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COVID-19 and SME Failures

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Abstract

We estimate the impact of the COVID-19 crisis on business failures among small and medium size enterprises (SMEs) in seventeen countries using a large representative firm-level database. We use a simple model of firm cost-minimization and measure each firm's liquidity shortfall during and after COVID-19. Our framework allows for a rich combination of sectoral and aggregate supply, productivity, and demand shocks. We estimate a large increase in the failure rate of SMEs under COVID-19 of nearly 9 percentage points, absent government support. Accommodation & Food Services, Arts, Entertainment & Recreation, Education, and Other Services are among the most affected sectors. The jobs at risk due to COVID-19 related SME business failures represent 3.1 percent of private sector employment. Despite the large impact on business failures and employment, we estimate only moderate effects on the financial sector: the share of Non Performing Loans on bank balance sheets would increase by up to 11 percentage points, representing 0.3 percent of banks' assets and resulting in a 0.75 percentage point decline in the common equity Tier-1 capital ratio. We evaluate the cost and effectiveness of various policy interventions. The fiscal cost of an intervention that narrowly targets at risk firms can be modest (0.54% of GDP). However, at a similar level of effectiveness, non-targeted subsidies can be substantially more expensive (1.82% of GDP). Our results have important implications for the severity of the COVID-19 recession, the design of policies, and the speed of the recovery.

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1 Introduction

The COVID-19 economic shock is unprecedented both in its complexity and severity. Nationwide lockdowns, in conjunction with behavioral changes due to the fear of the pandemic, not only caused disruptions in production, but also led to the largest collapse in demand for firms' output since the Great Depression. While revenues plummet, businesses must still meet their financial obligations to creditors, suppliers, and cover their operating costs. Given the global nature of the crisis, its severity, and the uncertainty surrounding the recovery, many businesses, especially the small firms that lack collateral, may not be able to secure fresh funding to tide themselves over until business conditions stabilize. The fear is that a large number of businesses will fail.

In this paper, we attempt to estimate the impact of the COVID-19 shock on business failures, with a focus on small and medium-sized enterprises (SMEs). In the European Union SMEs, consisting of firms with less than 250 employees, account for a striking 99.8 percent of all employer firms, 65 percent of private sector employment and 54 percent of private sector gross output.[1] Despite their importance, SMEs are exposed to a major vulnerability – they are critically dependent on debt, especially bank loans, for financing. Under normal circumstances, typical liquidity shortages can be managed via short-term loans or working capital without endangering the survival of the business.

During a crisis such as COVID-19, SMEs' dependence on bank financing and the inability to raise other sources of funds at short notice can turn a liquidity shortage into a solvency problem. This is a primary concern for policymakers everywhere. Should a wave of SME failures occur, the efforts to contain the economic consequences of the pandemic will have failed – the workers currently on temporary layoff or furloughed will instead become unemployed; banks will experience large losses on their C&I loan book; and the prospect of a financial crisis will increase significantly, with an increase in the associated fiscal costs. Public support to address these SMEs' liquidity shortages is thus essential to ensure a smooth recovery of the economy. Our approach allows us to estimate the impact of various policy proposals on the rate of business failures, and to quantify their fiscal costs.

To do this, we construct a model-based estimate of a firm's cash flow under COVID-19. Our analysis favors tractability. We begin with the simple partial equilibrium model of a firm's short-run cost-minimization problem when faced with a rich combination of sectoral and aggregate, supply and demand shocks. The total demand for a firm's output in each sector is affected by both an aggregate and a sectoral demand shock. The former captures the size of

[1]These statistics are derived from EUROSTAT's Structural Business Statistics. The corresponding numbers for the US SMEs are 99.8 percent, 50 and 46 percent respectively. The US definition of an SME is a firm with less than 500 employee. See www.sba.gov.

the slowdown in aggregate expenditures due to COVID-19, which we take as an input. It affects all firms proportionately. The latter reflects the change in relative demand in that sector that occurs as a result of adjustments by households and government policies. We distinguish between essential and non-essential sectors. As long as the virus remains a significant risk, the demand for socially intensive non-essential activities (e.g. sport events, concerts, restaurants, travel) declines relative to other sectors. In addition, the government may mandate the closure of certain activities. By contrast, the relative demand for socially non-intensive or essential goods rises during the same period.

On the supply side, we also make a distinction between essential and non-essential sectors. Essential sectors are unconstrained but may have to adapt their physical layout to enforce health rules. Non-essential sectors, by contrast, may be forced to send part of their workforce home during a lockdown. Depending on job requirements and skills, some of these workers may be able to work remotely, while others are effectively laid-off, either temporarily or permanently. In addition to this labor supply constraint, we allow for the productivity of remote and on-site workers to decline during the confinement, as they must adapt to their new environment.

We consider an environment where prices are fixed, and output is demand-determined. Each firm adjusts variable inputs to meet demand, subject to the labor supply constraint. From the solution to this cost-minimization problem, we construct a measure of the firm's projected cash-flow under COVID-19, either at a weekly or annual frequency. A firm experiences a liquidity shortfall if available cash and projected cash-flow are insufficient to cover fixed costs, taxes and financial expenses. We map the model to firm-level data using the latest version of the ORBIS global dataset.[2] We limit our analysis to the following subset of countries with good data coverage: Belgium, Czech Republic, Finland, France, Germany, Greece, Hungary, Italy, Japan, Korea, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, and the United Kingdom.[3]

Our approach has the advantage of being simple and easily mapped into available firm-level data. It suffers, however, from a number of shortcomings. First, our analysis is in partial equilibrium. We do not consider the implications of various policies on aggregate activity and how this might feed-back into the rate of business failures. A possible interpretation is that we focus on the initial impact of the COVID-19 crisis. But we acknowledge that general equilibrium considerations are likely to be important. Second, and related, we ignore input-output linkages. As many recent contributions have emphasized, input-output linkages induce significant amplification of COVID related output losses (Baqaee and Farhi, 2020a; Barrot, Grassi

[2]The firm level balance sheet data is reported with a two year lag. In the current draft we use 2017 as the benchmark. As 2018 data becomes available, we will update our results.

[3]In all but Germany, Japan, Korea, and the United Kingdom our analysis data cover over 40% of country gross output.

and Sauvagnat, 2020; Çakmaklı, Demiralp, Kalemli-Özcan, Yesiltas and Yildirim, 2020)x. Some sectors and firms are more central than others, and supporting those may be much more important than blanket policies. Third, our approach is static and keeps prices unchanged. Reality is more complex, with evidence of some upwards price adjustment for some goods and disagreement as to whether overall inflation is moving upwards or downwards (Jaravel and O'Connell, forth.; Cavallo, 2020; Shapiro et al., 2020). The data requirements needed to take into account price and capital adjustments would be much greater. There as well, we err on the side of simplicity. Fourth, without credit-registry data, we have very limited information on which firms may have immediate access to loans or draw on credit lines. For instance, although ORBIS balance sheet data provides data on the stock of short and long term debt, it does not contain information on undrawn credit lines. Fifth, our analysis focuses on liquidity, not solvency. A complementary approach, followed for instance by Carletti, Oliviero, Pagano, Pelizzon and Subrahmanyam (2020) would be to estimate equity shortfalls and focus on insolvency among large firms. To defend our approach, we note that the focus of our analysis is on SMEs, where book-value equity may be severely mis-measured, especially for illiquid and unlisted businesses.

We assume that the COVID-19 shock hits in week 9 of the year (beginning of March 2020) and that the subsequent lockdown and stringent social distancing period lasts 8 weeks, which coincides with the lockdown period imposed in many countries.[4] During these 8 weeks, the economy is affected by the sectoral and aggregate supply and demand shocks described above. After the lockdown ends, sectoral supply and productivity shocks return to their pre-COVID levels, while aggregate demand evolves according to IMF quarterly projections and sectoral relative demand reverts back to normal at a quarterly rate of 0.5. We consider the most stringent financing conditions for our baseline analysis, so as to obtain an upper bound on the rate of business failure induced by COVID-19. To do so, we evaluate our illiquidity condition week by week throughout the year. This imposes that firms cannot borrow against future within-year cashflow.

Across all countries in the sample, we estimate a quasi-doubling of business failures due to COVID-19: the non-COVID bankruptcy rate of 9.4 percent rises to 18.2 percent under COVID-19, an 8.8 percentage point increase. We find a great deal of sectoral heterogeneity in bankruptcy rates, with customer-oriented sectors most affected, including Accommodation & Food Service, Arts, Entertainment & Recreation, and Education. We show that the key drivers of this heterogeneity are differences in sector-specific demand and supply shocks and their interaction, rather than differences in aggregate demand. Differences in sectoral shocks, coupled with differences in sectoral composition and financial vulnerability of firms at the onset

[4]For a discussion of lockdown policies and length see "Coronavirus: How lockdown is being lifted across Europe." *BBC News, July 2, 2020.*

of the crisis, result in a high degree of cross-country heterogeneity in bankruptcy rates, with increases in bankruptcy rates ranging from 12.8 percentage points in Italy to 5.4 percentage points in the Czech Republic.

In addition to the direct effect failing businesses have on the economy through the loss of output and jobs, they also pose a risk to the banking sector through the rise in non-performing loans (NPLs). We estimate that the fraction of non-performing loans could increase from 2.3 percentage points in Belgium to 10 percentage points in Italy. On average, the increase in non-performing loans of SMEs puts 0.3 percent of banks' assets and 5.8 percent of Tier-1 capital at risk and results in a 0.75 percent decline in the common equity Tier-1 (CET1) capital ratio to risk-weighted assets. To put matters in perspective, the the European Banking Authority (EBA) 2018 EU-wide stress tests considered an adverse scenario with a decline in the CET1 capital ratio of around 4 percentage points.[5] With initial CET1 ratio around 14.7 percent, we conclude that the impact of SME business failures due to COVID-19 on the health of the financial sector is likely to remain modest.

Our baseline estimates are designed to be as stringent as possible: they assume that illiquidity at any point in time in 2020 pushes small businesses into insolvency. This assumes that businesses have no access to credit markets and that bankruptcy courts are unable to preserve viable concerns. It also ignores any policy governments implemented during the pandemic to support the business sector.[6] Governments, however, have not been sitting idly. Broadly defined, two types of measures have been implemented. Some measures, such as tax deferrals, direct cash transfers or interest free loans, are designed to provide temporary liquidity support to businesses. Others, such as government guaranteed bank loans and equity-like injections, improve solvency. The combined effect of these policies can significantly alleviate the direct hit on firms' cash flows.[7] We use our framework to explore the cost and effectiveness of various government interventions. First, we consider policies that provide the exact amount of relief either to *all* failing businesses, or targeted policies for at-risk firms who were viable and would have survived in the absence of COVID-19. While these policies are informationally extremely intensive and may be hard to implement in practice, they are also extremely cost-efficient: at a cost of 0.54 percent of GDP, the failure rate would decline by 8.6 percentage points, back to its pre-COVID level. Such a policy would save 3.1 percent of employment and 0.67 percent of GDP in labor costs. This finding illustrates that properly targeted policies can be extremely efficient at providing business relief, at only modest fiscal cost.

[5] See the EBA's 2018 EU-wide Stress Tests.

[6] The macroeconomic impact of some of these policies may be incorporated into the IMF projections we use to forecast *aggregate* economic activity. It is beyond the scope of our paper to estimate what counterfactual aggregate demand would have been in the absence of any policy intervention.

[7] For instance preliminary estimates from the French Treasury find that the measures implemented by the French government absorbed 95% of the initial shock to cash flow. See Benassy-Quéré (2020).

We do recognize, however, that such targeted interventions require much more granular information than fiscal authorities typically possess. We then turn to two other sets of policies: waiving financial expenses and firm subsidies. Waiving financial expenses has been mentioned as a possible form of relief for businesses. According to OECD (2020), 25 OECD countries are employing such policies. We find that, while the fiscal cost of waiving financial expenses for the duration of an eight-week lockdown would be quite low, at 0.26 percent of GDP, this policy would also have very minimal effect on business failures, reducing the bankruptcy rate by only 0.47 percentage points and saving only 0.2 percent of jobs. The modest impact stems from the fact that the drop in cash flow due to COVID-19 typically vastly exceeds financial expenses.

We also consider a direct firm subsidy, lasting for a fixed duration. Such policies have been implemented in some countries. France, for example, has set up a "Solidarity Fund" for very small businesses with up to 10 employees. These firms receive a one-off direct transfer whose amount varies between 1500-3000 Euros. In Germany, firms with up to 10 employees that declare a significant liquidity shortfall can receive up to 15,000 Euros.[8] To examine these type of policies, we analyze the effect of a subsidy equal to 100% of the pre-COVID wage bill for the duration of the lockdown (8 weeks), thus representing $8/52 = 15.4$ percent of the firm's pre-COVID annual wage bill. We find that such a policy can provide significant relief, with a reduction of 6.61 percentage points in the bankruptcy rate. At a fiscal cost of 1.82 percent of GDP, this would save almost as many jobs (2.96 percent, and 0.66 percent of GDP in labor income) as the efficient targeted policy. Such a policy, however, suffers from two drawbacks. First, at a cost of 1.82 percent of GDP, it is more than three times as costly as the efficient targeted policy. Second, it may provide support to firms that would have failed regardless of COVID-19 or that don't need it. To explore this question further, we decompose SMEs into three groups: 'survivor' firms that don't need support to weather the COVID-19 shock; 'viable' firms that would survive in normal times, but fail under COVID-19; and 'ghost' firms that would fail regardless of COVID-19. The efficient targeted intervention only provides relief to the group of 'viable' firms. By contrast, the direct firm subsidy indexed to the wage bill directs only 0.18 percent of GDP (out of 1.82 percent) to 'viable' firms, while 1.48 percent of GDP is wasted on 'survivor' firms that don't need it, and another 0.14 percent of GDP goes to 'ghost' firms that will fail when support ends. Moreover, while the policy in the aggregate preserves as many jobs (2.96 percent), only 2.17 percent of the jobs saved are in 'viable' firms while 0.79 percent of jobs are in 'ghost' firms. Our decomposition highlights the importance of proper targeting of policies and the trade-off between preserving 'viable' vs. 'ghost' firms, a point explored also by Barrero, Bloom and Davis (2020).

We consider a number of additional extensions. At the heart of our analysis is a tension

[8] For details for each country, see the IMF Policy Tracker.

between the desired labor a firm wishes to employ and the labor supply constraint it faces because of COVID-19. When desired labor exceeds available labor, the firm will – to the extent possible – try to find a substitute for workers, which will result in rising variable costs and a drain on cash-flows. This situation can arise either because the firm faces increased demand, or because the decline in labor supply exceeds that of labor demand. Some of the business failures in our baseline estimate result from the efforts firms make to meet the higher demand they face in this constrained environment. While it makes sense that firms' variable costs rise as labor is constrained in the short run, it also makes sense that firms would rather shut down than produce, if the latter would result in lower cash flows. We implement this extension by allowing firms to *'mothball'* for the duration of the lockdown. As in Bresnahan and Raff (1991), a mothballed firm is only responsible for its fixed costs. In a second extension, we evaluate the business failure condition at the end of the calendar year, instead of week-by-week. This is equivalent to allowing firms to smooth cash-flow over the calendar year by borrowing. A firm with negative cash flow in March-April may be able to recover if cash-flows are sufficiently positive in the latter part of the year. We interpret this extension as capturing the effect of loan guarantees on short term loans. These two extensions significantly reduce the increase in the rate of business failures, from 8.63 percentage points to 7.65 percentage points when we allow mothballing, and 5.48 percentage points when both mothballing and short-term credit are allowed.

Literature Review

The literature on the economic impact of the COVID-19 pandemic is in a rapid state of expansion. Our study connects with a number of important strands. First, a number of papers such as Dingel and Neiman (2020); Mongey, Pilossoph and Weinberg (2020); Coibion, Gorodnichenko and Weber (2020) explore the impact of COVID-19 on labor markets. Like Dingel and Neiman (2020), we use data from the Occupational Information Network (O*NET) to inform the model about sectoral supply and demand shocks. Second, some papers such as Goolsbee and Syverson (2020); Chetty, Friedman, Hendren, Stepner and Team (2020); Cavallo (2020); Cox, Ganong, Noel, Vavra, Wong, Farrell and Greig (2020) use real-time data to understand the impact of and recovery from COVID-19. Third, some papers such as Baqaee and Farhi (2020a,b); Barrot et al. (2020); Woodford (2020); Gottlieb, Grobovsek, Poschke and Saltiel (2020), explore the importance of networks and linkages for sectoral shocks and their aggregate consequences. Fourth, papers such as Barrero et al. (2020); Guerrieri, Lorenzoni, Straub and Werning (2020); Krueger, Uhlig and Xie (2020), explore the distinction between the demand and supply component of the COVID-19 shock, and the sectoral reallocation it induces. More closely related with our exercise, a number of papers also explore the consequences of COVID-19 for business failures (Demmou, Franco, Sara and Dlugosch, 2020; Carletti et al., 2020; Acharya and Steffen, 2020; Schivardi and Romano, 2020; Guerini, Nesta, Ragot and Schiavo, 2020). Unlike our approach, these papers do not rely on a structural model of the firm and often consider a simple empirical rule to project cash-flow under COVID-19.[9] Finally, some papers such as Granja, Makridis, Yannelis and Zwick (2020); Elenev, Landvoigt and Van Nieuwerburgh (2020); Core and De Marco (2020) evaluate the targeting and effectiveness of small business support programs like the PPP in the U.S.

