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

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Abstract

Early indicators suggest that startup activity is heavily disrupted by the COVID-19 pandemic and the associated lockdown. 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 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.

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1 Introduction

Due to the global coronavirus (COVID-19) pandemic, 2020 is set to be a tragic year for many businesses. Startups are likely to 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. This is already showing in the statistics. In the last week of March 2020, new business applications were down forty percent compared to the same week one year earlier, a contraction that is even sharper than during the Great Recession, see Haltiwanger (2020).

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. Therefore, startups deserve special attention in this situation.

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 developed a Startup Calculator, available on our websites, which allows anyone to easily compute employment losses under various scenarios of choice.[1]

The calculator allows one to vary three key margins, which pertain entry and exit of young businesses. As such, these effects are not easily reversed and may have important effects on the macroeconomy in the medium- and long run. The first margin is the number of startups. A fall in this number directly reduces the number of new jobs created by startups. Importantly, however, this "lost generation" of firms then creates 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).

The second margin is the growth potential of startups. Sedláček and Sterk (2017) show that firms born during recessions not only start smaller but also tend to stay smaller in future years even when the aggregate economy recovers. These movements in growth potential are attributed to changes in the composition of the type of startups. In the current situation, it seems particularly challenging to start a highly

[1]The calculator and an excel document with the underlying computations can be found at http://users.ox.ac.uk/ econ0506/Main/StartupCalculator.html.

scalable businesses, since supply chains are heavily distorted, credit conditions are poor, and customer may be demand difficult to acquire during a lockdown.

The third and final margin included in the calculator is the survival rate of young businesses. Startups and young firms in general have much higher exit rates than older firms, see e.g. Haltiwanger, Jarmin, and Miranda (2013), and during downturns these exit rates tend to increase.

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.

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 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. Finally, Section 5 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.

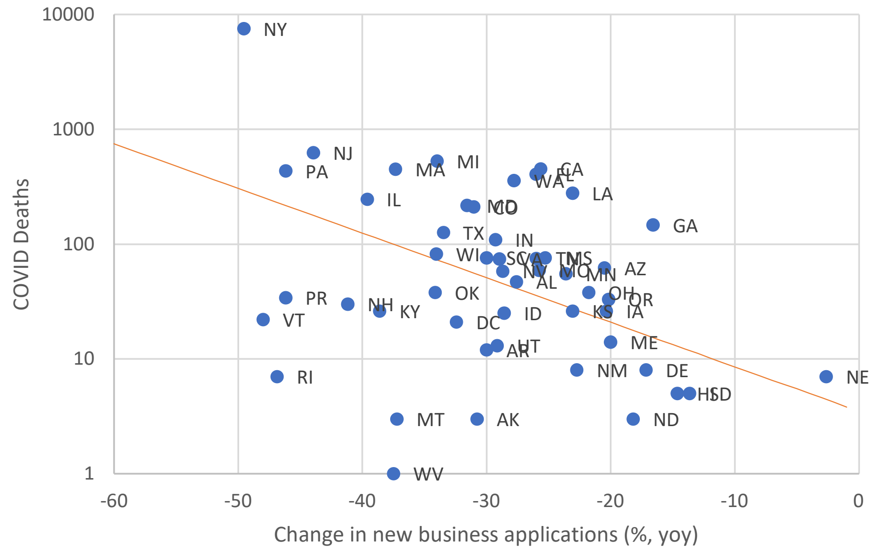
It is true, however, that young firms also exhibit a higher rate of exit, suggesting that not all jobs created by startups are long-lasting. Nevertheless, the data shows that surviving young firms tend to grow faster than the average incumbent, see e.g. Haltiwanger, Jarmin, and Miranda (2013). These 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, Haltiwanger, and Krizan (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, Messer, and Siemer (2016), Sedláček (forthcoming)) or via changes in the type of entrants (Sedláček and Sterk (2017)). In addition Pugsley, Sedláček, and Sterk (2017) 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: Decline in startups and COVID deaths by state.



Horizontal axis: Change in high-propensity Business Applications during week 12-15, 2020, relative to the same weeks in 2019, by US State. Source: Business Formation Statistics. Vertical axis: total number of COVID related deaths in the US. Source: Centers for Disease Control and Prevention. Data were downloaded on April 17, 2020.

2.1 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. Figure 1 plots state-level data on COVID deaths versus the number of (high-propensity) business applications, a strong 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).

Figure 1 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.

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 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 $s_{a,t} = e_{a,t}/n_{a,t}$.[2] 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.[3] 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

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

[3] 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.

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.

