Human Capital and Startup Financing*

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March 18, 2021

Abstract

We establish the relevance of human capital to startup financing. Using administrative databases from the Central Bank of Brazil, we obtain information on private firms, their founders and their access to bank credit. Our empirical strategy is based on the premature death of founders, which allows us to identify how losing founders' human capital affects startup financing. The results show that once a founder dies unexpectedly, there is a decrease in the amount of credit and an increase in interest rates and default rates. These findings are mainly driven by the death of founders who are also managers in the firm, which is consistent with the theory of founders contributing critical resources to their firms.

Keywords: Startups, Founding Teams, Entrepreneurship, Banking, Theory of the Firm

JEL Classification: D23, G21, G32, L26, M13

*Mauricio Medeiros Junior is grateful to Luke Taylor, Erik Gilje and Sylvain Catherine for their support and guidance throughout this project. The authors would also like to thank Sérgio Afonso Lago Alves, Gabriel Garber, Vincent Glode, Marius Guenzel, Sérgio Mikio Koyama, André Minella, Michael Schwert, and seminar participants at the Wharton School for helpful comments. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Central Bank of Brazil.

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1 Introduction

This paper asks whether and how founders matter for startup financing. This question relates to a central debate in entrepreneurial finance: which matters more, the jockey or the horse? In other words, how important is the founding team (the jockey) relative to the business idea and the line of business (the horse)?

Theories of the firm, such as Rajan and Zingales (2001) and Rajan (2012), have emphasized the importance of founding teams for startups since they contribute critical resources to their firms. However, the property right theories based on Hart and Moore (1990) consider that firms are defined by their non-human assets. This is ultimately an empirical debate. Nonetheless, the evidence provided by the literature is largely descriptive.

For example, Kaplan et al. (2009) analyze a sample of 50 venture capital-financed firms aiming to understand the importance of founding teams and the initial business idea. The firms from their sample tend to keep their initial business idea and the line of business while they commonly change their founding teams, suggesting that losing a founder would not have any significant implication for the startup.

Our goal is to contribute causal evidence to this debate about the importance of founding teams. Even though the literature has provided causal evidence on this matter recently, our understanding on how founders matter for startup financing is still quite limited. This paper shows that losing a founder reduces startup credit by 63%. Their credit becomes more expensive, as we observe an increase in interest rates of 6 percentage points. And startups struggle more to pay their debt, as we find an increase of 7 percentage points in the default probability.

These findings are mainly driven by the turnover of a founder who is also a manager. This dual role suggests that founders indeed matter for startup financing by contributing critical resources to their firms. By empirically establishing the importance of founders for startup financing, we shed new light on theories of the firm and supporting the view of Rajan and Zingales (2001) and Rajan (2012).

In order to do so, we first obtained a set of confidential databases from Brazil provided by the Central Bank of Brazil (BCB) and other institutions. These databases contain detailed information about startups ownership, their lenders and their respective deaths, if occurred.

Thus, the data allow us to apply an approach based on premature death of founders (Jaravel et al., 2018; Becker and Hvide, 2019; Choi et al., 2019) to identify a causal effect of the founder turnover on startup financing through bank lending.

We use the premature death of founders as a quasi-natural experiment to measure loss in the firm's human capital. This approach also mitigates the endogeneity concerns that might exist in our framework. One could argue that a founder turnover might be explained by a previous reduction in credit, for instance. Using the premature death of founders as an instrument, we can focus on a causal channel between the founder loss and startup financing.

To perform this analysis, we build a treated and a control group to be able to compare each treated firm with a placebo firm and to quantify the impact of an unexpected loss of a founder. Since we focus on young and early-stage firms, our treated group is built based on firms that experienced the premature death of a founder in their first five years. This approach is similar to the one applied by Choi et al. (2019). It also follows the definition of a startup applied in the entrepreneurial finance literature, which is a firm of at most five years of operation (Howell and Brown, 2019).

In our approach, a founder's premature death is one which the age of the deceased founder is between 18 and 60 years, since the death probability of people in this interval is significantly lower than people over 60 years (Jaravel et al., 2018; Cortes et al., 2019; Choi et al., 2019). In the context of Brazil, this definition of unexpected death is also reasonable given that the life expectancy there was higher than 70 years during our sample period, which is from 2003 to 2019.[1]

Since our shock introduces a bias due to the fact that we are analyzing its occurrence when the firms are young, we perform a matching procedure that allows us to find a suitable control group for each of our treated firms. We perform the matching procedure using information on year the firm was opened, age of founders, size of founding team, legal form, industry and if the firm hired employees.

Through this process we build the treated and the control groups. Our empirical analysis relies on the estimation of Difference-In-Differences models using our matched sample to

[1]Source: The World Bank, https://data.worldbank.org/indicator/SP.DYN.LE00.IN?locations=BR, accessed on October 25, 2020.

examine how our treated firms are affected by the unexpected death of a founder relative to the control group. Our shock happens in different years depending on the firm under analysis, thus we follow Gormley and Matsa (2011) to estimate our models properly.

We aim to quantify the impact of the loss of a founder on startup financing and to understand how it affects these firms. Our empirical strategy is based on the instrument of premature deaths, which allows us to mitigate the endogeneity issues that we have in our setting. Since our results suggest that the parallel trends are satisfied in our main models, we can make causal inferences of these findings.

By performing an intensive margin analysis, we find evidence showing that once the premature death of a founding team member occurs there is a decrease of 63% in the volume of credit and of 21% in the number of loans, implying that there is a reduction in startup financing when the premature death of a founder occurs. Besides this analysis related to quantity, we also analyze the pricing of debt. Specifically, we estimate the effect of the shock on interest rates. It suggests an increase of 6 percentage points one year after the shock occurred. This impact vanishes after three years of its occurrence.

Another important variable that we analyze is the probability of default. Once the shock occurs, there is an increase of 7 percentage points in the probability of default in the short term and this effect tends to vanish two years after the shock. This result on default is consistent with the decrease in credit and the increase in prices when the shock occurs.

We also perform an extensive margin analysis. Our evidence suggests that the premature death of a founder reduces the access to new credit significantly. The shock is associated with a decrease higher than 5 percentage points in the firm probability to establish a relation with a new bank. Our findings indicate that the shock is also associated with a reduction of 5% on volume of new credit one year after the premature death, and the founder's premature death is associated with a decrease of 0.5 percentage point in the probability of obtaining a new loan.

This evidence establishes a significant decrease in startup financing after the occurrence of the premature death of a founder. To understand the possible mechanisms that might explain these findings, we use the information on the type of founders. We can identify if a deceased founder is also a manager of the firm or an angel investor (a founder who only has shares but do not work for the firm).

Our findings suggest that the death of a founder of either type has negative effect on startup financing. Nonetheless, the death of an angel investor has a weaker impact on the firm compared to the death of a founder who is also a manager. For instance, the decrease of an angel investor death in the number of loans is 18.8% of the effect of a manager founder death. This implies that founders who are involved with their firms as managers contribute critical resources to them.

These results are consistent with the discussion presented by the theory of firms literature that emphasizes the importance of certain crucial human assets for early-stage firms and their growth (Rajan and Zingales, 2001; Rajan, 2012). To improve our understanding of these critical resources that founders might bring to their firms, we also study what is the effect of the premature death on measures related to firm performance aiming to analyze if our instrumental variable also represents a productivity shock for startups.

We observe a 27.5% reduction in firm size (measured by the number of employees), which is persistent throughout our sample period. Our evidence also shows a 50% reduction in sales (measured by credit card sales) one year after the shock occurred, but this effect occurs only in the short term (one year after the shock). These results suggest that the premature death of a founder is a meaningful negative shock for startups.

Aiming to understand how founders matter for the entry decision of new investors in their firms, we perform an analysis that estimates the effect of our shock on the entry probability of a new owner in the startup. In some of our models, we identify a reduction in the entry probability of a new investor (these results are either negative or not statistically significant) associated with the occurrence of the shock. This is additional evidence that suggests how founders are crucial for firms, since the entry decision of new investors tends to be negatively associated with the death of a founder.

Once we differentiate the effect of the founder's death on firm size defined by the number of employees and the entry probability of a new owner, we verify an even clearer distinction on how different types of founders can contribute to their firms. We observe that both types of investors (angel investor and manager investor) have a negative effect on firm size. However, the death of an angel investor decreases employment less than the death of a founder who is also a manager. We also find that the death of an angel investor increases the entry probability of a new owner while the death of a founder who is also a manager decreases that probability.

Thus, the deaths of these two different types of founders imply shocks that have different natures for the startups. Our evidence suggests the death of a founder who is also a manager is a negative productivity shock due to the loss of a critical resource to the firm, since it reduces financing through bank lending and the entry probability of a new owner. Whereas the death of an angel investor is also a negative shock for the firm but through a different channel. Once the premature death of an angel investor occurs, we observe an increase in the entry probability of a new owner in the firm. This suggests that the premature death of an angel investor might be mainly a financial negative shock to the firm.

These findings contribute to the extensive literature on the theory of the firm. As discussed in Kaplan et al. (2009) and Bernstein et al. (2017), this literature has different perspectives on how assets and their different types matter for how an organization is built and structured. The property rights theory (Grossman and Hart, 1986; Hart and Moore, 1990; Holmstrom, 1999) assigns to non-human assets the role of being the most important asset within an organization, while there is a different perspective that attributes this role to human assets (Wernerfelt, 1984; Rajan and Zingales, 1998, 2001; Rajan, 2012).

Our paper contributes to this theoretical debate by providing causal evidence on the importance of the founders to startup financing. We also analyze how different types of founders matter for startup financing, providing a better understanding about the importance of different human assets for the startup. Our setting does not allow us to compare human assets with non-human assets to identify which one is more important. Nonetheless, we do observe that founders are extremely relevant to their firms.

This paper also adds to the entrepreneurial finance literature and, specifically, the debate on the importance of the business idea relative to the founding team. Kaplan et al. (2009) is one of the first studies to empirically analyze this matter. They conclude that investors should place more weight on the business rather than on the management team, since the business idea is more stable than founding teams. However, the analysis of Kaplan et al. (2009) is mainly descriptive. Our contribution is to provide causal evidence on the relevance of founders to startup financing, especially those founders who are also managers and are more involved in the operation of their firms.

The studies closest to ours are Becker and Hvide (2019) and Choi et al. (2019), since they address questions related to the relevance of founding teams for startup performance and provide causal evidence of that relation. Our setting also allows us to analyze a few measures of startup performance, but our main contribution is related to how startup financing is affected by founding teams. We also explore the heterogeneity that we have across different types of founders to understand how that affects access to credit of these young and early-stage firms.

Within the entrepreneurial finance literature, there is also a discussion on how young and early stage firms are financed. Howell (2017) examines the effectiveness of R&D subsidies and how it helps startups to mitigate their financial constraints. We add to this literature by focusing on the access that these younger firms have to the credit markets and how their human capital affects their financing through bank lending.

Our paper also adds to the literature that studies early-stage investments. This literature has strong causal evidence establishing the importance of early-stage investments on firm success (Sørensen, 2007; Kerr et al., 2011; Bernstein et al., 2016). That is why recently it has focused on how early-stage investors choose the firms that they are financing (Bernstein et al., 2017; Gompers et al., 2020). Bernstein et al. (2017) provide causal evidence on the relevance of startups characteristics to investors, focusing more specifically on angel investors. Gompers et al. (2020) use surveys to study trends on the Venture Capital industry, the importance of angel investment for startups and what matters to these investors.

