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Abstract

We study entry into entrepreneurship during the COVID-19 recession of 2020 using new data from an extensive survey of more than 24,000 Spanish households, conducted between June and November 2020. We find that while the overall decline in the startup rate in 2020 was large, and of a similar magnitude as that during the Great Recession, the differential impact depending on ex ante income was starkly different. During 2020, the drop in firm entry was entirely concentrated among low- and medium-income households. We show that the entrepreneurship gap between these households and their high-income counterparts is not directly explained by social distancing, since it is mostly driven by the sectors not directly affected by lockdown measures, and it is larger among households that did not suffer a negative income shock during the pandemic. We instead find evidence indicating that high-income households performed relatively better during the COVID-19 recession because they had the means to exploit new business opportunities, thanks to their larger wealth and better access to external finance.

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1 Introduction

Income inequality and entrepreneurial dynamics are strongly related (Halvarsson et al., 2018, Packard and Bylund, 2018, Bruton et al., 2021). On the one hand, the rise of superstar innovative entrepreneurs is an important driving force behind rising inequality (Gabaix et al., 2016, Aghion et al., 2019). On the other hand, Braggion et al. (2021) show that inequality negatively affects the entrepreneurial activities of low-income households.[1] Relatedly, Doerr et al. (2021) show that rising income inequality reduces job creation in small firms.

How did the COVID-19 pandemic and the subsequent 2020 recession affect the relationship between inequality and entrepreneurship? The COVID-19 crisis caused large income losses for the affected households, and the high level of uncertainty reduced access to bank loans for potential entrepreneurs.[2] Despite the prompt policy measures to support incumbent firms hit by the shock, such as furlough schemes, guaranteed loans or moratoriums, there has been more limited and less timely government support for the creation of new business.[3] Since start-ups play a key role in terms of job creation, innovation and long-run growth, the lack of firm creation can hinder the recovery and future growth, generating a missing generation of firms.

The COVID-19 shock nonetheless also presented an opportunity to open new types of digitally oriented businesses, and the availability of public subsidies and a large pool of unemployed workers were also factors that should have promoted firm creation (Li-Ying and Nell, 2020). How did these positive and negative shocks affect the formation of new businesses? And were these effects heterogeneous along the income distribution?

Despite their importance, little is known about these issues, since most of the recent research focuses on the effect of the COVID-19 shock on incumbent businesses, and relatively few studies analyze how it has affected new business dynamics. Some descriptive early studies analyzed the overall dynamics of new business applications (see, e.g., Dinlersoz et al., 2021 for the US and Fritsch et al., 2021 for Germany) and net entrepreneurial flows (e.g., Fairlie, 2020). However, to the best of our knowledge, none of the existing

[1] They construct a measure of wealth inequality at the US county level, based on the distribution of financial rents, and find that in more unequal areas, entrepreneurs are less likely to apply for a loan, fearing that their applications will be turned down; instead, they use more of their own funds to finance their ventures.

[2] The ECB's Business Lending Survey (BLS) and Survey on the Access to Finance of Enterprises (SAFE) reveal a worsening of credit availability for SMEs during 2020; see Figure A.3 in the Appendix.

[3] At the begining of the COVID-19 crisis, policy measures typically did not target start-ups specifically, and many liquidity relief measures were not accessible for early stage entrepreneurs or new firms because of their eligibility criteria. While countries like Germany, France or Italy introduced later dedicated start-up packages, other countries like Spain did not take new actions targeting specifically new businesses. See OECD (2021) for further information about policy support for start-ups in OECD countries.

studies analyzes how the COVID-19 shock heterogeneously affected new entrepreneurial households or what the implications were for the types of new startups created.

In this paper, we provide an answer to these questions by analyzing real-time data from the COVID-19 recession. Specifically, we provide in-depth analysis of a new extensive survey of more than 24,000 households on their entrepreneurial attitudes and decisions (the 2020 wave of the Global Entrepreneurship Monitor – GEM – survey for Spain). The data are representative of the whole adult population of Spain, and rich and detailed enough to allow us to disentangle the main drivers of firm creation during COVID-19 while controlling for individual characteristics. Furthermore, since this survey has been conducted (as a repeated cross section) since 1999, we can compare our findings to the characteristics of firm entry during the Great Recession of 2008–2010. Importantly, the 2020 survey, while including all questions consistent with the surveys in previous years, also includes a set of additional questions on the COVID-19 recession (for example, asking whether the households directly suffered a loss of income because of the pandemic or whether they had new business opportunities), which allow us to disentangle the different factors driving our results.

Our main findings are as follows. Controlling for population characteristics (age, gender, income, and education), we find that the overall decline in the startup rate during the 2020 COVID-19 recession was large and of a similar magnitude to the decline during the Great Recession years. Entry declined by approximately 40% with respect to the long-run average entry rate (1.7 pp). We also find that the decline in firm entry has been more concentrated among startups with high growth potential, as also happened during the Great Recession.[4]

More importantly, we find that the COVID-19 recession and the Great Recession present striking differences regarding the impact on households with different income levels. During 2020, the drop in firm entry was entirely concentrated among low- and medium-income households. In fact, we find no reduction in entry among high-income households (defined as the top tercile income group). Furthermore, the changes in entry composition towards low-growth firms only occur among low- and medium-income households, while it increases among high-income households. These results, which hold when we control for education and age interacted with the recession dummies, are surprising and at odds with the patterns during the Great Recession, during which high-income households suffered a stronger decline in entry than those with medium or low income. In addition, we show that these differential results are not driven by an uneven surge in

[4]Furthermore, a preliminary analysis of the 2021 GEM survey shows that there was no 'catching-up' during 2021 for low- and medium-income households, while there is still a positive effect for high-income households, which is around half as large as that of 2020.

necessity entrepreneurs among income groups.

Next, we explore whether conditional on starting a firm, entrepreneurs with different income levels select different financing sources, and how such selection changed during COVID-19. Regarding the sources of funds, the last 4 waves of the survey (2017–2020) include detailed information on the amount of initial financing of startups and the main sources used to finance them. Consistent with other studies, the survey shows that smaller startups are mostly internally financed, while larger startups are more intensely bank-financed, a finding consistent with the pecking order of finance. During COVID-19, in addition to observing a reduction in startups from low/middle-income households, we also see that they greatly increased the use of their own savings (relative to the other sources), while we do not observe the same increase for high-income households. This finding is consistent with a tightening of financial conditions (in line with the findings of Ferrando and Ganoulis, 2020), pointing at financial frictions being important in explaining the different performance of entrepreneurs along the income distribution. One possible alternative explanation is that instead there were fewer opportunities of smaller size for low-income entrepreneurs than for high-income entrepreneurs. Because opportunities were smaller, internal finance was used relatively more than in the pre-COVID years, since the cheapest source of funds is used first. However, in this case, we would expect that internally financed projects should necessarily be on average smaller during COVID-19 than in the pre-COVID-19 years, because such smaller size is the necessary condition for observing an increase in the relative use of internal finance. However, our results do not find any evidence of this. We are also able to rule out that a possible lack of entrepreneurial skills of low-income households impeded them from exploiting new business opportunities during the pandemic. For this, we show that our main findings are robust to only including the subset of entrepreneurs that reports having the relevant skills for opening a business.

We then explore whether the COVID-19 recession, in addition to negatively affecting the income and wealth of many entrepreneurial households, also presented new opportunities, which were disproportionately taken by high-income households because of their larger wealth and better access to external finance. We find empirical evidence consistent with this explanation using detailed information on the type of business created and on the sources of funds used to create them. We use the unique information provided in the GEM surveys, where entrepreneurs describe in their own words the kind of business they are intending to create, to precisely identify new business that are digital and internet-oriented. We find that the fraction of digital businesses increased during COVID-19, and that this increase was entirely driven by high-income households, for which we observe a

70% increase in digital startups relative to the 2011–2019 period.

As robustness, we check whether these results are driven by possible confounding drivers. One potential explanation for the findings above is that low- and middle-income households are more likely to be engaged in sectors directly affected by the pandemic (e.g. leisure and hospitality, and transport), or in businesses that require more face-to-face interaction than the businesses of high-income households, and therefore are more directly exposed to the COVID-19 shock. However, we find no evidence supporting this. Our results show that high-income households did much better during COVID-19 than the other households in terms of entry into entrepreneurship in the non-affected sectors, while we find a smaller difference in the affected sectors. Furthermore, it seems that results are not driven by the 'size' of the negative income shock received by the household: the difference between high- and medium/low-income households was particularly large among those that did not suffer a negative income shock during the pandemic.

Therefore, although we cannot completely rule out possible alternative factors, a plausible interpretation of our findings is that low- and medium-income households had similar opportunities as high-income households, but because of more difficult access to external financial resources, many could not exploit them (more difficulty accessing banks and perhaps also more difficulty accessing family and friends because these sources increased their precautionary savings). Thus, while the funding channel is unlikely to be the sole driver of the large drop in the startup rate in 2020, these findings highlight that the constrained access to finance for low- and middle-income entrepreneurial households was an important reason for why their entrepreneurial activity was much more negatively affected than that high-income households.[5] Their implication is that, while policies directed at supporting current jobs during a pandemic are important, to ensure a durable recovery in the future, they should be accompanied by measures directed at reducing the cost of credit for new potential entrepreneurs.

Finally, in order to gauge the long-term consequences of these results on aggregate employment, the last section of the paper summarizes the findings of Appendix B, where we match GEM survey data with firm-level panel data from Central de Balances Integrada. We estimate that the employment of the 2020 cohort of firms is expected to be 2.4% smaller after 10 years because of the "missing generation" of low- and medium-income entrepreneurs.

[5]Evidence of financial frictions for new startups is also reported in Brown et al. (2020), who found that new equity transactions in the UK declined markedly during COVID-19, with seed financing being the main type of entrepreneurial finance most acutely affected.

2 Related Literature

An extensive body of research suggests that there is a meaningful association between income inequality and entrepreneurial outcomes (Bruton et al., 2021; Packard and Bylund, 2018; Halvarsson et al., 2018). In particular, our paper is related to recent research arguing that inequality might hamper entrepreneurship (Braggion et al., 2021, Doerr et al., 2021). One of the main mechanisms through which inequality can impact entrepreneurship and entrepreneurial entry is financial constraints. Corradin and Popov (2015) show that housing wealth helps to alleviate credit constraints for potential entrepreneurs by enabling homeowners to extract equity from their property and invest it in their business.[6] Our main contribution to this strand of literature is to show how income differences were critical for entrepreneurial outcomes during COVID-19, and to present evidence that financial frictions affecting differently low- and medium-income households are a key determinant of this finding.[7]

Our paper also relates to a growing strand of literature attempting to assess the impact of the COVID-19 shock on businesses and entrepreneurship. While a large literature examines the different ways that COVID-19 impacted several aspects of incumbent firms' and entrepreneurs' behavior, fewer papers analyse the impact of COVID-19 on the entry margin.[8] Ascari et al. (2021) document an asymmetric impact of the COVID-19 shock on business applications in the US, and using a firm dynamics model, they can rationalize the dynamics of entry and aggregate productivity during the crisis. Benedetti-Fasil et al.

[6] Adelino et al. (2015) document that, controlling for demand factors, small businesses in areas with greater increases in housing prices experienced stronger growth in employment than did large firms in the same areas. Schmalz et al. (2017) show that individuals affected by positive exogenous shocks to the collateral values of their properties are more likely to become entrepreneurs and, conditional on entry, use more debt, start larger firms, and remain larger in the long term. On the relation between downturns and entrepreneurial behaviour, see also Conti and Roche (2021). Furthermore, because of its focus on startups of different types and growth potential, our paper is also related to the literature that emphasizes the importance of transformational entrepreneurs, e.g., Schoar (2010)

[7] Indeed, there is evidence of changes in financing patterns during COVID-19. For instance, Bellucci et al. (2022) find that venture capital investment was reallocated during COVID-19 toward firms developing technologies relevant to an environment of social distancing and pandemic health concerns.

[8] The papers that analyse the effects on incumbent firms focus on liquidity needs (Schivardi and Romano, 2020), financial constraints (Ferrando and Ganoulis, 2020, Balduzzi et al., 2020), firms' activity (Hassan et al., 2020, Fairlie, 2020, Bartik et al., 2020), policy support (Groenewegen et al., 2021, Core and De Marco, 2021), firms' ownership (Amore et al., 2022) and economic beliefs (Armantier et al., 2021; Dietrich et al., 2022), among other aspects. Other papers focus on the exit margin instead, such as Gourinchas et al. (2020) who find that government support helped avoid a 9.4 p.p increase in failure rates of SMEs. Zoller-Rydzek and Keller (2020) argue that too high of a level of a specific support, loan guarantees, might increase the share of zombie firms in the economy; Hoshi et al. (2022) find that firms with low credit scores before the COVID-19 pandemic were more likely to apply for and receive the subsidies and concessional loans offered by the Japanese government in 2020. However, Gourinchas et al. (2021) find that these support policies seem not to have created a 2021 "time-bomb" for failure rates in SMEs in the US.

