Financial Frictions, Cyclical Fluctuations, and the Growth Potential of New Firms*

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Abstract

We develop a model in which entrepreneurs choose between startup types with heterogeneous short- and long-run growth potential, and we generate testable predictions on the differential effects of financial factors and cyclical fluctuations on these startups. Using a multi-country entrepreneurship survey, we find that, consistent with the model, higher borrowing costs during financial crises negatively affect high-growth startups considerably more than low-growth startups, especially during severe downturns. Our results, supported by additional tests using sector-level financial frictions indicators, uncover a new channel that is potentially important to explain slow recoveries after financial crises.

Keywords: Financial Crisis, Entrepreneurship

JEL Categories: E20, E32, D22, J23, M13.

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1 Introduction

The entry and exit of businesses are important for job creation and aggregate output. Young firms grow faster than old firms and account for a significant share of employment growth. New firms are also very heterogeneous. Most of them grow slowly or exit, but a small fraction grows very rapidly, driving higher mean net employment growth (Haltiwanger et al, 2016). Pugsley, Sedlaceck and Sterk (2018) argue that such heterogeneity is primarily driven by the ex ante characteristics of these startups, rather than by the ex post shocks they face during their lifetime.

It is therefore important to understand what factors affect the incentives of potential entrepreneurs to start different types of businesses. This paper studies the importance of financial factors. We combine several sources to develop a large dataset that links survey data on entrepreneurial decisions, country-level business cycle and financial frictions data, and sector-level information on technology. We use this rich dataset to study how cyclical conditions and financial frictions affect startups with high growth potential.

We begin by developing a stylized partial equilibrium model of startup decisions. Entrepreneurs decide whether to start a firm and choose among different types of businesses. All types have the same initial sunk cost κ and use the same technology but differ in the expected path of their total factor productivity. We simplify this heterogeneity by focusing on two types: Type 1, with low growth potential, and Type 2, with high growth potential. The productivity of Type 1 startups grows at a constant rate g. Type 2 startups initially grow at a rate lower than g, but every period, with probability γ, they become a fast-growing firm that grows permanently at a rate higher than g.

All entrepreneurs have the same ability to run Type 1 startups but heterogenous skills to run Type 2 startups. Their financial wealth a is lower than κ, and they need to borrow to finance the difference. We link the model to the data by assuming that a is procyclical, because households on average have higher wealth and income during booms, and that borrowing rates are equal to the risk-free rate plus a premium reflecting financial frictions.

How are the startups selected? Entrepreneurs compute the net present value of profits

V^j and the net present financing costs C^j (the net present value of the excess borrowing costs above the riskless rate) required by Type $j = 1, 2$. They then select the one with higher value of $V^j - C^j$. In the absence of financial frictions ($C^j = 0$), all entrepreneurs with skill above a certain threshold find that $V^2 > V^1$ and chose a Type 2 startup. All other entrepreneurs chose a Type 1 startup.

We use this model to derive the following results: first, for the marginal entrepreneur who is indifferent between the two types, Type 2 has lower profitability in the short term and higher profitability in the long term. It follows that, at the margin, it takes longer to repay the initial debt to finance a Type 2 startup. Second, without financing frictions, this longer repayment period is irrelevant, but with financial frictions, it is not. Any increase in the excess cost of external finance increases overall financing costs relatively more for Type 2 than for Type 1 startups. As a consequence, the minimum skill threshold to chose Type 2 increases, and fewer entrepreneurs chose Type 2 relative to Type 1 startups. Third, these effects are amplified when financial wealth a is lower during downturns.

These results imply the following testable predictions. Conditional on GDP growth, an increase in the excess cost of finance will reduce the number of all startups and Type 2 startups by relatively more than Type 1 startups. Moreover, a decline in GDP growth amplifies the negative effects of the excess cost of finance and does so relatively more for Type 2 startups than for Type 1 startups.

The model is highly stylized, and in the paper we discuss the robustness of the model's assumptions. We argue that while the overall cyclicality of startups might also be driven by factors outside the model, our predictions regarding the differential effects on Type 1 and Type 2 startups are quite general and robust to several alternative assumptions.

We test these predictions by combining multiple empirical sources. Our main dataset is the Global Entrepreneurship Monitor (GEM), a multi-country survey of entrepreneurial decisions. Our baseline sample includes the 2002-2013 period and a total of approximately 1 million individual-level observations from 21 OECD countries. Two features make this dataset particularly suited for our purpose. First, it includes individual characteristics such as age, gender, education, income bracket and entrepreneurial experience. Thus, we can study the dynamics of startups while controlling for the quality of the pool of potential entrepreneurs. Second, it is designed to be representative of a country's population and to obtain harmonized data across countries. Poschke (2018) shows that the firm size distribution obtained from GEM, using survey responses from entrepreneurs, matches remarkably well that obtained from administrative data sources.

We merge this dataset with a country-specific business cycle indicator (GDP growth) and a financial crisis indicator from Laeven and Valencia (2013). This indicator is positively correlated with the presence of financial frictions that increase the cost of financing new firms. However, it is unable to capture variations in the intensity of financial frictions over time and across countries. Therefore, we also consider the Gilchrist and Zakrajsek (2012) bond spreads of financial institutions. Using data on European countries from Gilchrist and Benoit (2016), we compute the indicator for the US, Spain, Italy, France and Germany. Gilchrist and Benoit (2016) show that such spreads are good proxies for credit availability to households and firms and have strong predictive power for the real effects of financial crises. Therefore, they are ideal measures of the intensity of financial frictions affecting new startups. Finally, we also check that the results are robust to using an alternative measure of financial frictions, the financial distress indicator of Romer and Romer (2017).

We identify startups that are likely to have high growth potential in the GEM dataset as those for which the entrepreneur is expecting high future employment (relative to the average size of firms in its country/sector). The GEM is a repeated cross section and therefore does not allow us to follow the growth performance of the different startups. However, for Spain (which has extensive coverage in GEM, with more than 200.000 observations), we obtained a sample comprising almost all new firms founded since 2003 from the Sistema de Análisis de Balances Ibéricos (SABI). We match these two datasets at the 2-digit sector level, so that every firm in SABI has associated with it the share of startups with high growth potential in its sector in the year it was founded. We interpret this value as the probability that this firm is a high-growth firm, and we show that, after controlling for year and sector fixed effects, this probability significantly increases the employment growth of young firms, supporting the identification assumption of the model.

To test our hypotheses, we perform several probit regressions in which the dependent variable is equal to one if the individual starts a business, zero otherwise. We consider as the dependent variable both any type of startups and startups with low and high growth potential separately. Among the regressors, we include GDP growth at the country level, a financial crisis dummy (or the time-varying indicator of financial frictions), and the interaction between the two. We include as control variables country fixed effects and individual characteristics such as age, education and income group.

Our main results confirm the model's hypotheses. We find that all startups, but especially startups with high growth potential, were negatively affected by the financial crisis. Moreover, we find a strong positive interaction between financial frictions and GDP growth. An increase in the cost of external finance significantly reduced the number of startups with high growth potential by more than the other types, especially when GDP growth was lower. This result is confirmed using as a financial frictions indicator either the Gilchrist and Zakrajsek (2012) bond spread or the Romer and Romer (2017) financial distress indicator. We provide several robustness checks of these results. First, we show that they hold when we exclude countries that did not experience the financial crisis, when we exclude selected sectors that might cause a spurious correlation, and when we include additional control variables that proxy for business expertise and expectations of future business opportunities. Second, we provide additional evidence in support of a causal link from financial frictions to startup decisions. We consider two indicators often used in the literature to select sectors more likely to face financial frictions: i) the external financial dependence (EFD) indicator (Rajan and Zingales, 1998) and an indicator of intangibility (share of intangible over total assets; see Falato et al., 2013, and Caggese and Perez, 2017). In sectors with high external financial dependence, startups need to finance larger initial investments (higher κ in the model). In sectors with a larger share of intangible assets, firms have lower collateral and face higher borrowing costs.

The model predicts that both types of startups should be more negatively affected by financial frictions than the other startups. Our empirical findings are consistent with this prediction.

Taken together, our results strongly support the view that financial frictions differently affect the entry of firms with high growth potential and that this *composition of entry* channel is potentially important to explain slow recoveries after financial crises.

The remainder of the paper is organized as follows. Section 2 outlines the related literature. Section 3 introduces a partial equilibrium model of the relationship between access to finance and entrepreneurial decisions. Section 4 describes the data. Section 5 conducts the empirical analysis and tests of the model predictions. Section 6 presents some robustness checks. Section 7 concludes the paper.

2 Related literature

Entrepreneurial choices among heterogeneous individuals have been extensively analyzed in the occupational choice and innovation literature (see, e.g., Poschke, 2013). Other authors focus on the mobility of inventors and disruptive innovators and on the reallocation of highly skilled labor (see, among others, Acemoglu, Akcigit and Celik, 2014, and Akcigit, and Kerr, 2016). We contribute to this literature by identifying the effects of financial conditions, and of their interaction with the business cycle, on heterogeneous startup types.

Our paper is also related to studies of firm dynamics during the financial crisis. Clementi and Palazzo (2016) show that the sharp decline in the number of startups during the 2007-2009 recession might have contributed to the slow recovery, and Siemer (2018) emphasizes the importance of financial frictions in this decline. Our work is especially related to Sedlaceck and Sterk (2017), who show that not only did firm entry decline strongly during the 2007-2009 financial crisis but also that the startups that did enter during that period were significantly weaker in their potential to create jobs in the future. These authors emphasize the importance of the ex ante decisions of entrepreneurs for the growth dynamics of young firms, but their empirical analysis focuses solely on firm-level data. Conversely, we analyze a rich cross-country survey of entrepreneurial choices and are able to study how financial factors affect the entrepreneurial decisions to create different types of businesses, while controlling for the quality of the entrepreneurial pool.

Our theoretical approach is related to the literature on financial frictions, firm dynamics, and the decisions of entrepreneurs to start different types of businesses (e.g., Buera et al., 2011, Caggese and Cunat, 2013, Midrigan and Xu, 2014, and Cole et al., 2016, among others). Although our model is highly stylized, the novelty of our analysis is the focus on deriving testable predictions on the cyclicality of startups with different degrees of growth potential.

Finally, our empirical analysis is related to those studies that analyze the effect of financial factors of the cyclicality of economic activity using multi-country and multi-sector data, in particular Braun and Larrain (2005), Kroszner, Laeven and Klingebiel (2007), and Dell'Ariccia, Detragiache and Rajan (2008). These studies analyze the cyclicality of industries by using sector-level data, while we analyze the dynamics of heterogeneous startups by using entrepreneur-level information.

3 Model

We develop a stylized partial equilibrium model of the relationship between access to finance and heterogeneous startup decisions. Section 3.1 characterizes the optimal choices of one entrepreneur. Section 3.2 generalizes the analysis to an industry with many entrepreneurs who have heterogeneous skills and derives testable predictions.

3.1 Technology

Consider a risk-neutral entrepreneur who can choose the type of startup j among N alternatives, with types indexed by $j = 1, 2, ..., N$. All types require the same initial sunk cost κ to operate. Every period, a Type j firm generates output:

$$y_t = \left(\theta_t^j\right)^\beta l_t^\alpha \tag{1}$$

where l is labor input, $0 < \alpha < 1$, and $0 < \beta \leq 1$. One unit of labor costs an exogenous wage w. θ_t^j can be interpreted literally as efficiency, or as shorthand for quality improvements that increase demand. Similarly, $\alpha < 1$ can be interpreted as decreasing returns to scale or as shorthand for monopoly power. Type j has initial productivity θ_0^j equal to:

$$\theta_0^j = \phi^j E. \tag{2}$$

E is a parameter that defines generic entrepreneurial ability, while ϕ^j measures the specific ability to run a Type j firm. In Section 3.2, these parameters determine heterogeneity across entrepreneurs and allow us to map the model results onto testable predictions. However, for the present, we assume that E is a constant and that ϕ^j is equal to 1 for all types, so that $\theta_0^j = \theta_0 = E$.

Startup types differ in their expected productivity growth. We simplify the analysis and set $N = 2$. *Type 1*, with low growth potential, and *Type 2*, with high growth potential. Type 1 represents the decision to provide mature and established products or services and/or products in well-known markets. It has low risk and is immediately profitable but also has low growth prospects. Type 2 represents the decision to provide a newer product or service and/or one in less well-known markets. It is riskier and needs more time to start generating revenues but has higher growth potential.[1]

Specifically, we assume that θ_t^j grows at an exogenous rate g_t^j. $g_t^1 = g^{med}$ in all periods $t \geq 0$ for Type 1 firms. Conversely, $g_0^2 = g^{low} < g^{med}$ initially for a Type 2 firm, but every year, with probability γ, g_t^2 might permanently increase from g^{low} to $g^{high} > g^{med}$. Profits are:

$$\pi_t = \left(\theta_t^j\right)^\beta l_t^\alpha - w l_t \tag{3}$$

[1] The growth potential of Type 2 projects might also depend on different managerial and organizational strategies. For example, a restaurant owner might choose whether to manage a small traditional family restaurant or to attempt to develop a new restaurant chain.

To keep the model tractable, we assume that wages are paid after earnings are realized, and thus not subject to financial frictions, and that $\beta = 1 - \alpha$. Therefore, the labor demand that maximizes profits is:

$$l_t = \left(\frac{\alpha}{w}\right)^{\frac{1}{1-\alpha}} \theta_t^j \tag{4}$$

Substituting l_t in Equation 3, we express profits as a linear function of θ_t:

$$\pi\left(\theta_t\right) = \Psi \theta_t^j \tag{5}$$

$$\Psi \equiv \left[\left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}} - \left(\frac{\alpha}{w}\right)^{\frac{1}{1-\alpha}} w\right] > 0$$

Equations 4 and 5 imply that labor demand and profits follow the dynamics of productivity. They initially grow faster for Type 1 firms, but on average, over time, their growth rate accelerates for Type 2 firms, which eventually become more profitable and larger than Type 1 firms. In the two following subsections, we compute the net present value of the firm types. If access to finance is frictionless, this value is given simply by the discounted value of net revenues. In the presence of financial frictions, the value is instead affected by the excess cost of external finance. We emphasize this by separating the firm values in two components: the net present value of the flow of profits V and the net present value of the "excess cost" of financing the startup C.

