Universitat Pompeu Fabra Barcelona
Department of Economics and Business

Economics Working Paper Series

Working Paper No. 1739

The short- and long-run employment impact of Covid-19 through the effects of real and financial shocks on new firms

Christoph Albert, Andrea Caggese,
and Beatriz González

August 2020

The Short- and Long-run Employment Impact of Covid-19 through the Effects of Real and Financial Shocks on New Firms

Christoph Albert[1], Andrea Caggese[2], and Beatriz González*[3]

[1] *CEMFI*

[2] *UPF, CREI and Barcelona GSE*

[3] *Banco de España*

14th August 2020

Abstract

The aim of this paper is 1) to use empirical evidence to make predictions about the impact of the Covid-19 shock on firm entry, its composition, and its short- and long-run impact on employment; and 2) to provide guidance on which policy tool would be more effective to counteract the negative impact of the shock on this margin. The Covid-19 shock caused a large GDP contraction and our predictions suggest that this would cause a reduction in firm entry that ranges from 60% in Germany to 80% in Spain. Moreover, if this collapse of GDP is also accompanied by an even moderate increase in financial frictions, this shock also reduces the share of high-growth firms among the new startups, implying substantially larger negative long-term consequences for the employment generated by the entering cohort. Our estimates for Spain predict employment losses of the entering cohort of nearly 80,000 jobs for 2021, which increase up to almost 115,000 in 2029. Finally, using a simple partial equilibrium model calibrated to match the empirical evidence, we show that a subsidy to initial financing costs is more effective to increase aggregate employment of the entering cohort in the long run than a wage subsidy, which is more effective in the short run only.

JEL: E20, E32, D22, J23, M13

Keywords: Recessions, Financial Crisis, Entrepreneurship, firm dynamics, Coronavirus, Covid-19

*E-mail: christoph.albert@cemfi.es, andrea.caggese@upf.edu, beatrizgonzalez@bde.es
Corresponding author: Christoph Albert, Calle Casado del Alisal 5, 28014, Madrid, Spain, Tel. +34 935422395.
Andrea Caggese acknowledges financial support from the Spanish Ministry of Economy and Competitiveness, through the AEI-FEDER project UE-ECO2017-82596-P, the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2015-0563) and a La Caixa Research Grant.

1 Introduction

The Covid-19 pandemic has caused a massive recession worldwide, with a predicted GDP contraction in the four largest EU economies in 2020 that ranges from -7.8% in Germany to -12.8% in Italy and Spain (see Figure 1, Panel A). Another consequence of this unexpected shock is a worsening of financial conditions. Figure 1, Panel B, shows that the country level index of financial stress (CLIFS) had very high levels in April and May 2020, reached in the past only during financial crisis episodes. In this context, proper economic policies are key to cushion the current fall in GDP and to stimulate a quick economic recovery in the short and medium run. With large amounts pledged to reach this goal, an ex-ante evaluation of the efficacy of alternative policies is important.[1]

In this paper, we estimate the effects of the Covid-19 shock on firm entry and the composition of new firms in terms of growth potential. We then use a stylized partial equilibrium model of firm entry based on Albert and Caggese (2020) to evaluate the short- and long-run job creation potential of alternative policies to stimulate business creation. It is important to understand the impact of the current crisis on firm entry because this margin plays a key role for employment creation, and a drop in entry due to a recession can have persistently negative consequences for employment growth (e.g. see Haltiwanger et al. (2016), and Sedláček (2020)). Furthermore, there is evidence that high-growth firms are especially penalized during periods of low GDP growth and higher-than-average financial stress (Albert and Caggese (2020)). Early evidence from the current recession shows that indeed entry is collapsing (e.g. see Haltiwanger et al. (2016) for the US). The most recent data for Spain indicates a 75% decline in firm entry in May 2020 and a 15% decline in June (relative to 2019), even after the strictest lockdown measures were lifted.

Firstly, we quantify for the four main EU economies the expected effect of the Covid-19 shock both on overall firm entry (the extensive margin) and on the growth potential of new firms (the intensive margin). For Spain, we also estimate the short- and long-run implications for aggregate employment creation caused by these two margins. Our results highlight that

[1]For example, some economic commentators and researches worry that too large subsidies to incumbent firms might create "zombie" firms (inefficient firms kept alive by excessively cheap credit) and slow down the economic recovery (e.g. see Zoller-Rydzek and Keller (2020)).

the two shock dimensions, the predicted large contraction in GDP and the moderate increase in financial frictions, strongly interact. A large drop in GDP alone reduces firm entry, but it does not significantly affect the share of high-growth firms, limiting the long-term employment consequences reduced firm entry. Instead, a large GDP contraction accompanied by even a relatively small increase in financial frictions strongly reduces the share of high-growth firms among the new startups, implying much larger negative long-term consequences.

Secondly, we set up a partial equilibrium model of the entry and growth of new businesses and implement an exogenous shock to demand and financial conditions to replicate the potential effects of Covid-19 on firm entry. We consider alternative policies and evaluate their ability to mitigate the fall in firm entry and, in particular, stimulate the entry of high-growth firms. Finally, we quantify the expected medium- and long-run effects on employment. The exogenous Covid-19 shock causes a drop of more than 80% in the employment of the entering cohort of firms during the first year relative to the counterfactual with no shock, and the employment losses persist even after 20 years. The two alternative policies we analyze are a wage subsidy staying in place during the first years after the shock and a one-time financing subsidy to entry cost. We find that the wage subsidy is more effective in the short-term whereas the financing subsidy increases employment more in the long-term. This is because the former is more beneficial for low-growth firms, while the latter is more beneficial for high-growth firms, which are initially smaller but grow faster.

We believe that these results are useful to inform policymakers. The US and the EU have pledged large government budgets for countering the economic effects of the pandemic, and it is important to identify the most efficient ways to use these funds not only to help firms and households in the current crisis but also to ensure a faster recovery. Our preliminary results emphasize the importance of supporting the access to finance for entrepreneurs, especially in countries with higher levels of financial distress.

This paper is organized as follows. Section 2 outlines the related literature. Section 3 describes the empirical analysis, Section 4 describes the model and policy evaluation. Section 5 concludes.

2 Related Literature

First, our paper relates to a growing strand of literature trying to assess the impact of the Covid-19 shock on firms. Hassan et al. (2020) find that the primary concerns for large businesses after the Covid-19 shock relate to the collapse of demand, increased uncertainty, and disruption in supply chains, while Bartik et al. (2020) find that many US small business are financially fragile, and 37% of them expect to close by the end of the year. In this line, many researchers and central bankers are analyzing carefully the liquidity needs of firms entering in distress during this crisis (see for instance Schivardi and Romano (2020)). Fairlie (2020) find that the number of active business owners in the US plummeted by 22% over the window from February to April 2020. While these papers focus on the impact of Covid-19 on incumbent firms, we focus on the impact of the Covid-19 shock on potential entrants and employment.

Second, this paper is related to the literature studying the role new firms play for employment creation, emphasizing how startups are very heterogeneous both cross-sectionally and over time (e.g. see Haltiwanger et al. (2016) and Pugsley et al. (2018)). Also related to the Covid-19 pandemic, Sedlacek and Sterk (2020) propose a "Startup Calculator", which estimates short- and long-term employment losses under different assumptions on firm entry and exit rates and growth rates of new businesses. They focus on how these three different margins matter for the long-term implications of the current drop in firm entry. Our work is complementary to theirs, since we quantify how one specific channel of the Covid-19 (drop in GDP and exogenous financial shocks) is predicted to affect the entry rates and the growth potential of new businesses, and we evaluate the effectiveness of alternative policies to stimulate firm entry and employment growth.

3 Empirical Analysis

In our empirical analysis, first, we use data from a large multi-country entrepreneurship dataset to estimate the effects of business cycle conditions and exogenous credit shocks on the decisions to start businesses with heterogeneous growth potential. Second, we use firm-level data to estimate the implications of the startup decisions for long-run job growth. Third, we combine our findings in the two previous steps to predict the effects of the Covid-19 shocks on firm entry and subsequent employment growth of these new firms.

3.1 The Covid-19 economic shock

Current forecasts predict a GDP contraction in 2020 in the EU of historical proportions due to the Covid-19 pandemic (see Figure 1, Panel A). Despite largely supportive monetary policy measures, these dire economic conditions also caused an increase in financial frictions. This is shown in Figure 1, Panel B, which plots the corporate bond spreads computed by Gilchrist and Mojon (2016) using the methodology in Gilchrist and Zakrajsek (2012) (hence we denote them as "GZ" spreads) for each country over the time period from January 1990 to May 2020. For comparison, we also plot the broader CLIFS provided by the ECB, which takes into account equity, bond and foreign exchange markets (Duprey et al. (2017)). The figures show several spikes in both measures during crisis periods. In spring 2020, there has been an increase in financial stress in all four economies, not witnessed at least since the 2010-2012 crisis.

3.2 Cyclical conditions, shocks and entry into entrepreneurship

In this section, we estimate the effect of the Covid-19 shock (characterized by a sharp decline in GDP growth and increase in the cost of credit) on the probability to start heterogeneous business types. We identify heterogeneous startup decisions using the Global Entrepreneurship Monitor (GEM), the most comprehensive cross-country entrepreneurial survey available (Reynolds and Hechavarria (2016)). The GEM includes yearly surveys of random samples of adult individuals from over 100 countries for the period 2002-2016.[2]

We restrict the sample of our analysis to France, Germany, Italy and Spain, for which the GZ spread is available and which are the four largest economies in the EU, accounting for 64% of the EU GDP in 2019.[3] Furthermore, for Spain, the country with the most extensive coverage in the GEM, we can link the GEM dataset with firm level data at the industry level, allowing us to compute the long-run employment effects of firm creation.[4]

Following Albert and Caggese (2020), we identify nascent entrepreneurs as those that were actively involved in starting a new business during the last twelve months and personally own at least a part of this business. Further, we follow their approach to classify startups by using

[2]The representativeness of this sample is confirmed by Poschke (2018), who shows that the firm size distribution in the GEM matches well that obtained from administrative data sources.