2 A Simple Theoretical Framework

The objective of our empirical exercise is to estimate the impact of the COVID-19 crisis on SMEs' failures, first under a baseline, then under various scenarios and later incorporate the role of support policies. The COVID-19 crisis is a complex and unusual shock to the economy that combines elements of supply, demand, and productivity shocks. On the supply side, labor inputs are reduced in many sectors, as a result of policies that force workers to stay home. On the demand side, final and intermediate demand for firms' output may change because of COVID-19. For instance, there may be less demand for restaurants, concerts, and retail shops. Aggregate demand may decrease as uncertainty increases households' precautionary savings and businesses shelve investment projects. In addition, labor productivity may decline, at least in the short run, as businesses are forced to space workers further apart, or as workers transition to off-site work.

We present a general framework that accommodates these different dimensions of the COVID-19 shock and allows us to estimate the impact on a firm's cash flows. Our approach focuses on first-round effects, insofar as we do not estimate the general equilibrium impact of the shock, nor do we incorporate the input-output structure that could well amplify the shock.

2.1 Supply

The economy consists of $\mathcal{S}$ sectors. In each sector $s \in \mathcal{S}$ there is a mass $\mathcal{N}_s$ of firms, indexed by i. Throughout the analysis, we consider the mass of firms in each sector as given. We assume that each firm i in sector s produces according to the following sector-specific production function:

$$y_{is} = z_{is} f_s(k_{is}, A_s n_{is}, m_{is}). \tag{1}$$

[9]The exception is Guerini et al. (2020). That paper borrows from our methodology. It uses a more comprehensive database of firms, including micro-firms, but limited to France.

In Eq. (1), y_{is} denotes gross output, k_{is} represents any fixed factor, including capital, entrepreneurial talent etc.., n_{is} is the labor input, while m_{is} denotes other variable inputs such as materials or intermediate inputs, including output produced by other firms in the same or other sectors. A_s is a sector-specific labor-augmenting productivity so that $A_s n_{is}$ is the effective labor supply in firm i, while z_{is} is a firm-specific productivity. Because our analysis is essentially static, we ignore time subscripts. We assume that, regardless of fixed factors, firms need both labor and intermediate goods to produce, so that $f_s(.,0,.) = f_s(.,.,0) = 0$.

We define the corresponding prices: p_{is} is the price of output of firm i in sector s, w_s denotes the wage rate per effective unit of labor, r_s is the user cost for fixed factors and p_{ms} is the price of other variable inputs. Factor prices only vary at the sector level. Prices, both for factors and output are assumed constant in the short run, perhaps because of nominal rigidities.[10]

2.2 Demand

Each firm within a sector sells a differentiated variety. We assume a nested CES demand structure, for both final and intermediate uses, of the form:

$$D = \left[\sum_s \mathcal{N}_s \xi_s D_s^{(\eta-1)/\eta} \right]^{\eta/(\eta-1)}. \tag{2}$$

In Eq. (2), D denotes aggregate demand, D_s is sectoral demand, ξ_s is a sectoral demand shifter, and η is the elasticity of substitution between sectors. For simplicity, we assume that sectors are symmetric before the COVID-19 shock, and set $\mathcal{N}_s \xi_s = 1, \forall s$. We denote ξ_s' the sectoral demand shifter during COVID-19. For many sectors, we expect $\xi_s' < 1$, i.e. sectoral demand falls. This can happen because final demand declines. For instance, the demand for restaurants declines as people are concerned about enclosed spaces. This can happen also because downstream industries are negatively affected and their demand for intermediate inputs declines. For instance, the shutdown of restaurants and open air markets may reduce the demand for fresh produce from local growers.[11] For some sectors, demand during the COVID-19 shock may increase, i.e. $\xi_s' > 1$. For instance, the demand for some online services or home delivery may increase during confinement.

[10] This is an important simplification. See Jaravel and O'Connell (forth.); Cavallo (2020); Baqaee and Farhi (2020b) for evidence that sectoral prices are not constant.

[11] Such input-output linkages can be important sources of amplification (Baqaee and Farhi, 2020b; Barrot et al., 2020), especially in open economies (Çakmaklıet al., 2020). We leave a more formal exploration of their impact to future work.

In turn, sectoral demands D_s satisfy:

$$D_s = \left(\frac{1}{\mathcal{N}_s} \int_0^{\mathcal{N}_s} d_{is}^{(\rho_s - 1)/\rho_s} \mathrm{d}i \right)^{\rho_s/(\rho_s - 1)}, \tag{3}$$

where ρ_s is the sector-specific elasticity of substitution between varieties.

From Eqs. (2) and (3), the demand for variety i in sector s is given by Eq. (4):

$$d_{is} = \xi_s^{\eta} \left(\frac{p_{is}}{P_s} \right)^{-\rho_s} \left(\frac{P_s}{P} \right)^{-\eta} D, \tag{4}$$

where P_s denotes the average sectoral price index per unit of expenditure, and P the overall price level. They satisfy:[12]

$$P_s = \left(\frac{1}{\mathcal{N}_s} \int_0^{\mathcal{N}_s} p_{is}^{1-\rho_s} \mathrm{d}i \right)^{1/(1-\rho_s)} \quad ; \quad P = \left(\sum_s \xi_s^{\eta} \mathcal{N}_s P_s^{1-\eta} \right)^{1/(1-\eta)}. \tag{5}$$

Because we assume that the price of individual varieties p_{is} and the mass of firms $\mathcal{N}_s$ are constant, sectoral price indices P_s given in Eq. (5) are also constant. The aggregate price index P, however, can change because of the demand shifters ξ_s. We denote with a prime the value of variables during COVID-19 and with a 'hat' the ratio of variables between normal and COVID-19 times, e.g. $\hat{\xi}_s \equiv \xi_s'/\xi_s$. From Eq. (4), we can use exact-hat algebra to express the relative change in demand from normal to COVID-19 times as:

$$\hat{d}_{is} = \hat{\xi}_s^{\eta} \hat{P}^{\eta-1} \widehat{PD}. \tag{6}$$

Under the assumption that the pre-COVID-19 equilibrium is symmetric, $P_s\mathcal{N}_s = P\mathcal{S}^{1/(\eta-1)}, \forall s$, and we can write:[13]

$$\hat{P}^{\eta-1} = \left(\frac{P'}{P} \right)^{\eta-1} = \left(\frac{\sum_s \hat{\xi}_s^{\eta} (P_s\mathcal{N}_s)^{1-\eta}}{P^{1-\eta}} \right)^{-1} = \left(\frac{1}{\mathcal{S}} \sum_s \hat{\xi}_s^{\eta} \right)^{-1}.$$

Putting the two previous equations together, we obtain a very simple expression for the

[12] P_s is a sectoral price index per unit of expenditure, so that the usual Fischer-ideal price index is given by $\mathcal{N}_s P_s$ and aggregate expenditure equals $\sum_s \mathcal{N}_s P_s D_s$.

[13] Recall that we assume $\xi_s \mathcal{N}_s = 1, \forall s$ in the symmetric equilibrium.

change in demand under COVID-19:

$$\hat{d}_{is} = \frac{\hat{\xi}_s^{\eta}}{\sum_\sigma \hat{\xi}_\sigma^{\eta} / \mathcal{S}} \widehat{PD}. \tag{7}$$

Eq. (7) indicates that the total change in sectoral demand is a function of two drivers: a relative and an aggregate one. First, sector-specific demand shocks $\hat{\xi}_s$ reallocate a given aggregate expenditure *across* sectors. Importantly, it is the relative pattern of sector-specific demand shocks that matters, not their absolute level. For instance, suppose there is no change in aggregate demand so $\widehat{PD} = 1$ and the economy consists of two sectors with $\hat{\xi}_s < \hat{\xi}_{s'}$, then $\hat{d}_s < 1 < \hat{d}_{s'}$: one sector is in recession, and the other must be in a boom. The elasticity of substitution across sectors η mediates the sectoral demand shocks $\hat{\xi}$: when goods are very substitutable (high η), small sectoral demand shocks lead to large demand responses. Conversely when demand is very inelastic (low η) demand responds is more similar across sectors (in the limit of $\eta = 0$, we obtain $\hat{d} = \widehat{PD}$). Second, for a given pattern of sector-specific demand shocks, all sectors respond proportionately to changes in aggregate demand. For instance, if all sectors are affected uniformly so that $\hat{\xi}_s = \hat{\xi}, \forall s$, then Eq. (7) indicates that total demand in all sectors is affected uniformly with $\hat{d}_{is} = \widehat{PD}$. For future reference, we define $\tilde{\xi}_s^{\eta} = \hat{\xi}_s^{\eta} / (\sum_\sigma \hat{\xi}_\sigma^{\eta} / \mathcal{S})$. $\tilde{\xi}_s^{\eta}$ succinctly summarizes the impact of sector-specific demand shocks on total demand and satisfies $\sum_s \tilde{\xi}_s^{\eta} / \mathcal{S} = 1$. With this notation, we can rewrite total demand as:

$$\hat{d}_s = \tilde{\xi}_s^{\eta} \widehat{PD}. \tag{8}$$

2.3 Modeling the COVID-19 Shock

We model the COVID-19 shock as a flexible combination of supply, productivity, and demand shocks at the sectoral and aggregate level.

First, on the *supply* side, we assume that fixed factors are immobile. Moreover, only a fraction of workers are allowed to work in each sector. This approach follows Mongey et al. (2020) and Dingel and Neiman (2020). Specifically, consider firm i with pre-COVID employment level n_{is}. We assume that this firm can only employ up to $x_s' n_{is}$ workers during the COVID-19 shock. Of course, the firm may decide to employ even fewer workers – for instance if demand for its goods declines significantly. Thus, COVID-19 introduces the following *labor supply constraint* in the firm cost-minimization problem:

$$n_{is}' \leq x_s' n_{is}, \tag{9}$$

where n'_{is} is the level of employment chosen by the firm during COVID-19.

It is natural to consider that x'_s varies by sector. For instance, for some essential sectors we may have $x'_s = \infty$, implying that Eq. (9) never binds. This captures the intuition that workers in these sectors are not sent home.[14] For non-essential sectors, we expect $x'_s \leq 1$. This captures the idea that a firm may retain workers who can work from home as well as a fraction of the current workers who cannot work from home, but may have to lay-off temporarily or permanently any remaining workers. For instance, a university may be able to shift all its courses online, so that $x'_s \approx 1$. By contrast, a construction company may be able to shift only part of its workers online (project managers, accountants, payroll, HR...) and lay-off temporarily the construction workers. In that case $x'_s < 1$.

In addition, we allow sectoral productivity A_s to change. This reflects the fact that, in the short term, workers who work remotely may perform their duties less efficiently. Some workers may face adjustment costs, others may face additional constraints such as taking care of dependents such as young children. Productivity may decrease even for on-site workers, since COVID-19 introduces additional constraints in the spatial organization of production. We denote A'_s the labor productivity in sector s during COVID and expect $A'_s/A_s \leq 1$.

On the *demand* side, we allow for both *sectoral* and *aggregate* demand shocks. Relative sector-specific demand shocks are represented by changes in the sectoral demand shifter from ξ_s to ξ'_s. These relative sector-specific demand shocks may represent adjustments in final or intermediate demand patterns as discussed previously. They may also reflect changes in behavior or in policy. For instance, most households may choose to stay away from restaurants during COVID-19, regardless of official instructions (see e.g. Goolsbee and Syverson (2020)). By contrast, some sectors may be shut down because of official policy. For instance, the government may implement a shelter-in-place policy which would imply $\xi'_s = 0$ for restaurants, beauty salons and gyms. Our approach encompasses equally well changes in demand that arise from either source. As discussed above, the set of sector-specific demand shifters $\{\xi'_s\}$ simply redistributes total demand for a given level of aggregate expenditures.

Our approach also allows us to model aggregate demand shocks, measured as the shift in aggregate nominal gross expenditures $\widehat{PD}$. In this paper, we take these changes in aggregate expenditures as exogenous and focus on the implications for business failures. A more ambitious agenda – left for future work – would loop back and derive the change in aggregate demand from more primitive economic forces, taking into account the impact of business failures. We simply note that aggregate demand could change through a variety of channels. First, increased precautionary savings by households and firms may delay spending on consump-

[14]Note however, that it is possible that $x'_s < 1$, even for some essential sectors, if these sectors rely on direct contact between workers or with customers. For instance, the labor supply in the health-care sector may decline as medical personnel decides to withdraw from the labor force to limit the risk of exposure.

tion or investment. Second, as explored by Guerrieri et al. (2020), the supply shock itself could generate an even larger decline in aggregate demand, when markets are incomplete. Third, as studied by Woodford (2020) in an economy with a 'circular flow of payments,' the decline of production (and income) in some sectors of the economy has the potential to dramatically reduce aggregate demand.

We assume that the COVID-19 shock is temporary and maintain the assumption that prices of goods and factors are sticky at that horizon. We also assume that labor cannot reallocate across sectors in the short run, so workers who cannot work for their original place of employment are laid off, either temporarily or permanently. In some countries, like the U.S., these workers may have access to unemployment insurance. In others, such as Germany, the U.K. or France, the government may cover part of the wage bill, allowing the workers to be on a temporary layoff. Either way, we assume that the workers who are not actively employed by the firm are not on the firm's payroll and generate no drain on its cashflow.[15]

Because prices are sticky, firms produce the level of output that is demanded. In Section 6, we consider an extension where firms can optimally 'mothball,' i.e. to temporarily shut down, if cash flows are lower under production.

2.4 The Firm's Cost Minimization Problem

Consider the cost minimization problem of a single firm. For simplicity we omit the firm and sector indices i, s in what follows. We specialize the problem by assuming that the production function $f_s(.)$ is Cobb Douglas:

$$y = zk^{\alpha}(An)^{\beta}m^{\gamma}, \tag{10}$$

with the (sector-specific) exponents α, β and γ summing to one.[16]

The cost-minimization problem of the firm can be written as:

$$\begin{aligned} \min_{m',n'} \quad & wn' + p_m m' \\ & zk^{\alpha}(A'n')^{\beta}m'^{\gamma} \geq d' \\ & n' \leq x'n, \end{aligned} \tag{11}$$

where d' is the level of demand faced by the firm, obtained from Eq. (8). The second line indicates that, if the firm produces, it must meet the demand. The third line is the labor supply

[15]Formally, we assume that either the firm lays off $n_{is} - n'_{is}$ workers, or that it hoards them, but that the labor costs are covered by the government via short-time work programs. Either way, these workers are not working and do not affect the firm's cash flow.

[16]Because we assume that k is fixed, the relevant part of this assumption is that production exhibits decreasing returns to labor and intermediate jointly, i.e. $\beta + \gamma < 1$.

constraint. We have two cases to consider: when the labor supply constraint doesn't bind, and when it does.

2.4.1 When Labor is Not Constrained

When the labor constraint does not bind, we can solve the above program for the demand for labor and materials, both in normal times and under COVID-19. Manipulating the first-order conditions we obtain:

$$\hat{m} = \hat{n} = \hat{d}^{1/(\beta+\gamma)} \hat{A}^{-\beta/(\beta+\gamma)} = \left(\tilde{\xi}^{\eta} \widehat{PD}\right)^{1/(\beta+\gamma)} \hat{A}^{-\beta/(\beta+\gamma)} \equiv \hat{x}^{c}. \tag{12}$$

Intermediate input and labor demand increase with output demand ($\tilde{\xi}^{\eta}\widehat{PD}$) and decrease with productivity $\hat{A}$. This solution obtains as long as $\hat{n} < \hat{x}$, that is, as long as $\hat{x}^c < \hat{x}$. $\hat{x}^c$ represents the unconstrained demand for labor that arises because of the sectoral and aggregate demand shocks as well as the productivity changes. We can rewrite Eq. (12) as follows:

$$\hat{x}^{c(\beta+\gamma)} \hat{A}^{\beta} = \hat{\xi}^{\eta} \widehat{PD}.$$

The left hand side of this expression captures the *supply side* of the model – the labor supply shock as well as the productivity change. The exponent on the labor supply shock is $\beta + \gamma$ because adjustment in labor forces also an adjustment in intermediate inputs, with a total exponent $\beta + \gamma$. The right hand side captures the *demand side* of the model, i.e. the reduction in demand coming from sectoral or aggregate demand shifts. The equation tells us for which firms the demand or supply side is the binding force on employment and output. Since all the variables in this expression are defined at the sectoral level, the threshold for supply vs. demand factors as the binding forces is also defined at the sectoral level.