Even though this literature focuses on the behavior of investors, we contribute to this debate by causally analyzing the importance of human capital for banks when they consider financing to startups. Bank lending is another relevant source of financing for younger and earlier-stage firms that seems to be significantly affected by the human capital that these firms have at their disposal. We provide causal evidence on how much founders matter for startups financing through bank lending.

There is another literature related to our study based on the use of premature death to build quasi-natural experiments to identify the importance of human capital in different contexts (Jones and Olken, 2005; Bennedsen et al., 2007; Azoulay et al., 2010; Nguyen and Nielsen, 2010). This instrument is also applied to understand the importance of human capital for innovation outcomes (Jaravel et al., 2018; Cortes et al., 2019) and entrepreneurship (Becker and Hvide, 2019; Choi et al., 2019). We leverage their methodological developments to estimate the causal effect of a founder's premature death on startup financing obtained through bank lending.

This paper has the following structure. In Section 2 we present the data and the institutional background. Section 3 describes the research design and the identification strategy we apply to address our question of interest. In Section 4 we focus on our empirical findings and on the discussion related to its interpretation. In Section 5 we discuss possible mechanisms that can explain our results related to human capital and startup financing. Finally, Section 6 concludes the paper.

2 Institutional Background and Data

To address our research question and to test how important human capital is to startup financing, we use Brazil as a laboratory and the premature deaths of founders of firms in the country as a quasi-natural experiment to study how founders matter for startup financing. This empirical strategy allows us to mitigate the possible endogeneity issues we might have in our setting.

We have access to administrative databases that have detailed information about all private firms in Brazil, providing access to relevant information related to their founders, ownership, investors, lenders, credit, proxies for sales and information on employment. These databases also provide information on the age of founders and the occurrence of their death, which is crucial to our identification strategy. [2]

The BCB provides access to a database from the Brazilian Internal Revenue Service (*Re-*

[2] All the databases used in this paper are confidential databases held by the BCB. The collection and manipulation of identified individual level data were conducted exclusively by the staff of the BCB. External researchers had access only to unidentified or aggregated data.

ceita Federal - RF) that has information on birth and death dates. This database allows us to identify the year of birth of every Brazilian citizen that has the Brazilian social security number (which is called *Cadastro de Pessoa Física* - CPF)[3] and the date of the deaths that were registered until the first quarter of 2020.

We have access to another database provided by the BCB which is organized by the RF called Membership Board (*Quadro Societário*). The main purpose of this database in our setting is to identify the founders of each firm, their current owners and when the firms in our sample were established. It also allows us to observe the current status of each firm in Brazil to determine whether they are still operating or not.

This database is filled out annually by all tax-registered firms. If a firm does not provide the required information to the Brazilian Internal Revenue Service, it can be subjected to severe penalties including the suspension of their activity. It is important to observe that we only have access to the most updated information provided by the firms in this database. In our sample, this was updated for the last time in March 2020.

Information on bank lending for each firm comes from the Brazilian Credit Registry (*Sistema de Informações de Crédito do Banco Central do Brasil* - SCR), a large and comprehensive data set maintained by the BCB for monitoring purposes. This data is confidential and protected by laws in Brazil related to bank secrecy. It has information about all loans with outstanding value above a minimum threshold of BRL 5,000 (approximately USD 1,000 in 2020) until 2011 and BRL 1,000 (approximately USD 200 in 2020) until 2017, and all banks are obligated to report this information to the BCB (Cortes et al., 2019; Fonseca and Van Doornik, 2019).

The SCR has detailed information at the loan level (i.e., all loans obtained by a firm with its banks). Since our focus is on the firm lending, we aggregate loan-level data at the firm level. We also perform analysis with the data on bank-firm level to understand how the heterogeneity in the lenders dimension matters to understand the importance of human capital to firm financing. This database contains detailed information on lending amount, interest rates,

[3] To be allowed to open a firm legally in Brazil, a founder must have a CPF. This allows us to merge the information on birth and death using this identifier at the person level with the databases on ownership to which we have access.

maturities, and credit rating.

We consider all commercial banks operating in Brazil between 2003 and 2016. We exclude investment banks, credit unions, and the Brazilian Development Bank (BNDES) as they are fundamentally different from commercial banks. We also drop inter-bank loans and focus exclusively on loans directed to non-financial firms following the practice applied by (Cortes et al., 2019).

The BCB has another database that provides information on receivables. It allows us to observe payments received by firms in Brazil that were made by credit and debit card. We also have access to information on anticipation of credit that these firms could obtain due to former payments they received. This database started to be organized in January 2017 and goes until 2019 at a monthly frequency.

Finally, we also use a database called Annual Relation of Social Information (*Relação Anual de Informações Sociais* - RAIS), which is a matched employer-employee administrative data from the Brazilian Ministry of Economy. RAIS is a mandatory survey filled out annually by all tax-registered firms in Brazil. Incomplete or late information results in severe penalties, which leads to a high degree of compliance and essentially complete coverage of all employees in the Brazilian formal sector as observed by Fonseca and Van Doornik (2019).

This database has information at firm and worker level from 1976 to the present. It allows us to track individuals over time and across firms since 2002. Through this database, we obtain information about the tax identifiers of firms and their establishments, their locations and industry. We also get information on individual payroll, hours they worked, hiring and firing dates, reason for firing, type of contracts (such as temporary contract, apprenticeship contract, etc), occupational category and some demographic information including gender, nationality, age, and education.

3 Research Design

Our goal is to understand the importance of human capital to startup financing. That is why we exploit a quasi-natural experiment based on the premature death of founders to quantify the effect of the human capital loss related to the founder's death on startup financing. Due to the nature of the databases available to us, we focus on startup financing through bank lending. Our main hypothesis is the following one:

Hypothesis: Human capital brought by founders matters for startup financing through bank lending.

We follow the methodologies of Jaravel et al. (2018); Choi et al. (2019) to build our shock based on the premature death of founders and to construct our treated and control groups. Then, we follow Gormley and Matsa (2011) to estimate the impact of our shock on measures related to startup financing. We extend our analysis to understand the importance of founders to the entry of new investors as well, but our focus is on startup financing through bank lending. The following subsections describe the methodologies we apply and our empirical analysis.

3.1 Sample construction and matching procedure

Initially we focus on the database provided by the RF with all the individuals that own a firm or at least have shares in a firm in Brazil. We merge this database with the other database provided by the RF that has information on the year these entrepreneurs were born and the year they passed away together with some information about their firms (i.e., its status and when it was established). Since our goal is to identify a causal relation between the premature death of a founder and firm financing, we focus on premature deaths defined by founders who passed away between the ages of 18 and 60 years. We follow the approach of Jaravel et al. (2018) and Choi et al. (2019) to address some of the endogeneity problems in our setting.

Our goal is to understand how human capital matters for startup financing. Following the recent literature on entrepreneurship (see Howell and Brown (2019)), we define a startup as a firm that is at most five years old. Given this definition, we focus our analysis on premature deaths that occurred in the first five 5 years of the startups in our sample following Jaravel et al. (2018) and Choi et al. (2019). While Jaravel et al. (2018) focus on the effect of premature death at the individual level, Choi et al. (2019) apply that to the firm level, which is the framework we rely on.

Considering our complete sample obtained from the database provided by RF, we have 11,572,606 firms, of which 62,481 suffered a premature death of one of their founders in their first five years of operation. Of these 62,481 firms, there are 5,298 firms that suffered the shock and have information on RAIS, while 9,787 of them have information on SCR. The firms that experience a premature death as we defined it tend to have a small number of employees and by construction are younger. Therefore, our empirical strategy creates a selection bias that can jeopardize our conclusions.

To mitigate this issue, we follow the approach of Choi et al. (2019) and perform a coarsened exact matching procedure to obtain a control group of firms that are going to be our placebo. The characteristics that we focus on are industry code (the five-digit industry code called National Classification of Economic Activity, *Classificação Nacional de Atividades Econômicas* - CNAE, from 1995), legal form, age of firm, age of founders, size of founding team and the firms should also have registered employees at least once (i.e., these firms belong to RAIS at least one time). By using this procedure, we build a control group that did not experience a premature death of one of their founders and we are able to compare this group to our treated group, defined as firms in which a founder dies prematurely in the first five years of operation.

By following this procedure, we have a sample of 8,728 firms, where 4,364 firms are treated and 4,364 firms are control. We have a small sample of firms because only 5,298 firms from RAIS suffered the shock as we defined it. Our firms are mainly small firms with a small founding team, since the average number of people on their founding team is 3.14 and the standard deviation is 2.

Our empirical analysis on startup financing focuses on two subsamples. We consider a sample that goes from 2003 to 2016 that has 58,648 firm-year observation to perform an extensive margin analysis with credit information. This paper also studies credit in an intensive margin analysis focusing on a sample that goes from 2003 to 2016 and has 14,218 firm-year observations, which are those with positive outstanding credit.

3.2 Descriptive statistics

In this subsection we provide the descriptive statistics of all variables that we built considering the samples used for the extensive margin analysis (i.e., full sample) and the intensive margin analysis (i.e., reduced sample). These descriptive statistics are presented in Tables 1 and 2. We also compute the summary statistics at the year before the shock differentiated by control and treated group to understand if there is any significant difference between them prior to the shock.

As it is presented in Table 3, we compute the differences between our main variables of interest for the full sample (variables used in our Extensive Margin Analysis) and a sample that focus only on the firm-year observations that have outstanding credit on the SCR database (variables used in our Intensive Margin Analysis).

Insert Tables 1, 2 and 3 Here.

3.3 Empirical approach

To address our research question, we focus our analysis on the matched sample built based on the strategy of Jaravel et al. (2018) and Choi et al. (2019) described previously. Initially we estimate a Dynamic Difference-In-Differences following the approach of Gormley and Matsa (2011) to test for the parallel trends hypotheses in our setting. Using this empirical strategy, we estimate the effect of human capital on startup financing and other dependent variables that are relevant for startups, which is given by Equation 1:

$$\begin{aligned} Y_{f,t} \quad = \quad & \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ & + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned} \tag{1}$$

where $Y_{f,t}$ is volume of credit, number of loans, average interest rate, probability of default, probability of new relation with a bank, volume of new credit and probability of a new loan.

We also perform analyses to estimate the effect on entry of new owner, employment and sales. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends.

This empirical approach is quite similar to Choi et al. (2019) as well. The only difference is that we do not include the variable $Post_{f,t}$ in our estimation, but we perform robustness tests to guarantee that our results are valid by estimating the model for each year that a shock occurs from 2005 to 2014.

Following the analysis of the aforementioned model, we also estimate a Staggered Difference-In-Differences described by Equation 2 following an empirical strategy similar to the one applied by Gormley and Matsa (2011). Once parallel trends are satisfied, we analyze the results provided by Equation 2 to establish the importance of human capital for startup financing.

$$
\begin{aligned}
Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
\tag{2}
$$

Our main goal is to estimate the parameter β to understand the effect of the premature deaths of founders on startup financing. We also perform an analysis using our shock to verify how startup performance is affected in our sample to provide a better understanding of what is happening with credit as well. Even though we cannot disentangle the impact of premature death on the supply of credit from the effect on the demand of credit, we are able to provide evidence on how this shock affects variables that are relevant for the supply and demand for credit.