[3]We calculate this percentage excluding the UK, which left the EU in January 2020. Source: Eurostat

[4]Of the 420,000 observations in the sample, almost 300,000 are from Spain only. The sample size for France, Germany and Italy are around 21k, 72k, and 29k, respectively.

the expected number of employees of the firm five years into the future reported by nascent entrepreneurs. Around 2.1% of the respondents in the sample are nascent entrepreneurs and 31% of them fall in the category of high-growth startups.[5]

We create a set of dummies $start^s_{i,j,t}$ indicating that individual i in country j in year t is starting a firm of type $s \in (a, h, l)$, where a indicates all startups and h and l startups with high and low growth potential, respectively. We use $start^s_{i,j,t}$ as dependent variable in the following Probit model:

$$Pr(start^s_{i,j,t} = 1|X_{i,j,t}) = \Phi(\beta^s_0 + \beta^s_1 bus_{j,t} + \beta^s_2 spread_{j,t} + \beta^s_3 bus_{j,t} \cdot spread_{j,t} + \sum_{k=0}^{K} \gamma^s_k X^k_{i,j,t} + \varepsilon_{i,j,t}). \quad (1)$$

Our two main explanatory variables are GDP growth and an index of credit availability. More specifically, the variable $bus_{j,t}$ is real GDP growth in terms of purchasing power parity in country j at time t. We take this as a summary indicator of all the cyclical conditions that might affect startup decisions. During periods of negative growth, firm entry might decrease not only because of lower current or expected demand but also because of lower disposable income of potential entrepreneurs, who need to borrow more to start a new businesses. Importantly, the sample period includes both the 2007-2009 recession and the 2010-12 sovereign crisis, making it suitable to evaluate the implications of extremely negative cyclical conditions for entry. The second explanatory variable is $spread_{j,t}$, the corporate bond spreads from Gilchrist and Mojon (2016). Our aim is to identify the additional effect of credit frictions on startup decisions for given business cycle conditions, and therefore we include $spread_{j,t}$ both independently and interacted with GDP growth. However credit spreads are countercyclical and thus in part driven by the business cycle. Therefore, to identify exogenous changes in credit spreads, we instrument them with exogenous monetary policy shocks identified by Jarocinski and Karadi (2020), which potentially affect the availability of credit and the bond spreads but are by construction orthogonal to contemporaneous shocks to investment opportunities.[6] A caveat of our identification strategy is that these exogenous credit shocks affect startup decisions through at least two distinct channels: by increasing borrowing costs for entrepreneurs and by reducing expected profits from the business due to lower demand. Both channels operate in the same direction through discouraging overall firm entry, but they might have different implications for the two firm types.

[5]Details on the classification of startups and other variables used in the analysis are described in online Appendix B.

[6]We describe the construction of these instruments and present the first-stage results in online Appendix C.

On the one hand, our results are relevant regardless of what channel is the main driving force behind our findings. On the other hand, for them to have more precise policy implications it is desirable to distinguish them. Therefore, in the empirical analysis we add two regressors that help to control for the second channel, the riskless interest rate and a variable indicating that a respondent in the GEM expects good business opportunities in the future.[7] We expect that, after controlling for these variables, credit shocks should mainly capture the effects of financial constraints to entrepreneurs.

The term $\sum_{k=0}^{K} \gamma_k X_{i,j,t}^k$ in Equation (1) indicates the K control variables, which further include country dummies, gender, age, educational level, income category and the share of respondents reporting to have shut down a business during the last 12 months.[8] Because we control for individual characteristics, we identify how the propensity to start different types of businesses is affected by cyclical conditions and exogenous changes in the cost of finance conditional on the quality of the entrepreneurial pool.

Estimation results are shown in Table 1, in the first three columns without and in the last three including the interaction term. As expected, the GDP growth coefficient is positive (except in column 3), generally significant, and quantitatively similar across types. A decline in GDP growth by one ppt reduces firm entry by around 3-5 ppt. The instrumented GZ spread, which is our measure of credit cost for entrepreneurs, has a negative and significant effect only for high-growth startups (columns 3/6). The coefficient of the interaction GZ spread $\times$ GDP growth is also positive, indicating that an increase in the GZ spread reduces more firm entry the more negative is GDP growth. Importantly, the coefficient is large and significant only for high-growth startups. The estimated coefficients of GZ spread and GZ spread $\times$ GDP growth suggest that, while lower GDP growth negatively affects all startup types in a similar way, a financial tightening affects disproportionately more high-growth than low-growth startups, especially during downturns.[9] The intuition for this result is that high-growth startups have

[7]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 who answer *Don't know*. Although the time horizon of these expectations is relatively short, we expect that, if the results of the *high-growth* startups are entirely driven by future expectations of the economy, they should at least partially be absorbed by this variable.

[8]We weight observations by using the weight variable for the 18-64 labor force included in the GEM. According to the description of the GEM, the weights are "developed such that proportions of different subgroups (gender and age, for example) match the most recent official data descriptions of the population of a country." Our results are robust to not weighting the observations.

[9]Estimating the regressions in columns 5 and 6 simultaneously, we have verified that both β_2 and β_3 are significantly different, i.e. we can reject the hypotheses $\beta_2^l = \beta_2^h$ and $\beta_3^l = \beta_3^h$.

better prospects in the future but take more time to become profitable. Therefore, they need more external financing in the short term and are more sensitive to current financial frictions. In the next section, we show firm-level empirical evidence consistent with this hypothesis.

We use the estimated coefficients in columns 4-6 of Table 1 to predict the impact of the Covid-19 shock on both firm entry and its composition in the four countries. For GDP growth, we use the IMF predictions shown in Figure 1. Unfortunately, there exist no reliable forecasts for financial frictions in 2020. We therefore consider two scenarios for the evolution of corporate bond spreads. In the first one, bond spreads remain at the same level as in 2019, while in the second we assume that they rise to the level of May 2020. Figure 1 shows that spreads increased in all countries and the most in Italy - nearly 0.8 ppt.

Panel A of Figure 2 presents the predictions for the overall fall in entry. When we assume no increase in spreads, it is the lowest in Germany (60%) and the highest in Spain (80%), which suffers a sharper fall than Italy despite similar forecasts for 2020 because of its higher GDP growth rate in 2019. If spread levels increase to that of May 2020, the fall reaches nearly 90% in Spain, Italy and France. Panel B presents the changes in the composition of startups, i.e. the percentage decrease in the share of high-growth firms among all entering firms. While the share remains almost unaffected (and actually even increases slightly) without spread increase, it drops strongly and by up to 90% in Italy otherwise. This result follows from the strong interaction effect between GDP growth and spreads.

Altogether, this exercise has two main findings. First, the Covid-19 shock is predicted to massively reduce firm entry in 2020. Second, due the observed increase in spreads in 2020, it disproportionately reduces high-growth startups. As preliminary evidence backing the huge fall in entry, Panel C of Figure 2 shows deseasonalized monthly data on firm entry in Spain, updated to include the pandemic period. For the months of April and May 2020, the figure shows a drop of around 75% with respect to the pre-pandemic period, not far from our predictions. The data for May is particularly important because the lockdown was lifted in that month and economic activity was generally improving. Despite the strong recovery in June, entry remained 15% lower than in 2019. Panel D compares the cumulative drop in firm entry with that during the Great Recession. Although that recession was particularly deep in Spain, it took eleven months to reach the same cumulative drop in firm entry experienced during the first three months of the

Covid-19 pandemic.

3.3 Startups and long-run employment growth

The second step of our analysis is to use the fall in firm entry to also predict future firm size and employment growth. We perform this prediction for Spain, for which we complement the GEM with firm level balance sheet data from Microdatos de la Central de Balances, a panel of Spanish firm-level data spanning from 1996 to 2017, which virtually covers the entire population of Spanish incorporated firms.[10]

We use this dataset to understand whether the composition of entry (high-growth versus low-growth firms) matters for the long-run job creation of a given cohort of firms. Since we cannot link directly GEM data with the firm-level data from the MCB, we proceed as follows: using GEM data, we compute the variable $Share\_growth_{s,t}$, i.e., the share of high-growth startups in the 2-digit sector s in year t in Spain. Then, we match these shares with the firm-level data from the MCB.[11] Using this matched data, we run the following regression:

$$\log Employment_{i,s,t} = \beta_0 + \sum_{k=0}^{K} \beta_{1,k} age^k_{i,s,t} + \sum_{k=0}^{K} \beta_{2,k} age^k_{i,s,t} Share\_growth^{t-k}_{i,s} + \phi_t + \psi_s + \epsilon_{s,t} \quad (2)$$

where $Employment_{i,s,t}$ is employment of firm i belonging to industry s at time t; $age^k_{i,s,t}$ is an indicator equal to 1 if the firm is k years old at time t, and $Share\_growth^{t-k}_{i,s,t}$ is the share of high growth firms in the year the firm was created $(t-k)$. If high-growth firms generate more employment than low-growth firms, we would expect the employment of firms in sectors with a high share of the former to be larger on average, and hence $\beta_{2,k}$ would be positive. The results are presented in online Appendix Table A.1. We find that the interaction coefficients are negative in the first periods and then become positive in the medium to long term. Hence, although during the first years these high-growth firms remain smaller, eventually they grow faster than low-

[10]This data come from the annual accounts that firms deposit at the Commercial Registry, which is collected and treated by Banco de España. In Spain, it is mandatory for all firms to deposit their annual accounts (balance sheet, income statements and annual reports) in the Commercial Registry. For a more detailed information about this dataset, see Almunia et al (2018). We exclude firms in the primary sector and mining, financial and insurance sector, and public administration. We also keep only firms that have at least one employee at some point of their lives as our goal is to focus on firms that create employment. Further, we drop firms that are part of a group, and those that have more than 100 employees and/or are publicly traded the year of their creation or the next one, since these are likely entities created through restructuring of already existing firms.