(2020) propose a "Startup Calculator", which uses historical data to extrapolate entry, growth and survival rates of firms from different cohorts under the COVID-19 shock. While their work is based on historical data, our contribution is to use timely new survey data on entrepreneurship during the COVID-19 crisis to study its impact on entry across the income distribution, the type of firms' entry, and on the long-run implications. Our paper is especially related to Dinlersoz et al. (2021) and Haltiwanger (2022). They use data on new business applications and transitions to employer businesses in the US to find that the decline in business applications was transitory, but that there was a change in composition of entry towards non-employers. Our paper complements their findings and enriches them thanks to the use of survey data: while we also find a change in the composition of entrants, we can dig deeper into the causes of this change and link it to income inequality and financial frictions.[9]

The rest of the paper is organized as follows. Section 3 presents the data used in the analysis and preliminary descriptive evidence of the COVID-19 shock. Section 4 presents the empirical analysis. Section 4.1 shows the impact of the COVID-19 shock on entry and its composition. Section 4.2 shows the heterogeneous entrepreneurial choices during COVID-19 depending on ex ante characteristics: the income distribution and the impact on necessity entrepreneurs. Section 4.3 shows the heterogeneous entrepreneurial financing during COVID-19. Section 4.4 presents the new entrepreneurial opportunities due to COVID-19 and the heterogeneity in their implementation. Section 4.5 presents robustness checks that exclude alternative explanations for the results: Section 4.5.1 shows the results are not driven by differences in sectoral composition; and Section 4.5.2 shows the heterogeneous entrepreneurial choices during COVID-19 depending on the income shock received. Section 4.6 briefly describes the results shown in Appendix B on the estimation of the medium- and long-term job losses caused by the drop in entrepreneurship among low- and middle-income households. Section 5 concludes the paper.

3 Data and Descriptives

In our empirical analysis, we use data from a large multi-country entrepreneurship dataset to investigate the impact of the COVID-19 shock on the decisions to start businesses with

[9] While they find that the decrease in entry was very short lived and rebounded over the course of 2020, we find that the fall in entry was more persistent and that it lasted at least throughout 2020. There are several potential reasons that can rationalize these different findings. First, the policies implemented and institutional background in the US and Spain differ greatly. Second, and most important, while our survey data capture entrepreneurial startups, data on business applications capture all new businesses that are created, which might be part of a larger group. Indeed, Bahaj et al. (2021) show that in the UK, business registrations increased during COVID-19 but that these new registrations are mostly driven by existing groups opening new businesses, in particular in online retail and in metropolitan areas.

heterogeneous growth potential. The great advantage of our analysis is that we have access to the 2020 wave of the survey for Spain, which is restricted to the general public and only published with an approximately 2-year delay. This provides us with a unique early picture of the impact of the COVID-19 shock on entrepreneurial decisions.

3.1 The COVID-19 economic shock

The COVID-19 pandemic has been an unprecedented shock for the world economy. Governments have imposed public health measures, such as social distancing, halting the flows of goods and people and stalling the economy, which caused the largest drop in GDP in developed countries witnessed during peacetime. The GDP contraction in 2020 in the EU was of historical proportions, despite the largely supportive fiscal and monetary policy measures: according to Eurostat, GDP fell by 10.8% in Spain, 8.9% in Italy, and 4.6% in Germany. There were swift and resolute policy measures to support incumbent firms, with the aim to avoid mass exit of firms due to a temporary shock.[10] However, in Spain there was no specific policy measure to support newly created businesses, which might have affected the entrepreneurship decision and the creation of firms.

3.2 Firm entry after the COVID-19 shock

By reducing demand, increasing uncertainty and tightening financing conditions, the COVID-19 shock significantly affected new business formation. However, the drop in firm entry has been heterogeneous across countries. Figure 1 shows the number of business registrations for different OECD countries. Although all countries suffered a drop in business registrations during the lockdown period (March and April 2020), the severity and persistence of the drop in entry was very heterogeneous.

In this section, we provide additional evidence for Spain. Figure 2, Panel A, shows the deseasonalized number of new firms entering (new incorporations) in Spain, with average entry being approximately 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 movement restrictions, 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 fully

[10]Actually, in many countries exit of firms suffered a very mild increase, or even decreased, in the early stages of the pandemic. Indeed, while during the Great Financial Crisis (GFC) in 2008 entry rates decreased and exit rates increased in similar proportions; during 2020 entry fell sharply, even more than during the GFC, while the increase in exit rates was very mild, even lower than that of 2019. See Figure A.4 in Appendix C.

rebound, remaining below its average until July 2020. This implies a sizable cumulative deficit in firm entry, as shown in Figure 2, Panel B: the cumulative drop in firm entry in the first 4 months after the beginning of the pandemic is as large as that of the first 8 months after the beginning of the Great Recession. Even after 15 months, this entry gap remains present. This suggests a missing generation of firms, which is likely to have important short- and long-run effects.

3.3 Global Entrepreneurship Monitor dataset (GEM)

The main objective of this paper is to analyze how the COVID-19 crisis affected the incentives of heterogeneous entrepreneurs to start a firm, focusing especially on income heterogeneity. Moreover, we analyze the implications for both overall firm creation and the nature of the new startups. We use the yearly 2005–2020 Spanish waves of the Global Entrepreneurship Monitor (GEM) database. The GEM research program is a project that focuses on one of the crucial drivers of economic growth: entrepreneurship. GEM began in 1999 as a joint research project between Babson College (USA) and London Business School (UK). GEM is the largest annual international research initiative that collects and analyzes data on various forms of entrepreneurial activity. The main idea of the project is to provide essential entrepreneurship-related knowledge by gathering harmonized data on an annual basis and across countries, facilitating international comparative analysis (Reynolds et al., 2005). Specifically, we use the individual observations from the Adult Population Survey (APS) of the Spanish GEM project. The APS allows us to obtain a representative sample of the Spanish population aged 18 to 64. The overall number of individuals in our sample ranging from 2005 to 2020 is 390,000. GEM captures a comprehensive variety of entrepreneurial outcomes and assesses entrepreneurial efforts at different stages of firm development ranging from nascent to established phases. The GEM 2020 dataset is particularly useful for us since it measures entrepreneurial efforts occurring during the pandemic. Data collection in 2020 started in mid-July 2020 and ended in early November 2020.

To identify entrepreneurs starting a firm, we use the question '*Are you, alone or with others, currently trying to start a new business, including any self-employment or selling any goods or services to others?*' (Reynolds et al., 2005). If the individual answers 'Yes' to this question, we classify him or her as a new entrepreneur.[11] Our sample contains approximately 16,500 new entrepreneurs, 4.25% of all individuals in our sample. Figure 3

[11]Our definition of new entrepreneurs differs from the one used by the GEM project, where new entrepreneurs are those between 3 to 42 months old. In our case, we are interested in new entrepreneurs who started during the pandemic.

shows the time series of entry according to this definition from the GEM database, where we observe a sharp decrease during the Great Recession and a significant drop during the COVID-19 crisis.

Furthermore, we classify startups as having low/high growth potential by using the expected number of employees of the firm five years into the future reported by new entrepreneurs: if their expected size in five years exceeds the average size of the established firms at the sector level, we classify this firm as a high-growth type. Approximately 35% of startups fall in the high-growth category.[12]

3.4 A first look at the effects of the pandemic on new and established entrepreneurs

We first explore how the motives that entrepreneurs indicate as drivers of their decision to start a new business changed in 2020 with respect to the previous year.[13] Figure 4 shows the percentages of entrepreneurs in each of the five categories that capture the degree of agreement (from strongly disagreeing to strongly agreeing) with four different motives: making a difference in the world, accumulating wealth, continuing a family tradition, and jobs being scarce. We observe pronounced shifts, particularly for the first and fourth motive, in 2020 relative to 2019. Many more entrepreneurs strongly disagree that their motive is to make a difference in the world in 2020 (26% instead of 15%). Moreover, for many more, the scarcity of jobs is the decisive factor. The percentage that strongly agree that scarce jobs is a motive for them increases from 18% to 29%. Interestingly, we observe both an increase in the share of households who strongly agree and strongly disagree with the statement that the main motive to start a firm is to accumulate wealth. Thus, it seems that the division into those that see the new business as an opportunity to increase their wealth and those that have nonpecuniary motives became stronger during the COVID-19 crisis. The figure suggests that the latter are probably driven into entrepreneurship particularly because it became more difficult to find regular employment.

Figure 5 shows the responses to a set of questions added to the 2020 survey intended to shed light on how COVID-19 has impacted the entrepreneurial decisions and businesses of respondents. Some of these questions are asked to new entrepreneurs and some to owners of established businesses. Moreover, the question on how the pandemic impacted household income shown on the bottom right is asked to all respondents. Due to the potentially very different personal impact of the crisis depending on income, we show

[12] Details on the classification of startups and other variables used in the analysis and a discussion about the validity of this high-growth measure during COVID-19 are shown in Appendix A.

[13] This question on the motives for business creation is not available before 2019.

separate results for respondents with low and with high household income.

There are three main findings to highlight. First, COVID-19 significantly impacted new business activity. Among those with low income, 60% strongly agree that the pandemic led to a delay in getting the business operating, while the corresponding share among those with high income is approximately 50%. Among those managing an incumbent firm, approximately 50% claim that their firm had to stop some of its activities. Second, COVID-19 generated a large income shock: nearly half of the respondents claim that their household income decreased due to the pandemic. Third, there is also substantial heterogeneity in the impact of the shock on the expectations for business growth depending on the pre-pandemic level of income: more than 57% of low-income respondents have the expectation that business growth will be lower compared to 2019 (adding those who say "somewhat lower" and those who say "much lower"), versus only 44% of high-income entrepreneurs. Furthermore, nearly 74% of low-income respondents feel that starting a business is more difficult than in 2019, while only 65% of high-income respondents do so. The expectation to start a new business is influenced by the pandemic in 51% of the answers, and this response is relatively homogeneous between those with high and low income. When starting a firm, 60% of low-income entrepreneurs strongly disagree with COVID-19 offering new opportunities to exploit, while this is the case for 50% of the high-income respondents. Among already established entrepreneurs, 73% of low-income entrepreneurs and 64% of those with high income strongly disagree with the pandemic leading to new business opportunities.

These results indicate a differential impact of the COVID-19 shock along the income distribution, suggesting that ex ante income inequality is potentially important to understand the impact of the COVID-19 shock on entry and its composition. Specifically, it could be that households at the bottom of the income distribution suffered a larger income decrease and/or suffered from lack of opportunities, hence preventing them from starting a firm during COVID-19. Moreover, while the GEM survey does not directly ask about financial constraints, the ECB's Business Lending Survey (BLS) and Survey on the Access to Finance of Enterprises (SAFE) report a worsening of credit availability for small businesses in Spain during 2020 (see Figure A.3 in the Appendix). Therefore, it could also be that access to finance was tightened during COVID-19, especially for low-income potential entrepreneurs, preventing them from gathering sufficient funds to start a firm and potentially impacting the kind of firm they want to start (low vs. high growth). The next section provides a regression-based analysis that characterizes the changes in the entry decision and composition of entry of entrepreneurs and allows us to quantify the importance of these different factors.

4 Empirical Analysis

In this section, we estimate the effect of the COVID-19 shock on overall startup creation and on the creation of different startup types conditional on the observable characteristics of entrepreneurs. Based on our classification described on Section 3.3, we create a set of dummies $start^s_{i,r,t}$ indicating that individual i in year t is starting a firm of type $s \in (a, h)$ in region r, where a indicates all startups and h startups with high growth potential, respectively.[14] We use $start^s_{i,r,t}$ as the dependent variable in the following model:

$$start^s_{i,r,t} = \beta^s_0 + \beta^s_1 COVID\text{-}19_t + \beta^s_2 GR_t + \sum_{k=0}^{K} \gamma^s_k X^k_{i,t} + \theta_r + \varepsilon_{i,r,t}. \tag{1}$$

We include a dummy $COVID\text{-}19_T$ that takes value 1 for $t = 2020$, 0 otherwise. For comparison, we include GR_T, which is a dummy that takes value 1 during the Great Recession (2009 and 2010), 0 otherwise.[15] The term $\sum_{k=0}^{K} \gamma_k X^k_{i,t}$ in Equation (1) indicates the K individual control variables. The controls include gender, age, educational level, and income category to account for differences in ex ante characteristics. We also include controls for individual perceptions: perception of skills to start a new firm, perception of fear of failure and expected opportunities within 6 months.[16] These characteristics control both for ex ante characteristics (ability, risk aversion) and for endogenous perceptions of opportunities.[17]

4.1 The effect of the COVID-19 shock on startup creation

Table 1 shows the baseline results of running regression (1). In Columns (1) and (3) we include all the observations, and the dependent variable is a binary variable equal to one if the household starts a firm of any type, zero otherwise. Conversely, in Columns (2) and (4) we keep only the observations of entrepreneurs entering (those with $start^a_{i,t} = 1$), so the coefficients can be interpreted as the effects on the share of high-growth firms entering. Column (1) shows that after controlling for observables, the likelihood of starting a firm is significantly lower in 2020: households are 1.7 pp less likely to start a firm during

[14] We use the autonomous communities level to define a region. The Spanish territory is divided into 17 autonomous communities and 2 autonomous cities, which are the second-level territorial and administrative divisions NUTS 2 under EUROSTAT classifications.

[15] Although the recession in Spain started during the second half of 2008, the drop in entrepreneurship was visible starting in 2009, see Figure 3.

[16] 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.

[17] See Appendix A.2 for a detailed definition of all the variables.

