What Does it Take to Be a Business Owner? Evidence from Transitions from Job Loss

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Abstract

The pathways leading to business ownership are varied, posing an empirical challenge in identifying the role of owners' skills. This paper focuses on a specific pathway: transitions to business ownership following job loss, leveraging mass layoff events for identification. I combine two comprehensive data sets from Brazil: the firm registry (which includes self-employed workers and small business owners) and matched employer-employee records. Comparing laid-off workers to a matched sample of non-laid-off workers, I find a four-fold increase in the quarterly business formation probability following job loss, a result driven by skilled individuals. In particular, managers are 5 percentage points more likely to start longer-lasting businesses (relative to an average of 60 percent), as they start ventures in industries where they worked before while also identifying industries with higher growth potential. To benchmark these results, I compare businesses started after job loss to those founded by workers who quit. While survival rates are similar, the skills driving survival are different: managerial experience is not associated with business survival among owners who quit. These findings highlight the importance of identifying post-job-loss business owners as a distinct group when evaluating the relationship between owners' skills and business outcomes. My results also suggest a path for more effective business support policies by both public and private actors, which should account for owners' career trajectories and skill sets.

Keywords: new firms; occupational choice; skills; job loss.
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1 Introduction

New businesses are essential to economic dynamism and innovation (Haltiwanger et al. 2013, Decker et al. 2014, Coad et al. 2016, Haltiwanger 2022), motivating significant attention to the determinants of business formation and survival. Among these determinants, owners' skills often appear as strong predictors of entrepreneurship and self-employment (Elfenbein et al. 2010, Berglann et al. 2011, Åstebro et al. 2011, Humphries 2017, Levine and Rubinstein 2017, Levine and Rubinstein 2018, Bernstein et al. 2022). In particular, "managerial talent" plays an important role in shaping business outcomes (Lucas 1978), as supported by empirical evidence on the relationship between the adoption of management practices and performance in both large (Bloom et al. 2013) and small (McKenzie and Woodruff 2017) businesses.

However, the pathways that lead individuals to start businesses are varied, posing an empirical challenge in identifying the role of owners' skills. Similar to the distinction between "push" and "pull" entrepreneurs (Amit and Muller 1995) or between "subsistence" and "transformational" entrepreneurship (Schoar 2010), each pathway to business ownership reflects different motives and selection patterns, which can confound the relationship between skills and business outcomes.[1] Disentangling these pathways is, therefore, crucial for understanding how owners' skills shape the formation and survival of new businesses.

In this paper, I focus on a specific pathway: transitions to business ownership after job loss. While most individuals who lose their jobs are fired and thus likely to be negatively selected in unobserved dimensions, this group also includes workers affected by mass layoffs. In such cases, selection is less pronounced, enabling a clearer analysis of the connection between owners' skills and business outcomes. Hence, by using mass layoff events as a quasi-experimental source of exogenous job separations, I identify workers who would otherwise continue to be employed but are shocked into making the decision of whether to start a business.

I leverage two comprehensive data sets from Brazil: the firm registry from *Receita Federal* (Brazil's tax revenue agency), a particularly rich data set covering a large number of small businesses and self-employed workers, and the *Relação Anual de Informações Sociais* (RAIS), a matched employer-employee administrative data set. By combining these data sets, I can track individuals' trajectories for an extended period, both before and after the

[1] Amit and Muller (1995) define "push" entrepreneurs as those who are pushed to start a business for reasons not related to their entrepreneurial characteristics, while "pull" entrepreneurs are those whose decision is driven by both the attractiveness of the business idea and the personal implication of owning a business. Schoar (2010) defines "subsistence" entrepreneurs as those whose primary motive is associated with the need for subsistence income, while "transformational" entrepreneurs are those associated with the intent to grow large businesses.

layoffs, observing their occupational choices as employees in the wage sector and as business owners. The information available in these data sets also allows me to investigate individuals with varying skill sets (such as educational attainment and managerial experience) that may influence business outcomes, providing information into which skills are most valuable for business formation and survival.

When exploring event study specifications around mass layoff events and comparing laid-off individuals to a matched sample of non-laid-off ones, my findings reveal an increase in business formation immediately after job loss. By the second quarter following layoffs, for laid-off workers who would otherwise have remained employed, I report a 0.16 percentage-point (p.p.) increase in the probability that they start a business, representing a four-fold rise compared to the pre-layoff probability. I then consider heterogeneity across two types of skills: general skills (proxied by college education) and specific skills (proxied by managerial experience). I find that the job loss effect is large among both college-educated workers (an increase of 0.53 p.p. two quarters after job loss) and managers (an increase of 0.60 p.p. five quarters after job loss). Given that skill levels are highly correlated with wage levels, I test whether the relationship between owners' skills and business formation remains significant after controlling for these wage effects. I first show that among high-wage workers, those with general and specific skills are more likely to start a business following layoffs. Then, using a linear probability model focusing on the business started by laid-off workers, I observe a positive correlation between skills and business formation that remains significant after controlling for pre-layoff wages.

Next, I show that managerial experience is a robust predictor of business survival. Focusing on businesses started by laid-off workers, I find that, after controlling for wage effects, managerial experience is associated with a statistically significant 5.3 p.p. increase (relative to an average five-year survival probability of 60.2 percent), while the coefficient for general skills is small and not statistically significant. My results also suggest that industry-specific knowledge is an important driver of these findings. Managers are 5.6 p.p. more likely (relative to an average probability of 19.1 percent) to start a business in a familiar industry (one where they have prior experience), a pattern correlated with longer-lasting businesses. Among individuals with managerial experience, those operating firms in familiar industries are 8.7 p.p. more likely to survive as business owners for at least five years (relative to an average probability of 65.8 percent). Additionally, managers are 3.0 p.p. more likely (relative to an average probability of 27.0 percent) to start businesses in high-growth industries, but the relationship with business survival, while positive, is not statistically significant.

Subsequently, I benchmark my findings regarding the relationship between business survival and skills among laid-off workers against a sample of businesses started by workers who quit their jobs and are thus more likely to have a strong motivation to pursue an entrepreneurial idea. My analysis shows that five-year survival rates are similar across the two groups of businesses (60.3 percent for post-job-loss businesses and 60.1 percent for post-quit businesses), indicating that laid-off workers (individuals who would otherwise have remained employed) might start businesses that perform just as well as people who had the grit to quit their jobs to follow this trajectory. However, the skills shaping business survival are strikingly different. For businesses started by workers who quit, managerial experience is not significantly correlated with survival rates, whereas general skills appear to be important. This difference relative to the results for post-job-loss businesses is driven at least in part by the lower likelihood that managers transition to a familiar industry after quitting (a 3.0 p.p. decrease relative to an average of 17.4 percent), indicating that business formation is more exploratory in nature among workers who quit their jobs.

My research is related to two main strands of literature. First, it contributes to studies examining business formation and survival. This literature has often highlighted that business ownership decisions result from the interaction of factors such as individuals' cognitive traits (Humphries 2017, Levine and Rubinstein 2017), attitudes towards risk (Levine and Rubinstein 2018, Hombert et al. 2020), motives and aspirations (Amit and Muller 1995, Schoar 2010), and economic conditions (Hacamo and Kleiner 2022, Bernstein et al. 2022). While the link with owners' skills and abilities has been established (Lucas 1978, Cooper et al. 1994, Lazear 2004, Elfenbein et al. 2010), my paper adopts an approach that focuses on individuals who are pushed into deciding whether to start a business following job loss. This allows me to disentangle the relationship between skills and business outcomes from confounding factors related to the existence of different pathways into business ownership. In particular, the difference between post-job-loss and post-quit businesses underscores how conflating these trajectories risks masking the relationship between owners' abilities and business outcomes.

Compared to the few papers on business formation following job loss (e.g., Hombert et al. 2020, da Fonseca 2022, Nunes 2023), my analysis explores the heterogeneity in skills among business owners, revealing that specific abilities (such as managerial talent) are more important than general ability measures when explaining business outcomes. Additionally, I investigate different mechanisms underlying this relationship, highlighting the role of industry-specific knowledge. My analysis also includes a large number of self-employed workers and small business owners in a developing country, thus deviating from the usual focus on larger, incorporated businesses.

Second, this study contributes to the literature on the consequences of job loss, which shows largely negative labor market outcomes for laid-off workers (Topel 1990, Gibbons and Katz 1991, Jacobson et al. 1993, Schmieder et al. 2016, Lachowska et al. 2020, Bertheau et al. 2022, Schmieder et al. 2023). Similar findings have been reported in the Brazilian context (Menezes-Filho and Fernandes 2004), where more recent literature has expanded the analysis to dimensions including domestic violence (Bhalotra et al. 2021), criminality (Britto et al. 2022), and health (Amorim et al. 2023, Fontes et al. 2023). My paper examines the transition to business ownership as an additional labor market outcome, confirming that business ownership is an important destination for laid-off workers, who open businesses that can often be linked to their career trajectory. It also suggests a positive unintended consequence of layoffs, which might lead to the opening of successful businesses by individuals who would have continued to be employed in the wage sector had they not been shocked into making an entrepreneurial decision.

This paper proceeds as follows. In Section 2, I present the two main data sets I use in this paper, outline the construction of the samples required for the analysis, and summarize their main characteristics. In Section 3, I discuss the formation of new businesses following job loss, while in Section 4 I focus on the survival of these ventures. Section 5 compares the post-layoff businesses to those started by workers who quit their jobs. Section 6 concludes.

2 Data

In this paper, I combine two main data sets for analysis. The first source of data is the firm registry maintained by *Receita Federal*, the Brazilian tax revenue agency, encompassing the universe of formal firms across the country. Businesses are identified by their CNPJ (*Cadastro Nacional da Pessoa Jurídica*), a unique tax identifier for legal entities. From 2009 to 2017, the data set features 26.5 million businesses, including 16.9 million businesses that started operating during this period. It also encompasses a large number of self-employed workers and small business owners. In fact, 90.9 percent of the businesses do not report any employees one year after starting to operate, with 94.6 percent reporting up to one employee and 98.2

percent reporting up to five employees.[2] Besides information such as sector, location, open date, changes to the registry, and tax classifications, the *Receita Federal* data set also includes information on business ownership.

The second data set employed in this paper is RAIS (*Relação Anual de Informações Sociais*), an administrative employer-employee data set covering the universe of formal job contracts in Brazil. Workers are uniquely identified by their CPF (*Cadastro de Pessoas Físicas*), an individual tax identifier. Similarly to the *Receita Federal* data set, businesses are identified by their CNPJ. In the period between 2009 and 2017, I observe 88.7 million workers and 5.3 million firms. Available information includes job-related attributes (such as wages, occupation, industry, hire date, and separation date) and worker characteristics (such as age, gender, race, and education).[3]

To merge the firm registry from *Receita Federal* with RAIS data, I leverage the fact that business ownership information is available for 70.8 percent of the businesses and disclosed in two formats. Both owner names and CPFs can be extracted from the firm registry in 80.1 percent of the available cases, enabling exact matching with RAIS. For the remaining 19.9 percent of businesses, besides owner names, only partial CPFs (six out of eleven digits) are disclosed.[4] In such cases, I apply a probabilistic matching algorithm that only requires owner names and partial CPFs, and I calibrate it using the set of businesses with complete CPFs. I can recover a complete tax identifier for 61.8 percent of the businesses for which this information was only partially available.[5]

I acknowledge two main data limitations. First, following the discussion in the previous paragraph, I do not observe ownership information for 29.2 percent of the businesses

[2]Brazil enacted new legislation in 2008 allowing businesses with at most one employee to be registered under the *Micro-Empreendedor Individual* (MEI) format. This reform aimed to reduce the burden associated with formal business ownership and extend certain social security benefits to business owners. The effects of this reform are discussed in Rocha et al. (2018) and Rocha and de Farias (2022). My analysis focuses on the period following the reform's implementation and leverages the fact that it led to the registration of many self-employed workers and small business owners, markedly increasing the number of businesses I observe in the *Receita Federal* firm registry. See Appendix B.

[3]RAIS is reported by firms, with no direct input from workers. Consequently, worker characteristics may not remain consistent over time and across different contracts. To address this, I assign workers their race classification, birth year, gender, and educational level based on the data reported in the quarter prior to the mass layoff event when constructing the panel dataset.