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

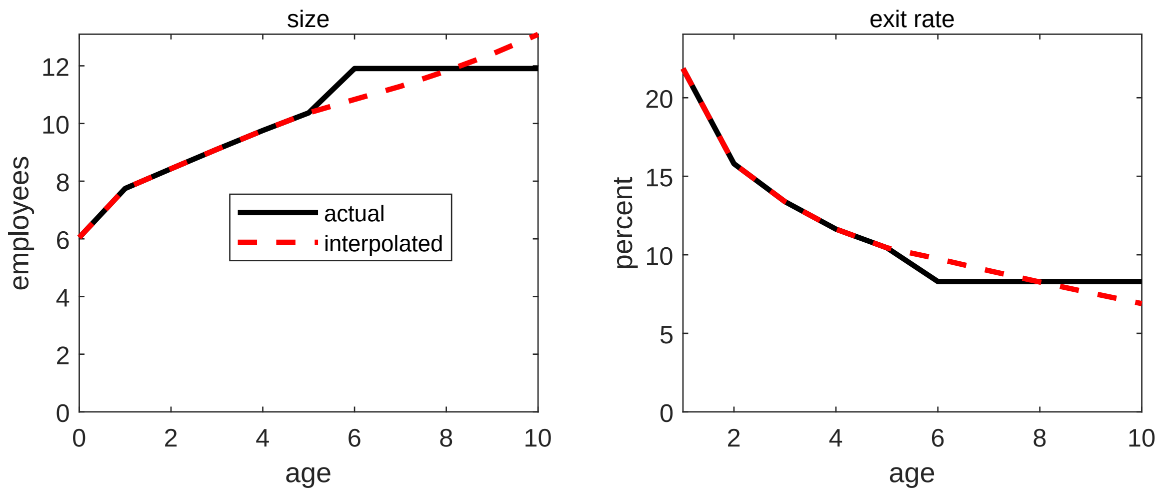
$$\left| s_{6-10,t} - \sum_{a=6}^{10} \left(\frac{n_{a,t}}{\sum_{a=6}^{10} n_{a,t}} s_{a,t} \right) \right|.$$

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

Figure 2: Actual and interpolated data



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

averages:

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

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

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

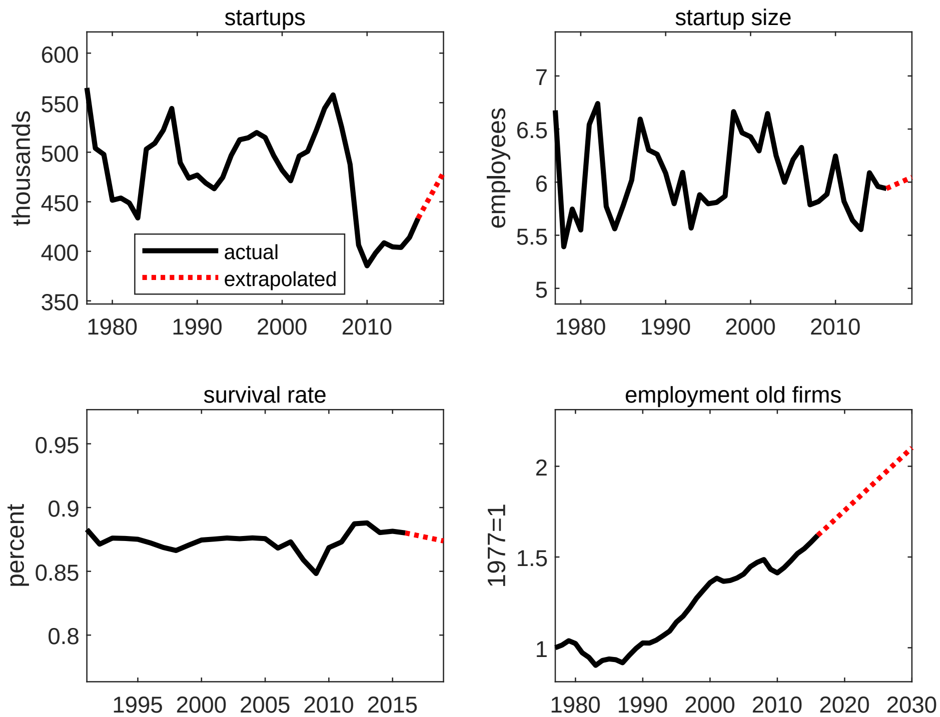
for $\tau = 1, 2, 3$ and $a = 1, 2, ..., 10$, and where $\overline{x}_a$, $\overline{s}_a$ and $\overline{n}_0$ denote the 1977 to 2016 averages of age-specific exit rates, firm sizes and the number of startups, respectively.[4] Using the above, we can then recover the number of firms for the ages of 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

[4] 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.

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.

