The Effects of Job Loss on Entrepreneurship: Evidence from Brazil *

Daniel Da Mata   Enlinson Mattos   Rafael Vilarouca

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Abstract

This paper examines the effect of job loss on entrepreneurship by combining mass layoffs with a difference-in-differences approach. Leveraging employer-employee administrative data from Brazil, we find that individuals who experience displacement are 73.7% more likely to start a business than those who do not experience job loss. Managers experience a larger effect, with an estimated increase of 132%. Our analysis also reveals that companies created after a layoff tend to be less complex and employ fewer workers, but their survival time is similar to those opened by individuals that did not undergo a layoff. To understand the mechanisms underlying this effect, we study the role of unemployment benefits and market warming. By leveraging a discontinuity in the unemployment insurance regulation, we perform a regression discontinuity design and find that receiving unemployment benefits further incentives entrepreneurship. Finally, market warming, while potentially facilitating rejoining the workforce, actually promotes entrepreneurship among the unemployed. Our findings contribute to a better understanding of the role of necessity in firm creation, which is a crucial consideration for the economic dynamics in low- and middle-income countries.

JEL Classification:

Keywords: Job-loss, Entrepreneurship, Mass-layoff, Labor Economics, Necessity Entrepreneurs, Unemployment

*Da Mata: Sao Paulo School of Economics - FGV, e-mail: daniel.damata@fgv.br. Mattos: Sao Paulo School of Economics - FGV, e-mail: enlinson.mattos@fgv.br. Vilarouca (Corresponding Author): World Bank, e-mail: rvilaroucanunes@worldbank.org. We are grateful to Joana Naritomi, Gabriel Ulyssea and participants at various seminars for their helpful comments and suggestions. Vilarouca gratefully acknowledges financial support from Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - CAPES. The usual disclaimer applies.

1 Introduction

Entrepreneurship is critical for economic development. By fostering new products and services, creating jobs, and stimulating innovation and growth, entrepreneurship can enhance the competitiveness and resilience of the economy. In recent years, many countries have experienced a rise in both the number of new businesses and the unemployment rate. This phenomenon confounds the interpretation of the relationship between unemployment and entrepreneurship. How can these two economic indicators go hand-in-hand? Is this (positive) relation caused by individuals' economic struggle? While several countries have implemented active policies to encourage entrepreneurship among the unemployed (Dvoulety and Lukes, 2016a), less is known about the effect of being dismissed on entrepreneurial behavior, which evolves labor career transitions with the dynamics of firm creation.

This paper aims to investigate the causal effect of being dismissed on the likelihood of starting a business. We provide estimates of the impact of shifting the employment status from employment to unemployment on the decision to become an entrepreneur by leveraging mass-layoff events as an exogenous variation that accounts for worker heterogeneity. We specifically focus on the effects of job loss on entrepreneurship in the Brazilian labor market between 2014 and 2017. To pursue this goal, we create a comprehensive employer-employee-owner database containing administrative data of the universe of Brazilian firms' owners and employees from 2010 to 2019. We also study the potential mechanisms behind this phenomenon and compare the performance of firms created after a mass layoff with firms created by individuals that did not undergo a mass-layoff event.

Theoretical models that seek to explain entrepreneurial choice and the subsequent firm outcomes can be traced back to Lucas (1978), who postulated that firms' performance could be explained by managerial talent. Since then, models have been developed to explain the dynamics of firm creation, development, and destruction. Lisi (2017) incorporates the notion of offensive and defensive entrepreneurs and distinguishes the value of being an entrepreneur from becoming one. da Fonseca (2022) shows that even with homogeneous individuals, being unemployed not only increases the propensity of starting a business but also shapes the expected outcome of new ventures. In terms of definition, we use a common ground and define necessity enterprises as the ones created by individuals that got unemployed—as opposed to the so-called opportunity entrepreneurs, those individuals that start the business to explore potential opportunities.

We employ two granular datasets to pursue the research question. First, we have access to data from the Ministry of Labor (RAIS), which allows us to connect employees and employers of the universe of formal firms in Brazil from 2010 to 2019. Compared to earlier works, an advantage of this dataset is that this data is register-based, diminishing the concerns with typical survey data measurement errors. This dataset identifies firms and staff by their unique tax code, making it possible to track the individual and obtain crucial demographic information from both company and staff. Second, we create a company owner registry using data from the Brazilian tax authority that contains the firm tax identifier and the date of creation of all formal firms in Brazil, together with an owner registry linking the company with its respective owner. In the end, we built an employee-employer-owner dataset where we can identify owners and the specific date of firm creation and hence, whether an individual is the owner of a company opened in a given year.

We start by using a dynamic difference-in-differences design to show that being dismissed increases the propensity to start a business. First, we considered as our treated units all individuals dismissed (without cause) in a mass-layoff event. Precisely, we define a mass-layoff event as a dismissal process where a specific company fires at least 33% of its staff without cause in the same calendar year.[1] The control units are non-fired individuals working for companies that displaced, at most, half of the mass-layoff definition (16,5%) in a given calendar year. Note that control units were not fired, but they can still choose to leave their jobs or to open a business while employed. In addition, to guarantee the comparability of treatment and control units, we match the controls in several characteristics such as working sector, age, gender, race, salary, job tenure and firm size.[2] Furthermore, we take into consideration recent advances regarding the staggered adoptions (Goodman-Bacon, 2021) and employ the method suggested by Sun and Abraham (2021) to account for cohort-specific heterogeneity.

Our main finding is that being dismissed increases the propensity to start a formal business by 73.7% in the year of dismissal, with the effect being persistent over the next two calendar years and reaching zero in the third year following the dismissal. Considering that we only access formal companies and individuals could also be starting informal enterprises it is likely that we are estimating a lower-bound of the overall outcome of being dismissed in entrepreneur activity.[3]

[1]Mass-layoff have widely being used as an external shock. The argument is that this sock is exogenous at least, at the worker level (Britto et al., 2022 and Martins-Neto et al., 2022). That is, even if the shock is not exogenous in a macro view or at the firm level, it is possible to interpret that a specific individual does not play a significant role in the event.

[2]Similar approach has being used by Britto et al. (2022) to show the role of job loss in criminal behavior.

[3]Some may concern that our analysis does not capture actual entrepreneurs due to a recent trend in Brazil called "pejotização". This trend involves individuals opening companies solely to circumvent CLT (Consolidation of Labor Laws) legislation by registering their company as a legal entity and providing services to firms in a way that resembles a classic employer-employee relationship. In section 6, we provide evidence that the companies we have identified are mostly limited organizations, which

In the Brazilian context, the entitlement of dismissed individuals to their severance savings account (SSA) and severance payment (SP) is a crucial consideration. These two benefits account for up to 300% of an individual's monthly income, on average. This influx of funds for those dismissed without cause can create a liquidity shock that might complicate the relationship between job loss and entrepreneurship by adding a third variable: liquidity. Therefore, we perform a second exercise to address this concern by examining whether individuals dismissed with cause also experience an increase in the chances of starting a company. Once this class of individuals does not have the right to access SP it is not reasonable to argue that they are getting a liquidity shock. We found that the positive and significant effect of job loss on entrepreneurship remains even among those who are ineligible for SP, with a 36% increase in the likelihood of starting a business in the year of dismissal followed by a positive and significant effect in the two next calendar years.

Shifting the employment status from employed to unemployed changes the structure of the opportunity cost on the decision to become an entrepreneur. This change is responsible for the gap between entrepreneur activity among the groups we are comparing. To shed light on the potential mechanisms that alter the opportunity costs we first examine the dual role of market conditions as a proxy for economic vitality by leveraging varying market conditions that are also exogenous to the individual. Second, we evaluate the role of unemployment benefits, namely, unemployment insurance (UI) and severance payment (SP). There are some other residual potential factors that we are not able to identify. For instance, the perceived value of *being your own boss* can differ after a layoff. Also, being dismissed leaves scars in the individual's career (Jacobson et al., 1993, Davis et al., 2011) which could change the expected value of employment.[4]

Consistent with the theoretical framework, recent research has shown that job market friction can drive individuals to entrepreneurship out of necessity. These studies, using various techniques, have demonstrated this phenomenon in different contexts. For example, Babina (2019) found that financial distress in the origin firm increases the likelihood of entrepreneurship, whereas Hacamo and Kleiner (2022) showed that students facing declines in the job market are more likely to start a business. Moreover, da Fonseca (2022) and Røed and Skogstrøm (2014) established a link between

differs significantly from the typical cases of pejotização.

[4]It is well documented in the literature, particularly when it comes to mass layoffs, that dismissal leaves a scar on a worker's career (Jacobson et al., 1993, Davis et al., 2011 and Menezes-Filho, 2004). These studies show that after being discharged when compared to stayers, individuals have lower wages not only in the short run but also in the long run. The person can internalize this scar, shifting the unemployment value function downwards. Noticing this drop in the expected salary and the higher probability of staying unemployed changes the opportunity cost and consequently lowers the reservation wage, pushing entrepreneurship among the unemployed.

being laid off and the decision to become an entrepreneur.

To gauge how market conditions affects the impact of dismissal on entrepreneurship, we categorize workers based on their origin company's sector as booming, neutral, and slumping - following Khanna et al. (2021). Then, we estimate the effects for each of those groups and find that they are more relevant for individuals working in a booming sector, followed by neutral and, finally, slumping sectors. The idea is that sector-specific job creation rate is a consequence of economic vitality in a given sector, representing at the same time a higher probability of finding a job and higher chances to find a business opportunity which might confound the role of this mechanism. Furthermore, we study the interaction of job creation rate in a specific sector's local market with being dismissed in a mass-layoff event and find that higher chances of finding a job are related to higher chances of starting a business. That is, we can argue that there is a recycling knowledge phenomenon that overturns the potential negative impact of the propensity to find a job on the decision to become an entrepreneur.[5]

We then investigate the potential effects of unemployment benefits. Unemployment benefits can alter reservation wages and, consequently, affect one's willingness to accept a job even if it pays less. A similar line of reasoning could also influence the decision to start a company. To investigate the extent to which unemployment benefits influence entrepreneur choices, we perform a regression-discontinuity design (RDD), taking advantage of a kink presented in the UI legislation. This discontinuity is based on the existence of a threshold of months one needs to work to access UI, creating a discontinuity in the running variable, which we better explain in section **??**.[6] In this exercise, we show that being eligible for UI further shifts the probability of starting a business, with a local effect of 11% in the year of dismissal. Furthermore, we follow Gerard and Naritomi (2021) in estimating the amount of SP individuals would be entitled to receive by tracking their career incomes and show that individuals entitled to a higher amount of SP face a higher effect of job loss on the likelihood to start a company. Yet, this does not necessarily mean that SP plays a role in entrepreneur choice, once individuals entitle to higher SP have higher wages and job tenure.

The economic literature refers to enterprises created by necessity as defensive or forced enterprises. Henceforth, we use these terms to refer to companies created after a dismissal, while firms created by non-dismissed individuals will be referred to as opportunity firms/companies. In this sense, an interesting question arises from our investigation: Do *necessity* enterprises have the same quality as those opened by op-

[5] Figure A6 shows that conditional on opening a business after dismissal, individuals are more prone to start a business in the sector they were working in before the layoff. This is what we are referring to as the recycling knowledge phenomenon.

[6] We are not the first to use this discontinuity to study the role of UI in the Brazilian context, Britto et al. (2022) studies the effect of UI on the criminal behavior of recently dismissed individuals.

portunity? To address this inquiry, we use common proxies for firm quality, such as survival and the number of employees. Surprisingly, we find that *necessity* companies have fewer workers; however, they have a higher survival time. One hypothesis is that early dismissed individuals perceive more opportunity costs to return to the labor market and thus are more resistant to closing their businesses. That is, there are some amenities in *being your own boss*, which might be overlooked when the individual was previously dismissed.