COVID-19 than in the rest of our sample years. Since the average likelihood of starting a firm is 4.25%, this decrease would imply a 40% drop in the likelihood of entry. The decrease is slightly lower than in the Great Recession (1.9 pp). Furthermore, column (2) shows that there was a significant decline in high-growth firms entering as their share decreased by 6.2 pp. The average share of high-growth firms among entrants is 35%, so this would imply an 18% decrease. Despite being slightly smaller quantitatively, all results are robust to also including controls for skills and perceptions in Columns (3) and (4).[18] This confirms the findings from the descriptive evidence shown before. That is, the pandemic has decreased the likelihood of starting a firm and hence firm creation. Moreover, these results suggest a potentially relevant composition effect: not only has firm entry decreased, but also the *composition* of firm entry has changed, with a lower share of high-growth firms entering. In the next sections, we explore different motives for this change in composition and perform some robustness tests on these results.

4.2 Heterogeneous entrepreneurial choices during COVID-19 depending on income

In this section, we investigate how the previous results vary across heterogenous households. Our main dimension of interest is the income distribution.[19] To investigate whether the impact of the COVID-19 crisis was heterogeneous depending on household income, we estimate a version of Equation (1), in which we allow the COVID and GR coefficients to vary across household groups defined by income level. For this, we interact these variables with *High Income*, which is a dummy equal to one if the income level of the entrepreneur is within the upper tercile of the distribution.[20]

The results, shown in Table 2, imply that the likelihood of starting a firm for low- and medium-income households decreases by 1.7 pp during COVID-19, while the share of high-growth startups decreases by 10.9 pp. However, this is not the case for high-income households, for whom the probability of starting a firm remains almost unchanged (-1.7 pp+1.9 pp=0.2 pp), and the share of high-growth firms even increases (-10.9 pp+13.4 pp=2.5 pp). This heterogeneity across income levels in terms of the impact of the shock

[18] The results are also robust to introducing a time trend.

[19] One could argue that it is wealth and not income which might be more relevant for the entrepreneurship decision. There is no wealth available in GEM, and hence we cannot use this variable directly. However, income and wealth in Spain are highly correlated: the top 10% of the wealth distribution have 56,800 euros of median income, which is close to the median income for the 20% households with the highest income – 55,100 euros – (Banco de España, 2019). Because of this, our measure of high income households can be understood as a proxy of high wealth households.

[20] We consider this definition of income inequality (first tercile of the income distribution versus the rest) because of data limitations. The surveys do not provide exact household income, only whether households belong to the first, second, or third tercile of the income distribution.

is very different from that observed during the Great Recession, during which firm creation actually fell more among high-income households.[21] Crucially, in our analysis of the relationship between the income level and entrepreneurial activity before and during the pandemic, we also have to take into account that both these measures are likely to be correlated with unobservable skills to create a new business. For instance, if those with higher income have different types of skills than those with lower income and precisely these skills mattered more for business creation during the pandemic, we would uncover a spurious change in the relationship between income and startup creation during the pandemic. While, due to the nature of our data, we cannot entirely rule out that heterogeneity in unobservable skills partly drives the results we show in the following, we control for several variables that are, arguably, good proxies for unobservable skills. In particular, we consider heterogeneity in terms of age and education and also allow their effects to be different during the pandemic and the Great Recession by including them as interaction terms similar to the income level. The results are in Table A.1 in the Appendix. *Educated* is a dummy equal to one if the entrepreneur has post-secondary or graduate experience, and *Young* is a dummy equal to one if the entrepreneur is younger than 35 years old. First, we can see that the coefficients on the interaction with high income are nearly unchanged and remain significant, which indicates that this level of heterogeneity is relevant even after controlling for the education and age interactions. Second, Column (1) shows that, during COVID-19, being educated decreases the likelihood of starting a firm by 0.7 pp, while being young decreases the likelihood of starting a firm by 1 pp. This suggests that these variables are relevant to explain the heterogeneous decrease in startups, although they are quantitatively less important than income. Column (2) unveils an important finding: only income heterogeneity during the pandemic matters for the change in the composition of entry because the coefficients on *young* and *educated* are not significant.

In Table A.2 in the Appendix, we conduct an additional check of the robustness of these results by running the regression in Columns (1) and (2) of Table A.1 splitting the sample into two subgroups. In the first two columns, we include only those who report having the skills required to start a new business. In the last two columns, we include only those who report *not* having these skills.[22] If such skills mattered more

[21] We will discuss about this difference in the next section, which examines Entrepreneurial financing during COVID.

[22] The exact question is *'Do you have the knowledge, skill and experience required to start a new business?'*. Several studies argue that motivation and performance achievement are controlled by individual socio-cognitive mechanisms such as self-efficacy (i.e., perception of skills to start a business), which in turn can influence entrepreneurs' inclination to take part in entrepreneurial projects (e.g., Boudreaux et al., 2019). In entrepreneurship studies, self-efficacy accounts for the beliefs of entrepreneurs towards their own skills and capabilities to start and develop a new venture (McGee et al., 2009).

for setting up a business during the COVID-19 crisis and are correlated with income, we would expect no significant effect of *COVID-19 x High Income* after splitting the samples. Indeed, 43% of those with low income but 53% of those with high income report having these skills. However, in both subsamples, we obtain coefficients that are qualitatively and quantitatively similar to those in the full sample. Hence, the (small) correlation of income with self-reported skills for starting a business is also not driving our results.[23] In Table A.3 we saturate the model with additional fixed effects. In column (1), we include region-year dummies, which absorb any region-specific time trends. Note that this implies that we cannot identify the main effects of *COVID-19* and *GR* anymore, as they are themselves year dummies. Thus, we only display the still identified interactions with high income. In columns (2) and (3), where we only consider starters, we additionally include sector-year dummies.[24] All shown coefficients are robust to adding these fixed effects.

In sum, we find that heterogeneity in income levels is the relevant dimension affecting entrepreneurship during the COVID-19 crisis, both for the choice of starting a firm and for the type of firm entrepreneurs start (high growth versus low growth).

Necessity entrepreneurs and COVID-19

One of the underlying reasons for the heterogeneity we uncovered might be the motivation for why entrepreneurs start a firm in the first place – if entrepreneurs create a firm simply out of necessity and not out of intrinsic motivation, then these firms are likely to have lower growth potential. We explore this angle by exploiting a question in the survey asking respondents '*Why did you start a firm?*'. We label an entrepreneur as starting a *necessity firm* if the answer to this question is '*To earn a living because there is scarcity of jobs*'. These types of subsistence firms are usually associated with low growth and hence might be another important composition driver. Column (3) of Table 2 shows the results of running the previous regression, where we only use the sample of entrepreneurs starting a firm, and the dependent variable is 1 if the entrepreneur is starting a necessity firm. Thus, we can interpret the coefficients as the effects on the share of necessity firms out of all started firms. The share of necessity firms increases by 35 pp during COVID-19, and this increase is homogeneous with respect to income, as well as with respect to age and education as can be seen in column (3) of Table A.1. This surge in necessity

[23]Only in Column (4) of Table A.2, in which the sample only includes those starting a business, are the coefficients of interest not significant This is because the number of observations is only approximately 1,000 as very few of those reporting not having business skills are entrepreneurs.

[24]Since sector information is only available for those that start a business, we cannot include these fixed effects in the regression in column (1).

entrepreneurs confirms the descriptive evidence presented in Figure 4. Importantly, it is not statistically significantly different between the two income groups, indicating that the surge in necessity entrepreneurship during COVID is not the reason why we see a large differential performance of high- versus low- and medium-income households. It should then be that high-income households were better able to take advantage of the new opportunities that arose during the crisis, because of their larger availability of finance and lower likelihood of being financially constrained. We explore this *"lack of finance"* hypothesis below in Section 4.3 and the rise of new opportunities in Section 4.4, while in Section 4.5 we show robustness checks that exclude alternative explanations for the results.

4.3 Entrepreneurial financing during COVID-19

Starting with the 2017 survey, the GEM asks new entrepreneurs to report the funding sources for their new businesses. In particular, they state the percentage of overall funds stemming from each of the following sources: personal savings, family savings, friends, subsidies, investors, banks, or other sources. Figure A.2 in the Appendix shows the average percentage of funds coming from each of these sources for each year, separately for low-income and high-income respondents. Notably, in each year and for each income group, the majority of funds (approximately 60%) stems from personal savings. The second most important source are banks, with approximately 20%, followed by family savings with 10%. This relationsip is consistent with the pecking order of finance, according to which the cheapest source of finance is used first (own savings); then, the potential entrepreneurs resort to personal relations (family and friends) and finally to institutional lenders (banks). Regarding the funding composition during the pandemic in 2020, we see, especially for the low and medium-income group, a rise in personal savings and a drop in funding from banks compared to 2019. This pattern is similar but less pronounced for high-income households.

Naturally, we can only observe the funding sources of GEM respondents that decided to become entrepreneurs. Thus, any analysis focusing only on the sample of entrepreneurs is likely to suffer from selection bias. For example, we do not observe entrepreneurs that refrained from creating a firm because their personal savings were insufficient or because their credit application was rejected. This issue could also be important when quantifying the effect of the pandemic on funding sources because the motives of entrepreneurs and the types of their projects differ in 2020, as we have shown above. To correct for this bias, we estimate a Heckman selection model, where we estimate as the selection equation the specification shown in Column 1 of Table 2 but without the terms involving the

GR dummy because we are constrained to using only the years 2017–2020. The main equation then includes only our variables of interest: a dummy indicating the year of the COVID-19 pandemic, a dummy for high income, and an interaction between these two. As dependent variables, we consider the share of funding coming from banks, the share coming from private savings, and the share coming from all residual categories. In other words, we examine whether, conditional on starting a firm, entrepreneurs with different income levels select different financing sources and how such selection changed during COVID-19.

Table 3 presents the results. We find that the pandemic decreased the share of funding coming from banks, because the coefficient of the $COVID$-19 dummy is negative in the first two columns, although it is not statistically insignificant. When we consider the share of personal savings (Own) as the outcome variable, we find a significantly positive effect (Column 3). Allowing the effect to differ between low-income and high-income respondents (Column 4) reveals that it is only the former who rely more on personal savings to fund their startups during the pandemic. Accordingly, as can be seen in the last two columns, low-income entrepreneurs instead rely less on funding classified in the residual category. These findings suggest greater difficulties obtaining financing from sources other than personal savings during the pandemic, especially for those with low income, who might have a particularly high need for such alternatives. Thus, this piece of evidence suggests that financial constraints could have played a prominent role in explaining the strong drop in the startup rate among those at the lower end of the income distribution.

Given the pecking order explained above, a possible alternative interpretation of this finding is that for some reason there were fewer opportunities for low-income households, which were also of smaller size, than for high-income households. Because opportunities were smaller, mostly internal finance was used. However, this *"lack of opportunities"* interpretation would necessarily imply that during COVID-19, the average size of startups should have declined more for low-income than for high-income households. We explore this angle in Table 4, where we show the results of estimating a similar Heckman selection model but using as the dependent variable of the main equation the amount of funding required for the startup (in logs) and adding the share of each type of funding among the regressors. This table restricts the sample to startups classified as non-necessity, but the results are robust to using all startups (Table A.4 in the Appendix) and non-digital startups only (Table A.5 in the Appendix). Column 1 shows the results for entrepreneurs of all income categories, where we see that all startups born during COVID-19 are smaller than those created in other years, regardless of their income category. Hence, we do not find that the average size of startups declined more for low- than for high-income households. Startups financed with own funding are in general smaller, and those financed with bank funds larger, than the omitted category (other funds). If we split the sample into low income (LI in Column 2) and high income (HI in Column 3), we observe that the qualitative results are the same for both income groups. Therefore, a plausible interpretation is that low-income households had the same opportunities as high-income households, but because of their greater difficulty accessing external finance, many could not seize them (more difficulty accessing banks and perhaps also more difficulty accessing family and friends because these sources engaged more in precautionary saving). On the other hand, those with larger buffers of savings might have been better able to exploit new business opportunities, which explains the surge in own financing described above.

Although we do not have direct information in the GEM surveys on the financial frictions faced by the households, information from external surveys support the view of tightening of financial frictions for households and small firms during COVID. Based on data from the ECB's Bank Lending Survey, Panel A of Figure A.3 shows that credit conditions worsened constantly during 2020, with the largest tightening happening during the third quarter of 2020, with a level of tightening not seen since the 2012 sovereign debt crisis. The tightening of 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), Panel B of Figure A.3 shows an increase in the financing gap, which is the difference between the change in demand for external financing and the change in its availability for surveyed SMEs, especially for Spain.

Given that financial frictions seem an important factor in explaining the lower entry into entrepreneurship of low- and middle-income households relative to high-income ones, it is interesting to note that, as mentioned in Section 4.2, during the 2008-09 financial crisis, which was also a period of pervasive financial frictions, firm creation actually fell more among high-income households than among other households. Unfortunately, the GEM surveys did not ask questions on the funding sources before 2017, so we could not include the great recession period in Table 3. Nonetheless, we think two factors are important to explain this difference. First, as we show in detail in the next section, the COVID-19 period presented new entrepreneurial opportunities, which were likely absent during the 2008-09 Great Recession. One of the main findings of this paper is that the higher entrepreneurial entry rates of high-income households was in part driven by their ability to better exploit these opportunities. Second, one possible reason for this divergence is that the Great Recession in Spain was characterized by the burst of a huge housing bubble. High-income households are more likely high-wealth households, and these own more (and more valuable) real estate (see Banco de España, 2019 for a detailed breakdown of real estate ownership and value by wealth percentile). During the Great Financial crisis, real estate values dropped dramatically, hence arguably affecting more high-income households. A large empirical literature shows the importance of housing as collateral to finance new entrepreneurial ventures, and therefore this might help to explain the larger drop among high-income entrepreneurs.