[11]Albert and Caggese (2020) use Spanish firm-level data from SABI to demonstrate that high-growth startups predict faster future employment growth. The MCB data has the advantage to be more comprehensive than SABI. We are able to match 2,686,508 firm-year observations to the share of high-growth firms in the sector and year they were created.

growth firms. In quantitative terms, the coefficients of column 1 imply that a sector composed of only high-growth firms would have an average size of newborn firms 13% smaller than a sector composed only of low-growth firms. However, the high-growth firms would on average be 23% larger after eight years. This finding highlights the importance of the composition effect of entry for medium- to long-run employment growth. It also confirms our hypothesis that high-growth firms are likely to be smaller and less profitable in the short term, and therefore might need more external finance and be more vulnerable to credit shocks, as emphasized in the previous section.

We now use these estimates to predict the long-run implications for firm size and job growth. We first predict the probabilities of startup creation for each type, as described in the previous section, and define the high-growth share as the probability to create a high-growth startup divided by the probability to create any startup. We then multiply the change in this share with the Age 10 $\times$ share coefficient in the first column of Table A.1 to obtain the percentage change in the predicted employment level at the age of 10.[12] The results are shown in Panel A of Figure 3. In the blue scenario with no increase in spreads, there is no change in the share of high-growth startups, and therefore almost no change in the average expected firm size after 10 years (even a slight increase). In the other scenario, average expected firm size falls by around 7% in Italy, 5% in France, 4% in Spain and 3.5% in Germany. This is a direct implication of the interaction between GDP growth and the spread shown in column 6 of Table 1. While the cyclicality is somewhat higher for low-growth startups given the GZ spread is at its mean, it increases sharply for high-growth startups when the spread increases.[13]

For Spain, we can also predict the impact of the decrease in entry and the change in composition on current employment and its evolution over the following years.[14] To do so, we first investigate how long-lasting the effects of firms entry on aggregate employment are by running the following regression:

$$\log \mathit{Employment\_cohort}_{k,s,t} = \gamma_{0,k} + \gamma_{1,k} \log \mathrm{New\_firms}_{s,t-k} + \phi_{t,k} + \psi_{s,k} + \epsilon_{k,s,t} \tag{3}$$

[12]The first step is done using data from all four countries in GEM. For the second step, we use the data from MCB for Spain, hence assuming that firm dynamics in France, Germany and Italy are similar to that of Spain.

[13]Note that we demean the GZ spread before running the regressions and hence the coefficient of GDP growth indicates the effect conditional on the spread being at the mean.

[14]We are abstracting from possible employment spillovers effects on firms from different cohorts. These more 'general equilibrium' effects are potentially important but we cannot analyze them here for reasons of space, therefore leaving them for future research.

where $Employment\_cohort_{k,s,t}$ is total employment of all firms of age k belonging to industry s at period t, and $\text{New\_firms}_{s,t-k}$ is the number of firms entering the year that cohort entered, $t-k$. We perform one regression for each time horizon $k \in [1, 10]$. The estimated coefficients are reported in Figure 3, Panel B. Next, we consider the predicted fall in firm entry shown in Panel A of this figure (for the case of no spread increase -blue- and spread increase as of May 2020 -red-) and multiply it with $\gamma_{1,k}$ from Equation (3), and the aggregate employment of firms of age k (averaged across all the years of our sample) to obtain the predicted job losses of the cohort entering in 2020 from 2021 ($k = 1$) to 2030 ($k = 10$) solely due to the entry channel (extensive margin).[15] Results are shown in Panel C of Figure 3. The jobs lost range from 70,000 jobs in 2021 to a maximum of 90,000 in 2029 in the case of no increase in spreads (solid blue line), and from 80,000 jobs in 2021 to more than 110,000 jobs in 2029 in the case of an increase in spreads (dashed red line).

Next, we add the employment impact of the change in the share of high-growth firms (intensive margin). To do so, we use the coefficients of the interaction terms of Equation (2) depicted in the first column of Table A.1. To compute the $t + k$ forward prediction, we multiply the predicted decrease in the share of high-growth firms from Panel B of Figure 3 with the coefficient $\beta_{2,k}$ and the aggregate employment of firms of age k. We finally add this number to the predicted employment drop due to changes in entry explained in the previous paragraph. This is plotted in dashed green in Panel C for the scenario of a spread increase 'as of May 2020'. Since the entry of high-growth firms is highly dependent on financial conditions, if they worsen, the share of high-growth firms drops. This implies that the composition channel contributes with negative job losses (or job creation) for a couple of years (driven by the initially negative coefficients of the $Age\ k \times share$ interactions up to the age of 3), which then rapidly revert to reach around 8,000 jobs lost in 2029. This is due to the characteristics of high-growth firms: although less profitable in the short-term, they are able to grow more rapidly in the medium to long term. Hence, a "missing generation" of high-growth firms can significantly hurt job creation even many years in the future.

[15] Despite the fact that the coefficients of the regression are decreasing in k, average aggregate employment of a firm cohort is increasing with age. This makes the predicted job losses of the 2020 cohort slightly increase over time.

4 Model and Policy Analysis

In this section, we set-up a stylized partial-equilibrium model of firm entry that is consistent with the above documented empirical patterns and extends the framework introduced in Albert and Caggese (2020). We then use the model to analyze the efficacy of different policy alternatives in counteracting an exogenous shock resembling the impact of the Covid-19 pandemic.

Technology

Consider many risk-neutral entrepreneurs, who can choose the type of startup j among two alternatives, with types indexed by $j = 1, 2$. Starting a business requires an initial sunk cost κ_j to operate. Every period, firms exit with a certain probability. A Type j firm that does not exit in period t generates profits producing a homogenous final good with a DRS production function:

$$\pi_{j,t} = p_t \theta_{j,t}^{1-\alpha} L_{j,t}^{\alpha} - wL_{j,t}, \tag{4}$$

where p_t is the price level of the final good, which follows an exogenous stochastic process, $\theta_{j,t}$ is productivity, $L_{j,t}$ is labor input, w is the exogenously given wage, and $0 < \alpha < 1$. To keep the model tractable, we assume that wages are paid after earnings are realized and thus not subject to financial frictions, resulting in profit-maximizing labor demand $L_{j,t} = \left(\frac{p_t \alpha}{w}\right)^{\frac{1}{1-\alpha}} \theta_{j,t}$. Substituting this in Equation (4), we express profits as a function of prices and productivity:

$$\pi(p_t, \theta_{j,t}) = \Psi p_t^{\frac{1}{1-\alpha}} \theta_{j,t}, \tag{5}$$

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

Startup types differ in their expected productivity growth. Type $j = 1$ indicates a startup with low growth potential, for which productivity $\theta_{1,t}$ grows at an exogenous rate g^{med} in all periods, so that $\theta_{1,t+1} = (1 + g^{med})\theta_{1,t}$. Starting a Type 1 business represents the decision to provide mature and established products in well-known markets. This decision to start a Type 1 business will result in immediate profits; however, the business also has low growth prospects.

Type $j = 2$ indicates a startup with high growth potential. Its productivity grows at a rate $g^{low} \leq g^{med}$ initially but every year, with probability γ, permanently increases to $g^{high} > g^{med}$.

Moreover, it requires a higher initial cost: $\kappa_2 > \kappa_1$. Starting a Type 2 business represents the decision to provide a newer product, which generates lower profits in the beginning; however, the business has higher long-run growth potential. We introduce heterogeneity across entrepreneurs by assuming that their productivity is a function of their skills:

$$\theta_{i,j,0} = \phi_{i,j} S_i, \tag{6}$$

where $\theta_{i,j,0}$ is the initial productivity of Type j for entrepreneur i. S_i is the entrepreneur's generic skills, and $\phi_{i,j}$ the skills specific to type j projects. We assume that S_i is uniformly distributed across entrepreneurs, $S_i \in [1-s, 1+s]$, with $0 < s < 1$. The skills required to operate Type 2 firms, $\phi_{i,2}$ are uniformly distributed over the interval $\phi_{i,2} \in [\phi_{min}, 1]$. Conversely, the skills required to operate Type 1 firms are $\phi_{i,1} = 1$ for all entrepreneurs. In other words, the draw of S_i determines one's chances of starting any type of firm, while the draw of $\phi_{i,2}$ determines the probability of starting a Type 2 rather than a Type 1 firm.

Choice of firm type

The entrepreneur has an initial endowment of $a \leq \kappa_j$ and needs to borrow $b_j = \kappa_j - a$ in order to start a business of type j. In subsequent periods, debt can be repaid by using the flow of profits π. One unit of debt implies a repayment of $\frac{1+r^b}{1-d}$ next period, which reflects the risk that the firm is liquidated before producing and unable to repay the debt with probability d. We normalize the interest rate to zero, and therefore, r^b can be interpreted as the financial spread or excess cost of debt caused by financial frictions. To ease notation, we henceforth drop the i subscript.