[4]Business ownership information is not available for firms operating under the "solo proprietor" format. However, owner names and complete CPFs are available for firms registered under the MEI format (see Appendix B), while owner names and partial CPFs are available for other businesses.

[5]The probabilistic matching algorithm consists of two steps. First, in both RAIS and the *Receita Federal* firm registry, individuals are categorized into cells based on their observed partial CPF. Next, within each cell, I compare individuals with similar names using a bigram string comparator. This comparator accounts for the initials of the first and last names (which are likely to be accurately reported in both datasets) as well as the full name.

started in the period from 2009 through 2017. The businesses for which I do not observe data are concentrated among licensed professionals (such as doctors, lawyers, and architects) and non-productive businesses (such as political candidates and homeowners' associations, which are required to register with the tax authority), and are thus not likely to be started in the context of a job loss. Second, my analysis is related to the formation and survival of formal businesses only, given data availability in both RAIS and the firm registry. While comprising 60 percent of wage-employed workers and 30 percent of all businesses in Brazil, formal firms are more likely to be the focus of support policies and to grow.

2.1 Sample Construction

To disentangle the trajectory of workers who are impacted by job loss from other existing trajectories and account for potential confounding factors related to the selection of workers whose job contracts are terminated, I define a sample of mass laid-off ("treated") workers along with a matched comparison sample of non-laid-off ("control") workers. The construction of these samples is outlined below.

Mass Layoff Events and Mass Laid-Off Workers

I use mass layoff events as a shock to identify plausibly exogenous separations, aiming to disentangle the business ownership trajectory after job loss from other transitions from wage employment, while also accounting for potential confounding factors related to the selection around separations.[6] To identify the mass layoff events, I create a quarterly employment panel at the establishment level, focusing on employee counts in the last day of each quarter. I then determine which establishments underwent a mass layoff event in quarter t according to the following criteria, adapted from Schmieder et al. (2023) to fit the structure of my quarterly panel. First, the establishment must have employed a minimum of 50 workers in both quarters $t-1$ (immediately before the layoff) and $t-4$ (one year before the layoff), ensuring that these events are sufficiently large and not reflecting typical employment movements in small establishments. Second, employment must drop at least 30 percent between quarters $t-1$ and t and between quarters $t-4$ and t. This implies a sharp employment drop between two consecutive quarters that, at the same time, does not

[6]Mass layoffs have been employed as an identification strategy for the consequences of job loss by papers such as Lachowska et al. (2020), Bertheau et al. (2022), Schmieder et al. (2023).

reflect seasonal variation.[7] Third, I exclude establishments outside the private sector[8] and cases where I cannot rule out joint movements of workers between two establishments due to restructuring, mergers or acquisitions.[9] I identify 11,615 mass layoff events adhering to these criteria between the first quarter of 2012 and the last quarter of 2014.

Using the same data, I construct a quarterly panel of workers from the first quarter of 2003 to the last quarter of 2017, tracking their employment status on the last day of each quarter. When a worker holds multiple job contracts on these dates, I select a primary contract by successively applying the following criteria until only one contract remains for each worker in each quarter. I prioritize the contract with higher wages, followed by the contract with the most contracted hours and, subsequently, higher tenure. In cases of persistent ties, a contract is randomly selected from the remaining options.

The next step entails identifying the mass laid-off workers. An individual is classified as a mass laid-off worker in quarter t under the following conditions. First, the establishment employing the worker must have experienced a mass layoff event in quarter t. Second, the worker must have undergone a job separation during the same quarter t. Third, I require that the worker is not employed in the mass layoff establishment in any of the quarters between $t+1$ and $t+12$, guaranteeing that the separations are permanent. I then focus on workers between the ages of 20 and 50 in the pre-layoff quarter $t-1$, excluding those nearing retirement, and employed in a full-time position with at least a 30-hour work week. Additionally, I require that workers have at least 24 months of tenure by the end of quarter $t-1$, thus concentrating on workers who are strongly attached to their jobs and for whom the layoff event was likely unexpected.[10] Lastly, to prevent overlaps between layoff events, workers experiencing more than one mass layoff event are excluded from the sample. Consequently, each laid-off worker is associated with a specific layoff cohort identified by quarter t. Following this procedure, I identify 294,701 laid-off workers between 2012 and 2014.

[7] Appendix Figure A.1 shows the distribution of the employment loss between quarters $t-1$ and t (Panel A) and between quarters $t-4$ and t (Panel B).

[8] Private sector establishments are those with a legal nature classified under *Entidades Empresariais* (1-digit CNAE code: 2), except for *Empresas Públicas* (4-digit CNAE code: 2011).

[9] I exclude cases when, between two consecutive years, either (i) more than 20 percent of the workers leaving a establishment move to other establishments belonging to the same firm, or (ii) more than 20 percent of the workers leaving a firm move to the same destination firm.

[10] As of the last quarter of 2017, 28.9 percent of the active job contracts had a tenure of less than 12 months, 42.9 percent had a tenure of less than than 24 months, and 83.1 percent had a tenure of less than 120 months.

Defining the Control Sample: Non-Laid-Off Workers

Having established the sample of laid-off workers, I select a counterpart sample of non-laid-off workers ("control" workers) based on observed covariates. The trajectory of these workers serves as the counterfactual trajectory of laid-off workers if they had not been laid off, allowing me to identify the effect of job loss on business ownership decisions. Importantly, my approach does not require non-laid-off workers to remain continuously employed at the same firm. It also allows a single worker to serve as the non-laid-off counterpart for laid-off workers in different cohorts.

I proceed in four steps. First, for each layoff cohort t, the pool of potential non-laid-off workers contains all workers who were not employed in a mass layoff establishment in quarter $t-1$. These potential non-laid-off workers adhere to the same criteria as laid-off workers: (i) employment in establishments with more than 50 employees in quarter $t-1$; (ii) age between 20 and 50 in quarter $t-1$; (iii) at least 30 hours of contracted work per week in quarter $t-1$; and (iv) at least 24 months of tenure by the end of quarter $t-1$. Second, the non-laid-off workers are categorized into cells defined by two key dimensions: 2-digit industry in quarter $t-1$ and gender. Laid-off workers are also categorized into these same cells. Third, within each cell, I apply an one-to-one matching algorithm, ensuring that the number of non-laid-off workers matches that of laid-off workers. This matching algorithm consists of creating a cell-specific score for the propensity that a worker is laid off based on the following observable dimensions: wages in quarters $t-8$ and $t-4$, age in quarter $t-1$ (in three groups: 20 to 29, 30 to 39, and 40 to 50), months of tenure in quarter $t-1$, employer size in quarter $t-1$ (measured by the number of employees), and educational group (measure by highest completed degree: elementary education, primary education, high school, and college). This procedure identifies 294,701 non-laid-off counterparts to the laid-off workers in the period from 2012 to 2014, which is by construction identical to the number of laid-off workers. Lastly, I construct my final data set by stacking the panels of laid-off and non-laid-off workers for each cohort t (Cengiz et al. 2019, Schmieder et al. 2023). By aligning cohorts in event time around quarter t, having a selection criteria that matches laid-off and non-laid-off workers, and including a large sample of "never-treated control" workers, this approach avoids the issues usually associated with staggered treatment timing in event studies (Baker et al. 2022), such as the forbidden comparisons discussed in Goodman-Bacon (2021) and Callaway and Sant'Anna (2021).

2.2 Sample Characteristics

Table 1 reports the summary statistics for the sample of laid-off workers and the matched sample of non-laid-off workers. Since the matching algorithm consists of a one-to-one link between laid-off and non-laid-off workers, both groups consist of an equal number of individuals. In total, I follow 294,701 laid-off individuals in the period between 2012 and 2014, along with 294,701 non-laid-off individuals. These two groups are similar across the dimensions accounted for the matching algorithm (wage in $t = -4$, wage in $t = -1$, age, tenure, education, gender, and $t = -1$ industry). Importantly, the remaining variables also reveal that the differences between laid-off and non-laid-off workers are generally small in magnitude, suggesting limited economic significance. Given my focus on business formation following job loss, it is reassuring to note that the share of individuals who were business owners *before* job loss (in $t = -1$) is identical across the two groups.

3 Business Formation After Job Loss

In this section, I explore the determinants of business formation among individuals impacted by job loss. I first employ an event study specification that compares the trajectory of laid-off workers to the trajectory of workers in the counterfactual sample of non-laid-off workers, aiming to identify the causal effect of job separations on business ownership decisions and its interaction with ability measures. Then, I focus on laid-off workers and further explore the link between workers' characteristics and business formation.

3.1 Event Study Around Job Loss

To identify the effect of job loss on transitions to business ownership and characterize its main determinants, I employ an event study design similar to Schmieder et al. (2023). Specifically, I use the stacked panel combining laid-off workers and their matched non-laid-off counterparts to estimate the following regression model:

$$\begin{aligned} Open_{it} = &\alpha + \beta \cdot LaidOff_i + \sum_{\ell=-8}^{12} \mu_\ell \cdot 1 \cdot \{t - E_i = \ell\} \cdot LaidOff_i \\ &+ \sum_{\ell=-8}^{12} \gamma_\ell \cdot 1 \cdot \{t - E_i = \ell\} + \phi_t + X_{it}\pi + \varepsilon_{it} \end{aligned} \tag{1}$$

In Equation 1, the outcome variable $Open_{it}$ is a binary indicator equal to 1 if worker i opens a business in quarter t. The variable $LaidOff_i$ is a binary indicator equal to 1 if worker i is laid off in any quarter during the analysis period. I define E_i as the quarter of the layoff event for worker i or, for non-laid-off workers, the quarter when their matched counterpart is laid off. Hence, the term ℓ measures the temporal distance (in quarters) between quarter t and the layoff quarter E_i. The coefficients μ_ℓ are the parameters of interest, capturing the differential effect of mass layoffs in business openings between laid-off and non-laid-off workers. I also include a "quarter relative to baseline" fixed effect (γ_ℓ), accounting for time trends around the baseline period, and a quarter fixed effect (ϕ_t), accounting for common calendar time trends across the cohorts. Finally, X_{it} includes time-varying individual characteristics (age squared), and ε_{it} represents the error term.

This specification is designed to identify the effect of job loss on business formation under three key assumptions: (i) parallel trends in the probability of starting a business between laid-off and non-laid-off workers in the absence of job loss, (ii) no anticipatory behavior before job loss, and (iii) homogeneous job loss effects across cohorts (Sun and Abraham 2021). As discussed in Section 2, my sample construction procedure based on stacking matched cohorts mitigates concerns associate with (iii). Similarly, concerns related to the potential violation of hypothesis (i) are also addressed through the matching procedure, which generates comparisons between workers who share observed characteristics, thereby increasing the likelihood of a parallel trajectory in the absence of the mass layoff event (Bhalotra et al. 2021, Schmieder et al. 2023). Additionally, it is reassuring that my results will underscore that a parallel trend in outcomes appears to hold during the pre-layoff period. Regarding hypothesis (ii), it is plausible to expect that some workers might anticipate a forthcoming mass layoff based on certain conditions they observe at the firm (although these conditions are not observed by me).[11] In this case, the trajectory of laid-off and non-laid-off workers could start drifting apart before the mass layoff quarter. I consider this possibility in the main specification and omit the dynamic layoff effect for $\ell = -2$ instead of $\ell = -1$. Consequently, hypothesis (ii) of no anticipatory behavior before job loss is required to hold before $\ell = -2$ only, and all regression estimates should be interpreted relative to this period.

Figure 2 presents the main results from estimating Equation 1, illustrating the effect of job loss on transitions to business ownership among laid-off workers. It shows that the

[11]It is also possible that workers receive advance notice of their layoff. However, workers in Brazil are typically informed of job separations no more than 30 days before the actual contract termination, which is the advance notice period required by law. Given that I work with a quarterly panel, this should have a limited impact on the estimates.

trajectories of laid-off and non-laid-off workers are similar up until the layoff event, which takes place between quarters $\ell = -1$ and $\ell = 0$. Notably, none of the coefficients are statistically significant in the period leading up to the mass layoff event. However, in the quarters following the layoff, I observe a sharp increase in the probability of laid-off workers starting a business. By quarters $\ell = 2$ and $\ell = 3$, laid-off workers are 0.16 p.p. more likely to open a business compared to non-laid-off workers, representing a four-fold increase relative to the baseline probability of 0.04 percent in quarter $\ell = -2$. While the transition probability declines in subsequent quarters, it remains higher than that of non-laid-off workers by the end of the analysis period, in quarter $\ell = 12$, three years after the layoff event.