Using information on the type of each founder, we can identify angel investors (i.e., owners that are not managers in the firm) and founders who are also managers. We use this information to extend the analysis discussed so far and to understand how the impact of the premature death of founders is affected by the founders' type. Theory would argue that founders who are also managers on startups bring a specific human capital to their firms that helps them to grow, while angel investors help the firm to deal mainly with its financial constraints. We can verify empirically the validity of this argument by comparing the effect of the premature deaths of manager founders to the premature deaths of angel investors.

To test the robustness of our main results, we estimate the effect of the shock separating our sample by every year that a shock occurred. We have premature deaths happening from 2005 to 2014, and through our matched sample we have for each treated firm a control firm. We split our samples in cohorts based on the years in which we observe a premature death in our sample, and we estimate the effect of the shock on startup financing using a Difference-In-Differences framework. This methodology is basically the application of multiple Difference-In-Differences approaches applied for all the years that a shock occurs.

Ideally Equations 1 and 2 would capture the average effect of the shocks in every year that has a premature death of a founder. By splitting our sample into these different cohorts based on the years in which a startup experienced the premature death of their founder, we can verify the years that are driving our results obtained through Equations 1 and 2 to guarantee that our set of fixed effects are capturing all the trends at the cohort level (Gormley and Matsa, 2011).

4 Main Empirical Findings

4.1 Intensive Margin Analysis - Premature death and Startup financing

4.1.1 The impact of the shock on credit

Our first set of results focuses on the effect of the premature death of founders on startup financing in the intensive margin. Initially we consider the volume of credit (i.e., credit size) and number of loans to analyze how these variables are affected by a change in human capital based on the premature death of a founder in the earlier stages of the firm. We perform an intensive margin analysis focusing on firm-year observations presented in the SCR with positive outstanding credit. Standard errors are clustered at the firm-year level throughout this analysis.

By estimating Equation 1 with credit size and number of loans as dependent variables, we observe that the parallel trends are satisfied. It suggests that there is no anticipation effect of the premature death within the startup. This mitigates the possibility of endogeneity issues in our framework, allowing us to causally identify a reduction in startup financing measured by credit size and number of loans. We perform this analysis with a subsample of firms that belong to our database on lending and have outstanding credit. It allows us to observe the effect of the shock within the group of young firms that get credit from Brazilian banks. Figures 1 and 2 present these results.

Insert Figures 1 and 2 Here.

We also estimate Equation 2 to quantify the effect of our shock on startup financing using both credit size and number of loans as dependent variables. Our evidence shows that there is a 63% decrease in the volume of credit and of 21% decrease in the number of loans when the premature death of a founding team member occurs as described in Table 4. This implies that there is a reduction in startup financing once the premature death occurs. These results are statistically significant at the 1% level. We also observe a reduction on startup financing when the variables credit size and number of loans are computed for the next period (see Table 5).

Insert Tables 4 and 5 Here.

Our shock allows us to causally identify how significant the reduction is on startup financing once there is the premature death of a founder. These findings establish the relevance that founders have for startup financing through bank lending. Even though we do not have access to detailed information about other sources of financing, such as venture capital investment, our results shed light on the importance of founders for external investors as well, which is in line with the discussion in Gompers et al. (2020).

4.1.2 The impact of the shock on interest rate

Besides the effects on quantity, we also examine how the premature death of a founder affects prices. Our goal is to understand how cost of debt is affected by the death of a founder. That is why we build interest rates weighted by the size of the loans that each firm has in a given year. Standard errors are clustered at the firm-year level throughout this analysis.

Insert Figure 4 Here.

Figure 4 reports the coefficients of the Difference-In-Differences model that we estimate to capture the effect of the shock on interest rate. Since there is evidence that the parallel trends are satisfied, we use these results to conduct a causal analysis of the premature death of founders on interest rate.

We observe that the shock increases interest rate by 6 percentage points, suggesting that startup financing through bank credit becomes more expensive for the treated firms. This increase is identified until three years after the shock, then the impact vanishes and remains not statistically significant after that. These findings are also consistent with the short-term decrease in credit and number of loans that we verified previously.

4.1.3 The impact of the shock on default

To understand how startup financing is affected, we also analyze how default is affected due to the occurrence of the founder's premature death. In this case, our main dependent is the probability that a firm defaults a certain loan captured by a dummy variable equal to 1 if default occurs and 0 otherwise. Figure 3 provides the estimates of the model using the sample based on the firm-year observations presented in the SCR with positive outstanding credit. Standard errors are clustered at the firm-year level throughout this analysis.

Insert Figure 3 Here.

By analyzing Figure 3, we compare the treated and control firms that have outstanding credit with at least one bank. Even though the parallel trends are not satisfied (the effect four years prior to the occurrence of the shock is statistically significant), we observe a short-term increase in the probability of default associated with the occurrence of the shock. This implies that there is a positive association between the shock and the probability of default. The rise in default happens when the shock occurs, and the impact of the shock vanishes becoming not statistically significant three years after the shock.

This evidence indicates that the premature death of a founder is positively associated with the default probability. Through Figure 3 we establish a causal effect of the shock on default suggesting that treated firms tend to default more than the control ones. These results are also consistent with the reduction in credit and the increase in interest rate discussed previously. All these findings suggest that young and early-stage firms are under struggle when one of their founders dies.

4.2 Extensive Margin Analysis - Premature death and Startup financing

We also perform an extensive margin analysis to estimate the effect of premature death on the creation of a connection with new banks, the size of new credit issued and the issuance of new loans. These results allow us to understand how the prospective of the startups in relation to financing is affected after the shock. Throughout this analysis, we cluster standard errors are clustered at the firm-year level.

Insert Figures 5, 6 and 7 Here.

Our first set of results described by Figure 5 shows an association between the shock and a decrease in the firm's probability of establishing a new relation with another bank. This association between the shock and new bank relationship seems to remain for five years after the premature death of a founder.

We also observe in Figures 6 and 7 that the human capital loss measured by the premature death of the founder is associated with a reduction in the amount of new credit, and with a reduction in the probability of obtaining new credit. Both variables are correlated with the shock one year after the premature death and these results remain statistically significant at the 5% level until the end of the second year after the shock.

Our first set of results described by Figure 5 shows an association between the shock and a decrease in the firm's probability of establishing a new relation with another bank. This association between the shock and this variable seems to remain for five years after the premature death of a founder.

We also observe in Figures 6 and 7 that the human capital loss measured by the premature death of the founder is associated with a reduction in the amount of new credit they obtain and a reduction in the probability of obtaining new credit. Both variables are correlated with the shock one year after the premature death and this result remains statistically significant at the 5% level until the end of the second year after the shock.

Both the extensive and the intensive margin analyses corroborate that credit becomes scarcer for startups once the shock occurs. Our evidence suggests that after the premature death of a founder, treated firms have more difficulty than the control firms to establish new credit lines with banks.

4.3 Robustness Tests

4.3.1 Estimating the model for each year that a shock occurs

To verify the robustness of our results, we estimate our models by each year of occurrence of the shock. The matching procedure allows us to find a control firm for each treated firm, thus we can build different cohorts based on the years that we observe a premature death of a founder. Once we do that, we can estimate our Difference-In-Differences models (both the dynamic version and the standard version) for each year that there is a shock in our sample. By estimating our models based on the cohorts given by each year that a shock occurs, we can verify which years explain most of our main findings. Standard errors are clustered at the firm-year level throughout this analysis.

Insert Figures 8, 9, 10 and 11 Here.

We run these models for both volume of credit and number of loans as described in Figures 8, 9, 10 and 11. Our results from Figures 8 and 10 suggest that only the shocks that occurred in 2005 and 2006 do not have a statistically significant and negative effect on our measures of credit. In most of the years the premature death of a founder has a statistically significant and negative effect, suggesting that our main findings are not driven by just a few years in our sample. They seem to be robust in relation to the year that the shocks occurred.

While Figures 8 and 10 focus on our full matched sample, in Figures 9 and 11 we estimate the models focusing on the sample used in our intensive margin analysis based on firm-year observations with positive outstanding credit. Once we focus on this reduced sample, we lose power in our tests since we have a smaller amount of observations in each year. Nonetheless, we still observe the negative effect on both credit size and number of loans once the shock occurs for most of the years that a founder dies in our sample.

4.3.2 Controlling the model for ex-ante characteristics

Table 3 shows that firm age and size of founding team the year prior to the shock are different when we compare treated and control groups and these differences are statistically significant. Therefore, we estimate our main models controlling for these variables at their level prior to the shock including their values and their interactions as described in Tables 6 and 7. Standard errors are clustered at the firm-year level throughout this analysis.

Our main results remain similar to those that we presented previously once we include firm age and size of founding team in the year prior to the shock in our regressions. The main difference is in relation to the findings of the models using number of loans as a dependent variable once we control for size of founding team in the year prior to the shock. Even though in the results of Table 7 we lose statistical significance once we estimate the effect on variables measured at the current level, we still have negative and statistically significant results on our measures related to startup financing measured in the next period.

Insert Tables 6 and 7 Here.

4.3.3 Controlling the model for industry fixed effects

We also estimate our main models controlling for industry fixed effects. Through this procedure, we aim to control our models for the fact that different industries might be differently exposed to our shock. Tables 8 and 9 show the results controlling for industry fixed effects.

In this case we use the five-digit industry codes provided by RAIS called CNAE from 1995. We perform the same analysis focusing on the first two digits of this code to be able to estimate the model including industry fixed effects in a broader way. These results are provided in Tables 10 and 11. The results remain the same in both approaches. Standard errors are clustered at the firm-year level throughout this analysis.

Insert Tables 8, 9, 10 and 11 Here.

5 Mechanisms

5.1 Premature death, firm performance and ownership

Now we focus on how the premature death affects measures related to firm performance. Through this strategy, we aim to understand if startups' performance may be affected by the premature death of a founder. We also aim to analyze if this effect could mean a negative productivity shock due to the fact that founders might contribute critical resources to their firms that go beyond financing.

We follow the approach applied to analyze startup financing and estimate a Dynamic Difference-In-Differences to understand how human capital matters for startup employment, sales and the anticipation of credit. Our findings show a statistically significant reduction in employment when the shock occurs. We also observe that parallel trends are satisfied, allowing us to make a causal analysis. These findings are shown in Figures 12 and 13. Standard errors are clustered at the firm-year level throughout this analysis.

Insert Figures 12 and 13 Here.

We estimate the effect of premature death on sales (measured by credit card sales) and credit anticipated by firms estimate. Since our data for receivables is from 2017 to 2019, we perform a matching using the same characteristics used before to build our matched sample and we also focus on firms for which we have information on receivables to analyze how the premature death of a founder affects sales and credit anticipation. Our focus here is just to study how this shock affects these other variables correlated to firm performance so we can understand how our shock matters for productivity. Standard errors are clustered at the firm level throughout this analysis.

Our findings show a reduction in startup sales once the premature death of a founder occurs.[4] These results related to sales and the ones related to employment indicate that startups struggle when they experience an unexpected death of one of their founders, which is similar to the findings of Choi et al. (2019). These findings are shown in Figures 14 and 15.

Insert Figures 14 and 15 Here.

Even though we observe that employment and credit are negatively affected by the premature death, we also analyze if there is the entrance of a new owner in the firm once the shock occurs. Our goal in this analysis is to understand if the expectations of the external investors are also affected by the premature death of founders. Standard errors are again clustered at the firm-year level throughout this analysis.

Insert Figures 16 and 17 Here.