Financial frictions matter if the entrepreneur needs to borrow an amount $b_{j,0} = \kappa_j - a > 0$ to start the firm and if the external financing is costly (r^b>0). We denote $C^j(\theta_{j,0})$ as the net present value of these expected excess financing costs for a new business with initial productivity equal to $\theta_{j,0}$. Let the value of a type j firm in a world without financial frictions be $V^j(\theta_{j,0})$. Hence, the value of a Type j startup is given by

$$V^j(\theta_{j,0}) - C^j(\theta_{j,0}) - \kappa_j, \tag{7}$$

and the entrepreneur will choose the firm type that maximizes (7). We derive the value function of the firm without financial frictions $V^j(\theta_{j,0})$ and the cost function $C^j(\theta_{j,0})$ in online Appendix D. Importantly, we choose the parameters of the model so that the following inequality is always true:

$$V^2(S_i) - V^1(S_i) > \kappa_2 - \kappa_1$$

This means that, in the absence of financial frictions, entrepreneurs with Type 2 skills $\phi_2 = 1$ (those with the same initial productivity for both types) will always choose Type 2. In other words, all else equal, the higher future growth potential of Type 2 projects more than compensates their higher initial cost. This assumption also implies that there is a threshold value of specific skills $\bar{\phi} < 1$, such that entrepreneurs with skills ϕ_2 above the threshold prefer a Type 2 and those below prefer a Type 1 startup.[16]

The cost $C^j(\theta_{j,0})$ increase more strongly for Type 2 startups when financial frictions become larger (e.g. $b_{j,0}$ or r^b increases), which reduces their relative frequency as the threshold for choosing Type 2 $\bar{\phi}$ rises.[17] Moreover, with higher financial frictions, not only will some entrepreneurs switch from Type 2 to Type 1 businesses but those with low general skills will decide to not start any business, if the cost become so high that also starting a Type 1 is not worthwhile anymore, i.e. $V^1(\theta_{1,0}) < C^1(\theta_{1,0}) + \kappa_1$.

Calibration and Covid-19 shock

We set the parameters of the model equal to their empirical counterparts whenever possible, while those for which there are no direct empirical measures available are chosen so that several moments predicted by the model match those in the data. The value of κ_1 is normalized to one, $\kappa_2 = 1.25$ and $a = 0.5$. These values match the share of external money required to start a firm observed in the GEM (see Albert and Caggese, 2020). α is set to 0.6, the labor share of output. The growth rates g^{low}, g^{med} and g^{high}, γ and the financing rate r^b are chosen so that the model matches the following two empirical patterns: first, the employment evolution uncovered in column 1 of Table A.1, in particular a lower employment level of high-growth startups up to

[16]For a formal proof of such a threshold to exist in a simplified version of this model, see Albert and Caggese (2020)

[17]This follows from the fact that Type 2 firms are initially less productive on average (because $\bar{\phi} < 1$) and thus need more time to repay their debt. See Albert and Caggese (2020) for a proof.

the age of 4 and a level that is 20% higher at the age of 10, and, second, a ratio of high-growth to low-growth firms of around 0.5 as observed in the GEM. An overview over these and the remaining parameters can be found in online Appendix Table A.2.

We simulate a sudden economic downturn and increase in financial stress due to the pandemic as a shock to demand, entrepreneurs' endowment and interest rates. The demand shock leads to a fall in the price of the final good p_t, which we assume to follow an AR(1) process with an autoregressive parameter of 0.5, hence implying a relatively quick convergence back to the long-run mean (which is normalized to one). Entrepreneurs' endowment falls from 0.5 to 0.2 and the interest rate r^b increases by 1.5 ppt. Combined, these shocks imply a fall in firm creation of around 40%.[18]

Policy alternatives

We compare two alternative policies with the aim to alleviate the negative consequences of the above described exogenous shock to demand and financing conditions. The first policy is a subsidy to wage payments. As this type of subsidy temporarily increases the stream of profits, V^j rises and $C^j(\theta_{j,0})$ falls, stimulating firm entry. We assume that the subsidy amounts to 50% of wage cost in the first year when the shock hits and that it is phased out over time (30% in year two and 10% in year three). The second policy is a one-time financing subsidy proportional to new firms' opening cost κ_j. This subsidy leaves V^j unaffected and only decreases the financing cost through directly lowering the initial amount of debt to be repaid, which also stimulates the entry of additional firms. We set the proportional financing subsidy to 17.4%, which is the value that generates the exact same total cost for the government as the wage subsidy.

Panel A of Figure 4 shows for each type the fall in entry relative to the entry before the shock in case there is no subsidy (blue), the wage subsidy (red) or the financing subsidy (green) in place. First, the figure shows that the entry of startups of Type 2 falls much more strongly than that of Type 1. This is due to the cost function of Type 2 startups, which increases more steeply

[18] Although we see a fall in firm entry in the data for Spain in Spring 2020 of up to 75%, we simulate a less severe shock as the model is at a yearly frequency and the annualized fall in firm entry will most likely be much smaller, as suggested by the starting recovery of firm entry observed in the latest data for June. We further acknowledge that our parameterization of the shock is somewhat ad-hoc but given that annual data encompassing the Covid-19 shock are not available yet, we lack precise calibration targets. However, qualitatively our conclusion regarding the most effective policy to implement is robust to any combination of shocks to parameters that leads to an at least temporary rise in financing cost.

when financing conditions deteriorate, implying that the threshold skill level to start a Type 2 firm $\bar{\phi}$ rises and relatively more entrepreneurs choose Type 1 startups. Second, we find that the financing subsidy more effectively dampens the fall in entry for both types. Implementing the latter, the entry almost returns to its pre-shock level for Type 1 and the fall is reduced from almost 80% to 55% for Type 2 startups, whereas the reduction only goes to 70% implementing the wage subsidy. The intuition behind this result comes from the fact that a subsidy to wages benefits relatively more those firms that are initially more productive and thus employ more workers. As highly productive firms also would have entered without any subsidy, a large part of the subsidy budget is spent ineffectively. In contrast, the financing subsidy is distributed to entrepreneurs independently of their initial productivity.

Panel B of Figure 4 compares the predicted 20-year ahead evolution of aggregate employment of the entering firms for the scenario without shock and the shock scenario combined with each subsidy. As a consequence of the transitory demand shock, employment falls strongly on impact and then catches up over the following years. However, because overall entry is lower, the aggregate employment of this firm cohort never reaches the level it would have in the absence of the shock. The difference between future employment with and without the shock even increases after around 10 years because the shock affects relatively more Type 2 firms, which tend to grow faster in the long-run. This is the intensive margin effect we have documented using our empirical predictions in Panel B of Figure 2. The paths of employment with the two subsidies suggest a short-term vs. long-term trade-off. While the wage subsidy increases employment in the short-term, it has smaller long-term effects than the financing subsidy, as its stimulation of firm entry is weaker. The difference between the employment effects of the two subsidies increases over time, again because Type 2 startups, which benefit relatively more from the financing subsidy, unfold their high growth potential in the long-run.

5 Conclusion

The Covid-19 pandemic forced a sudden and massive decline in economic activity worldwide, with most countries facing GDP declines beyond anything experienced since at least the Great Depression. Furthermore, there seems to be an increase financial frictions faced by firms: the latest available data (June 2020) of the country level index of financial stress (CLIFS) provided by the ECB shows historically high levels, normally associated with financial crisis episodes.

We use the methodology developed in Albert and Caggese (2020) to predict the impact of the Covid-19 shock (characterized by a huge drop in GDP, and a moderate increase in financial frictions) on firm entry and its composition. Our results show that the large drop in GDP in isolation, without an increase in financial frictions, is predicted to reduce firm entry. Our estimates range from a 60% decrease in Germany to a 80% in Spain. However, it would not significantly affect the share of high-growth firms, and this limits the long-term employment consequences of this reduction in firm entry. In contrast, a large GDP contraction that is also accompanied by a moderate increase in financial frictions strongly reduces the share of high-growth firms among the new startups, implying substantially larger negative long-term consequences. Using detailed data of Spanish firms, we estimate that employment losses of the entering cohort would be 80,000 in 2021 and increase up to almost 115,000 in 2029.

Finally, we consider a partial equilibrium model of the entry and growth of new businesses and use it as a laboratory to understand which policy tool would be more effective to counteract the negative impact of this shock on the employment of the entering cohort. While a wage subsidy is more effective in fostering employment in the short-term, we find that the financing subsidy is more effective in the long-term. This is because the latter benefits more high-growth firms, which contribute more to employment in the long-run.

Overall, our findings suggest that when evaluating policies that promote firm entry, it is important to also take into account the effects via the *composition channel* and the resulting long-term growth prospects of new firms, instead of only focusing on boosting employment in the short-term.

References

Albert, Christoph and Andrea Caggese, "Cyclical Fluctuations, Financial Shocks, and the Entry of Fast-Growing Entrepreneurial Startups," Forthcoming, Review of Financial Studies 2020. *Available at* `https://drive.google.com/file/d/1pYOM5SZA04J8t6hqJ58Pztki_sm12xmo/view`.

Bartik, Alexander W, Marianne Bertrand, Zoë B Cullen, Edward L Glaeser, Michael Luca, and Christopher T Stanton, "How are small businesses adjusting to covid-19? early evidence from a survey," Technical Report, National Bureau of Economic Research 2020.

Campbell, Jeffrey R., Charles L. Evans, Jonas D.M. Fisher, and Alejandro Justiniano, "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 2012, *43* (1 (Spring), 1–80.