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.[5] 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.[6] 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.[7] 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

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

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

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

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.[8] 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

[8]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 $\Psi \equiv \frac{1}{1-\kappa\epsilon_{nw}} \in (0,1)$, 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.[9] 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 (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

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

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.[10] 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 order to obtain the change in the growth potential of startups.[11]

4 Results

4.1 Baseline scenario

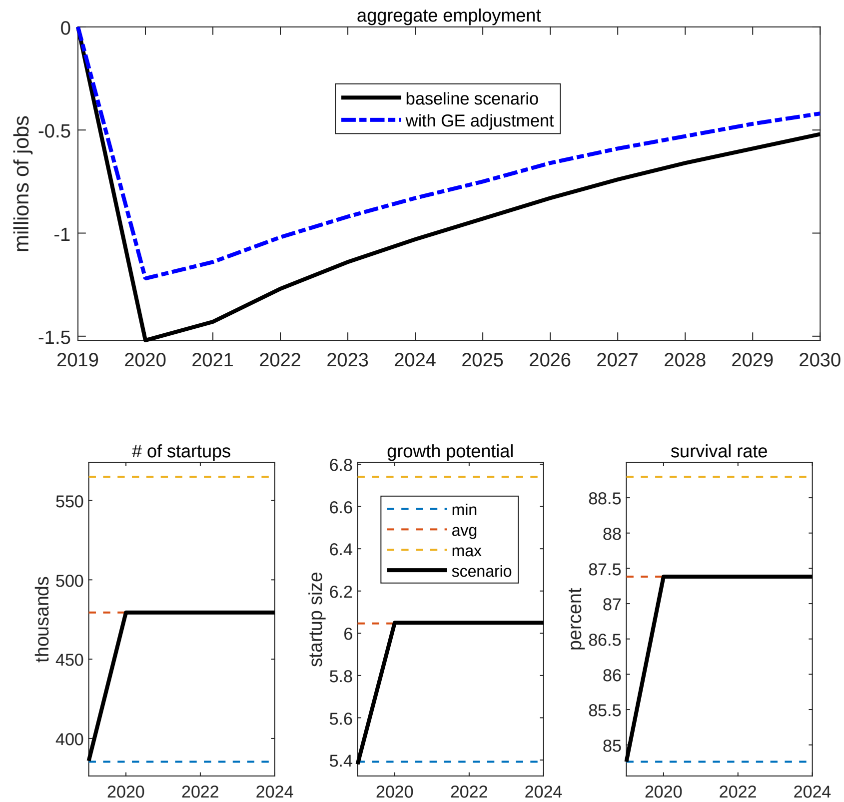
At this point, we do not know whether the current contraction will be short-lived or develop into a full-blown recession. Therefore, we take a scenario-based approach. Based on the early indicator discussed earlier, we select as a baseline scenario a strong but short-lived contraction. Specifically, 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. 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.

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

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

[11] 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.

Figure 4: Baseline scenario in the calculator



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

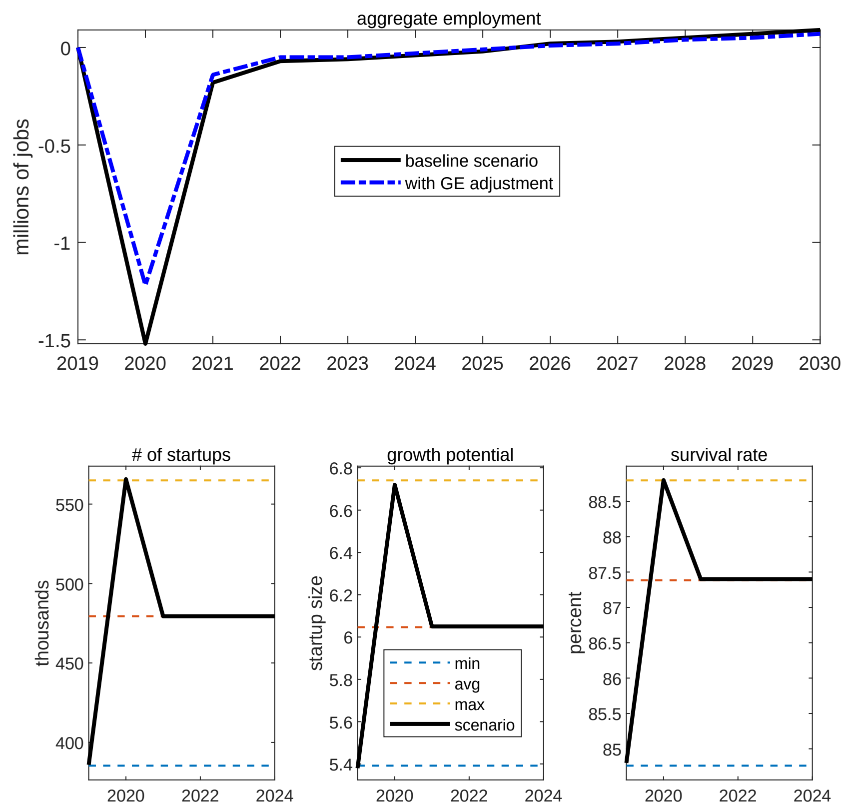
percent of aggregate employment.

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 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

Figure 5: Bounceback scenario in the calculator



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

will be followed by a "bounceback", which is also allowed for in the calculator. Figure 5 shows a scenario in which one year after the pandemic, all three margins reach 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-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.

5 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. 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.[12] 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.

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 to come up with new ideas and new ways of running businesses, which could foster growth in the long run.

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

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