We observe that there is a negative association between the shock and the entry probability of a new owner according to Figure 16. Our findings show that there is a reduction of 2 percentage points in the entry probability of a new owner once a founder dies prematurely. There are other settings where there is no effect as suggested by Figure 17. Thus, our evidence indicates that a founder's death has a negative or null effect on the entry probability of a new owner. We also analyze these results estimated in a standard staggered Difference-In-Differences setting (see Tables 12 and 13).

Insert Tables 12 and 13 Here.

Given the assumption that deaths of founders between 18 and 60 years old are unexpected (Jaravel et al., 2018; Choi et al., 2019) and the evidence suggesting that parallel trends are satisfied in our models, we can conclude that the premature death of a founder is a negative

[4]We obtain a similar result using debit card sales, which is available upon request.

shock for startups. Clearly it affects both demand for and supply of credit. However, in our setting is not possible to disentangle supply and demand to verify which effect prevails. All we can argue in relation to this matter is that if firms are demanding credit after the shock, they are paying higher interest to banks and are not getting it through the entry of new owners. This suggests that founders possess critical resources that are crucial to their firms' financing.

5.2 Differentiating by founders' types

We also estimate our models differentiating founders by their type to understand better the importance of founders to startup financing and how their death negatively affects their startups. We can identify founders who are only owners without working for the firm (we refer to them as angel investors) and distinguish them from founders who are also managers. This allows us to analyze better the hypothesis of founders as critical resources which helps us to understand the productivity impact that their death might have on their firm. Standard errors are clustered at the firm-year level throughout this analysis.

Insert Tables 14, 15, 16 and 17 Here.

Our results provided by Tables 14 and 15 indicate that the effect is bigger when the premature death of a founder who is also a manager occurs once we compare it with the premature death of an angel investor. Suggesting that these manager founders contribute something to their firms that angel investors do not. This is in line with the theoretical literature that argues about the importance of human assets for the development of young firms (Wernerfelt, 1984; Rajan and Zingales, 1998, 2001; Rajan, 2012).

In relation to the entry probability of new owner and employment, we observe that the premature death of both manager founder and angel investors have a negative effect on employment (see Table 16). However, the premature death of an angel investor has an effect that is only 18.8% of the effect observed when the premature death of a manager founder occurs. We also verify that once an angel investor dies there is an increase in the entry probability of a new owner, while the death of a founder who is also a manager reduces this probability.

When we focus on default (Table 17), we find a 7 percentage points reduction in the probability of default when a founder dies unexpectedly. We also observe that this decrease is statistically significant, and this effect is higher when a founder who is also a manager in the firm prematurely dies. These results are consistent with the reduction in the credit size and loan. Since the premature death of a founder who is also a manager has a higher effect on credit, these firms will have less access to credit, probably due to their higher probability of default.

These results are consistent with the theoretical argument that establishes founders as critical resources for their firms (Wernerfelt, 1984; Rajan and Zingales, 1998, 2001; Rajan, 2012). It is also an important contribution to the empirical literature on entrepreneurial finance, since we can estimate the relevance of different types of founders for startups. This is something that has not been analyzed in the literature due to the lack of data.

5.3 Founder relationship with banks or founder-specific capital

Our results on how deaths of different types of founders affect startup financing differently could be explained either by a human capital reasoning or just a relationship that founders might have with banks. Firstly, this is not necessarily a problem related to the perspective of founders as a critical resource to the firm because this relation with banks could be the critical resource that the founder would contribute to the firm. Secondly, the results about the entry of new owners indicate that indeed founders who are managers contribute something important that angel investors do not have, otherwise we would not see a decrease in the entry probability of a new owner. These findings suggest that there are founder-specific capital features that angel investors cannot provide.

5.4 Financial constraints

Another possible explanation for our set of results would be related to financial constraints getting tighter once the premature death of a founder occurs. This might be explained by the fact that this founder could be the main investor of the firm and a manager. However, the results on how differently this type of founder matters in comparison to an angel investor provide evidence against that reasoning.

If we were capturing mainly a change in how startups become financially constrained after the shock, we would not see a reduction in the entry probability of a new owner. Instead, we would actually observe a similar result to what happens with the death of an angel investor. Therefore, these findings suggest that indeed there is a productivity shock explained by the loss of a founder-specific capital that goes beyond the provision of financing to the firm.

6 Conclusion

This paper studies the importance of founders to startup financing. In particular, we focus on how the human capital that founders bring to their firms matter for the capacity of these firms to be financed. This is a question at the core of the recent discussion on the entrepreneurial finance literature about the relevance of human assets to the growth of early-stage firms.

We use a quasi-natural experiment based on the premature deaths of founders to analyze how it affects the credit to which firms have access through bank lending. Our results show that the premature death of a founder reduces credit size and number of loans. When this shock happens, there is also a short-term increase in the probability of default and in the interest rates. The results indicate that there is a reduction of credit and that startup financing through bank lending becomes more expensive when these firms lose their founders.

Our findings seem to be driven by the premature death of founders who are also managers in their firms. The death of these founders tends to decrease the entry probability of a new owner, while the death of an angel investors increases this probability. This suggests that founders contribute critical resources to their firms that angel investors do not, and this contribution improves the capacity of their firms to be financed.

Therefore, we provide evidence on how these young and early-stage firms are exposed to risks related to the human capital provided by founders. These results have important policy implications given the concern of policymakers with competition and innovation. Our findings also help us to understand how inclusive financial markets are to small business owners in Brazil.

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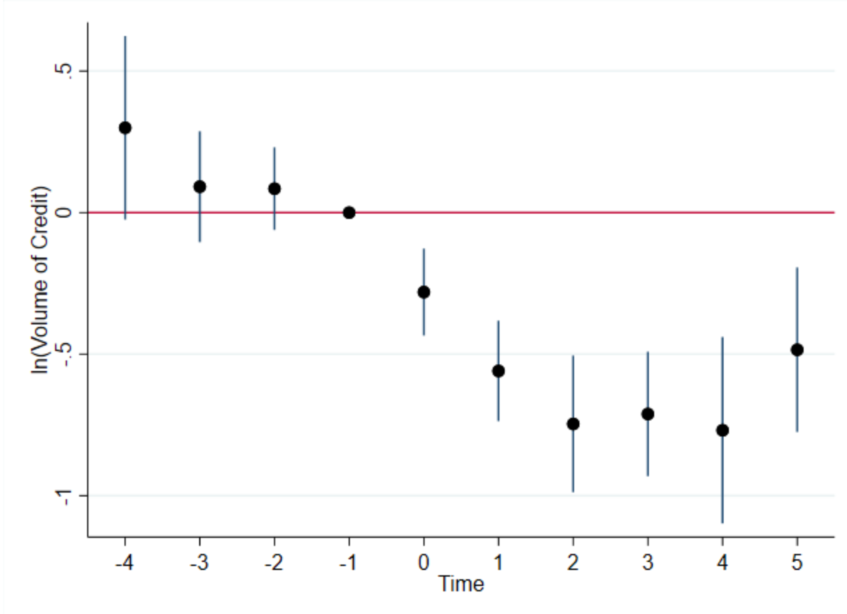
Figure 1: Intensive Margin Analysis - Premature death of founders and volume of credit

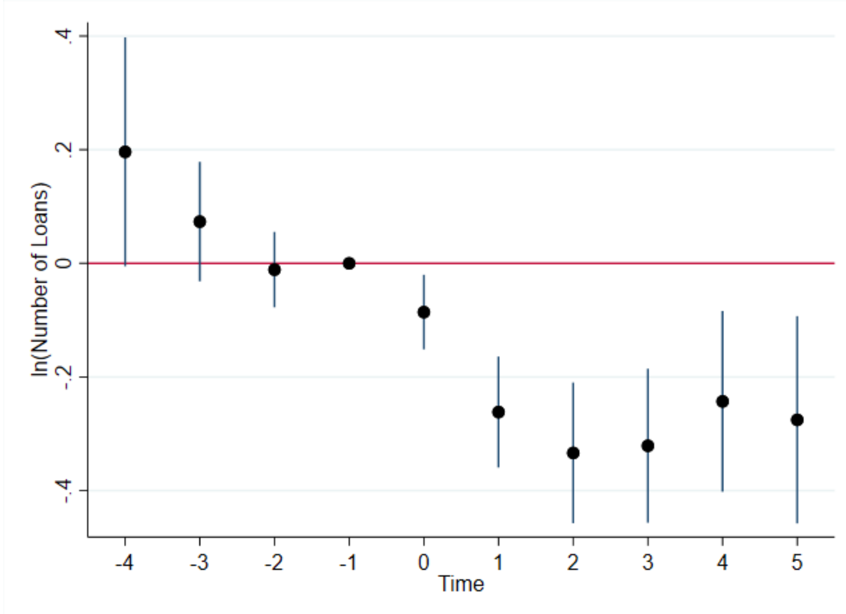


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} \quad = \quad & \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
& + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider only the observations at firm-year level from the matched sample that have outstanding credit on SCR. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 2: Intensive Margin Analysis - Premature death of founders and number of loans

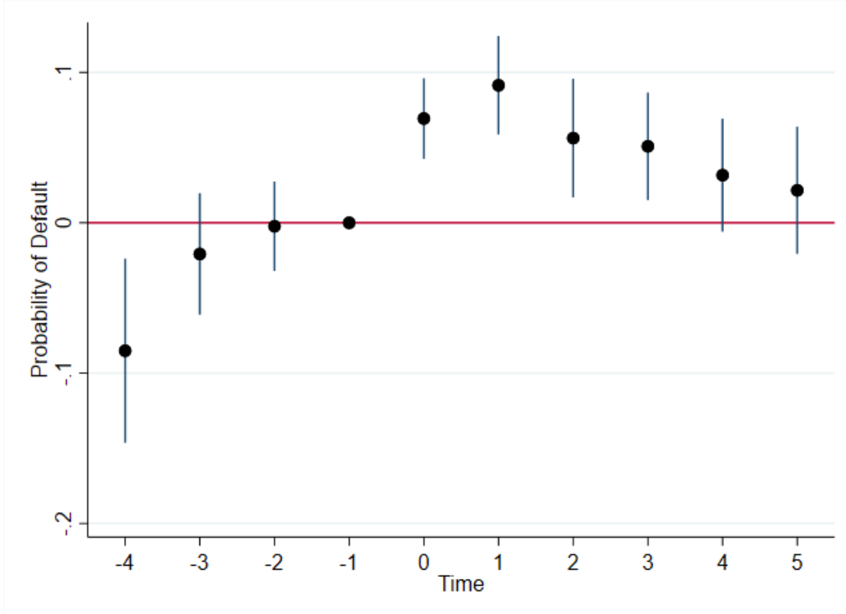


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} \;&=\; \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of number of loans plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider only the observations at firm-year level from the matched sample that have outstanding credit on SCR. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 3: Intensive Margin Analysis - Premature death of founders and probability of default