Variable profits for an unconstrained firm can be expressed as:

$$\pi' = pd' - wn' - p_m m' = pd\left(\tilde{\xi}^{\eta}\widehat{PD} - (s_n + s_m)\hat{x}^{c}\right), \tag{13}$$

where $s_n = wn/py$ and $s_m = p_m m/py$ denote respectively the firm's wage and material bill prior to COVID-19.[17]

[17] If the firm is behaving competitively and optimizing over its level of output prior to COVID, $s_n = \beta$ and $s_m = \gamma$, but we don't need to impose these conditions. The firm may have market power or be demand determined prior to COVID-19. We only impose cost-minimization.

2.4.2 When Labor is Constrained

When the labor constraint Eq. (9) binds, $\hat{x} < \hat{x}^c$ and we obtain, following similar steps:

$$\hat{n} = \hat{x} \quad ; \quad \hat{m} = \left(\tilde{\xi}^{\eta}\widehat{PD}\right)^{1/\gamma}(\hat{A}\hat{x})^{-\beta/\gamma} = \hat{x}^{-\beta/\gamma}\hat{x}^{c(\beta+\gamma)/\gamma}. \tag{14}$$

Compared to the unconstrained case, a binding labor supply reduces labor input and increase the use of intermediate inputs. The lower is the output elasticity of intermediates γ, the stronger is the response of intermediates when labor is constrained.

In the case of a constrained firm, variable profits are given by:

$$\pi' = pd\left(\tilde{\xi}^{\eta}\widehat{PD} - \hat{x}^c\left(s_n\left(\frac{\hat{x}}{\hat{x}^c}\right) + s_m\left(\frac{\hat{x}}{\hat{x}^c}\right)^{-\beta/\gamma}\right)\right). \tag{15}$$

Comparing this expression to Eq. (13) when labor is unconstrained, we observe that the lower use of labor tends to increase variable profits (the term $s_n\hat{x}/\hat{x}^c$ decreases since $\hat{x} < \hat{x}^c$), while the extra reliance on intermediate inputs tends to lower profits (the term $s_m(\hat{x}/\hat{x}^c)^{-\beta/\gamma}$ increases). On net and at unchanged demand, variable costs must increase when the firm is constrained. The increase in material costs is larger for firms with a relatively low output elasticity of materials (low γ) and a high output elasticity of labor (high β).

2.5 Business Failures

To evaluate business failure, we assume that firms follow a simple 'static' decision rule – they remain in business as long as their cash balances and their operating cashflow are sufficient to cover their financial expenses. Otherwise, we assume that they are forced to close. Operating cash flow of the firm is defined as:

$$CF_{is} = p_{is}d_{is} - wn_{is} - p_{ms}m_{is} - F_{is} - T_{is} = \pi_{is} - F_{is} - T_{is} \tag{16}$$

where the first term represents sales, the other two terms the wage and intermediate input bills, F_{is} represents any costs associated with fixed factors (rent, utilities, management compensation etc...), including capital costs, $r_sk_{i,s}$, and T_{is} denotes business taxes. The last expression writes operating cash flow in terms of the variable profits, minus payments to fixed factors and taxes. As long as fixed costs and taxes are not affected by COVID-19, we can difference them out by considering the change in cash-flows from CF to CF', i.e. from the observed to the predicted cash flows.[18] Since the predicted cashflows of the firms depend on whether it is labor constrained, there are two cases to consider.

- Case 1: When the labor supply does not bind ($\hat{x} > \hat{x}^c$), the change in cashflow during COVID-19 (compared to the non-COVID scenario) can be expressed using Eq. (13) as:

$$CF'_{is} - CF_{is} = p_{is} d_{is} \left[\tilde{\xi}_s^{\eta} \widehat{PD} - 1 + (s_{n,is} + s_{m,is}) \left(1 - \hat{x}_s^c\right) \right]. \tag{17}$$

- Case 2: When the labor supply binds ($\hat{x} < \hat{x}^c$), the change in cashflow under COVID-19 (compared to the non-COVID scenario) can be expressed using Eq. (15) as:

$$CF'_{is} - CF_{is} = p_{is} d_{is} \left[\tilde{\xi}_s^{\eta} \widehat{PD} - 1 + s_{n,is}(1 - \hat{x}_s) + s_{m,is} \left(1 - \hat{x}_s^{c(\beta_s + \gamma_s)/\gamma_s} \hat{x}_s^{-\beta_s/\gamma_s}\right) \right]. \tag{18}$$

We assume that the decision to close the firm occurs if there isn't enough cash, $\mathcal{Z}_{is}$, to cover operating cash flow minus financial expenses, ιL_{is}, i.e. if

$$\mathcal{Z}_{is} + CF'_{is} - \iota L_{is} < 0, \tag{19}$$

where the firm's financial expenses, ιL_{is}, are defined as interest and principal repayments. Subtracting CF_{is} from both sides, we obtain:

$$CF'_{is} - CF_{is} < \iota L_{is} - \mathcal{Z}_{is} - CF_{is}. \tag{20}$$

The term on the right hand side of Eq. (20) can be observed in our firm-level data. The term on the left hand side can be constructed using Eqs. (17) and (18).

The business failure condition Eq. (20) calls for a number of observations. First, while this rule has the advantage of simplicity it assumes that firms with a temporary cashflow shortfall cannot access credit markets and borrow against future profits. To the extent that future profits are sufficiently large, it would be optimal to do so to keep the business afloat. In other words, we are looking at situations where illiquidity turns into insolvency. In our baseline, we estimate bankruptcy rates weekly. This effectively imposes a very tight borrowing constraint: a firm that fails in week t is unable to borrow from cash flows at any later date $t' > t$ – regardless of its long term viability. In our view, the focus on liquidity shortfalls is appropriate for SMEs since the immediate danger for small businesses is that they will be forced to shut down in the short run. Our estimates directly get at this issue. In Section 6 we will instead evaluate the business failure condition at the end of the calendar year, even if the

[18] Many business taxes are paid in the following calendar year. Therefore, from a liquidity perspective the taxes a business needs to pay in 2020 were likely determined in 2019 and will not change until 2021.

length of the COVID-19 related lockdown is much shorter (8 weeks in our baseline). This will allow the firm to smooth cash flow shortages over the calendar year.

A second caveat is that we ignore the role of bankruptcy courts. In theory, as long as a business remains viable, the failure to repay creditors in the short run does not mean that it ceases to operate. Instead, business liabilities should optimally be restructured under bankruptcy proceedings. In practice, however, there is substantial variation in bankruptcy regimes across countries. The bankruptcy code may also work more efficiently for large corporations – for instance, over the years, many airlines in the U.S. have continued operating despite undergoing Chapter 11 restructuring – but it is less well suited for SMEs. Moreover, bankruptcy courts in many countries may not be able to efficiently preserve viable businesses in the middle of a pandemic if a wave of small business failures congests the courts. Our estimates should thus be interpreted as the predicted business failures in a scenario where no fresh capital is available and liquidation is the only possible outcome.

There are additional practical reasons why we focus on a liquidity criterion. First, we cannot hope to construct estimates of future revenues and costs at the firm level, which would be important for a solvency criterion. In addition, it is difficult to estimate accurately the initial equity position of SMEs since most are unlisted. In practice, this means that evaluating the equity shortfall that occurs because of COVID-19 is a difficult exercise. Second, we do not have direct information on the firms continued access to credit. There is mounting evidence that many firms responded to the very early phase of the COVID-19 crisis by borrowing (Acharya and Steffen, 2020). However, our understanding is that this was primarily relevant for large firms that increased their cash holdings by drawing upon pre-existing credit lines. Small and medium enterprises typically have more limited access to credit, and at a higher cost (Almeida and Campello, 2013; Almeida and Ippollito, 2014; Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez, 2017).

3 Taking the Model to the Data

To bring the model to the data, we need to construct empirical counterparts to the sectoral and aggregate demand shocks $\tilde{\xi}_s^{\eta}$ and $\widehat{PD}$, the sectoral labor supply $\hat{x}_s$ and productivity $\hat{A}_s$ shocks. Together with firm level factor shares $s_{n,is}, s_{m,is}$ and sales $p_{is}d_{is}$ in non-COVID times, this allows us to construct a counterfactual change in cashflows under COVID-19 according to Eqs. (17) and (18). With data on the firm's cash balances $\mathcal{Z}_{is}$, financial expenses ιL_{is} and non-COVID cashflow CF_{is}, we can then evaluate Eq. (20) to determine which businesses fail.

3.1 Firm-Level Data

We use a large firm level data set, Orbis, from BvD-Moody's. The advantage of Orbis is that BvD collects data from various sources, in particular, national business registries, and harmonizes the data into an internationally comparable format. The Orbis database covers more than 200 countries and over 200 million firms (private and publicly listed), with the longitudinal dimension and representativeness of firms varying from country to country depending on which firms are required to file information with business registries. We report the results for seventeen countries and use 2017 as our base year, as 2018 data is not yet available. The countries included are Belgium, Czech Republic, Finland, France, Germany, Greece, Hungary, Italy, Japan, Korea, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, and the United Kingdom.

As depicted in Table 1, we have good coverage of aggregate revenue for the countries in our sample, both for all firms and SMEs specifically. Our coverage ranges from 27 percent in Germany to nearly 66 percent in Finland.[19] Even after imposing additional data requirements for analysis, such as availability of intermediate costs, our data cover more than half of the aggregate revenue of SMEs for most countries – the exceptions are highlighted in grey, where we cover under 40% of aggregate revenue.[20]

The evaluate bankruptcy rates, our analysis requires data on firm revenue, wage bill, material cost, number of employees, net income, depreciation, cash stock and financial expenses.[21] Cash flow is calculated as the sum of net income and depreciation, less financial profits. Sectoral labor and material cost shares are constructed as the revenue weighted average of the firm-level wage bill over revenue and material costs over revenue at the 2-digit NACE level. The analysis focuses on private, non-financial firms.[22]

In addition to capturing a high share of aggregate revenue, Table 2 shows that firm failure

[19]To obtain coverage rates we sum up firm (and, separately, SME) revenue in Orbis by 1-digit NACE sector and merge it with 1-digit NACE sector total (and SME) revenue reported in the OECD's SDBS Business Demography Indicators. Keeping sectors covered in the Orbis and OECD data (for most countries the covered sectors are B, D, D, E, F, G, H, I, J, L, M,and N), we then aggregate the Orbis and OECD data to the country level and calculate the coverage rates for all firms and SMEs.

[20]Japan is also highlighted in grey because revenue data on SMEs is not available to evaluate coverage.

[21]We winsorize all of the level variables used for analysis at the 99.9th percentile. For a small subset of countries – Greece, Japan, Korea, and the United Kingdom – firms do not report labor and material costs separately. For these countries we use the costs of materials sold variable and divide it between labor and materials using 2-digit industry cost shares derived from the countries in the sample where labor and material costs are reported separately and country coverage of revenue exceeds 40% (Belgium, Czech Republic, Finland, France, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain).

[22]In particular, we focus on firms in NACE 1-digit sectors A, B, C, D, E, F, G, H, I, J, L, M, N, P, Q, R, S. We exclude financial and insurance activities (K), public administration and defense (O), activities of households as employers (T), and activities of extraterrestrial organizations and bodies (U). We also exclude sub-sectors 78 and 81 in the Administration (N) because they have very large labor cost shares which together with our labor constraint generates unrealistically high bankruptcy rates and cash shortfalls.

Table 1: Orbis Coverage (2017)

	% of OECD Revenue	
	(1)	(2)
	All	SMEs
Belgium	60.4	52.1
Czech Republic	63.4	62.8
Finland	66.0	68.3
France	46.3	46.3
Germany	27.2	17.7
Greece	48.0	48.1
Hungary	63.9	48.7
Italy	63.5	75.8
Japan	42.5	.
Korea	61.9	34.0
Poland	47.5	44.5
Portugal	63.2	72.9
Romania	60.6	40.0
Slovak Republic	52.0	73.2
Slovenia	49.3	61.0
Spain	58.4	69.9
United Kingdom	49.2	41.4

Notes: OECD revenue (for all firms and SMEs) in 2017 is obtained from the Structural Business Statistics Database. The SBSD provides data for a subset of sectors – for most countries the covered NACE 1-digit sectors are B, C, D, E, F, G, H, I, J, L, M, and N. For Japan, data on revenue are obtained from the Economic Census in 2015 (Orbis data are also for 2015). Only sectors covered in both the OECD (or Census) and Orbis data are used in calculating coverage statistics. To calculate coverage, Orbis revenue (for all firms and SMEs) is summed and divided by the total revenue (for all firms and SMEs) reported by OECD. The coverage rates are computed using cleaned Orbis data. Additional cleaning is done to generate the analysis data, including conditioning on variables needed to compute the bankruptcy condition. Highlighted in grey are countries where the coverage rate falls below 40% in the analysis data. Japan is also highlighted in grey because revenue data on SMEs is not available to evaluate coverage.

rates reported by the OECD in normal times are broadly in line with those obtained using Orbis data for many of the high coverage countries.[23] For most countries, business failure rates are higher than those reported by OECD. We suspect the reason for this is the fact that our failure rate calculation assume that all illiquid firms fail, not taking into account access to credit or possible debt restructuring that might allow a firm to continue operating when faced with a liquidity shortfall. Because of these differences in failure rates given by OECD and our estimation, we emphasize *changes* in the business failure rates before and after COVID-19 instead of levels.

An important feature of most economies is the over-sized contribution of SMEs to economic activity, defined as firms with less than 250 employees, play in the economy. As Fig. 1 shows, SMEs account for 53.4% of employment and over 48.9% of payroll, 50.1% of revenue, and 45.6% of total assets across our "good coverage" European countries (Belgium, Czech Re-

[23]To calculate failure rates in Orbis, we evaluate the fraction of firms that face a liquidity shortfall in 2017 (ie: the sum of their cashflow and cash is insufficient to cover financial expenses due).

Table 2: Pre-COVID Business Failure Rates

	OECD	Orbis
Belgium	3.0	8.3
Czech Republic	7.9	8.3
Finland	5.4	9.3
France	4.7	8.1
Germany	6.7	11.2
Greece	4.0	10.3
Hungary	8.7	8.9
Italy	6.7	9.7
Portugal	11.5	12.5
Romania	8.6	15.5
Slovak Republic	10.0	11.1
Slovenia	3.9	6.5
Spain	7.4	9.2
United Kingdom	13.9	11.4

Notes: Data on firm failure rates are obtained from the OECD's SDBS Business Demography Indicators. Failure rates are available for a subset of sectors – NACE 1-digit sectors B, C, D, E, F, G, H, I, J, L, M, N, P, Q, R, S. The coverage of sectors varies across countries. Only sectors available in both the OECD and Orbis data are used in calculating failure rates. Sector-level gross value added (GVA) shares in 2017 (OECD) are used for aggregation of both Orbis and OECD data to the country level (the exception is the United Kingdom where 2016 GVA is used because this is the last year in which sector level data are made available for the country). The failure rate comparison is only done for the subset of countries covered in the OECD data.

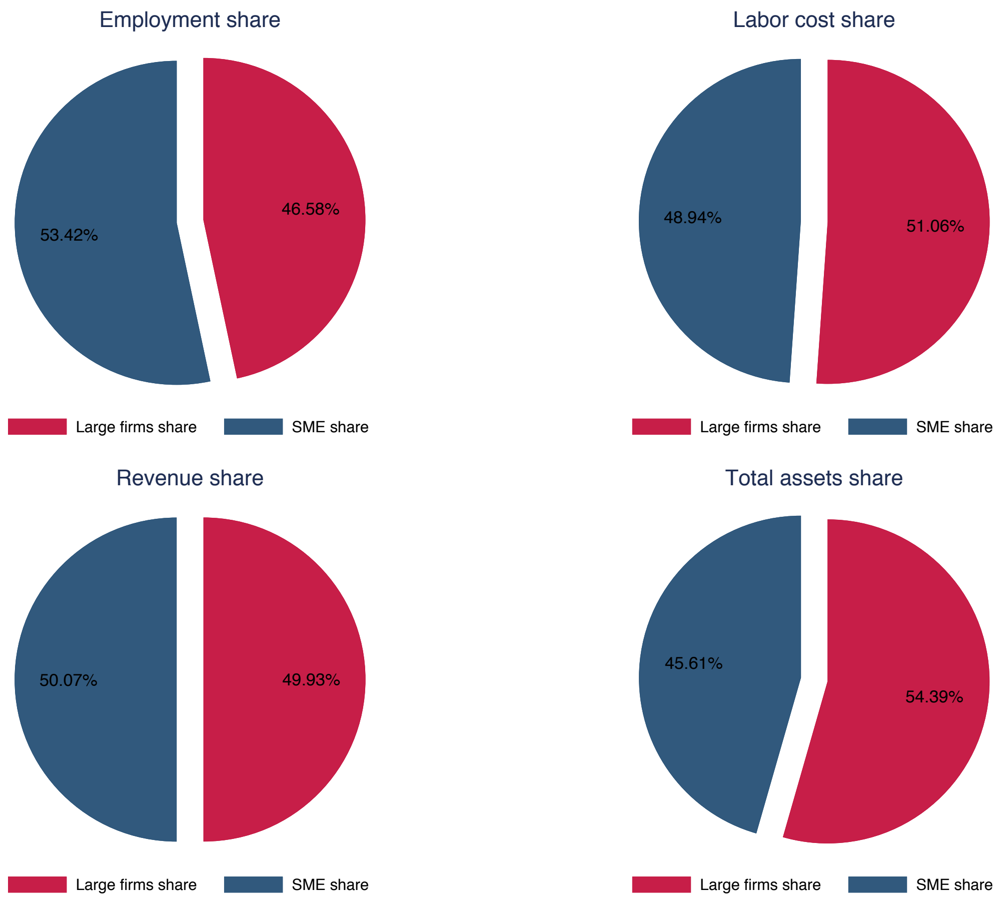
public, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain).[24] It is precisely these SMEs that are most vulnerable to the COVID-19 shock because they tend to be bank-dependent and have limited ability to draw on credit lines. Both of these features make them vulnerable to solvency problems that can follow the liquidity shortage.