4.4 New entrepreneurial opportunities due to COVID-19

In the previous section, we presented evidence consistent with the view that high-income entrepreneurial households performed well during the pandemic because they were better able to exploit investment opportunities. The GEM surveys allow us to provide additional evidence on this hypothesis because they ask new entrepreneurs to describe in their own words the kind of business they are intending to create. To make use of this information, we searched for a range of key words in the respondents' descriptions that suggest that their business is of a digital nature.[25] We then classify the startups as "digital" if at least one of these key words is used.

In Table 5, we show the regression results using the specification in Column (1) of Table 2 but replacing our previous dependent variable that indicated a start of any kind of business with a dummy indicating the start of a digital business. Note that the description of the nature of the business is only asked in the survey since 2011; thus, we can only use the 2011–2020 sample and are forced to drop the terms involving the GR dummy.

We find that the probability of starting a digital firm was unaffected by the pandemic for low-income households (Column 2), whereas the probability of starting a non-digital firm (Column 4) declines significantly. On the other hand, high-income respondents are 0.5 percentage points significantly more likely to start a digital firm during the pandemic than before. Note that the average probability of starting a digital firm is only 0.7% in the period 2011–2019 for individuals with high income. Thus, the coefficient of the interaction term in Column 2 of Table 5 implies a 70% increase in digital startups for high-income households during the COVID-19 crisis, relative to the 2011–2019 period. This result clearly indicates that these households were much better at exploiting new digital business opportunities during COVID-19 than low- and medium-income households. In contrast, the corresponding probability of starting a non-digital firm is 5.6%, and therefore the coefficient of the interaction term in Column 4 indicates a much smaller (and insignificant)

[25]For example, we searched for (variants of) words such as *online, digital, internet, web, informatico, virtual, e-commerce.*

relative effect.

In Table 6, we run regressions analogous to those in Table 3 but with the aim of investigating heterogeneity in funding sources depending on whether a startup is digital. As digital businesses rely more on intangible capital, they might find it more difficult to obtain external funding from financial institutions, and thus we expect them to rely even more on the personal savings of their founders. As in the previous section, we run a Heckman selection model but include in the main equation the following three variables of interest: a dummy indicating whether the respondent started a digital firm, a dummy indicating the year of the COVID-19 pandemic, and an interaction between these two. As dependent variables, we again consider the share of funding coming from banks, the share coming from private savings, and the share coming from all residual categories. To still be able to conduct a separate analysis for low- and high-income households and simultaneously avoid having a triple interaction, which would complicate the interpretation of the coefficients, we run the regression for the full sample and then separately for the low-income (LI) and high-income (HI) samples.

The estimates in Columns (1)–(3) reveal that starting a digital firm reduces the share of funds coming from banks regardless of the household's income. However, in Columns (4)–(6), we can see that the percentage of funds coming from personal savings is as much as 16 points larger when the business is digital. The fact that the $COVID\text{-}19 \times Digital$ interaction is small and insignificant in Column (4) suggests that the greater reliance on personal savings for digital startups was similar before and during the pandemic. However, this masks a notable pattern that we uncover by considering income groups separately in Columns (5) and (6). We find that *before* the pandemic, the own funding share of digital startups is 21 pp larger for high-income and 11 pp larger for low-income households. In contrast, as indicated by the interaction term, *during* the pandemic, *low-income* households relied even more on own savings when creating a digital startup, whereas there is no significant difference between digital and other startups for high-income households. Accordingly, we see (roughly) coefficients with the opposite signs when considering the residual category of "other" funding sources in Columns (7)-(9). Hence, low-income households starting new firms of a digital nature during the pandemic were especially dependent on personal savings as their main funding source. In quantitative terms, on average, a low-income entrepreneur starting a digital business in 2020 had a 40 pp larger share of personal savings among all sources of funding than a low-income entrepreneur starting a non-digital business before 2020. Thus, these results acknowledge once again the difficulty for households with low income levels in obtaining alternative financial resources to found digital firms during COVID-19.

4.5 Robustness Checks

In this section we verify the robustness of our results to possible alternative explanations. First, we verify that the results do not depend on sector heterogeneity. Second, we verify that low- and middle-income households did not start fewer firms because they are usually involved in activities that by their nature are more directly affected by the COVID shock.

4.5.1 Heterogeneity of the impact of COVID-19 depending on the sector

An important feature of the COVID-19 crisis is that it affected certain sectors more than others. Indeed, hotels and restaurants remained closed or could only open under restrictions for a long time during the pandemic. Moreover, the activities of transport businesses have been strongly reduced. Hence, our results could be in part driven by fact that low- and medium-income households were more involved in these affected sectors relative to high-income households.

To investigate this possibility, we separate firms into affected sectors (which includes hotels, restaurants and transports) and the remaining sectors that are not directly affected. Table 7 shows the outcome of estimating equation (1) adding heterogeneity by income, where the dependent variable is the likelihood to start a firm in a sector that is not affected (Column 1) or affected (Column 2). The likelihood to start a firm in not directly affected sectors is 1.5pp lower for low-income households, while it increases very slightly for high-income households (1.7pp-1.5pp=0.2pp). In relative terms, the negative effect on low-income households considering only unaffected sectors is almost identical to the one we estimated considering all sectors. For those with low income, the average probability to start a firm in any sector across the sample period is 3.8%. Thus, the coefficient in column 1 of Table 2, $-.017$, implies a 45% decrease. The average probability to start a firm in unaffected sectors for low-income individuals is 3.5%, so that the first coefficient in column 1 of Table 7 implies a 44% decrease in the startup probability for this income group.

On the other hand, in affected sectors, the decrease in the likelihood to start a firm is 0.16pp for individuals with low household income. In relative terms, this implies a decrease of 53%, since for this income group the probability of starting a firm in an affected sector is only 0.3%. Thus, as expected, affected sectors experienced a somewhat larger relative decline in startup creation in 2020. However, as our previous results remain almost unchanged when considering only unaffected sectors, we can conclude that they are not driven by a sector-composition explanation.

Columns (3) ad (4) show that there is also a change in the composition of entrants both in affected and unaffected sectors, although it is quantitatively larger in the former.

Among new entrepreneurs in unaffected sectors, low-income households are 10.2pp less likely to start a high-growth firm, while high-income households are 1.5pp more likely to do so (-10.2pp+11.7pp). This difference is exacerbated in affected sectors, where low-income households are 18.6pp less likely to start a high-growth firm, and high-income households are 12.5pp more likely to start a high-growth firm (-18.6pp+31.1pp=12.5pp), although these effects are imprecisely estimated due to the low number of observations.

4.5.2 Heterogeneous entrepreneurial choices during COVID-19 depending on the shock

In the previous section, we showed that our results are not driven by a sector effect. Nevertheless, it could be that, even within the same sectors, low-income households are involved in activities that by their nature are more directly affected by the COVID-19 shock. The richness of the GEM survey also allows us to verify this possibility. As shown in the bottom-right panel of Figure 5, the GEM includes a question asking respondents to state the extent to which their household's income was affected by the pandemic. Approximately 40% of low-income and 30% of high-income households report that their income decreased at least somewhat. In this section, we therefore investigate whether there is a relationship between the propensity to start a new business and the experience of a negative income shock due to the pandemic. Furthermore, we show how this relationship depends on the *level* of household income.

To do so, we run the same specification shown in the first two columns of Table 2 but allow both the $COVID$-19 dummy and its interaction with *High Income* to differ between the group of respondents that suffered a negative income shock (*Income Decreased*) and the group that did not (*Income Not Decreased*). Table 8 shows the results of this regression. We find that among those with low income (first two rows), those who were *not* hit by a negative income shock were even less likely to create a startup than those who suffered an income loss. On the other hand, as seen in the second column, the share of high-growth startups has fallen more for those that did experience a decline in income. Hence, these results suggest that entrepreneurship might have acted as a substitute for regular employment and therefore cushioned the decline in business creation among low-income households with a negative income shock. However, as these households are more likely to engage in business creation out of necessity, their businesses are less likely to have high growth potential. This interpretation is consistent with the previously shown evidence that job scarcity has become an important motive for becoming an entrepreneur during the pandemic.

With respect to high-income households (third and fourth rows), we see the opposite picture in terms of the relationship between starting a business and experiencing an income shock: those who saw their income *decrease* during the pandemic are less likely to become entrepreneurs than those that did not. Hence, it seems that, contrary to low-income households, the households that could keep their income stable during the pandemic were more likely to engage in entrepreneurship. Among the individuals that were not hit by an income shock, those with high income were 2.9 pp more likely to become entrepreneurs during the pandemic. In contrast, among these with a negative shock, there was no difference in the probability of becoming an entrepreneur.[26]

A possible explanation for this finding is that high-income entrepreneurs were able to recognize the pandemic as an opportunity rather than an obstacle for business creation. This is again in line with the prima facie evidence shown in Figure 4. While almost no respondents with low income answer that the expectations for business growth are much higher than one year ago, approximately 10% of those with high income do. Moreover, an even closer look at the data reveals that, among high-income households, those with a negative income shock are much less optimistic: only 2.6% of them report that their expectations for business growth are much higher than one year ago.

4.6 Effects on long-run employment growth

In Appendix B, we estimate the medium- and long-term job losses caused by the drop in entrepreneurship among low- and middle-income households. We do so by matching, at the sector level, the GEM survey data from 2005 to 2020 with Spanish firm-level data from Central de Balances Integrada (CBI) from the Banco de España. First, using past data, we document the employment growth patterns of entering cohorts and how changes in the share of high-growth firms impacts employment growth. Second, with the previous findings from the GEM regarding the entry choice and its composition (low- vs high-growth startups) during 2020 at hand, we predict the evolution of employment of the entering cohort in the coming years. We find that the employment of the generation of firms created during the pandemic is expected to be 2.4% smaller after 10 years, mostly because of the drop in startups with high growth potential from low-income entrepreneurs. If all households behaved as high-income households, we would not see a reduction in entry, and there would be employment gains in the long run. These results highlight the importance of income inequality for firm entry and long-run employment growth in the

[26]Note that the survey question does not further specify whether a decrease in income is due to a job loss, switch to a lower paid one, or a fall in income in the same job. However, the data include a variable indicating the employment status *before* the corona pandemic. Based on this information, we find that 5% of the respondents lost their job since the start of the pandemic. As 40% claim that their income decreased, we can conclude that for approximately 12.5% of them the cause is a job loss.

aftermath of the COVID-19 shock.

5 Conclusion

In this paper, we study entry into entrepreneurship during the 2020 COVID-19 recession using a new extensive survey of more than 24,000 Spanish households, conducted between July and November 2020. We find that while the overall decline in the startup rate in 2020 was large and overall quantitatively similar to that during the Great Recession, the heterogeneity in the impact of the crisis depending on household income was starkly different. During 2020, the drop in firm entry was entirely concentrated among households with low or medium income. In fact, we find no reduction in entry among those with high income (defined as the top tercile income group) and even a slight increase in the entry of startups with high growth potential. Conversely, during the Great Recession, high-income households suffered a significantly stronger decline in entry than other households. We show that these findings are not directly explained by social distancing, since they are mostly driven by the sectors not directly affected by lockdown measures. Furthermore, the difference between entry into entrepreneurship between high- and medium/low-income households was particularly large among those that did not suffer a negative income shock during the pandemic. We instead find evidence indicating that high-income households performed relatively better during the COVID-19 recession because they were better at exploiting new business opportunities, thanks to their larger wealth and better access to external finance. This finding is consistent with evidence of credit tightening and highlights the importance of constraints on the access to finance for low-income households as one of the main reasons for their reduced entrepreneurial activity during the pandemic compared to high-income households. Overall, the main implication of this paper is that while policies directed at supporting current jobs during a pandemic are important, to ensure a durable recovery in the future, they should be accompanied by measures directed at reducing the cost of credit for new potential entrepreneurs, especially those with low income.

