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Start-ups and Employment Following the COVID-19 Pandemic: A Calculator

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Startups and Employment Following the COVID-19 Pandemic: A Calculator[*]

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Abstract

Early indicators suggest that startup activity across countries is heavily affected by the COVID-19 pandemic and the associated lockdowns. At the same time, empirical evidence has shown that such disturbances may have long-lasting effects on aggregate employment. This paper presents a calculator which can be used to compute these effects under different scenarios regarding (i) the number of startups, (ii) the growth potential of startups, and (iii) the survival rate of young firms. We apply our calculator to the U.S. and four European countries: France, Germany, Italy and Spain. We find that employment losses can be substantial and last for more than a decade, even when the assumed slump in startup activity is only short-lived. Almost half of the long-run losses is caused by fewer high-growth firms, "gazelles", starting up during the pandemic. Our results also suggest that the long-run effects of the pandemic may vary across countries substantially with Germany possibly being shielded due to its low business dynamism.

Keywords: Startups, Macroeconomics, Employment, COVID-19

JEL Codes: D22, E23, E24, I10

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[†]In loving memory of our friend and co-author Cristiana Benedetti Fasil, who has been a tremendous driving force in this project. We will sorely miss her immense energy and kindness.

1 Introduction

The global coronavirus (COVID-19) pandemic has set 2020/2021 to be tragic years for many businesses. Startups may be affected particularly strongly, as they find themselves in a fragile stage of the lifecycle, being sensitive to disruptions in demand, supply, or credit conditions. Data from the U.S. shows that in the early weeks of April 2020, new business applications were down by more than 40 percent compared to the same period the year before. Such a contraction even surpasses the sharp drop observed during the Great Recession.[1]

These developments are likely to have important macroeconomic implications, which may last well beyond the pandemic itself. The reason is that seemingly small changes to startups can create persistent and increasingly strong ripple effects on the macroeconomy as cohorts of new firms age and grow into larger businesses. This paper provides an empirical perspective on what the disruption of startup activity may mean for the macroeconomy in terms of the severity and persistence of employment losses. To this end, we develop a Startup Calculator, applied to the U.S. and four European economies: France, Germany, Italy and Spain. This tool allows anyone to easily compute employment losses under various scenarios of choice.[2]

The calculator serves several purposes. First, it provides a tool for macroeconomic researchers and analysts to make projections on job creation by startups under various scenarios of choice. As such, it is particularly useful for policy makers as it can, among other scenarios, provide a quantification of the historical "worst case" – a useful benchmark in periods of unprecedented uncertainty, such as the current pandemic. Second, our calculator can provide a quantitative guide to the potential aggregate impact of various policy interventions aimed at startups. Finally, it helps with understanding the dimensions along which policy may be most effective. In particular, our results suggest that while supporting existing mature businesses from shutting down may be a desirable policy, it should not come at the expense of ignoring startups and young firms. This is because a disruption in the latter can, as we show below, can on its own generate large and persistent losses for the macroeconomy.

[1] The decline in business applications was steady from March until July, 2020. Since then business applications have picked up, see `www.census.gov/econ/bfs/index.html`.

[2] The calculator and an excel document with the underlying computations for the U.S. can be found at http://users.ox.ac.uk/~econ0506/Main/StartupCalculator.html. The adaptation of the calculator to the 23 EU Member States, together with a sectoral breakdown, can be found at https://ec.europa.eu/jrc/en/covid-19-start-up-calculator.

There are three key margins that our calculator considers: entry, exit and growth of young businesses. The number of startups and young firms is crucial for the economy, because young businesses are the dominant creators of new jobs. To get out of the current labor market contraction, hiring by firms will be key, see also Merkl and Weber (2020). In the U.S. an average of 16.3 million jobs are created and about 14.9 million jobs are destroyed every year. Put together, this means that annually about a third of all jobs in the U.S. are either new or get destroyed. Strikingly, startups create a net amount of 2.9 million jobs per year. These values suggest that startups are the only business category which is characterized by positive net job creation and existing firms only shed jobs on average. Importantly, however, "lost generations" of firms also create a persistent dent in aggregate employment as subsequent years are characterized by a lower number of young firms, see e.g. Gourio, Messer and Siemer (2016) and Sedláček (2020).

On the other hand, young firms also exhibit high rates of exit, suggesting that not all jobs created by startups are long-lasting. Nevertheless, the data shows that surviving young firms tend to grow faster than the average incumbent (see e.g. Haltiwanger, Jarmin and Miranda, 2013). These patterns of high rates of exit and growth among young firms have been dubbed "up-or-out dynamics". Therefore, it is important for our calculator to account for such up-or-out dynamics.

The final margin of adjustment in our calculator relates to firm growth. The high rate of labor market churn associated with startups has been linked to measures of productivity and profitability growth (see e.g. Bartelsman and Doms (2000) or Foster, Haltiwanger and Krizan (2001)). Therefore, the data suggest that surviving young businesses are the ones that are crucial for aggregate productivity growth.

Importantly, these findings are exacerbated by new evidence on young high-growth firms, so called gazelles. Haltiwanger, Jarmin, Kulick and Miranda (2016) document that this small share of startups with exception growth potential accounts for about 40 percent of aggregate TFP growth, 50 percent of aggregate output growth and 60 percent of aggregate employment growth.

Moreover, Sedláček and Sterk (2017) and Sterk ⓡ Sedláček ⓡ Pugsley (2021) show that firms born during recessions tend be smaller than their boom-born counterparts and that these effects are very persistent. These movements in growth potential are attributed to changes in the composition of the type of startups, meaning that gazelles tend to start in good times, rather than during downturns. In the current situation, it seems particularly challenging to start a highly scalable businesses, since supply chains are heavily distorted, credit conditions are poor, and customer may be demand difficult to acquire during a lockdown. Therefore, the current situation may well give rise to fewer gazelles which would cast a long shadow on the aggregate economy in the years to come.

Given a scenario for each of these three margins, the calculator computes the implied change in time path for aggregate employment, from 2020 onwards. The Startup Calculator is built with publicly available data, using the Business Dynamic Statistics for the U.S. and information from Eurostat for European economies. In both cases, we take a conservative stance and only consider changes to firms younger than 10 years of age. In other words, we leave about 40 percent of all businesses unaffected in our calculations and in this sense the results may be taken as lower bounds.

We begin by focusing on a historical worst case scenario in which all three margins fall to their minimum levels observed since 1977 (the starting point of the BDS).[3] Assuming that this decline lasts for one year, after which all three margins revert back to normal, we find that the effect on aggregate employment in 2020 is a 1.1 percent reduction. Importantly, however, the effect of aggregate employment is very persistent. Cumulated over the first 10 years, we find an employment loss of 10.6 million. We also evaluate a scenario based on recent, preliminary data from the Business Employment Dynamics. This scenario generates a somewhat smaller decline in aggregate employment than the historical worst case, possibly in part due to the strong policy response to the pandemic.

The calculator is an accounting tool, simulating employment of cohorts and then aggregating. As such, it abstracts from potential equilibrium feedback effects. To adjust for such effects, we integrate the calculator into a "shell" of a basic equilibrium heterogeneous-firms model. Based on this model (and assumptions on the wage elasticity of labour demand and supply) we provide an adjustment for equilibrium effects. We find that this adjustment dampens the aggregate employment effect by about 20 percent.