3.2 Demand and Supply Shocks

In addition to firm-level data, we require information on demand, supply, and productivity shocks. As a first step, we separate sectors, at the 4-digit NACE level, into essential and non-essential sectors based on the U.S. Department of Homeland Security Guidance on the

[24]The contribution of SMEs to the aggregate economy in the official data mimics the numbers here (which are the shares in our sample) as shown in Kalemli-Özcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas (2015). The shares are based on the cleaned Orbis data and unwinsorized variables. When the variables are winsorized at the 99.9th percentile, as we do for our analysis, the SME employment share is 63.2%, labor cost share is 61.6%, revenue share is 65.9%, and total asset share is 65.9%.

Figure 1: Share of SMEs in Employment, Payroll, Revenue, and Total Assets



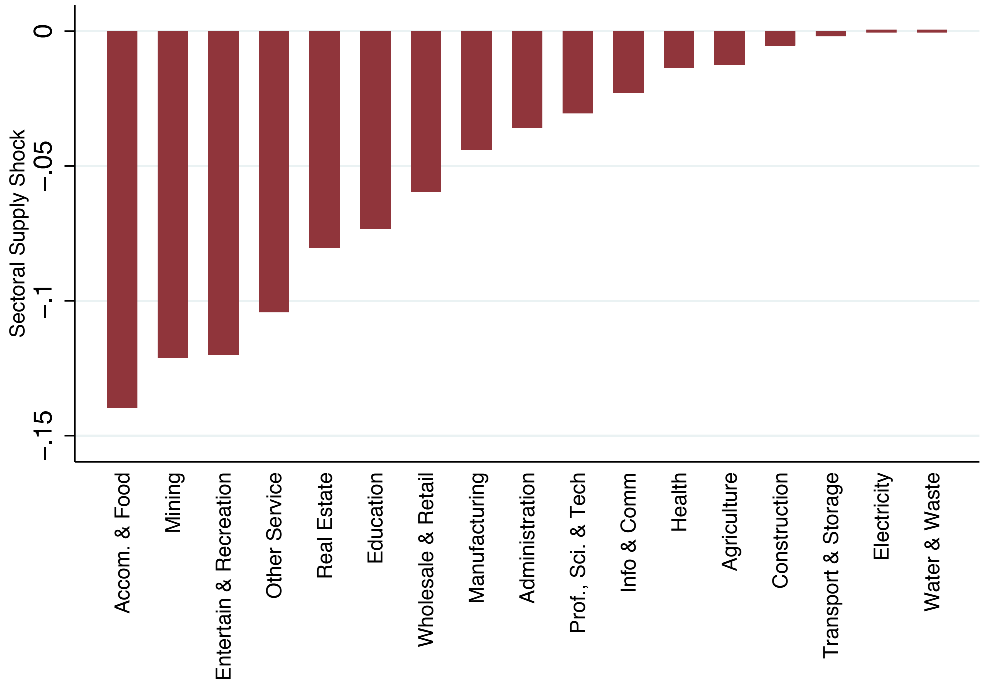
Notes: Figures depict the SME share of employment (top-left), payroll (top-right), revenue (bottom-left), and total assets (bottom-right). The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. The SME shares are first calculated at the country level and aggregated across countries using country GVA for weighting.

Essential Critical Infrastructure Workforce.[25] While the DHS does not provide a list of industry codes that are considered essential, we classify sectors based on the information provided regarding the types of workers and activities considered as part of essential critical infrastructure. Among those workers considered essential are those working in public health, public safety, food supply chain, energy infrastructure, transportation and logistics, critical manufacturing, hygiene products and services, among others.

To measure the sectoral supply shock, $\hat{x}_s$, we follow Dingel and Neiman (2020) and measure the feasibility of remote work by industry. To construct the measure, we start with the "work context" and "generalized work activities" surveys conducted by the Occupational Information Network (O*NET). Following Dingel and Neiman (2020), we classify occupations into those that can be performed remotely versus those that cannot based on charac-

[25]See Guidance on the Essential Critical Infrastructure Workforce.

Figure 2: Supply Shock by Sector



Notes: Depicts the COVID-19 demand shock by 1-digit NACE sector, as the percent change relative to the non-COVID scenario. Supply shocks are first aggregate from the 4-digit NACE to 1-digit NACE by taking a simple average across 4-digit sectors within each country. The gross value added sector share of each country is used to aggregate 1-digit sector shocks across countries. The countries used in aggregation are the the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Korea, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain.

teristics such as reliance on being outdoors, interacting with patients or prisoners, repairing and inspecting structures and equipment, controlling machines, handling and moving objects, among others. We then use information from the U.S. Bureau of Labor Statistics (BLS) on the prevalence of each occupation by NAICS code, along with a cross-walk between NAICS and NACE industry codes to arrive at the fraction of employees that can and cannot perform their work remotely by 4-digit NACE code. To construct the COVID-19 sectoral supply shock ($\hat{x}_s$), we assume that no workers in essential sectors lose their jobs, and that in non-essential sectors all workers that cannot work remotely lose their jobs temporarily. Fig. 2 illustrates the severity of the supply shock at the 1-digit NACE level by first averaging 4-digit NACE shocks to the 1-digit level in each country and then using the gross value added sector share of each country to aggregate 1-digit sector shocks across countries. As we would expect, the Accommodation and Food Service and Arts, Entertainment and Recreation sectors are among the most affected, while essential infrastructure sectors including Electricity and Water and Waste remain unaffected.

To calculate sector-specific demand, we follow a similar approach. Specifically, we first use the same O*NET surveys to classify occupations based on reliance on face-to-face interactions. We consider occupations as highly reliant on face-to-face interactions when working with external customers or in physical proximity, assisting and caring for others, working with the public, and selling to others are deemed important. Using the BLS data and NAICS-NACE crosswalks, we aggregate these occupation-level data to arrive at an estimate of the fraction of employees reliant on face-to-face interactions at the 4-digit NACE level. We assume that demand is unaffected in essential sectors and is one minus the "interaction share" for non-essential industries. We interpret the resulting estimate as a measure of $\hat{\xi}_s^{\eta}$.[26] The last step is to normalize our sectoral demand shocks to be consistent with aggregate demand Eq. (7). This is done by constructing $\tilde{\xi}_s^{\eta} = \hat{\xi}_s^{\eta} / (\sum_{\sigma} \hat{\xi}_{\sigma}^{\eta} / \mathcal{S})$.

Fig. 3 illustrates the size of the sector-specific demand shock ($\tilde{\xi}_s^{\eta}$) at the 1-digit NACE level. The figure illustrates that COVID-19 reallocates aggregate expenditure from highly affected non-essential sectors such as Arts, Entertainment, and Recreation to non-affected essential sectors including Water & Waste and Electricity.[27]

In addition to the sector-specific demand shock, we also measure changes in aggregate demand ($\widehat{PD}$) using projections of quarterly and annualized changes in GDP from the International Monetary Fund (IMF).[28] What matters for the estimation of bankruptcy rates is the combination of sector-specific demand and aggregate demand shocks, $\hat{d}_s = \tilde{\xi}_s^{\eta} \widehat{PD}$, which we refer to simply as the total demand shock.

3.3 Productivity shock

To measure the sectoral productivity shock ($\hat{A}$), we start by assuming that sectoral productivity is a combination of the productivity of on-site and remote work, according to:

$$\begin{aligned} A_s &= A_s^{work} \omega_s + A_s^{home} (1 - \omega_s) && \text{Before COVID,} \\ A_s' &= A_s^{work'} \omega_s' + A_s^{home'} (1 - \omega_s') && \text{COVID-19,} \end{aligned} \tag{21}$$

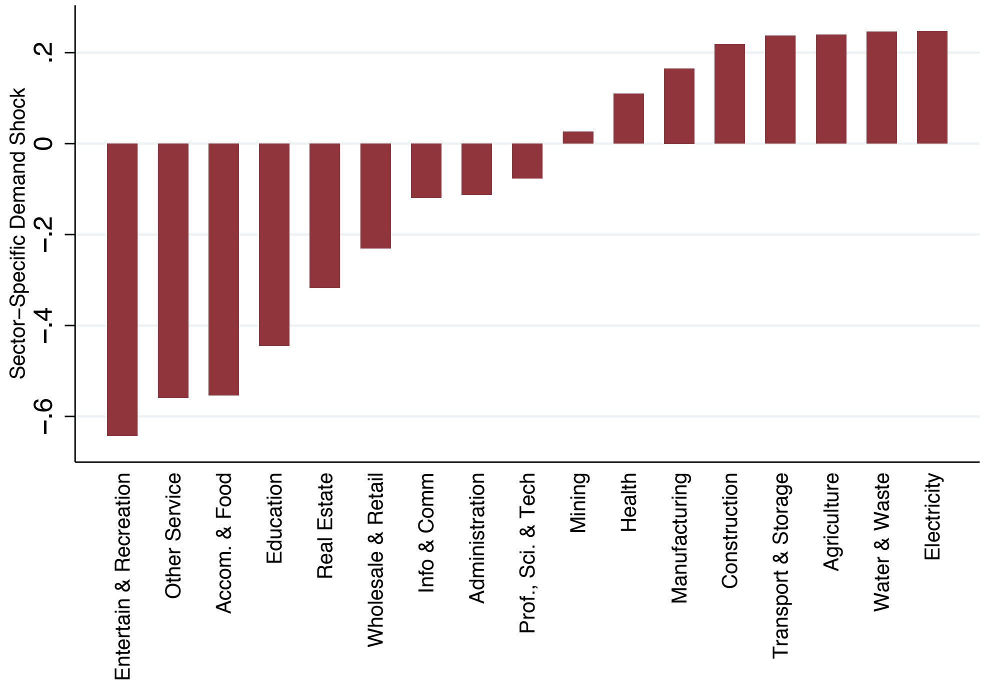
where all variables vary at the sector level, ω_s is the fraction of on-site workers in total employment, A^{work} is productivity of workers at work and A^{home} is productivity of telecommuting workers.

[26] Note that because we directly assess the change in sectoral demand according to Eq. (7), and not the underlying shock to preferences $\hat{\xi}_s$, we do not need to make an assumption about the elasticity of substitution η. This is already encoded in our measure of $\hat{\xi}_s^{\eta}$.

[27] Within each country $\sum_s \tilde{\xi}_s^{\eta} / \mathcal{S} = 1$ holds. However, Fig. 3 aggregates sector-specific demand shocks at the 1-digit NACE level across countries using the gross value added sector share of each country. Consequently, the sector-specific demand shocks depicted in the figure will not sum to one.

[28] We use quarterly projections from the June 2020 WEO in our analysis of bankruptcy rates to measure aggregate demand.

Figure 3: Demand Shock by Sector



Notes: Depicts the COVID-19 demand shock by 1-digit NACE sector, as the percent change relative to the non-COVID scenario. Demand shocks are first aggregated from the 4-digit NACE to 1-digit NACE by taking a simple average across 4-digit sectors within each country. The gross value added sector share of each country is used to aggregate 1-digit sector shocks across countries. The countries used in aggregation are the the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Korea, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain.

If we assume that A^{work} and A^{home} are the same before and during COVID-19 then we can write the ratio $\hat{A}_s$ as:

$$\hat{A}_s = \frac{\omega_s' + \frac{A_s^{home}}{A_s^{work}}(1-\omega_s')}{\omega_s + \frac{A_s^{home}}{A_s^{work}}(1-\omega_s)}. \tag{22}$$

Under the assumption that non-essential industries don't have onsite workers during the lockdown period, $\omega_s' = 0$ and this expression collapses to:

$$\hat{A}_s = \frac{\frac{A_s^{home}}{A_s^{work}}}{\omega_s + \frac{A_s^{home}}{A_s^{work}}(1-\omega_s)}. \tag{23}$$

We use data from the 2018 American Community Survey (ACS) on the share of remote workers by industry to measure ω_s. Absent any good data on this quantity, we opt to calibrate $\frac{A^{remote}}{A^{work}} = 0.8$. This implies that $\hat{A} = 0.8$ is the maximum decline in productivity possible for a sector where none of the workers worked remotely before COVID-19 to 100% during COVID-

19.

3.4 Production Function Parameters

Labor and materials elasticities (β_s and γ_s) are estimated at the 2-digit NACE level for each country.[29] Taking into account our modeling assumption that labor and intermediate inputs are variable inputs, and recent critiques of the key identifying assumptions of popular production function estimation techniques, we estimate elasticities as the weighted average of the firm revenue share of input expenditures (e.g., labor cost share of revenue and material cost share of revenue), where the weights are given by firm revenue.[30] Due to the lack of price data, the elasticities we estimate are revenue, rather than output, elasticities.

4 Bankruptcy Rates Absent Government Action

To evaluate SMEs' vulnerability to the COVID-19 crisis, we calculate Eqs. (17) and (18), and evaluate the bankruptcy condition given by Eq. (20) using firm-level data for seventeen countries and shocks constructed using O*NET, ACS, and IMF data. In our baseline analysis, we assume that the COVID-19 shock hits in week 9 of the year (beginning of March) and that the subsequent lockdown period lasts 8 weeks. We assume that the 8 week lockdown lowers sectoral labor supply ($\hat{x}_s$), demand ($\hat{d}_s = \tilde{\xi}_s^{\eta}\widehat{PD}$), and labor productivity ($\hat{A}_s$). Once the lockdown ends, the sectoral supply and productivity shocks return to pre-COVID levels. The demand shocks remain active, with the aggregate demand component ($\widehat{PD}$) of total demand evolving according to IMF projections and the sector-specific demand shocks ($\tilde{\xi}_s^{\eta}$) evolving according to an AR(1) process with persistence of 0.5 at quarterly frequency. Persistence in the total demand shock represents continued subdued demand due to continued uncertainty and fear of infection, even after stay-at-home order are lifted.

We evaluate bankruptcy rates at weekly frequency. This approach assumes that if at week's end a firm is illiquid it is unable to access any temporary credit and goes bankrupt.[31] To map our annual balance sheet data to a weekly frequency we assumed that revenue is earned

[29] Calculating country x sector specific elasticities is only possible in countries that separately report labor and material costs. Four countries in our sample – Greece, Japan, Korea, and the United Kingdom – firms do not report labor and material costs separately. The elasticities for thesee countries are the average of the elasticities estimated for the sample of countries where labor and material costs are reported separately and country coverage of revenue exceeds 40% (Belgium, Czech Republic, Finland, France, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain).

[30] See Ackerberg, Caves and Frazer (2015), Gandhi, Navarro and Rivers (2012), Levinsohn and Petrin (2003), and Wooldridge (2009). Our approach is similar to that of Blackwood, Foster, Grim, Haltiwanger and Wolf (forthcoming, 2020) for variable inputs and is an alternative to the parametric approach of Gandhi et al. (2012).

[31] Section 6 relaxes this assumption.

throughout the year in equal weekly increments, as are labor and materials costs paid. Financial expenses are assumed to be paid monthly and taxes twice a year in June and December.

Importantly, the goal of our initial analysis is to understand the potential vulnerability of SMEs, across sectors and countries to the COVID-19 crisis. As such, our baseline bankruptcy rates abstracts from any government or credit market interventions. In reality, governments stepped in quickly with a number of policies to help support firms and aggregate demand. These policies may have significantly alleviated or delayed the risk of business failure.[32,33] In Section 5, we evaluate the costs and impacts of a variety of government policies on the baseline bankruptcy rates. In Section 6, we further allow firms to smooth their cashflow to stay afloat during the worst of the crisis. Accordingly, we choose to interpret our baseline bankruptcy rates reported in this section as an upper bound.