Value of stream of profits V

First, consider a Type 1 firm. In every period, it might liquidate with probability d. If it does not liquidate, it generates profits equal to $\Psi[\theta_0(1 + g^{med})^{(t-1)}]$ in period t. We normalize the riskless discount rate to zero. It is straightforward to show that the value of this stream of profits is equal to:

$$V^1\left(\theta_0\right) = (1-d)\Psi \frac{\theta_0}{d - (1-d)\, g^{med}} \tag{6}$$

Similarly, the value of a Type 2 firm that switched permanently to high growth in period t is:

$$V^{high}\left(\theta_t\right) = (1-d)\Psi\frac{\theta_t}{d-(1-d)\,g^{high}} \tag{7}$$

Its initial value can be shown to be equal to (see Appendix A for details):

$$V^2\left(\theta_0\right) = (1-d)\Psi\Phi\frac{\theta_0}{1-(1-\gamma)(1-d)\left(1+g^{low}\right)} \tag{8}$$

where:

$$\Phi \equiv (1-\gamma) + \frac{\gamma}{d-(1-d)\,g^{high}}$$

Note that V^1 and V^2 do not depend on the cost of external finance r^b.

Excess cost of financing the startup C

The entrepreneur has an initial endowment of $a \leq \kappa$ and needs to borrow $b = \kappa - a$. In subsequent periods, she can repay the debt using the flow of profits $\pi\left(\theta\right)$. One unit of debt implies a repayment of $\frac{1+r^b}{1-d}$ next period, thus reflecting the risk that the firm is liquidated before producing and is unable to repay the debt with probability d. Since we normalized the lending rate to zero, r^b is a measure of the financial spread or excess cost of debt caused by financial frictions.

The entrepreneur is risk neutral and finds it optimal to not distribute dividends while the firm is in operation to use all earnings to repay the debt. Therefore, the law of motion of debt is:

$$b_{t+1} = \left(\frac{1+r^b}{1-d}\right)b_t - \pi(\theta_t) \tag{9}$$

The debt is repaid when the net present value of the flow of payments, discounted using $\frac{1+r^b}{1-d}$, is equal to the amount of debt b. Given the n periods necessary to repay the debt, for a Type 1 firm, this is equal to:

$$b = \Psi\theta_0\left[\frac{1-\left(\left(1+g^{med}\right)\frac{1-d}{1+r^b}\right)^n}{\frac{r^b+d}{1-d}-g}\right] \tag{10}$$

Solving for n yields:

$$n^*(b, g^{med}, \Psi\theta_0) = \frac{\log\left\{1 - \frac{b}{\Psi\theta_0}\left(\frac{r^b+d}{1-d} - g\right)\right\}}{\log\left(\left(1+g^{med}\right)\frac{1-d}{1+r^b}\right)} \tag{11}$$

$n^*(b, g^{med}, \Psi\theta_0)$ is the number of periods necessary to repay debt b with growth g^{med} and initial profits $\Psi\theta_0$. Once we find n^*, we compute Equation 10 discounting the flows using $r = 0$ instead of $r = r^b$:

$$b^* = \Psi\theta_0 \left[\frac{1 - \left(\left(1+g^{med}\right)(1-d)\right)^{n^*}}{\frac{d}{1-d} - g}\right] \tag{12}$$

b^* represents the net present value of the stream of revenues generated during the n^* periods. The difference between b^* and b is by construction the net present value of revenues that pay for the excess cost of financing the startup:

$$C^1 = b^* - b \tag{13}$$

Note that in general the procedure above can be used to compute $C(b, g, \theta_0, r^b)$, the excess cost of finance conditional on debt b, productivity growth g, initial productivity θ_0, and the interest rate premium r^b. It is then straightforward to show that $C(b, g, \theta_0, 0) = 0$ and that $C(b, g, \theta_0, r^b)$ increases in r^b. The calculation of C^2 is slightly more complicated, because of the stochastic nature of productivity growth for Type 2 firms, but it is possible to show that it can be approximated to:

$$C^2 = \sum_{t=0}^{n^e} \left[(1-d)(1-\gamma)\right]^t r^b b_t + \frac{\gamma}{1-\gamma} \sum_{t=1}^{n^e} \left[(1-d)(1-\gamma)\right]^t C(b_t, g^{high}, \theta_t, r^b)\Big] \tag{14}$$

See Appendix A for details. n^e is the expected number of periods needed to repay the debt, and b_t is the residual debt after t periods.

3.2 Predictions

To derive testable predictions, we assume that there are many potential entrepreneurs. The generic entrepreneurial skill E is uniformly distributed across entrepreneurs, so that entrepreneur i has a value of $E_i \in [1-e, 1+e]$, with $0 < e < 1$. Skills to operate Type 2 firms, ϕ_i^2, are uniformly distributed over the interval $\phi_i^2 \in [\phi_{min}^2, 1]$. Conversely, skills to operate Type 1 firms are $\phi_i^1 = 1$ for all entrepreneurs. In other words, the draw of E_i determines one's chances of starting any type of firm, while the draw of ϕ_i^2 determines the probability to start a Type 2 firm relative to a Type 1 firm. Growth rates g^{low}, g^{med}, and g^{high} are chosen so that $V^2(\theta) > V^1(\theta)$. That is, V^2 is higher than V^1 when both types have the same initial productivity. From equations 2, 6 and 8, it follows that, conditional on E_i, there exists a threshold value of $\overline{\phi^2}$ such that, for all entrepreneurs with $\phi^2 > \overline{\phi^2}$, the expected profits of a Type 2 firm are higher than those of a Type 1 firm, because its potential to eventually grow faster more than compensates its low initial growth rate.

Finally, we assume financial wealth a to be positively correlated with GDP growth, which is taken as exogenous in the model. We interpret a as funds that are either accumulated from previous periods or derive from current earnings. Intuitively, individuals with entrepreneurial abilities have on average larger own financial resources during booms, because they are more likely to be working and/or have a larger income stream than during recessions. One might argue that this assumption is restrictive, because the accumulation of financial wealth is very persistent over time and therefore less tightly correlated with the business cycle than is income. Nonetheless, we believe that this assumption is without loss of generality. On the one hand, empirical models of household precautionary saving show that households exhibit buffer stock behavior whereby their net financial wealth is highly sensitive to the income stream in the current and recent periods (e.g., Carroll, 2001). On the other hand, in our empirical analysis, we control for, among other things, the income group of the household within the country. These income groups are likely correlated with long-run household wealth and thus control for the effects of wealth unrelated to business cycle fluctuations.

3.2.1 No financial frictions ($r^b = 0$)

If there are no financial frictions ($r^b = 0$), then from Equation 13, it follows that $C^1 = C^2 = 0$, and the entrepreneurs make their startup decisions based exclusively on the value of V.

All entrepreneurs with $\phi_i^2 > \overline{\phi^2}(E_i)$ have $V^2 > V^1$. They start a Type 2 firm if their skill E_i is sufficiently high that $V^2 > 0$ and no firm if $V^2 \leq 0$.

All entrepreneurs with $\phi_i^2 \leq \overline{\phi^2}(E_i)$ start a Type 1 firm if $V^1 > 0$ and no firm if $V^1 \leq 0$. Importantly, fluctuations in a do not matter for the choice between Type 1 and Type 2 startups.

Therefore, in the absence of financial frictions ($r^b = 0$), GDP growth does not affect the trade-off between Type 1 and Type 2 firms. Notice that this particular result holds because we are implicitly assuming that neither productivity θ nor the riskless interest rate are correlated with the business cycle. We discuss these potentially restrictive assumptions later in section 3.2.3.

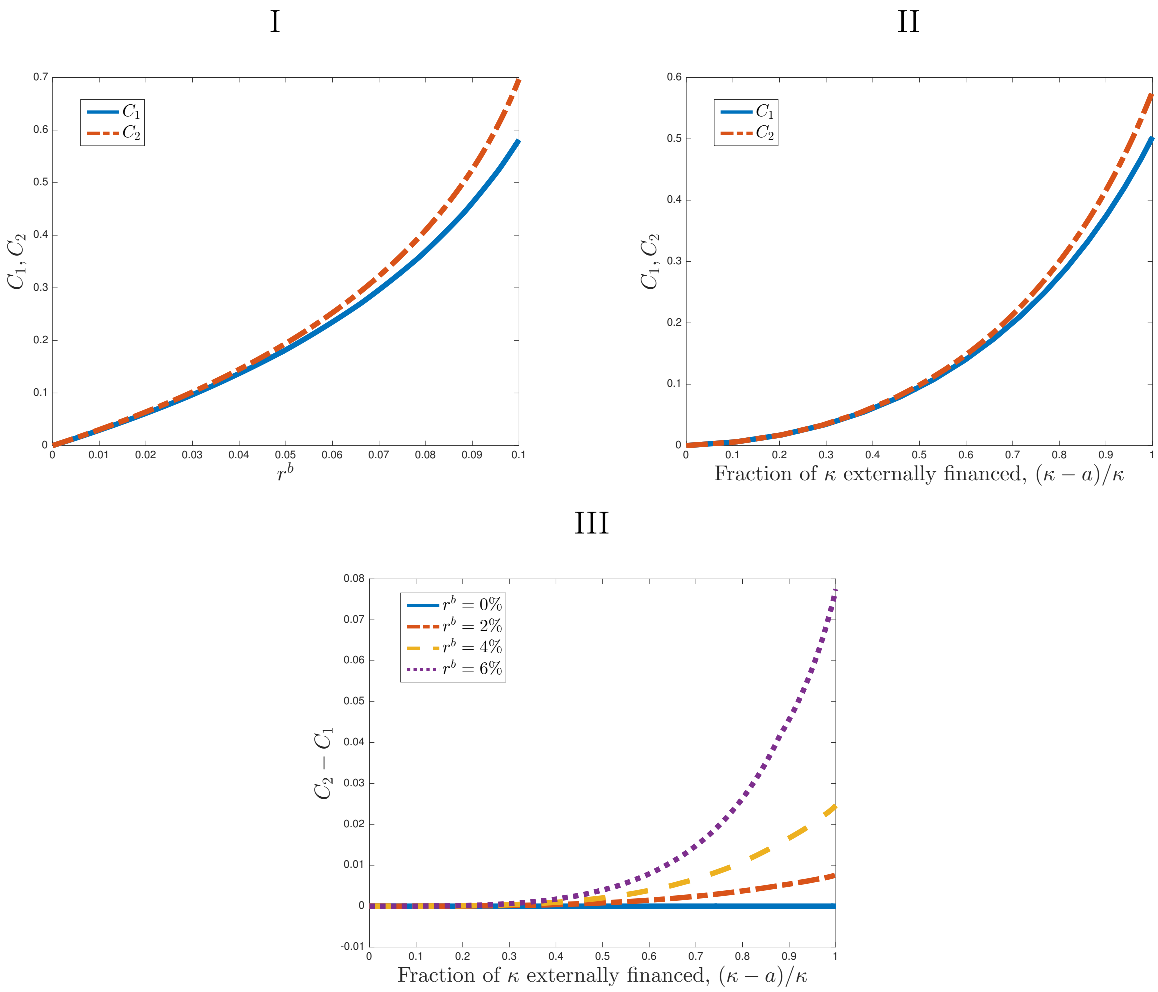
3.2.2 Financial frictions ($r^b > 0$)

If there are financial frictions ($r^b > 0$), then both C^1 and C^2 are positive. Therefore, each entrepreneur selects the project with the highest net value $V^j - C^j$. If this value is negative for both $j = 1$ and $j = 2$, then no project is selected. We begin by characterizing the properties of C^j. First, the comparison of equations 10 and 12 implies that, for given entrepreneurial skills E_i and ϕ_i^2, C^j is positive and increases in r^b (the additional cost of external finance) and falls in a (higher initial wealth means less debt needs to be financed). Higher values of C^j reduce the chances of starting a Type j firm, leading to the following prediction.

Prediction 1: conditional on GDP growth, an increase in the cost of external finance will reduce the frequency of startups. Moreover, conditional on a given cost of external finance, a reduction in GDP growth will reduce the frequency of startups.

The prediction that financial frictions reduce firm entry is not new in the literature.

Figure 1: Properties



Therefore, the most innovative part of our analysis is to derive and test predictions regarding the differential effects on heterogeneous startup types. For this purpose, we define the following three properties of C^1 and C^2:

I) $C^2 > C^1 > 0$ and $\frac{\partial C^2}{\partial r^b} > \frac{\partial C^1}{\partial r^b} > 0$; ;

II) $\frac{\partial C^2}{\partial a} < \frac{\partial C^1}{\partial a} < 0$;

III) $\frac{\partial \left[\frac{\partial \left(C^2 - C^1 \right)}{\partial a} \right]}{\partial r^b} < 0$.

We illustrate these properties graphically in Figure 1 for a realistic calibration of the parameters of the model. The probability of death d is equal to 0.05, yielding an average firm duration of 20 years. g^{med} is equal to 3%, so that the employment of Type 1 firms grows on average at 3% every year, consistent with the median employment growth rate of US firms.[2]. For Type 2 firms, g^{low} is normalized to zero, $g^{high} = 4\%$ and $\gamma = 20\%$, so that their resulting expected employment growth relative to Type 1 firms roughly matches the relative employment growth of the *high growth* startups we identify from matching the GEM and SABI datasets (see Section 4.1 for details). $\alpha = 0.6$ matches the labor share of output. The initial sunk cost κ is normalized to one, and the wage w is set equal to 1.2. This value implies that profits for the average firm in the industry are four times larger than κ, as in Midrigan and Xu (2014). Figure 1 demonstrates that the three properties hold for the chosen calibration. Moreover, they hold for a wide range of parameter values, provided that the long-run growth of Type 2 startups is sufficiently higher than that of Type 1 startups.