In the last section, we create alternative definitions for entrepreneurship: entrepreneurs with no employees and entrepreneurs with employees. Then, we run additional DiD regressions and show that almost half of the entrepreneurs we find are creating jobs. Also, we evaluate if the firm is a limited company or an individual owed company as a proxy for firm complexity.[7] We also show some of the characteristics of the new business owners. Finally, we re-estimate the effects for different sub-groups, giving some directions to further studies. An exciting feature of this exercise is that the effect goes up to 132% among managers.

This work aims to contribute to two strands of the literature. The first concerns job loss's consequences on life decisions and outcomes. This literature has consistently shown that discharges result in short- and long-term earnings losses for employees (Jacobson et al., 1993; Menezes-Filho, 2004; and Martins-Neto et al., 2022). Additionally, research has linked discharges with criminal behavior, with studies by Britto et al. (2022) and Khanna et al. (2021) highlighting the far-reaching consequences of layoffs and their impact on life choices. Furthermore, the main contribution of this study is to the literature on *necessity vs. opportunity entrepreneurs*, which attempts to document the existence of individuals that become business owners out of necessity as opposed to having found a great opportunity.[8]

The second strand of literature relates to entrepreneurship and firm dynamics literature. More specifically, we add to the necessity-driven entrepreneurship literature. Numerous empirical studies have demonstrated the existence of necessity entrepreneurs via direct question surveys (Carter et al., 2003; Block and Wagner, 2010; and Schjoedt and Shaver, 2007) and periodic panels that track individuals' employment status over time (Ritsilä and Tervo, 2002, Berglann et al., 2011). The difference between our approach and those aforementioned is that we are concerned with the specific effect of switching employment status. Additionally, some studies investigate whether businesses that arise out of necessity perform as well as those created out of an opportunity, while some show that necessity-driven businesses have lower performance (Block and

[7] Limited companies require the owner to have a business partner while individual ones do not.

[8] Authors also refer to the differentiation of necessity and opportunity as *push vs. pull* entrepreneurs (Dawson and Henley, 2012), *involuntary vs. voluntary* (Karaivanov and Yindok, 2022) and, to some extent, forced entrepreneurs (Hacamo and Kleiner, 2022)

Wagner, 2010; Nyström, 2020; and da Fonseca, 2022), some show that this is not necessarily true (Hacamo and Kleiner, 2022; and Babina, 2019).

Looking at self-employment, Von Greiff (2009) studied the effect of dismissal on the decision to become self-employed in Sweden. To the best of our knowledge, in terms of the direct impact of job loss on entrepreneurship, our work most relates to Røed and Skogstrøm (2014), which uses Norwegian data to show that job loss more than doubles the propensity to start a business and to da Fonseca (2022) that find similar results using Canadian data. Our paper fills at least four gaps. First, the literature has primarily focused on high-income countries, and it is ex-ante unclear whether the effects are likely to be similar in developing countries. Second, we explore our larger sample size to perform heterogeneity analyses to investigate the main characteristics of the new firms. Third, we also add by studying the role of market conditions and unemployment in explaining entrepreneurial decisions. Last, our empirical approach allows us to assess the persistence and trajectory of the effects, while existing studies primarily focus on the static impacts of job loss on entrepreneurship.

The results presented in this work highlight the importance of external shock in shaping an individual career. Additionally, it sheds light on a discussion on the role of market conditions and public policies in explaining the effect of job loss on entrepreneurial decisions, opening a gate for further discussion of what are the main reasons driving entrepreneurship among the unemployed. Furthermore, we evaluate entrepreneurs' characteristics and show that the effect is significantly higher among managers. Finally, we investigate firm characteristics and outcomes and find that *forced companies* have higher chances of being individually owned, but we find no evidence that *opportunity companies* survive longer.

The rest of this work is organized as follows. Section 2 gives a brief overview of labor regulation and unemployment benefits. Section 3 presents the data we use, exploring its advantages and disadvantages. Section 4 introduces the methodological approach used in the main analyses, and Section 5 presents the main results. Furthermore, Section 6 studies the potential mechanisms and the characteristics of the entrepreneurs and their opened firms. Finally, Section 7 concludes.

2 Background

This section provides an overview of the Brazilian institutional framework focusing on labor regulations. During the time span comprising years 2014 to 2017, we find an average of seventy million employment contracts in the Brazilian formal labor market per year. In the same period, the average of dismissed individuals was 11.3 million, 10.9 million of them without cause. The analyzed period has an average of almost two million individuals dismissed in a mass layoff process, in this sense, we provide information on what benefits those employees are entitled to access. Further, we provide information on the data we are working with, outlining its advantages and disadvantages.

In Brazil, every formal employee dismissed without cause has the right to access Severance Payment (SP), Unemployment Insurance (UI), and *Fundo de Garantia do Tempo de Serviço (FGTS)*, a worker's mandatory savings account (SSA). It is important to highlight that only employees dismissed without cause have the right to access these benefits, which means that if one gets fired with a cause or "forces" the dismissal, they can access neither of these three benefits.

To show how unemployment benefits are relevant worldwide, we look into the work of Gerard and Naritomi (2021), which states that more than 90% of developed Western countries have mandatory Unemployment Insurance (UI), while the percentage of countries with mandatory Severance Payment (SP) is almost 70%. In addition, approximately 10% of them have access to the worker's mandatory savings account (SSA). In contrast, in other countries, the number of mandatory UI programs is much lower, around 30%. Moreover, the share of countries with mandatory SP is over 80%, and access to SSA is also around 10% (Gerard and Naritomi, 2021).[9]

Mandatory savings account and Severance Payment: Every formal Brazilian employer has to deposit 8% of the employees' total earnings every month in an account held by a state bank. This amount is added monthly during the employment contract earning interest at a meager rate, typically below inflation, and can be withdrawn after being laid off. [10] There are some particular occasions one can access that balance before the layoff, but that is not the most common case.[11] In a survey, Gerard and Naritomi (2021) show that only 7% of the applicants had access to their balance before being laid off. In addition, in dismissing, the company must pay an extra 40% of the workers' SSA balance as SP, making the individual entitled to a total amount equivalent to 1.4 times the SSA balance (SSA + SP). Sometimes, we refer to these two benefits as one: the severance payment (SP). According to our estimations, together, they represent an effective replacement rate of 300%.

Unemployment Insurance: Since July 2015, any employee dismissed without cause that worked twelve months in the last eighteen months (for the first request), or nine months in the last twelve months (for the second request), or six months in a row

[9]We refer to these countries as developed Western nations and others. In the original work, the first group is composed of Western Europe, USA, CAN, AUS, NZ, and the second one of Africa, Asia, and the Rest of the Americas.

[10]The employee can access only the amount held in the account linked to the job he just got fired. If the individual has another account, they cannot access it after dismissal.

[11]There are some occasions the employee can access its SSA balance, such as some severe or rare diseases or when purchasing a residence or when perceived losses after a natural disaster.

(other requests) has the right to receive from three to five months of unemployment insurance. The recipients of UI benefits are granted an amount equivalent to one to two times the value of the monthly minimum wage. Before 2015 the rule was quite simpler the only working time requirement was working for the last six mounts regardless of how many times one has received the benefit. In addition, a 16 months minimum waiting period is necessary between one UI application and another for both before and after 2015.

3 Data

Our study relies on two datasets: RAIS, the employer-employee registry maintained by the Ministry of Labor (I), and a registry held by the Tax Authority that allows us to link all companies in Brazil with their respective owners (II).

For this study, RAIS provided us with a comprehensive overview of the formal sector in Brazil from 2010 to 2019. It is a high-quality employer-employee registry covering the universe of formal workers and firms. It enables us to identify all mass-layoff events, and to access detailed information about each worker, including their employment history, demographic information, monthly earnings, and hiring and dismissal dates. Using each employee's unique social code, we can track their employment history, salaries, and contract details. Additionally, RAIS allows us to track dates of hiring and dismissal of every formal job in an individual's career. Furthermore, it is also possible to access information on the firm level, such as their unique tax code (CNPJ), municipality, detailed sector, and size, among others.

There are some advantages to using RAIS. First, we avoid many potential biases compared to survey data, improving identification. Second, in comparison to other employer-employee datasets, RAIS holds an enormous amount of observations with approximately seventy million contracts per year, 2.5 times bigger than the Nordic countries' population together.[12] This number of observations allows us to perform an exact matching procedure in various characteristics and remain with almost four million observations. Finally, most employer-employee databases do not specify if the termination was with or without cause. In that way, they cannot distinguish if being laid off was somehow determined by employees' choices.

In order to enhance the rigor of our analysis, we adopt established methodologies commonly utilized in the literature on mass layoffs, as demonstrated in prior research by Britto et al. (2022) and Martins-Neto et al. (2022). In the main analysis, we limit our sample to urban non-temporary workers in private establishments on full-time

[12]There are a group of works using similar approaches to study the relation of being dismissed with a range of outcomes in these countries, see for instance Dvouletỳ and Lukeš (2016b) for a literature overview.

positions, i.e., those in which employees dedicate a minimum of 30 hours per week to their jobs. Additionally, we exclude companies with less than 15 workers from our analysis, which helps to ensure that the observed layoffs are an external shock at the individual level.

To address our research question, we track the post-discharge trajectory of workers to explore whether they choose to pursue entrepreneurship. We accomplish this by mapping treated and control units with the tax authority data, which identifies company owners. Nonetheless, utilizing the tax authority dataset poses several challenges. While we can access data pertaining to all formal companies, we cannot track changes over time. That is, we can only view a snapshot of the current status of each firm and cannot follow events such as changes in company ownership. However, we are still able to obtain valuable information regarding the owners of inactive companies. In order to overcome this limitation, we rely on a snapshot of data from 2020, got from Dahis et al. (2022), which represents the earliest available date we could access.

A second obstacle with our data is that we only have access to the owner's full name and part of their unique tax identifier. To be more precise, we have six out of nine digits.[13] Indeed, this may decrease the accuracy of our matching process. To overcome this limitation, we use a perfect matching of the full name and the six digits of the tax identifier while dropping accents and spaces between words.[14] Even if we are losing some enterprises, if there is no systematic imbalance in treatment and control, that should be a minor issue.

A further issue concerns a specific judicial category on the data set called "Empresário Individual" (EI). This kind of entrepreneur operates without separating their assets from the natural persons, and their owners cannot be found in the data set. Note that excluding EI from the study removes most self-employed individuals, which can differ from entrepreneurship depending on how it is defined. Moreover, we are also excluding a significant portion of employees hired through the *pejotização* process. In this process, a company still hires an individual to work as an employee, who does the same activities and has the same daily routine as regularly hired individuals, but bypassing labor regulations.

4 Empirical Strategy

To address our main research question, we combine a perfect matching process with a difference-in-differences approach. Similar combinations have been applied in various

[13] Note that we are excluding the two last digits of the tax identifier since they are just for validation. That is why we say it has nine digits instead of eleven.

[14] Further research could relax that matching by following Colonnelli et al. (2022) procedure to find more companies.

studies, including Heckman et al. (1997), Britto et al. (2022), Blien et al. (2021), and Martins-Neto et al. (2022). These studies provide examples of how the matching process united with differences-in-differences can be applied to different research questions in many disciplines.

We begin by limiting our analysis to urban non-temporary workers in private establishments that work at least 30 hours per week for a specific firm. This criterion ensures that we are dealing with full-time workers. Additionally, we filtered our data to include only firms with at least 15 workers to ensure that the identified mass-layoff events are external shocks.[15]

Our primary objective is to estimate the effect of job dismissal on the decision to become an entrepreneur. In our main analysis, we define a mass layoff as an event in which a firm fires at least 33% of its workers. However, we also examine the robustness of our findings by considering different threshold values. To prevent any spillover effects from affecting our control group, we limit the dismissal rate for firms in the control group to 16.5%, which is half of the treatment group threshold.

After identifying the treated units, we selected a control group by matching individuals in a set of key categories. Specifically, we defined the treatment group as all displaced workers who were displaced in a mass layoff process. To select the control group, we identified individuals who had not been dismissed in the same calendar year and matched them to the treated group based on key categories such as state (27), age, level of education (11), company number of employees, job tenure, salary, and sub-sector (87).[16] Additionally, in instances where multiple control units were identified for a treated unit, we randomly selected one control unit and vice versa.

