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

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Abstract

We use the latest available empirical evidence on the impact of the Covid-19 shock on the EU economy to predict its effect on firm entry, and in particular on high-growth startups, and on the related short- and long-run impact on employment growth. We find that the Covid-19 shock is expected to reduce firm entry and that its overall impact is very sensitive to financial conditions. A relatively small increase in financial frictions is likely to strongly reduce the entry of high-growth startups, with fewer jobs created in the short run but, more importantly, also slower employment growth in the long run. We then develop a model with heterogeneous startup types and simulate the effects of the Covid-19 shock on the entry and growth of a cohort of new firms to evaluate alternative policies. We find that a loan subsidy that reduces the excess cost of credit for new startups is the most efficient policy in promoting the entry of high-growth startups. The comparison of this subsidy with a wage subsidy that supports current employment shows that, for the same overall costs, the number of jobs created by the loan subsidy in the long term is significantly larger than that created by the wage subsidy in the short term. Our findings imply that, while policies aiming to stimulate current employment are important, in order to ensure also a faster recovery in the future they should be accompanied by measures directed at reducing the cost of credit for new businesses.

JEL: E20, E32, D22, J23, M13

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

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1 Introduction

The Covid-19 pandemic has caused a massive recession worldwide. In the EU, the most recent forecasts for 2020 predict a GDP contraction in the four largest EU economies ranging from -6.3% in Germany to -11.2% in Italy (see Table 1).

This crisis was counteracted with large and timely policy responses from the EU, amounting to more than 4 trillion euros.[1] A substantial part of these funds was assigned to support companies and their workers, and successfully limited job losses.[2] However, several commentators and researchers notice that these large subsidies could also increase the misallocation of resources, for example because they could contribute to create "zombie firms", and thus drag down productivity and employment growth and slow down the recovery.[3]

In this respect, one important element for the recovery is the creation of new firms. Reallocation through firm dynamics - the exit of unproductive businesses, and the entry and growth of new ones - is a key factor for employment growth in the medium/long run. Unfortunately, the current Covid-19 induced recession is likely to reduce new business formation, both because firm entry is procyclical, and because it is sensitive to the availability of external finance, and the most recent data show substantial worsening of financing conditions for small businesses in Europe (see Figure 2).[4] In Spain, average firm entry declined by around 40% during March-July 2020, and the cumulative deficit in entry in these 5 months was comparable to the same deficit accumulated in the first 11 months of the Great Recession (see Figure 3).

This paper has two main objectives. First, to predict the effects of the Covid-19 shock on firm creation and employment growth. Second, to derive a partial equilibrium model of startup

[1]The European Commission quantifies a total economic response of 4.2 trillion euros to combat the crisis (https://ec.europa.eu/info/live-work-travel-eu/health/coronavirus-response/jobs-and-economy-during-coronavirus-pandemic_en), and a substantial part of these funds are directed to support small and medium firms and their workers. Additionally, the ECB has launched the 1.35 trillion euros Pandemic Emergency Purchase Programme that also includes direct purchases of private sector credit.

[2]Unemployment increased in the Euro area from 7.3% in February 2020 to 7.9% in July 2020 (the latest available data from Eurostat at the time of this writing).

[3]See, for instance, the working paper of Zoller-Rydzek and Keller (2020) arguing that a too high level of loan guarantees might increase the share of zombie firms in the economy; or some articles in the press, such as the Financial Times ('The corporate zombies stalking Europe', or 'Pandemic debt binge creates new generation of zombie companies') or the Washington Post ('Here's one more economic problem the government's response to the virus has unleashed: Zombie firms'), among many others.

[4]New firms are particularly important for employment growth (Haltiwanger et al. (2013)), and there is substantial heterogeneity in startups (Haltiwanger et al. (2016), Pugsley et al. (2018)). Furthermore, the economic conditions, especially financial conditions, are important for the composition of entry and employment creation (Albert and Caggese (2020)).

dynamics and use it to evaluate the effectiveness of alternative policies directed to stimulate the entry of high-growth firms and thus promote employment growth in the medium and long run.

To pursue the first objective, we quantify, for the four main EU economies, the expected effect of the GDP decline and increase in financial frictions caused by the Covid-19 shock, both on overall firm entry (the extensive margin) and on the growth potential of new firms (the intensive margin). We follow the empirical strategy of Albert and Caggese (2020), who identify fast-growing entrepreneurial startups using the survey answers in the Global Entrepreneurship Monitor (GEM), a multi-year, multi-country household survey with a special emphasis on entrepreneurial choices. With respect to Albert and Caggese (2020), in this paper we consider a version of the GEM dataset updated with the latest publicly available data, and we provide also an instrumental variable approach, in which we identify exogenous variations in financial frictions (bond spreads) predicted by exogenous monetary shocks, identified by the methodology of Jarocinski and Karadi (2020).

Since the recession generated by the Covid-19 pandemic has characteristics and dynamics different from the previous recessions on which our model is estimated, we consider two alternative lower- and upper-bound scenarios, depending on how much we expect the current GDP contraction to matter for firm creation. For each of these scenarios, we consider two hypothetical outcomes for financial frictions, measured by bond spreads. Our main finding, which is confirmed by both the lower and the upper bound scenario, is that the contraction in GDP and the increase in financial frictions strongly interact. The drop in GDP alone, with spreads remaining in 2020 at the same level as in 2019, reduces firm entry, but it does not significantly affect the share of high-growth firms among the new entrants.[5] Instead, a GDP contraction accompanied by even a relatively small increase in financial frictions strongly reduces the entry of high-growth firms among the new startups. This causes a further reduction in entry and fewer jobs created in the short run but, more importantly, also slower employment growth of this cohort of firms in the long run. For Spain, we are able to quantify the job losses caused by these effects using the Spanish firm-level dataset of Central de Balances from the Bank of Spain. We find that if spreads in 2020 rise by 0.58 percentage points with respect to 2019 (from 1.33%

[5] In terms of overall drop in entry, for the lower bound we predict a reduction ranging around 35% for Germany to 55% for Spain. For the upper bound, these values increase to 60% ad 80%, respectively. The early evidence we have for Spain (See Figure 3) is consistent with the lower bound estimates.

to 1.91%), for the new cohort of firms there will be 18% more job losses in the short term and 28% more job losses after 8-9 years.

The implication of this finding is that policies counteracting the economic effects of the pandemic should include programs that incentivize the creation of new firms, especially high-growth ones. Therefore, the second main contribution of this paper is to set up a partial equilibrium model with entrepreneurs who have heterogenous skills in operating low- and high-growth startups. We use the model to simulate the entry and growth of a cohort of new firms, and implement an exogenous shock to demand and financial conditions that replicates the effects of the Covid-19 shock. We then consider two alternative policies and evaluate their ability to mitigate the fall in firm entry and, in particular, stimulate the entry of high-growth firms: first, a grant that partly finances the initial investment to start the firm, and thus reduces the borrowing needs of the entrepreneur. Second, a loan subsidy that reduces the cost of this borrowing. We compare these two policies with a third one aiming to support employment during the crisis: a subsidy to reduce the wage bills of the firms in this cohort. Importantly, we impose that all three alternative policies have the same overall cost.

Our main finding is that the loan subsidy is much more effective than the grant subsidy in stimulating the entry of high-growth firms and long-run employment growth. The intuition is that while both policies have similar firm-level implications in terms of reducing borrowing costs, the loan subsidy is much more efficient because it endogenously helps more the potential entrepreneurs that are relatively less productive and hence more affected by the Covid shock because they are the margin between entering the market or not. Very productive entrepreneurs, whose startup choices are not affected by the shock and who thus would not need any subsidy, receive large transfers under the grant subsidy but much smaller ones under the loan subsidy as their firms are more profitable and repay the debt very quickly. Finally, the comparison of the loan and the wage subsidy shows us that, for the same overall costs, the jobs created by the former in the long term are significantly larger than the jobs created by the latter in the short term. The implication of these findings is that while policies directed at supporting current jobs are important, in order to ensure also a faster recovery in the future they should be accompanied by measures directed at reducing the cost of credit for new potential entrepreneurs. We believe these findings are important for the current policy debate. Despite the large funds directed to firms in the EU, small attention has been devoted to new firms. The European Commission recently published a 106 pages long document with the detailed list of all the policy measures taken in the EU countries against the spread and impact of the coronavirus. The word “Firm/Firms” occurs more than 70 times and “Business/Businesses” more than 140 times, but they always refer to existing firms rather than new ones, and the word “Startups” only appears twice.[6]

The remainder of 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

Firstly, 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 businesses 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) finds 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.