Table 3 reports the overall non-COVID (col. 1) and COVID-19 (col. 2) bankruptcy rates, and the difference between the two (Δ, col. 3). The COVID-19 bankruptcy rate reports our estimated bankruptcy rate during 2020 under our COVID-19 scenario. A number of those firms would also have failed in the absence of COVID-19. Therefore, the difference between the two columns represents the *additional* effect COVID-19 has on firm bankruptcies in 2020. This is our preferred metric for business failures: it focuses on the *additional business failures* occurring under COVID-19. Under our baseline specification, the COVID-19 crisis increases the business failure rate by nearly 9 percentage points. These headline numbers mask considerable heterogeneity. In the following subsections, we detail the sources of cross-sector heterogeneity in bankruptcy rates, and the impact this heterogeneity has on bankruptcy rates across countries.

Table 3: Aggregate SME Bankruptcy Rate

	(1) Non-COVID	(2) COVID-19	(3) Δ
High coverage	9.56	18.19	8.63
All	9.43	18.17	8.75

Notes: Bankruptcy rates are first calculated at the 1-digit NACE level and aggregated to the country level using 2017 sector gross value added as weights (the exceptions, due to data availability, are the United Kingdom where 2016 sector gross value added weights are used, and Korea and Japan where Orbis sector gross value added weights are used). Bankruptcy rates are aggregated across countries using GDP as weights. The high coverage group includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. The all countries group incorporates Germany, Japan, Korea, and the United Kingdom. These countries have lower aggregate economy coverage in Orbis.

[32]For instance, the French Treasury estimates that 95 percent of the decline in the cashflow of French firms due to COVID-19 was absorbed via temporary support policies such as suspension of payroll taxes, direct assistance, or loan guaranties. See Benassy-Quéré (2020).

[33]While these are not incorporated in the analysis directly, as argued above, we recognize that they may be incorporated indirectly in the IMF WEO projections of aggregate economic activity.

Table 4: Sector SME Bankruptcy Rates

	(1) Non-COVID	(2) COVID-19	(3) Δ
Agriculture	9.44	13.52	4.08
Mining	12.50	36.03	23.54
Manufacturing	8.48	16.73	8.25
Electric, Gas & Air Con	9.35	11.31	1.96
Water & Waste	6.72	9.65	2.93
Construction	7.97	10.19	2.21
Wholesale & Retail	9.12	18.21	9.10
Transport & Storage	7.64	13.28	5.63
Accom. & Food Service	13.15	38.59	25.44
Info. & Comms	10.00	15.92	5.92
Real Estate	11.61	17.38	5.76
Prof., Sci., & Technical	10.24	18.85	8.60
Administration	8.32	19.39	11.06
Education	10.86	30.04	19.18
Health & Social Work	7.74	11.22	3.48
Arts, Ent., & Recreation	12.95	36.55	23.60
Other Services	12.80	31.42	18.62

Notes: Sector bankruptcy rates are first calculated at the 1-digit NACE level for each country, and then aggregated across countries using (country x sector) gross value added from the OECD as weights. The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Sloveian, and Spain.

4.1 Cross-Sector Heterogeneity

In our model, the rise in bankruptcy rates under COVID-19 is driven by the deterioration in firms' cashflow. This deterioration, in turn, is largely driven by the total demand, supply, and productivity shocks under COVID-19. Therefore, to understand why aggregate baseline bankruptcy rates increases by 9 percentage points under COVID-19, it is important to first understand heterogeneity in sectoral vulnerability to the crisis.

As for the previous table, Table 4 reports the non-COVID (col. 1) and COVID-19 (col. 2) bankruptcy rates and the difference between the two (Δ, col. 3). Given both the customer orientation and limited scope of remote work, some service sectors (Accommodation & Food Service, Arts, Entertainment & Recreation) experience an increase in bankruptcy rates under COVID-19 exceeding 20 percentage points. In fact, among the top five most affected sectors, the majority belong to the service sector.[34] In stark contrast, sectors with a high fraction of essential sub-sectors, with no sectoral supply shocks and higher sector-specific demand, including Agriculture, Health, and Water & Waste, are the least impacted by COVID-19, with

[34]Mining, a non-service sector, also experiences a large increase in bankruptcy rates. Mining faces a lower demand shock than service sectors, but faces a very severe labor supply shock with adverse consequences on their variable profits and cashflow.

bankruptcy rates rising less than 5 percentage point. Sectors with fewer essential workers, but relatively low total demand shocks (Manufacturing) and high scope for remote work (Information & Communications, Professional, Scientific & Technical Activities) are moderately effected, experiencing a rise in bankruptcy rates under 10 percentage points.

Because bankruptcy rates are calculated at a weekly frequency, we are able to evaluate the evolution of key variables to better understand the sources of cross-sector heterogeneity in bankruptcy rates under COVID-19. Fig. 4 depicts the evolution of six variables – the increase in bankruptcy rates due to COVID-19 (top left), average firm cash balance (top right), sector-specific demand shocks (middle left), total demand shocks (middle right), sectoral supply shocks (bottom left), and fraction of firms constrained (bottom right).[35,36]

Water & Waste (sector E) is only mildly affected by the crisis, experiencing a small uptick in bankruptcy rates during the lockdown and quickly leveling off at just under 10% through the rest of the year (top left). This minimal impact is due to the fact that most sub-sectors of sector E are classified as essential. Consequently, during the lockdown, the sector does not experience a labor supply shock (bottom left), and benefits from a reallocation of demand (middle right). During the post-lockdown period, the demand for sector E is redistributed back toward other sectors in the economy, causing total demand for this sector to fall.

More interesting is the comparison between a highly affected sector (Arts, Entertainment & Recreation, sector R) and a moderately affected one (Wholesale & Retail, sector G). The average cash balance (top right) of each sector prior to the onset of the COVID-19 crisis reflects firms' initial liquidity position. The fact that the average cash balance in sector G exceeds that of sector R indicates that sector R enters the crisis in a more precarious liquidity position than sector G, and helps explain the higher non-COVID bankruptcy rates in the former sector. As the crisis proceeds, and more firms go bankrupt in sector R, its average cash balance deteriorates relatively more than it does in sector G.

Although non-COVID bankruptcy rates (top left) in sector R exceed those of sector G, the gap between the two expands substantially, especially during the lockdown period. The core reason for this divergence is the severity of the sector-specific demand shock (middle left) in sector R, relative to sector G. Notice that the total demand shocks (middle right) are more severe than the sector-specific ones because all countries face negative aggregate demand shocks during the COVID-19 crisis. Importantly, at first glance, it appears that sector R faces a substantially more severe sectoral supply shock (bottom left) than sector G. However, the degree to which this shock impacts the sector is determined by the fraction of firms that become labor

[35]Sectoral labor productivity shocks are omitted from this figure because they play a more limited role in explaining bankruptcy rates.

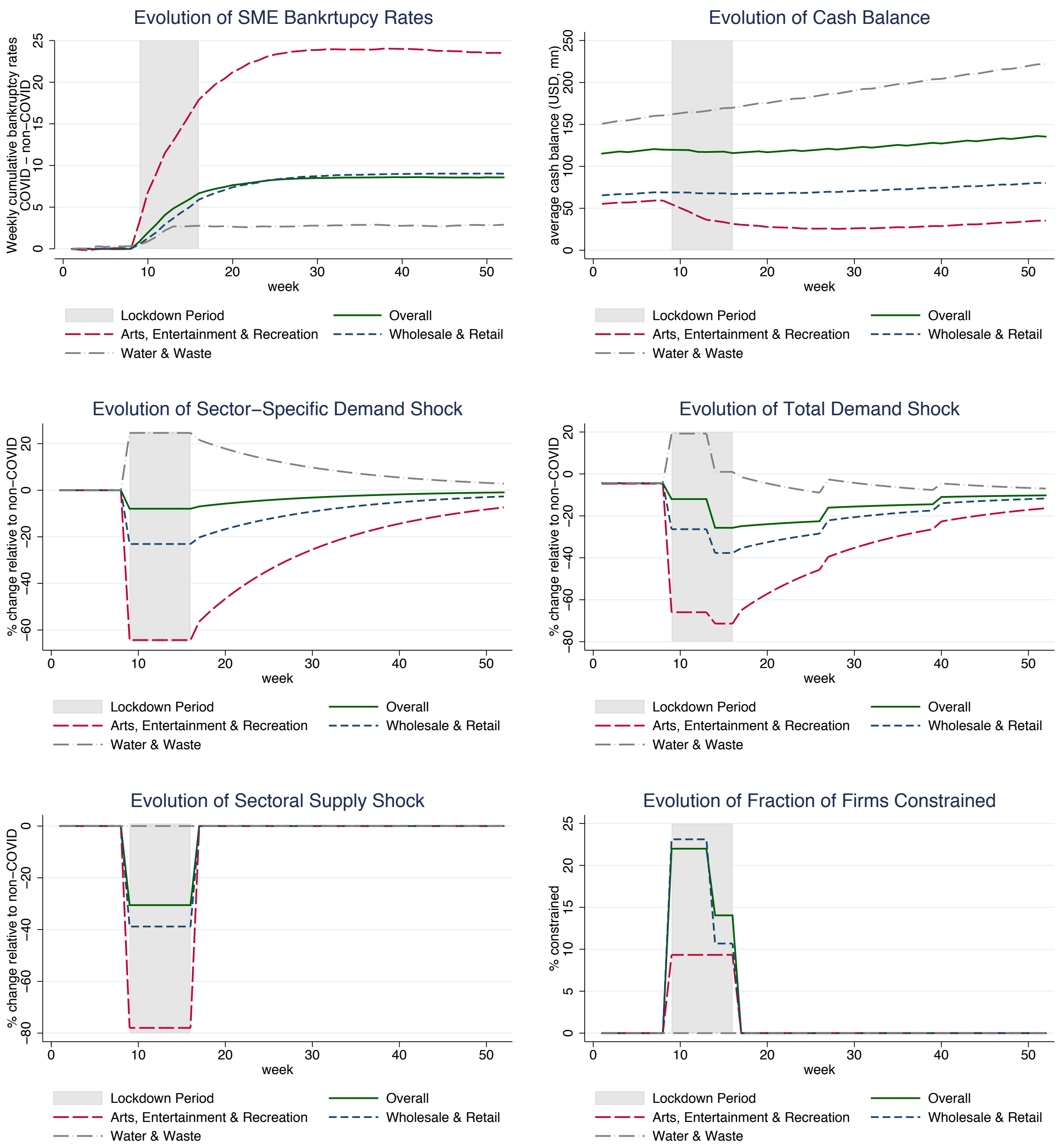
[36]Note that the difference between COVID-19 and non-COVID bankruptcy rates is not zero prior to the lockdown since COVID-19 already influences behavior and demand, as captured in the Q1 IMF WEO output estimates.

supply constrained (bottom right). Under 10% of firms in sector R are constrained by the near 80% decline in labor supply, while over 20% of firms in sector G are constrained by the 30% decline in labor supply. The reason why the labor constraint binds for a smaller fraction of firms in sector R is because the sector faces a severe total demand shock that lowers the optimal labor demand of most firms below the labor supply constraint (i.e., the labor constraint does not bind). In contrast, firms in sector G face a more severe sectoral labor supply shock than demand shock, which results in optimal labor demand exceeding the labor constraint for over 20% of firms. Ultimately, the crisis is felt more severely in Arts, Entertainment & Recreation, which results in bankruptcy rates reaching 36.5% by the end of the year, compared to 18.2% in Wholesale & Retail.

Fig. 4 highlights the importance of sectoral shocks and their interactions in driving cross-sector heterogeneity in COVID-19 bankruptcy rates. To further decompose the effects of different shocks, Table 5 evaluates changes in bankruptcy rates (COVID minus non-COVID) under five alternative scenarios that differ in the composition of shocks. The first column only includes the aggregate demand shock ($\widehat{PD}$). The second column includes both aggregate demand and sectoral supply shocks ($\widehat{PD}, \hat{x}_s$). The third includes total demand shocks ($\widehat{PD\tilde{\xi}^{\eta}_s}$), which incorporate both aggregate demand and sector-specific demand shocks. The fourth includes total demand and sectoral supply shocks ($\widehat{PD\tilde{\xi}^{\eta}_s}, \hat{x}_s$). The last is our baseline, which adds sectoral productivity shocks to column (4).

Column (1) of Table 5 shows that negative aggregate demand shocks only slightly raise bankruptcy rates under COVID-19 in most sectors. Including sectoral supply shocks (column 2) has a very large impact on bankruptcy rates in labor-intensive sectors, such as Accommodation & Food Services, where shocks are most severe. The pronounced rise in bankruptcy rates in these sectors occurs because the small demand shock relative to the labor supply shock leads to a high fraction of firms becoming labor constrained. For these firms to meet demand, they must make a costly substitution away from labor, which deteriorates their cashflow and leads to many bankruptcies. Total demand shocks (column 3), which include both aggregate and sectoral components, increases bankruptcy rates most in customer-oriented service sectors, including Arts, Entertainment & Recreation, and reduce bankruptcy rates slightly in sectors to which demand is redistributed during the crisis, such as Water & Waste. The additional introduction of sectoral supply shocks (column 4) has a negligible impact on the bankruptcy rates of sectors with high scope for remote work, including Information & Communications, and a larger impact on those with a low scope for remote work, such as Manufacturing. Importantly, in some labor-intensive sectors, the inclusion of both total demand and sectoral supply shocks lowers bankruptcy rates relative to the scenario with only sectoral supply shocks (column 2). The fall in bankruptcy rates arises from the fact that lower demand reduces firms' optimal labor demand, leading to fewer firms becoming labor constrained. This illustrates the impor-

Figure 4: Weekly Evolution (Sector)



Notes: Figures show the weekly evolution of six key variables – the increase in bankruptcy rates under COVID-19 (top left), average firm cash balance (top right), sector-specific demand shock (middle left), total demand shock (interaction between sector-specific demand and aggregate demand shock, middle right), sectoral supply shock (bottom let), and fraction of firms labor supply constrained (bottom right). In each week, sector variables are first calculated at the 1-digit NACE level for each country, and then aggregated across countries using (country x sector) gross value added from the OECD as weights. The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain.

Table 5: Δ Bankruptcy Rate Comparison (Alternative Shock Combinations)

	(1) $\widehat{PC}$	(2) $\widehat{PC}, \hat{x}_s$	(3) $\widehat{PC\xi_s^{\tilde{\eta}}}$	(4) $\widehat{PC\xi_s^{\tilde{\eta}}}, \hat{x}_s$	(5) Baseline
Agriculture	0.82	2.89	1.01	3.82	4.08
Mining	0.61	19.05	1.17	19.73	23.54
Manufacturing	1.00	6.11	0.95	6.56	8.25
Electric, Gas & Air Con	1.98	1.98	1.94	1.94	1.96
Water & Waste	3.33	3.33	2.73	2.73	2.93
Construction	1.48	1.77	2.00	2.00	2.21
Wholesale & Retail	1.65	4.83	8.84	8.73	9.10
Transport & Storage	6.83	7.00	5.13	5.16	5.63
Accom. & Food Service	0.07	75.04	9.20	20.04	25.44
Info. & Comms	2.12	3.56	4.99	4.99	5.92
Real Estate	1.60	2.18	5.76	5.71	5.76
Prof., Sci., & Technical	3.25	3.88	7.35	7.48	8.60
Administration	3.67	5.87	10.61	10.72	11.06
Education	2.01	49.45	18.60	18.60	19.18
Health & Social Work	1.85	12.16	3.14	3.14	3.48
Arts, Ent., & Recreation	1.92	51.04	18.92	21.27	23.60
Other Services	0.13	47.27	16.90	17.62	18.62
Average	2.02	11.78	6.19	7.75	8.63

Notes: The table reports the change in bankruptcy rates (COVID-19 - non-COVID) under 5 alternative scenarios – aggregate demand shock only ($\widehat{PD}$); both aggregate demand and sectoral supply shocks ($\widehat{PD}, \hat{x}_s$); both aggregate demand and sector-specific demand shocks ($\widehat{PD\xi_s^{\tilde{\eta}}}$); total demand and supply shocks ($\widehat{PD\xi_s^{\tilde{\eta}}}, \hat{x}_s$); and the baseline ($\widehat{PD\xi_s^{\tilde{\eta}}}, \hat{x}_s, \hat{A}_s$). Sector changes in bankruptcy rates are first calculated at the 1-digit NACE level for each country, and then aggregated across countries using (country x sector) gross value added from the OECD as weights. The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. The last row is the sector GVA weighted average.

tance of the accounting both for sectoral supply and demand shocks. The last column shows that in most sectors, the additional inclusion of labor productivity shocks has little effect on bankruptcy rates. Overall, Table 5 highlights the importance of sectoral supply and demand shocks, and in labor-intensive and customer-oriented sectors, their interaction, in determining sectoral vulnerability to the COVID crisis.

4.2 Cross-Country Results

We now evaluate the vulnerability of firms in our high data quality sample of countries to the COVID-19 crisis.[37] As before, Table 6 reports the country-level bankruptcy rates under non-COVID (col. 1) and COVID-19 (col. 2), as well as the difference between the two (Δ, col. 3). A striking feature of the results is the degree of cross-country heterogeneity in bankruptcy

[37] In this section we will present only summary results for each country. For more detailed results please refer to the online appendix which will present sectoral breakdowns by country as well country-specific effects of the different government interventions we discuss in Section 5.