4.1 Identification Strategy

After recognizing the mass layoffs and having a sample with matched-control pairs, we proceed with a staggered DiD design with the goal of recovering the average treatment effect among the treated units (ATT). Understating recent concerns with staggered DiD adoptions (Goodman-Bacon, 2021) that may arise due to the presence of heterogeneous effects among the cohorts (Roth et al., 2022), we use the approach designed by Sun and Abraham (2021) that accounts for this type of heterogeneity.

In our framework, the typical two-way-fixed-effects is specially concerning due to the dynamics of the process and the relevance of the year of dismissal. For instance, differences in the economic environment of a specific year can modify the opportunities

[15] The identification strategy is closely related to previous literature in mass layoff, following standard parameters adoptions such as Britto et al. (2022) and Martins-Neto et al. (2022)

[16] To ensure a close match, we utilized all available education levels in RAIS and created salary bins with intervals of 0.5 minimum wages. We also constructed firm size groups by quartile, and defined sub-sector using the CNAE two-digit code.

to start a business which can lead to time-varying effects and heterogeneity. Sun and Abraham (2021) estimates the DiD parameters robust to heterogeneous effects. Compared to other approaches in recent literature, this method is particularly appealing because it yields simple weighted averages of the specific cohort effect and is therefore easy to interpret. Furthermore, our specification is not using any covariates and we are using never-treated units as comparison group. Hence, our estimation should be identical to the one generated using Callaway and Sant'Anna (2021).[17]

We represent by $Y_{i,t}$ an indicator variable that equals one if individual i opens a new business in year t. Unit i is treated if was laid off in a mass-layoff event in time period t. Furthermore, we define $D^{\ell}_{i,t} := \mathbb{1}\left\{t - E_i = \ell\right\}$ to be an indicator function equals to one for unit i, in time t, being l periods from treatment year E_i. Also, $\mathbf{1}\left\{E_i = e\right\}$ returns one if unit i was treated in a year e. The goal is to recover the average treatment effect among the treated units and give a reasonable weight to the cohort-specific effects. That is, the ATT effect takes into consideration the cohort average treatment effects (Equation 1) weighted by the specific cohort sample size.

$$\mathrm{CATT}_{e,l} = \mathbb{E}\left[Y_{i,e+l} - Y^{\infty}_{i,e+l} \mid E_i = e\right]^{18} \tag{1}$$

To recover the parameter of interest, we start by estimating equation 2 obtaining the cohort average treatment effect $CATT_{e,l}$. Under the classic differences-in-differences hypothesis of no anticipation and parallel trends the parameter $\widehat{\delta}_{e,\ell}$, in equation 2, recovers the cohort-specific ATT. Equation 2 is somehow familiar to empirical researchers, where α_i and λ_t are individual and time-fixed effects, $\delta_{e,\ell}$ is the estimated parameter and $\epsilon_{i,t}$ the error term. Finally, C is a complementary set of the set that contains all the cohorts.[19]

In sequence, we estimate the weights $\widehat{\Pr}\left\{E_i = e \mid E_i \in h^l\right\}$ using the sample analogous. Where h^l is the set of cohorts that experience at least l periods of treatment relative to E_i. Finally, we use the estimated values to compute an interaction-weighted estimator $\widehat{v}_l$.

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{e \notin C} \sum_{\ell \neq -1} \delta_{e,\ell} \left(\mathbf{1}\left\{E_i = e\right\} \cdot D^{\ell}_{i,t}\right) + \epsilon_{i,t}. \tag{2}$$

$$\widehat{v}_l = \sum_{e} \widehat{\delta}_{e,\ell} \widehat{\Pr}\left\{E_i = e \mid E_i \in h^l\right\} \tag{3}$$

[17] In this case we use look at the conditional average treatment effect (Eq. 1) that would be analogous to the ATT_{gt} proposed in Callaway and Sant'Anna (2021). In both scenarios what we recover is the average treatment effect among treated units.

[18] $Y^{\infty}_{i,e+l}$represent the potential outcome of unit i, in time period t if is never-treated.

[19] In terms of notation $C = \infty$. That is, the set that contains an indicator for the never-treated group

The estimations captured by $\widehat{v}_l$ are the relative time effects of being dismissed in opening entrepreneurship. That is, if $\widehat{v}_0 = 0.015$. It means that in relative year 0 (year of dismissal), getting fired increases the chances of starting a business by 0.15%. Hypothetically, if the average chance of starting a formal business of 0.3%, this effect would represent a growth of 50% on the propensity of starting a business.

5 Results

Table 1 presents the results for estimations introduced in Section 4. The effect of being laid off on engaging in entrepreneurship is 0,084% in the year of dismissal, representing a 73,7% increase relative to the pre-treatment group baseline and a 62.1% increase compared to the full-sample average. As should be expected, the results relative to pre-treatment periods are all non-statically different from zero. Figure 1 illustrates how the effect is considerably more prominent in the year of dismissal but persists in the next two years.

In the year after dismissal, the effect is still quite relevant. Our DiD estimates show an increase of 0.049 percentage points, which represents 41.2% of the baseline. The following year, this effect drops to 0.014, around 12% of the baseline. In the subsequent sections, we show that this behavior is consistent for almost all subgroups. That is, dismissal drives people to become entrepreneurs, who take that decision in the year of dismissal and the two following years, with a considerably larger effect in the first year. However, part of the effect in the second and third years can be explained by a delay between the decision to start a business and the formalizing process.

5.1 Robustness

Workers are entitled to receive SP in contract termination without justifiable cause. Our calculations reveal that SP amounts to an average of 300% of the monthly income. This sudden inflow of cash could potentially result in heightened access to liquidity, thereby facilitating entrepreneurship. As a result, the primary driving factor behind these new entrepreneurial endeavors may be liquidity rather than job loss. To address this issue, we adopt a procedure similar to the matching process employed in the primary analyses, creating control pairs for individuals who were dismissed for cause. These individuals do not have access to SP and are thus not exposed to a liquidity shock. Table A1 indicates that even for individuals who were dismissed for cause, dismissal still has a 36% impact on entrepreneurship.

We acknowledge that our use of individuals dismissed for cause as a control group is problematic to a certain extent. First, there could be systematic potential non-observables between this group and the treatment group that we cannot account for in

Table 1: Results - Main Analysis

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	-0.002	-0.019	-0.016	0.004	-0.011	0.006
-6	-0.002	-0.019	-0.016	0.005	-0.011	0.007
-5	-0.002	-0.022	-0.018	0.004	-0.010	0.005
-4	-0.004	-0.035	-0.029	0.004	-0.011	0.003
-3	-0.002	-0.014	-0.012	0.004	-0.009	0.006
-2	-0.002	-0.020	-0.017	0.004	-0.009	0.005
0	0.084***	0.737	0.621	0.004	0.075	0.093
1	0.047***	0.412	0.347	0.004	0.039	0.055
2	0.014***	0.119	0.100	0.004	0.005	0.022
3	-0.002	-0.022	-0.018	0.005	-0.012	0.007
4	-0.009	-0.077	-0.065	0.006	-0.020	0.002
5	-0.016**	-0.144	-0.121	0.008	-0.032	-0.001

The table presents the results of the main analysis. Column (1) displays the estimated parameters for Section 5 in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The sample size for this analysis includes 1,987,554 treated control pairs, with one observation for each individual/year. The standard errors are clustered at the firm level (*** p≤ 0.01, ** p≤ 0.05, * p≤ 0.1).

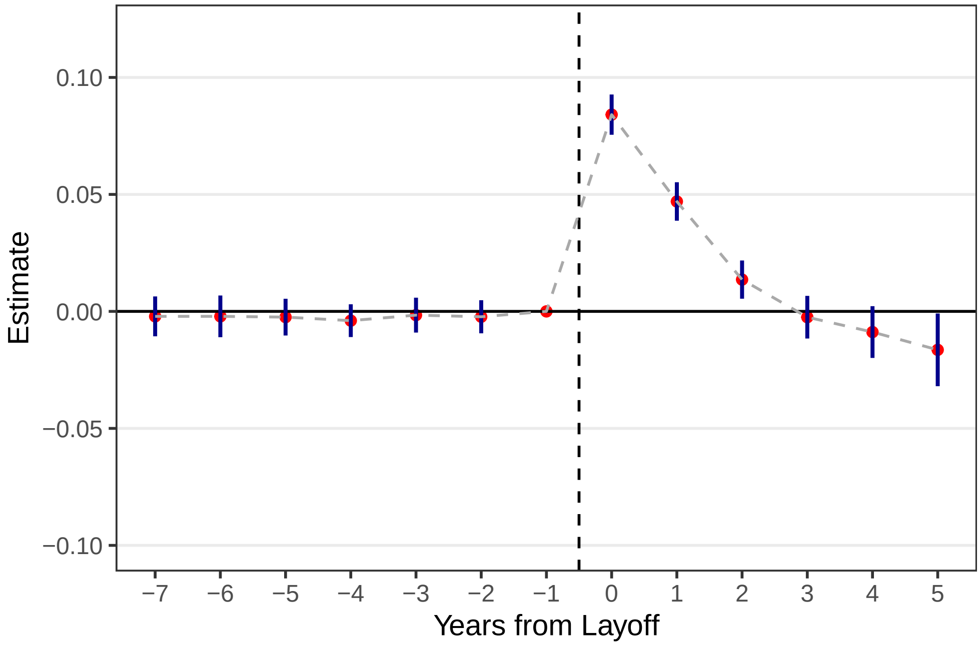
our analysis. Second, some sources of selection bias might affect the results. Finally, unlike a mass layoff, no external shock triggers dismissal for cause. Despite these limitations, we analyze individuals dismissed for cause in this separate framework to show that the entrepreneur's behavior after being laid off is consistent even for individuals not facing a liquidity shock. In addition, if the reader remains skeptical of our main findings, they may interpret them as the effect of job loss on entrepreneurship in a context with unemployment benefits similar to those in Brazil.

We note that we used a minimum of 15 employees as a threshold for firm size in our analyses. We also conducted robustness checks with greater values, strengthening the mass-layoff exogeneity assumption and producing similar results. Figure A1 shows that the entrepreneurial behavior is similar for different firm sizes. However, the effect drops slightly, which is not a problem once we deal with samples with potentially different characteristics.

6 Further Analyses

The primary analyses of this work showed that being dismissed increases the chance of starting a company by 73,7%. In this section, we explore the potential mechanisms be-

Figure 1: Effect of Job Loss on Entrepreneurship



The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

hind this phenomenon. Many factors could drive the difference in entrepreneur choices between employed and recently dismissed individuals. Among those, we highlight the role of unemployment benefits and market conditions.

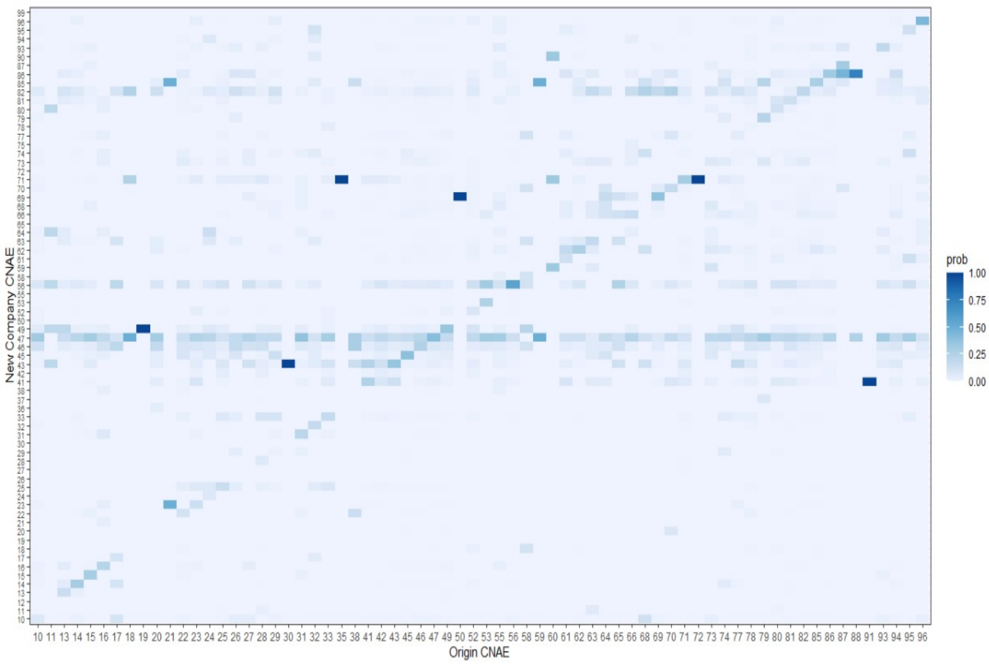
Note that we consider individuals as homogeneous, and the main difference between them is the shift in their employment status. Given this homogeneity, we understand that managerial abilities or willingness to start a business should be similar; however, individuals without a job face lower opportunity costs to start a business and hence, have a lower minimum expected profit threshold. Does that mean that companies opened after a layoff will likely have lower quality? Can the employment status of the firm founder shape firm outcomes? In the last section, we bring some suggestive evidence for this discussion, motivating further research.