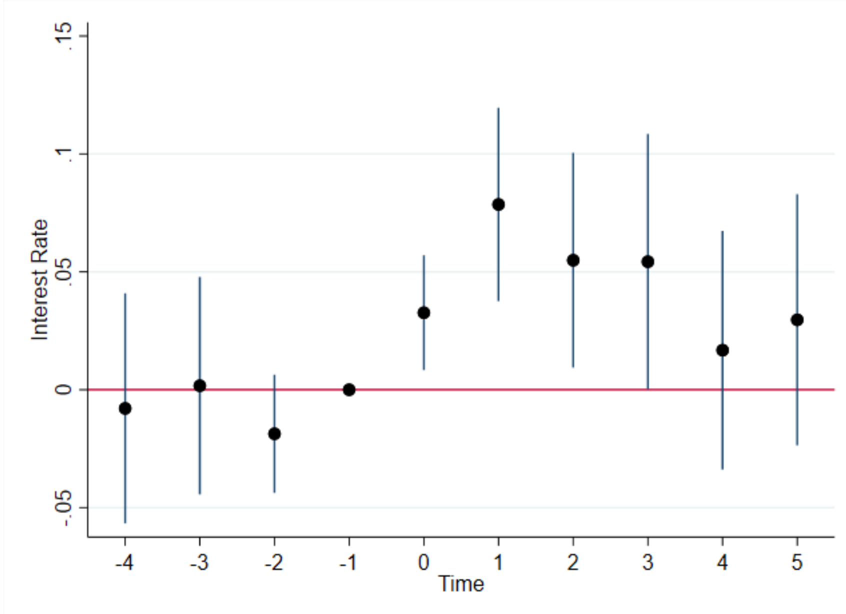


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} &= \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is a dummy variable equal to 1 if the firm defaults or 0 otherwise. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider only the observations at firm-year level from the matched sample that have outstanding credit on SCR. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 4: Intensive Margin Analysis - Premature death of founders and interest rates

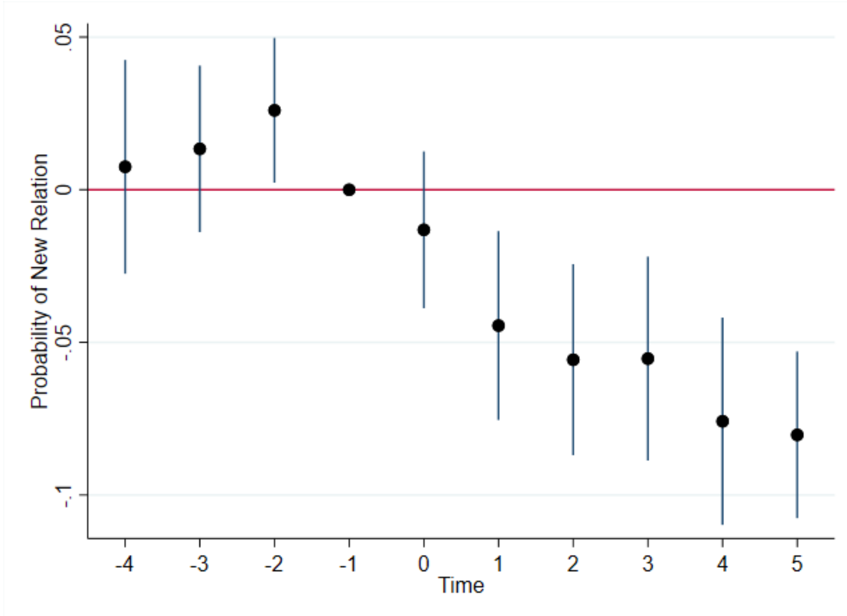


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &+ Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the average interest rate weighted by the size of the loans. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider only the observations at firm-year level from the matched sample that have outstanding credit on SCR. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 5: Extensive Margin Analysis - Premature death of founders and new relation with a bank

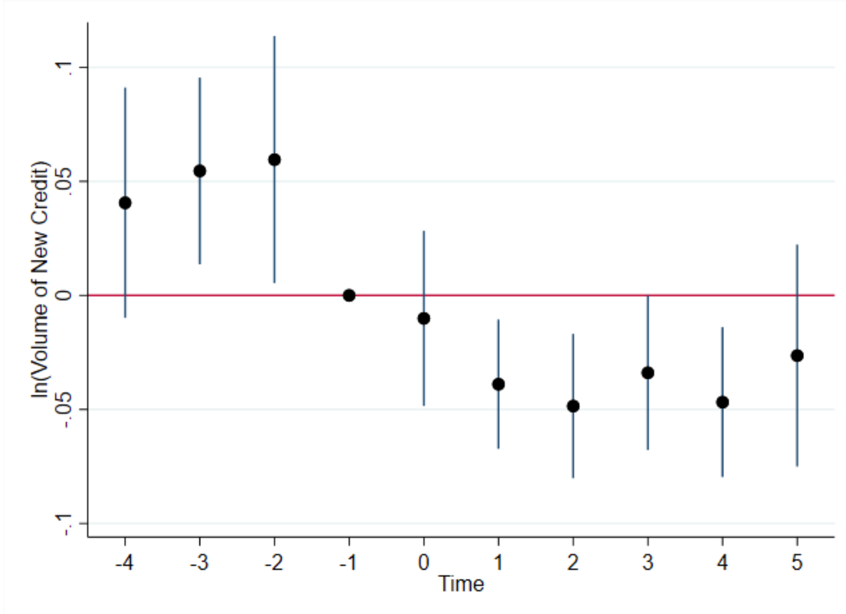


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &+Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is a dummy variable equal to 1 if a firm f creates a relation with a new bank at time t or 0 otherwise. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider the full matched sample. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 6: Extensive Margin Analysis - Premature death of founders and new credit

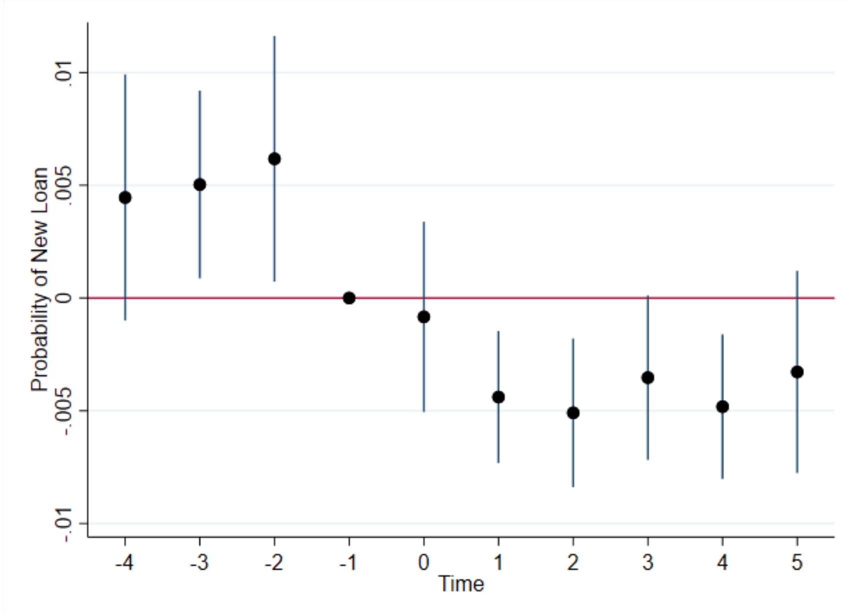


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &+ Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of the size of new credit to a firm f and time t. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider the full matched sample. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 7: Extensive Margin Analysis - Premature death of founders and new loan

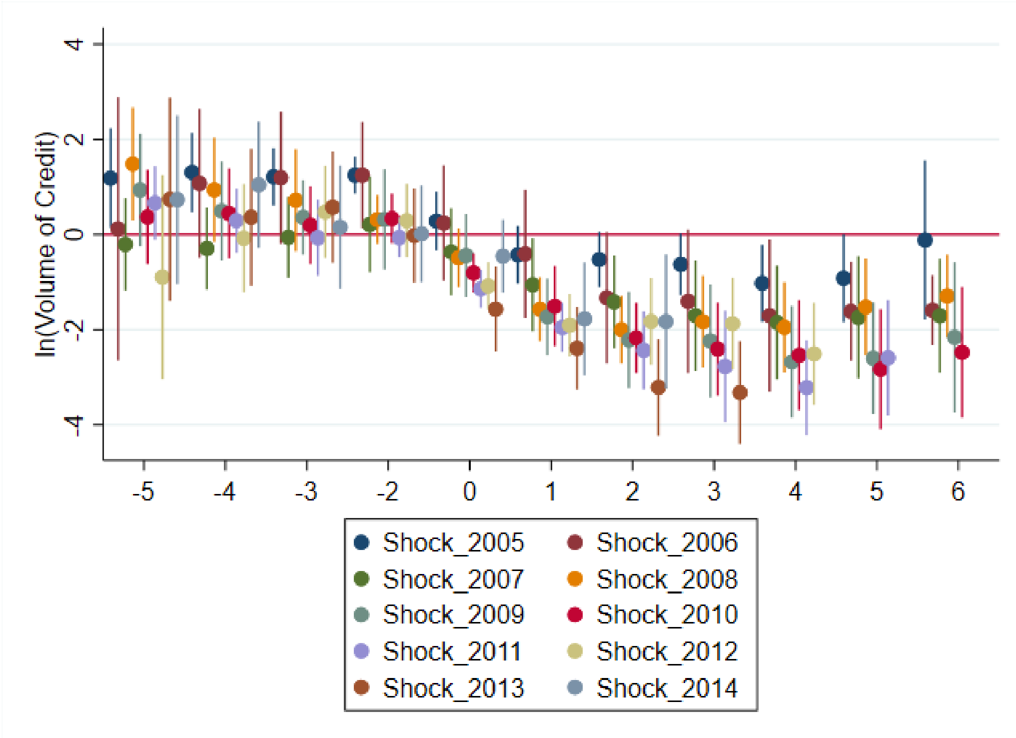


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} \quad = & \quad \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
& +Firm\ \ FE_f + Year\ \ FE_t + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is a dummy variable equal to 1 if a new loan is issued to the firm f and time t or 0 otherwise. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control for common trends. In this figure we consider the full matched sample. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 8: Premature death of founders and startup financing - Robustness Test with Credit Size

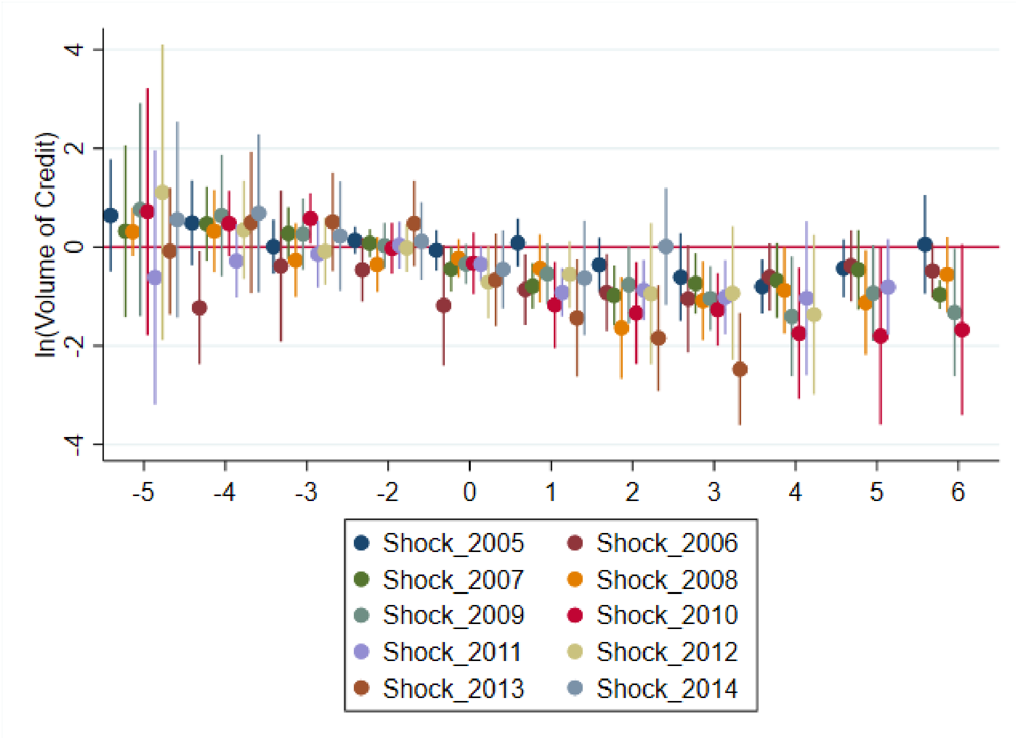


This figure plots the coefficient β varying by year before and after shock estimated from the equation below for each year that happened a shock from 2005 to 2014:

$$\begin{aligned} Y_{f,t} \;&=\; \sum_{k=-5}^{6} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this figure we consider the full matched sample and we estimate our model for every year from 2005 to 2014 that has a shock affecting some of our treated firms. We plot the estimated coefficients of all the models for each year before and after the shock. The figure also provides information about the 95% confidence interval of the coefficients and standard errors are clustered at year and firm level. The effect on time -1 before the shock is omitted because it is the one we normalize to 0.