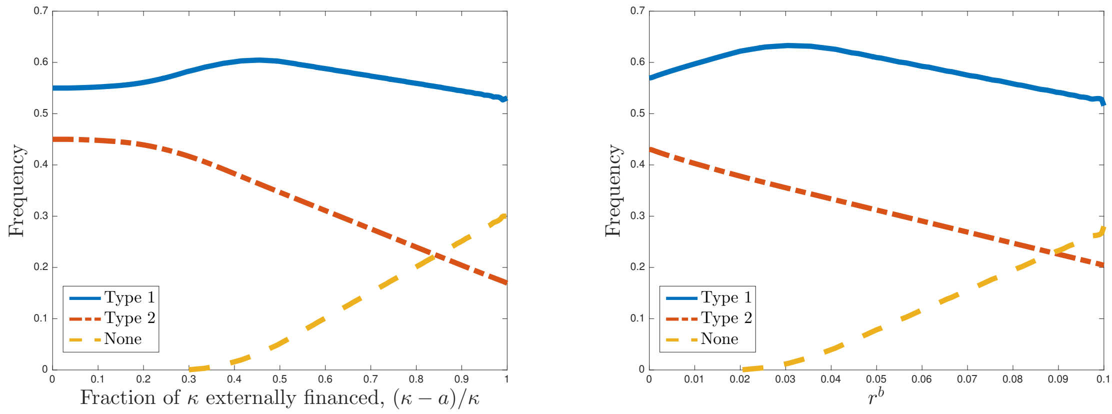
Property (I) is shown in Panel I of Figure 1. Financing costs are steeper in r^b for Type 2 than Type 1 startups, because the Type 2 project takes longer to generate earnings, and the entrepreneur has to pay the high external financing costs for a longer period. Property (II) is shown in Panel II. A reduction in own funds increases the financing costs of Type 2 startups by more than those of Type 1 firms. This has the same intuition as Property (I). A larger initial debt penalizes Type 2 firms relatively more than Type 1 firms, as the former require a longer repayment period.

Thus far, we have considered changes in external financing needs and in the cost of external finance in isolation. Property (III) shows how they interact with one another. That is, a reduction in a (a reduction in own financial resources during a downturn), which has no effect if $r^b = 0$, will instead progressively increase the funding costs of Type 2 more than those of Type 1 projects as r^b increases. This is illustrated in Panel III of Figure 1, and it implies that the effects of a downturn are amplified during financial crises, interpreted as periods of high r^b. These properties determine the following predictions.

Prediction 2: conditional on GDP growth, an increase in the cost of external finance will reduce the number of Type 2 startups relatively more than that of Type 1 startups.

[2]Source: own calculations using Compustat.

Figure 2: Predicted frequencies of startup types



Moreover, conditional on a given cost of external finance, a reduction in GDP growth will reduce the number of Type 2 startups relatively more than that of Type 1 startups.

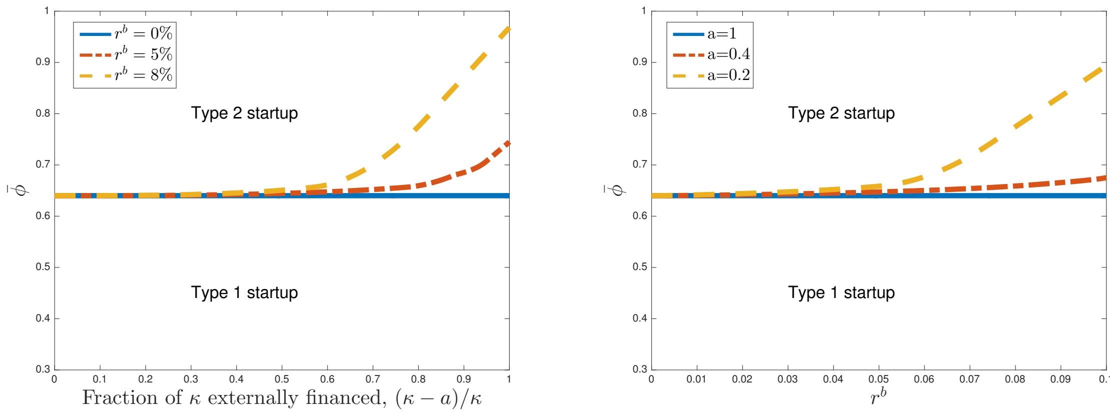
Prediction 3: A decline in GDP growth increases the negative effects of r^b *relatively more on Type 2 startups than on Type 1 startups.*

Prediction 2 is illustrated in Figure 2, which shows the frequency of each type of startup (or not starting any business) among all potential entrepreneurs.[3] In the left panel, the fraction of κ that cannot be self financed is on the x-axis. In periods of rapid GDP growth, this fraction is small, and the dashed yellow line is at zero, indicating that all potential entrepreneurs start some type of business. However, as a falls and $\kappa - a$ rises, the share of entrepreneurs not starting any business increases monotonically, as stated in Prediction 1.

With respect to the behavior of the different types, the increase in external financing needs initially induces the entrepreneurs with a value of ϕ^2 just above the threshold $\overline{\phi^2}$ to switch from Type 2 to Type 1 startups, because the financing cost increases more for the former than for the latter. As a consequence, we observe an increase in the frequency

[3]For these two plots, E is uniformly distributed between 0.3 and 1.7. We do not calibrate this parameter to match a specific moment. In equilibrium, it affects the fraction of entrepreneurs who innovate but does not affect the trade-off between types, which is our main object of analysis. ϕ_i^2 is uniformly distributed between 0.2 and 1, which results in a predicted ratio of Type 1 to Type 2 startups, when there are no financial frictions, that roughly corresponds to what we find in the data.

Figure 3: Prediction



of Type 1 startups following a moderate increase in $\kappa - a$. With a further increase in financing needs, the cost becomes so high that the entrepreneurs at the lower end of the distribution of E stop starting businesses, and therefore, the frequency of Type 1 startups begins to decrease, although much less strongly than for Type 2 startups, as stated in Prediction 2. The right panel shows a similar pattern for an increase in r^b with an earlier and more linear decline in the frequency startups of Type 2.

Prediction 3 is illustrated in the left panel of Figure 3, which depicts the choice between startup types for an entrepreneur with average skills of $E = 1$. The line is flat for the no financing frictions case of $r^b = 0$. In this case, the threshold $\overline{\phi^2}$ is constant because financing is irrelevant to the choice of type of project, as stated in Prediction 1. The line is instead moderately increasing when financial frictions are moderate (r^b is medium), because a higher fraction of κ (due to a decline in a during downturns) can easily be financed with little additional financing costs. The dashed yellow line instead corresponds to financial crisis periods (r^b is high). The line is steeply increasing because a decline in a sharply increases the financing costs of Type 2 firms more than Type 1 firms, and it implies a decline in the relative frequency of Type 2 startups. The right panel of Figure 3 considers the symmetric case of varying r^b during booms (high a) and downturns (low a). The intuition is the same. When a is low and new entrepreneurs need more external financing, higher excess cost of external finance, for example during a financial crisis, reduces the number of Type 2 startups relatively more 2 than that of Type 1 startups.

3.2.3 Discussion

Since the model is highly stylized, it is useful to discuss how other unmodeled factors might affect these predictions. One restrictive assumption is that neither the riskless interest rate nor the law of motion of productivity θ_t^j is correlated with the business cycle. With respect to the interest rate, in Appendix C, we show that all the results are robust to controlling for the effect of the country-specific riskless interest rates. With respect to productivity, one alternative possibility is that the growth potential of projects is procyclical, and the initial value of θ_t^j, its growth rate g_t^j, and the probability γ are positively related to GDP growth. This is likely to reinforce the procyclicality of startups stated in Prediction 1. However, its effect on Predictions 2 and 3 is more ambiguous. On the one hand, if the initial value of θ_t^j falls during downturns, this is likely to penalize Type 1 startups, which rely on higher productivity in the short run, more than Type 2 startups. On the other hand, if the expected productivity growth parameters (g_t^j and γ) fall during downturns, this penalizes Type 2 startups. Overall, these opposite effects might counteract one another. Nonetheless, even if one of the two effects prevails, they will only affect the predictions related to the effects of GDP growth, not the predictions related to the effect of the excess cost of external finance conditional on GDP growth.

Another important element excluded from the model is that financial frictions might differ across projects. Several theoretical and empirical papers argue that such frictions are stronger for Type 2 firms. These are firms that propose more innovative projects, are riskier and are more likely to be subject to asymmetric information and other financial frictions than Type 1 firms. On the one hand, in the model, this feature can be introduced by assuming that the excess cost of finance r^b is larger for Type 2 startups, and this assumption would of course reinforce the results described above. On the other hand, in Section 5.4, we exploit this feature of the model by considering sectorial indicators of the intensity of financial frictions and use them to provide additional testable predictions.

4 Data

4.1 GEM dataset

Our main data source is the GEM, the most comprehensive cross-country survey on entrepreneurial activity currently available (Reynolds et al., 2005). The GEM includes random samples of adult individuals from over 100 countries, with sample sizes ranging from approximately 1000 in some small countries to over 200,000 in Spain. The representativeness of this sample is confirmed by Poschke (2018), who shows that the firm size distribution obtained from the GEM, using survey responses from entrepreneurs, matches remarkably well that obtained from administrative data sources. The period of the sample used for our analysis is 2002-2013.[4] As data on many of the smaller countries are available for only a few years, we clean the data by dropping countries with observations in fewer than nine years. This leaves 26 countries in our sample, with five (Argentina, Brazil, China, Latvia, and Peru) being non-OECD countries, which we also drop.[5] Thus, our final sample includes 21 countries with approximately one million individual observations. We use the following two survey questions to identify individuals starting a business (nascent entrepreneurs):

1. "*Over the past twelve months have you done anything to help start a new business, such as looking for equipment or a location, organizing a startup team, working on a business plan, beginning to save money, or any other activity that would help launch a business?*"

2. "*Will you personally own all, part, or none of this business?*"

An individual is classified as starting a business if he/she answers "yes" to the first question and "all" or "part" to the second question. Thus, a nascent entrepreneur must have been active in establishing a new business during the last year and own at least part

[4]The survey began in 1999, but the first three years have fewer observations and variables; therefore, we include only the years 2002-2013

[5]We eliminate these developing countries to limit cross-country heterogeneity in the data. However, their inclusion does not significantly change the results.

of this business. Some studies (e.g., Koellinger and Thurik, 2012) impose the additional restriction that the business must not have paid salaries or wages for more than three months. However, we believe that this might lead to the exclusion of too many new nascent businesses, and therefore, we relax this restriction.[6]

There are several additional questions regarding the kind of business an individual is starting. In particular, two questions directly attempt to identify business with the potential to grow. The first asks about the expected size of the firm five years into the future. The second asks whether the startup will introduce innovative products or services. Since the first question is more directly related to our model, we use it to identify our benchmark category of high-growth startups. Specifically, we classify a startup as having "*high growth potential*" if the number of employees expected by the entrepreneur in 5 years is larger than the average size of firms in the same 2-digit sector and country. All remaining startups are classified as having low growth potential. Figure 10 and Table 15 in Appendix B show that the *high-growth* startups are widely distributed among all the different sectors, rather than being concentrated in few of them.

The question regarding future employees is intended to capture expectations of the growth potential of the business, but it might also capture expectations about the economy. In Section 6, we control for this possibility by including additional expectational variables present in the survey and show that the results are unaffected. Moreover, in the robustness checks in Section 6.3, we consider the questions on the innovative content of the startups as an alternative way to identify high-growth firms.

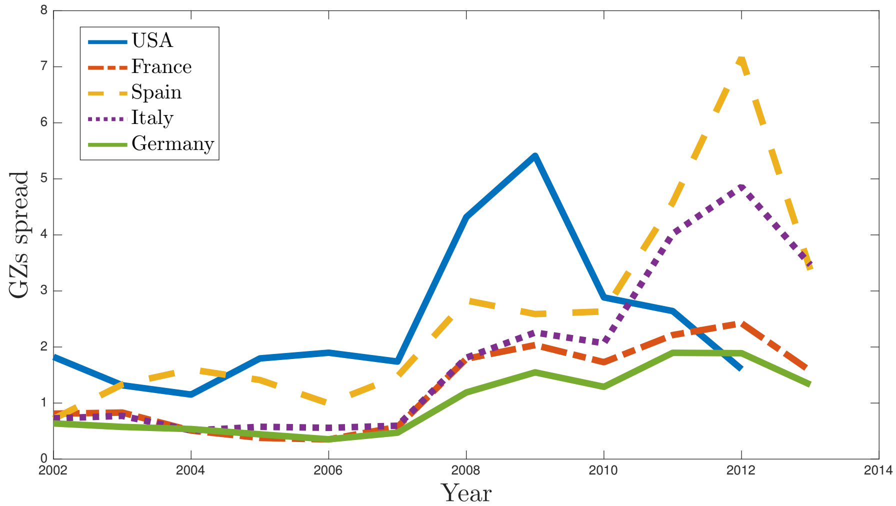
4.2 Business cycle and financial crisis data

In the model, we assume that self-financing of new startups a is procyclical. In our empirical analysis, we use yearly data on GDP per capita from the Penn World Tables and calculate yearly real GDP growth rates (details are in Appendix B.2).[7]

[6] Approximately 27% of nascent entrepreneurs in our sample report having paid salaries or wages for more than three months. The results remain qualitatively unaffected when we exclude them.

[7] Alternatively, we used the deviation from the GDP trend as an indicator of business cycle conditions and obtained qualitatively similar results.

Figure 4: GZ spread by country



The other key variable in the model is the excess cost of external finance r^b. We consider three empirical indicators related to it. The first is a financial crises dummy at the country-year level, which we base on data on systemic banking crises from Laeven and Valencia (2013). According to their measure, 14 countries in our sample suffered a financial crisis, lasting from 2007 to 2013 in the US and the UK and from 2008 to 2013 in the remaining countries. There were no financial crises in Chile, Croatia, Finland, Japan and Norway.

Second, we consider a more detailed indicator of stress in the financial sector, the Gilchrist and Zakrajsek (2012) (GZ) bond spread of financial institutions. Using also data on European countries from Gilchrist and Benoit (2016), we compute the indicator for the US, Italy, France and Germany (details are in Appendix B.4). Gilchrist and Benoit (2016) show that such spreads are good proxies for credit availability to households and firms and have strong predictive power for the real effects of financial crises. Therefore, they are ideal measures of the intensity of financial frictions affecting new startups. Figure 4 shows the evolution of the measure by country over the sample period. It spikes in 2009 in the US and in 2012 in Spain and Italy, while it is only moderately elevated between 2008 and 2013 in France and Germany.

