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 degree of business dynamism.

Keywords: Startups, Macroeconomics, Employment, COVID-19

JEL Codes: D22, E23, E24, I10

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1 Introduction

The global coronavirus (COVID-19) pandemic has set 2020 to be a tragic year 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 might imply for the U.S. economy, in terms of the severity and persistence of employment losses. To this end, we develop a Startup Calculator, available online, which allows anyone to easily compute employment losses under various scenarios of choice.[2]

The calculator provides a tool for macroeconomic researchers and analyst to make projections on job creation by startups. It also of use to policy makers interested in designing specific policies to support startups during challenging times. In particular, it helps to understand along which margins policies might be most effective.

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

[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 applied to the U.S. economy and an excel document with the underlying computations can be found at http://users.ox.ac.uk/~econ0506/Main/StartupCalculator.html. The calculator adapted to the economy of 23 EU Member States and their sectors can be found at https://ec.europa.eu/jrc/en/covid-19-start-up-calculator.

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 (forthcoming).

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 US employment, from 2020 onwards. The Startup Calculator uses publicly available data from the U.S. Business Dynamics Statistics (BDS). We take a conservative stance and only consider changes to firms younger than 10 years of age. In other words, we leave 40 percent of all businesses unaffected in our calculations and as such the results may be taken as lower bounds.

Our baseline scenario is one in which all three margins fall to their minimum levels observed since 1977 (the starting point of the BDS). 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.

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.

After studying the United States, we apply the calculator to four European Countries: France, Germany, Italy and Spain. The extent to which the economy in these countries was hit by the pandemic differed. Moreover. business dynamism varies across countries, their vulnerability to startup shocks differs. As a result of these two factors, we find substantial differences in the effect of the pandemic on aggregate employment. In particular, we find relatively small effects for Germany, which was relatively less affected by the pandemic in 2020, and is also characterized by a low degree of business dynamism, making it less reliant on startups for job creation.

The remainder of this paper is organized as follows. Section 2 reviews existing evidence on the importance of startups for aggregate job creation and 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. We emphasize, however, that using the calculator on our website it is easy for anyone to compute results under different scenarios. In Section 5 we apply the calculator to France, Germany, Spain and Italy, and make a comparison to the US. Finally, Section 6 concludes.

2 The Importance of Startups

There are four main reasons why we focus on startups, and in turn young firms. First, new and young businesses are the dominant creators of new jobs. 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.

It is true, however, that young firms also exhibit a higher rate 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".

The second reason to focus on startups relates precisely to the up-or-out dynamics described above. This 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 et al. (2001). Therefore, the data suggest that surviving young businesses are the ones that are crucial for aggregate productivity growth.

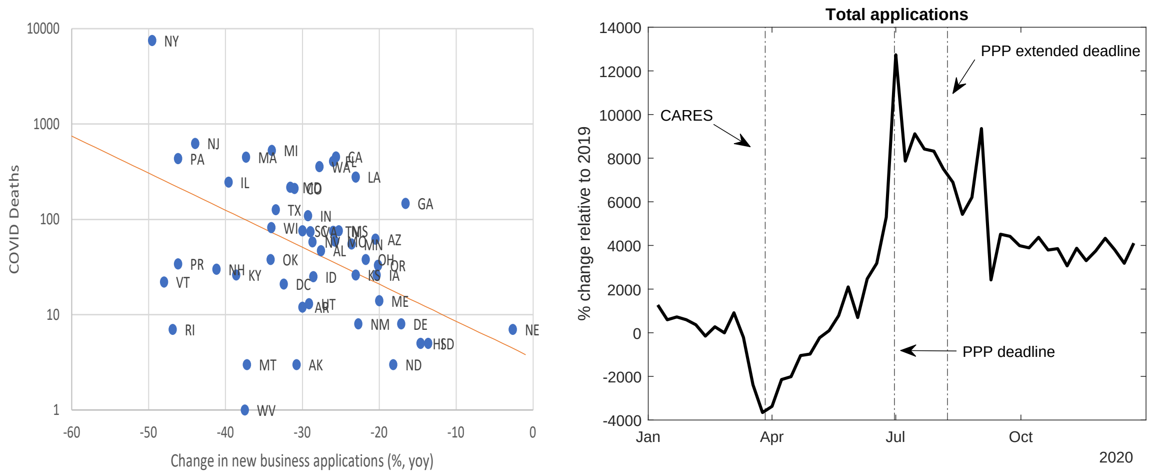
Third, these findings are exacerbated by new evidence on young high-growth firms, so called "gazelles". Haltiwanger, Jarmin, Kulick and Miranda (2017) document that this small share of startups with exceptional growth potential accounts for about 40 percent of aggregate TFP growth, 50 percent of aggregate output growth and 60 percent of aggregate employment growth.