Finally, the cross-country comparison in this paper highlights the importance of

[3]Note, however, that this scenario is by no means intended as a precise point forecast of the actual disruption to startups and young firms during the pandemic. Instead, it serves as a useful benchmark and we emphasize that anyone can easily compute results under various scenarios of choice by accessing the calculator on our website.

business dynamism for recoveries. In particular, economies with a relatively low pace of churn among firms (such as e.g. Germany), rely relatively less on startups and young firms to create jobs. Therefore, a disruption in startup activity has a milder impact in such economies, compared to countries in which firm dynamics are more dynamic (such as e.g. the U.S.).

The remainder of this paper is organized as follows. Section 2 discusses some early evidence on the effects of the COVID-19 pandemic on business formation. Section 3 presents the calculator, as well as the equilibrium heterogeneous-firms model. Section 4 presents results for the US under several scenarios and discusses the importance of the three margins mentioned above. In Section 5 we apply the calculator to France, Germany, Spain and Italy, and make a comparison to the US. Finally, Section 6 concludes and provides a discussion of potential policy implications of our calculator.

2 Startups during the COVID-19 pandemic

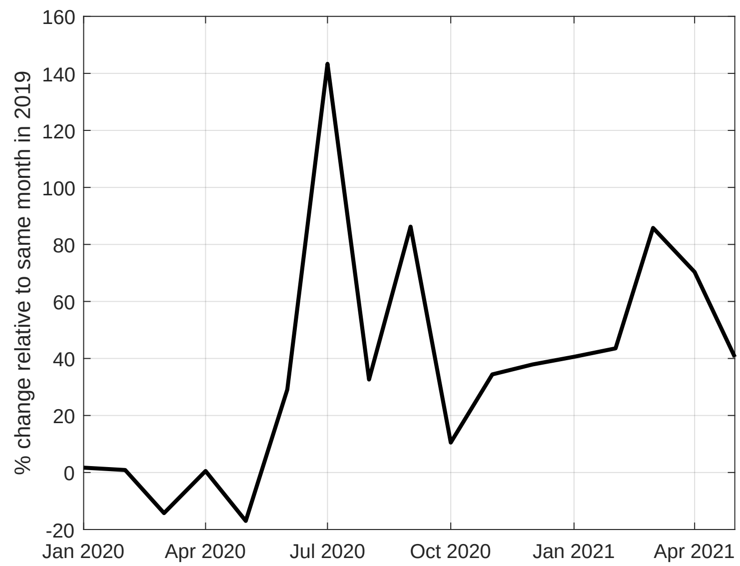
At the time of writing this paper, it is still too early to tell exactly how severely the COVID crisis hit startups, as several important data sources become available only with a substantial delay. Nevertheless, in this section we consider the data that are currently available in order to get a sense of the ongoing disruption to new businesses.

A first useful data sources are the Business Formation Statistics. These data measure *applications* for employer identification numbers. While a significant share of these applications never convert into an actual startup business, the time series is nonetheless a useful early indicator which has historically performed as an overall predictor of actual startups, see Bayard, Dinlersoz, Dunne, Haltiwanger, J. Miranda and Stevens (2017).

The BFS data in Figure 1 paint a remarkable picture. In the early stage of the pandemic, first and second quarter of 2020, there was a strong decline in business applications, see also Haltiwanger (2020). In the third quarter of 2020, however, the data show a very large increase in applications which is unprecedented historically. The timing of this surge coincides with the Coronavirus Aid, Relief, and Economic Security (CARES) act, suggesting that policy may potentially have had some role in this.[4] In the last quarter of 2020, applications fell but remained at elevated levels,

[4]Interestingly, however, new startups were not eligible for loans provided under the Paycheck Protection Program, which was initiated in order to help firms weather the pandemic.

Figure 1: Business applications in the U.S.



Note: The figure shows the time series of business applications from the Business Formation Statistics (BFS), relative to the same month in 2019. Data were downloaded in June, 2021.

and a second wave of applications followed in 2021.

Do these data imply a boom in job creation by startups took place, mitigating the impact of the pandemic on aggregate employment? Not necessarily. First of all, it is important to consider that the BFS data measure applications, not actual startups. Possibly, the conversion rate from applications into actual startups has weakened during the pandemic. To investigate this possibility, we consider data from the Business Employment Dynamics (BDM), an administrative data set of *actual* openings at the establishment level which, at the time of writing, are available up to the third quarter of 2020.[5] From the BDM data, we consider the rate of "births" of new establishments.

Table 1 does not show any sharp increase in the birth rate of establishments, at least up to the third quarter of 2020. According to this measure, startup activity actually fell somewhat during the pandemic, relative to a year earlier. Given the

[5]In many ways, the BDM are similar to the Business Dynamics statistics (BDS). The main differences are that the BDM data only provide establishment-level information and provide a less granular breakdown by firm age and year. On the other hand, the BDM data are available at a higher frequency (quarterly as opposed to annual).

Table 1: Startups during the pandemic: BDM data

	2019:Q2-Q3 27	2020:Q2-Q3
birth rate (percent)	3.10	3.05
closing rate (percent)	5.2	7.4
average employment births	3.3	2.9

Note: Data for the U.S. from the Business Employment Dynamics (BDM). Averages over quarterly data.

surge in applications visible in the BFS data, the BDM data suggest that the historical link between business applications and actual startups may have broken down during the pandemic. Future data will provide more clarity on the startup rate during the COVID-19 pandemic, in particular in the period after 2020Q3. Moreover, given that the surge in applications happened in the third quarter 2020 and that there may be considerable time lags between applications and the moment a new business becomes operational, (see Bayard, Dinlersoz, Dunne, Haltiwanger, Miranda and Stevens, 2018), it seems likely that any potential increase in startup activity may materialize only in 2021.

A second reason for caution is that the number of startups is not the only relevant margin: the exit rate of startups (young firms) and the size of startups are important factors as well. Indeed, Table 1 shows a sharp increase in the rate of establishment closings.[6] Moreover, there was a substantial reduction in the average size (employment) of new opening establishments, indicating that businesses born during the recession may not have the same growth potential as those born during normal times.

In the calculator to be presented below, we consider all three of these margins and consider the above evidence when constructing scenarios. Moreover, our calculator also allows for the possibility that 2021 will be characterized by a "bounce-back" in startup activity, as potentially suggested by the BFS data.

[6]One caveat is that the BDM data do not allow for a breakdown of this rate by age. However, from the BDS data we know young firms/establishments account for a large share of exit. A second caveat is that closings may lead to a later re-opening. The BDM also provides a measure of "deaths", i.e. closings excluding re-openings. However, this data only becomes available with a considerable lag.

3 The Startup Calculator

In this section, we provide details on the data and its treatment, used in our analysis. The next section presents the results.

3.1 Data

Throughout this paper, we use publicly available information from the Business Dynamics Statistics (BDS) of the U.S. Census Bureau spanning the period of 1977 to 2016. This dataset includes (among other things) information on the number of firms and employment by firm age. For our purposes, we use information on the number of firms, their employment and their exit rates by age, where the latter is considered in the following age categories: 0 (startups), 1, 2, 3, 4, 5, 6-10 and all. From this information, we can also construct aggregate employment.