Corsetti, Giancarlo, Joao B. Duarte, and Samuel Mann, "One money, many markets: a factor model approach to monetary policy in the Euro Area with high-frequency identification," LSE Research Online Documents on Economics 87182, London School of Economics and Political Science, LSE Library February 2018.

Duprey, Thibaut, Benjamin Klaus, and Tuomas Peltonen, "Dating systemic financial stress episodes in the EU countries," *Journal of Financial Stability*, 2017, *32*, 30–56.

Fairlie, Robert W, "The Impact of Covid-19 on Small Business Owners: Evidence of Early-Stage Losses from the April 2020 Current Population Survey," Technical Report, National Bureau of Economic Research 2020.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, January 2015, *7* (1), 44–76.

Gilchrist, Simon and Benoit Mojon, "Credit Risk in the Euro Area," *The Economic Journal*, 2016, *128* (608), 118–158.

_ **and Egon Zakrajsek**, "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, June 2012, *102* (4), 1692–1720.

Haltiwanger, John, Ron S. Jarmin, Robert Kulick, and Javier Miranda, "High Growth Young Firms: Contribution to Job, Output, and Productivity Growth," in "Measuring Entrepreneurial Businesses: Current Knowledge and Challenges" NBER Chapters, National Bureau of Economic Research, Inc, 2016, pp. 11–62.

Hassan, Tarek Alexander, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, "Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1," Technical Report, National Bureau of Economic Research 2020.

Jarocinski, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises - The Role of Information Shocks," *American Economic Journal: Macroeconomics*, April 2020, *12* (2), 1–43.

Nakamura, Emi and Jón Steinsson, "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *The Quarterly Journal of Economics*, 2018, *133* (3), 1283–1330.

Paul, Pascal, "The Time-Varying Effect of Monetary Policy on Asset Prices," *Review of Economics and Statistics*, forthcoming.

Poschke, Markus, "The Firm Size Distribution across Countries and Skill-Biased Change in Entrepreneurial Technology," *American Economic Journal: Macroeconomics*, July 2018, *10* (3), 1–41.

Pugsley, Benjamin, Petr Sedlacek, and Vincent Sterk, "The Nature of Firm Growth," CEPR Discussion Papers 12670, C.E.P.R. Discussion Papers January 2018.

Reynolds, Paul Davidson and Diana M. Hechavarria, "Global Entrepreneurship Monitor [GEM]: Adult Population Survey Data Set, 1998-2013," 2016.

Schivardi, Fabiano and Guido Romano, "A simple method to estimate firms liquidity needs during the Covid -19 crisis with an application to Italy*," July 2020.

Sedláček, Petr, "Lost generations of firms and aggregate labor market dynamics," *Journal of Monetary Economics*, 2020, *111*, 16–31.

Sedlacek, Petr and Vincent Sterk, "Startups and Employment Following the Covid-19 Pandemic: A Calculator," 2020.

Zoller-Rydzek, Benedikt and Florian Keller, "COVID-19: Guaranteed Loans and Zombie Firms," *Available at SSRN 3619744*, 2020.

Tables and Figures

Table 1: GDP growth, financial frictions and startup creation

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	2.606***	3.481***	-0.271	4.838**	4.419**	3.879
	(0.4033)	(0.4544)	(0.3429)	(2.2594)	(1.8838)	(2.3678)
GZ spread	-0.012	0.090	-0.239***	-0.007	0.064	-0.192**
	(0.0529)	(0.0551)	(0.0271)	(0.0599)	(0.0438)	(0.0869)
GZ spread x GDP growth				4.826	2.675	7.938***
				(3.0224)	(2.8518)	(2.2418)
Female	-0.145***	-0.118***	-0.158***	-0.145***	-0.118***	-0.159***
	(0.0076)	(0.0167)	(0.0274)	(0.0073)	(0.0164)	(0.0281)
Middle education	0.008	0.013	-0.005	0.008	0.013	-0.006
	(0.0185)	(0.0197)	(0.0135)	(0.0195)	(0.0202)	(0.0147)
High education	-0.009	-0.020	0.013	-0.011	-0.021	0.009
	(0.0209)	(0.0163)	(0.0263)	(0.0235)	(0.0183)	(0.0287)
Age	-0.008***	-0.008***	-0.006***	-0.008***	-0.008***	-0.006***
	(0.0020)	(0.0018)	(0.0020)	(0.0020)	(0.0017)	(0.0020)
Middle income	0.118**	0.075*	0.171***	0.126**	0.081	0.185***
	(0.0494)	(0.0437)	(0.0379)	(0.0585)	(0.0512)	(0.0495)
High income	0.070***	0.028	0.136***	0.088**	0.039	0.167***
	(0.0213)	(0.0262)	(0.0050)	(0.0385)	(0.0401)	(0.0197)
Share of exits	-9.938	-10.784	-5.065	-12.329	-11.312	-9.977
	(10.9636)	(10.5857)	(9.3457)	(11.6392)	(11.2900)	(9.4835)
Business expertise	0.851***	0.783***	0.786***	0.853***	0.784***	0.788***
	(0.0086)	(0.0087)	(0.0142)	(0.0100)	(0.0084)	(0.0163)
Opportunity expectations	0.356***	0.324***	0.313***	0.350***	0.320***	0.305***
	(0.0168)	(0.0115)	(0.0266)	(0.0195)	(0.0145)	(0.0283)
Riskless interest rate	0.057	0.068	0.014	0.062	0.067	0.029
	(0.0543)	(0.0553)	(0.0352)	(0.0480)	(0.0475)	(0.0320)
Observations	359791	359791	359791	359791	359791	359791
R-squared	0.127	0.110	0.118	0.128	0.110	0.122

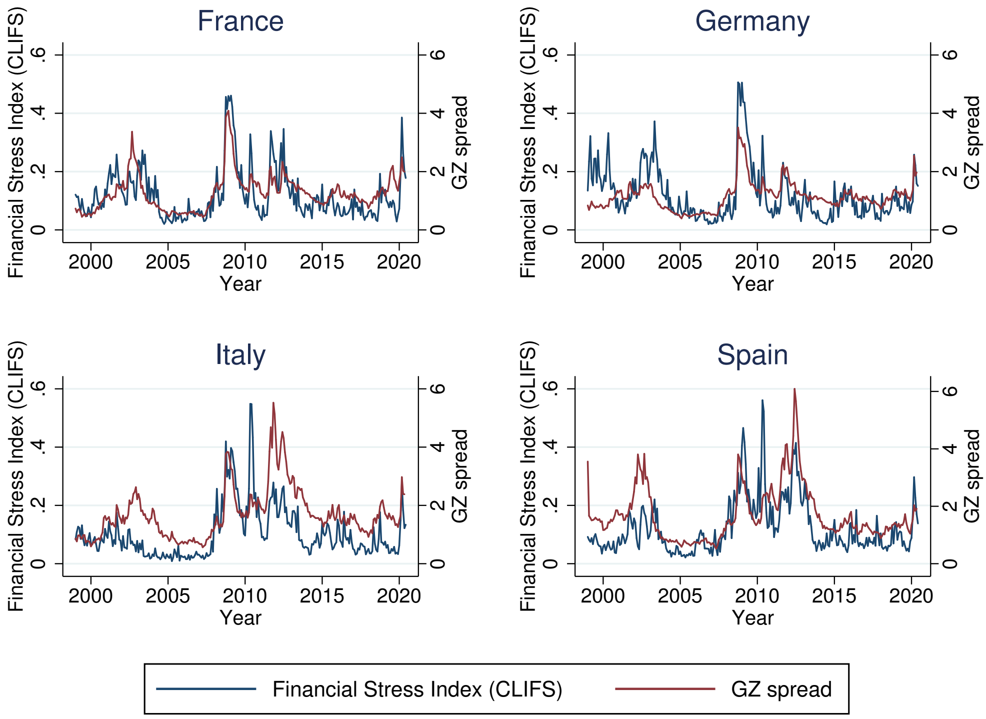
Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. All results are estimated with the GZ spread predicted by the IV specification described in online Appendix C. Standard errors are clustered at the country level. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure 1: Projected GDP growth and GZ spreads