Secondly, our paper is related to the literature studying the resource misallocation. Hsieh and Klenow (2009) show how capital misallocation can be one of the main drivers of TFP differences between countries, and Restuccia and Rogerson (2008) show how policy distortions might induce misallocation, decreasing aggregate output and TFP. Along these lines, some economic commentators and researches worry that too large subsidies to incumbent firms might indeed increase misallocation by creating “zombie” firms (inefficient firms kept alive by excessively cheap credit), hence slowing down the economic recovery. Related to the current Covid-19 crisis,

[6]The document is available at https://ec.europa.eu/info/sites/info/files/coronovirus_policy_measures_20_august.pdf

Zoller-Rydzek and Keller (2020) argue that a too high level of loan guarantees might increase the share of zombie firms in the economy. However, in order to have a complete view of the picture, it is important to understand the impact of the shock on the entry margin, and how policies would affect it. Indeed, Yang (2020) shows that the extensive margin is important for misallocation, since selection can magnify aggregate TFP losses from micro- distortions by over 40%. Hence, our contribution to this strand of literature is to shed light on the predicted contribution of the entry margin of the current Covid-19 crisis on aggregate employment losses, and to understand how effective policies should be designed in order to minimize misallocation coming from this margin.

Finally, 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 (Haltiwanger et al., 2016; Pugsley et al., 2018). Sedláček (2020) shows that a 'lost' generation of firms might lead to lower persistent employment. 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 crisis (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 Table 1). Despite largely supportive monetary policy measures, these dire economic conditions also caused an increase in financial frictions. This is shown in Figure 1, 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 index 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. Importantly, tightening financial conditions are clearly visible in bank credit standards too. Based on data from the ECB's Bank Lending Survey, Panel A of Figure 2 shows that credit conditions have worsened constantly. Worryingly, the largest tightening happened in the most recent period available, the third quarter of 2020, with a level of tightening not seen since the 2012 sovereign crisis.[7] The tightening of the financial conditions, paired with the increase in liquidity needs due to the Covid-19 shock, translates into a higher demand for credit, especially for SMEs. Using the ECB's Survey on the Access to Finance of Enterprises (SAFE), with data up to the final round comprising October 2019 - March 2020, Panel B of Figure 2 shows the financing gap, which is the difference between the change in demand for external financing and the change in its availability for surveyed SMEs. The financing gap increased significantly in the last round survey, pointing at an early worsening in credit availability for SMEs due to the Covid-19 shock.

Summing up, the current Covid-19 shock is characterized by a sharp decrease in GDP and a tightening of credit availability to firms. The purpose of the next sections is to understand how these are predicted to impact firm creation, its composition (low- vs high-growh firms) and ultimately the aggregate employment of the cohort of firms entering in 2020.

[7]The exact definition of this statistic is 'fraction of banks surveyed answering the general economic outlook considerably contributed to a tightening of credit standards to SMEs minus the frequency answering it considerably contributed to an easing'.

3.2 Early evidence on firm entry after the Covid-19 shock in Spain

By reducing demand, increasing uncertainty and tightening financing conditions, the Covid-19 shock is expected to significantly affect new business formation. In this section, we provide early evidence for Spain, which will be useful as a benchmark to evaluate the performance of our empirical model illustrated in the next section. In Figure 3, Panel A shows the deseasonalized number of new firms entering (new incorporations) in Spain, with average entry being around 8,000 firms per month before the shock. The largest drops are in April and May 2020, with entry falling 75% and 64% relative to the average value, respectively. It seems likely that this large drop in entry is not only caused by the restrictions of movements, but also by the worsening of the economic conditions and increase in uncertainty. This is plausible both because the large drop in entry continued in May when restrictions were being lifted, and because entry in the upcoming months did not rebound, remaining below its average until July 2020. This implies a huge cumulative deficit in firm entry, as shown in Figure 3, Panel B: the cumulative drop in firm entry in the first 5 months since the beginning of the pandemic is as large as that of the first 11 months after the beginning of the Great Recession. This early evidence of the decrease in firm entry is likely to have important short- and long-run effects, which we attempt to quantify in the next sections.

3.3 Cyclical conditions, shocks and entry into entrepreneurship

In this section, we estimate the effect of business cycle and financial conditions on the probability to start heterogeneous business types. The goal of this exercise is to use the estimated relationships to predict the impact of the Covid-19 shock on both overall startup creation and on the creation of different startup types. In the next section, we combine these predictions with estimates from firm level data to compute the long-run employment effects due to impact of the shock on firm entry.

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.[8]

[8] The representativeness of this sample is confirmed by Poschke (2018), who shows that the firm size distribution

We restrict the sample of our analysis to France, Germany, Italy and Spain, for which reliable measures of financing conditions are available (the GZ spread), and which are the four largest economies in the EU, accounting for 64% of the EU GDP in 2019.[9] 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.[10]

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 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.[11]

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 indicator for 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

in the GEM matches well that obtained from administrative data sources.

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

[10]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 21,000, 72,000, and 29,000, respectively.

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

(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. We describe the construction of these instruments and present the first-stage results in online Appendix B. 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 startup types. 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.[12] We expect that, after controlling for these variables, credit shocks should mainly capture the effects of financial constraints to entrepreneurs.

Our estimation strategy requires that cyclical fluctuations and financing conditions are not perfectly correlated in the data. We find that this is the case in our sample. The correlation between the predicted GZ spread and GDP growth is -0.39, thus low enough that their effects can be separately identified. This is shown in detail in Figure A.1 in the online Appendix, where we report the scatterplot between GDP growth (deviations from country averages) and the value of the predicted GZ spread. The plot shows a negative relation, which, however, is far from perfect, with many observations with higher than average levels of financial frictions associated with a wide range of GDP growth values.

[12] 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.

The term $\sum_{k=0}^{K} \gamma_k X^k_{i,j,t}$ in Equation (1) indicates the K control variables, which further include country dummies, gender, age, educational level, income category, whether the individual has previous experience in running the business, and the share of respondents in a country-year reporting to have shut down a business during the last 12 months.[13] As 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 2, 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. Furthermore, estimating the regressions in columns 2-3 and columns 5-6 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 $\beta_3^l = \beta_3^h$ (p-values are reported at the bottom of Table 2).[14] In the online Appendix, we present some robustness checks of this result. In Table A.3 we replicate the results in Table 2 using the spreads on the borrowing of financial institutions instead of corporate spreads. We do so because banking spreads are informative of the financial frictions faced by small businesses. The coefficients in this table are quantitatively similar to those found in Table 2, and confirm our main results. Furthermore, in Table A.2 we present the results of the OLS regressions that use the actual GZ spread as regressor instead of the instrumented ones, and also in this case we confirm that the β_2 coefficient is significantly more negative, and the β_3 coefficient is significantly larger, for high-growth than for low-growth startups.

The estimated coefficients of GZ spread and GZ spread $\times$ GDP growth suggest that, while

[13] 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.

[14] We obtain these p-values by performing a Hausman-type test implemented by the suest command in Stata.

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. In Section 4, we describe a simple model that generates startup dynamics consistent with this empirical evidence. The key intuition is that high-growth startups have 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.