Table 1: Percentage of individuals starting a firm

	All	Low growth	High growth
Full	2.40	1.29	1.11
No Fin. crisis	2.81	1.47	1.35
Fin. crisis	1.84	1.06	0.78
% Difference	-34.52	-27.89	-42.22

Third, in the robustness checks in Section 6.2, we consider, as an alternative, the financial distress indicator of Romer and Romer (2017) (RR). On the one hand, the GZ spread is conceptually more tightly related to the excess cost of finance in the model. The RR indicator is explicitly designed to capture other factors of financial distress beyond high bond spreads. On the other hand, these other factors might presumably be important for new firms' access to finance, and the RR indicator has the additional advantage of being available for almost all the countries in our dataset (details are in Appendix B.5). As expected, for the subset of countries with both indicators, the GZ spread and the RR indicator are tightly correlated, with the correlation coefficient being approximately 0.79.

Descriptive statistics are shown in Table 1. In terms of unconditional averages, the percentage of individuals starting a business is 34% lower during the financial crisis. The drop is larger for individuals starting new firms expecting high employment growth, the number of which falls by 42%. Accordingly, at approximately 28%, the drop is smaller in the complementary category of firms expecting low employment growth.

4.3 Financial dependence and intangible assets data

The GEM dataset contains information on the industrial sector in which a business is started. The sectors are classified following the ISIC Rev.3 classification until 2008 and the ISIC Rev.4 classification from 2009 onwards. We complement the analysis with two sector-level indicators that are related to the financing needs of firms and to the collateralizability of their assets.

First, Kroszner et al. (2007) provide a version of the Rajan and Zingales indicator of external financial dependence (EFD) for manufacturing sectors under the ISIC Rev.2

classification. EFD is defined as the fraction of capital expenditures not financed with cash flows from operations. We match these data to the sector variable of the GEM, obtaining information on EFD for approximately 2,000 manufacturing startups (5.4% of all business started). We use this information to classify startups into sectors with low or high EFD, where the latter proxy for sectors with higher external financing needs (a high value of $\kappa - a$ in the model).

Second, Caggese and Perez (2017) use Compustat data to compute an indicator of the share of intangible over total assets for US industrial sectors. We match their sectors to the sector variable of the GEM, obtaining information on the sector-level share of intangible assets for approximately 17,000 startups (54% of all businesses started). We use this information to classify startups into sectors with a high or low share of intangible assets. Several authors argue that intangible assets have low collateral value, and therefore we consider our category of *high intangibility* as a proxy for sectors with higher average costs of external finance (high r^b in the model). In other words, the categories of high EFD and high intangibility might both proxy for factors that increase the financial frictions of entrepreneurs and can be used as an additional test of the model. Interestingly, these categories are quite uncorrelated (the correlation coefficient is 0.14), indicating that they provide independent sets of information.

4.4 Firm-level dataset from SABI

The GEM dataset provides extensive information on the individuals starting new firms, but its repeated cross-sectional structure does not allow us to follow the performance of the individual firms over time. Therefore, we complement our data with a panel of Spanish firms from SABI, which contains detailed balance sheet information on nearly the entire universe of firms. In particular, we use data on the number of employees of all firms that were established in 2003 or later and that are not subsidiaries of another company or primarily owned by foreign shareholders. Spanish data are very useful because Spain is the country with the largest coverage in the GEM survey, with approximately 235,000 observations in total and at least 16,000 yearly observations from 2003. The richness of the data from both sources allows us to match the two datasets at the year and sector level. Of the 344,869 firms in our sample we can match 226,954 to sectors of startups identified in the GEM, of which 186,341 provide data on employment.

5 Empirical analysis

Our empirical strategy is based on two steps. First, we use the Spanish firm-level data in SABI to verify that the types of startups we classify as having high growth potential behave consistently with the assumptions of the model. Second, we directly test the predictions using the entrepreneur-level data from GEM.

5.1 Firm level analysis

Type 2 startups are more profitable in the long term because, although they grow slower initially, they accelerate and eventually grow faster than Type 1 startups.[8] In our model, productivity growth generates employment growth, which is consistent with several empirical studies showing that productivity and size grow over firms' and plants' life cycle (see, e.g., Hsieh and Klenow, 2014, and Caggese, 2018). Therefore, we analyze firm dynamics in the SABI dataset to verify whether the startups we identify as more likely to possess high growth potential have employment dynamics consistent with the model's assumptions.

We cannot link the GEM and SABI datasets at the firm level, but we can do so at the industry level. From GEM, we compute the variable $Share\_growth_{s,t}$, the share of *high-growth* startups in 2-digit sector s in year t in Spain. Then, we match this variable with the SABI data, so that all the matched 186,341 firms with employment data have the associated the value of $Share\_growth_{s,t}$ in their sector in their year of creation. We interpret this value as the likelihood of a firm being *high growth.* To ensure that we focus on entrepreneurial startups only, we eliminate subsidiaries of other companies and com-

[8] An alternative assumption that produces similar results would be to assume that Type 2 startups always grow faster but their initial productivity is lower.

panies primarily owned by foreign shareholders. Furthermore, we eliminate companies that have more than 100 employees during the first year of existence (443 in total). Then, we estimate the following model:

$$Employment_{i,s,t} = \beta_0+\sum_{k=0}^{10}\beta_1^k age_{i,s,t}^k+\sum_{k=0}^{10}\beta_2^k age_{i,s,t}^k \cdot Share\_growth_{i,s}+\sum_{k=0}^{N}\gamma_k X_{i,s,t}^k+\varepsilon_{i,s,t}, \quad (15)$$

The dependent variable $Employment_{i,s,t}$ is either the employment level relative to the sector-country average or the employment growth of firm i in sector s and year t. $Share\_growth_{i,s}$ is the share of high-growth startups in sector s in the year firm i was founded, and $age_{i,s,t}^k$ is a dummy variable equal to one if the firm is k years old. Among the control variables $X_{i,s,t}^k$, we include year and sector dummies.

A positive value of the coefficient β_2^k, which multiplies the product of $Share\_growth_{i,s}$ and $age_{i,s,t}^k$, means that the higher the probability of being *high growth*, the faster is employment growth or the higher is the employment level of firm i at k years of age.

The regression results are shown in Table 2 (β_2 coefficients only). In the first column, employment growth is significantly lower for likely *high-growth* firms than for the other firms in their first two years of existence. However, it becomes significantly higher from age four onward. The last two coefficients of ages 9 and 10 are no longer significant, plausibly because they are more noisily estimated, as there are fewer cohorts of firms with this age in the dataset, and because, as firms age, ongoing productivity shocks become more important drivers of productivity than the initial choice of business type. In the second column, the dependent variable is employment level relative to the sector average. For newborn firms, a higher share of high-growth startups is related to a size smaller than the sector average. The correlation instead becomes positive from five years old onward, growing stronger as firms become older. Since we control for year fixed effects and for the 2-digit sector, these results are not driven by business cycle dynamics or by sector-specific dynamics. They support our identification strategy used on the GEM dataset, as we selected as high growth precisely those entrepreneurs that expected to have, in five years' time, an employment level higher than the sector average. Importantly, they also support our modeling assumptions. The *high-growth* firms in the data have a behavior

Table 2: Employment growth from SABI

	(1) Emp. growth	(2) Employment
Age 0 x share		-0.177***
		(0.0198)
Age 1 x share	-0.315***	-0.252***
	(0.0355)	(0.0195)
Age 2 x share	-0.040**	-0.217***
	(0.0164)	(0.0230)
Age 3 x share	0.010	-0.125***
	(0.0132)	(0.0246)
Age 4 x share	0.057***	-0.012
	(0.0129)	(0.0268)
Age 5 x share	0.026**	0.063**
	(0.0132)	(0.0298)
Age 6 x share	0.052***	0.190***
	(0.0144)	(0.0330)
Age 7 x share	0.070***	0.303***
	(0.0146)	(0.0366)
Age 8 x share	0.065***	0.358***
	(0.0154)	(0.0472)
Age 9 x share	0.019	0.420***
	(0.0180)	(0.0539)
Age 10 x share	-0.020	0.452***
	(0.0227)	(0.0593)
Year FE	Yes	Yes
Observations	706578	947696
R-squared	0.110	0.150

Notes: Column 1: the dependent variable is the yearly employment growth of firms established in 2003 or later; 0.1% tails are winsorized. Column 2: the dependent variable is employment level, normalized by the average employment level in the 2-digit sector to which the firm belongs. *share* is the share of high-growth startups in the 2-digit sector to which the firm belongs in the year it was born. The regression in column 1 includes sector fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

consistent with Type 2 firms in the model: they initially grow more slowly but have the potential to grow faster in the medium/longer term and to become larger than the other firms in the industry.

5.2 Individual-level analysis: estimation strategy

We test the predictions of the model by estimating how the propensity to start a business correlates with the business cycle and how this relation is affected by financial conditions. Our baseline is the following probit model:

$$Pr(start_{i,j,t} = 1|X_{i,j,t}) = \Phi(\beta_0 + \beta_1 bus_{j,t} + \beta_2 fin_{j,t} + \beta_4 bus_{j,t} \cdot fin_{j,t} + \sum_{k=0}^{N} \gamma_k X^k_{i,j,t} + \varepsilon_{i,j,t}), \quad (16)$$

where $start_{i,j,t} = 1$ is a dummy indicating that individual i in country j in year t is starting a firm. $bus_{j,t}$ is a variable capturing the state of the business cycle in country j at time t, for which we use the real GDP growth rate, in terms of purchasing power parity. $fin_{i,j,t} = 1$ is a dummy indicating a financial crisis in country j in year t. As shown in Figure 4, it captures periods of high borrowing rates and bond spreads, and therefore, we use it as a proxy for high values of the excess cost of external finance r^b in the model. Importantly, we also include the interaction between these two factors $bus_{j,t} \cdot fin_{j,t}$ to test Prediction 3. $X^k_{i,j,t}$ is a vector of control variables including country dummies, sex, age and educational level.[9] We weight observations using the weight variable included in the GEM.

Equation 16 is estimated on the full sample. For the subset of the US, France, Italy, Spain and Germany, we can use the GZ spread, which is a more precise proxy for the excess cost of external finance r^b in country j at time t. Therefore, in an alternative specification, we replace the financial crisis indicator $fin_{i,j,t} = 1$ with $GZ_{j,t}$ and estimate:

$$Pr(start_{i,j,t} = 1|X_{i,j,t}) = \Phi(\beta_0 + \beta_1 bus_{j,t} + \beta_2 GZ_{j,t} + \beta_4 bus_{j,t} \cdot GZ_{j,t} + \sum_{k=0}^{N} \gamma_k X^k_{i,j,t} + \varepsilon_{i,j,t}). \quad (17)$$

Furthermore, in Section 6.2, we estimate equation 17 using the alternative RR indicator of financial distress. We estimate these models using the dummy for the start of any business as the dependent variable, as well as dummies for starts in subcategories only.

[9] In Section 6, we presents the results with dummies for the income level (three categories). Information on the actual income level of respondents is not available in the GEM data. Instead, the GEM contains a variable that indicates whether a person in a specific year and country is in the lowest 33%, the middle 33% or the upper 33% of the income distribution of all respondents. Thus, by construction, this variable cannot control for income differences in the pool of entrepreneurs over time or across countries. We therefore choose not to include it as a control variable in the baseline regressions.

Because we control for individual characteristics, our analysis identifies how the propensity to start different types of businesses varies over the business and financial cycle conditional on the quality of the potential entrepreneurial pool. In particular, we interpret the coefficients of the indicators of financial frictions ($fin_{i,j,t}$, $GZ_{j,t}$, and $RR_{j,t}$ and their interactions with GDP growth) as measuring the effects of such frictions on startup decisions conditional on the aggregate state of the economy. This estimation strategy requires that cyclical fluctuations and financing conditions are not perfectly correlated in the data, and we find that this is the case in our sample. The correlation between the GZ spread and GDP growth is -0.39, and that between the RR indicator and GDP growth is -0.40 and thus low enough that their effects can be separately identified. This is shown in detail in Appendixes B.4 and B.5, where we report the scatterplot between GDP growth (deviations from country averages) and the values of the two indicators. These plots show a clear negative relation, but far from perfect, with many observations with high levels of financial frictions and medium or moderately high values of GDP growth.

However, we cannot exclude alternative interpretations of the results. For example, it is possible that the causal link goes in the opposite direction (e.g., negative investment opportunity shocks generate financial crises). On the one hand, our results, even when they are interpreted as correlations, are valid tests of the model's predictions. Moreover, they document interesting dynamics in the cyclical behavior of startups, which are potentially important to explain the slow recoveries after financial crises. On the other hand, in Subsection 5.4, we provide additional evidence in support of a causal interpretation running from financial frictions to startup decisions. We do so by selecting startups according to their degree of external financial dependence and their intangibility. The hypothesis is that the different technological features of the industries determine the different financing needs of firms and the different collateral capacities of their assets. Industries with higher external financial dependence and higher asset intangibility are more likely to be affected by the increase in financial frictions during the financial crisis.