A. Projected GDP growth and spread

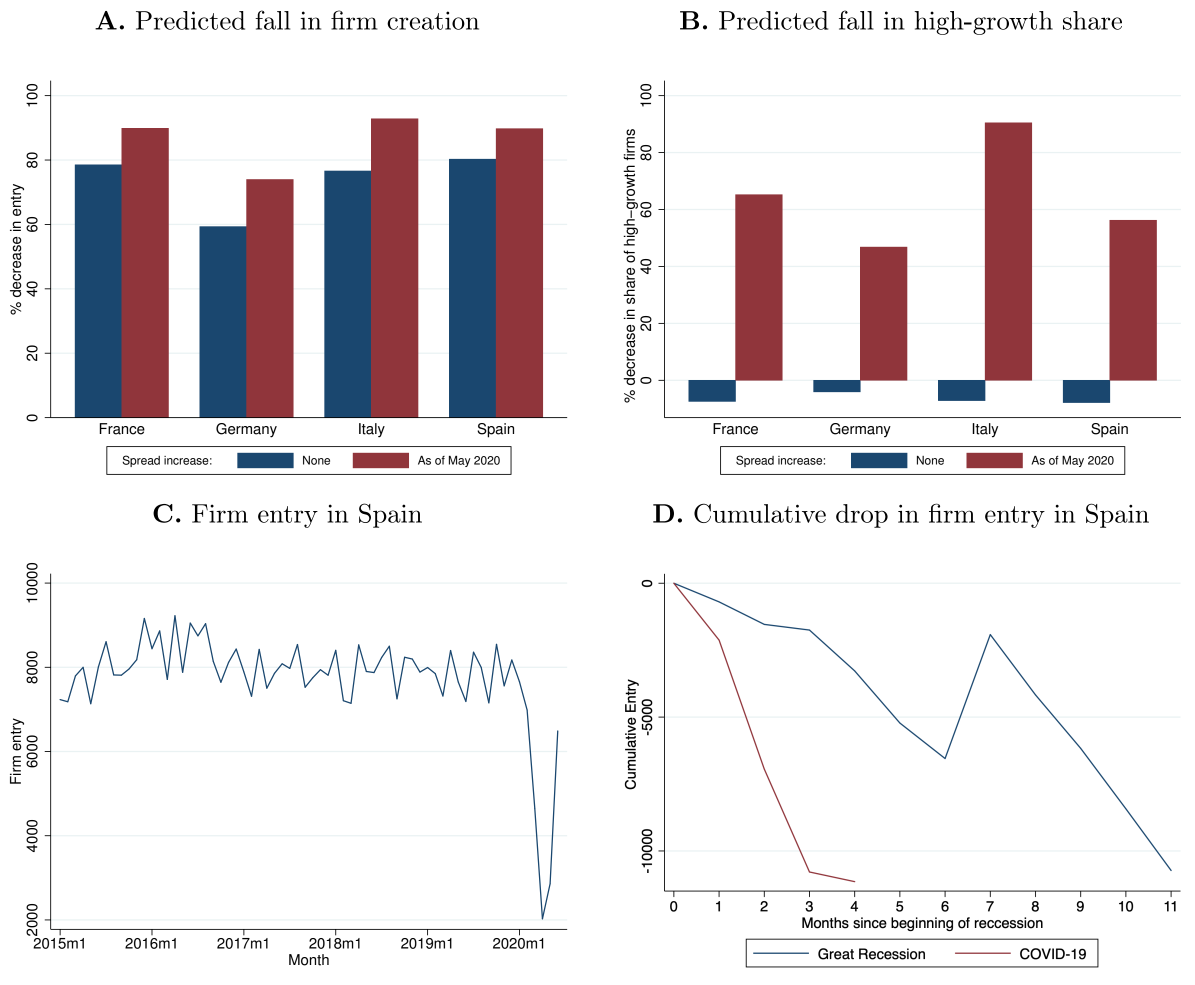
	Projected GDP growth 2019	Projected GDP growth 2020	Avg. spread in 2019	Spread in May 2020
France	1.50	-12.50	1.60	2.00
Germany	0.60	-7.80	1.22	1.97
Italy	0.30	-12.80	1.56	2.38
Spain	2.00	-12.80	1.33	1.91

B. Financial stress indicators and credit spreads



Notes:
Panel A: The projected levels of GDP growth for each country in 2019 and 2020 are taken from the IMF World Economic Outlook Update of June 2020. The values of the spread in 2019 are annual averages of the monthly series of the corporate bond spread based on Gilchrist and Mojon (2016). The value of May 2020 is also the spread from Gilchrist and Mojon (2016). **Panel B:** The country-level index of financial stress (CLIFS) is provided by the ECB. The credit spreads are updated series provided by the Banque de France based on Gilchrist and Mojon (2016).

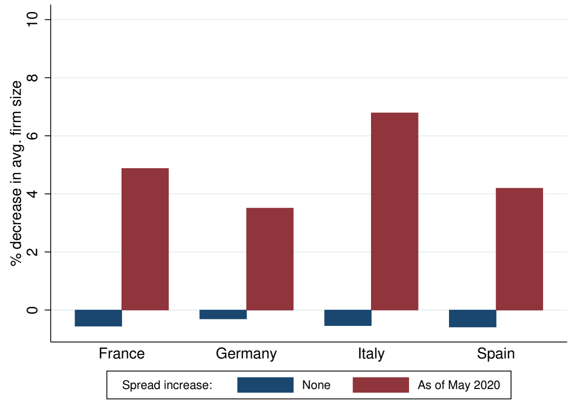
Figure 2: Predicted and realized fall in firm creation



Notes: **Panel A/B:** The fall in firm creation and the share of high-growth firms are predicted using the IV estimates in columns 5-6 of Table 1 and IMF GDP forecasts depending on the assumed increase in the spread. **Panel C/D:** Data at monthly frequency come from INE (`https://www.ine.es/jaxiT3/Tabla.htm?t=13912`). Panel C shows the deseasonalized number of new firms entering ("Constituidas"), which only includes firms recognized as independent legal entities. Panel D shows the cumulative deviations from the trend since the beginning of the crisis for the Great Recession (month 0 is April 2008) and the beginning of the Covid-19 shock (month 0 is Februrary 2020).

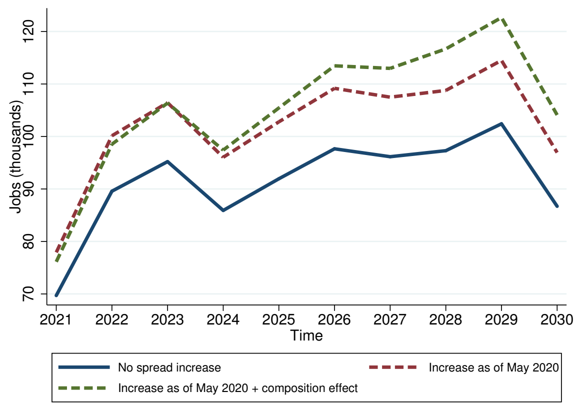
Figure 3: The predicted impact of Covid-19 shock on long-run employment

A. Fall in 10-year forward firm size(%)



B. Firm entry and future cohort employment

C. Predicted fall in employment for Spain

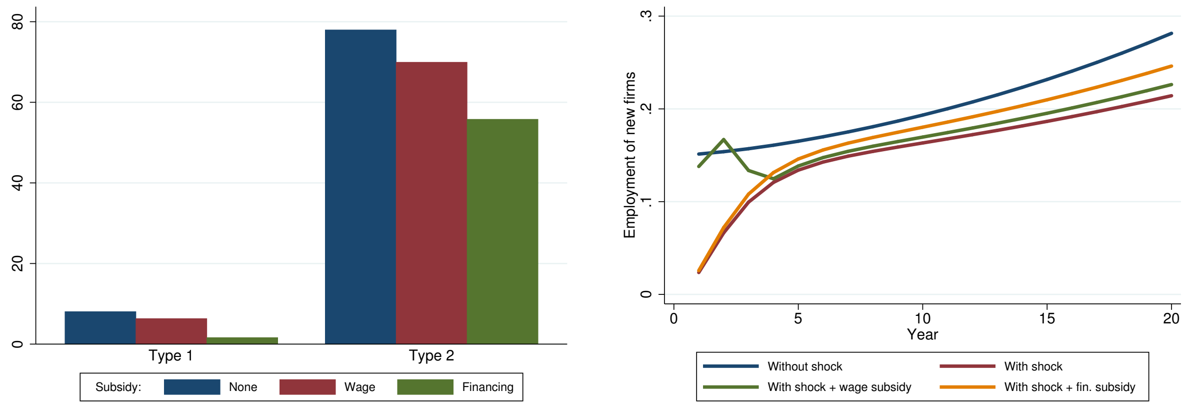


Notes: **Panel A:** The graph shows the fall in the size of firms born during the assumed scenario 10 years in the future by combining the change in the share of high-growth startups predicted using columns 5-6 of Table 1 with the estimated effect of this change on future employment from Table 2. The projected levels of GDP growth for each country in 2019 and 2020 are taken from the IMF World Economic Outlook Update of June 2020. The "as of May" scenario assumes an increase in the spread to the level of May 2020 (see Figure 1). **Panel B:** The figure plots the coefficients γ_1^k for each time horizon k from regression (3) in solid blue, with 95% CI in dashed red lines. **Panel C:** Predicted loss in aggregate employment in Spain driven by the fall in the creation of new firms if there is no spread increase (blue line), if spreads increase as of May 2020 (dashed red line) -extensive margin-, and the joint effect of the extensive margin and the change in composition of the share of new firms with high growth potential if spreads increase as of May 2020 (dashed green line). The extensive margin series are computed by combining the predicted fall in firm creation displayed with the effect of the change in firm creation on future employment and aggregate employment by firm age (cohort) given in the MCB data. The composition effect is computed by combining the predicted fall in forward aggregate employment of firms due to a change in the high-growth share of firms for each year with the aggregate employment by firm age (cohort) given by the MCB data.

Figure 4: Predicted impact of demand and financing shock in the model

A. Fall in firm entry by type (%)

B. Evolution of employment of entering cohort



Notes: **Panel A:** Model-predicted fall in firm entry for Type 1 firms (left), and Type 2 firms (right), under the Covid-19 shock (blue), with the shock and a wage subsidy (red) and with the shock and a financing subsidy (green). **Panel B:** Model-predicted evolution of aggregate employment of firms starting in the year the shock hits, if there was no shock (blue), if the shock occurs (red), if the shock occurs and the wage subsidy is in place (green) and if the shock occurs and there is a financing subsidy (yellow).