Figure 9: Premature death of founders and startup financing - Robustness Test with Credit Size - Intensive Margin Analysis Sample

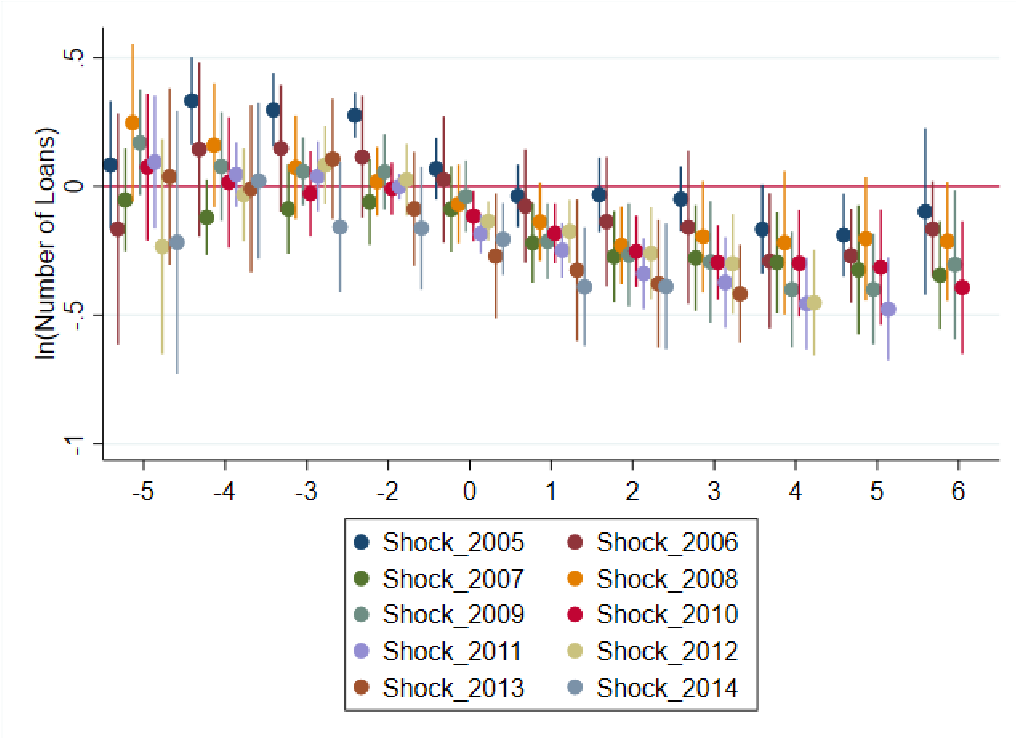


This figure plots the coefficient β varying by year before and after shock estimated from the equation below for each year that happened a shock from 2005 to 2014:

$$
\begin{aligned}
Y_{f,t} &= \sum_{k=-5}^{6} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this figure we consider only the observations at firm-year level from the matched sample that have outstanding credit on SCR and we estimate our model for every year from 2005 to 2014 that has a shock affecting some of our treated firms. We plot the estimated coefficients of all the models for each year before and after the shock. The figure also provides information about the 95% confidence interval of the coefficients and standard errors are clustered at year and firm level. The effect on time -1 before the shock is omitted because it is the one we normalize to 0.

Figure 10: Premature death of founders and startup financing - Robustness Test with Number of Loans

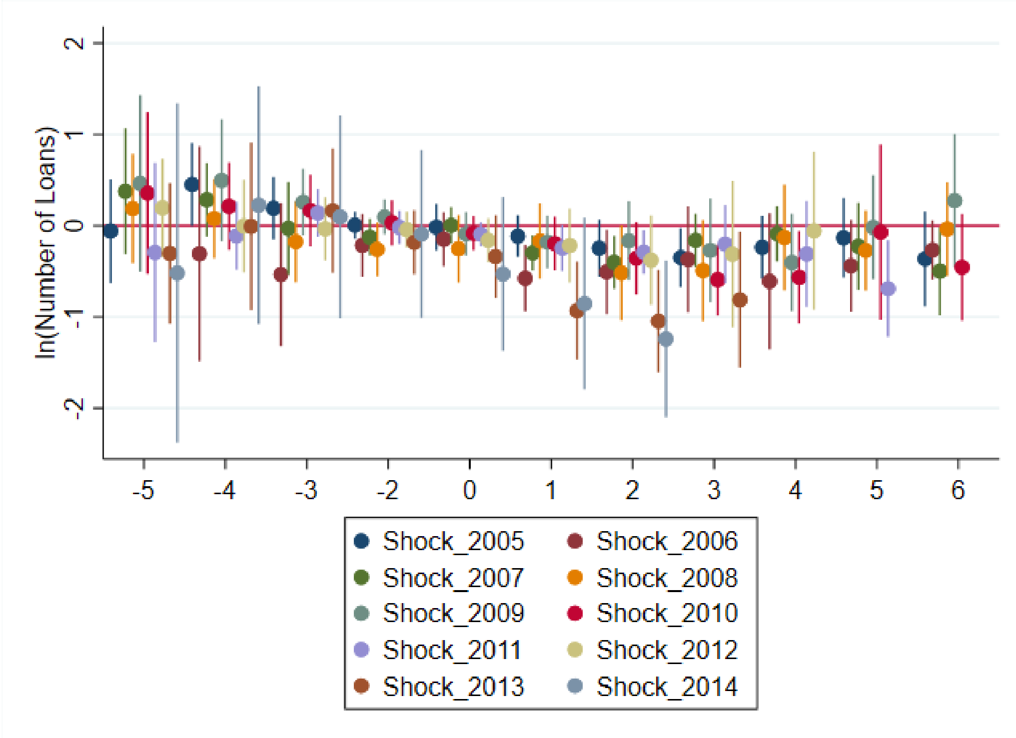


This figure plots the coefficient β varying by year before and after shock estimated from the equation below for each year that happened a shock from 2005 to 2014:

$$
\begin{aligned}
Y_{f,t} &= \sum_{k=-5}^{6} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of number of loans plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this figure we consider the full matched sample and we estimate our model for every year from 2005 to 2014 that has a shock affecting some of our treated firms. We plot the estimated coefficients of all the models for each year before and after the shock. The figure also provides information about the 95% confidence interval of the coefficients and standard errors are clustered at year and firm level. The effect on time -1 before the shock is omitted because it is the one we normalize to 0.

Figure 11: Premature death of founders and startup financing - Robustness Test with Number of Loans - Intensive Margin Analysis Sample

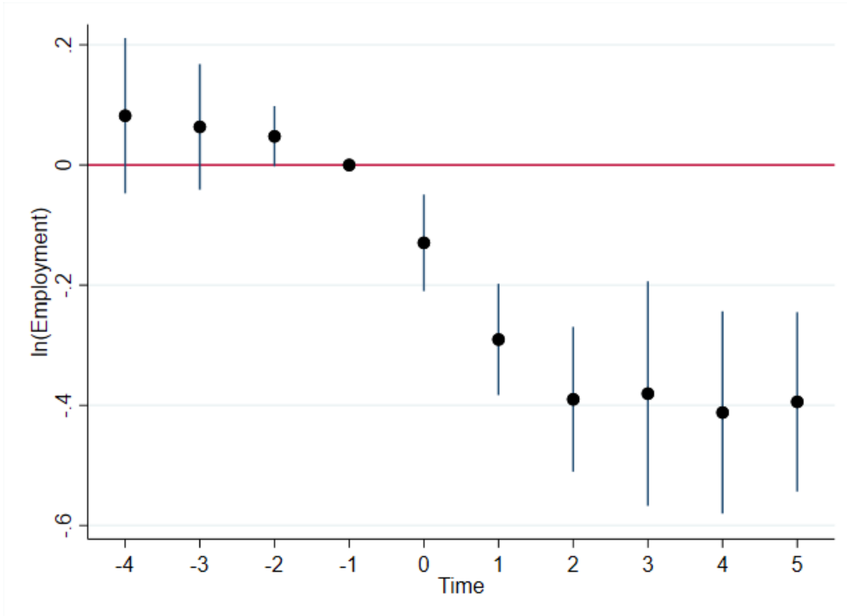


This figure plots the coefficient β varying by year before and after shock estimated from the equation below for each year that happened a shock from 2005 to 2014:

$$
\begin{aligned}
Y_{f,t} &= \sum_{k=-5}^{6} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of number of loans plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this figure we consider only the observations at firm-year level from the matched sample that have outstanding credit on SCR and we estimate our model for every year from 2005 to 2014 that has a shock affecting some of our treated firms. We plot the estimated coefficients of all the models for each year before and after the shock. The figure also provides information about the 95% confidence interval of the coefficients and standard errors are clustered at year and firm level. The effect on time -1 before the shock is omitted because it is the one we normalize to 0.