Finally, changes startup activity may have very persistent effects at the macroeconomic level, either via the number of firms (Gourio et al. (2016), Sedláček (forthcoming)) or via changes in the type of entrants (Sedláček and Sterk (2017)). In addition Sterk r al. (2021) show that most of the cross-sectional heterogeneity in firm-level employment can be attributed to ex-ante factors, already present at or before birth of the firm. Together, this body of evidence suggests that disruptions of startup activity, like the one experienced currently, may have long-lasting implications.

Figure 1: Business applications in the U.S. and the COVID-19 pandemic

(a) Business applications and COVID deaths

(b) Total business applications



Note: Panel (a) shows changes in business applications from the Business Formation Statistics (BFS) and COVID deaths from the Center of Disease Control and Prevention during the weeks 12-15 of 2020. Data were downloaded on April 17, 2020. Panel (b) shows the time series of business applications from the BFS.

2.1 U.S. startups during the COVID-19 pandemic

It is still too early to tell exactly how hard startups will be hit by the COVID crisis. The available data, however, suggest that the situation is severe. Panel (a) of Figure 1 plots state-level data on COVID deaths versus the number of (high-propensity) business applications. The latter are taken from the Business Formation Statistics and are an early indicator of startup activity, see Bayard, Dinlersoz, Dunne, Haltiwanger, J. Miranda and Stevens (2017). Haltiwanger (2020) shows that in late March 2020, business applications in the US declined strongly, about as much as during the Great Recession (although it is unclear how long the decline will last this time).

Panel of Figure 1 also shows that, not only have business applications declined strongly in many states, there is also a clear relation with the severity of the pandemic. Particularly striking is New York state (NY), which suffered both the largest number of deaths and the strongest declines in business applications.

However, Panel (b) of Figure 1 shows that in March 2020 there was a strong reversal in the decline in startup activity. The timing of this reversal coincides almost exactly with the introduction of the CARES stimulus act, and in particular the Paycheck Protection Program (PPP) which provided (forgiveable) loans to small firms in order to help them survive the economic crisis triggered by the pandemic. Similarly, the peak in startup activity coincides with the (initial) deadline of the PPP program. Interestingly, startups (established after February 15, 2020) were not eligible for PPP loans. Possibly, the surge in startup activity was due to existing firms taking their business online.[3] This explanation would be consistent with the fact that in earlier recessions, such as the Great Recession following the financial crisis, the startup rate declined substantially.

Future data on actual business startups will reveal if the increase in business applications will lead to a true increase in startup activity. In any case, it seems likely that most if this increase would realize in 2021, given that the search happened in the third quarter and given the typical delays of 2-3 quarters between application and actual establishment of the firm (see Bayard, Dinlersoz, Dunne, Haltiwanger, Miranda and Stevens, 2018). Therefore, we will use the calculator also to quantify a scenario with an increase in startup activity in 2021, in line with the BFS applications data.

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 Dynamcis 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 to 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

[3] Indeed, a sectoral breakdown of the BFS data by the Census Bureau showed that the increase in online retail was extraordinarily large.

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 $s_{a,t} = e_{a,t}/n_{a,t}$.[4] 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 $1 - x_{a,t} = 1 - d_{a,t}/n_{a,t}$.

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.[5] 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.