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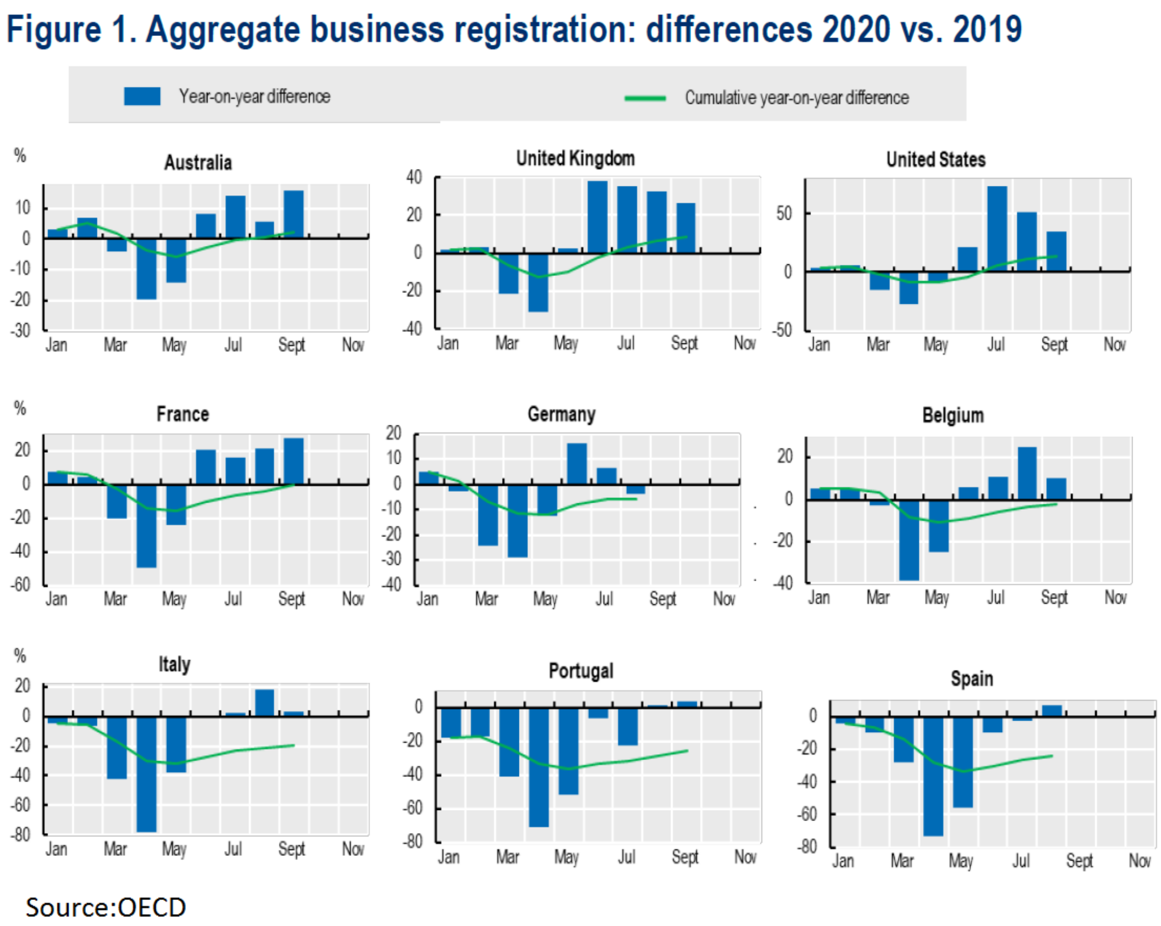
Tables and Figures

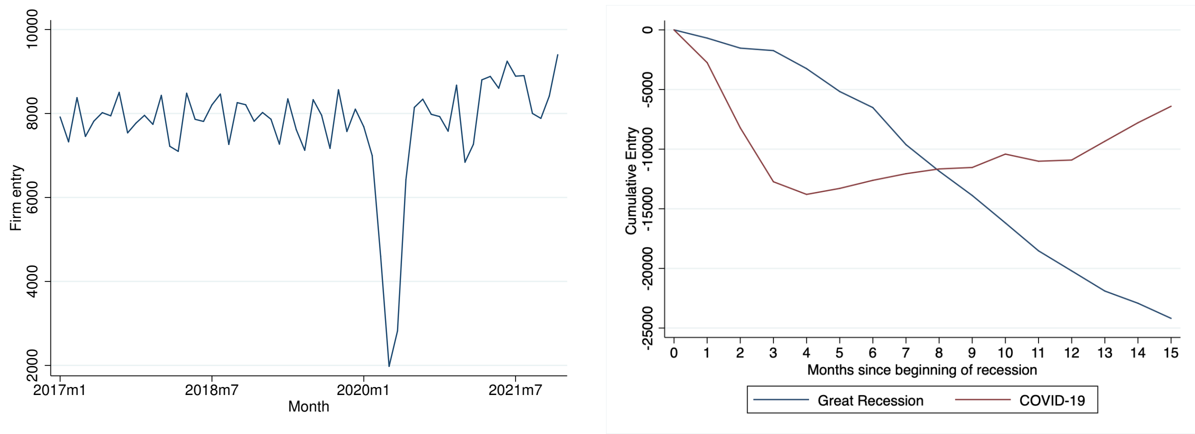
Figure 1: COVID-19 and Firm Entry.



Notes: Source: OECD (2020) "Business dynamism during the COVID-19 pandemic: Which policies for an inclusive recovery?", OECD Responses to Coronavirus (COVID-19), OECD, Paris.

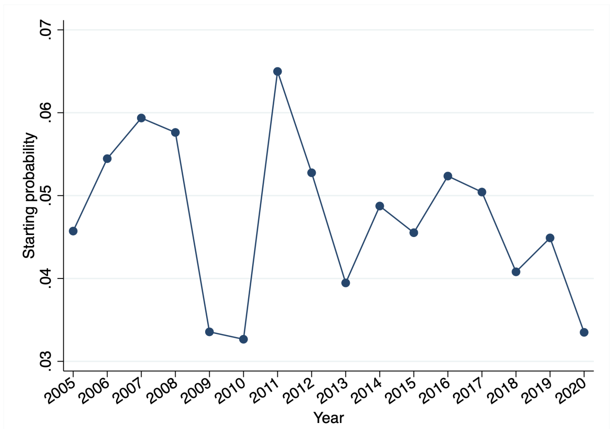
Figure 2: Firm entry in Spain

A. Firm entry in Spain **B.** Cumulative drop in firm entry in Spain



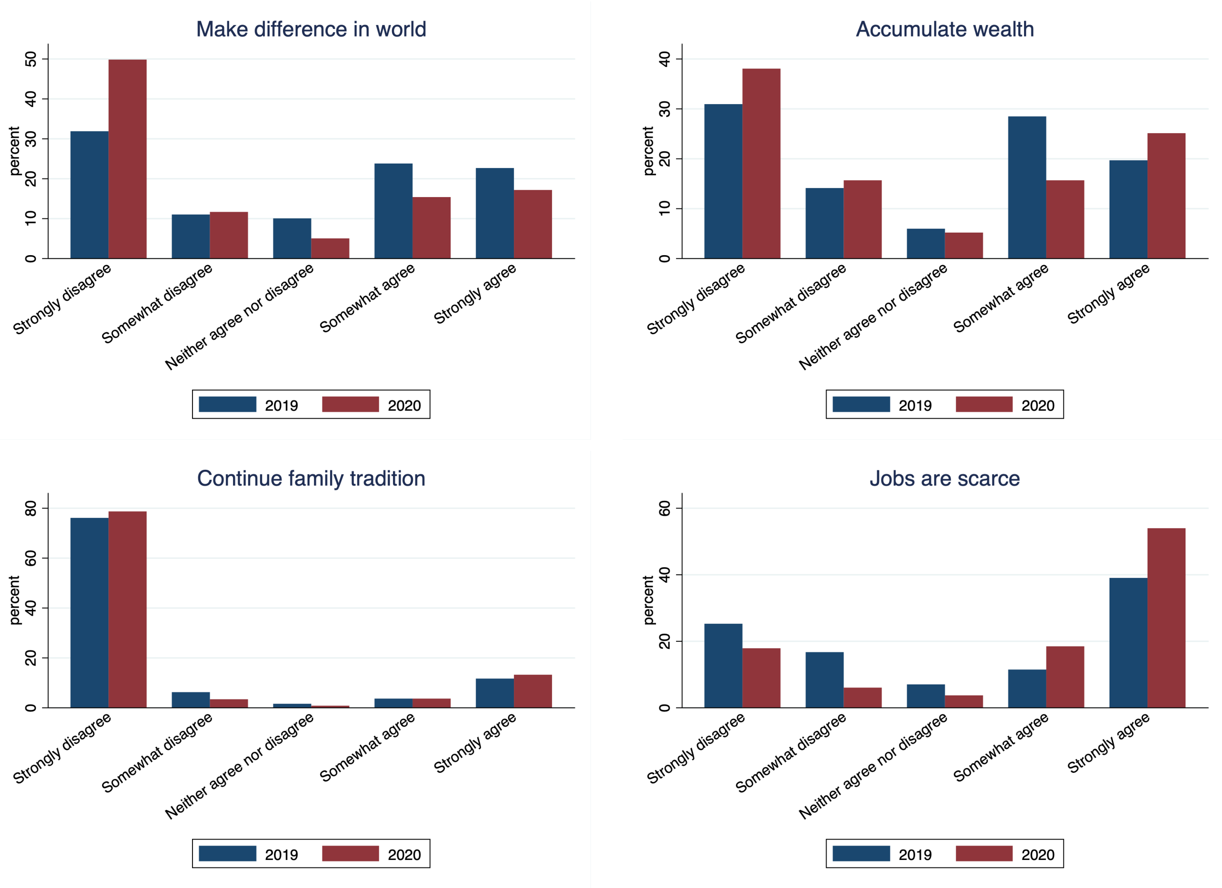
Notes: Data at monthly frequency is from INE (https://www.ine.es/jaxiT3/Tabla.htm?t=13912). Panel A shows the deseasonalized number of new firms entering ("Constituidas"), which only includes firms recognized as independent legal entities. Entry in March 2019 is normalized to 1. Panel B shows the cumulative 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 3: Entry according to GEM



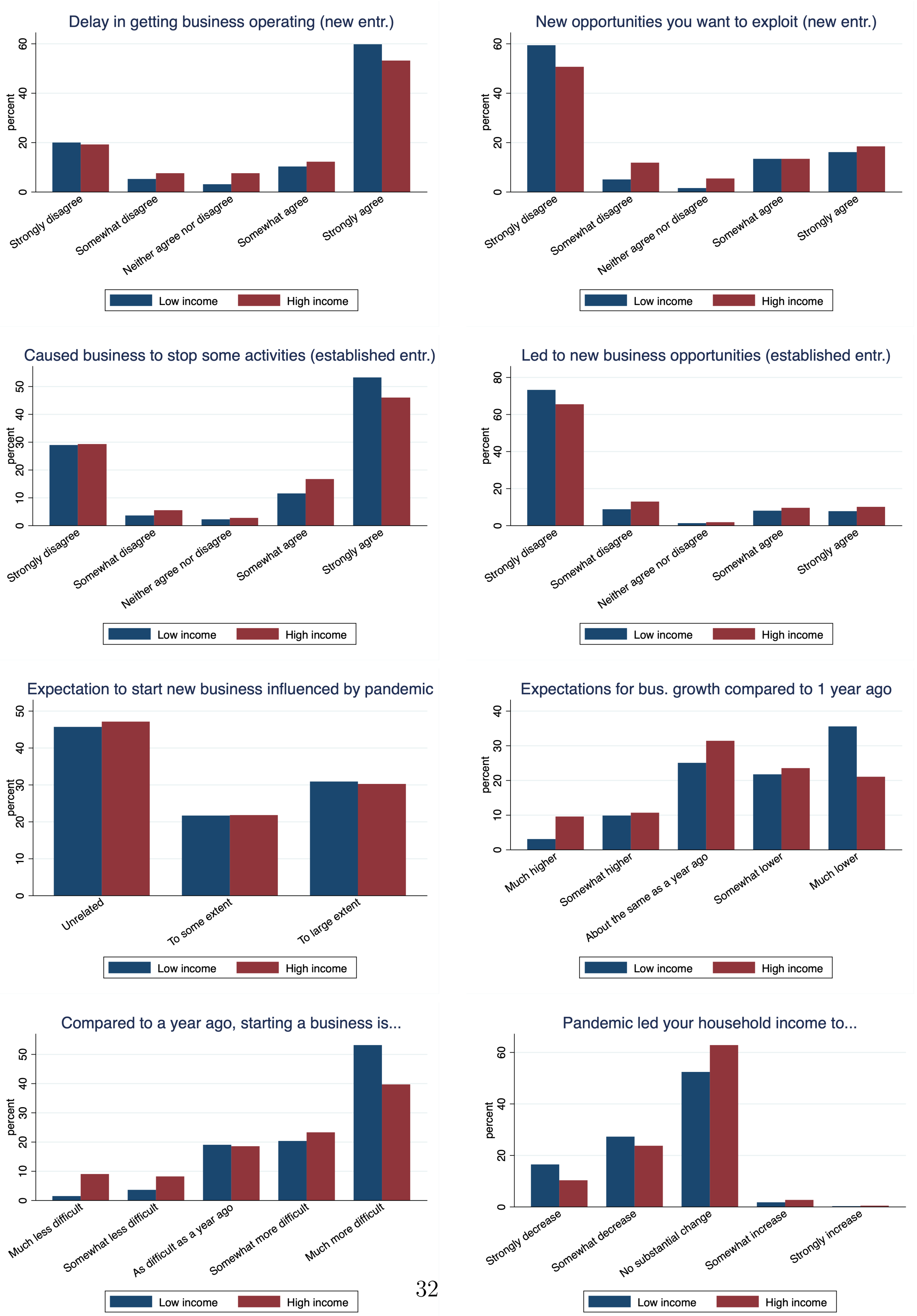
Notes: Share of individuals starting a new firm in each GEM survey wave since 2005.

Figure 4: Motives for business creation, 2019 vs 2020



Notes: The bars show the percent of entrepreneurs giving the indicated answers on questions in the 2019 and 2020 GEM waves on the motives for their decision to start a business.

Figure 5: Business and the COVID-19 Pandemic



Notes: The bars show the percent of respondents giving the indicated answers on COVID-19 related questions taken from the GEM 2020 wave.