Figure 12: Premature death of founders and employment

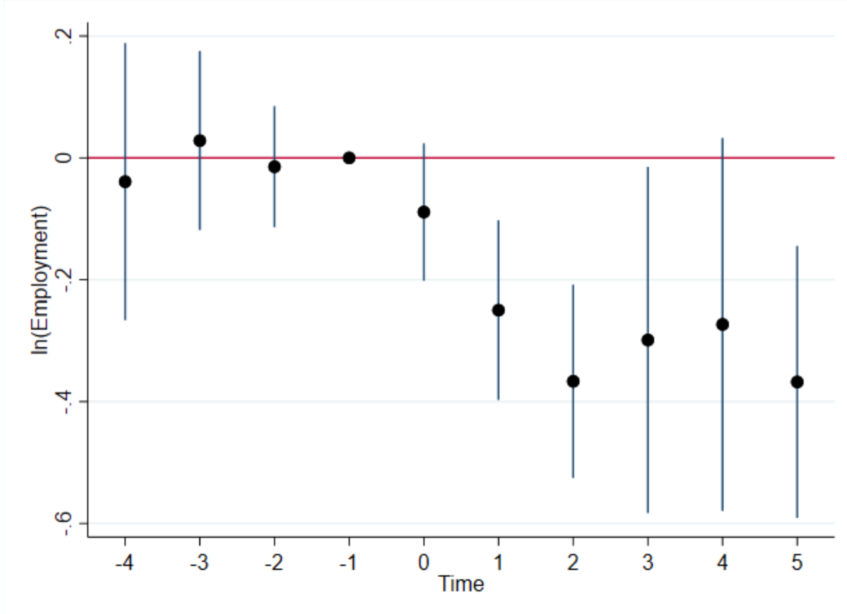


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of firm size given by number of employees plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control. In this figure we consider all the firms that we observe on RAIS (i.e., that has at least one worker registered for at least one time in our sample). We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 13: Premature death of founders and employment - Reduced Sample

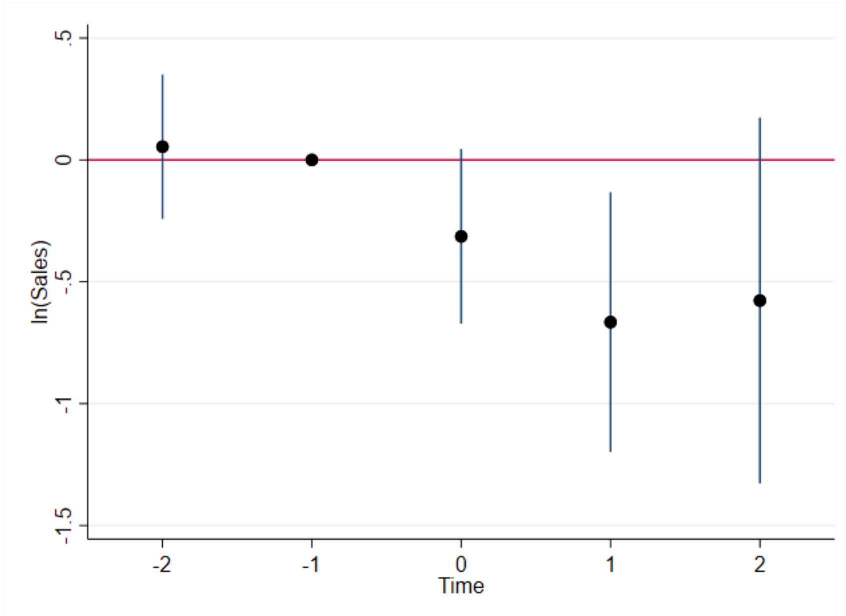


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} \quad = \quad & \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
& + Firm\ \ FE_f + Year\ \ FE_t + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of firm size given by number of employees plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control. In this figure we consider the firm-year observations in the matched sample that have positive outstanding credit observed on SCR and we also observe on RAIS (i.e., that has at least one worker registered for at least one time in our sample). We plot the estimated coefficients for each year and their 95% confidence interval clustered at firm and year level.

Figure 14: Premature death of founders and sales revenue

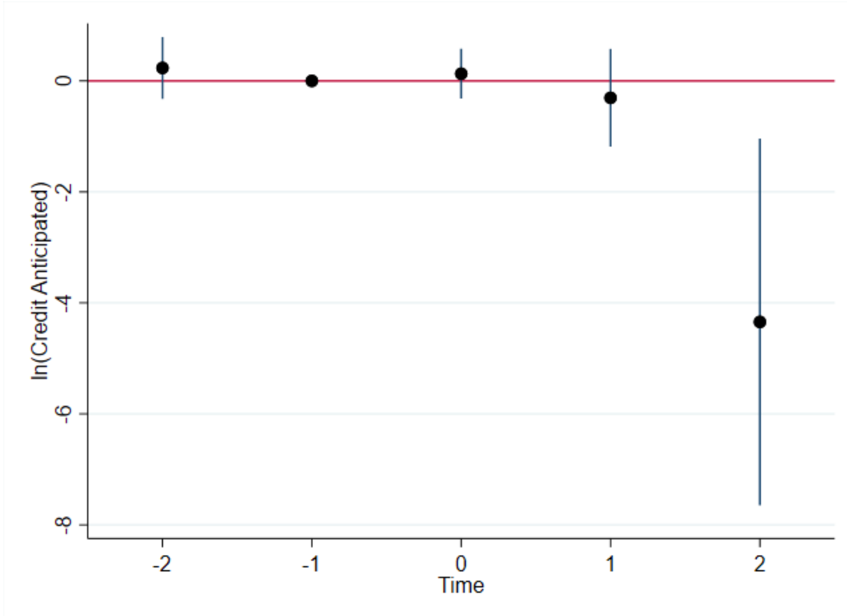


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} &= \sum_{k=-2}^{2} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the sales revenue received by the firms through credit card payments. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control. In this figure we consider the full matched sample from 2017 to 2019 and we perform the matching focusing on the firms that belong to the database on receivables. We plot the estimated coefficients for each quarter and their 95% confidence interval with standard errors clustered at firm level.

Figure 15: Premature death of founders and anticipation of credit due to payments firms received

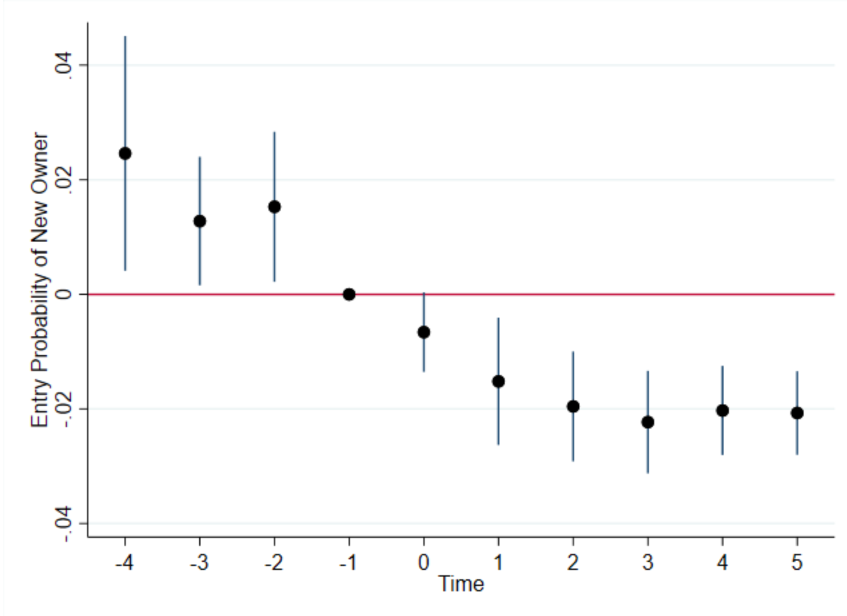


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \sum_{k=-2}^{2} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &+Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the anticipated credit by the firms that they receive through sales. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control. In this figure we consider the full matched sample from 2017 to 2019 and we perform the matching focusing on the firms that belong to the database on receivables. We plot the estimated coefficients for each year and their 95% confidence interval with standard errors clustered at firm level.

Figure 16: Premature death of founders and ownership - Full Sample

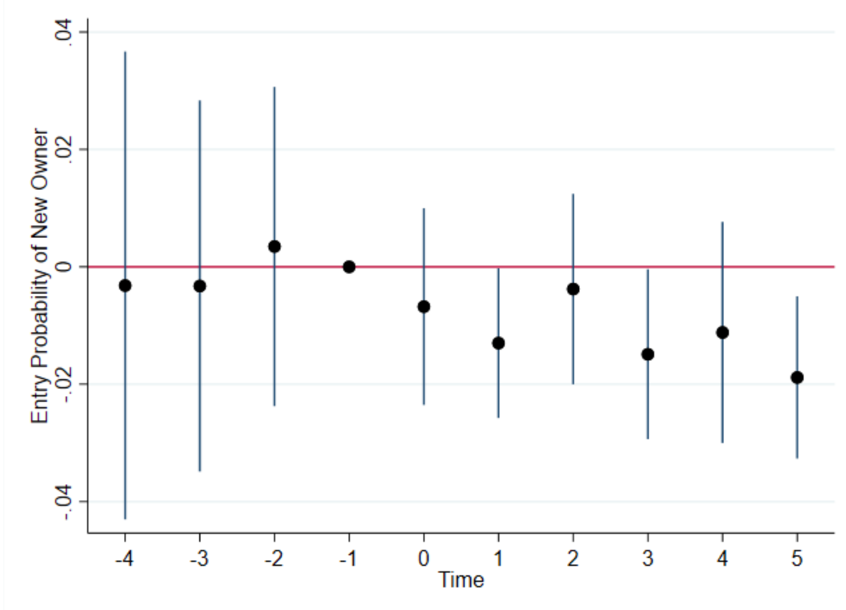


This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ &+Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is a dummy variable equal to 1 if there is the entry of a new owner and 0 otherwise. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. We also include year, firm and firm age fixed effects to control. In this figure we consider the full matched sample. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Figure 17: Premature death of founders and ownership - Reduced Sample



This figure plots the coefficient β varying by year before and after shock estimated from the equation below:

$$Y_{f,t} = \sum_{k=-4}^{5} \beta_{\mathbf{k}} \times \mathbf{Post_{f,t+k}} \times \mathbf{Treated_f} \\ +Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}$$

where $Y_{f,t}$ is a dummy variable equal to 1 if there is the entry of a new owner and 0 otherwise. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this figure we consider the firm-year observations in the matched sample that have outstanding credit on SCR. We plot the estimated coefficients for each year and their 95% confidence interval. Standard errors are clustered at year and firm level.

Table 1: Summary statistics - Extensive Margin Analysis Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
ln($Credit$)	58,648	3.17	4.86	0	18.41
ln($Number\ Loans$)	58,648	0.726	1.08	0	7.38
$Probability\ of\ Default$	58,648	0.023	0.148	0	1
$Interest\ Rate$	58,648	0.085	0.216	0	1
$Probability\ of\ New\ Relation$	58,648	0.389	0.488	0	1
ln($Volume\ of\ New\ Credit$)	58,648	0.083	0.903	0	14.36
$Probability\ of\ New\ Loan$	58,648	0.009	0.092	0	1
ln($Employment$)	58,648	1.12	1.5	0	9.43
$Entry\ New\ Owner$	58,648	0.139	0.346	0	1
$Firm\ Age$	58,648	4.04	3.62	0	24
$Size\ of\ Founding\ Team$	58,648	3.14	2.00	1	42

Table 2: Summary statistics - Intensive Margin Analysis Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
ln($Credit$)	14,218	10.50	1.793	0.01	18.41
ln($Number\ Loans$)	14,218	2.03	0.976	0.69	7.37
$Probability\ of\ Default$	14,218	0.063	0.243	0	1
$Interest\ Rate$	14,218	.349	.317	0	1
ln($Employment$)	14,218	1.90	1.71	0	8.47
$Entry\ New\ Owner$	14,218	0.073	0.26	0	1
$Firm\ Age$	14,218	4.43	3.69	0	24
$Size\ of\ Founding\ Team$	14,218	3.03	1.79	1	22

This table presents the summary statistics of the main variables we built to perform our analysis. Table 1 provides the descriptive statistics of the full sample, in other words, the sample that we use to perform our extensive analysis. Table 2 presents the descriptive statistics of the firm-year observations with positive outstanding credit given by the database SCR, in other words, this is our sample for the intensive margin analysis and other analyses we perform to understand the mechanisms behind our results.