3.2.1 Interpolation of age-specific information

Number of firms and exit rates. To interpolate information on the number of firms aged 6 to 10 years we assume that exit rates between the ages of 5 and 10 are linearly related such that

$$x_{a,t} = x_{a-1,t-1}(1 - \Delta_x) \quad \text{for } a = 5, ..., 10,$$

where $\Delta_{x,t}$ is a year-specific growth rate, but which is the same for firms between the ages of 5 and 10. Given the exit rates by age, we can compute the number of firms between the ages 6 and 10 as

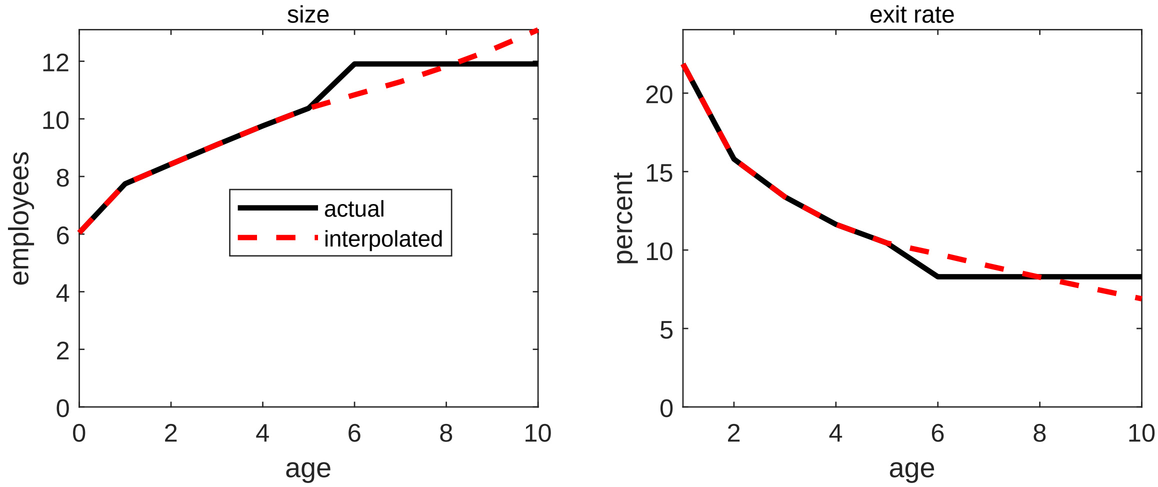
$$n_{a,t} = n_{6-10,t} \frac{\Pi_{j=1}^{a-5}(1 - x_{a-j+1,t-j+1})}{\sum_{a=6}^{10} \Pi_{j=1}^{a-5}(1 - x_{a-j+1,t-j+1})} \quad \text{for } a = 6, ..., 10.$$

The above therefore takes the observed number of firms aged 6 to 10 years and decomposes it into the shares of 6, 7, 8, 9 and 10 year old firms where the shares are computed using the age-specific survival rates.

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

[5] 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.

Figure 2: Actual and interpolated data



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

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 5 and 10 such that

$$s_{a,t} = s_{a-1,t-1}(1 + \Delta_{s,t}) \quad \text{for } a = 5, ..., 10,$$

where Δ_s is a year-specific growth rate, but which is the same for firms between the ages of 5 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.

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.[6] Using the above, we can then recover the number of firms for the ages of 1 to 10 as $n_{a,t} = n_{a-1,t-1}(1 - x_{a,t})$, 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.