General and Specific Ability

To explore the relationship between business formation and worker characteristics, I focus on two types of ability: (i) general ability, which encompasses a set skills transferable to any occupational choice workers might pursue following job loss; and (ii) specific ability, which refers to a set of skills directly related to owning and operating a business. I define two proxies for general ability: (i) education, measured by classifying workers according to their highest completed degree as of quarter $\ell = -1$, just before the mass layoff; and (ii) worker quality, measured by estimating worker wage premia following the Abowd et al. (1999) procedure, using wage data from the 2003-2009 period. This ensures that the estimates are not contaminated by the mass layoff events occurring between 2012 and 2014. For specific ability, I define two proxies: (i) managerial experience, leveraging the availability of separate occupational codes for managers; and (ii) firm quality, proxied by firm wage premia, which is measured similarly to worker quality. This second proxy is strongly correlated with the adoption of management practices in the Brazilian context (Cornwell et al. 2021), reflecting workers' potential exposure to good management practices.

The results from estimating Equation 1 separately for groups of workers classified by general ability proxies are shown in Figure 3. In Panel (a), I report the results according to my first proxy for general ability: educational level. While the trajectory of laid-off workers is similar to that of non-laid-off workers in the quarters preceding the layoff event, there is a notable increase in the probability of starting a business among laid-off workers after the layoff, regardless of their educational level. However, this effect is significantly larger for workers with a college degree (an increase of 0.53 p.p. by quarter $\ell = 2$) than workers with and without a high school diploma. In Panel (b), I show the results for my second proxy for general ability: workers' wage premium. I find that high-ability workers (those in the top quartile of the wage premium distribution) experience a marked increase in business ownership in the quarters following job loss. This 0.32 p.p. increase by quarter $\ell = 1$ is significantly larger than the increase for low-ability workers (those in the bottom quartile of the wage premium distribution) around the same quarter. Taken together, the results from Panels (a) and (b) are consistent with skilled workers being more likely to start a business in the quarters following job loss, with their trajectories also displaying the inverted-U shape reported in Figure 2.

In Figure 4, I focus on the relationship between business formation and specific ability measures. Panel (a) shows the results from estimating Equation 1 separately for workers with and without managerial experience. I find that workers with managerial experience are significantly more likely to start a business following job loss (an increase of 0.60 p.p. by quarter $\ell = 5$) than workers without managerial experience. Similarly, Panel (b) displays estimates for workers at the bottom and top of the firm wage premium distribution, which proxies for exposure to poor and high-quality management practices, respectively. Here, I observe increases of 0.28 p.p. by quarter $\ell = 2$ for workers employed in high-quality businesses. Overall, both Panels (a) and (b) indicate that specific abilities play a crucial role in shaping the transition to business ownership among laid-off workers.

Wage Effects

While the previous results have established a link between ability measures (whether general or specific) and transitions to business ownership, wages remain a potentially relevant confounder. Not only are the worker and firm wage premium measures derived from observed wages (albeit from different periods), but there is also (i) a positive correlation between my ability proxies and wages;[12] and (ii) a positive correlation between wages and business formation probability.[13] I account for these potential wage effects when exploring the relationship between ability and business formation in Figure 5. Focusing on high-wage workers (those in the top quartile of the within-state $\ell = -1$ wage distribution), I show that there is a marginal additional effect of having both general and specific abilities. Relative to non-laid-off workers, high-income workers with a college degree are more likely to start a business than high-income workers without a college degree (Panel (a)). Similarly, high-income workers with managerial experience are more likely to start a business than

[12] See Appendix Figure A.2.

[13] See Appendix Figure A.3, where I address this possibility by estimating Equation 1 based on workers' position in the within-state $\ell = -1$ wage distribution, reporting results for low-wage (those is the bottom quartile) and high-wage (those in the top quartiles) workers. I find that the effect of job loss on the probability that laid-off individuals start a business is markedly more pronounced for high-wage workers, with an increase of 0.37 p.p. by quarter $\ell = 2$

high-income workers without managerial experience (Panel (b)).

3.2 Correlates of Business Formation

To further evaluate the relationship between workers' characteristics and transitions to business ownership after job loss, I estimate regression models at the individual level, using the sample composed exclusively of laid-off workers. While these regression specifications do not recover the causal effects of college education, managerial experience, or wages on business formation, they allow me to examine how these characteristics correlate with business formation when focusing on the trajectory of laid-off workers.[14]

$$\begin{aligned} Open_{icjs} = \; & \beta_0 + \beta_1 \cdot College_{icjs} + \beta_2 \cdot Manager_{icjs} + \beta_3 \cdot Ln(Wage)_{icjs} \\ & + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \end{aligned} \tag{2}$$

In Equation 2, the outcome variable $Open_{icjs}$ is a binary indicator equal to 1 if worker i, from layoff cohort c, employed in industry j in state s, opens a business within three years of job loss. The main explanatory variables are $College_{icjs}$ (a dummy variable equal to 1 for workers with a college degree, serving as a proxy for general ability), $Manager_{icjs}$ (a dummy variable equal to 1 for workers classified as managers according to their occupational code in the pre-layoff quarter, $\ell = -1$, serving as a proxy for specific ability), and $Ln(Wage)_{icjs}$ (log wages in the pre-layoff quarter, $\ell = -1$). In addition, X_{icjs} includes controls for the gender and race of the laid-off worker. The model also includes fixed effects for the layoff cohort (δ_c), industry at the 2-digit level in the pre-layoff quarter (δ_j), and state in the pre-layoff quarter (δ_s). Finally, ε_{icjs} represents the error term.

Table 2 shows the results from estimating Equation 2 on the sample of laid-off workers. Columns (1) and (2) report the relationship between having a college degree and starting a business following job loss, indicating that there is a positive correlation even after controlling for the full set of worker controls and fixed effects. Similarly, Columns (3) and (4) report a positive correlation with managerial, while Columns (5) and (6) indicate the same relationship with pre-layoff wages. These results thus confirm my findings from Figures 3, 4, and 5. Columns (7) and (8) combine these three dimensions in the same specification, showing that they remain significant, thus indicating that the relationship between workers' skills and business formation is robust to controlling for wage effects.

[14] I focus on the college indicator and managerial experience instead of worker and firm wage premiums, respectively, due to the fact the wages premiums cannot be estimated for all workers.

4 Business Survival

Having established the relationship between ability and business formation, I proceed to evaluate the relationship between ability and business survival. While there is no direct counterfactual group for businesses started by laid-off workers, it is still possible to evaluate the characteristics of long-lasting businesses.

I employ a regression specification similar to Equation 2 to evaluate the survival of businesses started following job loss. Here, the sample is restricted to laid-off workers who started a business within three years of job loss.

$$\begin{aligned} Survival_{icjs} = \; & \beta_0 + \beta_1 \cdot College_{icjs} + \beta_2 \cdot Manager_{icjs} + \beta_3 \cdot Ln(Wage)_{icjs} \\ & + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \end{aligned} \tag{3}$$

In Equation 3, the outcome variable $Survival_{icjs}$ is a binary indicator equal to 1 if the business started by worker i, from layoff cohort c, employed in industry j in state s before the job loss, is still operating five years after its opening. The remaining terms are defined as in Equation 2.

The results from estimating Equation 3 are presented in Table 3. Column (2) shows that having a college degree is associated with a 2.2 p.p. increase in the probability of business survival over five years, relative to the average five-year survival probability of 60.2 percent. A similarly positive association is observed in Column (4), where managerial experience is linked to a 5.7 p.p. increase in survival probability. Column (6) highlights that the relationship between log wages and survival probability is also positive. However, when these variables are analyzed jointly in Column (8), only managerial experience remains statistically significant. Specifically, I report a 5.3 p.p. increase in the survival probability among managers, while the coefficient for a college degree and log wages are smaller (1.2 p.p. and 0.4 p.p., respectively) and not statistically significant.

To further explore outcomes associated with employment and business ownership, I examine the relationship between these variables and the return to wage employment among individuals who start a business following job loss. Table 4 displays the results of a model similar to Equation 3, where the outcome variable $Return_{icjs}$ is a binary indicator equal to 1 if worker $icjs$ returns to wage employment within five years of starting a business. Consistent with the earlier finding that managers are more likely to continue operating their businesses, they are also less likely to return to wage employment. In Column (8), I report that these business owners with managerial experience are 3.3 p.p. less likely to return to wage employment compared to the average return probability of 61.0 percent.

4.1 Mechanisms

In this subsection, I explore two potential mechanisms that explain why, in the context of a layoff event, businesses started by managers are more likely to survive. First, I investigate how industry choice, and its correlation with owners' skills, relates to business outcomes, in line with an extensive literature that explores this relationship (Ohyama 2007, Agarwal et al. 2004, Campbell et al. 2012, Dencker and Gruber 2015, Hvide and Oyer 2018). Second, I explore how outside options in the wage sector shape entrepreneurial decisions, building on papers that highlight how entrepreneurial decisions might be motivated by (i) a dissatisfaction with one's occupational situation (Amit and Muller 1995) and (ii) difficulties in finding a new job (Berglann et al. 2011).

Mechanism: Industry Choice

To explore the relationship between industry choice and business outcomes, I define two variables. The first, $SameInd_{icjs}$, is a binary indicator equal to 1 if the business operates in the same 2-digit industry where the owner was employed before the layoff. The second, $GrowthInd_{icjs}$, is a binary indicator equal to 1 if the business operates in a "growth industry". Growth industries are defined as 3-digit industries where the number of operating firms increases by at least 10 percent between quarters $\ell = -5$ and $\ell = -1$ (that is, in the year preceding the mass layoff event). I then estimate the following model, where the remaining variables are defined as in previous equations.

$$\begin{aligned} Y_{icjs} = \; & \beta_0 + \beta_1 \cdot College_{icjs} + \beta_2 \cdot Manager_{icjs} + \beta_3 \cdot Ln(Wage)_{icjs} \\ & + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \end{aligned} \tag{4}$$

Table 5 reports the results from estimating this equation for both $SameInd_{icjs}$ (Columns (1) to (4)) and $GrowthInd_{icjs}$ (Columns (5) and (8)). I find that managers are 5.6 p.p. more likely to start a business in the same 2-digit industry where they were employed before the layoff, compared to an average probability of 19.1 percent. Additionally, managers are 3.0 p.p. more likely to start businesses in high-growth industries, relative to an average probability of 27.0 percent. Conversely, the coefficients for having a college degree and log wages are not significant for either outcome variable, underscoring the particular role that managerial skills play in shaping business formation in this context.

Next, I evaluate whether industry choice correlates with business survival. I estimate the models in Equation 5 separately for workers with a college degree, managers, and high-wage workers (those in the top quartile of the within-state $\ell = -1$ wage distribution).

The coefficients of interest, β_1, capture the differences in survival rates based on the industry choice variables.

$$\begin{aligned} Survival_{icjs} = &\ \beta_0 + \beta_1 \cdot SameInd_{icjs} + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \\ Survival_{icjs} = &\ \beta_0 + \beta_1 \cdot GrowthInd_{icjs} + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \end{aligned} \tag{5}$$

The results are reported in Table 6. I find that businesses started in industries where the owner has some experience are more likely to survive across all worker groups. Since managers are more likely to start businesses in their previous industries in the first place, this finding at least partially explains why businesses started by them exhibit higher survival rates. The results related to starting a business in a growth industry suggest a similar pattern, though lacking statistical significance across all specifications.

Mechanism: Outside Options

To investigate whether differences in outside options contribute to the patterns I observe around business formation and survival, I introduce a measure of outside options that incorporates occupation-industry-specific wage premiums and transition probabilities between occupation-industry pairs. I begin by estimating the wage model in Equation 6, using data from all workers in Brazil. Here, $\ln w_{ijt}$ represents the observed log monthly wages of worker i in establishment j during quarter t, while $\delta_{\omega st}$ represents occupation-industry fixed effects, and Z_{it} is a vector of observed covariates, including tenure and a quadratic age polynomial interacted with education.

$$\ln w_{ijt} = \alpha + \delta_{\omega st} + Z_{it}\beta + \varepsilon_{ijt} \tag{6}$$

Next, I estimate the transition probability $P((\omega s)' \mid \omega s)$ from one occupation-industry pair ωs to another occupation-industry pair $(\omega s)'$ between quarters t and $t+4$. Subsequently, I calculate an outside fixed effect measure $\delta_{\omega st}^{Out}$ as follows:

$$\delta_{\omega st}^{Out} = \sum_{\omega s'} \delta_{\omega st} \cdot P((\omega s)' \mid \omega s) \tag{7}$$

Finally, I obtain the outside option measure I use in this analysis by computing the difference between outside fixed effects ($\delta_{\omega st}^{Out}$) and current fixed effects ($\delta_{\omega st}$): $\delta_{\omega st}^{Out} - \delta_{\omega st}$. This measure captures the relative attractiveness of alternative occupation-industry pairs compared to a given worker's current job position, which I then use to analyze its impact on business formation and survival.