Online Appendix

A Additional Tables

Table A.1: Firms' employment age profile depending on the share of high-growth firms

	(1) log(Employment)	(2) log(Employment)
Age 0	0.908***	0.832***
	(0.0719)	(0.0208)
Age 1	1.435***	1.362***
	(0.0634)	(0.0174)
Age 2	1.530***	1.459***
	(0.0633)	(0.0154)
Age 3	1.558***	1.498***
	(0.0642)	(0.0190)
Age 4	1.573***	1.527***
	(0.0650)	(0.0221)
Age 5	1.579***	1.541***
	(0.0664)	(0.0245)
Age 6	1.566***	1.538***
	(0.0673)	(0.0271)
Age 7	1.556***	1.544***
	(0.0700)	(0.0313)
Age 8	1.527***	1.525***
	(0.0751)	(0.0377)
Age 9	1.520***	1.514***
	(0.0794)	(0.0441)
Age 10	1.525***	1.505***
	(0.0840)	(0.0532)
Age 0 x share	-0.129**	-0.052
	(0.0499)	(0.0457)
Age 1 x share	-0.089**	-0.022
	(0.0357)	(0.0339)
Age 2 x share	-0.060**	0.001
	(0.0305)	(0.0231)
Age 3 x share	-0.002	0.030
	(0.0272)	(0.0224)
Age 4 x share	0.044*	0.043*
	(0.0267)	(0.0245)
Age 5 x share	0.083***	0.065**
	(0.0319)	(0.0285)
Age 6 x share	0.130***	0.094***
	(0.0385)	(0.0341)
Age 7 x share	0.163***	0.094**
	(0.0548)	(0.0430)
Age 8 x share	0.228***	0.141**
	(0.0775)	(0.0562)
Age 9 x share	0.230**	0.154**
	(0.0912)	(0.0688)
Age 10 x share	0.204**	0.156*
	(0.0997)	(0.0853)
Year FE	Yes	No
Sector FE	Yes	No
Year-sector FE	No	Yes
Observations	2066938	2066938
R-squared	0.396	0.399

Notes: Number of entrants and their employment is computed from MCB using the cleaning described in the main text. *share* is the share of high-growth startups (measured in the GEM data) in the 2-digit sector to which the observed firm belongs in the year it was born. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A.2: Model Calibration

Parameter	Value	Description
d	0.07	Exit probability
α	0.60	Labor share
κ_1	1.00	Cost of starting Type 1
κ_2	1.25	Cost of starting Type 2
g^{low}	0.00	Initial growth Type 2
g^{med}	0.02	Growth of Type 1
g^{high}	0.06	Growth Type 2 after switching
γ	0.20	Prob. of changing to g^{high} for Type 2
r_b	0.05	Financial Spread
a	0.50	Initial endowment
$\bar{p}$	1.00	Mean price of final good
Covid-19 shock		
Δp	-0.5	Temporary demand change
Δr_b	0.015	Change in financial costs
Δa	-0.3	Change in initial endowment.

Notes: Calibration of the model to target main moments of interest (see text).

B Data and Variable Definitions

Business types identified from GEM questions

To identify a startup with high growth potential, we refer to the following two questions:

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

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

We compute the size of the established firms by sector (at the 2-digit level) and country (averaged across all years) by using the answer to the first question given by respondents that are owners of firms that are 5 or more years old.[19] We then classify a startup as having high growth potential if the answer to the second question, i.e., the expected size in five years, exceeds the average size of the established firms at the sector-country level. Ideally, we would use only firms that are exactly five years old as the comparison benchmark. However, this process would result in very few observations in many country-sectors; therefore, we choose to consider all firms that are at least five years old.[20] Albert and Caggese (2020) show that there is indeed a strong relationship between actual sizes and expectations across sectors (correlation coefficient 0.54).

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.

Financial crisis data

To proxy the financing cost r^b at the country-year level, we rely on the excess corporate bond premium for France, Spain, Italy and Germany from Gilchrist and Mojon (2016), who aggregate it from the individual bond level.[21] We use the yearly means of the monthly series.

[19] As there is no information on the date of firm creation in the GEM data, we use the first year a firm paid wages or profits to the owners as a proxy.

[20] We confirm that the main results are not sensitive to using different ranges of the firm age, e.g., five to ten years, to compute the average size of established firms.

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

C Instrument Construction

Jarocinski and Karadi (2020) follow a well-established literature that uses high-frequency financial-market surprises around key monetary policy announcements to identify unexpected variations in monetary policy, e.g. see Campbell et al. (2012); Gertler and Karadi (2015); Nakamura and Steinsson (2018); Paul (forthcoming); Corsetti et al. (2018). The innovative aspect of Jarocinski and Karadi's approach is that they are able to separately identify exogenous monetary policy shocks and shocks about new information from the Central Bank regarding the state of the economy. Therefore, these monetary policy shocks potentially affect the availability of credit and the bond spreads but are by construction orthogonal to contemporaneous shocks to investment opportunities.

To obtain the instrumented GZ spread and interaction term, we proceed as follows. Since both the monetary policy shocks and the bond spreads are available at the monthly level, we estimate two first-stage regressions with the GZ spread and its interaction with GDP growth as dependent variables. We instrument the dependent variable in year t and month j with the monetary policy shocks in year t from month 1 to month j and with their interactions with GDP growth.[22] We exclude lagged monetary policy shocks from previous years because they might indirectly affect startup decisions through their delayed effect on economic activity. In other words, our identification assumption is that a monetary policy shock in month j of year t affects startup decisions from month j+1 to month 12 of the same year only trough its effect on credit spreads. We believe this identification strategy is valid given our purposes. On the one hand, it is reasonable to assume that monetary policy shocks are likely to immediately affect financial variables but to have a more lagged impact on real variables. On the other hand, we are aware that monetary policy shocks also immediately affect real interest rates, which themselves might affect startup decisions. However, this is not a problem for our analysis because we directly include the real interest rate among the regressors. Finally, since the nature of monetary policy changed substantially during the financial crisis, we allow the estimated

[22]In each first-stage regression, we also add all the non-instrumented regressors used in the second stage. Moreover, the control variables, gender, education, and age, are relevant in the second stage because of their cross-sectional variation, while they are roughly constant over time within countries. In the first stage they would be highly collinear with the country dummies and would not provide relevant information. Therefore we add them in the second stage after subtracting their country-year mean (this demeaning procedure leaves the results of both the instrumented and non-instrumented regressions largely unaffected).

coefficients to be different in the years 2008-2013.

The results of the first-stage regressions are shown in Table A.3 (we report only the first three lags due to space constraints). From these regressions, we compute the yearly averages of the predicted monthly spreads to replace the actual spread in the estimations.

Table A.3: IV first stage regression results

	(1)	(1) × crisis dummy	(2)	(2) × crisis dummy
FRA × MP shock	7.284*	21.290**	20.097	30.596
	(3.9341)	(9.1878)	(13.0779)	(20.8646)
FRA × MP shock (t-1)	6.459*	32.631***	21.852*	46.590*
	(3.5461)	(10.9093)	(12.6139)	(25.6226)
FRA × MP shock (t-2)	-0.031	38.111***	18.444	49.083*
	(3.7018)	(12.0654)	(14.8447)	(28.5037)
FRA × MP shock (t-3)	1.886	30.478***	12.441	46.354*
	(3.8501)	(10.6236)	(15.7027)	(26.2549)
SPA × MP shock	-1.024	7.807*	-3.803	2.910
	(3.4198)	(4.4882)	(12.5750)	(5.7393)
SPA × MP shock (t-1)	-0.220	11.319*	-12.869	0.136
	(4.7156)	(6.4891)	(14.4674)	(8.5463)
SPA × MP shock (t-2)	-3.062	12.795	-0.825	3.032
	(5.4135)	(8.5231)	(16.4092)	(11.0358)
SPA × MP shock (t-3)	-1.787	8.492	-7.453	-0.881
	(6.0663)	(7.3005)	(16.2378)	(11.4271)
ITA × MP shock	2.854	10.210	-1.999	-13.171
	(2.4292)	(7.1409)	(4.5133)	(12.4152)
ITA × MP shock (t-1)	3.195	12.019*	-3.022	-17.527*
	(3.1002)	(7.0414)	(5.2152)	(10.3769)
ITA × MP shock (t-2)	-1.006	10.940	4.061	-24.405**
	(3.4278)	(6.6477)	(5.0401)	(10.8037)
ITA × MP shock (t-3)	1.225	10.705*	5.630	-21.502**
	(3.7194)	(6.3278)	(6.0416)	(8.9451)
GER × MP shock	3.736	12.882***	7.131	2.536
	(2.9312)	(4.4708)	(8.9826)	(33.3220)
GER × MP shock (t-1)	0.976	23.496***	7.941	15.060
	(3.8070)	(5.0256)	(9.2639)	(43.1976)
GER × MP shock (t-2)	-2.818	28.079***	11.839	10.402
	(4.0282)	(6.3604)	(7.3690)	(45.9784)
GER × MP shock (t-3)	-0.733	23.031***	9.863	16.670
	(3.9111)	(5.5471)	(6.2689)	(51.9078)
SPA	0.562***	0.562***	0.349	0.349
	(0.1038)	(0.1038)	(0.3762)	(0.3762)
ITA	0.457***	0.457***	1.181***	1.181***
	(0.1080)	(0.1080)	(0.3283)	(0.3283)
GER	0.011	0.011	0.773**	0.773**
	(0.0985)	(0.0985)	(0.3258)	(0.3258)