6.1 Market Conditions

Market conditions, may have a dual effect on entrepreneurship decisions. On the one hand, good market conditions should make easier to individuals to find a new job after being dismissed, and thus, their behavior may not be significantly affected. However, on the other hand, it is also easier to find good business opportunities when it is easy to find a job, as both opportunities depend on the same economic vitality. Therefore, the relationship between market conditions, the ease of finding a new job, and business opportunities may be complex and context-dependent. In order to shed light on the role of market conditions on entrepreneurial decisions, we explore local and sector variations in job creation rate and their potential impact on entrepreneurship decisions.

Another feature of the dual role of market conditions on entrepreneurship activity can be seen in the phenomenon of recycling knowledge. As shown in Figure A6, individuals who start a business after being displaced are likelier to start a business in the same sector as their previous employment. This phenomenon suggests that individuals may leverage their existing knowledge and expertise to start a business rather than seek new areas of expertise. Again, this corroborates the idea that the economic environment plays a dual role in this career decision; if the individual's area of expertise is experiencing a period of growth and opportunity, then it is likely that not only will job prospects be abundant but also the chances of success for a new business venture will be high.

Figure 2: Sector Migration



The picture shows the probability of opening a company in sector y conditional on being dismissed in sector x and on having opened a company. Darker colors are related to higher probabilities. The diagonal show that there is a high probability of opening a company in the same sector. The darker region between CNAE 40 and 50 are small retail companies, bars, and restaurants

We start by following Khanna et al. (2021) in dividing the economy into sectors and calculating a job creation rate for each sector. In that way, we calculate $J_{k,t}$ according to equation 4, where k belongs to a set of sectors [20]. $J_{k,t}$ is the number of employed

[20]For the purpose of this analysis we divide the economy in Manufacturing, Construction, Trade,

workers in a given sector k in time period t. Then, we rank these sectors by their average job creation rate in our period of analysis (2014-2107) and separate them into three groups: booming, neutral, and slumping. After that, we separately estimate the ATT for each of these groups following section 4.

$$j_{k,t} = \frac{J_{k,t} - J_{k,t-1}}{J_{k,t-1}} \tag{4}$$

Once we create subcategories for the analyses, we estimate the DiD parameters for the three sectors: booming, neutral and slumping. Our results show that the ATT is notably bigger for individuals dismissed in a booming sector. In the year of dismissal, the effect in the booming sector is 80%, followed by 43% in the second year. The effect is quite smaller for the neutral sector, going from 51% in the first year to 24% in the second year. Finally, the slumping sector brings even smaller effects with 41% in the first year and 15% in the second. Figure 3 illustrate these results. In green, we plot the DiD result for workers in the booming sector, in red the neutral sector, and purple the slumping sector. The blue line represents the average treatment effect found in the main analyses. Table A3 to A4 detail this results.

In sequence, we exploit the individual-specific local working sector to consolidate our findings. In this approach, we define the sectors as in the matching process (two digits CNAE) and use the data we obtained after the matching process. A *local market* is a region that technically embraces the places one could work without needing to move out from their home, the micro-regions. We also show that our results are robust to changing from micro-regions to macro-regions or municipalities.[21] Finally, we create a dummy E_i equals to one if the individual starts a business in the year or the two following years after dismissal. Then, we regress E_i as represented in Equation 5 where $j_{k,l}$ is the job creation rate of sector k in the micro-region region l, $year_{FE}$ is the year of dismissal fixed effects, and T_i is a dummy equals to one if individual i is a treated unit.

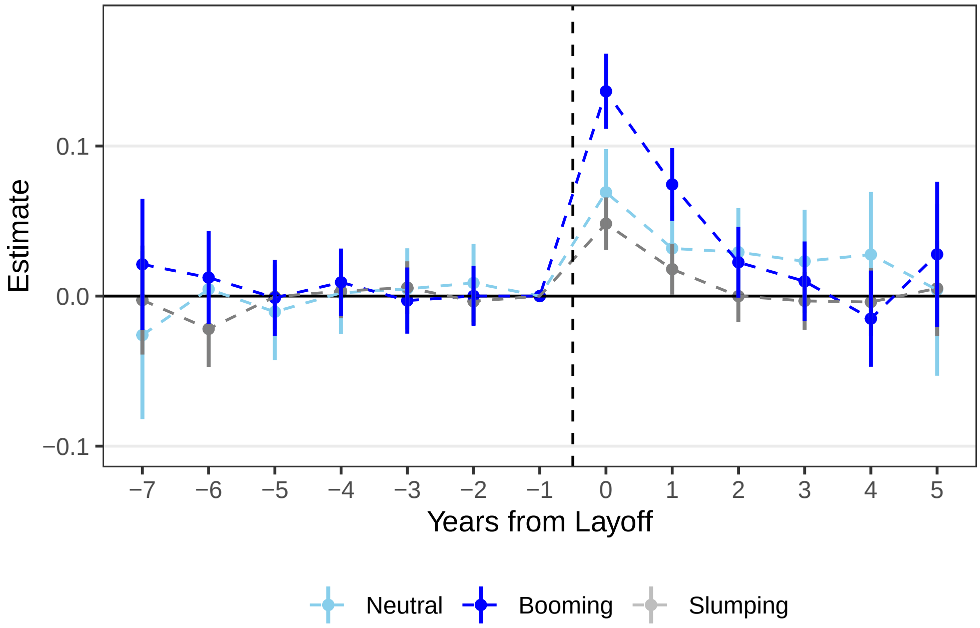
$$E_i = \gamma + \beta \cdot j_{k,l} + \beta_2 \cdot j_{k,l} \cdot T_i + \beta_3 \cdot T_i + \text{year}_{FE} + \epsilon_i \tag{5}$$

Table 2 presents the results from estimating equation 5. The job loss rate has no significant impact on entrepreneurial activity. However, the parameter of the inter-

Transportation, Services and a category called Others which includes Professional, scientific, technical, and administrative activities and complementary services. Note that we do not include the primary sector because our analyses exclude non-urban workers.

[21]Micro-region is a set of neighbors municipalities with features in common. Usually, these municipalities are strongly related in terms of job markets and business. Learn more in ¡https://www.ibge.gov.br/geociencias/organizacao-do-territorio/divisao-regional/15778-divisoes-regionais-do-brasil.html?=&t=o-que-e¿.

Figure 3: Effect of Job Loss on Entrepreneurship (By sector)



The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. Every line represents the result by subgroup defined as Booming, Slumping, or Average sector. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

action from being dismissed and the job loss rate is positive and significant. A 1% increase in the job creation rate increases 0.6% the chances of starting a business. To give a better view of the dimension of this effect, when going from the first quartile to the third, there is a difference of 11.3% in terms of job creation rate. Thus going from the first to the third quartile should increase in 6,68% the probability of starting a business. Table 2 also shows that our results are not sensitive to adding time fixed-effects or changing the reference region to a macro-region or municipality.

The results found in this section show that economic vitality sponsors entrepreneurship among those that got dismissed. Due to our matching process, treatment and control pairs worked in the same sector. Hence, they should have had similar business opportunities. However, dismissed individuals take more advantage of the opportunities that arise. Notice that we are not saying they take the best opportunities or are on better terms regarding wealth. We conclude that in moments of sector boom, there are more opportunities *on the table* which pushes even further entrepreneur willingness among the unemployed.

Table 2: The Role of Job Creation Rate by Region

	Micro-Region		Macro-Region		Municipality		
	Estimate	Relative	Estimate	Relative	Estimate	Relative	$Sector_{FE}$
(Intercept)	0.416***	0.857	0.413***	0.459	0.419***	0.863	No
Treat	0.185***	0.382	0.188***	0.371	0.192***	0.396	No
J. Loss Rate	0.002	0.004	0.003	-0.001	0.000	0.001	No
Treat*J. Loss Rate	0.003***	0.006	0.004***	0.005	0.003***	0.006	No
(Intercept)	0.223***	0.459	0.219***	0.450	0.230***	0.474	Yes
Treat	0.180***	0.371	0.184***	0.379	0.185***	0.381	Yes
J. Loss Rate	-0.000	-0.001	-0.001	-0.002	-0.000	-0.001	Yes
Treat*J. Loss Rate	0.003***	0.005	0.004***	0.008	0.002***	0.005	Yes

This table presents the estimations for equation 5. The top part shows the results for the analyses with no fixed effects while the bottom displays the effects with two-digit sector fixed effects. (*** p≤ 0.01, ** p≤ 0.05, * p≤ 0.1)

6.2 Unemployment Benefits

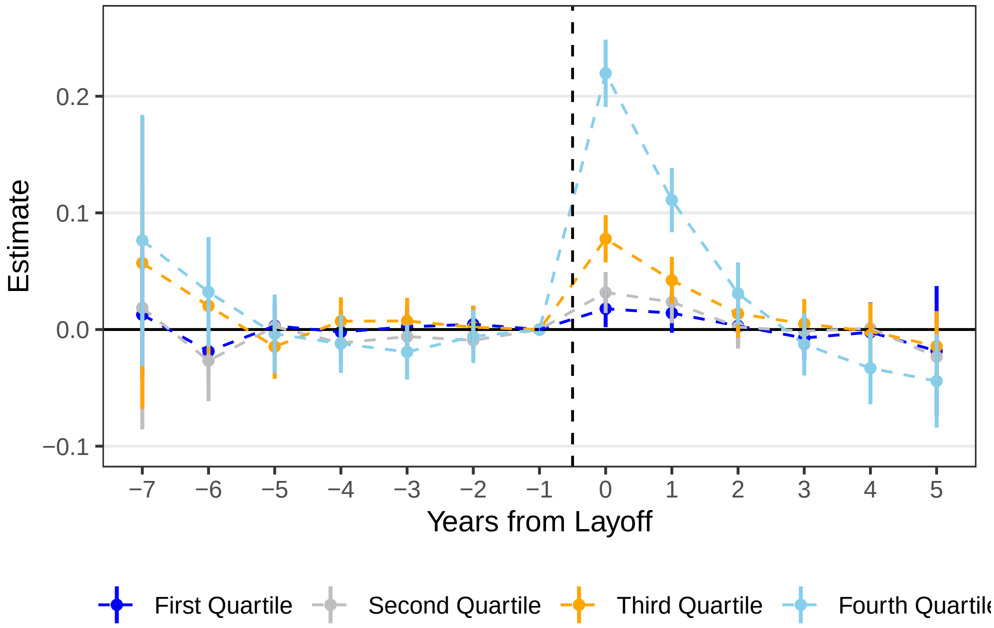
Another feature is the role of unemployment benefits. On the one hand, unemployment benefits work as a subsistence salary, so individuals would have more time to search for a job. However, on the other hand, it can also work as liquidity, which could push entrepreneurship. More specifically, we study the role of severance payment (SP) and unemployment insurance (UI).