5.3 Individual-level analysis: baseline results

Table 3: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.663	0.885	0.217	5.447***	3.711**	6.371***
	(0.7114)	(0.6892)	(0.5551)	(1.9928)	(1.6903)	(1.7418)
Fin. crisis	-0.162***	-0.105***	-0.202***			
	(0.0516)	(0.0386)	(0.0669)			
Fin. crisis x GDP growth	4.679***	3.192**	5.755**			
	(1.7898)	(1.2848)	(2.5212)			
GZ spread				-0.020	-0.008	-0.034*
				(0.0197)	(0.0189)	(0.0198)
GZ spread x GDP growth				2.450	1.011	3.751**
				(1.6126)	(1.2510)	(1.5612)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.062	0.042	0.074	0.039	0.031	0.042

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

In Table 3, we show the results of the baseline probit model. In the first column, we consider all types of startups. Because we add country fixed effects, the effect of the regressor *GDP growth* is measured relative to the country average. The coefficient is positive, indicating that startup creation is procyclical, but it is not statistically significant. The dummy *Financial crisis* is negative and significant. It corresponds to a 17% lower probability of starting a company during such a period.[10] Finally, the interaction between *GDP growth* and *Financial crisis* is positive and statistically significant. In general, a positive interaction coefficient indicates greater cyclicality of startups during the financial crisis period. Moreover, since GDP growth was slower during the financial crisis relative to the previous period, the positive interaction coefficient can also be interpreted as showing a significant slowdown in startups during the financial crisis for those countries that experienced larger contractions in GDP. Columns 2 and 3 show that both the financial crisis coefficient and its interaction with GDP growth are larger for the likely high-growth

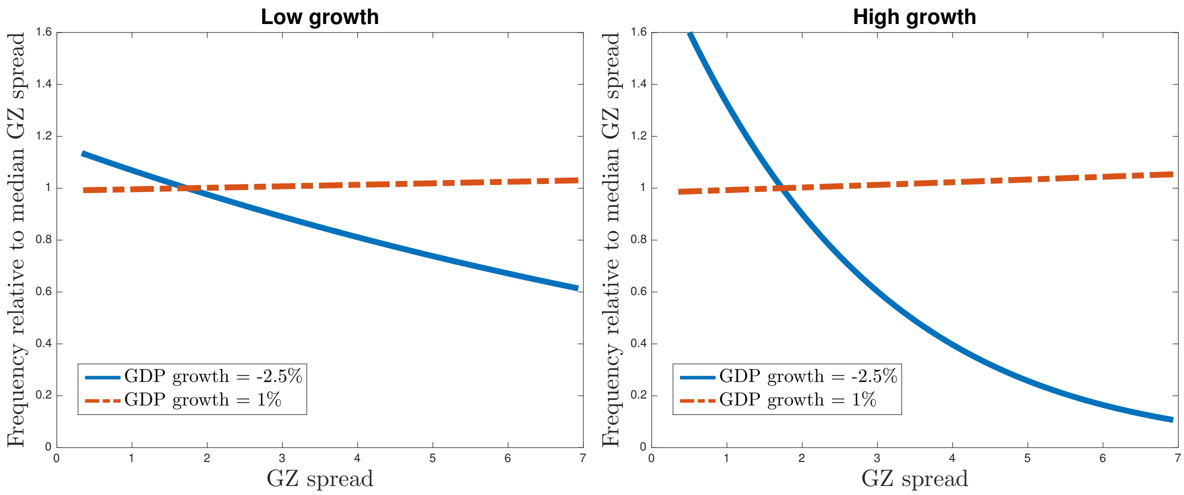
[10] We obtain this value by computing the marginal effect of a financial crisis with the variables being evaluated at the mean.

startups than for the complementary group, confirming the predictions of the model. In terms of marginal effects at the mean, the financial crisis period reduced high-growth startups by 23.4% (versus 11.7% in the complementary group). Moreover, during the financial crisis, an additional 1% decrease in GDP growth reduced high-growth startups by an additional 2.7% (versus 1.5% in the complementary group).

In columns 4-6, we estimate Equation 17, which replaces the financial crisis dummy with the bond spread of financial institutions (GZ spread). The *GDP growth* coefficient is larger and more significant than in the first three columns. The difference is explained by the difference in sample selection. The specification in the last three columns is estimated on a smaller subset of countries (the US, Spain, France, Germany and Italy), for which startups are more procyclical over the whole sample period. Because of the presence of the interaction term, the coefficient of *GZ spread* measures the effect of an increase in the excess cost of external finance conditional on GDP growth being equal to zero. This coefficient is negative but not statistically significant except for the high-growth startups in column 6. This result is consistent with the model, which predicts that the excess cost of finance has a significant effect on startup decisions only when the own financial wealth of potential entrepreneurs is very low. This might happen to many entrepreneurs during downturns, while it is less likely during periods of flat or growing GDP. Importantly, the interaction term *GZ spread x GDP growth* is large and statistically significant for the startups with high growth potential. In other words, a worsening of GDP growth increases the negative effect of *GZ spread* much more for high-growth startups than for the complementary sample, consistent with Prediction 3.

To relate more clearly these results to the model, we use the estimated coefficients to compute the marginal effects of *GZ spread* conditional on a given value of GDP growth, for the high-growth startups and the complementary group. They are depicted in Figure 5. The solid line represents a contractionary period (GDP growth equals -2.5%) and the dashed line a mildly expansionary one (+1%). The lines are normalized to 1 for the median value of the GZ spread. Figure 5 is useful because it provides a graphical test of the predictions. Prediction 1 is satisfied if the solid lines are decreasing in the GZ spread.

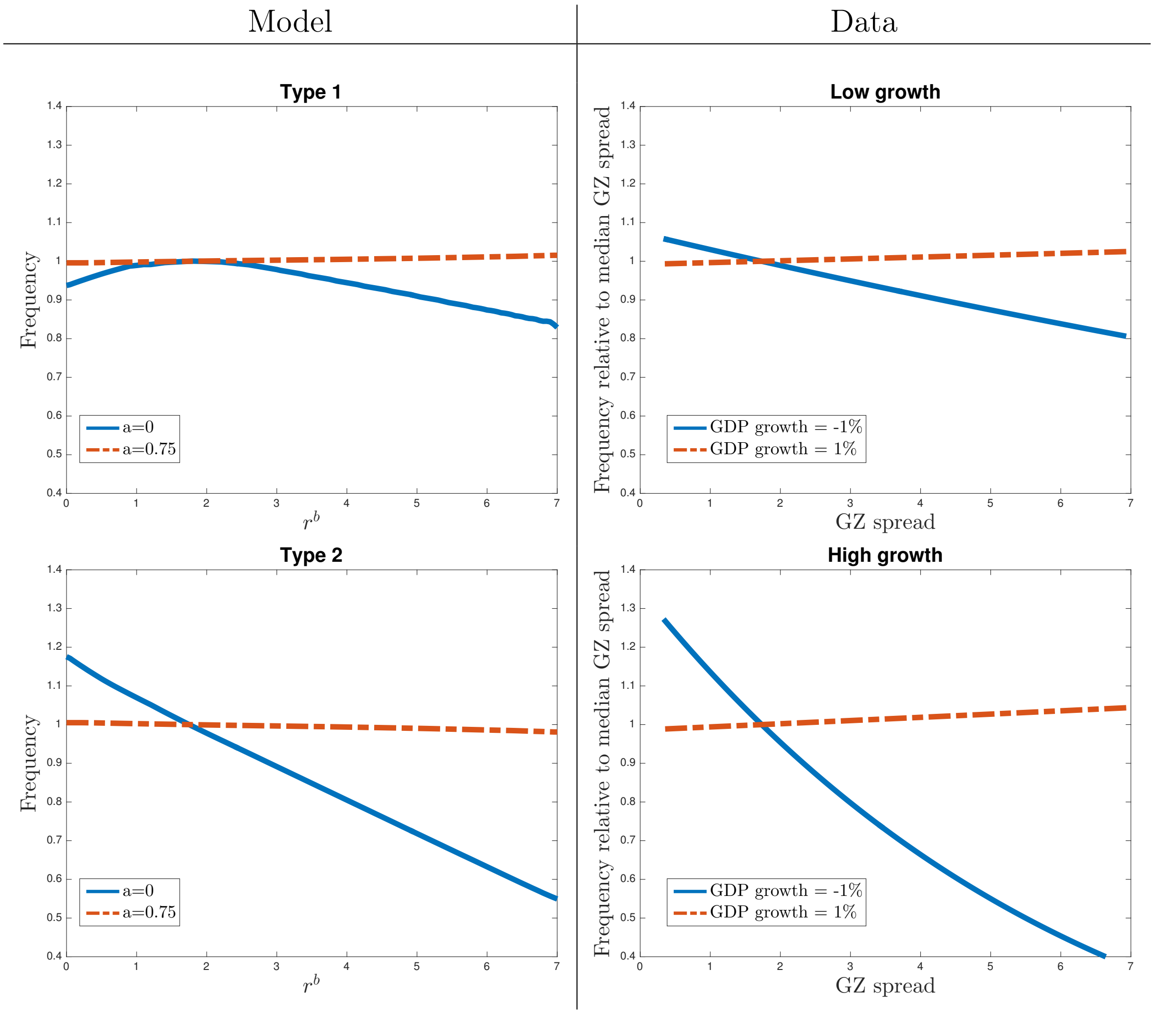
Figure 5: GZ spread and probability of starting a firm



Prediction 2 is satisfied if the solid line is steeper for the likely high-growth-potential startups than for the complementary group. The dashed line should also be more steeply decreasing for the high-growth startups, unless this line is approximately flat, meaning that, for positive values of GDP growth, most entrepreneurs are wealthy and able to self finance and therefore not affected by variations in the cost of external finance. Finally, Prediction 3 is satisfied if the difference in slope between the solid line and the dashed line is larger for the high-growth startups than for the complementary group.

Figure 5 is consistent with all the predictions. The dashed line is approximately flat for both low- and high-growth startups, while the solid line is negatively sloped and steeper for high-growth startups. In terms of significance, a Wald test confirms that the negative slope of the solid line for the high-growth startups is significantly different from zero and significantly steeper than the dashed line, while for the low-growth firms, we cannot reject the hypothesis that the solid line has the same slope as the dashed one. Since these are separate regressions, we cannot test whether the slopes of these lines are different across these two graphs. Therefore, in Appendix C, we estimate a two-step Heckman selection model, where the first step determines the probability of starting any type of business, and the second step determines the specific type. This approach allows us to test and confirm that the interaction term *GZ spread x GDP growth* is significantly

Figure 6: Comparison of model and empirical predictions



larger for high-growth startups than for the complementary group.

Importantly, the SABI analysis confirmed that these firms have a pattern of employment growth consistent with the pattern we assume in the model, further validating our theoretical framework. We illustrate graphically the correspondence between the model and data in Figure 6, which compares the lines predicted by the model for Type 1 and Type 2 startups and those estimated in the data. Specifically, we choose the values of a for the two lines in the top-left graph such that the relation between the excess cost of finance and low-growth startups in the model coincides with the estimated relation in the top-right graph. Then, in the bottom-left graph, we use the same values of a for the Type 2 startups, and we compare these predictions of the model with the behavior of high-growth startups in the data in the bottom-right graph. The other parameters are those defined for the benchmark calibration described in Section 3.2.2. Comparing the two bottom graphs, we show that the greater sensitivity to the cost of finance of Type 2 startups in the model matches well the greater sensitivity of the high-growth startups in the data.

5.4 Industry-level measures of financial frictions

The previous section shows that high-growth startups are more negatively affected by financial frictions than their complementary startup types. Moreover, this negative differential is amplified during downturns, which is consistent with the predictions of the model. The analysis from SABI data for Spain shows that high-growth startups on average grow faster and employ more people in the longer term than the other startups. Thus, we find support for the prediction that businesses with high growth potential are more difficult to start during a financial crisis.

In this section, we provide additional evidence in support of a causal link from financial frictions to startup decisions. In the model, we assume that Type 1 and Type 2 startups have different patterns of productivity growth but need to finance the same initial investment κ and face the same excess cost of external finance r^b. An alternative approach is to instead select projects that differ in terms of κ and r^b. It is straightforward that Predictions 1-3 can also be extended to these cases. First, a higher value of κ means that startups need higher initial financing and are more affected by changes in r^b. This is the basic intuition behind the Rajan and Zingales (1998) EFD indicator, which measures the fraction of investment needs not covered by internally generated funds. Thus, it is plausible to assume that a high value of the EFD indicator for operating firms in an industry is related to a high value of our parameter κ for the startups in the same industry.

To investigate this hypothesis, in this section, we repeat our estimations considering only starts in the manufacturing sector. We use data on industry-level financial dependence from Kroszner et al. (2007), and we identify the manufacturing startups with low and high external financial dependence (*low EFD* and *high EFD*).

Second, the corporate finance literature has identified the tangibility of assets as a key factor for firms to obtain loans (see, e.g., Almeida and Campello, 2007). More tangible assets have more collateral value, which can be pledged to obtain loans with low excess cost r^b. Therefore, industries with a higher share of intangible assets should have less pledgeable collateral and higher values of r^b. We match the Compustat SIC classification with the 2-digit sectors in the GEM dataset and assign to each GEM sector the intangible capital share computed in Caggese and Perez (2017). We then calculate the median values and classify a sector as having a high (low) intangible share if its value is above (below) the median.

5.4.1 Intangible assets

Table 4: Percentage of individuals starting a firm (sectors with tangibility information)

	All	Low intan.	High intan.
Full	2.07	1.42	0.65
No Fin. crisis	2.42	1.63	0.79
Fin. crisis	1.58	1.13	0.45
% Difference	-34.71	-30.67	-43.04

In this section, we analyze the behavior of startups classified according to the amount of intangible assets. Analogously to Table 1, Table 4 compares the percentages of startups inside and outside the period of the financial crisis but only considers the sectors for which the measure of intangibility is available.[11] The percentage difference between the two periods is very similar to that reported in Table 1 for all startups. When comparing the drop in startups between low- and high-intangible sectors, we see that it is much larger for the latter than for the former, in line with our expectations.

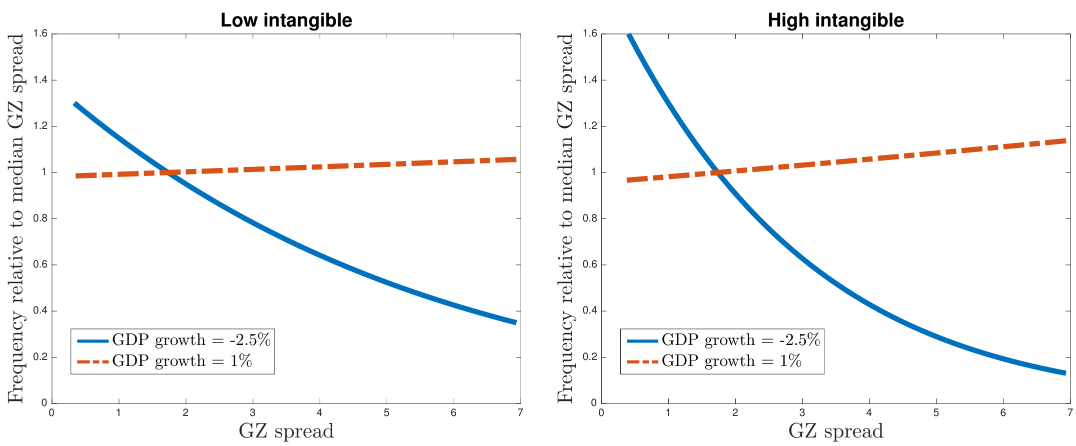
[11]We can classify only a subset of all startups (approximately 54%) because the information on the intangible share is not available for all sectors in the GEM data. We have verified that the main results shown in Table 3 also hold in this subsample.