The **number of firms** of age a in year t, $n_{a,t}$, is directly observable in the BDS data, as is employment by age, $e_{a,t}$. We use employment and the number of firms by age to compute **average firm size** as $s_{a,t} = e_{a,t}/n_{a,t}$.[7] Finally, we are also interested in survival rates of firms by age. We compute these by using the information on firm deaths, $d_{a,t}$, which give the number of firms of a given age in which all establishments shut down. We define the **survival rate** by age as $1 - x_{a,t} = 1 - d_{a,t}/n_{a,t}$.[8]

3.2 Accounting for startups: methodology

Because firms aged 6 to 10 are grouped together in the BDS, it is necessary to interpolate information for each of the individual age categories.[9] In addition, because the sample period ends in 2016, it is necessary to extrapolate the information up until 2019, just before we perform our scenario analysis. In what follows, we describe the interpolation and extrapolation methods employed in the Startup Calculator.

[7] This is the so-called "current-year" definition of size.

[8] An alternative definition of survival rates utilizes only the number of firms by age: $1 - x_{a,t} = n_{a,t}/n_{a-1,t-1}$. However, because firms aged 6 to 10 are grouped together in the BDS, this definition is possible only up to the age of 5. In contrast, the BDS does report the number of firm deaths in the group of 6 to 10 year old firms, allowing for the calculation of the average survival rate in this firm age category.

[9] Not interpolating gives similar results but overstates the impact of changes in startups. This is because when new firms reach the age of 6, they are assigned the average size of 6 to 10 year old firms. This exacerbates the impact of changes in startups on aggregate employment.

3.2.1 Interpolation of age-specific information

Number of firms and exit rates. To interpolate the numbers of firms aged 6, 7, 8, 9 and 10 years we use the observed number of 6 to 10 year old firms in a given year and decompose it into the individual age categories using the law of motion for the number of firms, $n_{a,t} = n_{a-1,t-1}(1 - x_{a-1,t-1})$. In doing so, we assume that exit rates between neighboring ages are linearly decreasing such that

$$x_{a,t} = x_{a-1,t-1}(1 - \Delta_{x,t}) \quad \text{for } a = 6, ..., 10,$$

where $\Delta_{x,t}$ is a year-specific change, but which we assume to be the same for firms between the ages of 6 and 10. Given the exit rates by age, we can compute the number of firms in ages 6 to 10 as[10]

$$n_{a,t} = n_{6-10,t} \frac{\Pi_{j=1}^{a-5}(1 - x_{a-j+1,t-j+1})}{\sum_{a=6}^{10} \Pi_{j=1}^{a-5}(1 - x_{a-j+1,t-j+1})} \quad \text{for } a = 6, ..., 10.$$

Finally, we compute $\Delta_{x,t}$ by minimizing

$$\left| x_{6-10,t} - \sum_{a=6}^{10} \left(\frac{n_{a,t}}{\sum_{a=6}^{10} n_{a,t}} x_{a,t} \right) \right|.$$

Firm size. We interpolate firm size for businesses aged 6 to 10 in the same way as above. We assume that firm size is linearly increasing between the ages of 6 and 10 such that

$$s_{a,t} = s_{a-1,t-1}(1 + \Delta_{s,t}) \quad \text{for } a = 6, ..., 10,$$

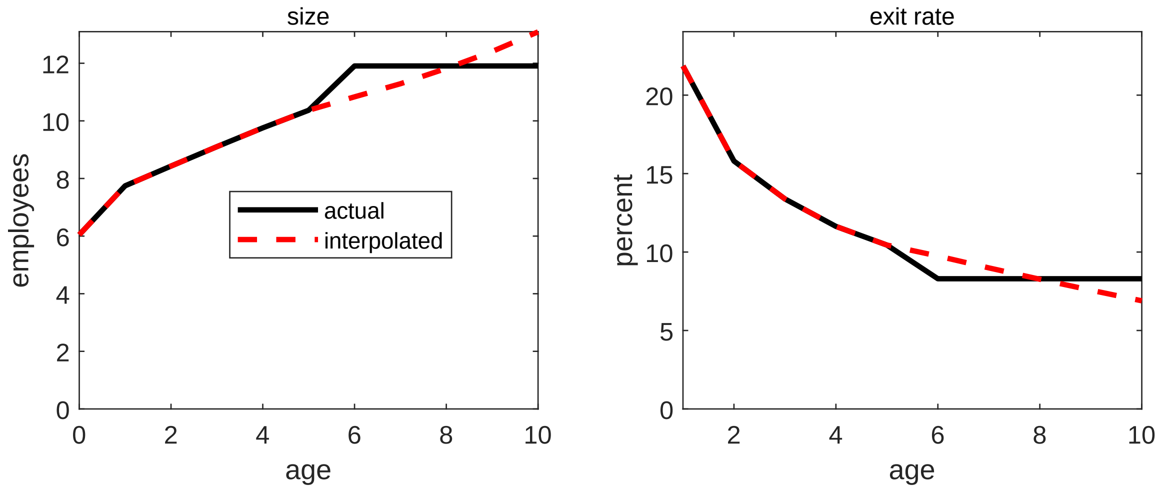
where $\Delta_{s,t}$ is a year-specific growth rate, but which is the same for firms between the ages of 6 and 10. Given the age-specific exit rates described above, we then compute $\Delta_{s,t}$ by minimizing

$$\left| s_{6-10,t} - \sum_{a=6}^{10} \left(\frac{n_{a,t}}{\sum_{a=6}^{10} n_{a,t}} s_{a,t} \right) \right|.$$

The results of this interpolation are shown in Figure 2, which depicts the actual and the interpolated data for firm size and exit rates by age.

[10] In doing so we implicitly average the numbers of incoming five year old firms, i.e. $n_{5,t-j} = \overline{n}_{5,t}$ for $j = 1, ..., 5$. This effectively allows for an approximation error in the age distribution of firms aged 6 to 10 years, but ensures that the overall number of 6 to 10 year old firms is exactly equal to that in the data.

Figure 2: Actual and interpolated data



Note: Actual and interpolated data for firm size and exit rates by age.

3.2.2 Extrapolation of information until 2019

Information on startups and young firms. In order to extrapolate the necessary data between 2017 and 2019, we assume that firm size by age and exit rates by age (up to age 10), and the number of startups, all linearly converge to their 1977-2016 averages:

$$x_{a,2016+\tau} = x_{a,2016} + \frac{\tau}{3}(\overline{x}_a - x_{a,2016}),$$

$$s_{a,2016+\tau} = s_{a,2016} + \frac{\tau}{3}(\overline{s}_a - s_{a,2016}),$$

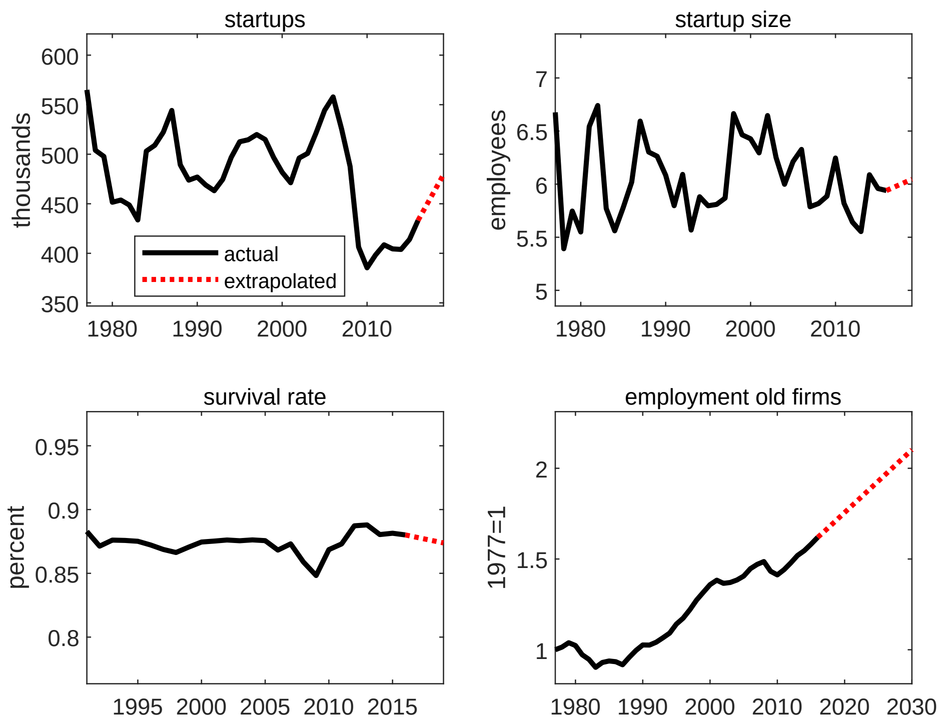
$$n_{0,2016+\tau} = n_{0,2016} + \frac{\tau}{3}(\overline{n}_0 - n_{0,2016}),$$

for $\tau = 1, 2, 3$ and $a = 1, 2, ..., 10$, and where $\overline{x}_a$, $\overline{s}_a$ and $\overline{n}_0$ denote the 1977 to 2016 averages of age-specific exit rates, firm sizes and the number of startups, respectively.[11] Using the above, we can then again recover the number of firms for the ages of 1 to 10 as $n_{a,t} = n_{a-1,t-1}(1 - x_{a-1,t-1})$, for $a = 1, 2, ..., 10$ and $t = 2017, 2018, 2019$.

The result of this extrapolation are shown in Figure 3, which depicts the actual and extrapolated number of startups, average startup size and exit rates of 1 to 10 year old firms.

[11] Only startups are observed from 1977. Therefore, averages of older businesses of age a are taken over the period 1977+a to 2016. For instance, the averages for two-year-old firms is based on 1979 to 2016. Similarly, information on 6-10 year old firms starts only in 1987.

Figure 3: Actual and extrapolated data



Note: Actual and extrapolated data for the number of startups, startup size, survival rates (of young, i.e. <10 years) firms and employment in old (11+ years) firms.

Number of older firms. The number of all businesses in the US economy has been steadily increasing over the sample period. This is, however, essentially entirely because of an increasing number of older firms. This can be seen from Figure 3 which shows that the *number* of startups has fluctuated cyclical around a relatively stable mean.

The increasing number of firms is then reflected in rising aggregate employment. Given that our analysis focuses on the impact changes in young firms' performance have on aggregate employment, we need to account for the trend growth of older firms. We do so by estimating a linear trend for employment in firms aged 11 years and more, using the period between 2010 and 2016. The estimated trend is then used to extrapolate employment in this group of firms for the years 2017 to 2030.

The bottom right panel of Figure 3 shows the actual and extrapolated employment in firms aged 11 and more, where we scale both time-series by their values in 1977.

3.2.3 Constructing alternative scenarios

Having the above information, we are ready to conduct scenarios starting in 2020 and running through to 2030. We consider three types of margins: (i) changes in the number of startups, (ii) changes in growth potential and (iii) changes in survival rates.

Scenarios involving (i) and (iii) are straightforward. Upon impact, we lower the number of startups and/or the survival rates of young firms by a certain value and keep this value for a certain period. Growth potential works on the same principle, but applies to the *cohort* of startups which enters in 2020. Therefore, lowering the growth potential by a certain percentage value results in the entire *growth profile* of firms born in 2020 shifting downwards. Importantly, the size of firms which in 2020 are older than 0 years is unaffected.

To be concrete, for a given scenario, let us denote the initial percentage decreases in the number of startups, the growth potential of startups and the survival rate of young firms by $\zeta_j \in (0,1)$, where $j = \{n, s, x\}$, respectively. Let us further denote the duration of these effects by $\tau_j > 0$, where $j = \{n, s, x\}$, respectively. The given scenarios are then given by

$$
\begin{aligned}
n_{0,2019+t} =& n_{0,2019}(1-\zeta_n), \quad \text{for } t = 1, ..., \tau_n, \\
s_{a,2019+t+a} =& s_{a,2019}(1-\zeta_s), \quad \text{for } t = 1, ..., \tau_s, \text{ and } a = 0, 1, 2, ..., 10, \\
x_{a,2019+t} =& x_{a,2019}(1-\zeta_x), \quad \text{for } t = 1, ..., \tau_n, \text{ and } a = 1, 2, ..., 10.
\end{aligned}
$$

Notice that in the above, the changes in growth potential apply to *cohorts* of startups. For instance, if the effect of the pandemic lasts only for one year ($\tau_s = 1$), then only startups in 2020 are affected. In 2021, it is one year old firms which have lower growth potential, i.e. the cohort born in 2020, while firms of all other ages (including new startups), are unaffected. In contrast, the pandemic affects the survival rates of all young firms simultaneously and therefore businesses aged 0 to 10 years experience a drop in survival rates in 2020.

Our calculator can also accommodate bounce-back scenarios. These are always defined as certain values above the 1977-2016 averages of the number of startups, average sizes and survival rates of young firms. Recall that all these margins converge precisely to the respective 1977-2016 averages by 2019.

Specifically, let us denote the percentage increase (above the respective long-run average) in the bounce-back scenario related to the number of startups, the growth potential of young firms and their survival rates by χ_j, where $j = \{n, s, x\}$, respectively. Furthermore, let us denote the length of the bounce-back period by σ_j, where $j = \{n, s, x\}$, respectively. The given bounce-back scenarios are then given by

$$
\begin{aligned}
n_{0,2019+\tau_n+t} =& n_{0,2019}(1+\chi_n), \quad \text{for } t = 1, ..., \sigma_n, \\
s_{a,2019+\tau_s+t+a} =& s_{a,2019}(1+\chi_s), \quad \text{for } t = 1, ..., \sigma_s, \text{ and } a = 0, 1, 2, ..., 10, \\
x_{a,2019+\tau_x+t} =& x_{a,2019}(1+\chi_x), \quad \text{for } t = 1, ..., \sigma_n, \text{ and } a = 1, 2, ..., 10.
\end{aligned}
$$

Finally, in all scenarios aggregate employment in a given year is computed simply as the sum of employment in firms aged 0 to 10 and the (extrapolated) employment of firms older than 11 years. Therefore, we are being conservative in the sense that we are not allowing businesses aged 11 and more years to be affected by the crisis. Our results should, therefore, be considered as a lower bound on the given scenarios. While the margins of startups and growth potential would only "kick in" after 2030 for these older firms, their survival rates may very well be affected in 2020 already.[12]

3.3 Adjusting for equilibrium effects

The calculations above abstract from potential equilibrium effects. In this subsection, we describe how to adjust for this, by placing the calculator within a "shell" formed by a basic but standard heterogeneous-firm model. This model also clarifies how the calculator connects to canonical equilibrium models of firm dynamics.