In Figure 6, I show that, on average, laid-off managers have worse outside options than laid-off non-managers, as the distribution of outside options for non-managers stochastically dominates the distribution of outside options for managers. I then proceed to analyze the relationship between outside options and business formation by estimating the model specified in Equation 8

$$\begin{aligned} Open_{icjs} = \; & \beta_0 + \beta_1 \cdot Outside_{icjs} + \beta_2 \cdot College_{icjs} + \beta_3 \cdot Outside_{icjs} \cdot College_{icjs} \\ & + \beta_4 \cdot Manager_{icjs} + \beta_5 \cdot Outside_{icjs} \cdot Manager_{icjs} \\ & + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \end{aligned} \tag{8}$$

This specification extends Equation 2 by incorporating the outside options measure, $Outside_{icjs}$, and its interactions with college education and managerial experience.[15]

The results are reported in Table 7. In Columns (1) and (2), I first show a negative correlation between outside options and the probability that a laid-off worker starts a business. Specifically, when laid-off workers are expected to transition to a well-paying industry-occupation pair in the wage sector, they are less likely to become entrepreneurs. The interaction term in Column (3) indicates that this negative relationship is more pronounced among workers with a college degree, while the findings from Column (4) reveal that managers do not appear significantly more responsive to outside options when deciding whether to start a business. These findings persist in Column (5), which includes all explanatory variables.

Next, I evaluate whether the correlation between outside options and business formation extends to business survival. Using a model similar to Equation 8, I replace the outcome variable with the 5-year survival of businesses started by laid-off workers, $Survival_{icjs}$. Table 8 reports the results. The negative coefficients in Columns (1) and (2) suggest that business owners are less likely to continue to operate their business when their wage sector options are appealing (although the correlation reported in Column (2) is not statistically significant). However, Columns (3) to (5) show that this negative relationship is driven largely by interactions with skills proxies, as the individual coefficient for outside options becomes positive while the interactions with college degree and managerial experience are largely negative – although not statistically significant for managers.

Overall, these results indicate that, while managers face worse outside options after

[15]Log wage terms are omitted from this specification as they are used when constructing the outside options measure. Results including these terms are reported in Appendix Tables A.1 and A.2.

wage loss, they are not particularly responsive to these outside options when deciding whether to start and continue to operate a business. This suggests that managers are more likely to transition to business ownership due to their ability to identify promising entrepreneurial opportunities (as discussed in the previous subsection) or intrinsic motivation.

5 Business Survival Among Quits

In this section, I benchmark my findings regarding the relationship between business survival and skills among laid-off workers against a sample of businesses started by workers who quit their jobs. This comparison uncovers new patterns in business formation and survival while allowing me to directly verify whether accounting for business owners' pathways into business ownership matters.

I construct a sample of workers who quit their jobs by leveraging the fact that the Brazilian matched employer-employee data set (RAIS) reports the cause of separation when job contracts terminate. To ensure a proper comparison, I replicate the sample selection criteria outlined for laid-off workers, including restrictions on establishment size, worker age, contracted hours, and tenure, besides requiring separations to be permanent. Additionally, I exclude individuals who are part of the sample of laid-off workers and who are employed in a mass layoff establishment to avoid overlapping the two samples. This procedure identifies 574,334 workers who quit their jobs between 2012 and 2014.

I then directly compare the businesses started by laid-off workers to those started by workers who quit their jobs by estimating Equation 9. In this model, $Quits_{icjs}$ is a binary indicator equal to 1 identifying workers who quit, while the remaining variables are defined as in previous models.

$$Survival_{icjs} = \beta_0 + \beta_1 \cdot Quits_{icjs} + \beta X_{icjs} + \delta_c + \delta_j + \delta_s + \varepsilon_{icjs} \tag{9}$$

The results from estimating Equation 9 are reported in Table 9, Columns (1) and (2). I show that businesses started by workers who quit their jobs are just as likely to survive as those started by laid-off workers. Even after controlling by differences between these two groups, the coefficient β_1 is not statistically significant in either column.

Next, I estimate a model similar to Equation 3 but for the sample of businesses started by workers who quit their jobs. Results are reported in Columns (3) to (6) of Table 9. They reveal that, while survival rates are comparable across the two groups, the factors shaping business survival differ markedly. For businesses started by workers who quit, managerial experience is significantly correlated with five-year survival in Column (4). However, this significance disappears when all variables are included in Column (6), reversing the findings for laid-off workers in Table 3.

I continue to explore the differences between these two groups in Figure 7. Panel (a) repeats the results discussed above. Panel (b) and (c) estimate Equation 4 for the sample of workers who quit, while Panel (d) estimates Equation 8. These panels also report the results for laid-off workers. The findings suggest that the negative correlation between managerial experience and business survival among workers who quit their jobs is partially driven by the lower likelihood that managers transition to a familiar industry (Panel (b)). Managers who quit are also less likely to identify growth industries (Panel(c)). Together, these results suggest that, for managers who quit, starting a business may be driven more by a desire to explore entrepreneurial opportunities in new industries rather than by a focus on growth industries. As shown in Panel (d), managers remain not particularly responsive to outside options in this context.

These results underscore the importance of identifying businesses started after job loss as a separate group from other business owners. Failing to account for this distinction risks confounding the relationship between owners' abilities and business outcomes. For laid-off workers, managerial experience appears to facilitate transitions into familiar and growth industries. In contrast, for managers who quit, business formation appears more exploratory, characterized by moves into different industries with less focus on growth, driving the reported negative correlation between managerial experience and business survival.

6 Concluding Remarks

In this paper, I examine the determinants of business formation and survival, focusing on the relationship between business outcomes and owners' skills. To address the challenges associated with the existence of different pathways into business ownership, I concentrate on transitions following job loss, using mass layoffs for the identification of plausibly exogenous job separations. My analysis combines comprehensive information on business ownership with administrative data covering the universe of job contracts in Brazil. Employing an event study design, I compare the trajectories of laid-off workers with a matched sample of non-laid-off individuals. Additionally, I explore the relationship between skills and business survival by focusing on the businesses started by laid-off individuals and benchmark my findings against a sample of businesses started by workers who quit their jobs.

The results reveal a significant increase in the probability that workers transition to business ownership following job loss, particularly among high-ability individuals. Managerial skills are particularly important predictors of business survival in this context, as managers are more likely to leverage their experience when opening businesses in industries where they worked before the job loss and to focus on high-growth sectors. The comparison of post-job-loss businesses to post-quit businesses reveals that, while survival rates are similar across the two groups, the skills that correlate with business survival are different. Among owners who quit their jobs, I observe a negative correlation between managerial experience and business survival.

These findings underscore the importance of identifying post-job-loss business owners as a distinct group and suggest that effective business support policies should consider owners' career trajectories and skill sets. For individuals who lose their jobs and transition into business ownership, the skills acquired in the wage sector (such as managerial experience) are highly relevant. This opens up opportunities for targeted support, such as training in business practices, which may be relevant for this group. In contrast, entrepreneurial decisions among those who quit their jobs are more likely driven by intrinsic motives and seem less likely to benefit from such interventions.

The results also suggest the existence of entrepreneurial potential among high-ability workers in the wage sectors, who can succeed as business owners but may not make this transition unless they are shocked into considering it. While welfare implications are difficult at this point, the fact that some individuals become successful entrepreneurs when forced into the decision indicates they might be better off than if they had remained wage employees. Future research could explore this implication with access to revenue data, providing a clear picture of the trade-offs individuals face.

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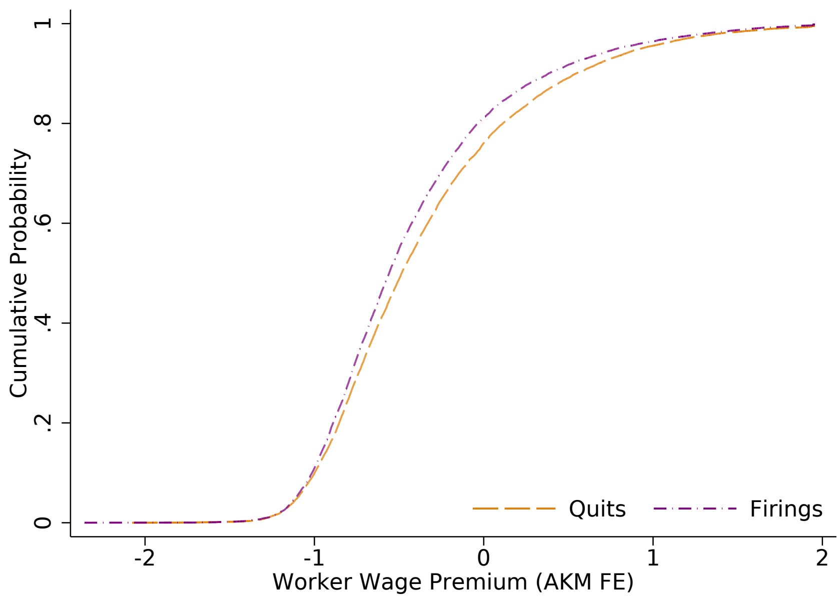
Figures and Tables

Figure 1: Worker Selection: Quits and Firings



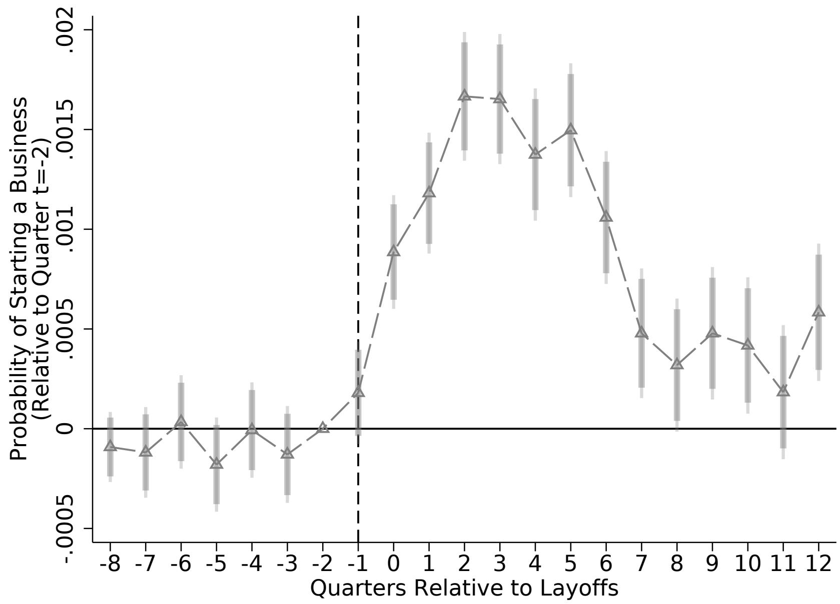
Note: Figure 1 shows the wage premium distribution, estimated using an AKM (Abowd et al. 1999) model. **Firings**: sample of workers who are fired from their jobs in the 2012-2014 period. **Quits**: sample of workers who quit their jobs in the 2012-2014 period. See Section 2.