Table 6: Country-Level SME Bankruptcy Rates

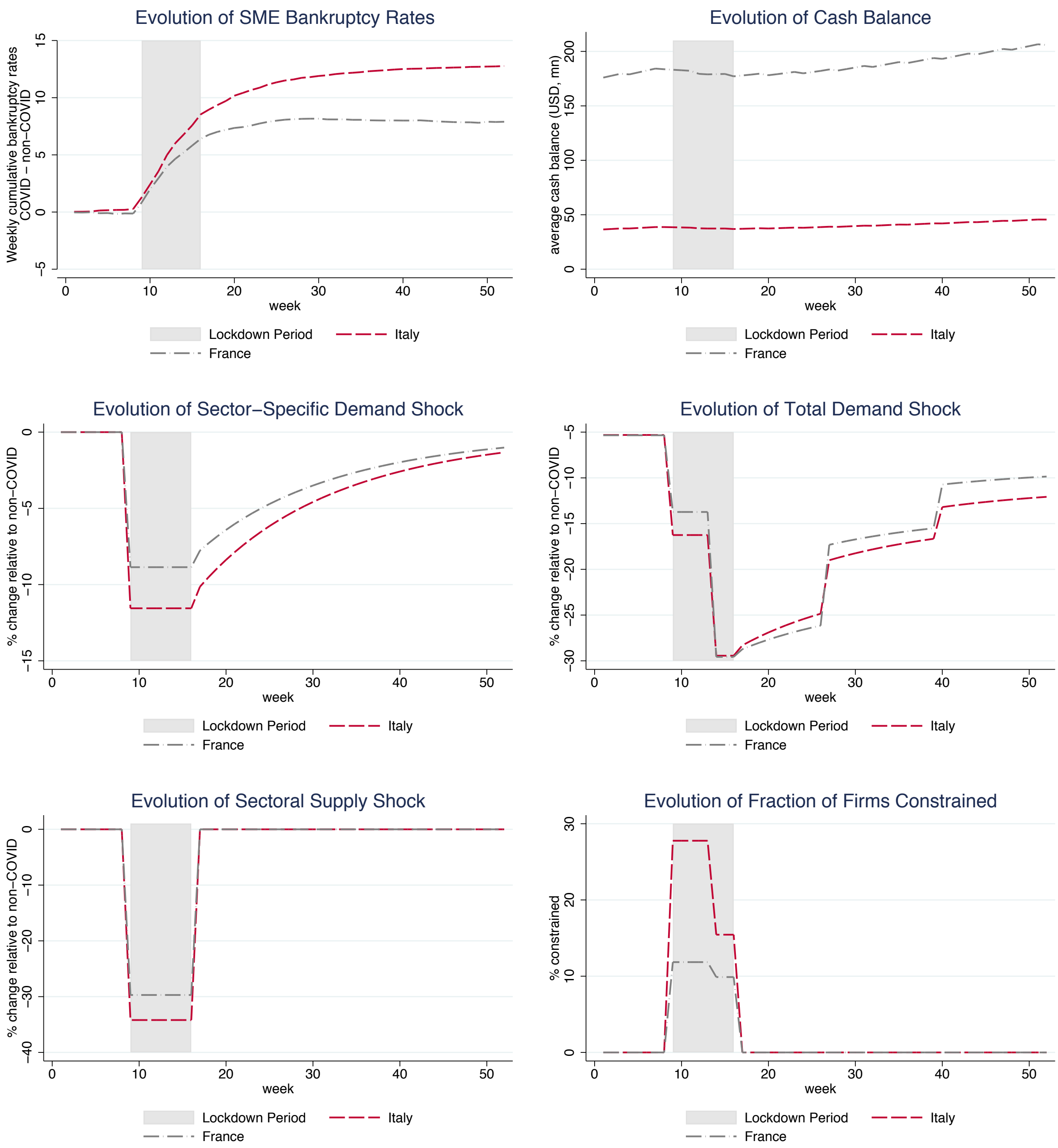
	(1) Non-COVID	(2) COVID-19	(3) Δ
Belgium	7.75	14.18	6.42
Czech Republic	8.24	13.59	5.35
Finland	8.35	16.91	8.56
France	9.03	16.94	7.91
Greece	10.43	16.37	5.94
Hungary	8.22	14.01	5.79
Italy	9.91	22.68	12.77
Poland	11.68	20.45	8.77
Portugal	12.21	19.65	7.44
Romania	15.77	23.18	7.41
Slovak Republic	10.41	16.05	5.64
Slovenia	7.25	15.95	8.71
Spain	8.98	15.50	6.52

Notes: Baseline bankruptcy rates at the country level. Country-level bankruptcy rates under non-COVID evaluate the fraction of firms facing a liquidity shortfall in 2017, and under COVID are evaluated under our baseline scenario. Country level results represent the weighted average of 1-digit NACE bankruptcy rates, where weights are given by 2017 sector gross value added.

rate changes, which range from 5.4 percentage points in the Czech Republic to 12.8 percentage points in Italy. The industrial composition and financial position of firms prior to the crisis drive the differential impact of COVID across countries.

A comparison of Italy and France, which, respectively, experience a 12.8 and 7.9 percentage point increase in bankruptcy rates under COVID-19, affirms the importance of both factors. Fig. 5 depicts the weekly evolution of the increase in bankruptcy rates under COVID-19 (top left), average firm cash balances (top right), sector-specific demand shocks (middle left), total demand shocks (middle right), sectoral supply shocks (bottom left), and fraction of firms that are labor constrained (bottom right) in the two countries. At first glance, it appears that Italy faces a more severe demand shock than France, as evidenced by the larger sector-specific demand shock. Yet, the evolution of the total demand shock appears more similar in the two countries, with Italy experiencing a slightly more severe initial total demand shock and slower recovery. Italy also experiences a larger sectoral supply shock. Most striking is the wide gap between the average cash balance of Italian and French firms. Ultimately, Italian firms enter the crisis in a worse financial position than French firms. This and slightly more severe sectoral labor supply and total demand shocks at the onset of the crisis is enough to generate a much larger rate of business failures for Italian SMEs.

Figure 5: Weekly Evolution (Country)



Notes: Figures show the weekly evolution of six key variables – increase in bankruptcy rates due to COVID-19 (top left), average firm cash balance (top right), sector-specific demand shock (middle left), total demand shock (interaction between sector-specific demand and aggregate demand shock, middle right), sectoral supply shock (bottom left), and fraction of firms labor supply constrained (bottom right). In each week, country-level variables represent the weighted average of 1-digit NACE variables, where weights are given by 2017 sector gross value added.

4.3 Financial Stability Implications of SME Bankruptcies

As SMEs go bankrupt, we can expect they will fail to repay their loans. We now present some estimates of the risks to the banking sector resulting from rising non-performing loans (NPL). To do so, we qualify a loan as non-performing for firms that fail, both under COVID-19 and in normal times. Table 7 reports the fraction of loans that belong to illiquid firms under non-COVID (col. 1) and COVID-19 (col. 2), as well as the difference between the two (Δ, col. 3).[38] The increase in the share of non-performing loans ranges from 2.3 percentage points in Belgium to almost 11 percentage points in Italy.

Fig. 6 explores this further by plotting side-by-side the increase in bankruptcy rates under COVID-19 and the increase in the NPL share across countries. The figure highlights that banking sector risk is not perfectly correlated with firm bankruptcy rates. Consider Poland, Slovenia, and Finland. The three countries have a very similar change in bankruptcy rate, around 8.5 percentage points, but differ in the change in NPL share, ranging from 5.9 percentage points in Poland to 7.8 percentage points in Finland. These differences reflect cross-country heterogeneity in the level of indebtedness among businesses predicted to fail under COVID-19.

To better understand the risk to the banking sector, Table 8 reports the change in NPLs of SMEs under COVID-19 (compared to non-COVID) as a fraction of the banking sector's total assets (col. 1), of common equity Tier-1 (CET1) of the banking sector (col. 2), and reports the resulting change in the CET1 capital ratio due to COVID-19 (col. 4).[39] The change (relative to non-COVID) SME NPL share of total assets can be viewed as a lower bound on the risk to the banking sector. Across countries, it averages 0.3%, and ranges from 0.13% in Belgium to 1.12% in Greece. Meanwhile, the change in SME NPL share of Tier-1 Capital can be interpreted as an upper bound on risk. It averages 5.8% across countries, ranging from 2.1% in Belgium to 12.5% in Greece. Finally, we estimate a moderate decline in the CET1 capital ratio of -0.75

[38] We define loans as the sum of short-term and long-term loans.

[39] Four sources of data are used to calculate this share. (1) Orbis is used to calculate the share of total SME loans that belong to failing SMEs under COVID-19 relative to non-COVID (Δ SME NPL share from Orbis). (2) The European Banking Authority's (EBA) 2018 country level bank stress test data are used to calculate the SME share of all loans (Bank SME share from EBA) and the ratio of CET1 to total bank assets (CET1 share from EBA). (3) The Financial Balance Sheet data from Eurostat is used to calculate total loans (total loans from Eurostat) and total assets (total assets from Eurostat) of depository institutions. (4) The European Central Bank's (ECB) Supervisory Banking Statistics first quarter 2019 data are used to obtain the CET1 capital ratio (risk-weighted) for a subset of countries (CET1R). No data was available for Romania and Hungary. The change in the NPL value of SMEs under COVID as a fraction of total bank assets (column 1) is calculated as [(total loans from Eurostat × (bank SME share from EBA) × (Δ SME NPL share from Orbis)]/[total assets from Eurostat]. The change in the NPL value of SMEs under COVID-19 as a fraction of Tier-1 capital (column 2) is calculated as [(total loans from Eurostat × (bank SME share from EBA) × (Δ SME NPL share from Orbis)]/[(total assets from Eurostat) × (CET1 share from EBA)]. The country CET1 ratio (risk-weighted) from the ECB is reported in column 3, and the change in the CET1 ratio due to COVID, calculated as [(1-SME NPLs % CET1) × CET1R]/[1-(SME NPLs % CET1 × CET1R)], is reported in column 4.

Table 7: Country-Level Fraction of Non-Performing Loans

	(1) Non-COVID	(2) COVID-19	(3) Δ
Belgium	9.92	12.24	2.32
Czech Republic	7.37	12.90	5.53
Finland	9.91	17.74	7.83
France	17.91	24.42	6.51
Greece	21.80	27.14	5.34
Hungary	8.43	12.45	4.02
Italy	11.87	22.54	10.67
Poland	16.59	22.50	5.91
Portugal	10.22	17.92	7.69
Romania	20.48	29.06	8.58
Slovak Republic	10.48	17.20	6.72
Slovenia	13.81	20.87	7.07
Spain	14.10	20.62	6.53
Average	14.47	21.71	7.24

Notes: Report fraction of non-performing loans (NPLs) of illiquid firms under non-COVID and COVID and the difference between the two. NPLs are aggregated to the country-level by summing short plus long term loans of illiguid firms to the country level. The last row is the country GDP weighted average.

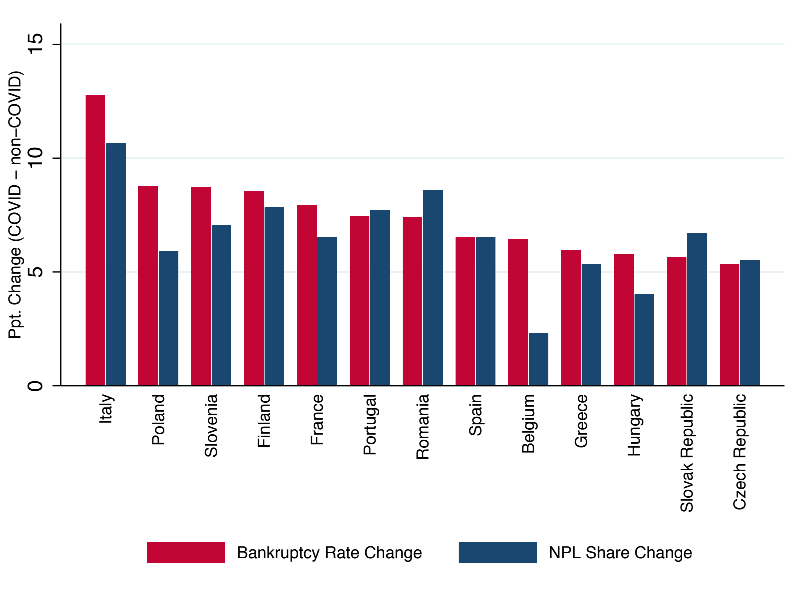
percentage points, ranging from -0.31 percentage points (Belgium) to -1.61 percentage points (Greece). Given the initial levels of the CET1 capital ratio, ranging from 11.8 percent (Spain) to 18.3 percent (Belgium), we conclude that the shock to the banking system from SME's failures due to COVID-19 remains modest. As a point of comparison, we note that the adverse scenario used in the EBA's 2018 EU-wide stress tests implied a decline of about 4 percentage points in the CET1 capital ratio (from a similar initial level of 14.5 percent).[40]

5 Impact of Government Intervention

Our findings thus far suggest that, in the absence of government action, firm bankruptcies would rise considerably. In this section we discuss how these costs might be mitigated with different forms of support from the government. First we discuss the effects of two benchmark policies and then turn to policies that might be more feasible in practice.

[40] See the EBA's 2018 EU-Wide Stress Tests.

Figure 6: Bankruptcy Rate and NPL Share Changes (Country)



Notes: Figure shows the change in bankruptcy rates (COVID minus non-COVID) and change in NPL rate (Non-performing loans relative to total loans, COVID minus non-COVID, where loans are the sum of short and long term debt). NPLs are aggregated to the country-level by summing loans of illiguid firms to the country level.

Table 8: Country-Level COVID-19 Risk to the Banking Sector

	SME NPLs Due to COVD-19			
	(1)	(2)	(3)	(4)
Country	% Total Assets	% Bank Tier-1 Capital	CET1 ratio (risk-weighted)	Δ CET1R
Belgium	0.13%	2.1%	18.3%	- 0.31%
Finland	0.45%	8.3%	16.3%	-1.15%
France	0.30%	6.2%	14.3%	-0.77%
Germany	0.24%	5.1%	15.4%	-0.68%
Greece	1.12%	12.5%	14.9%	-1.61%
Hungary	0.26%	2.7%		
Romania	0.69%	8.2%		
Spain	0.44%	8.5%	11.8%	-0.90%
Average	0.30%	5.83%	14.69%	-0.75%

Notes: Report change in the value of non-performing loans (NPLs) of illiquid firms under COVID-19 relative to non-COVID as a fraction of banks' total assets (1) and Tier-1 capital (2); the 2018 risk-weighted CET1 capital ratio (unavailable for Hungary and Romania) (3); and the change in the CET1 capital ratio due to COVID-19. The change in the NPL value of SMEs under COVID-19 as a fraction of total bank assets (column 1) is calculated as [(total loans from Eurostat × (bank SME share from EBA) × (Δ SME NPL share from Orbis)]/[total assets from Eurostat]. The change in the NPL value of SMEs under COVID-19 as a fraction of CET1 (column 2) is calculated as [(total loans from Eurostat × (bank SME share from EBA) × (Δ SME NPL share from Orbis)]/[(total assets from Eurostat) × (CET1 share from EBA)]. Column 3 reports the 2018 country CET1 ratio (risk-weighted) from the ECB (CET1R). Column 4 reports the change in the CET1 capital ratio due to COVID-19, calculated as [(1-SME NPLs % CET1) × CET1R]/[1-(SME NPLs % CET1 × CET1R)]. The last row is the country GDP weighted average.

5.1 Evaluating Policy Interventions

The first policy we consider is a bailout of all SME firms that are predicted to fail in our baseline scenario. Under that policy, each firm receives the minimum amount required to leave it with a zero cash balance at the end of 2020. The exact cash deficit of each firm is not observable in practice, but this scenario serves to benchmark the approximate level of resources needed to meaningfully lower the bankruptcy rate. The second scenario is more targeted to account for the existence of "ghost firms", i.e. firms that would not survive 2020 even without COVID. Instead of bailing out all firms indiscriminately, the targeted bailout policy restricts support to firms we classify as "viable", i.e. firms that would fail under COVID-19, but would survive otherwise.

The costs and effects of these two policies for our high quality countries are depicted in the first two rows of Table 9. Column (1) shows the reduction in the COVID-19 bankruptcy rate from each policy, in percentage points. This is calculated as the difference between the COVID-19 bankruptcy rate when each policy is implemented, less the baseline COVID-19 bankruptcy rate absent policy support. Bailing out all SME firms reduces the overall bankruptcy rate to zero for 2020 – a reduction of 18.19 percentage points. The second row of this column shows that the targeted bailout would reduce the business failure rate to that of a normal year, i.e. from 18.19 points to 9.56 percent, by bailing out all 'viable' firms.