In the model, there is a measure M of heterogeneous firms.[13] Let the production function of firm i be given by

$$y_i = z_i n_i^{\alpha},$$

where y_i is the firm's output, n_i its employment level, z_i is the firm's productivity level, and $\alpha \in (0, 1)$ is the elasticity of production with respect to labor input.[14] The wage per employee is taken as given by firms, and denoted by w. The firm chooses

[12] Old firms (11+ years), which account for 40 percent of all businesses but almost 80 percent of employment, are also characterized by pro-cyclical changes in size and survival rates. Therefore, the impact of young firms on the aggregate is unlikely to be dampened by older businesses.

[13] Although the model is dynamic, it can be described entirely in static terms, hence we omit time subscripts.

[14] We abstract from capital for simplicity. Augmenting the model with capital would not change any of our results.

its level of employment in order to maximize profits, given by $y_i - wn_i$. This implies the following familiar solution for labor demand by firm i:

$$n_i = (z_i)^{\frac{1}{1-\alpha}} \left(\frac{w}{\alpha}\right)^{\frac{1}{\alpha-1}}$$

Aggregating over all firms, aggregate labor demand is given by:

$$N = M \left(\frac{w}{\alpha}\right)^{\frac{1}{\alpha-1}} \chi$$

where $\chi \equiv \int z^{\frac{1}{1-\alpha}} dF(z)$, where F is the CDF of the productivity distribution. Taking logs and differentiating (keeping idiosyncratic productivities constant), we can decompose changes in aggregate labor demand as:

$$d\ln N = \underbrace{d\ln M}_{\#\text{firms}} + \underbrace{d\ln\chi}_{\text{growth potential}} + \underbrace{\frac{1}{\alpha-1} d\ln w.}_{\text{wages}} \tag{1}$$

The first two terms reflect changes in, respectively, the number of firms and their growth potential (productivity), whereas the third term captures equilibrium effects due to wage conditions.[15] Equation (1) can be understood as an aggregate labor demand curve, which is shifted by the number of firms and their growth potential.

To close the model, we need to specify how labor supply is determined. We assume there is a representative household with Greenwood-Hercowitz-Huffmann preferences. Specifically, the household's level of utility is given by: $U(C,N) = \frac{1}{1-\sigma}\left(C - \mu\frac{N^{1+\kappa}}{1+\kappa}\right)^{1-\sigma}$, where C denotes consumption and μ, κ, $\sigma > 0$ are preference parameters. The household chooses C and N to maximize utility, subject to a budget constraint given by $C = wN + \Pi$, where Π are aggregate firm profits. Utility maximization implies the following labor supply curve: $\mu N^\kappa = w$. Taking logs and differentiating gives the labor supply schedule:

$$d\ln N = \frac{1}{\kappa} d\ln w \tag{2}$$

Combining the labor demand and supply schedules, Equations (1) and (2), we can

[15] Other sources of equilibrium dampening could derive from endogenous entry and exit, which we abstract from here.

solve for the equilibrium level of aggregate employment:

$$d \ln N = \underbrace{\Psi}_{\text{equilibrium dampening}} \underbrace{(d \ln M + d \ln \chi)}_{\text{calculator output}} \tag{3}$$

where $\Psi \equiv \frac{1}{1-\kappa\epsilon_{nw}} \in (0,1)$, with $\epsilon_{nw} = \frac{1}{\alpha-1}$ being the wage elasticity of labor demand. Equation (3) expresses aggregate employment (in deviation from some baseline trend) as a function of the number of firms and their growth potential. The latter two we obtain as outputs from the calculator. The parameter Ψ is an equilibrium dampening coefficient, which depends on the elasticity of labor demand (ϵ_{nw}) and the Frisch elasticity of labor supply ($\frac{1}{\kappa}$). Based on these two parameters and the output from the calculator, we can thus compute the equilibrium change in aggregate employment from Equation (3).

To gauge how large such equilibrium dampening effects could be we consider standard values for the model parameters. Specifically, we assume a unit Frisch elasticity of labor supply ($\kappa = 1$) which is in the ballpark of the estimates in the micro and macro literature. The parameter α could be set in accordance with the labor share of aggregate income, which is around sixty percent in the US, implying $\alpha = 0.6$. Given these numbers, we obtain $\Psi = 0.29$, i.e. equilibrium effects dampen just over seventy percent of the decline in aggregate employment.

Note however, that the above model does not contain any labor market frictions. In the presence of such frictions, labor demand is likely to be less sensitive to wages. We therefore prefer to use a direct empirical estimate of the labor demand elasticity. Lichter, Peichl and Siegloch (2015) conduct a meta study of empirical estimates and recommend an elasticity of -0.246. Setting $\epsilon_{nw} = -0.246$ (and again $\kappa = 1$) we obtain a coefficient of $\Psi = 0.80$, i.e. 20% dampening. We will use this value as our baseline for the dampening coefficient. This value also conforms with other evidence that equilibrium dampening effects may not be that strong. For instance, Sedláček (2020) shows that a search and matching model with heterogeneous firms displays relatively weak equilibrium dampening effects. In a recession, the slack labor market (increasing the chances of hiring and reducing wages) is not a strong enough force to overturn the impact of a missing generation of startups.

4 Results

In this Section, we discuss the results from a set of scenarios. Our "baseline" scenario is meant to reflect the historical worst case in which all three margins in the calculator fall to their lowest points measured in our sample. Next, we instead consider a scenario based on the latest data from the BDM. Finally, the last two scenarios are meant to depict the effects of quick bounce-backs in economic activity. The first is, again, based on a historical best case, while the second considers latest information on business applications from the BFS.

4.1 Baseline scenario - the historical worst case

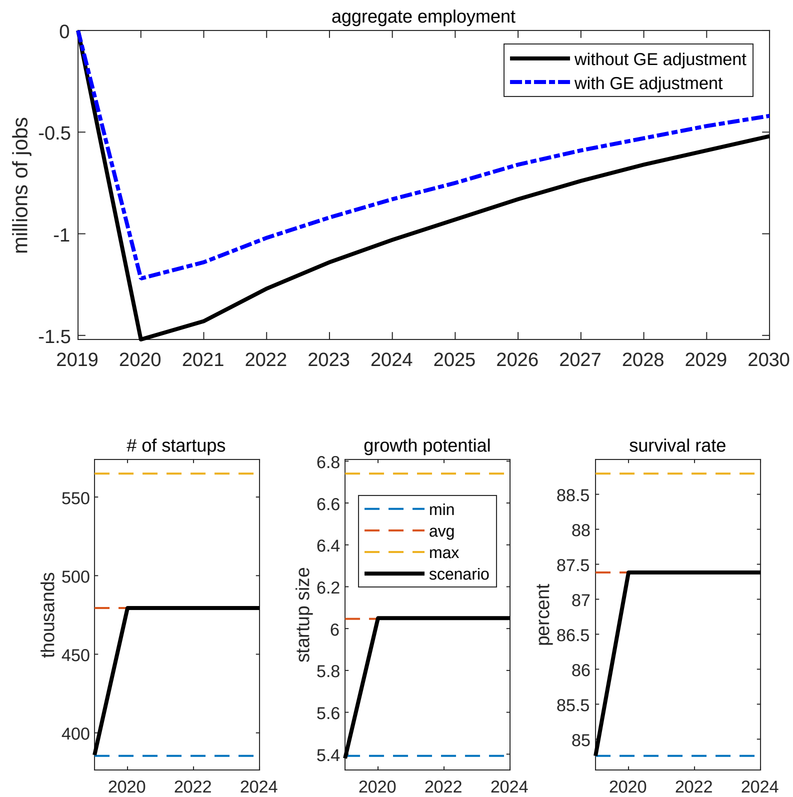
At this point, we do not know whether the current contraction will be short-lived or develop into a full-blown recession. Therefore, we take a scenario-based approach. Based on the early indicator discussed earlier, we select as a baseline scenario a strong but short-lived contraction. Specifically, we assume that the startup rate, the growth potential and the survival rate all drop to their lowest levels since 1977 (the beginning of our data sample). These values are in fact closely linked to the Great Recession, which was the worst period for startup activity since the start of the sample.[16] However, we let the contraction last for just one year, based on the observation that several countries seem to have moved past the peak of the pandemic within a several months, and assuming a relatively swift recovery of overall macroeconomic conditions.