We use the estimated coefficients in columns 4-6 of Table 2 to predict the impact of the decline in GDP and of the increase in financial frictions, caused by the Covid-19 Pandemic, on both firm entry and its composition in the four countries. Since the recession generated by the Covid-19 pandemic has characteristics and dynamics different from the previous recessions on which our model is estimated, we consider two alternative lower- and upper-bound scenarios for the expected decline in GDP, depending on how much we expect the current GDP contraction to matter for firm creation. The upper bound is the decline in GDP predicted by the Summer 2020 Economic Forecast of the European Commission, shown in Table 1. We call this upper bound because of several reasons. First, given the different nature of this shock (i.e., the temporary restrictions to physical movements due to the complete lockdowns, implying huge GDP losses driven in particular by certain sectors like tourism, transportation or food services) compared to the previous recessions we use for prediction, we believe this might bias upwards our predictions in the fall of entry. Second, there has been a fast policy response to counteract the effect of the Covid-19 shock, something that might have cushioned the fall in firm entry. As a lower bound, we use half of the decrease in GDP growth expected by the Summer 2020 Economic Forecast of the European Commission. For financial frictions, there exist no reliable forecasts 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. Table 1 shows that spreads increased moderately in all countries and the most in Italy - nearly 0.8 ppt.

We start by analyzing the *lower bound* case in Figure 4. Panel A presents the predictions for the overall fall in entry. When we assume no increase in spreads, it is the lowest in Germany (around 35%) and the highest in Spain (55%), which suffers a sharper fall than Italy despite similar forecasts for 2020 because of its higher average GDP growth rate. This drop in entry is consistent with the early evidence from Spanish data presented in Section 3.2, and implies this *lower bound* is probably the most appropriate one to evaluate the effects of the Covid-19 shock on Business formation. If spread levels increase to that of May 2020, the fall reaches around 65% in Spain, Italy and France. This additional fall in entry is mainly due to the decline in high-growth startups. This is shown in Panel B, which 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 (even increases slightly) without spread increase, it drops strongly when spreads increase at the May 2020 level, up to 65% in Italy. This result follows from the strong interaction effect between GDP growth and spreads on the entry of high growth firms.

In Figure 5, we show the same estimates for the *upper bound* case. Although quantitatively the effects are larger, with a decrease in entry up to 90% in Italy, and a decrease in the share of high-growth firms of up to 85%, the broader conclusions are still the same: first, the Covid-19 shock is predicted to reduce firm entry in 2020; and second, if it is furthermore accompanied by a moderate worsening in credit conditions, like the observed increase in spreads in May 2020, it is predicted to decrease significantly the share of high-growth firms entering the economy.

3.4 Startups and long-run employment growth

The second step of our analysis is to use the fall in firm entry to 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 (MCB), a panel of Spanish firm-level data spanning from 1996 to 2017, which virtually covers the entire population of Spanish incorporated firms.[15]

We use this dataset to answer two questions: First, how long-lasting are the effects of firms entry, regardless of the type of firm created, on aggregate employment? Second, does the composition of entry (high-growth versus low-growth firms) matter for the long-run job creation

[15]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.

of a given cohort of firms?

In order to understand the first issue, we run the following regression:

$$\log Employment\_cohort_{k,s,t} = \beta_{0,k} + \beta_{1,k} \log \text{New\_firms}_{s,t-k} + \phi_{t,k} + \psi_{s,k} + \epsilon_{k,s,t} \quad (2)$$

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 $k \in [1, 10]$. Thus, the set of coefficients $\beta_{1,k}$ indicates the deviation in employment from the average employment of firms of age k due to fluctuations in the number of firms that had initially entered. The estimated coefficients are reported in Figure 6. An increase of 1% in firm entry will increase the employment of that cohort by nearly 0.9% in the first period. The figure shows that the employment impact of firm entry declines with time, but it still remains large and significant: after 10 years, the impact on the cohort's employment is still 0.63%.

Regarding the second issue, we verify whether the entry of relatively more high-growth startups predicts faster ex-post employment growth of the specific cohort. 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 industry shares with the firm-level data from the MCB. 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. Using this matched data, we run the following regression:

$$\log Employment_{i,s,t} = \beta_0 + \sum_{k=0}^{K} \beta_{1,k} age^k_{i,s,t} + \sum_{k=0}^{K} \beta_{2,k} age^k_{i,s,t} Share\_growth^{t-k}_{i,s} + \phi_t + \psi_s + \epsilon_{s,t} \quad (3)$$

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 the interaction term $\beta_{2,k}$ would be positive. The results are presented in Table 3. In column 1 we control by any aggregate shock and sector specific factor by controlling for time and sector fixed effects. In column 2 we further saturate the model by including sector-year fixed effects. We find that the interaction coefficients are negative in the first periods and then become positive in the medium to long term. This implies that, although during the first years these high-growth firms remain smaller, eventually they are able to realize their full potential and end up growing above average. In quantitative terms, the coefficients in column 1 imply that a sector composed of only high-growth firms would have an average size of newborn firms 13% smaller than the newborn firms in a sector composed only of low-growth firms. However, the high-growth firms would grow faster and be on average 23% larger than the low-growth firms when both types are 8 years old. This finding highlights the importance of the composition effect of entry for the 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 for Spain, as shown in Figure 7. This analysis focuses the impact of the entry and composition margin on aggregate employment of the cohort of firms entering in the current year and on its evolution over the following years. Hence, we are abstracting from possible general equilibrium effects on prices and interest rates, as well as on employment spillovers effects on firms in different cohorts and sectors.[16] As before, we consider two scenarios for GDP growth: *lower bound* (Panel A of Figure 7) and *upper bound* (Panel B of Figure 7); and for each of these scenarios, we assume there is no increase in spreads (blue line), or spreads increase as of May 2020 (green line). We construct these predictions in the following way. First, we consider the predicted fall in firm entry (from Figure 4 for the lower bound, or Figure 5 for the upper bound). Then, with this predicted decrease in firm creation, we multiply $\beta^{1,k}$ from Equation (2) with the aggregate employment of firms of age k from MCB (averaged across all the years of our sample) to compute the predicted job losses of the cohort entering in 2020 from 2021 ($k = 1$) to 2030 ($k = 10$). This is the long-run effect of the entry channel. Second, we want to include also the impact of the composition channel on aggregate employment. In order to do so, with the coefficients of the interaction terms of Equation (3) depicted in the first column of Table 3, we get the effect of the share of high-growth firms in a new cohort on its average firm-level employment at each age $k = 1, 2, ..., 10$. Then, to compute the $t + k$ forward prediction on the

[16]These effects are potentially important but we cannot analyze them here for reasons of space, therefore leaving them for future research.

change in overall cohort employment due to a change in the composition of entry, we multiply the predicted decrease in the share of high-growth firms for each scenario (depending on the assumption on GDP growth and the assumption of the increase in spreads) with the coefficient $\beta_{2,k}$ of Equation (3) and the aggregate employment of firms of age k. We then add these changes in employment due to the composition channel to the changes in employment due to the entry channel, to obtain the overall predicted impact on long-run aggregate employment of the cohort.

We start by analyzing the scenario of the lower bound (Panel A of Figure 7). If spreads do not increase (blue line), overall aggregate employment losses of the cohort range from around 45,000 jobs in 2021 to a maximum of around 70,000 in 2029. If spreads increase as of May (green line), job losses range from around 55,000 jobs in 2021 to 90,000 jobs in 2029. Note the distance between the blue and green line widen as time goes by. This is because of the composition channel: if lower GDP growth is paired with an increase in spreads, the share of high growth firms decreases significantly, while this is not the case with lower GDP growth alone (see Figure 4, Panel B, red vs blue bar). In order to highlight this, we plot in Panel A of Figure 7 the impact on aggregate employment of the entry channel alone for the case of increase of spreads as of May 2020 (red line), and compare it to the predicted overall decrease in aggregate, which includes the entry *and* the composition channel (green line). Note that until 2024, the lines nearly overlap, while from year 2024 on, lines start diverging, with more predicted jobs lost if we include the composition effect. 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. Because of this, a "missing generation" of high-growth firms can significantly hurt job creation even many years in the future.