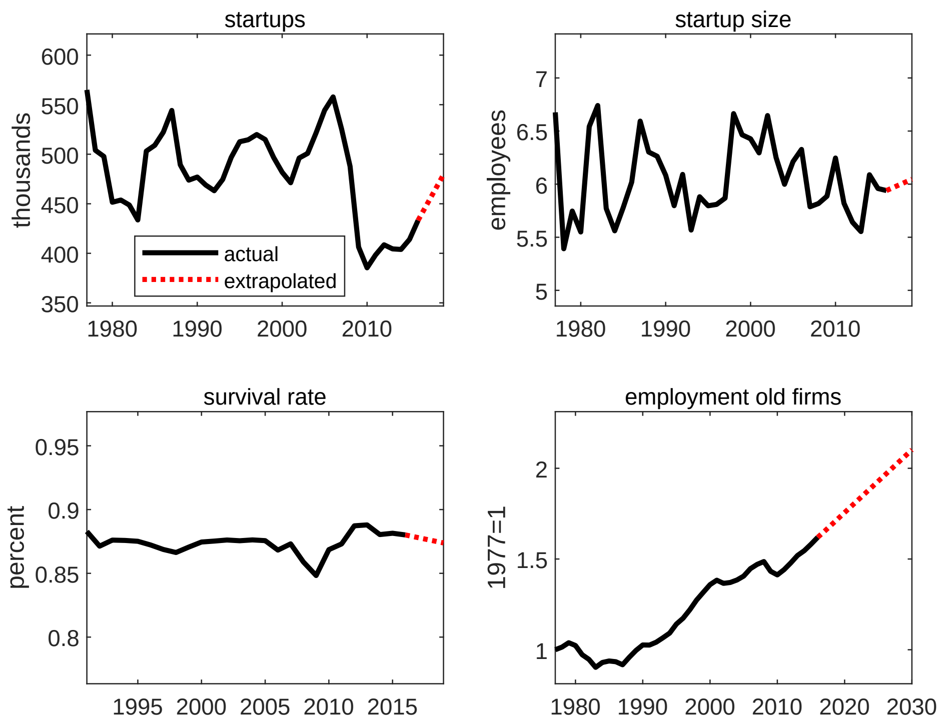
Number of older firms. The number of all businesses in the US economy has been steadily increasing over the sample period. This is, however, essentially entirely because of an increasing number of older firms. This can be seen from Figure 3 which shows that the *number* of startups has fluctuated cyclical 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. Using this estimated trend we then 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.

[6] 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.

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.

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. Also note that the number of businesses older than (i.e. $a > 0$) years is given by $n_{a,t} = (1 - x_{a,t})n_{a-1,t-1}$.

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

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

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.[7] 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.

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.[8] 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.[9] The wage per employee is taken as given by firms, and denoted by w. The firm chooses 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

[7] Old firms (11+ years) account for 40 percent of all businesses, but almost 80 percent of employment.

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

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

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.[10] 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 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 $\Psi \equiv \frac{1}{1-\kappa\epsilon_{nw}} \in (0,1)$, where $\epsilon_{nw} = \frac{1}{\alpha-1}$ is 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.[11] 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

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

[11] Alternatively, one could model an explicit entry and exit block of the model.

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 (forthcoming) 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.

Finally, we note that if a scenario is based on empirical observations for average size of young firms (for the startup growth potential margin), then it may be important to account for the fact that this number itself is subject to equilibrium dampening. Therefore, the true change in growth potential might be larger than what the data suggest. To do so, we use Equation (1), but this time aggregated over only startups, as opposed to all firms.[12] Using Equation (2) to substitute out the wage and rearranging, we obtain the following expression for startup growth potential:

$$d \ln \chi^{startup} = \underbrace{d \ln N^{startup} - d \ln M^{startup}}_{\text{avg startup size}} - \underbrace{\kappa \epsilon_{nw} d \ln N}_{\text{equil. adjustment}} .$$

On the right hand side, the first two terms jointly are the change in average startup size. From this one subtracts the $\kappa\epsilon_{nw}$ times the change in *aggregate* employment in

[12] This gives $d \ln N^{startup} = d \ln M^{startup} + d \ln \chi^{startup} + \epsilon_{nw} \ln w$.

order to obtain the change in the growth potential of startups.[13]

4 Results

4.1 Baseline scenario

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.[14] However, we let the contraction last for just one year, assuming a recovery in 2021, possibly due to the widespread roll-out of vaccination programs.