Of course, it may very well be that in reality some or all of the three margins may turn out less affected than assumed here. Nonetheless, we believe the kind of worst case scenario assumed here is useful in guiding policy makers during times of high "Knightian" uncertainty, such as the start of an unprecedented global pandemic. That said, below we will consider an alternative scenario as well, based on recent (but preliminary) data during the pandemic.

Figure 4 plots the effects on aggregate employment. Two key observations stand out. First, the decline in startup activity has sizeable aggregate effects. In the first year, about 1.5 million jobs are lost, relative to a scenario without the pandemic. This loss is about six percent of the employment of firms aged below ten, and 1.1

[16] That said, the nature of the current contraction is clearly very different from the Great Recession. An important motivation for our calculator is to give the possibility of computing different alternative scenarios.

Figure 4: Baseline scenario in the calculator (historical worst case)



Note: General Equilibrium (GE) adjustment is obtained based on Equation (3) $\Psi = 0.8$.

percent of aggregate employment.

Second, the macroeconomic effects are very persistent, even though the shock itself lasts for only one year. Cumulated from 2020 until 2030, the job losses are about 10.6 million. Moreover, each of the three margins plays a substantial role. The decline in the number of startups accounts for about 4.6 million of the cumulated job losses, the decline in growth potential for about 2 million, and the decline in survival for about 3.5 million. The remaining 0.5 loss is due to interactions between the three margins.

4.2 Scenario based on the most recent BDM data

As discussed previously, we also information related to startups from the BDM, which has recently been made available up to the third quarter of 2020. We now consider a scenario based on these data. Specifically, we make the following assumptions based on the three margins, using the BDM data shown in Table 1: a decline in the number of startups by 1.2 percent, a decline in growth potential of 11.9 percent and an increase in exit rate of 3.6 percentage points.[17]

The 3.6 percentage point change assumed in this scenario is much lower than the 8.8 percentage point increase in closing rates (on an annualized basis) shown in Table 1. However, as discussed previously, the BDM closing rate does not include only permanent exits, but also temporary closures. In order to adjust for this, we look at the relative volatility of the death rate (permanent closings) and the closing rate in the period 2010-2019 during which both variables are observed in the BDM data. Over this period, the death rate is only about 40% as volatile as the closing rate. Therefore, we consider an increase in the exit rate of 0.4*8.8=3.6 percentage points.

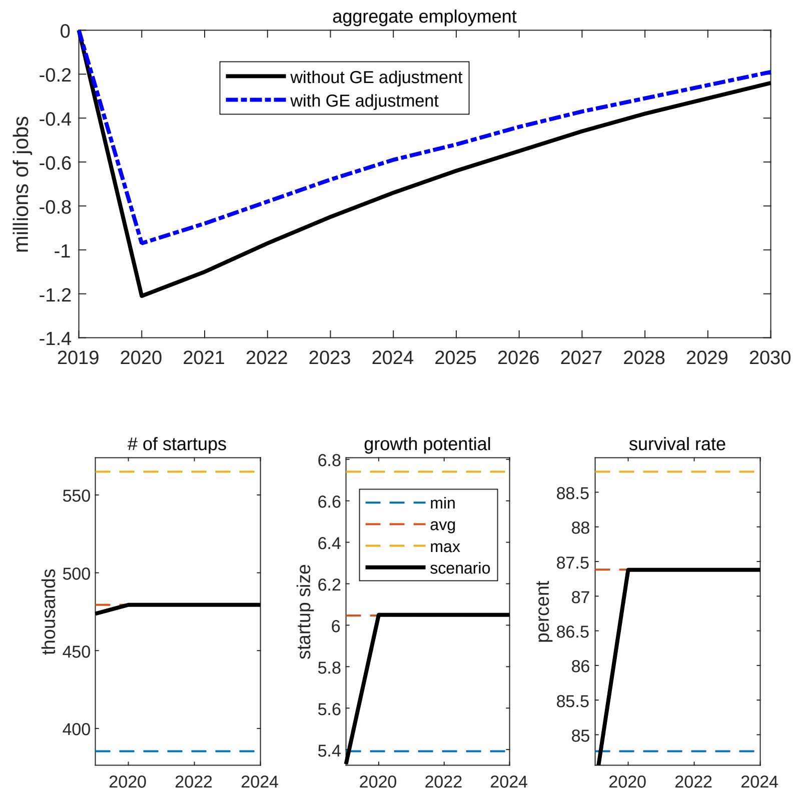
Before discussing the results, it is important to keep in mind that the BDM data is still preliminary and run only up to the third quarter of 2020 at the time of writing. The full extent of the change in startup activity will become clearer once new data points will become available.

Figure 5 shows the results of this scenario. Again, the effects are very persistent. The maximum decline in aggregate employment is 1.2 percent, somewhat smaller than the maximum decline in the "baseline" scenario (about 1.5 percent). This is mainly because the number of startups declines by less in the scenario based on BDM data. Possibly, the latter has to do with the large-scale economic stimulus measures that were implemented during the COVID-19 pandemic, although we cannot observe what would have happened without these unprecedented policy interventions.

However, two key lessons can be derived from our results for future policy. First, focusing policy initiatives solely on the continued survival of existing, older, businesses ignores a part of the economy which is quantitatively important for aggregate job creation. Our calculator shows that disruptions to startups and young firms alone can have sizeable effects on aggregate job creation. Second, if policy turns its attention to startups and young firms, it should not be concerned with the number of startups, but also with the other two margins - the growth potential of startups and the survival rates of young firms. Both of the latter turn out to be quantitatively important drivers of the job creation prowess of young firms.

[17] Since the BDM data are quarterly, we annualize the change in the birth rate and the exit rate by multiplying by four.