Summing up, we find that a moderate increase in bond spreads in Spain (from 1.33% to 1.91%), is expected to strongly reduce the entry of high-growth firms, with additional 18% jobs lost in the short term, and up to additional 28% jobs lost after 8-9 years.

The results of the same analysis for the *upper bound* of the decrease in GDP growth are shown in Panel B of Figure 7. Again, although quantitatively larger, all the intuitions and mechanisms previously explained still apply: a drop in GDP growth predicts a decrease in entry that has long-lasting effects on employment; and if this is paired with a worsening of credit conditions, employment losses are even larger, especially in the long run.

4 Model and Policy Analysis

In this section, we set-up a stylized partial-equilibrium model of firm entry and post-entry growth 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 $j = 1, 2$. Both types produce the same homogeneous consumption good. 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:

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

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, which will result in higher 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 $g^{high} > g^{med}$. 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.

Financing

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.

Value of the business without financial frictions

The access to finance is not a problem if either $a < \kappa_j$ but $r^b = 0$, meaning that the entrepreneur can borrow at the market interest rate, or $r^b > 0$ but $a \geq \kappa_j$, meaning that access to finance is costly but the entrepreneur can self-finance the startup cost. In this case, the value of a new business with initial productivity $\theta_{j,0}$ is given by the discounted sum of the future expected revenues net of κ_j. First, consider a type 1 firm. In every period, it might liquidate with probability d. If it does not liquidate, it generates profits $\Psi p_t^{\frac{1}{1-\alpha}}\theta_{1,t}$, where θ_t grows at the rate g^{med}. As shown in online Appendix C.1, assuming that p_t follows a stationary process with mean $\bar{p}$, the net present values of profits for each startup type with initial productivity $\theta_{j,0}$ are equal to:

$$V^1\left(\theta_{1,0}\right) = (1-d)\Psi\frac{\bar{p}^{\frac{1}{1-\alpha}}\theta_{1,0}}{d-(1-d)\,g^{med}} \tag{7}$$

and

$$V^2\left(\theta_{2,0}\right) = (1-d)\Psi\Phi\frac{\bar{p}^{\frac{1}{1-\alpha}}\theta_{2,0}}{1-(1-\gamma)(1-d)\left(1+g^{low}\right)} \tag{8}$$

with

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

The value of a type j startup is thus given by $V^j(\theta_{j,0}) - \kappa_j$ and an entrepreneur chooses the type with the higher value. We denote the level of skills ϕ_2 at which an entrepreneur is indifferent between startup types as $\bar{\phi}$. Thus, those with skills below this threshold will choose a type 1 startup, while those with skills above will chose type 2. As long as $\bar{\phi}$ lies within the support for ϕ_2, there always exist startups of both types.[17]

Value of the business with financial frictions

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 with $C^j(\theta_{j,0})$ the net present value of these expected excess financing costs for a new business with initial productivity equal to $\theta_{j,0}$. Hence, the value of a type j startup is given by

$$V^j(\theta_{j,0}) - C^j(\theta_{j,0}) - \kappa_j, \tag{9}$$

and the entrepreneur will choose the firm type that maximizes (9). We derive the cost function $C^j(\theta_{j,0})$ in online Appendix C.2.

The key implication of this model is that these costs increase more strongly for type 2 startups when financial frictions become larger (e.g. $b_{j,0}$ or r^b increases). This increases the threshold

[17]For a formal proof the existence of such a threshold in a simplified two-periods version of this model, see Albert and Caggese (2020).

$\bar{\phi}$ and hence reduces the frequency of type 2 relative to type 1 startups. The intuition is as follows. Consider the marginal entrepreneur who is indifferent between choosing one of the two types, because they have identical net present value. For this entrepreneur, the type 2 startup is more profitable in the long term than the type 1 startup, but less profitable in the short term, which implies more time needed to repay the debt. It follows that an increase in financing costs will damage this option more than the alternative one (see Albert and Caggese, 2020, for a formal proof). Therefore, with higher financial frictions, not only will some entrepreneurs switch from type 2 to type 1 businesses, but also those with low general skills will decide to not start any business, if the cost becomes so high that the net present value of the startup ($V^j(\theta_{j,0}) < C^j(\theta_{j,0}) + \kappa_j$) becomes negative.

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. We assume the price p_t of the final good to be constant and normalized to one. We also normalize the value of κ_1 to one, and set $\kappa_2 = 1.25$ and $a = 0.5$ so that these parameters jointly match the average share of external money needed by entrepreneurs in the GEM, which is around 50% for low-growth and 60% for high-growth startups (see Albert and Caggese, 2020). α is set to 0.6, the labor share of output. The exit rate d is set to 7%, implying an average firm age of 14 years, which matches the average age of established businesses owned by GEM respondents in France, Germany, Italy and Spain.[18]

The growth rate g^{low} is normalized to zero, which leaves four parameters remaining to be determined: g^{med}, g^{high}, γ, and the financing rate r^b. We jointly choose their values so that the model matches the following four empirical moments. First, the ratio of high-growth to low-growth firms is around 0.5 as observed in the GEM. Second, according to the employment evolution uncovered in column 1 of Table 3, high-growth firms are around 13% smaller than low-growth firms in the year of establishment. Third, the former overtake the latter at the age of 4, and, fourth, are around 20% larger at the age of 10. The values we obtain by matching these patterns are $g^{med} = 2\%$, $g^{med} = 6\%$, $\gamma = 20\%$ and $r^b = 5\%$. An overview over all parameters

[18] The actual firm age is not reported in the GEM, so we proxy the year of establishment by the first year a firm paid wages.

can be found in Table 4.

We use the calibrated model to simulate a sudden unexpected economic downturn and increase in financial stress due to the pandemic by implementing a sudden shock to demand, entrepreneurs' endowment and interest rates. First, the demand shock leads to a 50% 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 in our calibration). Second, entrepreneurs' endowment falls from 0.5 to 0.2. This represents both a reduction in their disposable income because of difficulties in their current business, and also a possible increase in precautionary saving due to the increased uncertainty caused by the Covid-19 pandemic. Third, the borrowing cost r^b increases by 1.5 ppt. Combined, these shocks imply a fall in firm creation of 36%.[19]

Policy alternatives

We compare three 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 choose the level of this subsidy so that it counteracts exactly half of the fall in employment due to the demand shock. This make its value straightforward to compute because labor demand depends on the ratio of prices to wages. Hence, given that we assume a 50% decline in prices on impact, the wage subsidy is 25% in the first period and then declines at the same rate as that with which the shock fades away.

The second policy is a one-time grant 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 choose the level of this subsidy so that it has exactly the same cost as the wage subsidy, which implies that it amounts to 6% of κ_j.

Finally, we consider a loan subsidy, through which entrepreneurs can borrow at a reduced

[19] This value is consistent with the average drop in firm entry observed in Spain during the first five months of the pandemic for which we have data available (see Figure 3). Nonetheless, we 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.

interest rate. Again choosing the level to make the cost of this subsidy equal to that of the other subsidies, we obtain a reduction in the rate by 61% to around 0.025.[20]

Panel A of Figure 8 shows for each type, and for both types together, the fall in entry relative to the entry before the shock in case there is no subsidy (blue), the wage subsidy (red), the grant subsidy (green) or the loan subsidy (brown) in place. First, the figure shows that in the absence of subsidies the entry of startups of Type 2 falls much more strongly than that of Type 1, consistently with our empirical results in Figure 4. This is due to the fact that the net present value of expected financing costs increase more steeply for the former 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. Second, we find that the grant subsidy dampens the fall in entry for both types somewhat more effectively than 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 grant subsidy is distributed to entrepreneurs independently of their initial productivity.