Table 1: Probability to start a firm during COVID-19

	(1) Start	(2) High Growth Share	(3) Start	(4) High Growth Share
COVID-19	-0.017***	-0.062***	-0.013***	-0.051***
	(0.0017)	(0.0186)	(0.0017)	(0.0190)
GR	-0.019***	-0.070***	-0.018***	-0.071***
	(0.0019)	(0.0229)	(0.0017)	(0.0226)
Female	-0.016***	-0.047***	-0.007***	-0.045***
	(0.0011)	(0.0139)	(0.0010)	(0.0138)
Age	0.004***	-0.007	0.002***	-0.007
	(0.0003)	(0.0047)	(0.0003)	(0.0047)
Age squared	-0.000***	0.000	-0.000***	0.000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
High Income	0.018***	0.037**	0.012***	0.034**
	(0.0025)	(0.0159)	(0.0025)	(0.0159)
Educated	0.014***	0.034***	0.007***	0.031***
	(0.0015)	(0.0118)	(0.0014)	(0.0118)
Expected Opport.			0.044***	0.017
			(0.0024)	(0.0118)
Fear			-0.019***	-0.014
			(0.0011)	(0.0135)
Skill			0.062***	0.039
			(0.0020)	(0.0238)
Constant	-0.003	0.462***	-0.007	0.434***
	(0.0053)	(0.0918)	(0.0053)	(0.0902)
Observations	389426	9234	389426	9234
R-squared	0.009	0.010	0.043	0.011

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Columns (1) and (3) show the results for starting any firm, Columns (2) and (4) for starting a high growth firm conditional on starting a firm. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. Controls include sex, age and age squared, a dummy for post-secondary education, income and region fixed effects. Columns (3) and (4) include controls for individual perceptions: perception of skills to start a new firm (Skill), perception of fear of failure (Fear) and expected opportunities within 6 months (Expected Opport.). Standard errors are clustered at the region-year level.

Table 2: Probability to start a firm during COVID-19: High vs Low income

	(1) Start	(2) High Growth Share	(3) Necessity Share
COVID-19	-0.017***	-0.109***	0.347***
	(0.0014)	(0.0287)	(0.0217)
COVID-19 x High Income	0.019***	0.134***	-0.012
	(0.0062)	(0.0438)	(0.0485)
GR	-0.014***	-0.068***	-0.042**
	(0.0020)	(0.0208)	(0.0189)
GR x High Income	-0.013***	-0.005	0.025
	(0.0041)	(0.0360)	(0.0247)
Controls	Yes	Yes	Yes
Observations	389426	9234	15839
R-squared	0.043	0.012	0.044

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Column (1) shows the results for starting any firm, Column (2) the results for starting a high growth firm conditional on starting a firm, and Column (3) the results for starting a necessity firm conditional on starting a firm. A necessity entrepreneur is a new entrepreneur that starts a firm because of lack of employment. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. *High income* is a dummy that takes the value 1 if the individual is in the upper 33th income percentile. Additional controls include sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table 3: Funding sources of entrepreneurs during COVID-19

	(1) Bank	(2) Bank	(3) Own	(4) Own	(5) Other	(6) Other
COVID-19	-2.925	-4.658	8.459**	12.509***	-5.462*	-7.284**
	(2.9975)	(3.3226)	(3.4576)	(3.5908)	(2.8740)	(3.4457)
High Income		-1.254		5.101		-4.430
		(3.8444)		(3.8799)		(3.5451)
COVID-19 x High Income		4.907		-12.339**		6.484*
		(4.9810)		(6.2381)		(3.8647)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92718	92718	92718	92718	92718	92718
R-squared						

Notes: The dependent variable is the percentage of funds coming from the source indicated in the column headers among all sources of financing of the businesses of new entrepreneurs in the GEM. Due to limited data availability, the sample is restricted to the years 2017-2020. "Own" denotes the category "Private savings". "Other" includes the categories family savings, friends, subsidies, investors and crowdfunding. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. The coefficients are the second-stage results of a Heckman selection model, where the selection equation has a dummy variable indicating a new entrepreneur as dependent variable and the following explanatory variables; sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table 4: Amount of funding of entrepreneurs during COVID-19, non-necessity

	(1) All	(2) LI	(3) HI
COVID-19	-0.720**	-0.778***	-0.656
	(0.2840)	(0.2778)	(0.4176)
High Income	0.386		
	(0.3295)		
COVID-19 x High Income	0.003		
	(0.5416)		
Share of own funding	-1.028***	-1.022***	-0.845***
	(0.3169)	(0.3148)	(0.2264)
Share of own funding x High Income	0.177		
	(0.4174)		
Share of bank funding	0.881*	0.876*	0.667***
	(0.4958)	(0.5030)	(0.2507)
Share of bank funding x High Income	-0.237		
	(0.5028)		
Controls	Yes	Yes	Yes
Observations	93662	75506	18156
R-squared			

Notes: The dependent variable is the (log) amount of funding required for the startup. Due to limited data availability, the sample is restricted to the years 2017-2020. "Own" denotes the category "Private savings". The coefficients are the second-stage results of a Heckman selection model, where the selection equation has a dummy variable indicating a new entrepreneur as dependent variable and the following explanatory variables; sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level. Regression using only start-ups classified as non-necessity (see definition in Section 4.2).

Table 5: Probability to start a 'digital' firm during COVID-19

	(1) Start Digital	(2) Start Digital	(3) Start No Digital	(4) Start No Digital
COVID-19	0.0008	-0.0003	-0.0117***	-0.0127***
	(0.0008)	(0.0007)	(0.0018)	(0.0015)
COVID-19 x High Income		0.0052**		0.0050
		(0.0025)		(0.0055)
Controls	Yes	Yes	Yes	Yes
Observations	224691	224691	228170	228170
R-squared	0.009	0.009	0.033	0.033

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Column (1) shows the results for starting any firm, Column (2) the results for starting a low growth firms, and column (3) the results for starting a high growth firms conditional on starting a firm. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. Controls include sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table 6: Funding sources of entrepreneurs during COVID-19

	(1) Bank	(2) Bank, LI	(3) Bank, HI	(4) Own	(5) Own, LI	(6) Own, HI	(7) Other	(8) Other, LI	(9) Other, HI
COVID-19	-2.920	-3.406	-3.153	9.743***	12.122**	5.352	-7.134**	-8.581*	-3.386
	(3.2622)	(3.8166)	(5.5455)	(3.7406)	(4.8051)	(5.7467)	(3.3790)	(4.5025)	(3.5551)
Digital	-12.708***	-14.013**	-10.940***	16.628***	11.373	20.968***	-4.609	0.611	-9.150*
	(4.2630)	(5.6635)	(3.4766)	(5.3184)	(7.4226)	(4.5421)	(4.7763)	(5.7270)	(5.4915)
COVID-19 x Digital	1.333	2.430	0.823	-1.444	16.650**	-20.440***	2.409	-13.498**	18.566***
	(5.5361)	(8.3009)	(5.2675)	(7.0052)	(8.4712)	(7.4570)	(5.7633)	(6.7578)	(7.0890)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92654	74781	17873	92654	74781	17873	92654	74781	17873
R-squared									

Notes: The dependent variable is the percentage of funds coming from the source indicated in the column headers among all sources of financing of the businesses of new entrepreneurs in the GEM. Due to limited data availability, the sample is restricted to the years 2017-2020. "Own" denotes the category "Private savings". "Other" includes the categories family savings, friends, subsidies, investors and crowdfunding. "LI" indicates that the sample is restricted to individuals with low income. "HI" indicates that the sample is restricted to individuals with high income. $Digital$ is a dummy that indicates starting a digital business. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. The coefficients are the second-stage results of a Heckman selection model, where the selection equation has a dummy variable indicating a new entrepreneur as dependent variable and the following explanatory variables; sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table 7: Probability to start a firm during COVID-19: High vs Low income, Affected vs not affected

	(1) Start Not affected	(2) Start Affected	(3) High Growth Share Not affected	(4) High Growth Share Affected
COVID-19	-0.0155***	-0.0016***	-0.1021***	-0.1863*
	(0.0013)	(0.0005)	(0.0298)	(0.0959)
COVID-19 x High Income	0.0172***	0.0014*	0.1173***	0.3109
	(0.0058)	(0.0008)	(0.0418)	(0.2761)
GR	-0.0119***	-0.0022***	-0.0648***	0.0037
	(0.0019)	(0.0004)	(0.0234)	(0.1258)
GR x High Income	-0.0141***	0.0006	-0.0033	-0.1218
	(0.0040)	(0.0008)	(0.0377)	(0.1700)
Controls	Yes	Yes	Yes	Yes
Observations	389426	389426	8108	1126
R-squared	0.039	0.004	0.015	0.037

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Affected sectors (second and fourth column) include hotels, restaurants and transport. Column (1) and (2) show the results for starting any firm and Column (3) and (4) the results for starting a high-growth firm conditional on starting a firm (in the indicated group of sectors). $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. *High income* is a dummy that takes the value 1 if the individual is in the upper 33th income percentile. Additional ontrols include sex, age and age squared, a dummy for post-secondary education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table 8: Probability to start a firm during COVID-19: High vs Low income, Income decreased vs Income not decreased

	(1) Start	(2) High Growth Share
COVID-19 x Income Decreased	-0.012***	-0.134***
	(0.0019)	(0.0372)
COVID-19 x Income Not Decreased	-0.021***	-0.068*
	(0.0015)	(0.0395)
COVID-19 x High Income x Income Decreased	0.000	0.153***
	(0.0070)	(0.0574)
COVID-19 x High Income x Income Not Decreased	0.029***	0.096*
	(0.0083)	(0.0500)
Controls	Yes	Yes
Observations	389426	9234
R-squared	0.043	0.013

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Column (1) shows the results for starting any firm and Column (2) the results for starting a high growth firms conditional on starting a firm. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. *Income decreased* is a dummy that takes the value 1 if income of the household decreased during COVID-19, 0 otherwise. *Income not decreased* is the complement set of *Income decreased.* Controls include sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Appendix

A Data and Variable Definitions

A.1 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 subcontractors, 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 who are owners of firms that are 5 or more years old.[27] 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.[28]

A.1.1 Validity of the high-growth type measure during COVID-19

One issue regarding the change in the composition of entrants in low- vs. high-growth firms is that our classification depends on the perception of the entrepreneur.[29] Although

[27] 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.

[28] 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.

[29] We classify startups as low/high growth by using the expected number of employees of the firm five years into the future reported by new entrepreneurs.

in Appendix B.1, we validate this measure using historical data matched with firm-level data, it might be the case that due to the very unique features of this crisis, including the large surge in uncertainty, our measured decrease in the high-growth share among new firms is just a reflection of a worsening of the perception of future performance due to uncertainty. We believe that this is not the case because the increase in the perception of uncertainty by firms is generalized and relatively homogeneous within sector and region once the size of the shock is accounted for. If the compositional change were only driven by changes in perceptions due to the shock, this would affect in a similar way low- and high-income entrepreneurs, so we would expect a homogeneous drop in high-growth firms, while we find that the compositional change was heterogeneous depending on the ex ante level of income. Second, if uncertainty were playing a large role, we would also expect all entrepreneurs in affected sectors to be more pessimistic and hence see a more marked decrease of high-growth firms in these sectors. However, we show that high-income households are actually more likely to start high-growth firms in affected sectors than in non-affected sectors during COVID-19. We believe that this evidence suggests that the compositional changes of entrants are not solely driven by the large increase in uncertainty surrounding the pandemic.

A.2 Variable definitions from GEM questions

Apart from identifying startups and high-growth firms as explained above, we construct the following variables to use as regressors and controls:

- *Gender.* Variable GENDER is a dummy taking value 1 if male, 0 if female.
- *Age.* Variable AGE gives the age of the respondent in years.
- *Educational level.* Variable GEMEDUC gives 5 categories for education: pre-primary education, primary education or first stage of basic education, lower secondary or second stage of basic education, (upper) secondary education, post-secondary non-tertiary education, first stage of tertiary education, and second stage

of tertiary education. We create a dummy that takes value 1 if the individual has post-secondary non-tertiary education, first stage of tertiary education or second stage of tertiary education, 0 otherwise.

- *Income category.* Variable GEMHHINC gives the income tercile that the respondent belongs to. We create a dummy that takes value 1 if the respondent is in the highest 33% of the income distribution, 0 otherwise.

- *Perception of skills to start a new firm.* In the variable SUSKILL, GEM asks respondents the following yes/no question: '*Do you have the knowledge, skill and experience required to start a new business?*'. We create a dummy from the response to this question.

- *Perception of fear of failure.* In the variable FEARFAIL, GEM asks respondents the following yes/no question: '*Would fear of failure prevent you from starting a business?*'. We create a dummy from the response to this question.

- *Expected opportunities within 6 months.* In the variable OPPORT, GEM asks respondents the following yes/no question: '*In the next six months, will there be good opportunities for starting a business in the area where you live?*'. We create a dummy from the response to this question.

- *Region.* Autonomous community where the household lives. The Spanish territory is divided into 19 autonomous communities and cities which are the second-level territorial and administrative divisions NUTS 2 under EUROSTAT classifications.

- *Sector.* Main sector of activity of the business. Sectors are defined at the 2-digit level.

B COVID-19 and Expected Employment Growth

In this Appendix we use the fall in firm entry and the changes in its composition that we documented in the main text to predict future firm size and employment growth. For this purpose, we complement the GEM with firm-level balance sheet data from Central de Balances Integrada (CBI), a panel of Spanish firm-level data spanning from 1996 to 2018, which virtually covers the entire population of Spanish incorporated firms.