Figure 5: Scenario based on BDM data



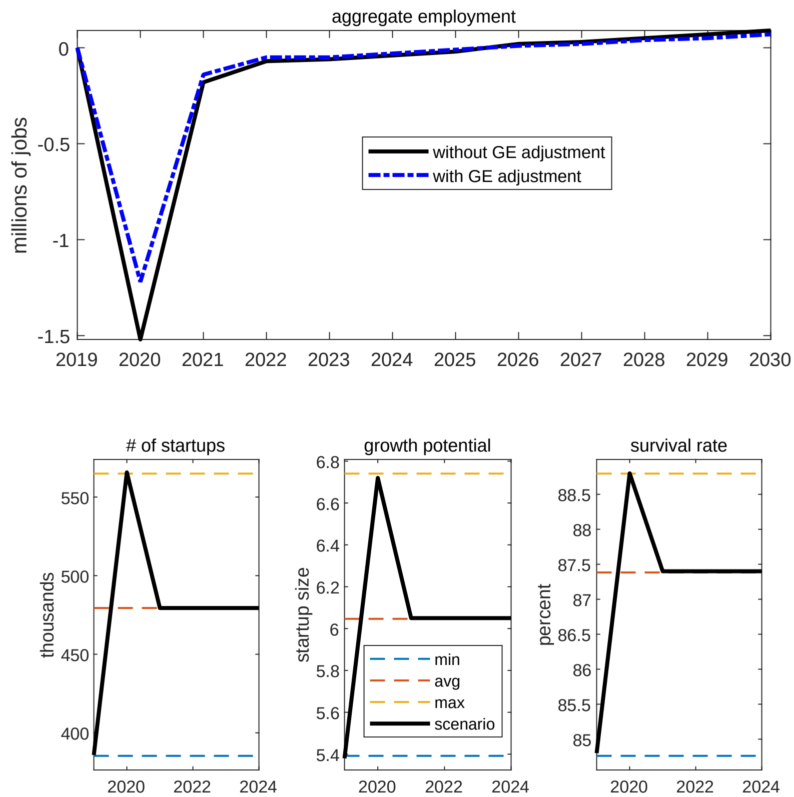
Note: General Equilibrium (GE) adjustment is obtained based on Equation (3) $\Psi = 0.8$.

4.3 Bounce-back scenarios

Quite possibly, however, the shock will last longer than 1 year. Based on the calculator, we find that the cumulative employment loss is roughly proportional to the duration of the shock. If the crisis lasts for two years, it will result in roughly 20 million jobs lost between 2020 and 2030. Alternatively, it is possible that the shock will be followed by a "bounce-back" in 2021. This scenario, which would be consistent with the surge in 2020Q3 applications in the BFS, is also allowed for in the calculator.

We consider two bounce-back scenarios, starting from the historical worst case scenario described above. The first bounce-back scenario, shown in Figure 6, is one in which 2021 is characterized by all three margins reaching the highest levels observed in our data sample. The second, shown in Figure 7, only considers a strong recovery in the number of startups. In particular, the size of the recovery is calibrated such that the bounce-back is twice the size of the initial decline in the number of startups,

Figure 6: Bounce-back scenario in the calculator



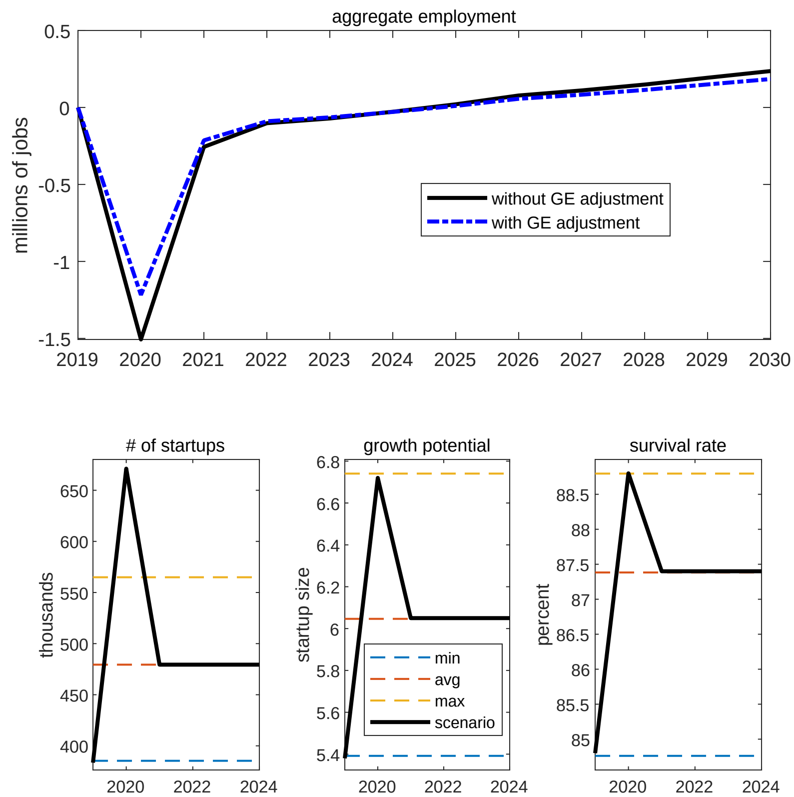
Note: General Equilibrium (GE) adjustment is obtained based on Equation (3) with $\Psi = 0.8$.

in line with the BFS data.

Importantly, while in both scenarios aggregate employment losses are much shorter-lived, quantitatively sizeable effects persist. For instance, in the first bounce-back scenario in Figure 6, the cumulative job loss up to 2030 remains to be about 2 million. Moreover, it is only around 2028 when aggregate employment finally catches up to its initial trajectory. In other words, even a short-lived crisis with a strong bounce-back will have a sizeable negative impact on the aggregate economy for the next decade. Similar effects can be seen in the second bounce-back scenario in Figure 7, although there is a reversal around 2025.

How likely are such reversal scenarios? This question is difficult to answer. Historically, however, strong bounce-backs have been uncommon, as in the data all three margins show strong and positive autocorrelations over time. Another possibility is that older firms will hire more, compensating for the employment losses due to

Figure 7: Bounce-back scenario in the calculator



Note: General Equilibrium (GE) adjustment is obtained based on Equation (3) with $\Psi = 0.8$.

startups. To fully offset the startup job losses in the baseline scenario, this would mean that older firms would need to create an additional 1.5 million jobs in 2020. For comparison, in 2016 net job creation by firms older than 10 was only about 0.6 million. From this perspective, creating the needed 1.5 million extra jobs appears to be a large challenge for older businesses. In fact, our equilibrium dampening effect suggests that only about 0.3 million jobs may be created by older firms in reaction to the slump in young firms' activity.

5 Application to France, Germany, Italy and Spain

We now apply the calculator to four major European economies: France, Germany, Italy and Spain. The analysis we present here is relatively brief. More expanded work (including analysis for other European countries and splits by industry) can be found in reports of the European Commission (see Benedetti-Fasil, Sedláček and Sterk, 2020a,b,c), with the respective calculators being publicly available online.[18] As for the US, data on the extent to which the pandemic has affected startup is not yet fully available, and hence the results will be based on preliminary scenarios.

The effect of the pandemic on startups may very well differ across countries, for several reasons. First, the extent to which COVID-19 spread across the population varied across countries, with for instance Germany being relatively less affected initially. Second, due to structural differences, economies may be affected differently by a pandemic. Third, the policy response to the pandemic varied across countries. Finally, firm dynamics differ substantially across countries, which impacts the propagation of a shock to startups. For instance, a country with a high firm turnover rate (i.e. high entry and exit rates) may rely relatively heavily on startups to sustain job creation, and hence be more sensitive to a disruption of startup activity.

5.1 Data

The data used to calibrate the calculator for European countries are taken from Eurostat's Business Demography Statistics. This dataset contains information on the number of startups and the average employment of startups in the age categories 0, 1, 2, 3, 4, and 5 years. Data are available from 2008 to 2017, except for Germany where coverage ranges from 2012 to 2017. As for the United States, the data set only contains information on employer businesses. Since in the Eurostat data there are no further age bins, we cannot apply the interpolation procedure used for the US. Instead we apply an extrapolation, in which we target the average size profiles of firms aged 0-5, as well as average size unconditional on age. The details of this procedure can be found in (see Benedetti-Fasil et al., 2020a,b,c).