The second column shows jobs saved under each policy, as a fraction of total employment. Our estimates indicate that 3.1 percent of jobs are at risk: they would disappear because of COVID-19. The third column reveals the amount of wages 'saved', i.e. the total labor compensation that is preserved under each policy, as a share of GDP. These numbers take into account that firms saved from bankruptcy may choose to operate at lower scale – employing fewer workers and paying less in labor compensation – than in pre-COVID. The fourth columns reports the fraction of SME loans saved. Finally, the fifth column reports the fiscal cost of each policy, expressed as a fraction of GDP.

The two bailout policies illustrate that, provided enough information is available, the overall fiscal cost of saving most small and medium businesses affected by COVID remains quite modest. At an overall cost of 0.54 percent of GDP, the targeted bailout policy saves 0.67 percent of GDP in wages, 8.6 percent of businesses and 3.1 percent of employment.[41] It is particularly interesting to note that each dollar spent on this policy generates 1.24 dollars in direct aggregate demand (0.67/0.54) in the form of wages saved. We call this ratio the *fiscal-bankruptcy multiplier*. While this multiplier may look like a traditional Keynesian multiplier, it is a multiplier of a different sort: it reflects the fact that businesses may be inefficiently shut down as a

[41] Note that ORBIS does not cover the full universe of firms, so to compute columns 2,3 and 5 in Table 9 we compute sectoral coverage rates by employment and labor costs and scale up the numbers computed here to account for the incomplete coverage.

Table 9: The Effects and Costs of Various Policy Options

	(1) Firms Saved (% Firms)	(2) Jobs Saved (% Employed)	(3) Wages Saved (% GDP)	(4) Loans Saved (% Loans)	(5) Policy Cost (% GDP)
All Firms Bailed Out	-18.19	7.04	1.67	21.61	1.91
Targeted Bailouts	-8.63	3.10	0.67	8.02	0.54
Financial Expenses Waived	-0.47	0.20	0.06	1.39	0.26
8-week 100% Labor Subsidy	-5.61	2.96	0.66	4.11	1.82
8-week 50% Labor Subsidy	-3.59	1.92	0.44	2.49	0.91
16-week 100% Labor Subsidy	-7.43	3.71	0.81	5.65	3.63

Notes: The scenarios considered are as follows: All Firms Bailed Out closes the cash shortfall of all bankrupt firms; Targeted Bailouts closes the cash shortfall of business we estimate would have survived in the absence of COVID-19; Interest Costs Waived pays firms a subsidy that equals their monthly financial expenses for the 8-week lockdown. The final scenarios are all in the form of wage subsidies. The first consists of a 100% of wage subsidy assessed on the prior year wage bill, paid during the 8 week lockdown; the next is a subsidy for 8 weeks at 50% the firm's prior year wage bill. The final labor subsidy lasts 16 weeks and refunds 100% of the prior year wage bill. Jobs saved from each policy are presented as a percent of economy wide Employment (column 2) and wages saved are presented relative to GDP (column 3). Non-performing loans are presented as a percent of all SME loans (column 4) and the overall policy cost is presented as a percent of overall economy-wide GDP (column 5). Firm coverage in ORBIS is imperfect and so to get aggregate costs we scale the total costs by the inverse of the coverage ratio of ORBIS (based on 1-digit data on value added for policy costs, total remuneration for wages saved and employment). For some sectors the country-wide 1-digit data was unavailable. For these sectors we assume the coverage ratio is the same as the average ORBIS coverage ratio for the sectors we do observe. All data is based on 2017 numbers. The numbers presented here are GDP-weighted averages based on our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain.

consequence of the pandemic, and that fiscal resources deployed to preserve viable businesses help increase overall output and employment.[42]

The next four rows of Table 9 show a set of alternative policies that better reflect the policy responses implemented by countries in practice. The policy responses have varied considerably by countries but have tended to take the form of either support provided by the banking system in terms of cheap loans (or cheaper refinancing of existing loans), encouraging banks to allow delays on loan repayments, and interest and wage subsidies. Rather than cover the rich set of specific policies implemented, we have chosen here to focus on some simple policy interventions that together span most of the set of policies chosen by governments. Notice that, in our model, it is economically equivalent to give a direct subsidy to the firm or to give it a partially guaranteed loan at concessional terms: both policies transfer public resources to private sector firms. In what follows we consider two policies that directly transfer resources to firms: a subsidy that covers financial expenses, and one that partially covers payroll costs.

The first of these policies consists of rebating to firms their financial expenses during the lockdown. This policy is an extreme version of policies that guarantee existing firm loans or refinance them at lower interest rates. As can be seen in Table 9, this policy is extremely cheap but largely ineffective – the bankruptcy rate is estimated to fall by 0.47 percentage points at a

[42]Traditional Keynesian multipliers would add to that, so that one dollar in fiscal resources used to preserve viable businesses may increase overall output by much more than 1.42 dollars. However, as stated earlier, we ignore these general equilibrium considerations in this paper and focus on the first-round effects of the fiscal interventions.

Table 10: To what extent do non-needy or non-viable firms receive policy support?

	Firms that Survive COVID-19 & non-COVID			**Firms Bankrupt Regardless of COVID-19**			**Firms Bankrupt Only in COVID-19 Scenario**			**Total**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Bankruptcy Rates Baseline Scenario (pp.)	Bankruptcy Rates Policy Scenario (pp.)	Cost of Policy (% GDP)	Bankruptcy Rates Baseline Scenario (pp.)	Bankruptcy Rates Policy Scenario (pp.)	Cost of Policy (% GDP)	Bankruptcy Rates Baseline Scenario (pp.)	Bankruptcy Rates Policy Scenario (pp.)	Cost of Policy (% GDP)	Cost of Policy (% GDP)
All Firms Bailed Out	0.00	0.00	0.00	100.00	0.00	1.37	100.00	0.00	0.54	1.91
Targeted Bailout	0.00	0.00	0.00	100.00	100.00	0.00	100.00	0.00	0.54	0.54
8-week 100% Labor Subsidy	0.00	0.00	1.48	100.00	81.25	0.14	100.00	53.32	0.18	1.80
8-week 50% Labor Subsidy	0.00	0.00	0.74	100.00	89.02	0.07	100.00	65.84	0.09	0.90
16-week 100% Labor Subsidy	0.00	0.00	2.97	100.00	72.60	0.28	100.00	42.97	0.36	3.61

Notes: The scenarios considered are as follows: Targeted Bailouts closes the cash shortfall of business we estimate could have survived a non-COVID 2020; All Firms Bailed Out closes the cash shortfall of all bankrupt firms; Interest Costs Waived pays firms a subsidy that equals their monthly financial expenses for the 8-week lockdown. The final scenarios are all in the form of wage subsidies. The first is 100% of wages and is paid only during the 8 week lockdown; the next is a subsidy for 8 weeks at 50% of each firm's wages. The final labor subsidy lasts 16 weeks and refunds 100% of wages during the period. The policy cost is presented as a percent of overall economy-wide GDP. There is a slight discrepancy between the policy costs quoted in this table and those in Table 9 due to a small number of firms (approximately 0.5%) that survive COVID-19 but fail in non-COVID. We decided to omit these firms from the firm groupings in this table. Firm coverage in ORBIS is imperfect and so to get aggregate costs we scale the total costs we by the inverse of the coverage ratio of ORBIS (based on 1-digit data on value added). For some sectors the country-wide 1-digit data was unavailable. For these sectors we assume the coverage ratio is the same as the average ORBIS coverage ratio for the sectors we do observe. All data is based on 2017 numbers. The numbers presented here are GDP-weighted averages based on our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain.

cost of 0.26 percent of GDP. Note that the cost of this policy is small as the policy only applies to the lockdown period instead of the whole year.

The remaining three rows of Table 9 consider instead a direct firm subsidy indexed to the size of the firm's wage bill in the reference year, 2017. The first such policy considers a subsidy that covers the entire wage bill of each firm during the 8 weeks of the lockdown. This represents a subsidy of 8/52=15.4 percent of the annual wage bill of the firm. The next two rows consider alternatively a less generous policy equal to only 50 percent of the wage bill for the same 8 weeks (or 7.7 percent of the annual wage bill), and a more generous policy equal to 100 percent of the 2017 wage bill for 16 weeks (or 31 percent of the annual wage bill).[43]

Importantly, because the payments are lump-sum, assessed on the basis of the wage bill in the reference year, they do not affect the current cost of labor or firms' employment decision. We observe that these firm subsidies have a much larger impact than a waiver of financial expenses on business failures, jobs and wages saved, but at a substantially higher fiscal cost. For instance, the 8-week labor subsidy at 100 percent more than halves the rise in the bankruptcy rate (bankruptcy rates decline of 5.61 percentage points relative to the no-policy benchmark), saves 2.96 percent of jobs and 0.66 percent of GDP in wages, but at an overall fiscal cost of 1.82 percent of GDP.[44] The fiscal-bankruptcy multiplier is now only 0.36: each dollar of fiscal

[43] Cash transfers of this form are discussed in a recent policy note by one of the authors, Drechsel and Kalemli-Özcan (2020).

[44] Several sectors (e.g. the financial sector or the government sector) are not included in our analysis, which may help explain why the overall policy costs of this subsidy may appear small.

Table 11: Wages Saved and Jobs Saved by viability of firm?

	Firms that Survive COVID & non-COVID				**Firms Bankrupt Regardless of COVID**				**Firms Bankrupt Only in COVID Scenario**			
	(1) Jobs Saved (% Emp)	(2) Wages Saved (% GDP)	(3) Loans Saved (% Loans)	(4) Policy Costs (% GDP)	(5) Jobs Saved (% Emp)	(6) Wages Saved (% GDP)	(7) Loans Saved (% Loans)	(8) Policy Costs (% GDP)	(9) Jobs Saved (% Emp)	(10) Wages Saved (% GDP)	(11) Loans Saved (% Loans)	(12) Policy Costs (% GDP)
All Firms Bailed Out	0.00	0.00	0.00	0.00	3.03	0.78	13.25	1.37	4.02	0.89	8.35	0.54
Targeted Bailout	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.02	0.89	8.35	0.54
8-week 100% Labor Subsidy	0.00	0.00	0.00	1.48	0.79	0.18	0.87	0.14	2.17	0.48	3.23	0.18
8-week 50% Labor Subsidy	0.00	0.00	0.00	0.74	0.45	0.11	0.53	0.07	1.47	0.33	1.96	0.09
16-week 100% Labor Subsidy	0.00	0.00	0.00	2.97	1.06	0.24	1.54	0.28	2.64	0.57	4.11	0.36

Notes: The scenarios considered are as follows: Targeted Bailouts closes the cash shortfall of business we estimate could have survived a non-COVID 2020; All Firms Bailed Out closes the cash shortfall of all bankrupt firms; Interest Costs Waived pays firms a subsidy that equals their monthly financial expenses for the 8-week lockdown. The final scenarios are all in the form of wage subsidies. The first is 100% of wages and is paid only during the 8 week lockdown; the next is a subsidy for 8 weeks at 50% of each firm's wages. The final labor subsidy lasts 16 weeks and refunds 100% of wages during the period. Jobs saves are presented as a percent of employment and both wages saved and the policy's cost are presented as a percent of overall economy-wide GDP. There is a slight discrepancy between the policy costs quoted in this table and those in Table 9 due to a small number of firms (approximately 0.5%) that survive COVID but fail in non-COVID. We decided to omit these firms from the firm groupings in this table. Firm coverage in ORBIS is imperfect and so to get aggregate costs we scale the total costs we by the inverse of the coverage ratio of ORBIS (based on 1-digit data on value added). For some sectors the country-wide 1-digit data was unavailable. For these sectors we assume the coverage ratio is the same as the average ORBIS coverage ratio for the sectors we do observe. All data is based on 2017 numbers. The numbers presented here are GDP-weighted averages based on our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain.

resources only saves 0.36 cents in direct aggregate demand. More generous policies, such as a subsidy assessed on 16 weeks of wage bill, preserve more jobs and avoid more bankruptcies, but at an increasingly high fiscal cost. That policy's fiscal-bankruptcy multiplier drops to 0.81/3.63 = 0.22.

The reason for the poor performance of this policy is explored in Tables 10 and 11. Both tables split firms into three groups based on their performance in our COVID-19 and non-COVID scenarios (in the absence of policy interventions): 'survivor' firms that are able to remain liquid during our baseline COVID-19 crisis scenario; 'ghost' firms that fail both with or without COVID; and 'viable firms' that survive without COVID but fail when COVID hits in the absence of any intervention.

Columns (1)-(3) of Table 10 refer to 'survivor' firms, columns (4)-(6) to 'ghost' firms and columns (7)-(9) to 'viable' firms. Within each group the first column shows the bankruptcy rate under our baseline COVID-19 scenario. By construction, that bankruptcy rate is 0% for the 'survivor' firms and 100% for both the 'ghost' firms and 'viable' firms, since the latter two groups are defined to contain only firms that fail under COVID-19 without intervention. The middle column in each group shows the bankruptcy rates for each group under a variety of support policies. For instance if all firms are bailed out, then the bankruptcy rates for 'ghost' firms and 'viable' firms falls to 0; under the targeted bailout scenario the 'ghost' firms bankruptcy rate remains at 100% since they do not receive any support, while the bankruptcy rate of 'viable' firms falls to 0. The last column in each group reports the associated fiscal costs of the intervention, as a percent of GDP.

By construction, the targeted bailout policy does not waste any resources on 'survivor' firms (they don't need it), or 'ghost' firms (the support would make no difference). By contrast, the labor subsidies prove to be highly inefficient. With an 8-week 100% labor subsidy, almost 50% percent of viable firms are saved, at a cost of 0.18 percent of GDP. But the policy 'wastes' 1.5 percent of GDP on survivor firms that don't need it. It also devotes a small amount of resources (0.14 percent of GDP) to inefficiently saving 19 percent of 'ghost firms' (bankruptcy rates fall from 100% to 81.25%). The cost of bailing out these 'ghost firms' is small because there are few ghost firms to start with, but this remains inefficient since these firms will fail as soon as fiscal support ends.

Table 11 further breaks down the jobs, wages and non-performing loans saved numbers into these firm groupings. It can further be seen that approximately 25% of the jobs saved and wages saved (and 20% of loans saved) from the labor subsidies can be attributed to retaining workers at 'ghost firms'. This hinders a proper reallocation of resources towards more productive uses. From a macroeconomic perspective, however, the table reveals clearly that the major defect of such policies is that it wastes fiscal resources on surviving firms that don't need it. One way to reduce the fiscal burden would be to implement a mechanism by which fiscal authorities could recoup some of the relief provided in future years – in case the firm makes enough profits. Such a tax on future excess profits could substantially lower the fiscal cost of the policy without impacting its effectiveness.[45] In effect, it is akin to the government taking an equity position in small and medium size businesses: the subsidy in 2020 becomes a claim on future profits.

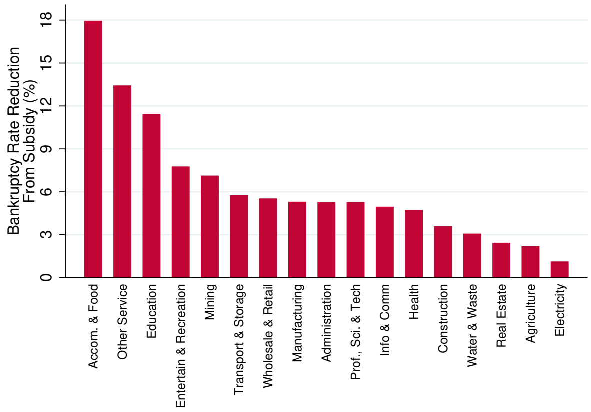
Alternatively, one might hope that targeting support to only some sectors may help to mitigate the risk of directing government resources to firms that do not need it. Fig. 7 shows the sectors most affected by the labor subsidy and those where the cost of the policy is the largest. The top left panel shows how the 8-week labor subsidy reduces bankruptcy rates by 1-digit sector. As can be seen bankruptcy rates fall in every sector, with the largest falls in Accommodation and Food, Other Services and Education.

The top right panel shows the policy cost by 1-digit sector (sorted from sectors with the largest reduction in bankruptcy rates to the fewest – same as the top left panel). All costs are normalized by country level GDP and the panel shows a GDP-weighted average of these cost ratios across our high coverage set of countries. As can be seen the sector which receives the bulk of the policy spending is Manufacturing. However, the top left panel shows that this sector does not have the highest overall bankruptcy rate reductions. Accommodation and Food does require a fairly high amount of spending but also bankruptcy rates in this sector

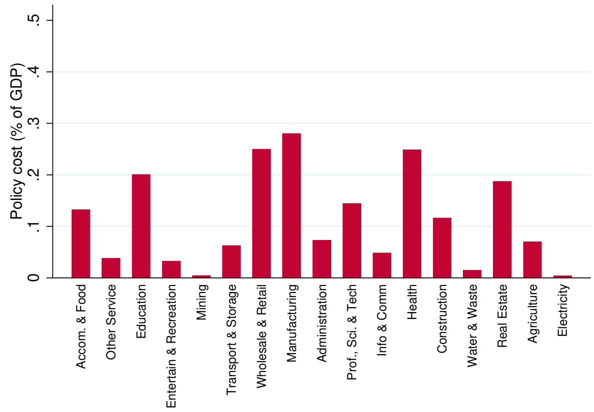
[45] A negative tax now that will work as a direct transfer can be turned into a positive tax in later years conditional on excess profits if the policy scheme implemented through the tax system. See Drechsel and Kalemli-Özcan (2020).

can be influenced considerably by the labor subsidy. By contrast, subsidies toward the Real Estate sector are fairly high yet the reduction in bankruptcy rates modest.