Firm-level balance sheet data: Central de Balances Integrada

We make use of firm balance sheet data to predict the long-run employment implications of the changes in entrepreneurial choices we find in the GEM. Firms' balance sheet data come from *Central de Balances Integrada*, the business registry data available at the Bank of Spain, which contains the quasi universe of incorporated Spanish firms. This data comes 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.[30] We exclude firms in the primary sector and mining, the financial and insurance sector, and public administration. We also only retain firms that have at least one employee at some point of their lives because our goal is to focus on firms that create employment. Furthermore, we drop firms that are part of a group and those that have more than 100 employees and/or are publicly traded in the year of their creation or the next, since these are likely entities created through restructuring of existing firms. We link the information on startups from GEM with this firm-level dataset at the sector-year level.[31] *Employment* is defined as the average number of employees during the year, and *age* is computed as the difference between the current year and incorporation year.

[30] For more detailed information on this dataset, see Almunia et al. (2018).

[31] Sectors are defined as the 2-digit CNAE in the CBI dataset, and we convert them into ISIC-2 sectors to match the GEM dataset

B.1 The relationship between startups and future firm growth

We use this dataset to answer two questions. First, how long-lasting are the effects of firm entry, regardless of the type of firm created, on the aggregate employment of the cohort? Second, does the composition of entry (high-growth vs. low-growth firms) matter for the long-run job creation of a cohort of firms? To understand the first issue, we run the following regression:

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

where $Employment\_cohort_{k,s,t}$ is total employment of all firms of age k belonging to industry s in 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 $\gamma_{1,k}$ 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 A.5. 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 directly link GEM data with the firm-level data from CBI, we proceed as follows: using GEM data, we compute the variable $Share\_growth_{s,t}$, i.e., the share of high-growth startups in 2-digit sector s in year t in Spain. Then, we match these industry shares with the firm-level data from CBI. We are able to match 3,359,683 firm-year observations to the share of high-growth firms in the sector and year they were created. Using these 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 the 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 A.6. In Column (1), we control for any aggregate shock and sector-specific factors 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, they are eventually 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 29% 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 25% 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 medium- to long-run employment growth.

B.2 Predictions of the impact of the pandemic on future employment

We now use these estimates to predict the long-run implications for firm size and job growth for Spain, as shown in Figure A.6. 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 spillover effects on firms in different cohorts and sectors.[32]

We construct these predictions in the following way. First, we consider the change in overall entry and change in the composition of entry we obtain in Table 1. Then, with this predicted decrease in firm creation, we multiply $\gamma_{1,k}$ from Equation (2) by the aggregate employment of firms of age k from CBI (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, which is depicted in blue in Figure A.6. Second, we also want to include the impact of the composition channel on aggregate employment. To do so, with the coefficients of the interaction terms in Equation (3) depicted in the first column of Table A.6, we obtain 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 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 by the coefficient $\beta_{2,k}$ in 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 the long-run aggregate employment of the cohort, which is depicted in red in Figure A.6. Using the same methodology but using the predicted changes in entry and composition of entry for high- and low-income households in Table 2, we obtain counterfactual scenarios in a world where all agents behave either as high-income or low-income households (Panels B and C of Table 2).

Panel A of Figure A.6 shows the long-run employment effect for the full sample. Due to the fall in entry predicted by Table 1, there would be a loss of approximately 1,000 jobs for the entering cohort in the year of entry, and this loss would be persistent and relatively stable even after 10 years (blue line of Panel A, Figure A.6). If we also add the composition effect, job losses in the entering cohort in the first year after the shock

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

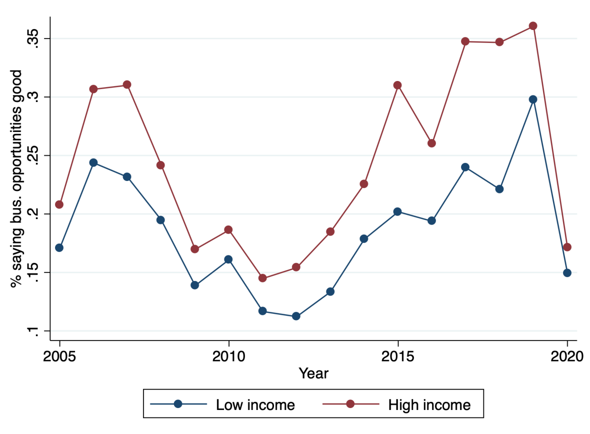
would be near zero. This is because there is a higher share of low-growth firms entering, and these firms are larger when very young (see Table A.6). However, as firms grow older, high-growth firms grow much faster than low-growth firms. This creates larger employment losses in the medium to long run, which peaks at nearly 4,000 jobs lost in 2028 and 2029 in the 2020 firm cohort. To put this number in perspective, we can compare it to the average size of a cohort of firms, depending on age, in Spain. Firms that are one year old employ on average approximately 100,000 workers. Over the life-cycle, the employment grows to approximately 170,000 for firms that are nine years old. Thus, assuming that the cohort of firms that entered in 2020 would have grown at the average rate in the absence of COVID-19, the combined entry and composition effects of the pandemic imply 2.4% lower employment for this firm cohort in 2029.

Panel B and Panel C of Figure A.6 show the counterfactuals if all the population behaved as high-income households (Panel B) or as low-income households (Panel C). As we discussed in the previous section (see Table 2), respondents with high income actually start slightly more firms during COVID-19, so there would be slight job gains in the short run that would persist in the long run (see the blue line in Panel B, Figure A.6). Nonetheless, there is a stark change in composition for high-income entrepreneurs, since they start more high-growth firms, which create fewer jobs in the short run but more in the long run. Taking this composition channel into account, there would be approximately 500 jobs lost in this entering cohort in 2021, but these job losses would turn into gains in 2024, reaching more than 1,000 additional jobs in 2028. On the other hand, if all households had low income, entry would decrease significantly, with close to 2,000 jobs lost in the entering cohort in the first two years. Furthermore, since there is a compositional change toward low-growth firms, if we take into account the composition channel, we would actually see slightly more than 1,000 jobs gained in 2021, but this would rapidly turn into job losses, peaking in 7,000 fewer jobs in 2028 (see red line of Panel B, Figure A.6).

In summary, these results indicate the importance of the composition effect for long-run employment creation and show that the underlying household income heterogeneity is very relevant for predicting the employment implications of changes in entry and its composition due to the COVID-19 recession.

C Additional Tables and Figures

Figure A.1: Business sentiment according to the GEM



Notes: The figures shows the percentage of GEM respondents reporting that they expect business opportunities to be good during the coming six months.

Table A.1: Probability to start a firm during COVID-19: High vs Low income

	(1) Start	(2) High Growth Share	(3) Necessity Share
COVID-19	-0.012***	-0.129***	0.362***
	(0.0022)	(0.0348)	(0.0398)
COVID-19 x High Income	0.020***	0.132***	-0.015
	(0.0061)	(0.0480)	(0.0525)
COVID-19 x Educated	-0.007**	-0.001	0.026
	(0.0026)	(0.0635)	(0.0544)
COVID-19 x Young	-0.010***	0.018	-0.085
	(0.0027)	(0.0433)	(0.0633)
GR	-0.013***	-0.026	-0.072***
	(0.0026)	(0.0304)	(0.0176)
GR x High Income	-0.011***	-0.005	0.022
	(0.0042)	(0.0349)	(0.0243)
GR x Educated	-0.008**	-0.023	0.024
	(0.0036)	(0.0358)	(0.0191)
GR x Young	0.006**	-0.053	0.034
	(0.0029)	(0.0361)	(0.0254)
Controls	Yes	Yes	Yes
Observations	389426	9234	15839
R-squared	0.043	0.013	0.045

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Column (1) shows the results for starting any firm, Column (2) the results for starting a high growth firms conditional on starting a firm, and Column (3) the results for starting a necessity firm conditional on starting a firm. A necessity entrepreneur is a new entrepreneur that starts a firm because of lack of employment. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. *High income* is a dummy that takes the value 1 if the individual is in the upper 33th income percentile. Educated is a dummy that takes the value 1 if the individual has post-secondary or graduate experience, 0 otherwise. Young is a dummy that takes the value 1 if the individual is younger than 35 years old, 0 otherwise. Additional controls include sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table A.2: Probability of starting a firm during COVID-19: High vs. low income

	(1) Start	(2) High Growth Share	(3) Start	(4) High Growth Share
COVID-19	-0.024***	-0.119***	0.000	-0.103
	(0.0040)	(0.0366)	(0.0021)	(0.0637)
COVID-19 x High Income	0.028***	0.156***	0.015**	0.088
	(0.0093)	(0.0456)	(0.0067)	(0.1406)
COVID-19 x Educated	-0.009**	-0.041	0.001	0.132
	(0.0044)	(0.0726)	(0.0027)	(0.0898)
COVID-19 x Young	-0.017***	0.022	-0.006*	0.009
	(0.0039)	(0.0543)	(0.0032)	(0.0790)
GR	-0.029***	-0.053	-0.003*	0.050
	(0.0048)	(0.0328)	(0.0016)	(0.1063)
GR x High Income	-0.011	-0.000	-0.007***	0.104
	(0.0072)	(0.0344)	(0.0018)	(0.1566)
GR x Educated	-0.006	0.006	-0.004**	-0.350***
	(0.0058)	(0.0353)	(0.0019)	(0.1111)
GR x Young	0.007	-0.062	0.003	0.163
	(0.0050)	(0.0394)	(0.0024)	(0.1542)
Controls	Yes	Yes	Yes	Yes
Observations	178230	8195	211196	1039
R-squared	0.027	0.013	0.004	0.050
Sample	With business creation skills		Without business creation skills	

Notes: Outcomes of estimating OLS regression. The dependent variable takes value 1 if the individual is starting a firm, 0 otherwise. Columns (1) and (3) show the results for starting any firm, Columns (2) and (4) present the results for starting a high-growth firm conditional on starting a firm. $COVID$-19 is a dummy that takes value 1 in 2020, 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. *High income* is a dummy that takes value 1 if the individual is in the top income tercile. Educated is a dummy that takes value 1 if the individual has post-secondary or graduate experience, 0 otherwise. Young is a dummy that takes value 1 if the individual is younger than 35 years old, 0 otherwise. Additional controls include sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table A.3: Probability of starting a firm during COVID-19: High vs. low income

	(1) Start	(2) High Growth Share	(3) Necessity Share
COVID-19 x High Income	0.019***	0.151***	0.030
	(0.0062)	(0.0555)	(0.0300)
GR x High Income	-0.012***	0.016	0.026
	(0.0042)	(0.0491)	(0.0277)
Controls	Yes	Yes	Yes
Region-year FE	Yes	Yes	Yes
Sector-year FE	No	Yes	Yes
Observations	389426	9225	15835
R-squared	0.045	0.173	0.148

Notes: Outcomes of estimating OLS regression. The dependent variable takes the value 1 if the individual is starting a firm, 0 otherwise. Column (1) shows the results for starting any firm, Column (2) the results for starting a high growth firm conditional on starting a firm, and Column (3) the results for starting a necessity firm conditional on starting a firm. A necessity entrepreneur is a new entrepreneur that starts a firm because of lack of employment. $COVID$-19 is a dummy that takes the value 1 in 2020, and 0 otherwise. GR is a dummy for the Great Recession, which takes a value of 1 if the year is 2008 or 2009, 0 otherwise. *High income* is a dummy that takes the value 1 if the individual is in the upper 33th income percentile. Additional controls include sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table A.4: Amount of funding for entrepreneurs during COVID-19

	(1) All	(2) LI	(3) HI
COVID	-0.609***	-0.616***	-0.730***
	(0.1922)	(0.1867)	(0.2183)
High Income	0.850**		
	(0.3676)		
COVID x High Income	-0.190		
	(0.2764)		
Share of own funding	-0.453*	-0.451*	-0.789***
	(0.2719)	(0.2694)	(0.2094)
Share of own funding x High Income	-0.339		
	(0.3258)		
Share of bank funding	1.315***	1.315***	0.932***
	(0.5035)	(0.5052)	(0.3164)
Share of bank funding x High Income	-0.420		
	(0.5436)		
Controls	Yes	Yes	Yes
Observations	94298	76003	18295
R-squared			

Notes: The dependent variable is the (log) amount of funding required for the startup. Due to limited data availability, the sample is restricted to the years 2017–2020. "Own" denotes the category "Private savings". The coefficients are the second-stage results of a Heckman selection model, where the selection equation has a dummy variable indicating a new entrepreneur as dependent variable and the following explanatory variables: sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level.