Before applying the calculator, we consider a number of descriptive statistics on firm dynamics across countries, shown in Table 2. The table shows that, overall, businesses in the EU 27 countries are somewhat more dynamic compared to the United States, as measured by their startup and exit rates which are both higher. Within Europe, however, there is substantial heterogeneity, with France being more dynamic and Germany less dynamic than the average. In Spain and Italy, the firm startup and survival rates are similar to the EU 27 average.

[18] See `https://ec.europa.eu/jrc/en/covid-19-start-up-calculator/calculators`.

Table 2: Firm dynamic statistics across countries

	US	EU 27	France	Germany	Italy	Spain
startup rate	8.0	9.2	11.6	7.4	9.3	10.0
survival rate	92.5	92.0	88.5	94.0	90.0	88.0
share of young firms	32.6	36.0	38.0	19.1	36.6	37.0
employment share of startups	1.8	2.5	3.4	1.3	2.5	3.5
employment share of young firms	10.5	12.0	13.6	4.2	16.2	16.0

Note: Data for the U.S. is taken from the Business Dynamic Statistics of the Census Bureau, data for Europe are taken from the Business Demography Statistics of Eurostat. Startups are classified as age 0 firms, while young firms are classified as 0-5 year old firms.

Part of the cross-country differences are driven by sectoral composition. In particular, dynamism tends to be low in the manufacturing sector. However, even within the manufacturing sector, dynamism is low in Germany by international comparisons (see Benedetti-Fasil et al., 2020a,b,c).

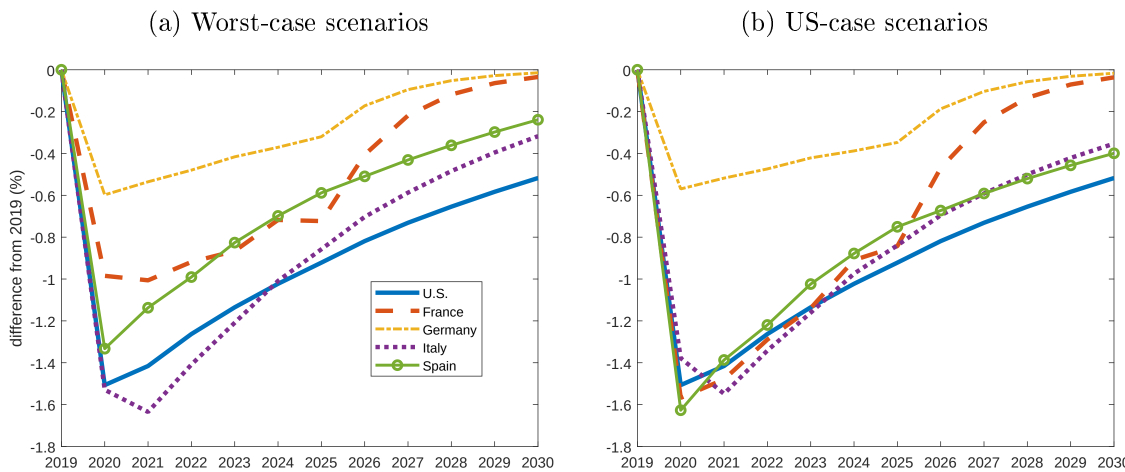
When considering the employment share of startups instead of the startup rate, we observer that this share is higher in France, Italy and Spain, compared to the US, but lower in Germany. Moreover, if we consider the firm share and employment share of young firms (age zero to five), we see that Italy and Spain rely particularly heavily on young firms for job creation. In those countries, about 16 percent of all employment is provided by young firms, whereas in Germany this is only about 4 percent. These patterns suggest that employment in Spain and Italy might be particularly sensitive to a decline in startups and their growth potential, as well as to an increased exit rate among young firms.

5.2 Results from the calculator

We now present the calculator results for Europe. The shock is calibrated in the same ways as for the US, i.e. by taking the worst realisations of the three margins over the sample period. For the survival rate in Germany we have insufficient data. Here we assume a 4 percent drop, which is the same as in Spain as in Italy.

The results are shown in Panel (a) of Figure 8. Considering the maximum drop in employment, we find a similar magnitude for France, Spain and Italy as for the US, roughly a 1.5 percent drop. Interestingly, however, the decline is much less persistent in these countries compared to the US. This seems to be due to the higher degree

Figure 8: Aggregate employment response to the pandemic across countries



Note: Panel (a) shows changes aggregate employment under the worst-case scenario in each country. Panel (b) shows the same but where all countries face the same shock as the U.S.

of dynamism in these economies, as startups born after the shock quickly rebuild employment. In Germany, the drop is substantially smaller, about 1 percent.

To study the effect of dynamism on the impact and propagation of the shock more explicitly, we now consider a scenario in which the shock hitting all four European countries is the same as the one hitting the US economy. The results are shown in Panel (b) of Figure 8. The impact effects are again very similar in France, Italy, Spain and the US. Also, effects are again less persistence in the former three economies. Similarly to before, the impact is again much smaller in Germany. These results confirm that cross-country differences in firm dynamics indeed matter greatly for the impact and propagation of shocks to startups.

6 Policy Implications and Concluding Remarks

In this paper, we provide an empirical analysis of the medium-run impact of the coronavirus-induced slump in startup activity on aggregate U.S. employment. The analysis specifically recognizes three margins through which young firms may impact the aggregate economy: (i) decline in the number of startups, (ii) decline in the growth potential of startups and (iii) a decline in survival rates of young firms.

The key contribution of this paper is to develop a simple tool – the Startup

Calculator – which is accessible to anyone on our websites.[19] Analysing a few possible scenarios, the results suggest that even a short-lived disruption in startup activity may have large and very persistent effects on the aggregate economy in the next decade.

By allowing the analysis of various scenarios, including the "worst case", the calculator can help policy makers assess the potential implications of policy actions, or lack thereof. This is particularly useful during unprecedented situations with a high degree of fundamental uncertainty, such as the current pandemic. The flexibility of the calculator also allows one to quickly update scenarios based on the latest incoming data or forecasted outcomes of policy interventions.

In the debate on policies responding to the pandemic, much discussion has focused on the potential advantages of policies designed to help existing firm survive. Instead, our results draw the attention to the importance of sustaining startup numbers (and quality) in order to avoid a significant and persistent fall in aggregate real activity. A key point of our analysis is that there are three key margins which matter importantly for the aggregate economy: not only the number of startups but also their growth potential and the survival chances of young firms. Especially the latter two margins may be easily overlooked, but the most recent data suggest that they are particularly relevant to the slump in activity following the start of the COVD-19 pandemic.

In future work, once more data is available, it would be interesting and important to investigate the extent to which policies implemented during the COVID-19 pandemic affected startups. For instance, exploiting cross-country or cross-region variation in policies and outcomes may be a fruitful way forward in this regard. Researchers pursuing such questions can then readily use the Startup Calculator to evaluate the aggregate impact of policies, aimed at any of the three margins, during the pandemic and in subsequent years.

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[19] To access the Calculator, please visit http://users.ox.ac.uk/~econ0506/Main/StartupCalculator.html

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