Table 5: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low intan.	(3) High intan.	(4) All	(5) Low intan.	(6) High intan.
GDP growth	0.637	0.535	0.617	5.520**	4.082***	7.337**
	(0.6258)	(0.5267)	(0.6626)	(2.1986)	(1.5757)	(3.2281)
Fin. crisis	-0.163***	-0.108***	-0.252***			
	(0.0545)	(0.0403)	(0.0858)			
Fin. crisis x GDP growth	4.446**	3.155**	6.663**			
	(1.8791)	(1.5244)	(2.7952)			
GZ spread				-0.020	-0.017	-0.026
				(0.0221)	(0.0155)	(0.0362)
GZ spread x GDP growth				2.660	2.067*	3.415
				(1.7119)	(1.1846)	(2.6825)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.062	0.057	0.063	0.039	0.028	0.053

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure 7: GZ spread and probability of starting a firm in intangible sectors



The first three columns of Table 5 show the regression results of Equation 16. If we distinguish new firms by the degree of intangibility of the assets in their sectors, we find that the financial crisis dummy and the interaction with GDP growth are much larger and more significant for the high-intangible sectors, which is consistent with the predictions of the model. The last three columns and Figure 7 show the results of Equation 17 using the *GZ spread*. Both the table and the figure show that high-intangible firms are more sensitive to financial conditions, especially during downturns, than the complementary sample. However, the interaction coefficient in column 6 is not statistically significant.

5.4.2 External financial dependence

Table 6: Percentage of individuals starting a manufacturing firm

	All	Low EFD	High EFD
Full	0.24	0.14	0.10
No Fin. crisis	0.29	0.17	0.13
Fin. crisis	0.16	0.10	0.06
% Difference	-44.83	-41.18	-53.85

In this section, we analyze the behavior of startups classified according to external financial dependence for the smaller sample of manufacturing startups (approximately 5% of the total). Table 6 shows the percentages of individuals starting manufacturing firms. The decline in the probability of starting any type of manufacturing firm between crisis and non-crisis periods is -45%, whereas the drop is -54% in the high-EFD sectors and -41% in the low-EFD sectors.

Table 7 shows the regression results. We find that the financial crisis dummy and the interaction with GDP growth are much larger and more significant for the high-EFD sectors than for the low-EFD sectors, which is consistent with the predictions of the model. Using the *GZ spread*, we also find large differences between the two categories, in line with the predictions of the model, as confirmed also by Figure 8.

As a final check, we interact the two measures of financial frictions. Since, as argued above, these two classifications are almost completely orthogonal, we should find that the sensitivity to financing conditions is highest for the startups in sectors that are both high intangible and high EFD. Table 8 confirms this.

Table 7: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low EFD	(3) High EFD	(4) All	(5) Low EFD	(6) High EFD
GDP growth	0.463	1.650**	-0.973	5.544**	3.856*	7.181***
	(1.3067)	(0.8264)	(1.7349)	(2.1866)	(2.1633)	(1.7670)
Fin. crisis	-0.163***	-0.089**	-0.240**			
	(0.0605)	(0.0385)	(0.0941)			
Fin. crisis x GDP growth	5.104**	2.672*	7.688**			
	(2.1893)	(1.5425)	(3.3112)			
GZ spread				0.003	-0.016	0.025
				(0.0223)	(0.0194)	(0.0275)
GZ spread x GDP growth				1.407	0.406	2.693***
				(1.5613)	(1.8754)	(0.7913)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.057	0.047	0.067	0.032	0.032	0.032

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure 8: GZ spread and probability of starting a firm in the manufacturing sector

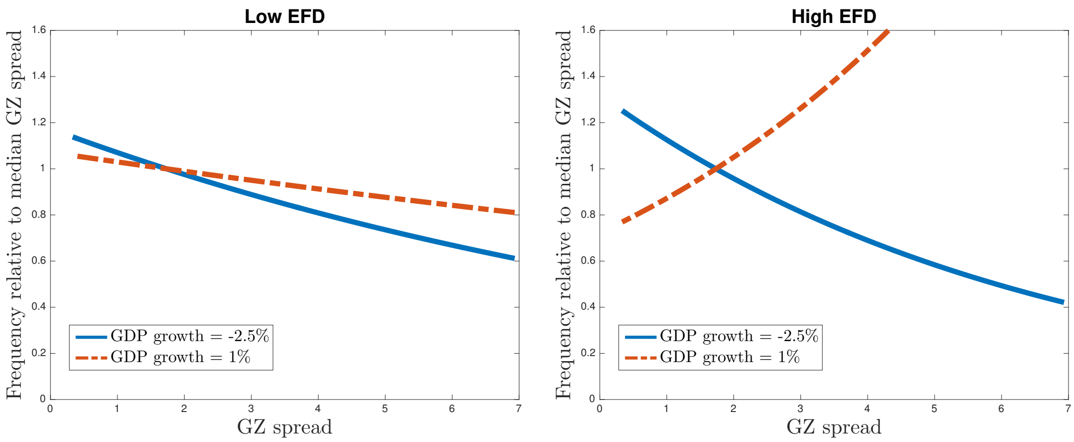


Table 8: GZ spread and probability of starting a firm

	(1) Low intan x low EFD	(2) Low intan x high EFD	(3) High intan x low EFD	(4) High intan x high EFD
GDP growth	7.609**	4.309***	3.160	15.017***
	(2.9628)	(1.2827)	(2.1811)	(3.2694)
GZ spread	-0.053	0.023	-0.017	-0.020
	(0.0511)	(0.0229)	(0.0205)	(0.0708)
GZ spread x GDP growth	6.490**	-0.163	0.040	11.927***
	(3.0995)	(0.5431)	(1.8869)	(1.3701)
Observations	370280	370280	370280	370280
R-squared	0.063	0.027	0.031	0.074

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

6 Robustness checks

In this section, we complement the analysis with additional information from the GEM surveys. We use an alternative measure of financial frictions, and we consider an alternative method to identify high-growth startups.

6.1 Additional control variables

In the previous sections, we found a strong effect of financial conditions on *high-growth* startups, defined as firms with entrepreneurs who expect, in 5 years' time, to become larger than the average firm size in their country/industry. This question on the expected future size of the firm was included by the designers of the survey precisely to attempt to capture startups with high growth potential. However, the answer might contain both subjective growth expectations, driven by the nature of the business started, and the expectations on the future state of the economy. In other words, it is possible that periods of financial crisis, or periods in which the variable *GZ spread* is high, are periods in which potential entrepreneurs expect slow growth in the future, independent of the

Table 9: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.022	0.428	-0.462	4.944*	2.982	6.040**
	(0.6840)	(0.6581)	(0.5036)	(2.9373)	(2.6185)	(2.3887)
Fin. crisis	-0.223***	-0.155***	-0.253***			
	(0.0642)	(0.0465)	(0.0813)			
Fin. crisis x GDP growth	4.959**	3.094*	6.214**			
	(2.4058)	(1.6732)	(3.1500)			
GZ spread				-0.034	-0.020	-0.046*
				(0.0275)	(0.0265)	(0.0257)
GZ spread x GDP growth				2.445	0.721	3.958*
				(2.5180)	(2.1502)	(2.1615)
Opportunity expectations	0.378***	0.308***	0.361***	0.381***	0.312***	0.362***
	(0.0296)	(0.0263)	(0.0307)	(0.0568)	(0.0510)	(0.0516)
Business expertise	0.836***	0.746***	0.767***	0.888***	0.806***	0.803***
	(0.0302)	(0.0352)	(0.0213)	(0.0126)	(0.0181)	(0.0104)
Observations	701734	701734	701734	316450	316450	316450
R-squared	0.148	0.115	0.146	0.139	0.117	0.126

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

nature of their new business. Importantly, our results are already conditional on GDP growth. Therefore, to the extent that the pessimistic expectations are correlated with current growth, which is likely, our estimated effect of financial frictions on high-growth startups is robust to this problem.

We can further check the robustness to this potential problem because the GEM surveys contain a question on expectations of future business opportunities. The exact question is "*In the next six months, will there be good opportunities for starting a business?*", which can be answered with *Yes*, *No* or *Don't know*. We exclude respondents with the answer *Don't know* and include in the analysis the variable *Opportunity expectations*, equal to 1 for *Yes*, 0 otherwise. Although the time horizon of this expectations variable is relatively short, we should expect that, if the results of the *high-growth* startups are entirely driven by future expectations of the economy, they should be at least partially absorbed by the inclusion of this variable.

Tables 9 repeats the analysis in Table 3, after adding the *Opportunity expectations*

Table 10: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.846	1.075*	0.355	5.489***	3.808***	6.395***
	(0.5810)	(0.5637)	(0.4751)	(1.6142)	(1.3408)	(1.4722)
Fin. crisis	-0.165***	-0.109***	-0.204***			
	(0.0478)	(0.0358)	(0.0644)			
Fin. crisis x GDP growth	4.562**	3.064**	5.667**			
	(1.8739)	(1.2947)	(2.6404)			
GZ spread				-0.020	-0.008	-0.034*
				(0.0200)	(0.0195)	(0.0197)
GZ spread x GDP growth				2.468*	1.046	3.762***
				(1.4484)	(1.1228)	(1.4360)
Share of exits	2.638	2.854	1.782	0.426	1.060	0.230
	(2.4544)	(2.0943)	(2.2091)	(4.4940)	(4.7565)	(3.2137)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.062	0.042	0.074	0.039	0.031	0.042

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

variable, as well as the variable *Business expertise*, which is a dummy variable equal to one if the potential entrepreneur has had previous experience running a company.[12] The coefficients of both variables are positive and strongly significant in all specifications. Importantly, their presence does not significantly affect any of the results obtained above. In Table 9, we still find that the stronger negative effect of a financial crisis, and of high bond spreads, is concentrated among the *high-growth* startups. The fact that expectations do not affect the previous results on *high-growth* startups is an important finding, because it supports the validity of this variable in measuring the nature of the new business rather than just general expectations about the economy.

In Table 10, we add as a control variable the share of firm exits for each sector/country/year observation. This variable captures the possibility that new startups are driven by the presence of serial entrepreneurs who seek to start a new business. We find this variable to be generally not statistically significant and not to affect the previous results.

[12]The exact question is "*Do you have the knowledge, skill and experience required to start a new business?*"

Table 11: Financial crisis, GZ spread and probability to start a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.582	0.840	0.106	5.350***	3.620**	6.286***
	(0.6673)	(0.6574)	(0.5131)	(2.0213)	(1.7067)	(1.7724)
Fin. crisis	-0.193***	-0.121***	-0.246***			
	(0.0510)	(0.0367)	(0.0649)			
Fin. crisis x GDP growth	4.756***	3.208**	5.905**			
	(1.8002)	(1.2650)	(2.5440)			
GZ spread				-0.027	-0.013	-0.043**
				(0.0195)	(0.0192)	(0.0193)
GZ spread x GDP growth				2.422	0.972	3.763**
				(1.6770)	(1.2916)	(1.6384)
Middle income	0.093***	0.073***	0.098***	0.158***	0.129***	0.157***
	(0.0333)	(0.0258)	(0.0355)	(0.0234)	(0.0222)	(0.0211)
High income	0.133***	0.053**	0.193***	0.145***	0.092***	0.177***
	(0.0177)	(0.0218)	(0.0207)	(0.0249)	(0.0242)	(0.0301)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.064	0.042	0.078	0.042	0.033	0.046

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

In Table 11, we add income categories (for the definition, see footnote 9). We find that being in a higher income category increases the probability of starting a new firm, but again in this case, the inclusion of these additional control variables does not significantly change the results obtained previously, and if anything, it makes them slightly stronger.

6.2 Alternative indicator of financial frictions

Table 12 and Figure 9 replicate the last three columns of Table 3 and Figure 5. They use, as an alternative measure of financial frictions, the financial distress indicator of Romer and Romer (2017). As argued above, the RR indicator is explicitly designed to capture both high bond spreads and other factors of financial distress that might be important for new firms' access to finance, and it is available for our full sample.[13] The results show that the predictions of the model are fully confirmed with this alternative measure.