Table A.5: Amount of funding of entrepreneurs during COVID-19, non-digital

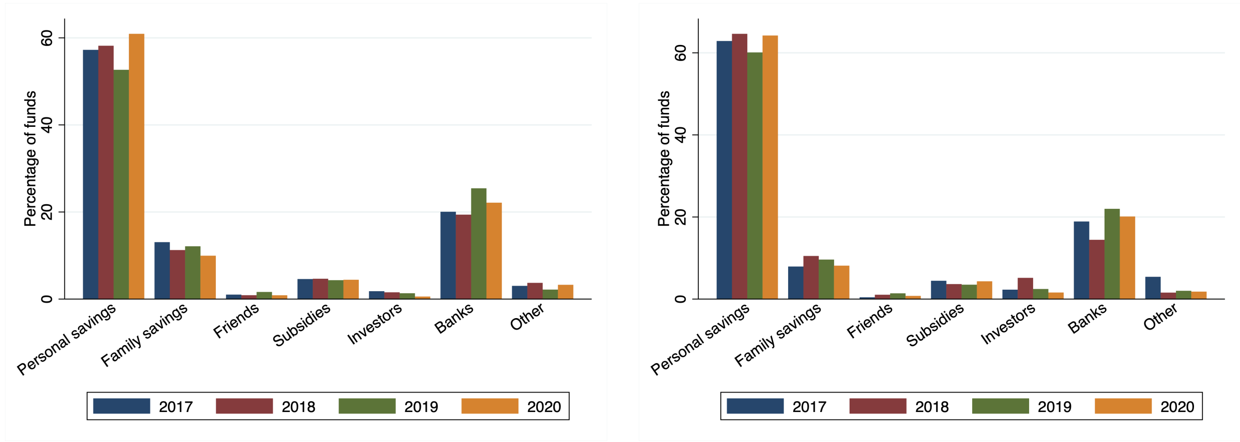
	(1) All	(2) LI	(3) HI
COVID	-0.566***	-0.571***	-0.876***
	(0.1868)	(0.1927)	(0.2604)
High Income	0.855*		
	(0.4402)		
COVID x High Income	-0.407		
	(0.2529)		
Share of own funding	-0.343	-0.341	-0.723***
	(0.3291)	(0.3241)	(0.2692)
Share of own funding x High Income	-0.389		
	(0.4091)		
Share of bank funding	1.343**	1.343**	0.939**
	(0.5451)	(0.5448)	(0.3883)
Share of bank funding x High Income	-0.447		
	(0.6299)		
Controls	Yes	Yes	Yes
Observations	94006	75837	18169
R-squared			

Notes: The dependent variable is the (log) amount of funding required for the startup. Due to limited data availability, the sample is restricted to the years 2017–2020. "Own" denotes the category "Private savings". The coefficients are the second-stage results of a Heckman selection model, where the selection equation has a dummy variable indicating a new entrepreneur as dependent variable and the following explanatory variables: sex, age and age squared, education, income, and individual perceptions of skills to start a new firm, perception of fear of failure, expected opportunities within 6 months and region fixed effects. Standard errors are clustered at the region-year level. The regression uses only startups classified as non-digital (see the definition in Section 4.4).

Figure A.2: Sources of startup funding

a) Low income

b) High income

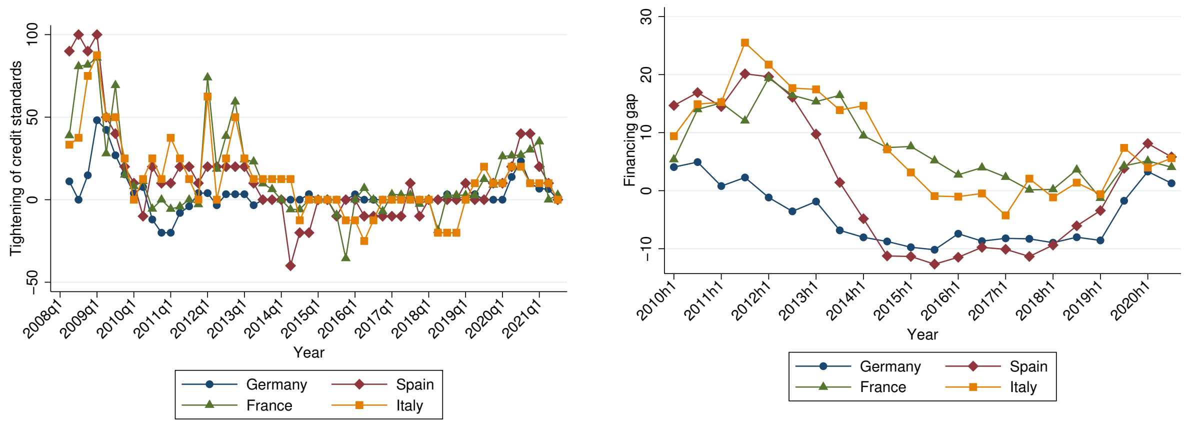


Notes: The bars indicate the average percentage of funds coming from the indicated sources based on the survey respondents of new entrepreneurs in the GEM.

Figure A.3: Worsening of credit conditions

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

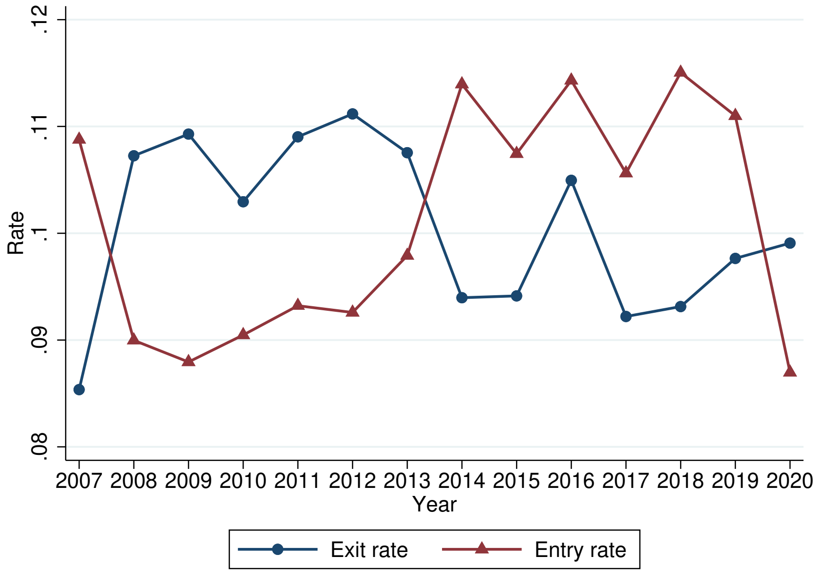
B. Change in financing gap (SMEs)



Notes: **Panel A:** Shows the frequency of surveyed banks answering that the general economic outlook considerably contributed to a tightening of credit standards minus the frequency of answering that it considerably contributed to an easing of credit standards. Source: BLS, accessed from https://sdw.ecb.europa.eu/browse.do?node=9691151.

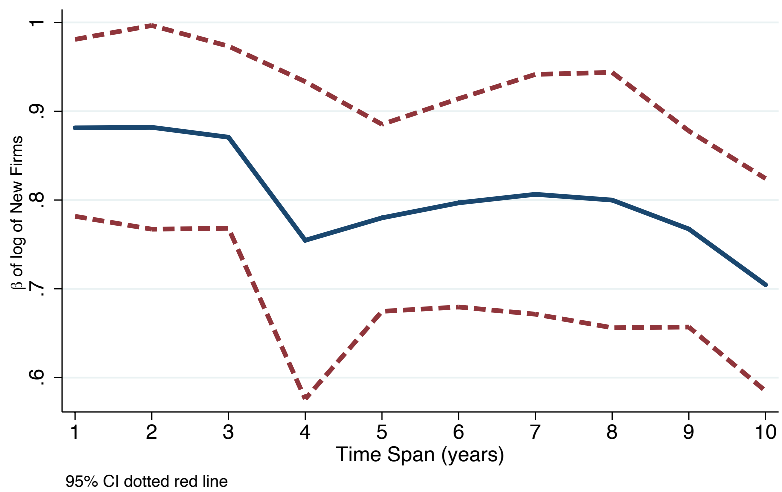
Panel B: The figure shows the difference between the change in demand for and the change in the availability of external finance for surveyed SMEs. Source: SAFE, accessed at https://sdw.ecb.europa.eu/browse.do?node=9689717.

Figure A.4: Annual exit and entry rates in Spain



Notes: Notes: Data at yearly frequency comes from DIRCE, a database created by the Spanish Statistical Institute INE (https://www.ine.es/dynt3/inebase/index.htm?padre=52&capsel=52). The graph shows annual exit rate and entry rates.

Figure A.5: Effect of firm entry of future cohort employment



Source: CBI. 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.

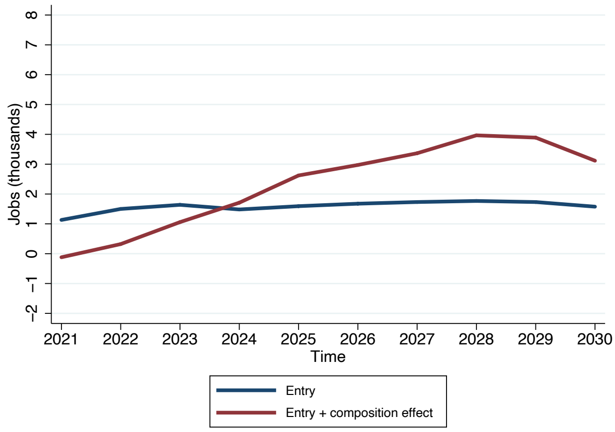
Table A.6: Firms' employment age profile depending on the share of high-growth firms

	(1) log(Employment)	(2) log(Employment)
Age 0	1.003***	0.716***
	(0.0826)	(0.0368)
Age 1	1.508***	1.215***
	(0.0677)	(0.0310)
Age 2	1.580***	1.283***
	(0.0677)	(0.0274)
Age 3	1.587***	1.308***
	(0.0706)	(0.0352)
Age 4	1.568***	1.329***
	(0.0704)	(0.0376)
Age 5	1.540***	1.339***
	(0.0694)	(0.0355)
Age 6	1.537***	1.353***
	(0.0715)	(0.0370)
Age 7	1.526***	1.362***
	(0.0714)	(0.0324)
Age 8	1.502***	1.357***
	(0.0736)	(0.0320)
Age 9	1.502***	1.360***
	(0.0772)	(0.0364)
Age 10	1.531***	1.369***
	(0.0808)	(0.0456)
Age 0 x share	-0.289***	-0.094
	(0.0976)	(0.0806)
Age 1 x share	-0.251***	-0.044
	(0.0627)	(0.0512)
Age 2 x share	-0.178***	0.027
	(0.0630)	(0.0394)
Age 3 x share	-0.079	0.084*
	(0.0619)	(0.0493)
Age 4 x share	0.030	0.110**
	(0.0550)	(0.0509)
Age 5 x share	0.130***	0.142***
	(0.0476)	(0.0475)
Age 6 x share	0.159***	0.139***
	(0.0578)	(0.0515)
Age 7 x share	0.196***	0.138***
	(0.0682)	(0.0480)
Age 8 x share	0.256***	0.161***
	(0.0866)	(0.0522)
Age 9 x share	0.247**	0.149**
	(0.0975)	(0.0635)
Age 10 x share	0.177*	0.117
	(0.0972)	(0.0725)
Year FE	Yes	No
Sector FE	Yes	No
Year-sector FE	No	Yes
Observations	1755792	1755792
R-squared	0.400	0.402

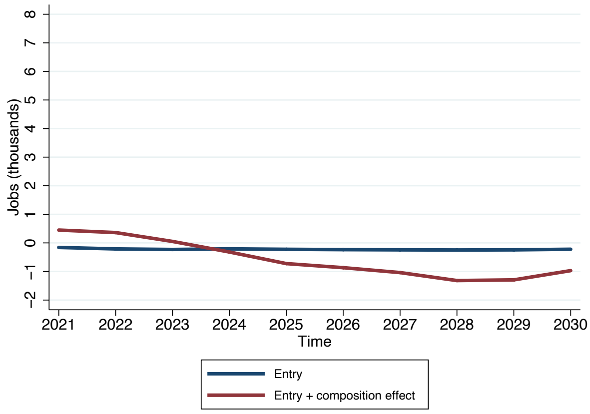
Notes: Number of entrants and their employment is computed from CBI using the cleaning described in the main text. *share* is the share of high-growth startups (measured in the GEM data) in the 2-digit sector to which the observed firm belongs in the year it was born. Significance levels: * $p<0.1$,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

Figure A.6: Predicted long-run job losses due to the Covid-19 shock.

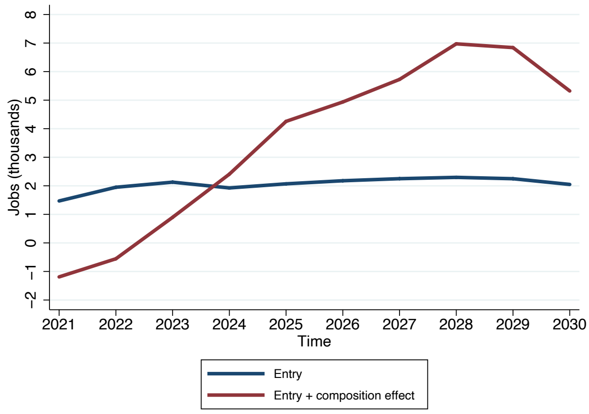
A. Overall



B. Only High Income



C. Only Low Income



Notes: Overall predicted loss in aggregate employment in Spain through the entry margin. The entry margin series are computed by combining the fall in firm creation observed in GEM with the effect of the change in firm creation on future employment and aggregate employment by firm age (cohort) given in the CBI 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 CBI data. The overall predicted loss in aggregate employment is the sum of the entry margin and the composition margin. **Panel A** shows the results from the overall economy using the results of Table 1. **Panel B** shows the results as if there were only high income households, using results of Table 2. **Panel C** shows the results as if there were only low income households, using results of Table 2.