Finally, the loan subsidy can be seen to have contrary effects on type 1 and type 2 startups. It further *increases* the fall of the former, whereas it strongly reduces the fall of the latter, even a level below that without the shock. The intuition is that by reducing the borrowing rate, this subsidy most effectively alleviates the financial frictions. Moreover, while the two subsidies we considered before also allocate large funds to very productive entrepreneurs whose entry and startup type decision is not affected by the shock, the loan subsidy allocates more funds towards those entrepreneurs that need to take on a larger amount of debt and that take longer for repayment, which are primarily less productive type 2 entrepreneurs. The lower financing cost allows them to enter despite the Covid-19 shock, and in addition many of them switch from type 1 to type 2 projects, leading to the larger fall in entry of the former seen in the figure. Summing up, we find that the loan subsidy not only to be the most effective in promoting high-growth startups but also to be overall more efficient than the grant and wage subsidies. Overall entry

[20]We calculate the cost of the loan subsidy as the difference between interest payments under the reduced rate and payments under the non-reduced rate. Given that governments are able to raise funds at almost zero rates, the cost of the loan subsidy can be rather interpreted as an opportunity cost than an actual cost.

falls by 36% (relative to the no-shock case) without subsidies and by 34% and 32% with the wage and grant subsidy, respectively. Instead, if the same amount of funds is allocated to the loan subsidy, entry falls only by 13%.

Panel B compares the predicted 20-year ahead evolution of aggregate employment of the entering firms under 5 scenarios: the first scenario is without the Covid-19 shock, the second is with the shock but without any policy response, and the three remaining scenarios are with the shock and each of the different policy responses. 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 with neither of the subsidies.

Comparing first the no-shock (black) and shock scenario without subsidy (blue), we see that the difference in future employment even increases again after around 10 years. This is because the shock affects much more type 2 firms, which tend to grow faster in the long run and whose absence thus leads to relatively lower overall employment growth in the future (the above documented intensive margin effect).

Comparing next the evolution of employment with the different subsidies, we find that in the short-term, the wage subsidy has the most positive effect on employment as it is designed to stimulate employment directly until demand has recovered. However, it has little effect in the long run because of the limited effect on startup composition. While less effective in the beginning, the grant subsidy leads to a somewhat higher employment level in the long run as it is more efficient in reducing the fall in entry as seen in panel A. Finally, despite also having little effect in the beginning, the loan subsidy allows employment to almost convergence to to its level in absence of the shock in the long run, which is due to its higher efficiency in stimulating entry, and to its strong promotion of type 2 startups.

Overall, this exercise illustrates the importance of not only taking into account the short-term effect on overall entry but also the compositional effect and its long-term implications when designing a subsidy for new firms. Therefore, while policies directed at supporting current jobs are important, in order to stimulate growth in the long run, they should be accompanied by measures directed at reducing the cost of credit for new potential entrepreneurs.

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: Based on data from the ECB's Bank Lending Survey, Panel A of Figure 2 shows that credit conditions have worsened constantly, especially in most recent period available, the third quarter of 2020, with a level of tightening not seen since the 2012 sovereign crisis.

We use the methodology developed in Albert and Caggese (2020) to predict the impact of the Covid-19 shock on firm entry and its composition, assuming different scenarios for the drop in GDP growth and the increase in financial frictions (credit spreads). We find that a decrease in GDP growth is expected to reduce firm entry, and its overall impact is very sensitive to financial conditions. This is because the share of high growth firms entering is very sensitive to a rising cost of credit. The aggregate employment implications for the entering cohort are sizeable, especially with a worsening of financial conditions, 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. Because of this, a "missing generation" of high-growth firms can significantly hurt long run job creation.

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 a loan subsidy reducing interest rates on debt is the most effective in the long term. This is because it benefits more high-growth firms, which contribute more to employment growth in the future.

Overall, our findings highlight the importance of the entry and composition margin to stimulate short- and long-run employment, a margin overlooked by policymakers so far during this Covid-19 crisis. Hence, in order to ensure a faster recovery of employment, current policy tools should be accompanied by measures directed at reducing the cost of credit for new businesses.

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/1pYOM5SZAO4J8t6hqJ58Pztki_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, and Javier Miranda, "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

_ , **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.

Hsieh, Chang-Tai and Peter J Klenow, "Misallocation and manufacturing TFP in China and India," *The Quarterly journal of economics*, 2009, *124* (4), 1403–1448.

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.

Restuccia, Diego and Richard Rogerson, "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic dynamics*, 2008, *11* (4), 707–720.

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.

Yang, Mu-Jeung, "Micro-level Misallocation and Selection," *American Economic Journal: Macroeconomics (Forthcoming)*, 2020.

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

Tables and Figures

Table 1: Projected GDP growth and spread

	Projected GDP growth 2019	Projected GDP growth 2020	Spread avg. 2019	Spread May 2020
France	1.5	-10.6	1.60	2.00
Germany	0.6	-6.3	1.22	1.97
Italy	0.3	-11.2	1.56	2.38
Spain	2.0	-10.9	1.33	1.91

Notes: The projected levels of GDP growth are taken from the Summer 2020 Economic Forecast of the European Commission. 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).

Table 2: 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
P-value for $\beta_2^{low} = \beta_2^{high}$		0			0	
P-value for $\beta_3^{low} = \beta_3^{high}$					0	

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 B. Standard errors are clustered at the country level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 3: 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

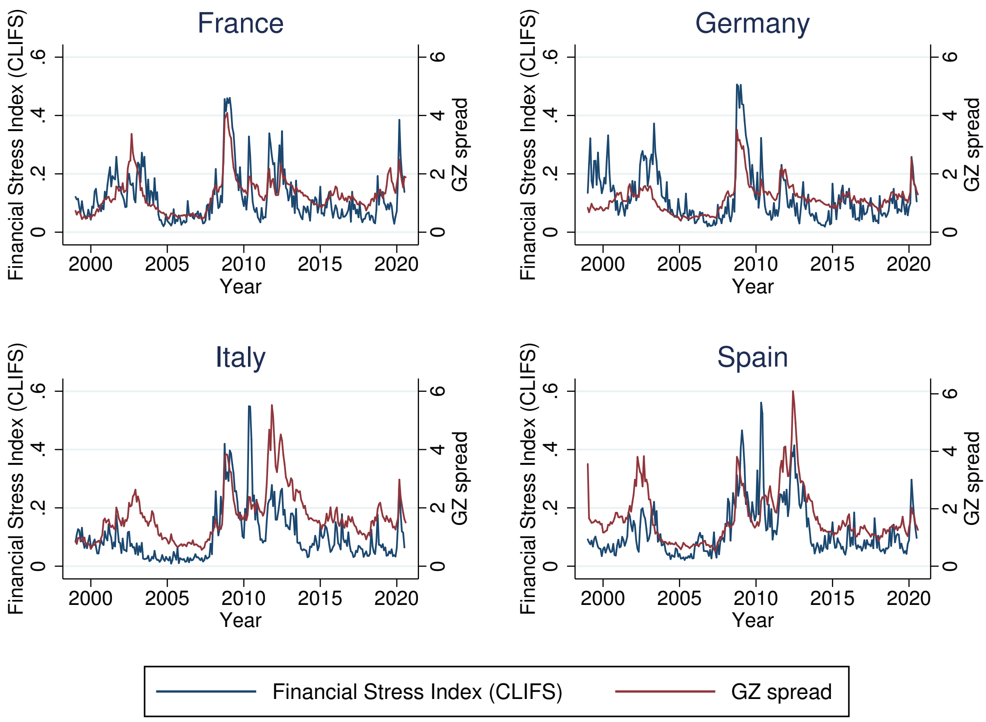
Notes: Number of entrants and their employment is computed from MCB using the cleaning described in the main text. *share* is the share of high-growth startups (measured in the GEM data) in the 2-digit sector to which the observed firm belongs in the year it was born. Significance levels: * $p<0.1$,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

Table 4: 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).