Table 1: Summary Statistics: Laid-Off and Matched Non-Laid-Off Workers

	Laid-Off			**Matched Non-Laid-Off**		
	Mean	Median	SD	Mean	Median	SD
Matching variables						
Worker: Wage in t=-8	2123.92	1536.65	2183.34	2172.66	1542.77	2547.02
Worker: Wage in t=-4	2291.96	1651.05	2371.70	2342.57	1666.52	2686.22
Worker: Age	35.09	35.00	7.98	35.01	34.00	8.02
Worker: Months of Tenure	17.89	13.00	14.37	17.34	13.00	13.56
Worker: Years of Education	10.12	12.00	3.34	10.21	12.00	3.26
Worker: Female	0.31	0.00	0.46	0.31	0.00	0.46
Firm: Manufacturing	0.30	0.00	0.46	0.31	0.00	0.46
Firm: Retail	0.03	0.00	0.18	0.03	0.00	0.16
Firm: Services	0.26	0.00	0.44	0.25	0.00	0.43
Firm: Other	0.41	0.00	0.49	0.42	0.00	0.49
Other variables						
Worker: White	0.46	0.00	0.50	0.53	1.00	0.50
Worker: Business Owner	0.03	0.00	0.17	0.03	0.00	0.17
Worker: Manager	0.07	0.00	0.25	0.07	0.00	0.25
Worker: Wage Premium (AKM FE)	-0.43	-0.53	0.53	-0.42	-0.51	0.52
Firm: Wage Premium (AKM FE)	0.02	0.01	0.21	0.01	-0.01	0.22
Observations	294701			294701		

Note: Table 1 displays the sample characteristics of individuals included in the sample of laid-off ("treated") and matched non-laid-off ("control") workers in the 2012-2014 period. See Section 2.

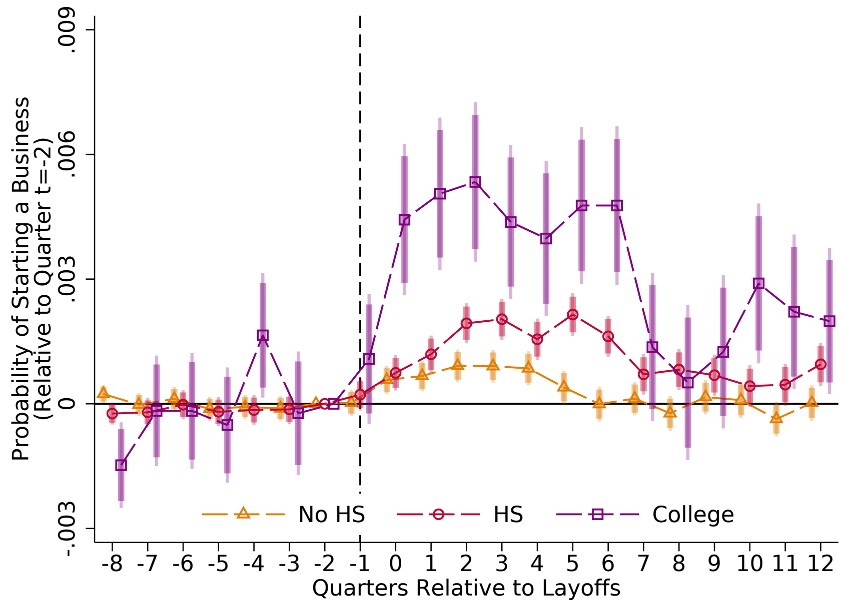
Figure 2: Job Loss and Business Registrations



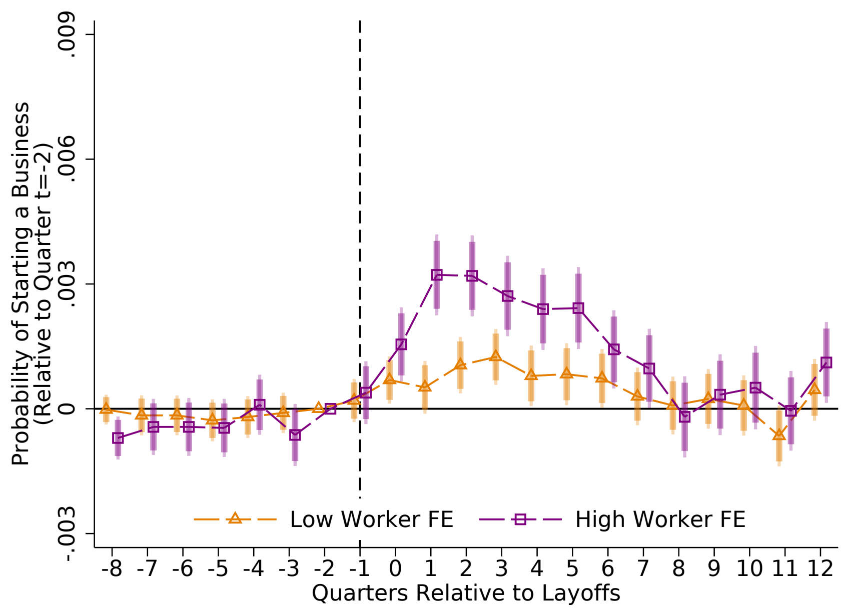
Note: Figure 2 shows the results from estimating Equation 1 on the samples of laid-off and non-laid-off workers. Outcome variable is a binary indicator equal to 1 when a worker opens a business in a given quarter. All regressions include a binary indicator identifying mass laid-off workers, "quarter relative to baseline" fixed effects, quarter fixed effects, and controls for time-varying individual characteristics (age squared). Omitted period is $\ell = -2$.

Figure 3: Job Loss and Business Registrations: General Ability

(a) By Education



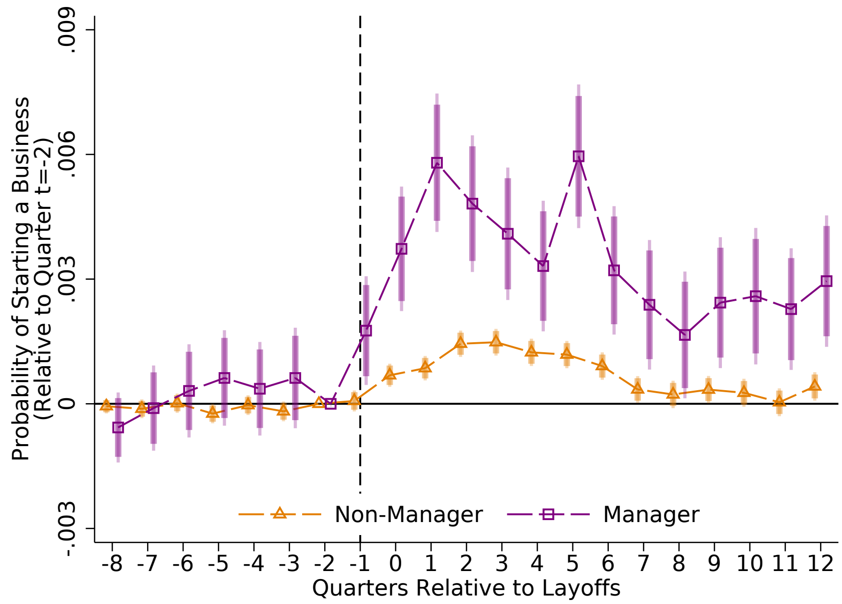
(b) By Worker Quality



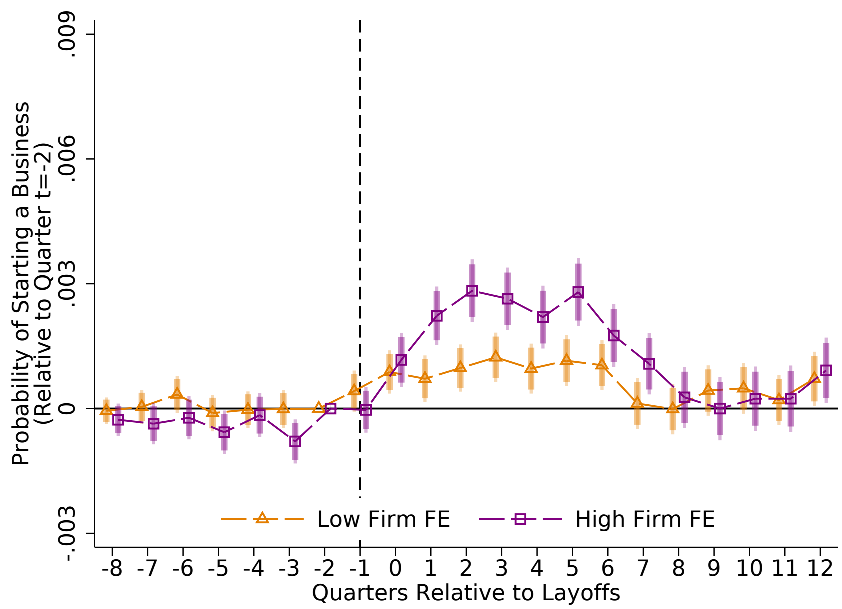
Note: Figure 3 shows the results from estimating Equation 1 on the samples of laid-off and non-laid-off workers. In Panel (a), workers are classified according to their educational level by quarter $\ell = -1$ (**No HS**: workers without a high school diploma, **HS**: workers with a high school diploma, **College**: workers with a college degree). In Panel (b), workers are classified according to their position in the wage premium distribution, estimated using an AKM (Abowd et al. 1999) model (**Low Worker FE**: bottom quartile, **High Worker FE**: top quartile). Outcome variable is a binary indicator equal to 1 when a worker opens a business in a given quarter. All regressions include a binary indicator identifying mass laid-off workers, "quarter relative to baseline" fixed effects, quarter fixed effects, and controls for time-varying individual characteristics (age squared). Omitted period is $\ell = -2$.

Figure 4: Job Loss and Business Registrations: Specific Ability

(a) By Managerial Experience



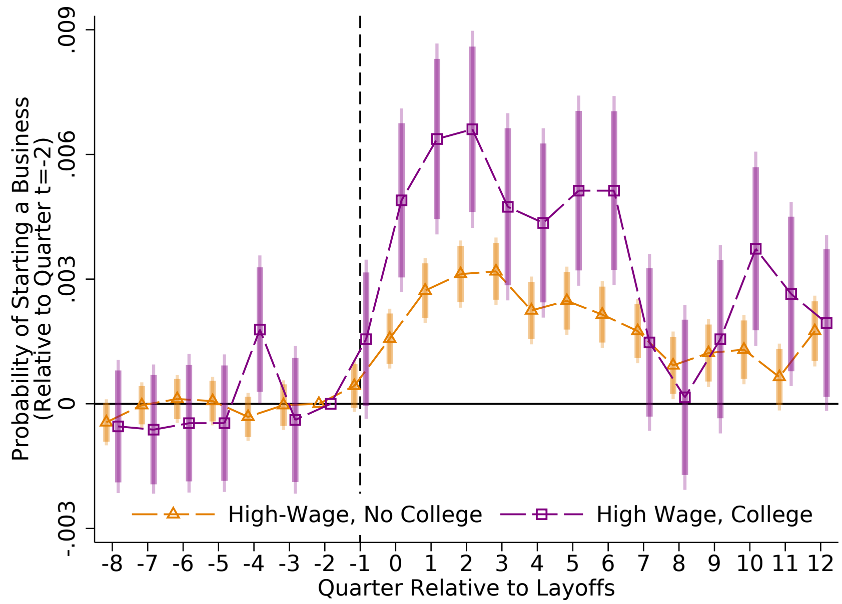
(b) By Firm Quality



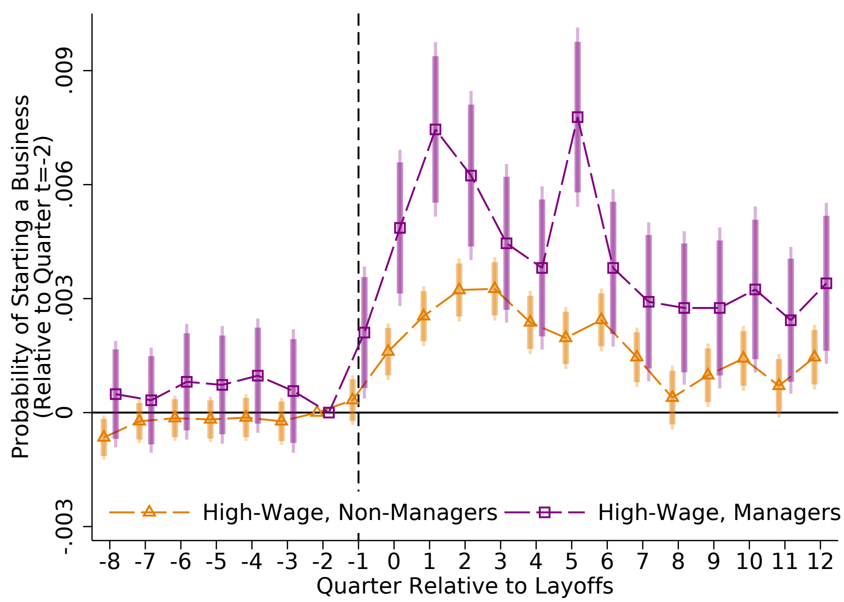
Note: Figure 4 shows the results from estimating Equation 1 on the samples of laid-off and non-laid-off workers. In Panel (a), workers are classified according to their managerial experience by quarter $\ell = -1$ (**Non-Managers**: workers who were not managers in $\ell = -1$, **Managers**: workers who were managers in $\ell = -1$). In Panel (b), workers are classified according to their position in the firm wage premium distribution, estimated using an AKM (Abowd et al. 1999) model (**Low Firm FE**: bottom quartile, **High Firm FE**: top quartile). Outcome variable is a binary indicator equal to 1 when a worker opens a business in a given quarter. All regressions include a binary indicator identifying mass laid-off workers, "quarter relative to baseline" fixed effects, quarter fixed effects, and controls for time-varying individual characteristics (age squared). Omitted period is $\ell = -2$.