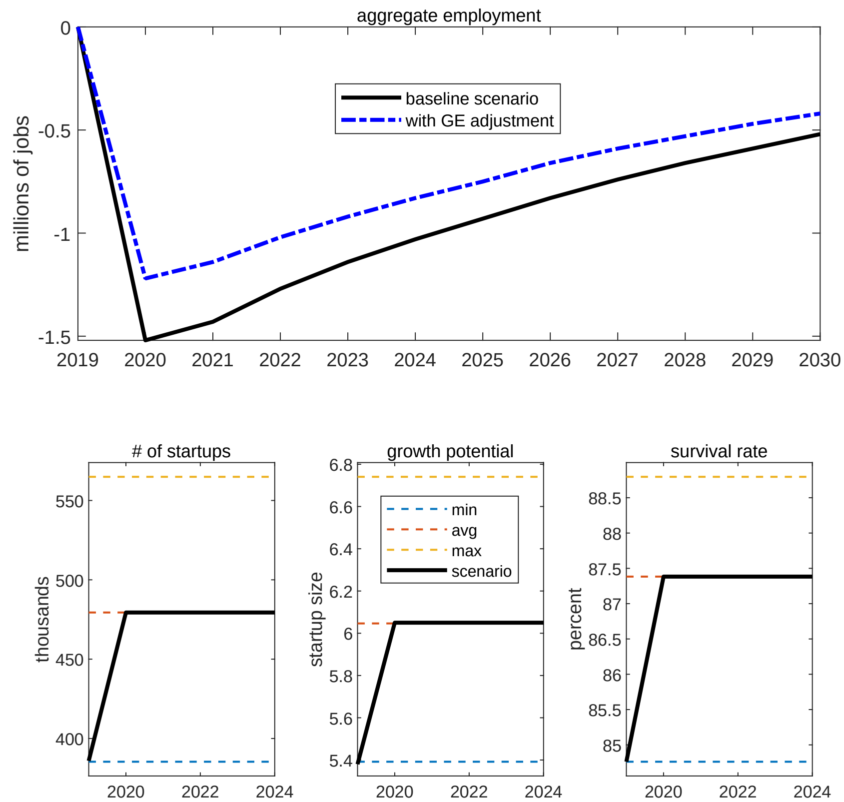
Figure 4 plots the effects on aggregate employment. Two key observations stand out. First, the decline in startup activity has sizeable aggregate effects. In the first year, about 1.5 million jobs are lost, relative to a scenario without the pandemic. This loss is about six percent of the employment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

[13]Note that the adjustment only matters when aggregate employment is away from its trend level. It turns out that in our application here, this adjustment has only negligible effects, and hence we omit it in our calculations.