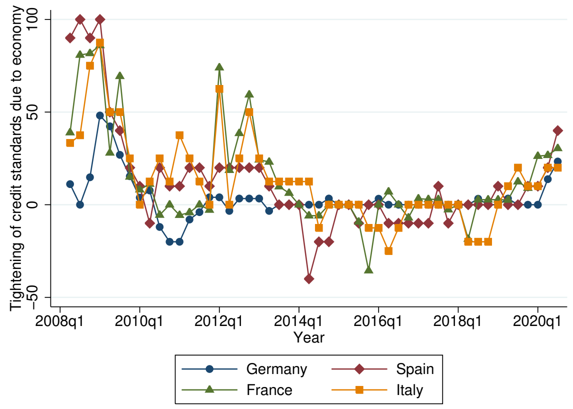
Figure 1: Financial stress indicators and credit spreads



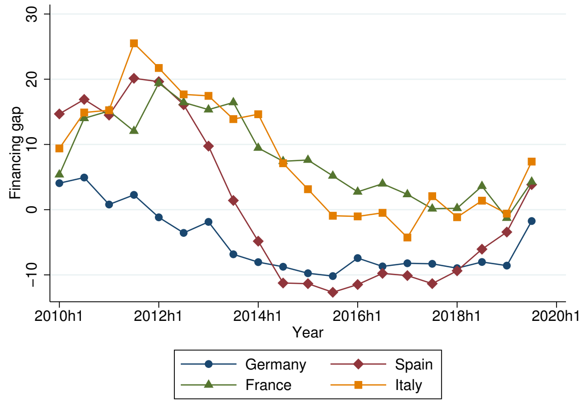
Notes: The country-level index of financial stress (CLIFS) is provided by the ECB. The credit spreads are updated series provided by the Banque de France based on Gilchrist and Mojon (2016).

Figure 2: Worsening of credit conditions

A. Tightening of credit standards to SMEs due to economic conditions (Banks)



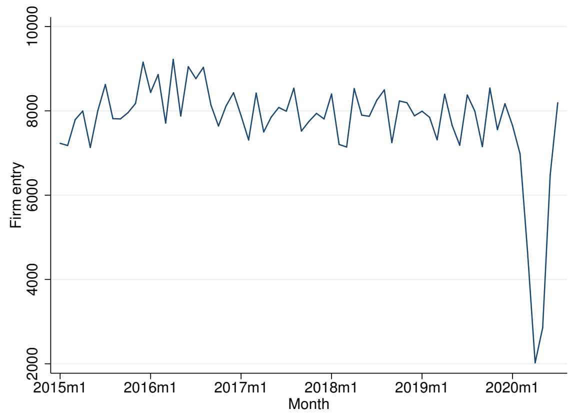
B. Change in financing gap (SMEs)



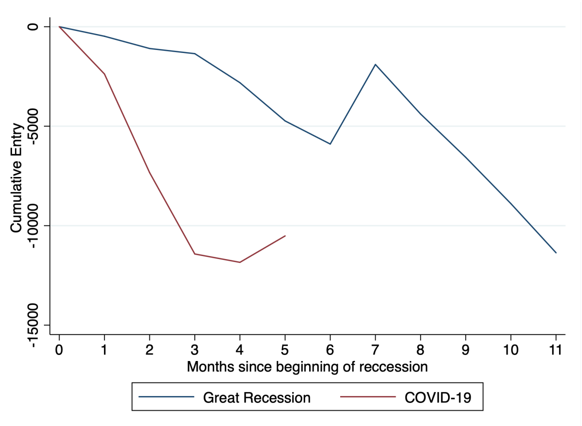
Notes: **Panel A:** Shows the frequency of surveyed banks answering the general economic outlook considerably contributed to a tightening of credit standards minus the frequency answering it considerably contributed to an easing. Source: BLS, accessed from `https://sdw.ecb.europa.eu/browse.do?node=9691151`. Last data available for Q3 2020. **Panel B:** The figure shows the difference between the change in demand for and the change in the availability of external finance for surveyed SMEs. Source: SAFE, accessed at `https://sdw.ecb.europa.eu/browse.do?node=9689717`. The last survey in the series was conducted between October 2019 and March 2020.

Figure 3: Firm entry in Spain

A. Firm entry in Spain



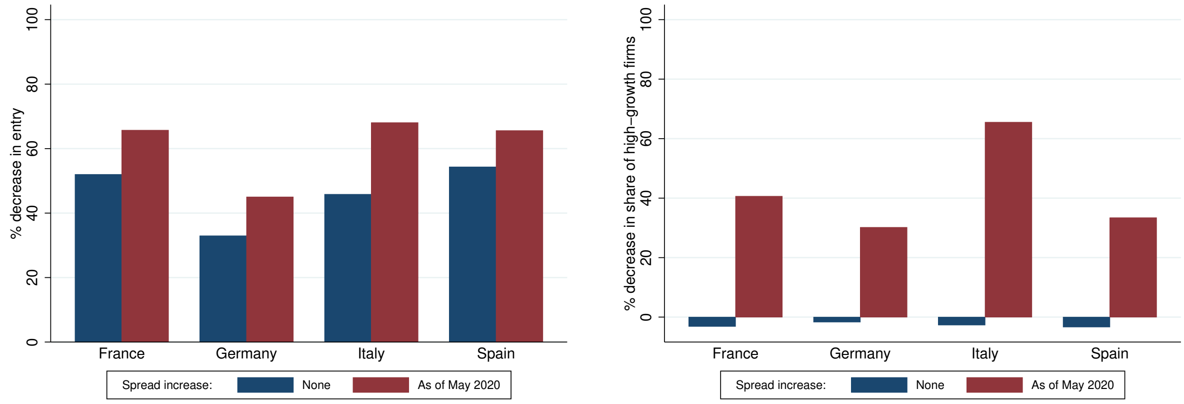
B. Cumulative drop in firm entry in Spain



Notes: Data at monthly frequency come from INE (`https://www.ine.es/jaxiT3/Tabla.htm?t=13912`). Panel A shows the deseasonalized number of new firms entering ("Constituidas"), which only includes firms recognized as independent legal entities. Panel B 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 4: Predicted fall in firm creation (Lower Bound)

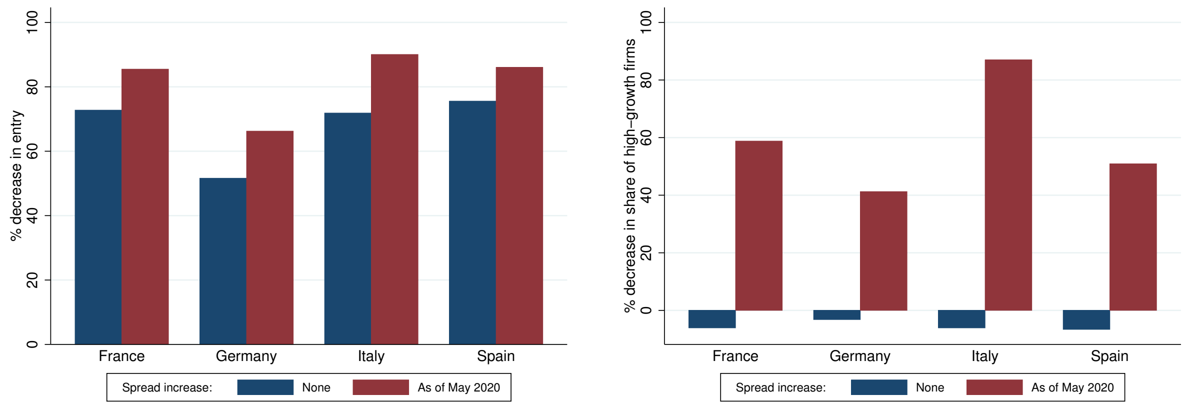
A. Predicted fall in firm creation **B.** Predicted fall in high-growth share



Notes: 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 European Commission GDP forecasts (applying a reduction of 50% to the predicted GDP contraction) depending on the assumed increase in the spread.