Figure 5: Job Loss and Business Registrations: High-Wage Workers and Ability

(a) College Degree



(b) Managerial Experience



Note: Figure 5 shows the results from estimating Equation 1 on the samples of **high-wage** laid-off and non-laid-off workers. High-wage workers are those in the top quartile of the pre-layoff wage distribution. In Panel (a), workers are classified according to their educational level by quarter $\ell = -1$ (**College**: workers with a college degree). In Panel (b), workers are classified according to their managerial experience by quarter $\ell = -1$ (**Managers**: workers who were managers in $\ell = -1$). Outcome variable is a binary indicator equal to 1 when a worker opens a business in a given quarter. All regressions include a binary indicator identifying mass laid-off workers, "quarter relative to baseline" fixed effects, quarter fixed effects, and controls for time-varying individual characteristics (age squared). Omitted period is $\ell = -2$.

Table 2: Business Formation After Job Loss

	Prob(Start a Business After Job Loss)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Degree	0.060***	0.055***					0.039***	0.035***
	(0.002)	(0.002)					(0.002)	(0.002)
Managerial Experience			0.045***	0.040***			0.021***	0.020***
			(0.002)	(0.002)			(0.002)	(0.002)
Ln(Wage) in $\ell = -1$					0.033***	0.033***	0.024***	0.023***
					(0.001)	(0.001)	(0.001)	(0.001)
Average LHS	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
Observations	294701	294701	294701	294701	294701	294701	294701	294701
R-Squared	0.007	0.013	0.003	0.010	0.010	0.016	0.014	0.018
Worker Controls		✓		✓		✓		✓
Industry FE		✓		✓		✓		✓
State FE		✓		✓		✓		✓
Layoff Quarter FE		✓		✓		✓		✓

Note: Table 2 reports the results from estimating Equation 2 on the sample of laid-off workers. **Outcome variable**: binary indicator equal to 1 for workers who open a business within three years of job loss. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree, binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$, log wages in the pre-layoff quarter $\ell = -1$. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value $< .1$; ** p-value $< .05$; *** p-value $< .01$.

Table 3: Business Survival After Job Loss

	P(5-Year Survival)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Degree	0.018	0.022*					-0.010	0.012
	(0.012)	(0.013)					(0.014)	(0.014)
Managerial Experience			0.065***	0.057***			0.052***	0.053***
			(0.012)	(0.013)			(0.013)	(0.013)
Ln(Wage) in $\ell = -1$					0.026***	0.015**	0.021***	0.004
					(0.006)	(0.006)	(0.007)	(0.008)
Average LHS	0.602	0.602	0.602	0.602	0.602	0.602	0.602	0.602
Observations	12844	12844	12844	12844	12844	12844	12844	12844
R-Squared	0.000	0.035	0.002	0.036	0.002	0.035	0.003	0.036
Worker Controls		✓		✓		✓		✓
Industry FE		✓		✓		✓		✓
State FE		✓		✓		✓		✓
Layoff Quarter FE		✓		✓		✓		✓

Note: Table 3 reports the results from estimating Equation 3 on the sample of laid-off workers who started a business within three years of job loss. **Outcome variable**: binary indicator equal to 1 if the business started by a laid-off worker was operating five years after its opening. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree, binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$, log wages in the pre-layoff quarter $\ell = -1$. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value $<$ .1; ** p-value $<$ .05; *** p-value $<$ .01.

Table 4: Return to Wage Employment Among Post-Layoff Business Owners

	P(Return to Wage Employment | Starting a Business)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Degree	0.037***	0.045***					0.040***	0.043***
	(0.012)	(0.013)					(0.014)	(0.014)
Managerial Experience			-0.036***	-0.022*			-0.044***	-0.033**
			(0.013)	(0.013)			(0.013)	(0.013)
Ln(Wage) in $\ell = -1$					0.006	0.012*	0.003	0.007
					(0.006)	(0.007)	(0.007)	(0.008)
Average LHS	0.610	0.610	0.610	0.610	0.610	0.610	0.610	0.610
Observations	12844	12844	12844	12844	12844	12844	12844	12844
R-Squared	0.001	0.036	0.001	0.036	0.000	0.036	0.002	0.037
Worker Controls		✓		✓		✓		✓
Industry FE		✓		✓		✓		✓
State FE		✓		✓		✓		✓
Layoff Quarter FE		✓		✓		✓		✓

Note: Table 4 reports the results from estimating a linear probability model on the sample of laid-off workers who started a business within three years of job loss. **Outcome variable**: binary indicator equal to 1 if the laid-off worker who started a business returns to wage employment. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree, binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$, log wages in the pre-layoff quarter $\ell = -1$. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value $< .1$; ** p-value $< .05$; *** p-value $< .01$.

Table 5: Business Formation and Industry Choice

	P(Same Industry | Starting a Business)				P(Growth Industry | Starting a Business)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Degree	-0.005			-0.018	-0.010			-0.009
	(0.010)			(0.011)	(0.011)			(0.012)
Managerial Experience		0.058***		0.057***		0.025**		0.030**
		(0.011)		(0.012)		(0.012)		(0.012)
Ln(Wage) in $\ell = -1$			0.010*	0.005			-0.003	-0.006
			(0.005)	(0.006)			(0.006)	(0.007)
Average LHS	0.191	0.191	0.191	0.191	0.270	0.270	0.270	0.270
Observations	12844	12844	12844	12844	12844	12844	12844	12844
R-Squared	0.071	0.074	0.072	0.074	0.058	0.059	0.058	0.059
Worker Controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Layoff Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓

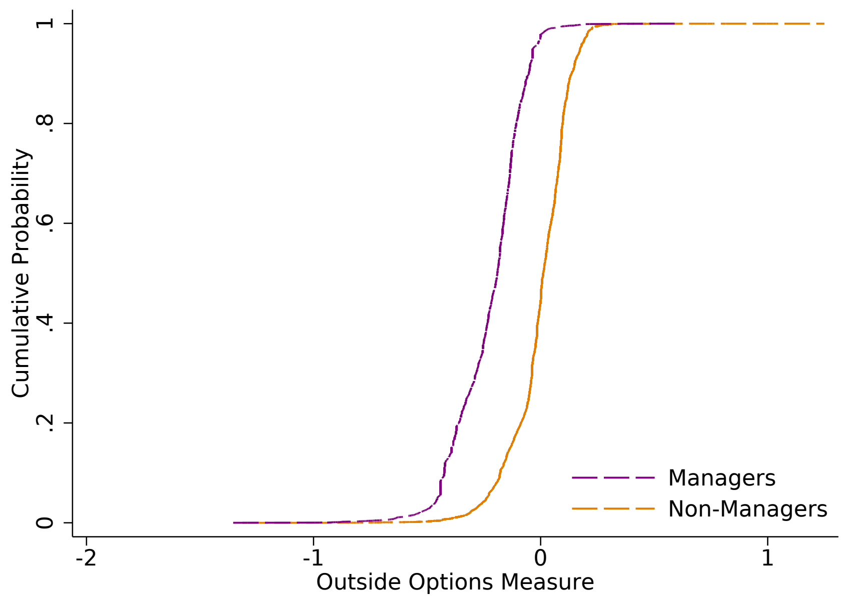
Note: Table 5 reports the results from estimating Equation 4 on the sample of laid-off workers who started a business within three years of job loss. **Outcome variables**: in Columns (1) to (4), binary indicator equal to 1 if the laid-off worker starts a business in the same 2-digit industry they were employed in pre-layoff quarter $\ell = -1$; in Columns (5) to (8), binary indicator equal to 1 if the laid-off worker starts a business in a growth industry. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree, binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$, log wages in the pre-layoff quarter $\ell = -1$. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value $<$ .1; ** p-value $<$ .05; *** p-value $<$ .01.

Table 6: Business Survival and Industry Choice

	P(5-Year Survival)							
	(1) All	(2) All	(3) Cllg	(4) Cllg	(5) Mgr	(6) Mgr	(7) HghWg	(8) HghWg
Same Industry	0.068***		0.058*		0.086***		0.078***	
	(0.011)		(0.030)		(0.028)		(0.021)	
Growth Industry		0.019*		-0.018		0.027		0.020
		(0.010)		(0.027)		(0.026)		(0.019)
Average LHS	0.602	0.602	0.618	0.618	0.658	0.658	0.633	0.633
Observations	12844	12844	1850	1850	1707	1707	3211	3211
R-Squared	0.016	0.013	0.052	0.050	0.041	0.036	0.035	0.031
Worker Controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table 6 reports the results from estimating Equation 5 on the sample of laid-off workers who started a business within three years of job loss. **Outcome variable**: binary indicator equal to 1 if the business started by a laid-off worker was operating five years after its opening. **Explanatory variables**: binary indicator equal to 1 if the laid-off worker starts a business in the same 2-digit industry they were employed in pre-layoff quarter $\ell = -1$ and binary indicator equal to 1 if the laid-off worker starts a business in a growth industry. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Figure 6: Outside Options: Managers and Non-Managers



Note: Figure 6 shows the outside option distribution, estimated following the procedure outlined in Section 4. **Managers** and **Non-Managers** refer to the subsamples of workers who are fired from their jobs in the 2012-2014 period, classified according to their occupation in $\ell = -1$.

Table 7: Business Formation and Outside Options

	Prob(Start a Business After Job Loss)				
	(1)	(2)	(3)	(4)	(5)
Outside Option	-0.086***	-0.086***	-0.058***	-0.065***	-0.042***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
College Degree			0.047***		0.046***
			(0.002)		(0.002)
# Outside Option			-0.034***		-0.032***
			(0.011)		(0.011)
Managerial Experience				0.031***	0.026***
				(0.004)	(0.004)
# Outside Option				0.019	0.017
				(0.015)	(0.015)
Average LHS	0.042	0.042	0.042	0.042	0.042
Observations	294605	294605	294605	294605	294605
R-Squared	0.004	0.011	0.015	0.011	0.016
Worker Controls		✓	✓	✓	✓
Fixed Effects		✓	✓	✓	✓

Note: Table 7 reports the results from estimating Equation 8 on the sample of laid-off workers. **Outcome variable**: binary indicator equal to 1 for workers who open a business within three years of job loss. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree and binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$. Outside option is estimated following the procedure outlined in Section 4. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value $<$ .1; ** p-value $<$ .05; *** p-value $<$ .01.

Table 8: Business Survival and Outside Options

	P(5-Year Survival)				
	(1)	(2)	(3)	(4)	(5)
Outside Option	-0.083***	-0.020	0.027	0.078**	0.112***
	(0.027)	(0.030)	(0.034)	(0.037)	(0.039)
College Degree			0.000		0.000
			(0.016)		(0.016)
# Outside Option			-0.168**		-0.148**
			(0.068)		(0.071)
Managerial Experience				0.037*	0.044**
				(0.021)	(0.022)
# Outside Option				-0.150*	-0.110
				(0.080)	(0.082)
Average LHS	0.602	0.602	0.602	0.602	0.602
Observations	12845	12845	12845	12845	12845
R-Squared	0.001	0.034	0.035	0.036	0.037
Worker Controls		✓	✓	✓	✓
Fixed Effects		✓	✓	✓	✓

Note: Table 8 reports the results from estimating a model similar to Equation 8 on the sample of laid-off workers who started a business within three years of job loss. **Outcome variable**: binary indicator equal to 1 if the business started by a laid-off worker was operating five years after its opening. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree and binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$. Outside option is estimated following the procedure outlined in Section 4. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value $<$ .1; ** p-value $<$ .05; *** p-value $<$ .01.

