Economics, 34(S1), S55-S93.

Neumeyer, P. A., & Perri, F. (2005). Business cycles in emerging economies: the role of interest rates. Journal of monetary Economics, 52(2), 345-380.

Pastore, J. (2006) Cadernos de Economia da FECOMERCIO, November, São Paulo.

Petrin, A.; Levinsohn, J; Poi, B. P. (2003). Production function estimation in Stata using inputs to control for unobservables. Stata Journal, 4(2), 113-123.

Rua, A., & Nunes, L. C. (2005). Coincident and leading indicators for the euro area: A frequency band approach. International Journal of Forecasting, 21(3), 503-523.

Syverson, C. (2011). What determines productivity?. Journal of Economic literature, 49(2), 326-65.