Table 3: Comparing treatment and control before the shock

	Treatment	Control	p-value of difference
	(1)	(2)	(3)
Intensive Margin Analysis			
ln($Credit$)	2.40	2.89	0.10
	(0.202)	(0.225)	
ln($Number\ Loans$)	0.465	0.543	0.22
	(0.042)	(0.047)	
$Interest\ Rate$	0.097	0.091	0.65
	(0.010)	(0.010)	
$Probability\ of\ Default$	0.014	0.006	0.21
	(0.005)	(0.003)	
ln($Employment$)	0.39	0.40	0.85
	(0.048)	(0.053)	
$Entry\ New\ Owner$	0.136	0.131	0.79
	(0.015)	(0.015)	
Extensive Margin Analysis			
$Probability\ of\ New\ Relation$	0.084	0.092	0.20
	(0.004)	(0.004)	
ln($Volume\ of\ New\ Credit$)	0.020	0.018	0.78
	(0.006)	(0.006)	
$Probability\ of\ New\ Loan$	0.002	0.001	0.63
	(0.0007)	(0.0006)	
$Size\ of\ Founding\ Team$	3.31	2.97	0.00***
	(0.030)	(0.030)	
$Firm\ Age$	0.352	0.387	0.07*
	(0.012)	(0.014)	

This table presents the mean, the standard errors (in parentheses) and the p-value of the differences between treated and control groups for all variables of interest computed in the year prior to the shock. Treated firms are those that one of their founders died between 18 and 60 years old in the first five years of their existence. For the variables applied in the Intensive Margin Analysis, we consider the reduced sample that focus on the firm-year observations that have outstanding credit defined by the database SCR. For the variables applied in the Extensive Margin Analysis, we consider the full matched sample. For $Size\ of\ Founding\ Team$ and $Firm\ Age$, we computed these statistics based on the full matched sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Intensive Margin Analysis - Human capital and startup financing

	$\ln(Credit_{f,t})$	$\ln(Number\ \ Loans_{f,t})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.635***	-0.215**
	(0.062)	(0.033)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\ &\quad + Firm\ \ FE_f + Year\ \ FE_t + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1, log of number of loans plus 1 and average interest rate weighted by the respective size of the loans. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. Standard errors are clustered at year and firm level.

Table 5: Intensive Margin Analysis - Human capital and next period startup financing

	ln($Credit_{f,t+1}$)	ln($Number\ Loans_{f,t+1}$)
	(1)	(2)
$Post_{f,t} \times Treated_f$	-1.64***	-0.160**
	(0.318)	(0.062)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t+1} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\ &\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t+1}$ is the log of credit volume (i.e., credit size) plus 1 computed in the next period and log of number of loans plus 1 computed in the next period. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. Standard errors are clustered at year and firm level.

Table 6: Robustness Test - Controlling for Ex-ante Firm Age

	ln($Credit_{f,t}$)	ln($Number\ Loans_{f,t}$)
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.658***	-0.209***
	(0.069)	(0.036)
$Post_{f,t} \times Treated_f \times FirmAge_f$	0.053	-0.013
	(0.077)	(0.037)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These tables show the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} + \beta_{\mathbf{FirmAge}} \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \times \mathbf{FirmAge_f} \\ &\quad + \alpha \times FirmAge_f + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1 and log of number of loans plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. $FirmAge_f$ is the firm age of firm f at the year prior to the shock. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. Standard errors are clustered at year and firm level.

Table 7: Robustness Test - Controlling for Ex-ante Size of Founding Team

	ln($Credit_{f,t}$)	ln($Number\ \ Loans_{f,t}$)
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.863***	-0.108
	(0.143)	(0.068)
$Post_{f,t} \times Treated_f \times SFT_f$	0.069*	-0.032*
	(0.037)	(0.019)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

	ln($Credit_{f,t+1}$)	ln($Number\ \ Loans_{f,t+1}$)
	(1)	(2)
$Post_{f,t} \times Treated_f$	-1.909***	-0.185*
	(0.583)	(0.092)
$Post_{f,t} \times Treated_f \times SFT_f$	0.079	-0.001
	(0.125)	(0.012)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These tables show the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} + \beta_{\mathbf{SFT}} \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \times \mathbf{SFT_f} \\ &\quad + \alpha \times SFT_f + Firm\ \ FE_f + Year\ \ FE_t + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1 computed in the next period and log of number of loans plus 1 computed at the current period and at the next period. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. SFT_f is the size of founding team of firm f at the year prior to the shock. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. Standard errors are clustered at year and firm level.

Table 8: Robustness Test - Controlling for Industry Fixed Effects

	ln($Credit_{f,t}$)	ln($Number\ \ Loans_{f,t}$)
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.693***	-0.213***
	(0.066)	(0.031)
N	12,213	12,213
Firm FE	YES	YES
Year $\times$ Industry FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Robustness Test - Controlling for Industry Fixed Effects

	ln($Credit_{f,t+1}$)	ln($Number\ \ Loans_{f,t+1}$)
	(1)	(2)
$Post_{f,t} \times Treated_f$	-1.78***	-0.209**
	(0.34)	(0.077)
N	12,213	12,213
Firm FE	YES	YES
Year $\times$ Industry FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These tables show the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\ &\quad + \alpha \times FirmAge_f + Firm\ \ FE_f + Year \times Industry\ \ FE_{f,t} + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1 and log of number of loans plus 1 computed at current level and in the next period. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. We include firm, year-industry and firm age fixed effects. To compute the year-industry fixed effects, we use CNAE 5 digits codes from 1995 provided by RAIS. Standard errors are clustered at year and firm level.

Table 10: Robustness Test - Controlling for Industry Fixed Effects

	$\ln(Credit_{f,t})$	$\ln(Number\ \ Loans_{f,t})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.629***	-0.211***
	(0.061)	(0.032)
N	13,098	13,098
Firm FE	YES	YES
Year × Industry FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Robustness Test - Controlling for Industry Fixed Effects

	$\ln(Credit_{f,t+1})$	$\ln(Number\ \ Loans_{f,t+1})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-1.71***	-0.202**
	(0.325)	(0.072)
N	13,098	13,098
Firm FE	YES	YES
Year × Industry FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These tables show the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\ &\quad + \alpha \times FirmAge_f + Firm\ \ FE_f + Year \times Industry\ \ FE_{f,t} + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1 and log of number of loans plus 1 computed at current level and in the next period. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. We include firm, year-industry and firm age fixed effects. To compute the year-industry fixed effects, we use the first 2 digits of the CNAE 5 digits codes from 1995 provided by RAIS. Standard errors are clustered at year and firm level.

Table 12: Human capital, ownership and employment

	$Entry\ New\ Owner_{f,t}$	$\ln(Employment_{f,t})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.028**	-0.275***
	(0.005)	(0.031)
N	58,294	25,864
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is a dummy variable equal to 1 if there is an entry of a new owner and log of number of employees plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this table we consider the full matched sample for the ownership regression. For the regression that focus on employment we consider only the observations on RAIS. Standard errors are clustered at year and firm level.

Table 13: Human capital, ownership and employment focusing on firms from SCR

	$Entry\ New\ Owner_{f,t}$	$\ln(Employment_{f,t})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.011	-0.190***
	(0.007)	(0.047)
N	13,110	8,667
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \\
&\quad + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is a dummy variable equal to 1 if there is an entry of a new owner and log of number of employees plus 1. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. In this table we consider the firm-year observations in the matched sample that have outstanding credit on SCR. For the employment model, we are focusing on those firms that have employees (i.e., they have information on RAIS). Standard errors are clustered at year and firm level.

Table 14: Human capital and startup financing - Differentiating Type of Founders

	$\ln(Credit_{f,t})$	$\ln(Number\ \ Loans_{f,t})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.736***	-0.292***
	(0.079)	(0.037)
$Post_{f,t} \times Treated_f \times AngelInv_f$	0.308*	0.237***
	(0.147)	(0.073)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$
\begin{aligned}
Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} + \beta_{\mathbf{AngelInv}} \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \times \mathbf{AngelInv_f} \\
&\quad + \alpha \times AngelInv_f + Firm\ \ FE_f + Year\ \ FE_t + Firm\ \ Age\ \ FE_{f,t} + \varepsilon_{f,t}
\end{aligned}
$$

where $Y_{f,t}$ is the log of credit volume (i.e., credit size) plus 1 and log of number of loans. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. $AngelInv_f$ is equal to 1 if the deceased founder is an angel investor or 0 if the deceased founder is also a manager in the firm. In this table we consider the firm-year observations in the matched sample that belong to SCR. Standard errors are clustered at year and firm level.

Table 15: Human capital and startup financing - Differentiating Type of Founders in the next period

	$\ln(Credit_{f,t+1})$	$\ln(Number\ Loans_{f,t+1})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-2.20***	-0.212**
	(0.425)	(0.09)
$Post_{f,t} \times Treated_f \times AngelInv_f$	1.70***	0.069
	(0.488)	(0.109)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t+1} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} + \beta_{\mathbf{AngelInv}} \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \times \mathbf{AngelInv_f} \\ &\quad + \alpha \times AngelInv_f + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t+1}$ is the log of credit volume (i.e., credit size) plus 1 and log of number of loans. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. $AngelInv_f$ is equal to 1 if the deceased founder is an angel investor or 0 if the deceased founder is also a manager in the firm. In this table we consider the firm-year observations in the matched sample that belong to SCR. Standard errors are clustered at year and firm level.

Table 16: Human capital and startup financing - Differentiating Type of Founders

	$Entry\ New\ Owner_{f,t}$	$\ln(Employment_{f,t})$
	(1)	(2)
$Post_{f,t} \times Treated_f$	-0.020**	-0.259***
	(0.008)	(0.062)
$Post_{f,t} \times Treated_f \times AngelInv_f$	0.028*	0.211*
	(0.016)	(0.127)
N	13,110	8,667
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} \quad = \quad & \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} + \beta_{\mathbf{AngelInv}} \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \times \mathbf{AngelInv_f} \\ & + \alpha \times AngelInv_f + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is a dummy variable equal to 1 if there is the entry of a new owner and 0 otherwise and number of employees (i.e., firm size). The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. $AngelInv_f$ is equal to 1 if the deceased founder is an angel investor or 0 if the deceased founder is also a manager in the firm. In this table we consider the firm-year observations in the matched sample that belong to SCR. For the employment model, we are focusing on those firms that have employees (i.e., they have information on RAIS). Standard errors are clustered at year and firm level.

Table 17: Human capital and probability of default - Differentiating Type of Founders

	$Probability\ of\ Default_{f,t}$	
	(1)	(2)
$Post_{f,t} \times Treated_f$	0.077***	0.101***
	(0.012)	(0.015)
$Post_{f,t} \times Treated_f \times AngelInv_f$		-0.073***
		(0.023)
N	13,110	13,110
Firm FE	YES	YES
Year FE	YES	YES
Firm Age FE	YES	YES

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the coefficient β estimated from the equation below:

$$\begin{aligned} Y_{f,t} &= \beta \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} + \beta_{\mathbf{AngelInv}} \times \mathbf{Post_{f,t}} \times \mathbf{Treated_f} \times \mathbf{AngelInv_f} \\ &\quad + \alpha \times AngelInv_f + Firm\ FE_f + Year\ FE_t + Firm\ Age\ FE_{f,t} + \varepsilon_{f,t} \end{aligned}$$

where $Y_{f,t}$ is a dummy variable equal to 1 if the firm defaults at least one of its loans and 0 otherwise. The variable $Treated_f$ is equal to 1 if the firm is a treated firm and 0 otherwise. $Post_{f,t}$ is equal to 1 when the shock occurs and 0 otherwise varying by firm f and year t. $AngelInv_f$ is equal to 1 if the deceased founder is an angel investor or 0 if the deceased founder is also a manager in the firm. In this table we consider the full matched sample. Standard errors are clustered at year and firm level.