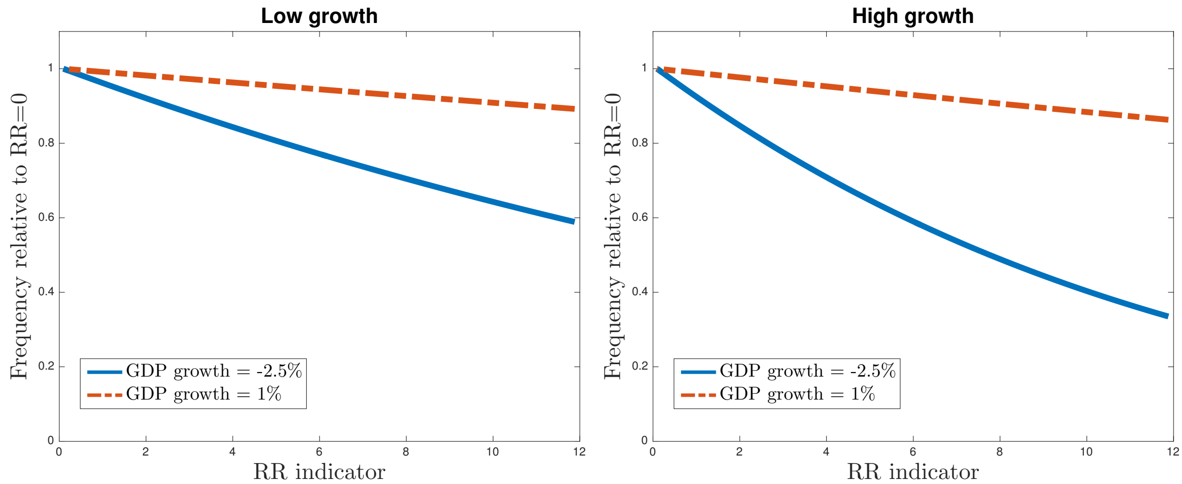
[13] As this indicator is mostly zero outside the period of the financial crisis, its median in the data is zero, and thus Figure 9 shows the predicted frequency of startups relative to the frequency that is predicted when the indicator is equal to zero

Table 12: Romer and Romer financial distress indicator and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth
GDP growth	2.812**	2.266**	2.968*
	(1.4047)	(1.0222)	(1.6174)
RR indicator	-0.012	-0.009	-0.014*
	(0.0088)	(0.0089)	(0.0081)
RR indicator x GDP growth	0.667**	0.427*	0.880*
	(0.3384)	(0.2505)	(0.4633)
Observations	731881	731881	731881
R-squared	0.043	0.036	0.044

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure 9: RR indicator and probability of starting a firm



6.3 Alternative classification of startups

In this subsection, we consider an alternative classification of startups. We use additional survey questions from the GEM to identify entrepreneurs who plan to offer a product or service considered new by the potential customers and/or embodies new technologies. These startups, which we call *innovative*, might grow faster in the long run because new products or services have the potential to capture larger market shares.[14] However, these

[14] We classify a startup as innovative if an entrepreneur responds "Yes" to the question "Will/do all, some, or none of your potential customers consider this product or service new and unfamiliar?" and

Table 13: Financial crisis, GZ spread, RR indicator and probability of starting a firm

	(1) Not inn	(2) Inn	(3) Not inn	(4) Inn	(5) Not inn	(6) Inn
GDP growth	1.009*	-0.094	4.892***	5.274***	2.718**	2.300*
	(0.5543)	(0.6750)	(1.8046)	(1.9308)	(1.2650)	(1.3715)
Fin. crisis	-0.140**	-0.156***				
	(0.0624)	(0.0349)				
Fin. crisis x GDP growth	4.095**	4.552***				
	(1.8890)	(1.2877)				
GZ spread			-0.030	0.010		
			(0.0199)	(0.0241)		
GZ spread x GDP growth			2.042	2.829**		
			(1.6368)	(1.1941)		
RR indicator					-0.010	-0.012
					(0.0083)	(0.0137)
RR indicator x GDP growth					0.542	0.793***
					(0.3498)	(0.2464)
Observations	894126	894126	370280	370280	731881	731881
R-squared	0.046	0.087	0.038	0.028	0.040	0.036

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

firms supplying novel products are also likely to be associated with higher risk and are thus additionally affected by fluctuations in risk premia, which are not captured by our model. Nevertheless, we expect similar results as in our baseline classification because in most countries risk premia increased during the period of the financial crisis and the financing of innovative and potentially risky projects became more difficult.

Table 13 shows the regression results for the two complementary subgroups of not innovative and innovative startups. The results obtained using the previous classification of low- and high-growth startups are fully confirmed, regardless of the indicator of financial frictions used. The effect of the interaction term is always significant and larger for innovative than for non-innovative startups.

"Less than a year" to the question "How long have the technologies or procedures required for this product or service been available?".

6.4 Additional robustness checks

In Table 16 in Appendix C, we replicate all the regressions after excluding the countries that did not experience a systemic banking crisis (according to Laeven and Valencia 2013). Thus, the crisis dummy is identified by comparing the crisis period with the pre-crisis period only for countries that experienced the crisis. In Table 17, we exclude the construction sector. We do this because in most countries, the collapse of this sector caused the banking crisis, rather than vice versa. Both of these robustness checks confirm the results shown above. In Table 18, we exclude startups that have already paid some wages and thus might have been established before, and once again we confirm the previous results.

In Table 19, we estimate the baseline model when additionally including year fixed effects, which control for any time-varying factor common to all countries. As expected, the financial crisis dummy becomes insignificant, being a common shock to almost all countries in our dataset. Nonetheless, the main results regarding the interaction between financial frictions and GDP growth are confirmed.

In Table 20, we replace the financial crisis indicator with an indicator for the Great Recession. This is a dummy equal to one if a country suffered two subsequent quarters with negative economic growth during the period 2008-2010. We find that the interaction term is strongly significant and larger for high-growth startups. This finding implies that these startups declined more during the great recession in countries that experienced a larger contraction in GDP during that period.

In Table 21, we estimate a two-step Heckman selection model. The first-stage selection equation determines the probability of starting a business and includes, in addition to GDP growth, the indicator for financial frictions, and their interaction; it also includes the additional control variables of sex, education, age and country dummies. The second-stage equation estimates the effects of GDP growth and financial frictions on the type of business created. This specification allows us to disentangle the effect of demographics on the likelihood of opening a business from the effect of financial conditions on starting a business with high growth potential. The results of the second stage shown in the table confirm that startups with high growth potential are less frequent during a financial crisis and are significantly more sensitive to financing conditions than are the other startups.

In Table 22, we include the country-specific riskless interest rate and its interaction with GDP growth as regressors.[15] In the model, we abstract from movements in the riskless interest rate. However, it is possible that movements in the GZ spread are correlated with movements in the interest rate. The table shows that the riskless rate generally has a positive relation with startups, probably because empirically it is a leading indicator of the business cycle. Its interaction with GDP growth is negative and significant for high-growth startups in column 6. The magnitude of the estimated coefficients implies that riskless rates are always positively correlated with high-growth startups but more so during downturns than during upturns. Importantly, our main results are confirmed, as the coefficients of the interaction between the GZ spread and GDP growth become somewhat larger in absolute value and gain significance compared to our baseline estimation in Table 3.

7 Conclusion

This paper studies whether financial frictions affect startups with high growth potential differentially. Our stylized model predicts that, at the margin, a high-growth-potential startup is less profitable in the short term and more profitable in the long term. We use the survey-level information from the GEM dataset to identify high-growth startups in the data. For the case of Spain, which has very extensive coverage in the GEM dataset, we use firm-level data from SABI to confirm that high-growth startups are more likely to grow faster and employ more people in the longer term than are other startups. The model predicts that high-growth startups are more negatively affected by increases in the cost of external finance, especially when GDP growth is low, and our empirical results confirm

[15]We obtain the series of 3-month nominal interest rates (computed by the OECD using either treasury bills or money market rates), and we subtract the inflation rates to obtain the real rates.

these predictions. Importantly, we find additional evidence consistent with a financial accelerator story. Access to finance matters especially for startups in sectors with a high share of intangible assets and in sectors with high dependence on external financing. Taken together, our results support the view that this *composition of entry* channel is important to explain slow recoveries after financial crises. The policy implication of our analysis is that credit subsidies specifically targeted at high-growth startups should be effective in countering the negative long-term effects of financial crises.

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Appendix

A Derivations of value functions

Using as the discount factor the interest rate on lending (equal to zero), the value of a newly created Type 1 firm (gross of the start-up costs C^1 and κ) is equal to:

$$V^1(\theta_t) = (1-d)[\pi(\theta_t) + V^1((1+g^{med})\theta_t)] \tag{18}$$

where $\theta_{t+1} = (1+g^{med})\theta_t$. Using Equation 5 and substituting recursively yields:

$$\begin{aligned} V^1(\theta_0) &= (1-d)\Psi\left[\theta_0 + \frac{1}{1+\rho}\theta_0(1+g^{med}) + \frac{1}{(1+\rho)^2}\theta_0(1+g^{med})^2 + ...\right] \\ &= \Psi\frac{\theta_0}{\frac{d}{1-d} - g^{med}} = (1-d)\Psi\frac{\theta_0}{d-(1-d)\,g^{med}} \end{aligned}$$

The value of a Type 2 firm that switched permanently to high growth is:

$$V^{high}(\theta_t) = (1-d)\Psi\frac{\theta_t}{d-(1-d)\,g^{high}} \tag{19}$$

To compute the initial value, assume that with probability $1-\gamma$, the firm continues to grow at rate g^{low}, so that $\theta_{t+1} = (1+g^{low})\theta_t$, while with probability γ, it switches permanently to high growth, and its value becomes that determined in 19. Therefore, the initial value is:

$$V^2(\theta_0) = (1-d)\Psi\left[(1-\gamma)\theta_0 + \gamma\frac{\theta_0}{d-(1-d)\,g^{high}} + ...\right] \tag{20}$$

rearranging yields:

$$V^2(\theta_0) = (1-d)\Psi\Phi \left\{ \begin{array}{c} \theta_0 + (1-\gamma)(1-d)(1+g^{low})\theta_0 \\ + \left[(1-\gamma)(1-d)(1+g^{low})\right]^2 \theta_0 + ... \end{array} \right\} \tag{21}$$

$$\Phi \equiv (1-\gamma) + \frac{\gamma}{d-(1-d)\,g^{high}} \tag{22}$$

Solving recursively yields:

$$\begin{aligned} V^2(\theta_0) &= (1-d)\Psi\Phi(1-\gamma)(1-d)\frac{\theta_0}{\frac{1-(1-\gamma)(1-d)}{(1-\gamma)(1-d)} - g^{low}} \\ &= (1-d)\Psi\Phi\frac{\theta_0}{1-(1-\gamma)(1-d)\left(1+g^{low}\right)} \end{aligned}$$

A.1 Calculation of C^2

In the first period, the firm pays excess return $r^b b_0$. The residual debt is $b_1 = \left(1+r^b\right) b_0 - \Psi\theta_0$. In the second period, with probability γ, the firm switches to high growth, so that $\pi_1 = \Psi\theta_0\left(1+g^{high}\right)$, and the residual cost is $C(b_1, g^{high}, \pi_1)$. With probability $(1-\gamma)$, the firm remains low growth and pays excess return $r^b b_1$, so that $b_2 = \left(1+r^b\right) b_1 - \pi_1^{low}$, where in this case $\pi_1^{low} = \Psi\theta_0\left(1+g^{low}\right)$. Substituting recursively, this yields:

$$C^2 = \sum_{t=0} \left[(1-d)(1-\gamma)\right]^t r^b b_t + \frac{\gamma}{1-\gamma}\sum_{t=1} \left[(1-d)(1-\gamma)\right]^t C(b_t, g^{high}, \pi_t) \tag{23}$$

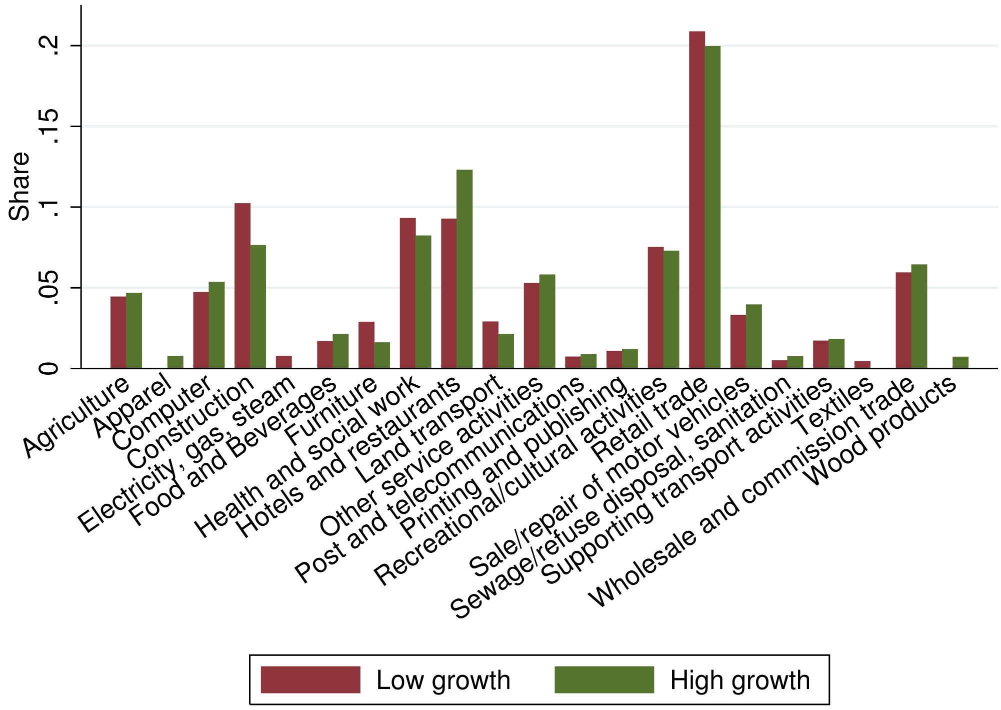
B Data and variable definitions

B.1 Business types identified from GEM questions

High-growth startups

To classify a startup as having high growth potential, we refer to the following two questions:

Figure 10: Distribution across 2-digit sectors



Notes: The figure shows the sector shares of startups in the 21 most common sectors, which account for approximately 94% of all startups, separately for the low-growth and high-growth categories.

1. "Right now how many people, not counting the owners but including exclusive subcontractors, are working for this business?"

2. "How many people will be working for this business, not counting the owners but including all exclusive sub-contractors, when it is five years old?"

We compute the average size of established firms by sector (at the 2-digit level) and country using the answer to the first question given by respondents that are currently owners of established firms. We then classify a startup with a high growth potential as one for which the answer to the second question, i.e., the expected size in five years, exceeds the average size of firms in the same sector and country.

B.2 Business cycle data

We take yearly GDP per capita data from the Penn World Tables. We compute yearly GDP growth as the percentage change in expenditure-side real GDP in chained PPP values.

B.3 Financial crisis data

We identify years in which a particular country is in a financial crisis by using data on systemic banking crises from Laeven and Valencia (2013). The following table shows the countries in our sample, the corresponding crisis period and the number of observations.