[14]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

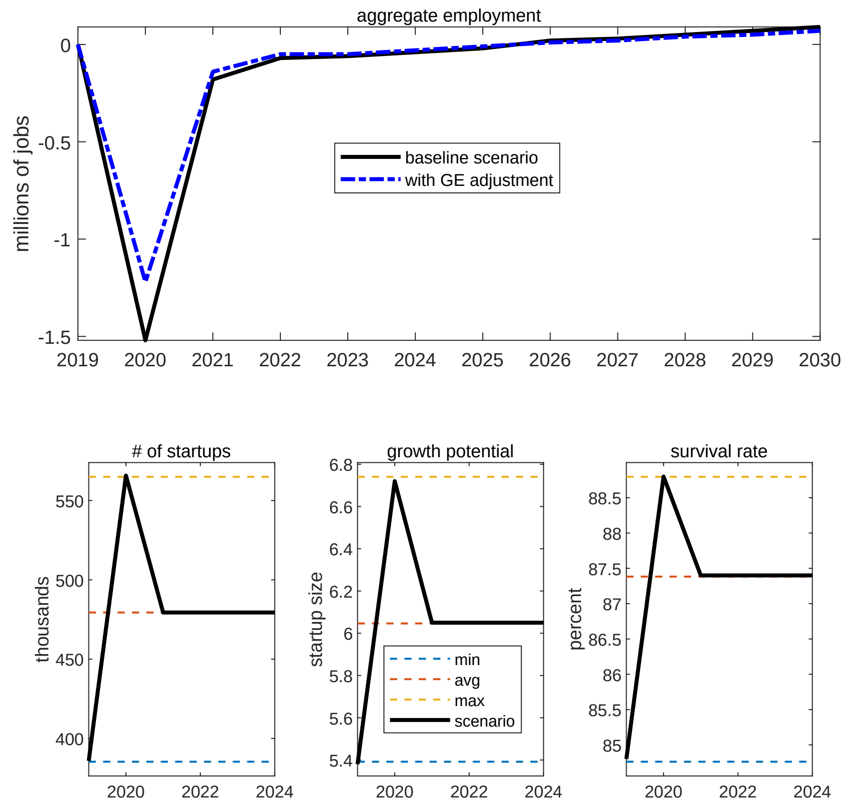


Note: General Equilibrium (GE) adjustment is obtained based on Equation (3) $\Psi = 0.8$.

4.2 Bounce-back scenario

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 "bounceback" 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 bounceback scenarios. The first, shown in Figure 5, is one in which 2021 is characterized by all three margins reaching the highest levels observed in our data sample. In this case, aggregate employment losses are much shorter-lived, but nonetheless some effects persist. Not only is the cumulative job loss up to 2030 about 2 million, but 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-

Figure 5: Bounceback scenario in the calculator



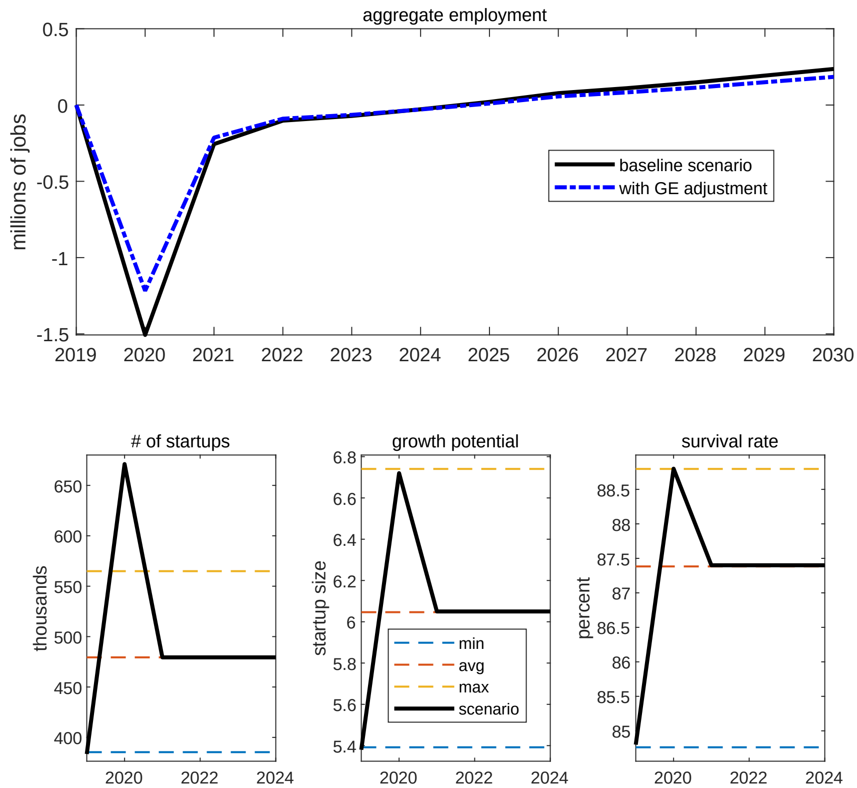
Note: General Equilibrium (GE) adjustment is obtained based on Equation (3) with $\Psi = 0.8$.

back will have a sizeable negative impact on the aggregate economy for the next decade.

How likely is such a reversal scenario? This question is difficult to answer. Historically, however, strong bouncebacks 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 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, net job creation by firms older than 10 was only about 0.6 million. From this perspective, creating the 1.5 million extra jobs needed appears to be a large challenge. 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.

In the second bounceback scenario in Figure 6, we consider only a recovery in the

Figure 6: Bounceback scenario in the calculator



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

number of startups. The size of the recovery is calibrated such that the bounceback is twice the size of the initial decline in the number of startups, in line with the BFS data. Figure 6 shows that aggregate employment still falls persistently, although there is a reversal around 2025.