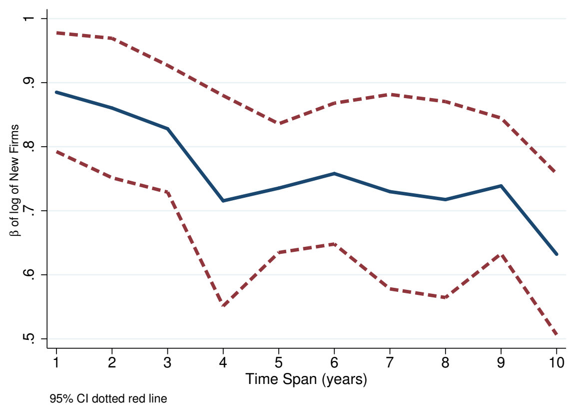
Figure 5: Predicted fall in firm creation (Upper Bound)

A. Predicted fall in firm creation **B.** Predicted fall in high-growth share



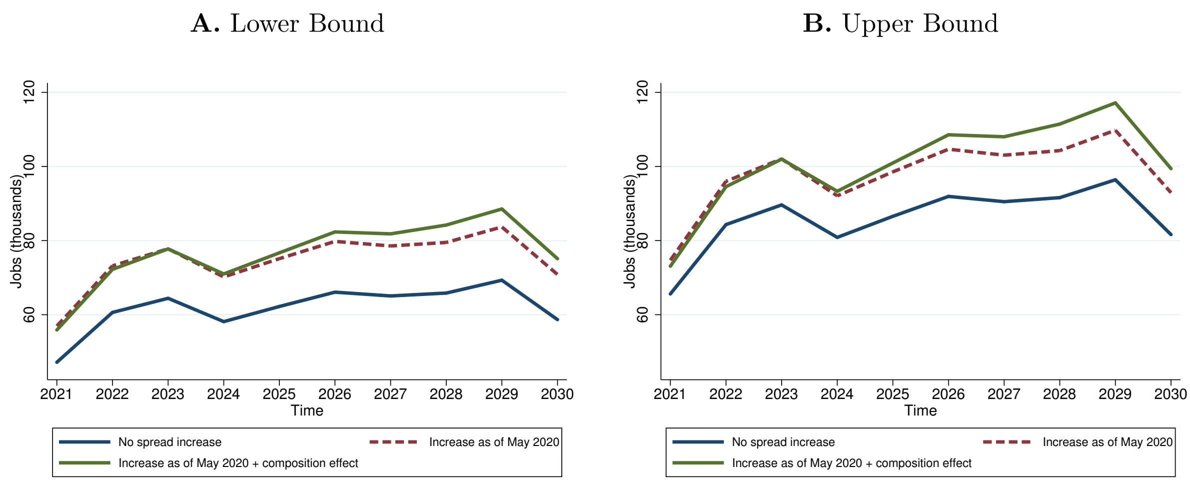
Notes: The fall in firm creation and the share of high-growth firms are predicted using the IV estimates in columns 5-6 of Table 1 and European Commission GDP forecasts depending on the assumed increase in the spread.

Figure 6: Effect of firm entry of future cohort employment



Notes: The figure plots the coefficients γ_1^k for each time horizon k from regression (2) in solid blue, with 95% CI in dashed red lines.

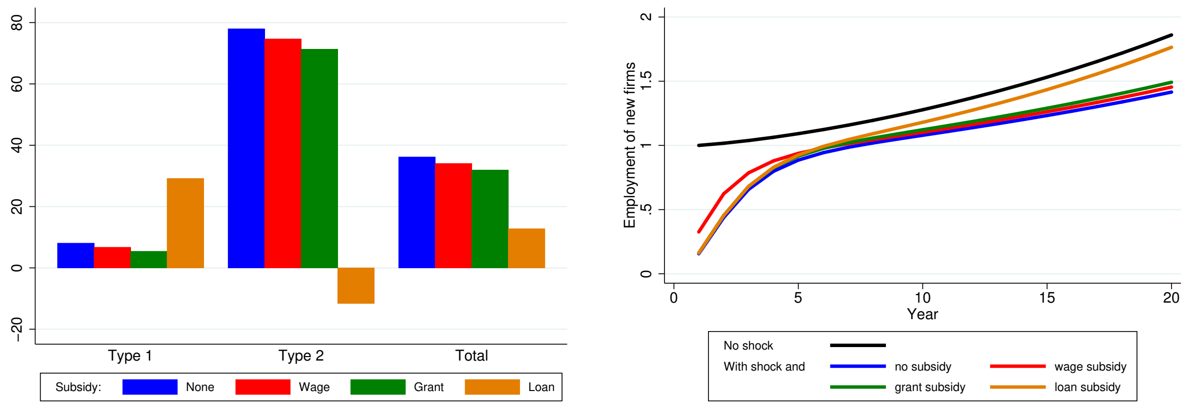
Figure 7: The predicted impact of Covid-19 shock on long-run employment for Spain.



Notes: Overall predicted loss in aggregate employment in Spain if there is no spread increase (blue line), if spreads increase as of May 2020 (green line), and only the effect of the entry margin on aggregate employmen of the cohort if spreads increase as of May 2020 (dashed red line). **Panel A** assumes the decrease in GDP growth is 50% of the Summer 2020 Economic Forecast of the European Commission (Lower Bound), and **Panel B** assumes the decrease in GDP growth is that of the Summer 2020 Economic Forecast of the European Commission (Upper Bound). The entry margin series are computed by combining the predicted fall in firm creation 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. The overall predicted loss in aggregate employment is the sum of the entry margin and the composition margin.

Figure 8: 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), Type 2 firms (center), and both types together (right) under the Covid-19 shock (blue), with the shock and a wage subsidy (red), with the shock and the grant subsidy (green), and with the shock and the loan subsidy (brown) . **Panel B:** Model-predicted evolution of aggregate employment of firms starting in the year the shock hits, if there was no shock (black), if the shock occurs (blue), if the shock occurs and the wage subsidy is in place (red), if the shock occurs and there is the grant subsidy (green), and if the shock occurs and there is the loan subsidy (brown).

Online Appendix

A 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.[21] 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.[22] 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

[21] 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.

[22] 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.

it from the individual bond level.[23] We use the yearly means of the monthly series.

B 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.[24] 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,

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

[24] 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).

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 coefficients to be different in the years 2008-2013.

The results of the first-stage regressions are shown in Table A.1 (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.1: IV first stage regression results

	(1)	× crisis dummy	(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)	× crisis dummy	(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.

C Model Derivations

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

C.1 Calculation of V^j

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:

$$V^1(p_t, \theta_{1,t}) = (1-d)[\pi(p_t, \theta_{1,t}) + V^1(E[p_{t+1}|p_t], \theta_{1,t+1})], \tag{10}$$

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:

$$V^{high}(\theta_{2,t}) = (1-d)\Psi\frac{\bar{p}^{\frac{1}{1-\alpha}}\theta_{2,t}}{d-(1-d)\,(g^{high})} \tag{11}$$

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 (11). Therefore, the initial value is:

$$V^2(\theta_{2,0}) = (1-d)\Psi\bar{p}^{\frac{1}{1-\alpha}}\left[(1-\gamma)\theta_{2,0} + \gamma\frac{\theta_{2,0}}{d-(1-d)\,(h-1)} + ...\right] \tag{12}$$

Rearranging yields:

$$V^2(\theta_{2,0}) = (1-d)\Psi\Phi\bar{p}^{\frac{1}{1-\alpha}}\left\{\begin{array}{c} \theta_{2,0} + (1-\gamma)(1-d)l\theta_{2,0} \\ +\left[(1-\gamma)(1-d)\right]^2\theta_{2,0} + ... \end{array}\right\} \tag{13}$$

$$\Phi \equiv (1-\gamma) + \frac{\gamma}{d-(1-d)\,(h-1)} \tag{14}$$

Solving recursively yields:

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

C.2 Calculation of C^j

In presence of financial frictions, the entrepreneur uses all earnings to repay $b_{j,0}$ as quickly as possible, and the law of motion of debt is:

$$b_{1,t+1} = \left(\frac{1+r^b}{1-d}\right) b_{1,t} - \pi(p_t, \theta_{j,t}) \tag{15}$$

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 (15) recursively and given the n periods necessary to repay the debt, for a Type 1 firm, its initial debt can be written as:

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

Solving for n yields:

$$n^*(b, g^m, \Psi\theta_{1,0}) = \frac{\log\left\{1 - \frac{b}{\Psi\theta_{1,0}}\left(\frac{r^b+d}{1-d} - (m-1)\right)\right\}}{\log\left((1+g^{med})\frac{1-d}{1+r^b}\right)} \tag{17}$$

$n^*(b, g^{med}, \Psi\theta_{j,0})$ 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 (16) discounting the flows using $r = 0$ instead of $r = r^b$ as

$$b^* = \Psi\theta_{1,0}\left[\frac{1-\left(\left(1+g^{med}\right)(1-d)\right)^{n^*}}{\frac{d}{1-d} - g^{med}}\right] \tag{18}$$

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:

$$C^1 = b^* - b \tag{19}$$

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 $b_{2,1} = \left(1 + r^b\right) b_{2,0} - \Psi p_0^{\frac{1}{1-\alpha}} \theta_{2,0}$. In the following period, with probability γ, the firm switches to high growth so that $\pi_{2,1} = \Psi p_1^{\frac{1}{1-\alpha}} \theta_{2,0}(1 + g^{high})$ 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, $\pi_{2,1}^{low} = \Psi p_1^{\frac{1}{1-\alpha}} \theta_{2,0}$. Substituting recursively, this expression can be approximated to

$$C^2 = \sum_{t=0}^{n^e} \left[(1-d)(1-\gamma)\right]^t r^b b_t + \frac{\gamma}{1-\gamma} \sum_{t=1}^{n^e} \left[(1-d)(1-\gamma)\right]^t C(b_t, g^{high}, \theta_{2,t}, r^b)] \tag{20}$$

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

D Additional Tables and Figures

Table A.2: Main GEM results using OLS estimation

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	2.301***	2.094***	1.903***	2.936	2.006	3.981**
	(0.7778)	(0.7814)	(0.5175)	(1.7900)	(1.3663)	(1.9618)
GZ spread	-0.036	-0.027	-0.047	-0.043	-0.027	-0.072
	(0.0463)	(0.0413)	(0.0433)	(0.0406)	(0.0336)	(0.0444)
GZ spread x GDP growth				1.158	-0.163	3.633*
				(1.8422)	(1.4102)	(1.9756)
Female	-0.142***	-0.116***	-0.155***	-0.143***	-0.116***	-0.157***
	(0.0094)	(0.0191)	(0.0255)	(0.0100)	(0.0196)	(0.0243)
Middle education	-0.063***	-0.054***	-0.064***	-0.069***	-0.053***	-0.081***
	(0.0142)	(0.0133)	(0.0158)	(0.0199)	(0.0172)	(0.0211)
High education	-0.040***	-0.047***	-0.016*	-0.043***	-0.047***	-0.023**
	(0.0092)	(0.0093)	(0.0086)	(0.0128)	(0.0122)	(0.0110)
Age	-0.009***	-0.008***	-0.007***	-0.009***	-0.008***	-0.007***
	(0.0021)	(0.0018)	(0.0020)	(0.0019)	(0.0017)	(0.0018)
Middle income	0.121***	0.080**	0.167***	0.120***	0.080**	0.165***
	(0.0355)	(0.0319)	(0.0254)	(0.0341)	(0.0313)	(0.0240)
High income	0.074***	0.035**	0.131***	0.077***	0.034*	0.140***
	(0.0069)	(0.0154)	(0.0175)	(0.0121)	(0.0182)	(0.0106)
Share of exits	-9.809	-8.362	-9.962	-10.217	-8.303	-10.980
	(10.7709)	(10.3362)	(9.0873)	(11.3877)	(10.8166)	(9.8694)
Business expertise	0.870***	0.802***	0.800***	0.872***	0.802***	0.806***
	(0.0074)	(0.0077)	(0.0159)	(0.0095)	(0.0070)	(0.0190)
Opportunity expectations	0.357***	0.323***	0.318***	0.356***	0.323***	0.312***
	(0.0145)	(0.0095)	(0.0245)	(0.0167)	(0.0112)	(0.0269)
Riskless interest rate	0.053	0.048	0.046*	0.052	0.048	0.041
	(0.0386)	(0.0401)	(0.0239)	(0.0433)	(0.0409)	(0.0349)
Observations	359791	359791	359791	359791	359791	359791
R-squared	0.130	0.113	0.119	0.130	0.113	0.121
P-value for $\beta_2^{low} = \beta_2^{high}$		0			0	
P-value for $\beta_3^{low} = \beta_3^{high}$					0	

Notes: The dependent variable is a dummy that is equal to one if an individual is a nascent entrepreneur in the respective category. Standard errors are clustered at the country level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A.3: Main GEM results using bank spread instead of corporate spread

	(1) All	(2) Low growth	(3) High growth	(4) All	(5) Low growth	(6) High growth
GDP growth	2.205***	2.511***	0.766**	5.271*	4.564*	4.895*
	(0.5989)	(0.6792)	(0.3748)	(3.0538)	(2.6890)	(2.8598)
GZ spread	-0.050**	0.007	-0.169***	0.035	0.065	-0.056
	(0.0239)	(0.0273)	(0.0109)	(0.0566)	(0.0399)	(0.0800)
GZ spread x GDP growth				5.624	3.673	7.746*
				(5.2194)	(4.7740)	(4.3057)
Female	-0.145***	-0.118***	-0.159***	-0.146***	-0.118***	-0.160***
	(0.0075)	(0.0167)	(0.0276)	(0.0077)	(0.0171)	(0.0278)
Middle education	0.008	0.013	-0.006	0.009	0.014	-0.004
	(0.0188)	(0.0198)	(0.0135)	(0.0184)	(0.0192)	(0.0136)
High education	-0.010	-0.020	0.012	-0.010	-0.020	0.011
	(0.0216)	(0.0168)	(0.0270)	(0.0227)	(0.0176)	(0.0283)
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	0.121**	0.077*	0.178***	0.119**	0.075	0.175***
	(0.0517)	(0.0455)	(0.0394)	(0.0523)	(0.0457)	(0.0421)
High income	0.077***	0.031	0.151***	0.080**	0.032	0.157***
	(0.0251)	(0.0295)	(0.0050)	(0.0330)	(0.0357)	(0.0115)
Share of exits	-9.555	-8.829	-8.413	-0.327	-2.648	4.006
	(10.5046)	(10.2635)	(8.6055)	(6.2493)	(6.8573)	(3.5489)
Business expertise	0.851***	0.783***	0.786***	0.854***	0.784***	0.789***
	(0.0086)	(0.0086)	(0.0143)	(0.0113)	(0.0077)	(0.0182)
Opportunity expectations	0.353***	0.323***	0.309***	0.350***	0.320***	0.305***
	(0.0178)	(0.0127)	(0.0272)	(0.0182)	(0.0140)	(0.0264)
Riskless interest rate	0.034	0.057	-0.030	0.077**	0.087**	0.025
	(0.0595)	(0.0622)	(0.0357)	(0.0325)	(0.0357)	(0.0175)
Observations	359791	359791	359791	359791	359791	359791
R-squared	0.127	0.110	0.119	0.128	0.111	0.122
P-value for $\beta_2^{low} = \beta_2^{high}$		0			.006	
P-value for $\beta_3^{low} = \beta_3^{high}$					0	

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 B. Standard errors are clustered at the country level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure A.1: Correlation between GDP growth (deviation from country mean) and predicted GZ spread