First, we explore the heterogeneity by comparing individuals with high access to SP with those with low access. We analyze if there is any difference in the ATT effect between people with a high SP balance in opposition to those with a low balance. In the ideal scenario, we would access the amount of SP each worker has the right to get. However, this is sensitive data and is not available. Hence, we follow Gerard and Naritomi (2021) and estimate the SP balance using RAIS earnings in the past years. In this case, we only focus on workers that have been hired, at most, five years before dismissal. By doing that, we lose approximately 3% of the sample.

We then rank our sample based on their severance payments balance and divide it into quartiles. Then, we separately estimate the ATT for each of these groups. Although capable of revealing the heterogeneity treatment effect among the groups, these estimations do not show that this difference is driven by severance payment once other variables, such as salary and job tenure, are highly correlated with SP balance and could be the reasons underlining those differences.

Tables A5 to A8 show the results from the first to the fourth quartile of SP balance. The results show that the effect is positive and significant for all four groups. However, it is clear that as bigger the balance, the bigger the effect. For the fourth quartile, the effect is 0.22 percentage points in the year of dismissal, about 107% of the treated average. That is, the chances of becoming an entrepreneur for this specific group are more than doubled. For the first quartile, the results are quite smaller, about 0.018 percentage points in the year of dismissal, around 15% of the sample average. Figure 4 illustrates these results. We also provide the estimations of dividing the sample by the median, table A9 and A10 show the results. [22]

Figure 4: Effect of Job Loss on Entrepreneurship by SP Quartile



The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. Every line represents the result by subgroup defined by the quartile of SP distribution. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

The second benefit we evaluate is unemployment insurance. Brazilian legislation states that any employee dismissed without cause that worked 12 months in the last 18 months (for the first request), nine months in the last 12 months (for the second request), or six months in a row (other requests) has the right to receive from 3 to 5 months of unemployment insurance. In addition, a 16 months minimum waiting period is necessary between one UI application and another.

Because we do not have access to other UI requests nor the number of previous requests, it is hard to use these discontinuities to estimate the role of UI on entrepreneurship. However, until the end of 2014, the only working time requirement was working for the last six mounts. Therefore, we do not create matched treatment and control pairs for this exercise. Moreover, we compose our sample by all formal-urban full-time

[22] Figure A2 illustrates the results for above and bellow the median.

workers dismissed in 2014. Using that subgroup, we perform a regression discontinuity design (RDD) to estimate if there is any difference in entrepreneur behavior between those eligible and ineligible near the cutoff. This idea is similar to Britto et al. (2022), which uses the same discontinuities to estimate the importance of UI on criminality.

The RDD estimation (Equation 6) measures the local average treatment effect. It compares being just on the right of the cutoff with being just on the left. Our outcome, $Y_{i,k}$, equals one if an individual i starts a business in k calendar years after dismissal. Coefficients α and β estimate the intercept and the parameter of interest. D_i is a dummy variable such as $D = 1 (X_i \geq 0)$, X_i is the running variable, ϵ_i is the error term and $f(.)$ is a linear function of X_i.

$$Y_{i,k} = \alpha + \beta D_i + f(X_i) + \epsilon_i \tag{6}$$

In the RDD analysis, we estimate using a triangular kernel function because when combined with a bandwidth that minimizes the mean squared error, it has optimal proprieties (Cattaneo et al., 2019). Generally, this choice assigns less weight to observations far from the cutoff and zero to observations out of the bandwidth. Furthermore, to avoid over-fitting, we choose a polynomial of degree one for the estimating function. Lastly, we choose a window for the bandwidth that minimizes the mean square error, producing consistent and optimal estimators. We then estimate the RDD for k from $\in$ 1, 2, 3. Table 3 presents the results.

Table 3: Effects of UI in Entrepreneurship

	Same Year	2nd Year	3rd Year
	(1)	(2)	(3)
RDD Coefficient	0.00031	0.00041	0.00055
Sample Mean	0.00281	0.00532	0.00733
Effect Relative to sample mean	0.11253	0.07827	0.07503
P-Value	0.06465	0.07699	0.04600

This table provides de RDD estimations using 180 days as the cutoff and turnover as the running variable. Column (1) represents the results of opening a company in the year of dismissal. Columns (2) for the year of dismissal and the second year and column (3) for the year of dismissal and the next two.

Table 3, column I presents the results for the chances of opening a business in the year of dismissal. Columns II and III present the chances of opening a business within two and three years after dismissal. Individuals above the UI regulation threshold have, in the year of dismissal, 11.25% more chances of starting a company. However, notice that the effect drops in the next two years, pointing out that the effect of UI on the decision to become an entrepreneur is concentrated right after the dismissal.

Unemployment benefits may promote entrepreneurship among the unemployed. This finding is noteworthy as it contributes to various potential indirect effects of unemployment benefits. However, regarding policy implications, further research is necessary to understand the extent of these impacts better and inform future discussions on the costs and benefits of unemployment benefits.

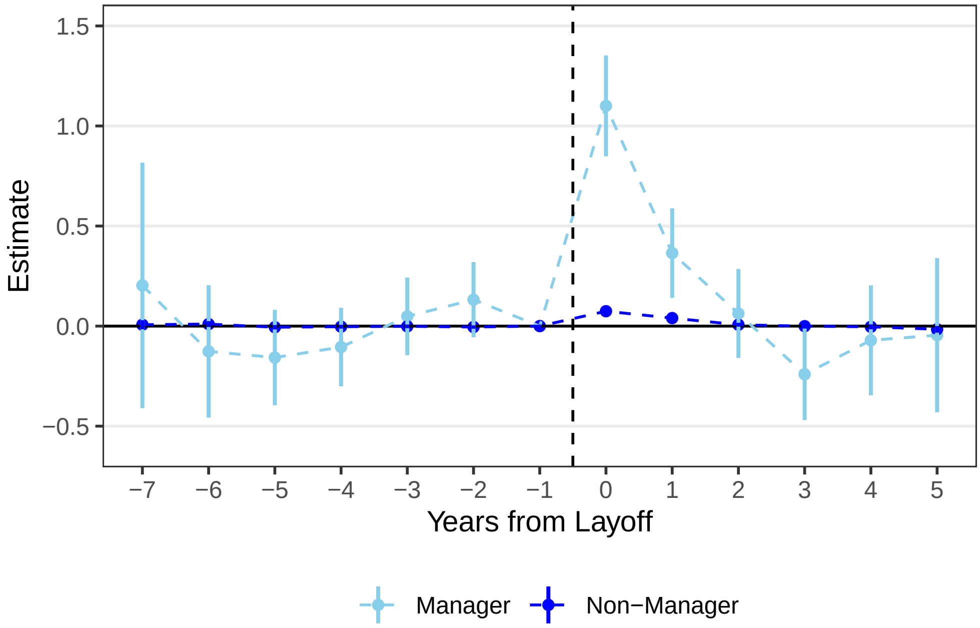
6.3 Entrepreneur Characteristics

In this section, we descriptively analyse the characteristics of entrepreneurs. Additionally, we examine the impact of separately estimating the effect for specific sub-samples divided into gender, race, and age. Furthermore, we divide our sample into managers and non-managers to see if there is an impact of having managerial knowledge on entrepreneurial choice.

Table A11 shows that the entrepreneurs we find are mainly males (75%) with an average monthly income of approximately 2.2 minimum wages (around 2060 BRL in 2017) and, on average, 31 years old. Treated and control units that decide to become entrepreneurs do not differ in race and gender. There is a slight difference in age, education, and income, but the magnitude is considerably small. Tables A12 to A16 show the estimated ATT effects for sub-groups. We notice that the effect seems to be more intense among white individuals, 89% but no meaningful difference when looking for gender. Also, this effect seems smaller for individuals with more than 45 years old. Finally, we emphasize the significant gap in comparing managers with non-managers: Table A12 shows that in the first year, the relative effect on managers is 135%, 2.5 times bigger than 51% for non-managers. Figure 5 shows the the effect of job loss among managers is significantly higher in comparison with non-managers.[23]

[23]To define managers and non-managers we use the Brazilian Occupational Code (CBO), managers are individuals in managerial positions such as directors (First CBO digit equal to 1). Workers with CBO one-digit different from 1 are considered non-managers. See more in ¡https://www.ocupacoes.com.br/tabela-completa-da-cbo¿

Figure 5: Effect of Job Loss for Managers and Non-Managers

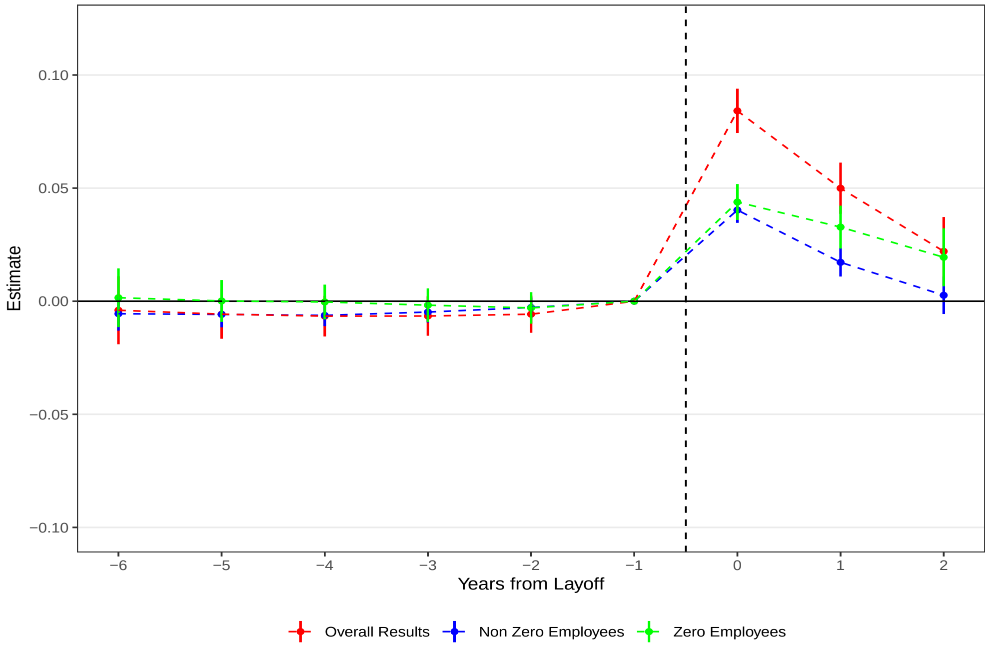


The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. In this figure, we divided the sample into managers and non-managers. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

6.4 Firms Characteristics and Outcomes

A question that may arise during our investigation is how to distinguish between those who establish ventures with employees and those who operate as self-employed. To address this query, we modify our definitions of entrepreneurship, dividing them into two categories: entrepreneurs hiring employees and self-employed entrepreneurs. The analysis leverages data from the RAIS to verify if the newly opened enterprises have reported a positive number of employees in their RAIS records in their first year or the subsequent year. Figure 6 shows that the effect of job loss on entrepreneurship seems to be half represented by each of those groups, at least in the first year.

Figure 6: Effect of Job Loss on Different Definitions of Entrepreneurship



The picture shows the dynamics of the difference between dismissed individuals and matched control pairs over time for two different definitions of entrepreneurship. In this case, we have fewer years to study because we are only using RAIS until 2017 (which we need to categorize these alternative definitions of entrepreneurship). Hence we do not have 2018 and 2019. Additionally, around 20% of the companies opened according to the data from "Receita Federal" could not be found in RAIS in the correspondent year. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

We also investigate some of this new ventures characteristics and their outcomes, highlighting the differences between the companies opened by necessity and those opened by opportunity entrepreneurs. Table 4 shows that a company opened by necessity is more likely to be of the category EIRELI, an individually owned type of firm. In contrast, they have less chance of being a limited company. In terms of the number of workers, we find a slight difference for the company's first year, and this distance grows with time. However, the difference in the number of workers is not statistically significant.