	(1)	(1) × crisis dummy	(2)	(2) × crisis dummy
FRA × MP shock × GDP growth	1.203	-8.227**	3.503	-12.488
	(0.8794)	(3.5191)	(3.5888)	(7.6933)
FRA × MP shock (t-1) × GDP growth	1.596	-12.108***	1.751	-19.640**
	(0.9696)	(3.8693)	(4.1356)	(8.9341)
FRA × MP shock (t-2) × GDP growth	1.173	-14.562***	-1.633	-23.300**
	(0.7904)	(4.0453)	(4.7120)	(9.1815)
FRA × MP shock (t-3) × GDP growth	0.859	-12.001***	1.014	-24.023***
	(0.8364)	(3.7657)	(4.9203)	(9.0410)
SPA × MP shock × GDP growth	1.736	3.437	9.808**	-3.133
	(1.0674)	(3.8852)	(4.1764)	(6.4948)
SPA × MP shock (t-1) × GDP growth	1.707	7.522*	11.272***	-10.690*
	(1.2456)	(4.2909)	(3.5673)	(6.1838)
SPA × MP shock (t-2) × GDP growth	1.128	9.984	6.346	-13.532*
	(1.1187)	(6.1579)	(4.6752)	(7.2253)
SPA × MP shock (t-3) × GDP growth	1.137	7.595*	9.085*	-12.048
	(1.0877)	(4.4159)	(4.7080)	(7.4569)
ITA × MP shock × GDP growth	-0.363	3.070	6.147**	10.147
	(0.8997)	(5.2947)	(2.7391)	(10.3164)
ITA × MP shock (t-1) × GDP growth	-0.139	5.150	6.437*	16.448*
	(0.8188)	(5.4931)	(3.3962)	(9.0111)
ITA × MP shock (t-2) × GDP growth	1.092	1.965	5.726	16.618
	(0.9053)	(6.1605)	(3.6850)	(11.4928)
ITA × MP shock (t-3) × GDP growth	0.820	2.458	8.770**	13.962*
	(0.8620)	(4.4377)	(4.3465)	(8.1898)
GER × MP shock × GDP growth	-1.369	-2.927**	0.915	1.340
	(1.2729)	(1.1496)	(4.9268)	(8.7681)
GER × MP shock (t-1) × GDP growth	-0.979	-5.123***	1.235	-2.448
	(1.4503)	(1.1429)	(4.4207)	(10.8499)
GER × MP shock (t-2) × GDP growth	0.335	-5.707***	0.147	-3.193
	(1.3485)	(1.3172)	(4.1882)	(11.6140)
GER × MP shock (t-3) × GDP growth	-0.492	-5.183***	-0.728	-8.254
	(1.4288)	(1.4649)	(4.2692)	(13.5766)
Opportunity expectations	-1.447***	-1.447***	2.750**	2.750**
	(0.5184)	(0.5184)	(1.2048)	(1.2048)
Riskless interest rate	-0.181***	-0.181***	-0.365***	-0.365***
	(0.0358)	(0.0358)	(0.0950)	(0.0950)
GDP growth	-0.099***	-0.099***	-0.248***	-0.248***
	(0.0130)	(0.0130)	(0.0578)	(0.0578)
Observations	684		684	
R-squared	0.439		0.520	
F-statistic	20.15		64.00	

Notes: The four columns pertaining to model (1) show the first-stage coefficients with the GZ spread as the dependent variable. The remaining columns show the coefficients with the GZ spread x GDP growth interaction as the dependent variable. Columns 2 and 4 show the coefficients estimated in the same regression as in columns 1 and 3 interacted with the an indicator variable for the years 2008-2013 ("crisis dummy"). The country fixed effects are restricted to be the same across periods. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

D Model Derivations

Below, we derive the value of the business under frictionless finance and under financial frictions.

Using the risk-free interest rate (equal to zero) as the discount factor, the value of a newly created Type 1 firm (gross of the start-up costs κ_1) is equal to:

$$V^1(p_t, \theta_{1,t}) = (1-d)[\pi(p_t, \theta_{1,t}) + V^1(E[p_{t+1}|p_t], \theta_{1,t+1})], \tag{8}$$

where $\theta_{1,t+1} = (1+g^{med})\theta_{1,t}$. Using Equation 5 and assuming that p_t follows a stationary process with mean $\bar{p}$, by substituting recursively we obtain:

$$\begin{aligned} V^1(\theta_{1,0}) &= (1-d)\Psi\bar{p}^{\frac{1}{1-\alpha}}\left[\theta_{1,0} + (1-d)\theta_{1,0}(1+g^{med}) + (1-d)^2\theta_{1,0}(1+g^{med})^2 + ...\right] \\ &= (1-d)\Psi\frac{\bar{p}^{\frac{1}{1-\alpha}}\theta_{1,0}}{d-(1-d)\,g^{med}} \end{aligned}$$

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

$$V^{high}(\theta_{2,t}) = (1-d)\Psi\frac{\bar{p}^{\frac{1}{1-\alpha}}\theta_{2,t}}{d-(1-d)\,(g^{high})} \tag{9}$$

To compute its initial value, assume that with probability $1-\gamma$, the firm continues to grow at rate $g^{low} = 0$, so that $\theta_{2,t+1} = \theta_{2,t}$. However, with probability γ, it switches permanently to high growth and its value becomes that determined by Equation (9). Therefore, the initial value is:

$$V^2(\theta_{2,0}) = (1-d)\Psi\bar{p}^{\frac{1}{1-\alpha}}\left[(1-\gamma)\theta_{2,0} + \gamma\frac{\theta_{2,0}}{d-(1-d)\,(h-1)} + ...\right] \tag{10}$$

Rearranging yields:

$$V^2(\theta_{2,0}) = (1-d)\Psi\Phi\bar{p}^{\frac{1}{1-\alpha}}\left\{\begin{array}{c} \theta_{2,0} + (1-\gamma)(1-d)l\theta_{2,0} \\ +\left[(1-\gamma)(1-d)\right]^2\theta_{2,0} + ... \end{array}\right\} \tag{11}$$

$$\Phi \equiv (1-\gamma) + \frac{\gamma}{d-(1-d)\,(h-1)} \tag{12}$$

Solving recursively yields:

$$V^2(\theta_{2,0}) \quad = \quad (1-d)\Psi\Phi\frac{\bar{p}^{\frac{1}{1-\alpha}}\theta_{2,0}}{1-(1-\gamma)(1-d)}$$

D.1 Calculation of C^1 and C^2

Financial frictions matter if the entrepreneur needs to borrow $b_{j,0} = \kappa_j - a > 0$ to start the firm and if the external financing is costly (r^b>0). We denote $C^j(\theta_{j,0})$ as the net present value of these expected excess financing costs for a new business with initial productivity equal to $\theta_{j,0}$. The value of a Type j startup is thus given by $V^j(\theta_{j,0}) - C^j(\theta_{j,0}) - \kappa_j$. In the presence of these frictions, the entrepreneur uses all earnings to repay $b_{j,0}$ as quickly as possible, and the law of motion of debt is:

$$b_{1,t+1} = \left(\frac{1+r^b}{1-d}\right) b_{1,t} - \pi(p_t, \theta_{j,t}) \tag{13}$$

For a Type 1 firm, we first compute n^*, the expected number of periods necessary to repay the debt. To simplify formulas, we make the normalization $\bar{p} = 1$ from here on. Substituting Equation (13) recursively and given the n periods necessary to repay the debt, for a Type 1 firm, its initial debt can be written as:

$$b = \Psi\theta_{1,0}\left[\frac{1-\left((1+g^{med})\frac{1-d}{1+r^b}\right)^n}{\frac{r^b+d}{1-d} - g^{med}}\right] \tag{14}$$

Solving for n yields:

$$n^*(b, g^m, \Psi\theta_{1,0}) = \frac{\log\left\{1 - \frac{b}{\Psi\theta_{1,0}}\left(\frac{r^b+d}{1-d} - (m-1)\right)\right\}}{\log\left((1+g^{med})\frac{1-d}{1+r^b}\right)} \tag{15}$$

$n^*(b, g^{med}, \Psi\theta_{j,0})$ is the number of periods necessary to repay debt b with productivity growth m and initial profits $\Psi\theta_{j,0}$. Once we find n^*, we compute Equation (14) discounting the flows using $r = 0$ instead of $r = r^b$ as

$$b^* = \Psi\theta_{1,0}\left[\frac{1-\left((1+g^{med})(1-d)\right)^{n^*}}{\frac{d}{1-d} - g^{med}}\right] \tag{16}$$

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:

$$C^1 = b^* - b \tag{17}$$

Note that in general, the procedure above can be used to compute $C(b, g, \theta_{j,0}, r^b)$, the excess cost of finance conditional on debt b, productivity growth g, initial productivity $\theta_{j,0}$, and the interest rate premium r^b. It is then straightforward to show that $C(b, g, \theta_{j,0}, 0) = 0$ and that $C(b, g, \theta_{j,0}, r^b)$ increases in r^b.

Consider now a Type 2 firm. In the first period, the firm pays an excess return $r^b b_{2,0}$. The residual debt is $b_{2,1} = \left(1 + r^b\right) b_{2,0} - \Psi\theta_{2,0}$. In the second period, with probability γ, the firm switches to high growth so that $\pi_{2,1} = \Psi p_2^{\frac{1}{1-\alpha}} \theta_{2,0}(1 + g^{high})$ and the residual cost is $C(b_1, g^{high}, \pi_{2,1})$. With probability $(1 - \gamma)$, the firm remains a low-growth firm and pays an excess return $r^b b_{2,1}$, so that $b_{2,2} = \left(1 + r^b\right) b_{2,1} - \pi_{2,1}^{low}$. In this case, $\pi_{2,1}^{low} = \Psi p_2^{\frac{1}{1-\alpha}} \theta_{2,0}$. Substituting recursively, this expression can be approximated to

$$C^2 = \sum_{t=0}^{n^e} \left[(1-d)(1-\gamma)\right]^t r^b b_t + \frac{\gamma}{1-\gamma} \sum_{t=1}^{n^e} \left[(1-d)(1-\gamma)\right]^t C(b_t, g^{high}, \theta_{2,t}, r^b)] \tag{18}$$

where n^e is the expected number of periods needed to repay the debt and b_t is the residual debt after t periods.