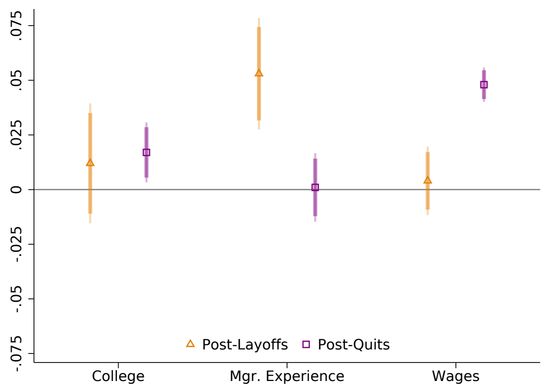
Table 9: Business Survival After Quits

	P(5-Year Survival)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Quit Business	-0.002	-0.002				
	(0.005)	(0.006)				
College Degree			0.063***			0.017**
			(0.006)			(0.007)
Managerial Experience				0.043***		0.001
				(0.007)		(0.008)
Ln(Wage) in $\ell = -1$					0.054***	0.048***
					(0.003)	(0.004)
Average LHS	0.601	0.601	0.601	0.601	0.601	0.601
Observations	51429	51429	38585	38585	38585	38585
R-Squared	0.000	0.018	0.021	0.018	0.025	0.025
Worker Controls		✓	✓	✓	✓	✓
Industry FE		✓	✓	✓	✓	✓
State FE		✓	✓	✓	✓	✓
Layoff Quarter FE		✓	✓	✓	✓	✓
Sample	**Pooled**	**Pooled**	**Quits**	**Quits**	**Quits**	**Quits**

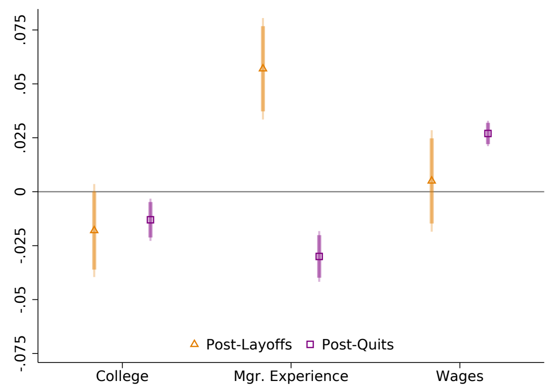
Note: In Table 9, Columns (1) and (2) report the results from estimating Equation 9 on the sample that combines laid-off workers and workers who quit their jobs, while Columns (3) through (6) report the results from estimating Equation 3 on the sample of workers who quit their jobs. **Outcome variable**: binary indicator equal to 1 if the business was operating five years after its opening. **Explanatory variables**: in columns (1) and (2), binary indicator equal to 1 identifying business started by workers who quit their jobs; in columns (3) through (6), binary indicator equal to 1 for workers with a college degree, binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$, log wages in quarter $\ell = -1$. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Figure 7: Post-Layoff and Post-Quit Businesses

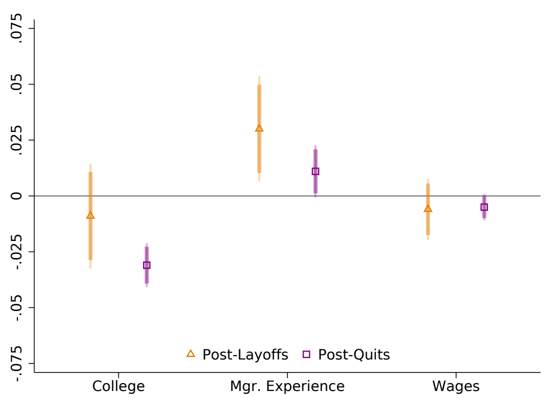
(a) P(5-Year Survival)



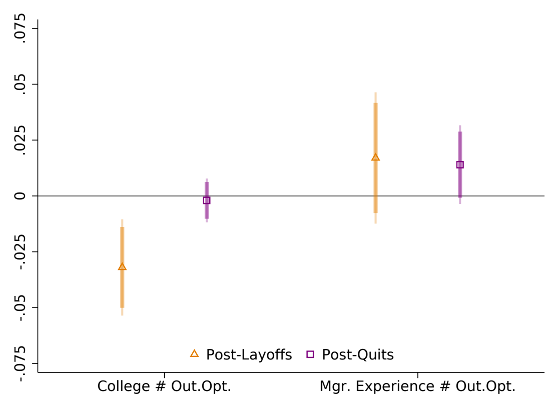
(b) P(Same Industry | Start)



(c) P(Growth Industry | Start)



(d) P(Start a Business)

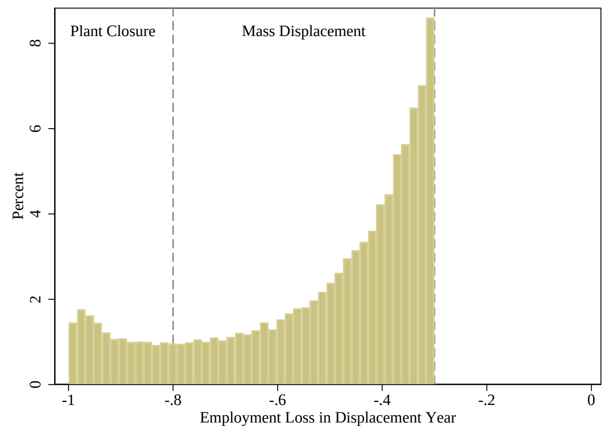


Note: Figure 7 plots the main coefficients from estimating Equation 3 (Panel (a)), Equation 4 (Panels (b) and (c)), and Equation 8 (Panel (d)) on the samples of laid-off workers and workers who quit their jobs.

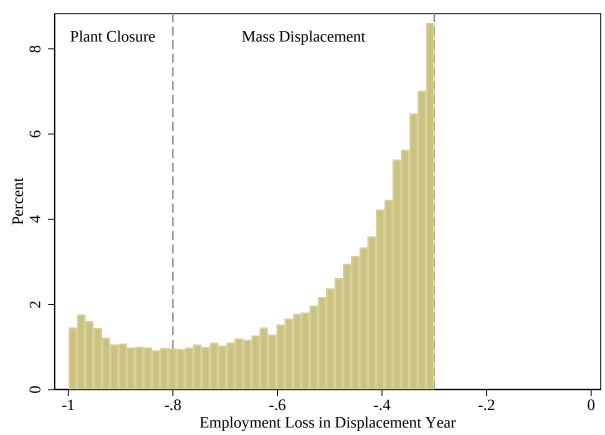
A Appendix: Figures and Tables

Figure A.1: Mass Layoff Events

(a) Employment Loss between $t-1$ and t



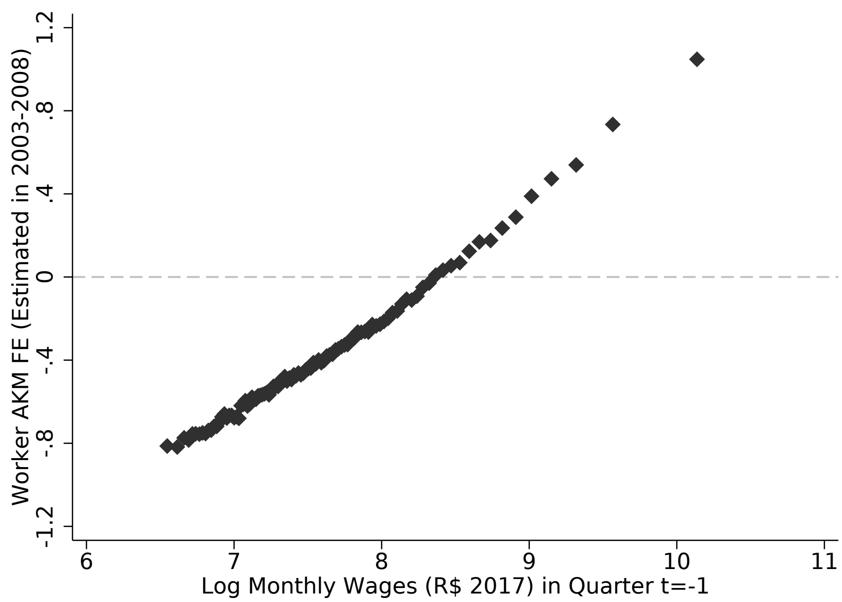
(b) Employment Loss between $t-4$ and t



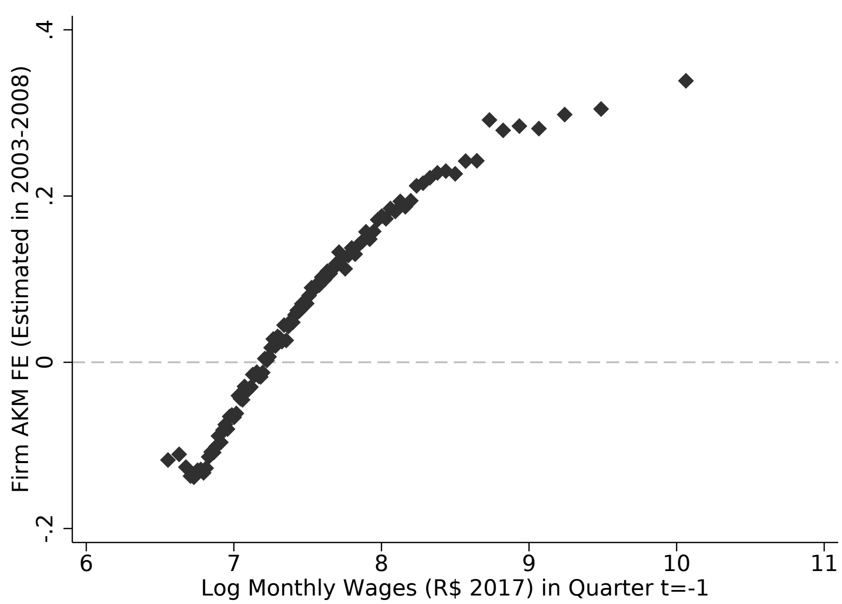
Note: Figure A.1 shows the establishment-level distribution of the employment loss between quarters $t-1$ and t (Panel (a)) and $t-4$ and t (Panel (b)) for the mass layoff events included in my sample.

Figure A.2: Wages and Ability Proxies

(a) Worker Wage Premium

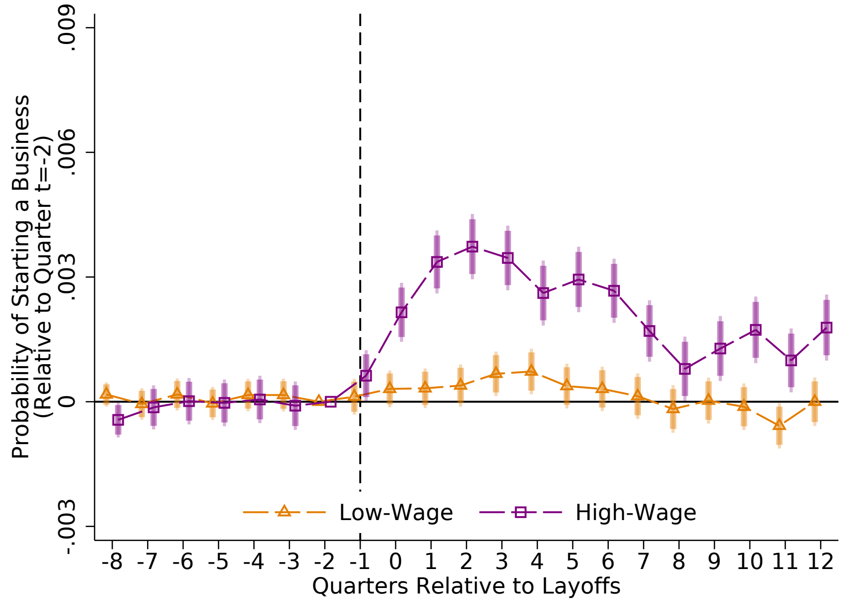


(b) Firm Wage Premium



Note: Figure A.2 shows the correlation between real log wages (in R$ 2017) and ability proxies, using binned scatterplots. **Ability proxies**: in Panel (a), worker wage premium; in Panel (b), firm wage premium. Both premia are estimated using an AKM (Abowd et al. 1999) model.