Finally, we study if there is any difference in the surviving time of these companies. The survival variable represents how many days the company remained open, with a limit of three years. To evaluate if being treated impacts survival chances, we perform a regression on the survival time on the treatment dummy using time and sector fixed effects. Table 5 shows the estimated parameters and the estimation without fixed effects. We are adding the fixed effects to this test because we are not only interested in survival as a characteristic of the firm but as an outcome. The idea is to evaluate whether necessity entrepreneurs tend to have less successful enterprises. Surprisingly, we find that those companies survive fifty extra days. This result is

Table 4: Differences in Firm Characteristics

	Difference	Control	Treated	P-value	Conf. low	Conf. high
	(1)	(2)	(3)	(4)	(5)	(6)
Share LTDA	0.0158***	0.7401	0.7243	0.0256	0.0019	0.0296
Share EIRELI	-0.0207***	0.2319	0.2526	0.0024	-0.0341	-0.0073
N Workers t = 0	0.287	2.284	1.997	0.239	-0.191	0.766
N Workers t = 1	-0.118	2.791	2.909	0.577	-0.531	0.296
N Workers t = 2	0.453	3.803	3.350	0.451	-0.725	1.631
N Workers t = 3	2.219	5.909	3.689	0.243	-1.511	5.949

The table shows the difference in average from companies opened by treat and control individuals. The confidence intervals were estimated allowing for variance heterogeneities with a 95% significance level. The first two lines represent the probability of the company being an LTDA or EIRELI. The other lines are the average number of workers in this firm in time t, relative to the dismissal year.

counter-intuitive and requires further investigation. One hypothesis we raise is that individuals previously laid off value *being their own bosses* more than others. Also, individuals previously laid off have lower expected gains in the labor market. These two reasons could make the entrepreneur more resistant to closing their business resulting in longer survival for necessity entrepreneurs.

Table 5: OLS Survival Days

	Estimate	P-value	t-statistc	Fixed Effects
	(1)	(2)	(3)	(4)
(Intercept)	1739***.	0.000	60.28	Yes
Treat	11.93*	0.050	1.95	Yes
(Intercept)	1248.17***	0.000	211.65	No
Treat	49.79***	0.000	6.51	No

The table estimates the role of opening a business after dismissal in the company survival time compared with control pairs. Panel 1 controls for time and sector fixed effects. The table presents the estimation of γ in following equation $Survival = \alpha + \gamma T + Sector_{FE}$

In summary, it seems that around half of the effect is driven by individuals that are not hiring anyone, while another half is by individuals that actually create jobs.

Additionally, the new ventures opened by necessity have a higher probability of being individually owned and a lower chance of being a limited company. We also investigate the survival time of these companies, and surprisingly, results show that necessity entrepreneurs tend to have longer survival times than opportunity entrepreneurs. Further investigation is required to understand this result.

7 Concluding Remarks

Extensive literature indicates that in high-income countries, transition rates for entrepreneurship tend to be higher among the unemployed. However, while these works make noteworthy contributions, they cannot identify the effect of being unemployed on the choice of becoming an entrepreneur. At the same time, recent studies have shown primary evidence of this effect for rich countries. In contrast, our study is the first to demonstrate the impact of job loss on entrepreneurship in a low-to-middle-income country with high informality.

By combining mass layoffs with a perfect matching algorithm and utilizing a differences-in-differences approach, we find that job loss increases the probability of starting a formal company by 73.7% in the year of dismissal. Interestingly, this effect persists in the following two years but monotonically decreases over time, ultimately returning to zero in the fourth year. We also examine different sub-samples and found that while the dynamics of the effects are similar across all groups, the magnitude of the effect varies across these subgroups. In particular, managers face an effect 2.5 times bigger than non-managers.

Moving on to the key innovations of our study, we explore the role of job market tightness as a proxy for market conditions and evaluate the impact of certain unemployment benefits. Specifically, we divide the economy into three categories based on job market conditions: booming, neutral, and slumping. Empirically, we show that the changes in the likelihood of starting a business are greater for individuals working in booming sectors, followed by neutral and slumping. In addition, we also utilize two-digit sectors and micro-regions to study the specific local sector market and find a positive relationship between economic vitality and entrepreneurship among the unemployed.

Unemployment benefits, in turn, play a dual role in the effect, providing individuals with more time to search for a job while also providing them with access to liquidity, which is a common constraint for new ventures. Our study reveals heterogeneous effects among individuals in different parts of the severance payment distribution. Specifically, we find that individuals with the right to receive a higher amount of severance exhibit a higher likelihood of starting a new business after losing their job. To further explore the impact of unemployment benefits on entrepreneurship, we investigate the effect of unemployment insurance by using a regression discontinuity design and show that being eligible to receive UI increases the likelihood of starting a new business by 11%.

Upon examining the characteristics and outcomes of the firms opened by individuals who suffered from a mass layoff, we found that they tend to be less complex. In particular, there is a higher likelihood that these firms are structured as EIRELIs (Individual Limited Liability Companies) and a lower likelihood of them being LTDAs (Limited Liability Companies). However, the difference in the number of workers employed by these firms is not statistically significant.

Finally, we analyzed whether companies that started by displaced individuals were doomed to failure, specifically looking at whether necessity-driven firms had lower survival times, but found that this was not the case. We suggest that this is due to two main reasons: first, individuals who were laid off may value being their own boss more, and second, they may suffer from job loss scars and have fewer (or worst) opportunities when returning to the labor market.

In conclusion, our study provides robust evidence that job loss can act as a catalyst for entrepreneurship. We are the first to demonstrate this effect in a low-to-middle-income country with high informality, and we also innovate by empirically testing the roles of unemployment benefits and job market tightness in shaping the decision to become an entrepreneur in such a context. Our findings may help researches as well ass policy makers to understand how necessity can drive entrepreneurship, which is crucial for those seeking to promote entrepreneurship and economic growth in similar contexts. Further research could delve deeper into the outcomes of those entrepreneurs to give a better sense of general well-being.

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For Online Publication

Online Appendix to "The Effects of Job Loss on Entrepreneurship: Evidence from Brazil "

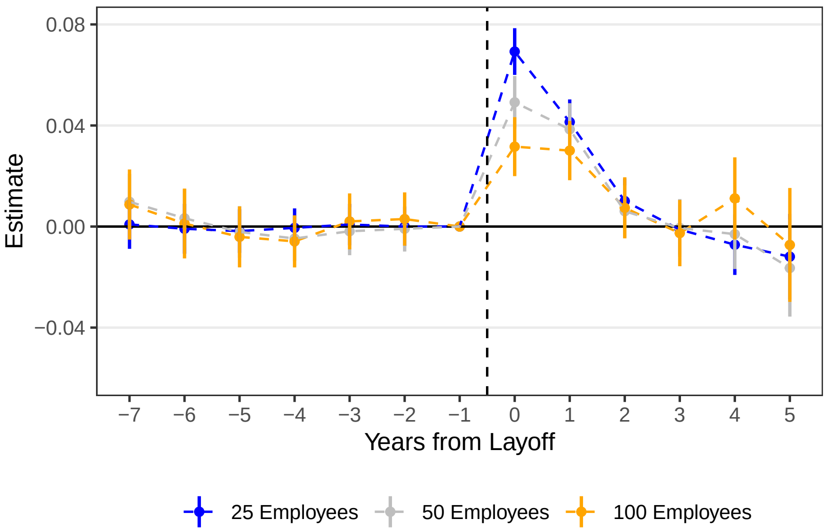
Daniel Da Mata, Enlinson Mattos and Rafael Vilarouca

July 26, 2023

A Extra Tables and Figures

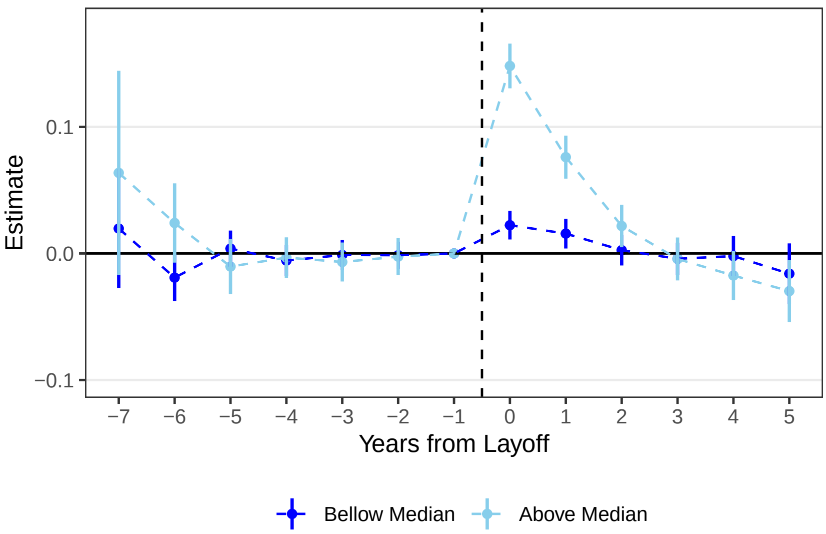
A.1 Figures

Figure A1: Robustness Check - Changing Firm Size



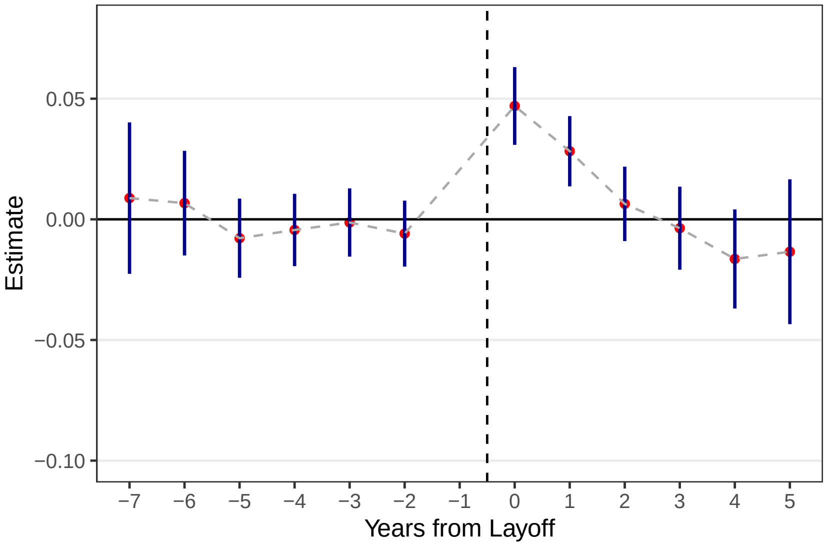
The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. It shows the effects when changing the minimum firm size to 25, 50, or 100 employees. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

Figure A2: Effect of Job Loss on Entrepreneurship by SP Median



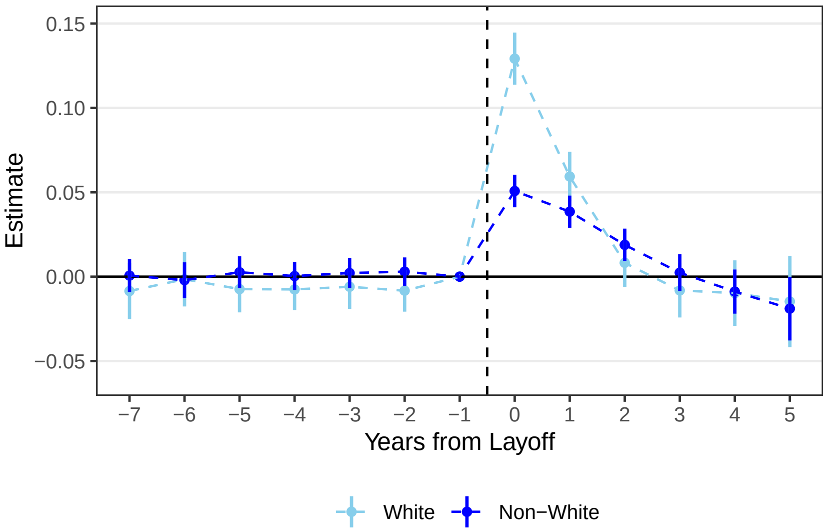
The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. It shows the effects for the sub-samples above and bellow the median. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