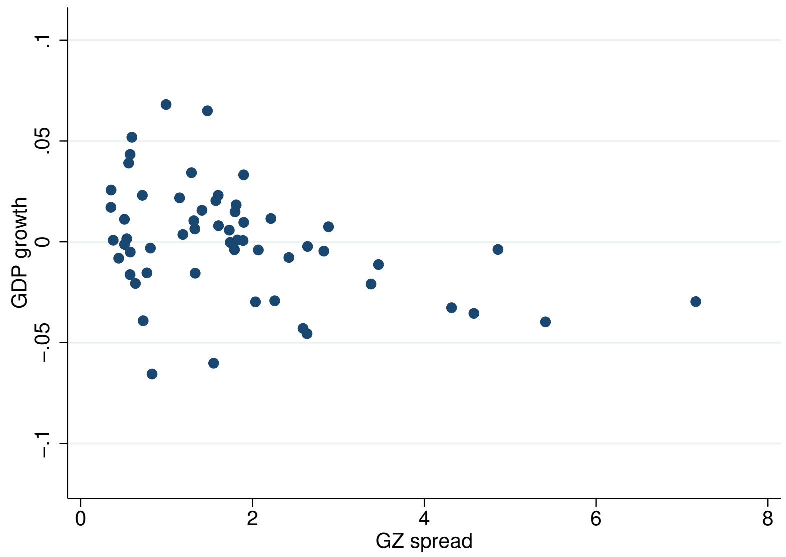
Table 14: Countries and financial crisis years

Country	Start year	End year	Obs.
Belgium	2008	2013	29995
Chile	-	-	36306
Croatia	-	-	22377
Denmark	2008	2013	28183
Finland	-	-	22231
France	2008	2013	23089
Germany	2008	2013	67619
Greece	2008	2013	20430
Hungary	2008	2013	22029
Iceland	2008	2013	16477
Ireland	2008	2013	20601
Italy	2008	2013	24572
Japan	-	-	22042
Netherlands	2008	2013	39500
Norway	-	-	22016
Slovenia	2008	2013	28865
Spain	2008	2013	233625
Sweden	2008	2013	45298
Switzerland	2008	2013	21079
United Kingdom	2007	2013	187967
United States	2007	2013	50589

Notes: The periods are systemic banking crises taken from Laeven and Valencia (2013)

B.4 GZ bond spread

Figure 11: Correlation between GDP growth (deviation from country average) and bond spread



As a proxy for the financing costs of firms r^b at the country-year level, we rely on the excess bond premium for financial firms from Gilchrist and Zakrajsek (2012), who measure the bond premium with respect to the yields of 10-year US government bonds. We make our index comparable across countries by measuring the premiums of all countries with respect to the German bund. For the US, we take the domestic spread directly from Gilchrist and Zakrajsek (2012)[16] and add the spread between US and German government bonds.[17] For France, Spain, Italy and Germany, we take the data from Gilchrist and Mojon (2018), who calculate the spread at individual bond level and aggregate it.[18] We finally compute the yearly means of the monthly data.

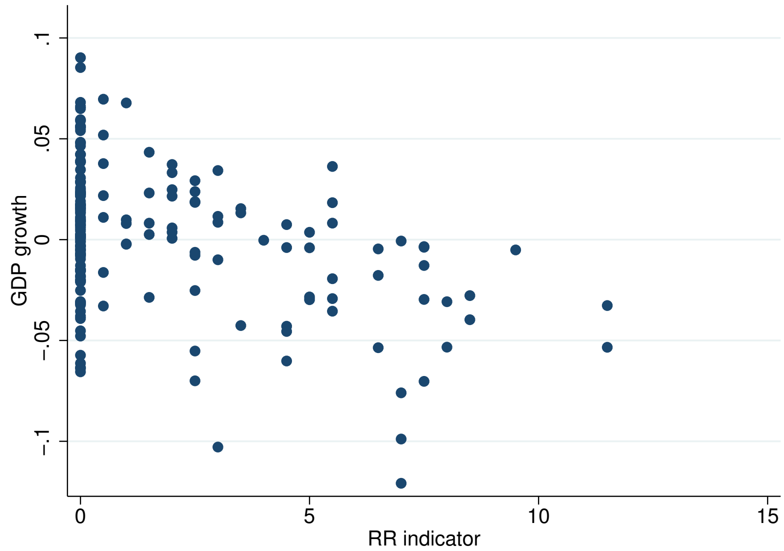
[16]Data are available at `http://people.bu.edu/sgilchri/Data/data.htm`

[17]Retrieved from `https://fred.stlouisfed.org/series/IRLTLT01USM156N`

[18]Data are available at `https://publications.banque-france.fr/en/economic-and-financial-publications-working-papers/credit-risk-euro-area`

B.5 Romer & Romer indicator

Figure 12: Correlation between GDP growth (deviation from country average) and RR indicator



Romer and Romer (2017) develop a measure of financial distress for 24 advanced countries based on qualitative information from the OECD Economic Outlook reports, which have been published by the OECD for individual countries since 1967. The indicator ranges from 0 to 14 and covers all countries in our sample until 2012 except Hungary, Chile, Croatia and Slovenia. The aim of this measure is to capture the "cost of credit intermediation", i.e., the costs of obtaining funds for financial institutions (relative to the riskless rate) and the costs of screening, monitoring and administering loans to borrowers. This makes it a suitable indicator for the spread between the lending rate and the riskless rate, represented by r^b in our model.

B.6 Financial dependence and intangibility data

We match the values for external dependence (1980-1999) from Table 12 of Kroszner et al. (2007) to the 22 manufacturing sectors identified in the GEM dataset. For the sectors that we can match across the Compustat SIC classification and the 2-digit sectors in the

Table 15: External financial dependence, intangible asset share and startups by sector

Sector	Name	EFD	Intangible	# start-ups	% high growth
1	Agriculture and hunting	-	low	951	47.4
2	Forestry, logging and related service activities	-	-	76	40.9
5	Fishing	-	-	67	27.8
14	Other mining and quarrying	-	-	48	43.2
15	Food and Beverages	high	low	442	52.2
17	Textiles	high	high	90	50.2
18	Apparel	-	-	113	68.4
19	Leather	low	low	24	28.4
20	Wood products	high	low	124	58.1
21	Paper products	low	low	12	0
22	Printing and publishing	low	high	243	48.8
23	Petroleum and coal	high	low	10	0
24	Other chemical products	low	high	83	45.9
25	Rubber and plastic products	high	low	16	22.4
26	Non-metal products	low	low	67	57.8
27	Iron and steel	high	low	55	34.3
28	Metal products	low	high	88	55.6
29	Machinery	high	high	81	48.5
30	Office and computing	high	high	16	20.6
31	Electrical machinery	high	high	41	40.0
32	Radio	high	high	17	24.9
33	Professional equipment	high	high	29	53.0
34	Motover vehicles, trailers	low	low	48	43.1
35	Other transport equipment	low	high	23	45.2
36	Furniture	low	high	506	32.4
37	Recycling	-	high	25	22.8
40	Electricity, gas, steam	-	-	166	43.3
41	Collection, purification and distribution of water	-	-	12	21.8
45	Construction	-	high	1773	39.1
50	Sale, maintenance, repair of motor vehicles	-	low	769	50.6
51	Wholesale and commission trade	-	high	1280	48.2
52	Retail trade	-	low	4305	45.2
55	Hotels and restaurants	-	low	1925	53.0
60	Land transport; transport via pipelines	-	-	520	37.5
61	Water transport	-	-	15	68.0
63	Supporting and auxiliary transport activities	-	-	382	47.0
64	Post and telecommunications	-	-	188	49.9
71	Renting of machinery and equipment	-	high	85	54.1
72	Computer and related activities	-	high	1063	49.2
73	Research and development	-	high	87	51.6
85	Health and social work	-	low	2071	44.6
90	Sewage and refuse disposal, sanitation	-	-	122	54.7
91	Activities of membership organizations n.e.c.	-	-	61	45.6
92	Recreational, cultural and sporting activities	-	low	1459	46.2
93	Other service activities	-	-	1144	48.8
95	Activities of private households as employers of domestic staff	-	-	31	50.8

Notes: External financial dependence based on Kroszner et al. (2007) and intangible share based on Caggese and Perez (2017).

GEM dataset, we take the intangible capital share from Caggese and Perez (2017). We then calculate the median values for both measures and classify a sector as having high (low) external dependence or intangible share if its value is above (below) the median.

C Additional robustness checks

Baseline results excluding countries without financial crisis

Table 16: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	1.163**	1.383**	0.561	5.447***	3.711**	6.371***
	(0.5501)	(0.6068)	(0.4065)	(1.9928)	(1.6903)	(1.7418)
Fin. crisis	-0.138***	-0.083**	-0.185***			
	(0.0392)	(0.0340)	(0.0563)			
Fin. crisis x GDP growth	4.096***	2.627**	5.339**			
	(1.5200)	(1.1212)	(2.3059)			
GZ spread				-0.020	-0.008	-0.034*
				(0.0197)	(0.0189)	(0.0198)
GZ spread x GDP growth				2.450	1.011	3.751**
				(1.6126)	(1.2510)	(1.5612)
Observations	800019	800019	800019	370280	370280	370280
R-squared	0.042	0.035	0.044	0.039	0.031	0.042

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Baseline results excluding construction sector

Table 17: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.689	0.952	0.197	4.979***	3.115**	6.147***
	(0.7050)	(0.7052)	(0.5305)	(1.8103)	(1.5214)	(1.5445)
Fin. crisis	-0.152***	-0.088**	-0.202***			
	(0.0490)	(0.0388)	(0.0659)			
Fin. crisis x GDP growth	4.203***	2.581**	5.561**			
	(1.6229)	(1.1804)	(2.3887)			
GZ spread				-0.018	-0.005	-0.035*
				(0.0184)	(0.0185)	(0.0179)
GZ spread x GDP growth				2.076	0.501	3.617***
				(1.3994)	(1.0407)	(1.3307)
Observations	891932	891932	891932	369436	369436	369436
R-squared	0.060	0.041	0.073	0.035	0.027	0.040

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Baseline results excluding startups that have paid wages

Table 18: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.458	0.724	0.015	2.757**	1.807*	3.510***
	(0.4883)	(0.5713)	(0.3072)	(1.0722)	(1.0464)	(0.7802)
Fin. crisis	-0.094***	-0.056	-0.127***			
	(0.0311)	(0.0348)	(0.0415)			
Fin. crisis x GDP growth	2.974***	2.093**	3.616***			
	(0.9589)	(1.0566)	(1.0963)			
GZ spread				-0.015	-0.004	-0.029**
				(0.0126)	(0.0141)	(0.0130)
GZ spread x GDP growth				1.088	0.095	2.296***
				(0.8799)	(0.7842)	(0.7583)
Observations	888862	888862	888862	367460	367460	367460
R-squared	0.054	0.037	0.067	0.029	0.025	0.028

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Baseline results with year fixed effects

Table 19: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	0.855	1.057*	0.399	2.757***	1.327***	3.857***
	(0.6419)	(0.5816)	(0.5565)	(0.7804)	(0.4002)	(1.0825)
Fin. crisis	-0.120	-0.064	-0.172			
	(0.1110)	(0.0989)	(0.1049)			
Fin. crisis x GDP growth	3.005***	1.862**	3.970***			
	(1.0741)	(0.8580)	(1.4319)			
GZ spread				-0.022	-0.018	-0.028***
				(0.0157)	(0.0194)	(0.0101)
GZ spread x GDP growth				1.652**	0.513	2.785**
				(0.7490)	(0.4240)	(1.1274)
Observations	894126	894126	894126	370280	370280	370280
R-squared	0.065	0.044	0.078	0.049	0.037	0.054

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Results with dummy for Great Recession

Table 20: Great Recession and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth
GDP growth	2.006	1.740*	1.828
	(1.4180)	(1.0438)	(1.5625)
Great Recession	0.039	0.024	0.045
	(0.0948)	(0.0724)	(0.0999)
GR x GDP growth	3.949***	3.211**	4.131***
	(1.3555)	(1.2721)	(1.3530)
Observations	894126	894126	894126
R-squared	0.061	0.041	0.072

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Heckman selection model

Table 21: Financial crisis, GZ spread, RR indicator and probability of starting a firm

	(1)	(2)	(3)
GDP growth	-0.533*	3.023***	0.239
	(0.2813)	(0.9615)	(0.3904)
Fin. crisis	-0.090***		
	(0.0260)		
Fin. crisis x GDP growth	2.172***		
	(0.7201)		
GZ spread		-0.038**	
		(0.0191)	
GZ spread x GDP growth		3.144***	
		(0.7037)	
RR indicator			-0.007
			(0.0052)
RR indicator x GDP growth			0.373***
			(0.1323)
Observations	894126	370280	731881

Notes: The first-stage selection equation for starting a business includes sex, education, age and country dummies. The second-stage equation for starting a high-growth business includes country dummies in addition to the reported variables.

Baseline results including riskless interest rate

Table 22: Financial crisis, GZ spread and probability of starting a firm

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	1.303**	1.541***	0.637	6.221***	4.159***	7.449***
	(0.5113)	(0.4995)	(0.5119)	(1.8901)	(1.4521)	(1.9492)
Fin. crisis	-0.111**	-0.055	-0.165***			
	(0.0442)	(0.0345)	(0.0636)			
Fin. crisis x GDP growth	3.882**	2.393**	5.234**			
	(1.6439)	(1.1046)	(2.5061)			
GZ spread				0.014	0.017	0.003
				(0.0178)	(0.0183)	(0.0186)
GZ spread x GDP growth				2.593**	1.134	3.935***
				(1.2518)	(0.8050)	(1.4910)
Riskless interest rate	0.039***	0.033***	0.038**	0.075***	0.062***	0.071***
	(0.0126)	(0.0093)	(0.0158)	(0.0048)	(0.0104)	(0.0057)
RIR x GDP growth	-0.201	-0.235	-0.114	-0.861*	-0.404	-1.229***
	(0.2497)	(0.1821)	(0.3275)	(0.4673)	(0.4690)	(0.3751)
Observations	816895	816895	816895	370280	370280	370280
R-squared	0.043	0.036	0.045	0.041	0.033	0.044

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Controls include dummies for three education levels, sex, age and country fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.