Figure A.3: Job Loss and Business Registrations: Wages



Note: Figure A.3 shows the results from estimating Equation 1 on the samples of laid-off and non-laid-off workers. Workers are classified according to their position in the within-state $\ell = -1$ wage distribution (**Low-Wage**: bottom quartile, **High-Wage**: top quartile). Outcome variable is a binary indicator equal to 1 when a worker opens a business in a given quarter. All regressions include a binary indicator identifying mass laid-off workers, "quarter relative to baseline" fixed effects, quarter fixed effects, and controls for time-varying individual characteristics (age squared). Omitted period is $\ell = -2$.

Table A.1: Business Formation and Outside Options

	Prob(Start a Business After Job Loss)					
	(1)	(2)	(3)	(4)	(5)	(6)
Outside Option	-0.086***	-0.086***	-0.058***	-0.065***	0.136***	0.088**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.039)	(0.042)
College Degree			0.047***			0.033***
			(0.002)			(0.002)
# Outside			-0.034***			-0.020*
			(0.011)			(0.012)
Managerial Experience				0.031***		0.023***
				(0.004)		(0.004)
# Outside				0.019		0.023
				(0.015)		(0.015)
Ln(Wage) in $\ell = -1$					0.029***	0.022***
					(0.001)	(0.001)
# Outside					-0.020***	-0.012**
					(0.005)	(0.005)
Average LHS	0.042	0.042	0.042	0.042	0.042	0.042
Observations	294605	294605	294605	294605	294605	294605
R-Squared	0.004	0.011	0.015	0.011	0.016	0.018
Worker Controls		✓	✓	✓	✓	✓
Industry FE		✓	✓	✓	✓	✓
State FE		✓	✓	✓	✓	✓
Layoff Quarter FE		✓	✓	✓	✓	✓

Note: Table A.1 reports the results from estimating Equation 8 on the sample of laid-off workers. **Outcome variable**: binary indicator equal to 1 for workers who open a business within three years of job loss. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree and binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$. Outside option is estimated following the procedure outlined in Section 4. **Worker controls**: gender and race. Table A.1 also includes log wages in the pre-layoff quarter $\ell = -1$ as an explanatory variable. Standard errors in parentheses. Significance stars: * p-value $< .1$; ** p-value $< .05$; *** p-value $< .01$.

Table A.2: Business Survival and Outside Options

	P(5-Year Survival)					
	(1)	(2)	(3)	(4)	(5)	(6)
Outside Option	-0.083***	-0.020	0.027	0.078**	0.340	-0.173
	(0.027)	(0.030)	(0.034)	(0.037)	(0.248)	(0.316)
College Degree			0.000			-0.011
			(0.016)			(0.017)
# Outside Option			-0.168**			-0.184**
			(0.068)			(0.081)
Managerial Experience				0.037*		0.034
				(0.021)		(0.023)
# Outside Option				-0.150*		-0.154
				(0.080)		(0.094)
Ln(Wage) in $\ell = -1$					0.012	0.015
					(0.008)	(0.009)
# Outside Option					-0.040	0.039
					(0.030)	(0.040)
Average LHS	0.602	0.602	0.602	0.602	0.602	0.602
Observations	12845	12845	12845	12845	12845	12845
R-Squared	0.001	0.034	0.035	0.036	0.035	0.037
Worker Controls		✓	✓	✓	✓	✓
Industry FE		✓	✓	✓	✓	✓
State FE		✓	✓	✓	✓	✓
Layoff Quarter FE		✓	✓	✓	✓	✓

Note: Table A.2 reports the results from estimating a model similar to Equation 8 on the sample of laid-off workers who started a business within three years of job loss. **Outcome variable**: binary indicator equal to 1 if the business started by a laid-off worker was operating five years after its opening. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree and binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$. Outside option is estimated following the procedure outlined in Section 4. **Worker controls**: gender and race. Table A.2 also includes log wages in the pre-layoff quarter $\ell = -1$ as an explanatory variable. Standard errors in parentheses. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

Table A.3: Business Formation and Industry Choice: Quits

	P(Same Industry | Starting a Business)				P(Growth Industry | Starting a Business)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Degree	0.008*			-0.013***	-0.034***			-0.031***
	(0.004)			(0.005)	(0.004)			(0.005)
Managerial Experience		-0.012**		-0.030***		-0.001		0.011*
		(0.005)		(0.006)		(0.006)		(0.006)
Ln(Wage) in $\ell = -1$			0.018***	0.027***			-0.014***	-0.005
			(0.002)	(0.003)			(0.003)	(0.003)
Average LHS	0.174	0.174	0.174	0.174	0.204	0.204	0.204	0.204
Observations	38585	38585	38585	38585	38585	38585	38585	38585
R-Squared	0.107	0.107	0.108	0.109	0.052	0.051	0.052	0.053
Worker Controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Layoff Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table A.3 reports the results from estimating Equation 4 on the sample of workers who quit their jobs and started a business within three years. **Outcome variables**: in Columns (1) to (4), binary indicator equal to 1 if the worker starts a business in the same 2-digit industry they were employed in quarter $\ell = -1$; in Columns (5) to (8), binary indicator equal to 1 if the worker starts a business in a growth industry. **Explanatory variables**: binary indicator equal to 1 for workers with a college degree, binary indicator equal to 1 for workers classified as managers according to their occupational code in quarter $\ell = -1$, log wages in quarter $\ell = -1$. **Worker controls**: gender and race. Standard errors in parentheses. Significance stars: * p-value < .1; ** p-value < .05; *** p-value < .01.

B Appendix: *Micro-Empreendedor Individual* (MEI)

Due to Brazil's pervasive informality, many self-employed workers and small business owners never formalized their businesses. For example, Rocha and de Farias (2022) show that in 2008, only 17% of micro-entrepreneurs in Brazil made regular contributions to the tax authority.[16] To address this issue, Brazil enacted new legislation in 2008 allowing businesses with at most one employee to be constituted under a format called *Micro-Empreendedor Individual* (MEI) or *Individual Micro-Entrepreneur*. This change aimed to reduce the burden associated with formal business ownership and extend certain social security benefits to business owners.

The attractiveness of the MEI model rests on three main differentials. Firstly, registering a MEI firm is a straightforward online process, often requiring a single form to be completed. By contrast, in 2013, the typical time to start a business in Brazil stood at 83 days, according to the World Bank. Secondly, operating a MEI firm does not necessitate the involvement of an accountant for tax compliance, as the firm is subject to a fixed monthly tax of approximately R$50, regardless of revenue.[17] Thirdly, MEI owners enjoy social security benefits, including maternity leave, sickness benefits, and retirement benefits.[18] A 2019 survey revealed that access to social security benefits ranked as the most commonly cited motivation to open a MEI firm. Additionally, complying with regulations, issuing invoices, and accessing the banking system were also cited as incentives for individuals (Sebrae 2019).[19]

MEI firms are limited to specific sectors listed by the national tax authority, primarily encompassing activities that do not require formal education (that is, do not require a college degree) and rely heavily on manual skills. Examples include hairdressers, construction workers, administrative assistants, advertisers, photographers, and gardeners. MEI owners

[16] Rocha and de Farias (2022) define micro-entrepreneurs as the combination of self-employed workers and employers with at most one employee.

[17] The monthly tax is equivalent to 5% of the national minimum wage plus an additional fee from R$1 to R$6 depending on the nature of the business activity. The minimum wage is adjusted annually.

[18] MEI owners enjoy social security benefits after a waiting period (10 months for maternity leave; 12 months for sickness benefits and ill-health retirement benefits; and 180 months for general retirement benefits), discouraging workers from strategically opening a MEI firm to claim benefits for pre-existing or anticipated conditions.

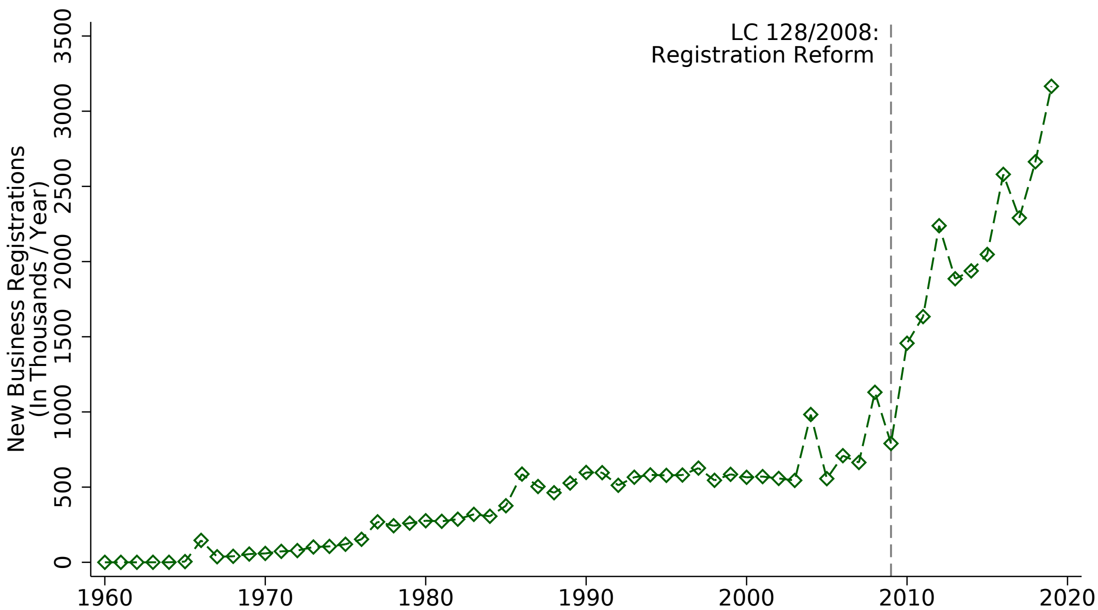
[19] MEI firms have also been used as an alternative method of hiring employees in Brazil. In such cases, individuals who would otherwise be formal employees establish MEI firms and work as contractors, avoiding certain taxes and labor protection regulations. This phenomenon was less significant in the period I evaluate in this paper since outsourcing many activities was not allowed before a labor reform in 2017. After the reform, although employment relationships satisfying some criteria (e.g., being under the control of another party, being carried out personally by the worker, requiring the payment of remuneration to the worker, and having a certain continuity) mandate the hiring of a formal employee, a legal gray area has led to the widespread use of MEI firms as a hiring tool in Brazil.

are not allowed to own other firms (whether MEI or not), but they can simultaneously hold a formal job as an employee in another organization. To maintain the MEI status, firms' annual revenues were capped at R$36,000 from 2009 to 2011 and subsequently raised to R$ 60,000 from 2011 to 2017.[20] Businesses that do not meet these conditions have the option to be established under alternative legal formats.

Since their introduction in 2009, MEI firms have gained widespread adoption. In particular, they have been largely used as the registration format for self-employed workers. Figure B.1 shows an important shift in the number of firm openings in Brazil, which a sharp increase after 2009. This surge was driven by MEI firms, which now account for three out of four new firm openings in Brazil. The number of firm openings under alternative legal formats has remained relatively stable. In terms of the consequences to informality levels in Brazil, Rocha and de Farias (2022) show that the formality rate among micro-entrepreneurs rose to 32% in 2015 (from 17% in 2008), and argue that this was mostly driven by the formalization of businesses that would operate in the informal sector had the 2009 business registration reform not taken place.

[20]In 2018, the limit was increased again to R$ 81,000. It is important to note that exchange rate fluctuations should be considered when comparing these limits to USD values (for example, R$60,000 was equivalent to approximately $ 32,258 USD in 2011 and $ 18,126 USD in 2017.

Figure B.1: New Business Registrations in Brazil



Note: Figure B.1 shows the number of new business registrations in Brazil in each year, in thousands per year. Data from the *Receita Federal* firm registry, years 1960-2019. The vertical line in 2009 indicates the first year after the approval of the *Lei Complementar* 128/2008, which introduced the *Micro-Empreendedor Individual* (MEI) as a registration format for self-employed workers and small business owners.