Figure A3: Effect of Job Loss With Cause on Entrepreneurship



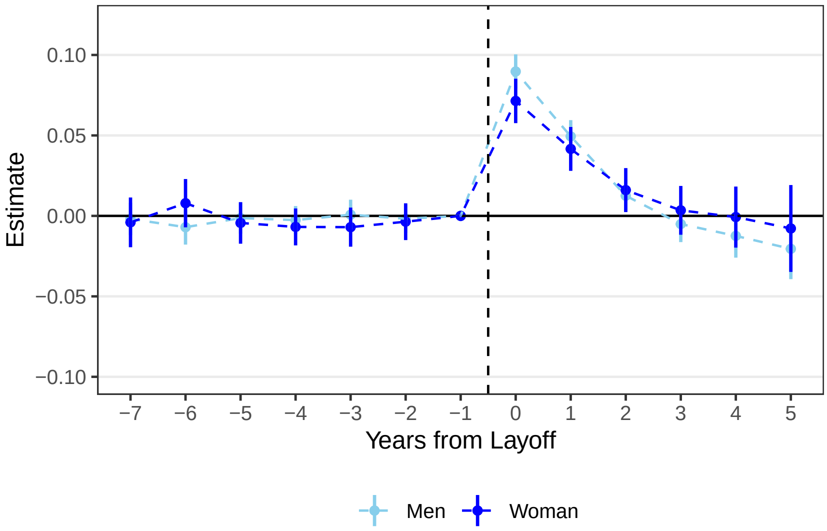
The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. This dismissed individuals were dismissed with cause and do not have access to SP. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

Figure A4: Effect of Job Loss for White and Non-white Individuals



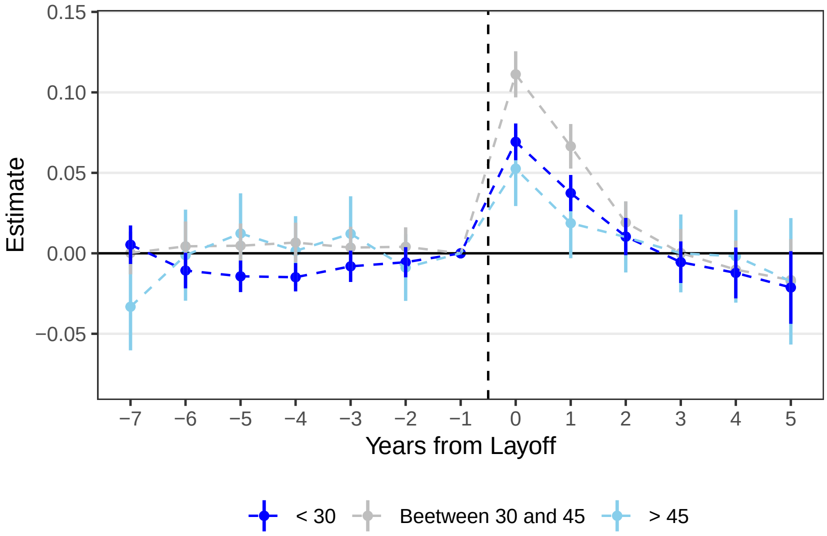
The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. In this figure, we divided the sample into white and non-white individuals. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

Figure A5: Effect of Job Loss With Cause on Entrepreneurship



The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. In this figure, we divided the sample by gender. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

Figure A6: Effect of Job Loss by Age Group



The picture shows the dynamics of the difference between dismissed individual and matched control pairs over time as a result of the Equation 3. In this figure, we divided the sample into 3 age ranges: less than 30, between 30 and 45, and more than 45. Confidence intervals were constructed using a 95% level of significance. Standard errors are clustered at the firm level.

A.2 Tables

Table A1: Results - Dismissed With Cause

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.009	0.067	0.066	160.169	-0.023	0.040
-6	0.007	0.051	0.050	110.674	-0.015	0.028
-5	-0.008	-0.060	-0.059	83.758	-0.024	0.009
-4	-0.004	-0.034	-0.033	76.511	-0.019	0.011
-3	-0.001	-0.010	-0.010	72.197	-0.015	0.013
-2	-0.006	-0.045	-0.044	69.765	-0.020	0.008
0	0.047	0.358	0.352	82.222	0.031	0.063
1	0.028	0.215	0.211	74.276	0.014	0.043
2	0.006	0.049	0.048	78.706	-0.009	0.022
3	-0.004	-0.028	-0.028	87.744	-0.021	0.014
4	-0.016	-0.125	-0.123	104.803	-0.037	0.004
5	-0.013	-0.102	-0.101	153.149	-0.043	0.017

The table presents the results of the Difference-in-Difference analyses for individuals dismissed with cause. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A2: Results - Slump Sector

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	-0.003	-0.023	-0.022	0.019	-0.039	0.034
-6	-0.022	-0.186	-0.184	0.013	-0.047	0.003
-5	0.000	-0.004	-0.004	0.011	-0.022	0.021
-4	0.003	0.028	0.027	0.009	-0.015	0.021
-3	0.006	0.048	0.048	0.009	-0.012	0.023
-2	-0.003	-0.030	-0.029	0.008	-0.019	0.012
0	0.048	0.410	0.406	0.009	0.031	0.066
1	0.018	0.152	0.151	0.009	0.001	0.035
2	0.000	0.000	0.000	0.009	-0.017	0.017
3	-0.003	-0.028	-0.027	0.010	-0.022	0.016
4	-0.004	-0.034	-0.033	0.012	-0.027	0.019
5	0.005	0.044	0.043	0.016	-0.027	0.037

The table presents the results of the Difference-in-Difference analyses for individuals working in a Slumping sector: Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A3: Results - Average Sector

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	-0.026	-0.192	-0.178	0.029	-0.082	0.030
-6	0.005	0.034	0.032	0.020	-0.034	0.043
-5	-0.011	-0.078	-0.072	0.016	-0.043	0.022
-4	0.002	0.016	0.015	0.014	-0.025	0.030
-3	0.005	0.035	0.033	0.014	-0.022	0.032
-2	0.009	0.065	0.060	0.013	-0.017	0.035
0	0.069	0.512	0.475	0.015	0.040	0.098
1	0.032	0.235	0.218	0.014	0.003	0.060
2	0.029	0.216	0.201	0.015	0.000	0.059
3	0.023	0.171	0.159	0.018	-0.011	0.057
4	0.028	0.205	0.190	0.021	-0.014	0.069
5	0.004	0.031	0.028	0.029	-0.053	0.061

The table presents the results of the Difference-in-Difference analyses for individuals working in a neutral sector. That is, not booming, but also not slumping. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A4: Results - Booming Sector

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.021	0.124	0.114	0.022	-0.022	0.065
-6	0.012	0.072	0.067	0.016	-0.019	0.043
-5	-0.001	-0.007	-0.006	0.013	-0.026	0.024
-4	0.009	0.054	0.050	0.011	-0.013	0.032
-3	-0.003	-0.018	-0.016	0.011	-0.025	0.019
-2	0.000	0.000	0.000	0.010	-0.020	0.020
0	0.136	0.797	0.737	0.013	0.111	0.161
1	0.074	0.434	0.402	0.012	0.050	0.099
2	0.023	0.132	0.122	0.012	-0.001	0.046
3	0.010	0.058	0.053	0.014	-0.017	0.036
4	-0.015	-0.088	-0.081	0.016	-0.047	0.017
5	0.028	0.162	0.150	0.025	-0.021	0.076

The table presents the results of the Difference-in-Difference analyses for individuals working in the booming sector. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A5: Results - First Quartile

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.013	0.106	0.109	0.028	-0.043	0.069
-6	-0.019	-0.157	-0.161	0.012	-0.043	0.005
-5	0.003	0.026	0.027	0.010	-0.016	0.022
-4	-0.002	-0.018	-0.018	0.009	-0.020	0.016
-3	0.002	0.019	0.020	0.009	-0.015	0.020
-2	0.005	0.038	0.039	0.008	-0.011	0.020
0	0.018	0.149	0.153	0.008	0.002	0.033
1	0.014	0.118	0.121	0.009	-0.003	0.031
2	0.003	0.026	0.026	0.009	-0.014	0.021
3	-0.007	-0.061	-0.062	0.010	-0.026	0.012
4	-0.002	-0.019	-0.020	0.013	-0.028	0.023
5	-0.018	-0.154	-0.158	0.028	-0.074	0.037

The table presents the results of the Difference-in-Difference analyses for individuals in the first quartile of SP distribution. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A6: Results - Second Quartile

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.019	0.153	0.155	0.053	-0.086	0.123
-6	-0.027	-0.220	-0.223	0.018	-0.061	0.008
-5	0.002	0.020	0.021	0.012	-0.022	0.027
-4	-0.012	-0.095	-0.096	0.009	-0.030	0.007
-3	-0.006	-0.050	-0.050	0.009	-0.024	0.012
-2	-0.009	-0.076	-0.077	0.008	-0.026	0.007
0	0.032	0.262	0.265	0.009	0.014	0.049
1	0.024	0.195	0.197	0.009	0.005	0.042
2	0.002	0.017	0.018	0.009	-0.016	0.021
3	-0.001	-0.012	-0.012	0.010	-0.020	0.018
4	0.001	0.009	0.009	0.011	-0.021	0.023
5	-0.023	-0.193	-0.195	0.015	-0.052	0.006

The table presents the results of the Difference-in-Difference analyses for individuals working in the second quartile of SP distribution. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A7: Results - Third Quartile

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.057	0.406	0.398	0.064	-0.068	0.182
-6	0.020	0.144	0.141	0.021	-0.021	0.061
-5	-0.015	-0.105	-0.102	0.014	-0.042	0.013
-4	0.007	0.051	0.050	0.010	-0.013	0.028
-3	0.007	0.052	0.051	0.010	-0.012	0.027
-2	0.002	0.014	0.014	0.009	-0.017	0.021
0	0.078	0.554	0.543	0.010	0.058	0.098
1	0.042	0.301	0.294	0.010	0.022	0.062
2	0.014	0.097	0.095	0.011	-0.007	0.034
3	0.005	0.035	0.035	0.011	-0.016	0.026
4	-0.002	-0.011	-0.011	0.012	-0.026	0.023
5	-0.014	-0.102	-0.100	0.015	-0.044	0.016

The table presents the results of the Difference-in-Difference analyses for individuals working in the third quartile of SP distribution. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A8: Results - Forth Quartile

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.076	0.375	0.337	0.060	-0.031	0.184
-6	0.032	0.158	0.142	0.024	-0.015	0.079
-5	-0.004	-0.018	-0.016	0.017	-0.037	0.030
-4	-0.012	-0.060	-0.054	0.013	-0.037	0.013
-3	-0.019	-0.094	-0.085	0.012	-0.042	0.004
-2	-0.006	-0.029	-0.026	0.012	-0.028	0.0169
0	0.220	1.079	0.970	0.015	0.191	0.249
1	0.111	0.545	0.490	0.014	0.083	0.139
2	0.031	0.152	0.136	0.014	0.004	0.058
3	-0.013	-0.062	-0.056	0.014	-0.039	0.0142
4	-0.033	-0.163	-0.146	0.016	-0.064	-0.002
5	-0.044	-0.217	-0.195	0.020	-0.084	-0.004

The table presents the results of the Difference-in-Difference analyses for individuals working in the fourth quartile of SP distribution. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A9: Results - Bellow Median

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.020	0.164	0.167	0.024	-0.027	0.067
-6	-0.019	-0.159	-0.162	0.009	-0.038	-0.001
-5	0.004	0.032	0.033	0.007	-0.010	0.018
-4	-0.006	-0.047	-0.048	0.006	-0.018	0.007
-3	-0.001	-0.010	-0.010	0.006	-0.013	0.011
-2	-0.001	-0.012	-0.012	0.005	-0.012	0.009
0	0.022	0.186	0.190	0.006	0.011	0.034
1	0.016	0.131	0.133	0.006	0.004	0.027
2	0.003	0.022	0.022	0.006	-0.009	0.015
3	-0.004	-0.035	-0.036	0.006	-0.017	0.009
4	-0.002	-0.017	-0.018	0.008	-0.018	0.014
5	-0.016	-0.133	-0.136	0.012	-0.040	0.008

The table presents the results of the Difference-in-Difference analyses for individuals below the median of SP distribution. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A10: Results - Above Median

Time	ATT	Rel. Effect	Rel. Sample Avg.	Std. Error	Low CI	High CI
	(1)	(2)	(3)	(4)	(5)	(6)
-7	0.064	0.370	0.344	0.041	-0.017	0.144
-6	0.024	0.140	0.130	0.016	-0.007	0.055
-5	-0.010	-0.060	-0.056	0.011	-0.032	0.011
-4	-0.003	-0.019	-0.018	0.008	-0.019	0.013
-3	-0.007	-0.039	-0.036	0.008	-0.022	0.009
-2	-0.003	-0.015	-0.014	0.007	-0.017	0.012
0	0.148	0.860	0.801	0.009	0.130	0.166
1	0.076	0.442	0.412	0.009	0.059	0.093
2	0.022	0.126	0.117	0.009	0.005	0.039
3	-0.004	-0.025	-0.024	0.009	-0.021	0.013
4	-0.017	-0.101	-0.094	0.010	-0.037	0.002
5	-0.030	-0.173	-0.161	0.012	-0.054	-0.005

The table presents the results of the Difference-in-Difference analyses for individuals above the median of SP distribution. Column (1) displays the estimated parameters in percentage points, while columns (2)-(3) show the effect relative to the pre-treatment period and the effect relative to the entire sample average, respectively. The standard errors are presented in column (4), while columns (5) and (6) show the lower and upper interval estimates, respectively. The standard errors are clustered at the firm level.