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). As for the U.S., data on the extent to which the pandemic has affected startups are 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 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 direction affects the propagation of a shock to startups. For instance, a country with a high firm turnover rate (i.e. low 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 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 1. 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 rate and exit rates which are both higher. Within Europe, however, there is substantial heterogeneity, with France being more dynamic than average and Germany less dynamics. In Spain and Italy, the firm startup and survival rates are similar to the EU 27 average.

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 comparison, see (see Benedetti-Fasil et al., 2020a,b,c).

Table 1: 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.

When considering the employment share of startups instead of the startup rate, we observer that this share is higher in France, Italy in 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 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. This suggests 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

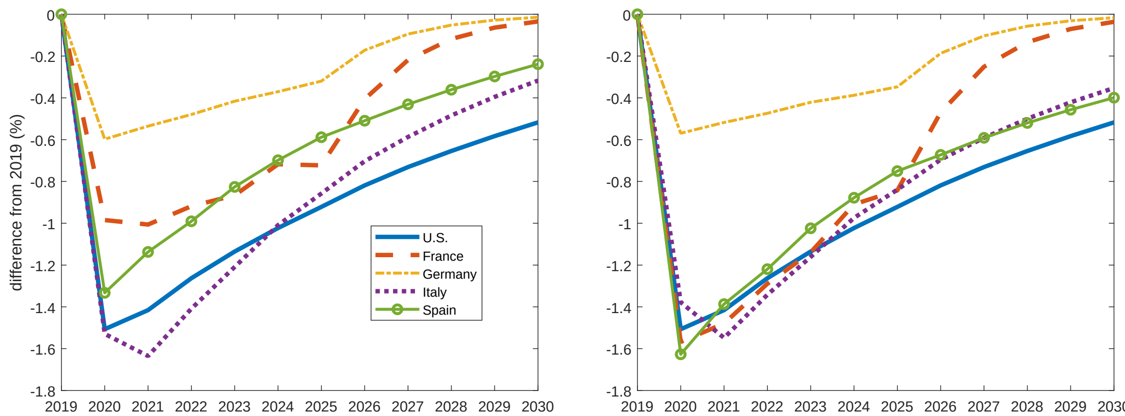
We now present the calculator results for Europe. The shock is calibrated in the same way as for the US, i.e. by taking the most negative realisations of the three margins over the sample period. For the survival rate in Germany we have insufficient data. Here we assume a 4 percent drop, which is the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

The results are shown in Panel (a) of Figure 7. Considering the maximum drop in employment, we find a similar magnitude for France, Spain and Italy as for the US, about 1.5 percent drop. Interestingly, however, the decline is much less persistent in France, Italy and Spain, compared to the US. This seems to be due to the higher degree of dynamism in these countries, 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

Figure 7: Aggregate employment response to the pandemic across countries

(a) Worst-case scenarios (b) US-case scenarios



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.

countries is the same as the one hitting the US economy. The results are shown in Panel (b) of Figure 7. The impact effects are again very similar in France, Italy, Spain and the US. Also, effects are again less persistence in the former of these three. Moreover, the effects are again much smaller in Germany. These results confirm that cross-country differences in firm dynamic indeed matter greatly for the impact and propagation of shocks to startups.

6 Conclusion

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 and compare it briefly with the impact in France, Germany, Italy and Spain. 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 online.[15] Analysing a few possible scenarios, the

[15] To access the Calculator for the US economy, please visit http://users.ox.ac.uk/~econ0506/Main/StartupCalculator.html and to access the Calculator

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.

While the outlook for startups may look gloomy, there are also some glimmers of hope. First, the high sensitivity of startups to economic conditions likely implies that they may also respond positively to policies which aim to support them. Given that startups can be relatively easily identified, such policies might be relatively cost effective. Second, the change in our daily lives might inspire entrepreneurs, and create new opportunities, to come up with new ideas and new ways of running businesses, which could foster growth in the long run.

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