Table A11: Entrepreneurs Characteristics

	Control	Treated	Dif	P-value
	(1)	(2)	(3)	(4)
Age	31.16	31.46	0.30	0.015
Race (white)	0.572	0.577	-0.005	0.480
Salary (MW)	2.149	2.255	0.105	0.000
Gender (Male)	0.753	0.744	-0.009	0.163
High School	0.755	0.752	0.003	0.644
College Ed.	0.104	0.114	0.010	0.037
Observations	7531	11121	3590	-

The table presents the average of each variable for control (1) and treated (2) units. Column (3) presents the difference. And (4) presents the P-value for a 95% significance level. Race is a binary variable equal to 1 if the individual is white. Salary is calculated in minimum wages. The other three lines present the share of male, individuals with completed high school and completed college education.

Table A12: Effect of Being Laid off in Entrepreneurship - Manager vs Non-Manager

	Managers				Non-Managers			
Time	ATT	Rel. Effect	Low CI	High CI	ATT	Rel. Effect	Low CI	High CI
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
-7	0.203	0.243	-0.410	0.817	0.007	0.047	-0.016	0.030
-6	-0.126	-0.151	-0.458	0.205	0.010	0.069	-0.005	0.025
-5	-0.157	-0.188	-0.396	0.081	-0.006	-0.039	-0.017	0.005
-4	-0.105	-0.126	-0.301	0.091	-0.003	-0.022	-0.013	0.006
-3	0.049	0.058	-0.145	0.242	-0.001	-0.009	-0.010	0.008
-2	0.132	0.158	-0.056	0.320	-0.005	-0.033	-0.013	0.004
0	1.100	1.318	0.848	1.352	0.074	0.515	0.065	0.084
1	0.365	0.437	0.141	0.588	0.040	0.277	0.030	0.049
2	0.063	0.075	-0.159	0.285	0.007	0.046	-0.003	0.016
3	-0.241	-0.289	-0.470	-0.012	0.000	-0.003	-0.011	0.010
4	-0.071	-0.085	-0.346	0.203	-0.004	-0.025	-0.016	0.009
5	-0.045	-0.054	-0.431	0.340	-0.016	-0.110	-0.033	0.001

The table presents the results of the Difference-in-Difference analyses for individuals classified by manager and Non-manager. Column (1) displays the estimated parameters in percentage points, while column (2) the effects relative to the pre-treatment period. Confidence Intervals were constructed with a 95% significance level (3) and (4). The standard errors are clustered at the firm level.

Table A13: Effect of Being Laid off in Entrepreneurship - White vs Non-White Individuals

	White				Non-White			
Time	ATT	Rel. Effect	Low CI	High CI	ATT	Rel. Effect	Low CI	High CI
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
-7	-0.009	-0.059	-0.025	0.008	0.001	0.007	-0.009	0.010
-6	-0.002	-0.011	-0.018	0.015	-0.002	-0.023	-0.013	0.008
-5	-0.007	-0.051	-0.021	0.006	0.003	0.029	-0.007	0.012
-4	-0.008	-0.052	-0.020	0.005	0.000	0.004	-0.008	0.009
-3	-0.006	-0.041	-0.019	0.007	0.002	0.024	-0.007	0.011
-2	-0.008	-0.057	-0.021	0.004	0.003	0.033	-0.005	0.011
0	0.129	0.890	0.114	0.145	0.051	0.559	0.041	0.060
1	0.059	0.409	0.045	0.074	0.039	0.424	0.029	0.048
2	0.008	0.056	-0.006	0.022	0.019	0.207	0.009	0.028
3	-0.008	-0.056	-0.024	0.008	0.002	0.026	-0.009	0.013
4	-0.010	-0.067	-0.029	0.010	-0.009	-0.097	-0.022	0.004
5	-0.015	-0.101	-0.042	0.012	-0.019	-0.209	-0.038	0.000

The table presents the results of the Difference-in-Difference analyses for white and non-white individuals. Column (1) displays the estimated parameters in percentage points, while column (2) the effects relative to the pre-treatment period. Confidence Intervals were constructed with a 95% significance level (3) and (4). The standard errors are clustered at the firm level.

Table A14: Effect of Being Laid off in Entrepreneurship - Man and Woman

	Man				Woman			
Time	ATT	Rel. Effect	Low CI	High CI	ATT	Rel. Effect	Low CI	High CI
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
-7	-0.002	-0.015	-0.012	0.008	-0.004	-0.045	-0.019	0.011
-6	-0.007	-0.056	-0.018	0.004	0.008	0.088	-0.007	0.023
-5	-0.001	-0.011	-0.011	0.008	-0.004	-0.049	-0.017	0.009
-4	-0.003	-0.021	-0.011	0.006	-0.007	-0.076	-0.018	0.005
-3	0.001	0.006	-0.009	0.010	-0.007	-0.078	-0.019	0.005
-2	-0.002	-0.014	-0.011	0.007	-0.004	-0.040	-0.015	0.008
0	0.090	0.718	0.079	0.100	0.071	0.796	0.058	0.085
1	0.049	0.395	0.039	0.060	0.042	0.464	0.028	0.055
2	0.013	0.100	0.003	0.023	0.016	0.179	0.002	0.030
3	-0.005	-0.040	-0.016	0.006	0.003	0.039	-0.012	0.019
4	-0.012	-0.099	-0.026	0.001	-0.001	-0.008	-0.020	0.018
5	-0.020	-0.164	-0.039	-0.002	-0.008	-0.087	-0.035	0.019

The table presents the results of the Difference-in-Difference analyses for man and woman. Column (1) displays the estimated parameters in percentage points, while column (2) the effects relative to the pre-treatment period. Confidence Intervals were constructed with a 95% significance level (3) and (4). The standard errors are clustered at the firm level.

Table A15: Relative effects of treatment over time by age category

	< 30				> 30 and < 45				> 45			
Time	ATT	Relative Effect	Low CI	High CI	ATT	Relative Effect	Low CI	High CI	ATT	Relative Effect	Low CI	High CI
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
-7	0.005	0.060	-0.007	0.017	0.000	0.001	-0.013	0.013	-0.033	-0.279	-0.060	-0.006
-6	-0.011	-0.120	-0.022	0.000	0.004	0.030	-0.011	0.020	-0.001	-0.010	-0.029	0.027
-5	-0.014	-0.161	-0.024	-0.004	0.005	0.033	-0.009	0.019	0.012	0.104	-0.013	0.037
-4	-0.015	-0.167	-0.024	-0.006	0.007	0.047	-0.006	0.019	0.001	0.012	-0.020	0.023
-3	-0.008	-0.091	-0.018	0.002	0.004	0.025	-0.009	0.017	0.012	0.102	-0.011	0.035
-2	-0.006	-0.062	-0.015	0.004	0.004	0.028	-0.008	0.016	-0.009	-0.074	-0.030	0.012
0	0.069	0.779	0.058	0.081	0.111	0.780	0.097	0.126	0.053	0.442	0.029	0.076
1	0.037	0.421	0.026	0.049	0.066	0.466	0.053	0.080	0.019	0.157	-0.003	0.041
2	0.010	0.117	-0.001	0.022	0.019	0.134	0.006	0.032	0.010	0.085	-0.012	0.032
3	-0.006	-0.062	-0.018	0.007	0.000	0.001	-0.015	0.015	0.000	0.000	-0.024	0.024
4	-0.012	-0.137	-0.028	0.004	-0.010	-0.071	-0.028	0.008	-0.002	-0.015	-0.031	0.027
5	-0.021	-0.239	-0.044	0.001	-0.017	-0.117	-0.042	0.009	-0.017	-0.146	-0.057	0.022

The table presents the results of the Difference-in-Difference analyses for individuals with less than 30 years old, between 30 and 45, and more than 45. Column (1) displays the estimated parameters in percentage points, while column (2) the effects relative to the pre-treatment period. Confidence Intervals were constructed with a 95% significance level (3) and (4). The standard errors are clustered at the firm level.

Table A16: Relative effects of treatment: Changing the Definition of Entrepreneurship

	Overall Results				Non Zero Employees				Zero Employees			
Time	ATT	Relative Effect	Low CI	High CI	ATT	Relative Effect	Low CI	High CI	ATT	Relative Effect	Low CI	High CI
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
6	-0.004	-0.028	-0.019	0.011	-0.006	-0.039	-0.013	0.002	0.002	0.011	-0.011	0.015
-5	-0.006	-0.040	-0.017	0.005	-0.006	-0.041	-0.012	0.000	0.000	0.001	-0.009	0.009
-4	-0.007	-0.046	-0.016	0.002	-0.006	-0.044	-0.011	-0.001	0.000	-0.002	-0.008	0.007
-3	-0.007	-0.046	-0.015	0.002	-0.005	-0.034	-0.009	0.000	-0.002	-0.012	-0.009	0.006
-2	-0.006	-0.040	-0.014	0.002	-0.003	-0.019	-0.007	0.002	-0.003	-0.021	-0.010	0.004
0	0.084	0.592	0.074	0.094	0.040	0.283	0.035	0.046	0.044	0.308	0.036	0.052
1	0.050	0.351	0.039	0.061	0.017	0.121	0.011	0.023	0.033	0.230	0.023	0.042
2	0.022	0.155	0.007	0.037	0.003	0.018	-0.006	0.011	0.019	0.137	0.007	0.032

The table presents the results of the Difference-in-Difference analyses changing the definition of entrepreneur. Column (1) displays the estimated parameters in percentage points, while column (2) the effects relative to the pre-treatment period. Confidence Intervals (3 and 4) were constructed with a 95% significance level. The standard errors are clustered at the firm level. **Note:** In this case, we have fewer years to study because we are only using RAIS until 2017 (which we need to categorize these alternative definitions of entrepreneurship). Hence we do not have 2018 and 2019. Additionally, around 20% of the companies opened according to the data from "Receita Federal" could not be found in RAIS in the correspondent year.

Table A17: Correlation Between Unemployment Rate and Firm Creation

Year	Correlation	N of Countries
2006	-0.03	103
2007	-0.03	105
2008	-0.01	111
2009	0.05	117
2010	-0.00	117
2011	-0.02	121
2012	-0.02	123
2013	-0.02	129
2014	-0.02	134
2015	-0.00	137
2016	0.02	142
2017	-0.08	139
2018	-0.08	140
2019	0.02	115
2020	0.03	115

Correlation Between Unemployment Rate and Firm Creation according to the data available in https://data.worldbank.org/indicator/

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