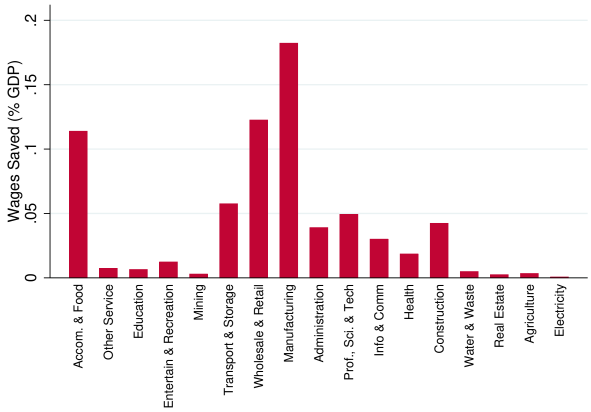
Figure 7: Policy Responses: 100% labor subsidies during lockdown (SME firms only)



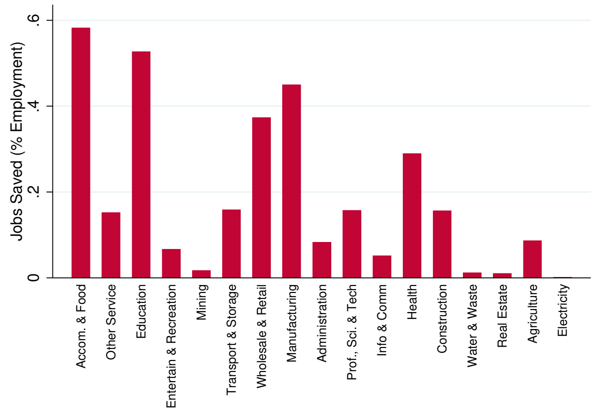
(a) Reduction in Bankruptcy Rates



(b) Policy Cost (% of GDP)



(c) Wages Saved (% of GDP)



(d) Jobs Saved (% of Total Employment)

Notes: The results presented in these panels are aggregated across several countries using total revenue of firms in Orbis as weights. The aggregation is done over our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain. All panels show the effects of a 100% labor cost subsidy to SME firms during the 8 week lockdown. The top left panel shows the reduction in overall bankruptcy rates from the labor subsidy by sector ordered from largest to smallest. The top right panel shows the policy cost of the labor subsidy by sector (as a percent of GDP) ordered as in the top left panel. The bottom row shows wages saved relative to GDP (bottom left) and jobs saved by sector relative to overall employment (bottom right).

The bottom two panels show the effects of the labor subsidy on jobs lost (bottom left) and wages lost (bottom right) due to firm bankruptcies by 1-digit sector. Other than Accommodation & Food, the sectors where the most wages can be saved are not the sectors where the highest proportion of firms can be saved. Also it appears that there are sectors such as Education and Other Services where there are many jobs but not necessarily high wage jobs that can be saved.

Overall, there is considerable heterogeneity in which sectors contribute toward the labor subsidy's effectiveness and therefore, offering support targeted to some sectors would likely make the labor subsidy more effective per dollar spent. In particular, sectors such as Accomodation & Food, Education, Wholesale & Retail and Manufacturing appear to save the majority of saveable jobs is less than half the total policy cost.

5.2 Policy Support Timing and Additional Lockdowns

At the time of writing, many countries are facing the prospect of a second wave of COVID-19 infections and some consider re-implementing temporary lockdowns. A natural question is whether policy support during additional lockdowns will be needed or whether selection pressures will have left surviving firms with strong enough balance sheets to withstand additional lockdowns. We investigate this question in two steps in Fig. 8. In the left panel we show the effects of varying the timing of policy support within our single lockdown baseline. The graph shows the evolution of bankruptcy rates throughout the year with the black dashed line showing the cumulative bankruptcy rate week-by-week under our baseline COVID-19 scenario absent policy support.

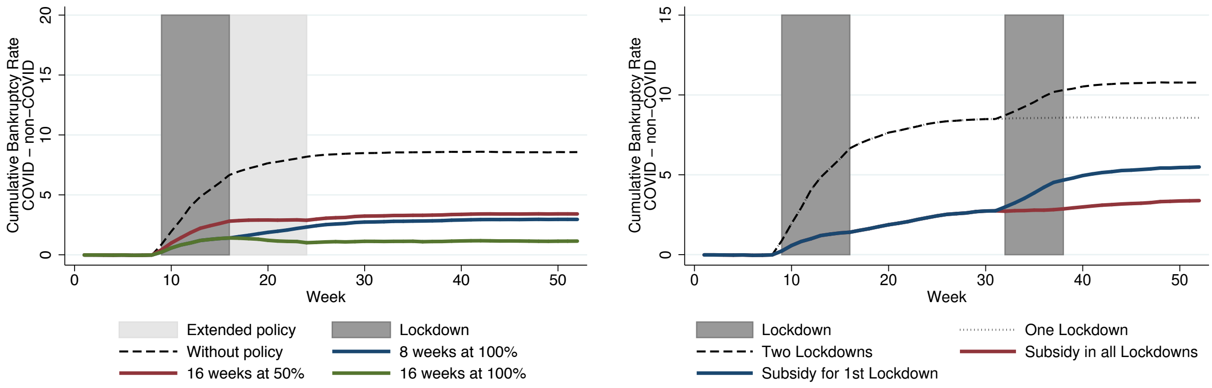
Next, the blue solid line shows the bankruptcy rate evolution when providing a 100% wage subsidy during the 8 week lockdown beginning on the 1st week of March (shown in the Figure in dark grey). We assume that once a firm runs out of cash, it cannot be saved by a subsequent cash injection. As can be seen, the labor subsidy policy lowers the bankruptcy rate considerably. The rise in bankruptcies is both lower during the lockdown and less steep after the lockdown. This suggests the policy support has had permanent effects in lowering the bankruptcy rate.

Then, we consider the effects of slowing payment of the 8-week 100% labor subsidy to be paid over 16 weeks at 50% per week. Note that this does not vary the total subsidy given to each firm, provided the firm survives to 16 weeks after the lockdown. This is shown with the red line (with the extended payment period shown in light-grey).[46] In terms of fiscal cost, covering 50% of wages for 16 weeks or 100% for 8 weeks is essentially the same, however, delaying the payments to firms does lead to a small but higher path for the bankruptcy rate over 2020. This implies that while timing matters, it does not matter as much as whether or not the support is received. To further illustrate this point the green line extends the original 100% labor subsidy for an additional 8 weeks (costing approximately twice as much as the 8-week subsidy). As can be seen, this lowers the bankruptcy rate profile even after the support ends. Overall, the bankruptcy rate decreases by approximately 2 percentage points.

The right panel of Figure 8 shows the effects of a second lockdown and different labor

[46]Delayed policies will end up costing less in aggregate because some firms will go bankrupt before receiving all of (or any of) the policy support.

Figure 8: Policy Response: Bankruptcy Rates by week for a variety of policy responses



(a) 1 Lockdown

(b) 2 Lockdowns

Notes: The results presented in these panels are aggregated across several countries using total revenue of firms in Orbis as weights. The aggregation is done over our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain. Each panel shows the bankruptcy rates over the year for each country in a variety of scenarios. The black dashed line shows the bankruptcy rates over time without any policy interventions. On the left panel, the navy line shows bankruptcy rates if policymakers give a 100% labor cost subsidy during the 8 week lockdown. The red line shows bankruptcy rates under an extended labor cost subsidy for 16 weeks (ending 8 weeks after the lockdown ends) but at 50% of labor costs. The green line shows the bankruptcy rate with an extended labor cost subsidy for 16 weeks but paid out at 100% of labor costs during the period. For the panel on the right we impose 2 lockdowns: the no-policy effect is shown with the black dashed line and the dotted line shows the effect on bankruptcy rates if only the first lockdown is imposed. Next, the navy blue line represents the effects of a 100% of wages subsidy paid during only the first lockdown and the red line represents the effects of also implementing the same subsidy in the second lockdown.

subsidy policies. We assume that the second lockdown is only 6 weeks instead of 8 (to model that policymakers are likely reluctant to impose a lockdown of similar length a second time) and starts in week 32 of the year (mid-August). The black dotted line in this panel shows the weekly evolution of bankruptcy rates with only 1 lockdown (our baseline) and the black dashed line shows the effect of a second lockdown.

Note that without policy support the second lockdown raises bankruptcy rates by between 2-3% – much less than the marginal effect of the first lockdown. This occurs for three reasons. First, we are assuming that the second lockdown is shorter. Second, and more importantly, our simulations suggest that, by the time the second lockdown occurs, a large number of vulnerable businesses have already been forced into bankruptcy by first lockdown and remaining businesses have considerably stronger cash positions.[47] Third, because we assumed that sectoral demand would recover only gradually, the net fall in sectoral demand during the second lockdown is smaller than in the first.

Next, the blue and red lines show the effect of 100% labor subsidies on the bankruptcy rate. The blue line shows the effect of implementing a labor subsidy only in the first lockdown and

[47]Note that this finding is not mechanical result of our analysis. The first lockdown could easily have left many businesses with precarious cash positions that might be easily eroded in a second lockdown. We do not find that this is the case.

the red line shows the effect of implementing an additional 6-week 100% labor subsidy during the second lockdown. As can be seen, imposing a second lockdown without providing policy support raises bankruptcy rates by around 2-3 percentage points relative to providing policy support during both lockdowns. Note that providing policy support in both lockdowns leads to an end-of-year bankruptcy rate level that is almost the same as the end-of-year bankruptcy rate from our single lockdown scenario with 8-week labor subsidy scenario. This suggests that, provided the government has the fiscal capacity to provide the needed policy support, additional lockdowns may be imposed without necessarily requiring additional rises in firm bankruptcies.

This section has focused on the effects of policy support on lowering firm bankruptcy rates. Typical policy tools proposed such as covering firms' financial expenses or subsidizing payroll have been shown to be either too small or very imprecisely targeted relative to infeasible targeted benchmarks. Nonetheless, while the cost of generous policies is much higher, they still have noticeable effects on bankruptcy rates and on jobs lost – in particular, the Accomodation & Food, Manufacturing, Education and Wholesale & Trade sectors. Optimizing the timing of support is considerably less important than providing adequate support and we show that imposing additional lockdowns may not require noticeable rises in bankruptcy rates provided additional policy support is provided.

6 Extensions

The assumptions behind our baseline COVID-19 scenario were designed to present an upper bound of the impact of COVID-19 and associated lockdowns on economic activity. In particular, we assumed firms meet demand even if workplace restrictions make that prohibitively expensive. Similarly, we assumed firms are unable to access any temporary credit in order to smooth through the worst phase of the pandemic. In this section we relax these assumptions by introducing two changes.

Firstly, we allow firms to choose to temporarily shutdown operations if workplace restrictions during lockdown are too restrictive to allow the firm to meet demand while making profits. We refer to this as "mothballing" (see Bresnahan and Raff (1991)) : the firm chooses to temporarily shutdown. It still pays its rent and other fixed costs but incurs no variable costs during the period during which it is closed. Once labor restrictions ease or demand rises sufficiently, the firm may then choose to re-open and restart production. Mothballing allows us to capture in our framework firms such as restaurants that may prefer to remain close rather than switch to curbside pickup or online delivery. For symmetry, we also allow the mothballing option in our non-COVID scenario. The modification to the baseline model is

Table 12: Bankruptcy Rates under Extensions

	Baseline			Mothballing			Mothballing + Annual		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Non-COVID	COVID-19	Δ	Non-COVID	COVID-19	Δ	Non-COVID	COVID-19	Δ
High coverage	9.56	18.19	8.63	9.32	16.97	7.65	9.32	14.80	5.48
All	9.43	18.17	8.75	9.25	16.28	7.03	9.25	13.92	4.67

Notes: This table shows Bankruptcy Rate changes by including two changes to our baseline: firstly allowing firms to "mothball" – shutting down temporarily when unprofitable to operate and re-opening later – and allowing firms to potentially smooth their cash position over 2020 by assessing our bankruptcy condition only at the end of 2020. Bankruptcy rates are first calculated at the 1-digit NACE level and aggregated to the country level using 2017 sector gross value added as weights (the exceptions, due to data availability, are the United Kingdom where 2016 sector gross value added weights are used, and Korea and Japan where Orbis sector gross value added weights are used). Bankruptcy rates are aggregated across countries using GDP as weights. The high coverage group includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. The all countries group incorporates Germany, Japan, Korea, and the United Kingdom. These countries have lower aggregate economy coverage in Orbis.

presented in Appendix A.

Secondly, to approximate that firms may be able to tap into short-term credit facilities during the worse phase of the pandemic, we adjust the frequency with which we assess the firm's liquidity conditions. Instead of assessing the cash balance of each firm at the end of each week and determining them as bankrupt as soon as their end-of-week balance becomes negative, we only make a determination of bankruptcy status at the end of the calendar year. This allows firms to make up for cash deficits during the earlier parts of 2020 over the remainder of the year when demand is higher and workplace restrictions are reduced. This different timing assumption is conceptually similar to allowing firms to access zero-interest loans during 2020 that must be repaid by 31st December 2020.

Table 12 compares the non-COVID, COVID-19 and change in bankruptcy rates (Δ) for these two extensions. Mothballing leads to a reduction in both the overall non-COVID and COVID-19 bankruptcy rates. It has a larger impact during COVID-19, which leads to a lower impact of COVID-19 (Δ) by about one percentage point. In our second scenario we allow firms to mothball and also assess bankruptcy rates at the end of the year. Relative to our baseline, the inclusion of both mothballing and an annual bankruptcy rate assessment reduces the impact of COVID-19 on bankruptcy rates (Δ) by 3 to 4 percentage points depending on our country sample. These results suggest that allowing firms some mechanisms to cope with the worst parts of COVID-19 – in particular smoothing their cash balance throughout the year – could significantly lower the resulting bankruptcy rate.

Next Table 13 shows the impacts across sectors of these different assumptions. Introducing mothballing has a negligible impact on many sectors – for example, lowering the change in bankruptcy rates by 0.07 in Wholesale & Retail (the bankruptcy rate change falls from 9.10 to 9.03). But in other sectors the impact is large, including Mining (-6.97) and Accommodation & Food Service (-5.35). The large impact is felt primarily in sectors with large labor supply shocks and high fraction of firms that are labor constrained during COVID. Combining mothballing

Table 13: Bankruptcy Rates under Extensions by Sectors

	Baseline			Mothballing			Mothballing + Annual		
	(1) Non-COVID	(2) COVID-19	(3) Δ	(4) Non-COVID	(5) COVID-19	(6) Δ	(7) Non-COVID	(8) COVID-19	(9) Δ
Agriculture	9.44	13.52	4.08	8.95	10.96	2.01	8.95	9.80	0.85
Mining	12.50	36.03	23.54	12.22	28.79	16.57	12.22	17.35	5.13
Manufacturing	8.48	16.73	8.25	8.25	13.95	5.70	8.25	10.41	2.16
Electric, Gas & Air Con	9.35	11.31	1.96	9.12	10.14	1.02	9.12	8.71	-0.41
Water & Waste	6.72	9.65	2.93	6.65	8.85	2.20	6.65	7.47	0.82
Construction	7.97	10.19	2.21	7.59	9.53	1.94	7.59	8.31	0.72
Wholesale & Retail	9.12	18.21	9.10	8.86	17.89	9.03	8.86	16.40	7.55
Transport & Storage	7.64	13.28	5.63	7.55	11.92	4.36	7.55	9.48	1.92
Accom. & Food Service	13.15	38.59	25.44	12.88	32.97	20.09	12.88	25.46	12.59
Info. & Comms	10.00	15.92	5.92	9.68	15.29	5.61	9.68	13.75	4.07
Real Estate	11.61	17.38	5.76	11.30	17.18	5.89	11.30	16.36	5.06
Prof., Sci., & Technical	10.24	18.85	8.60	10.01	18.29	8.28	10.01	16.94	6.92
Administration	8.32	19.39	11.06	8.13	18.65	10.52	8.13	17.04	8.91
Education	10.86	30.04	19.18	10.73	29.94	19.21	10.73	27.04	16.32
Health & Social Work	7.74	11.22	3.48	7.67	11.09	3.42	7.67	10.14	2.47
Arts, Ent., & Recreation	12.95	36.55	23.60	12.51	32.22	19.71	12.51	28.75	16.24
Other Services	12.80	31.42	18.62	12.51	30.45	17.94	12.51	25.83	13.32

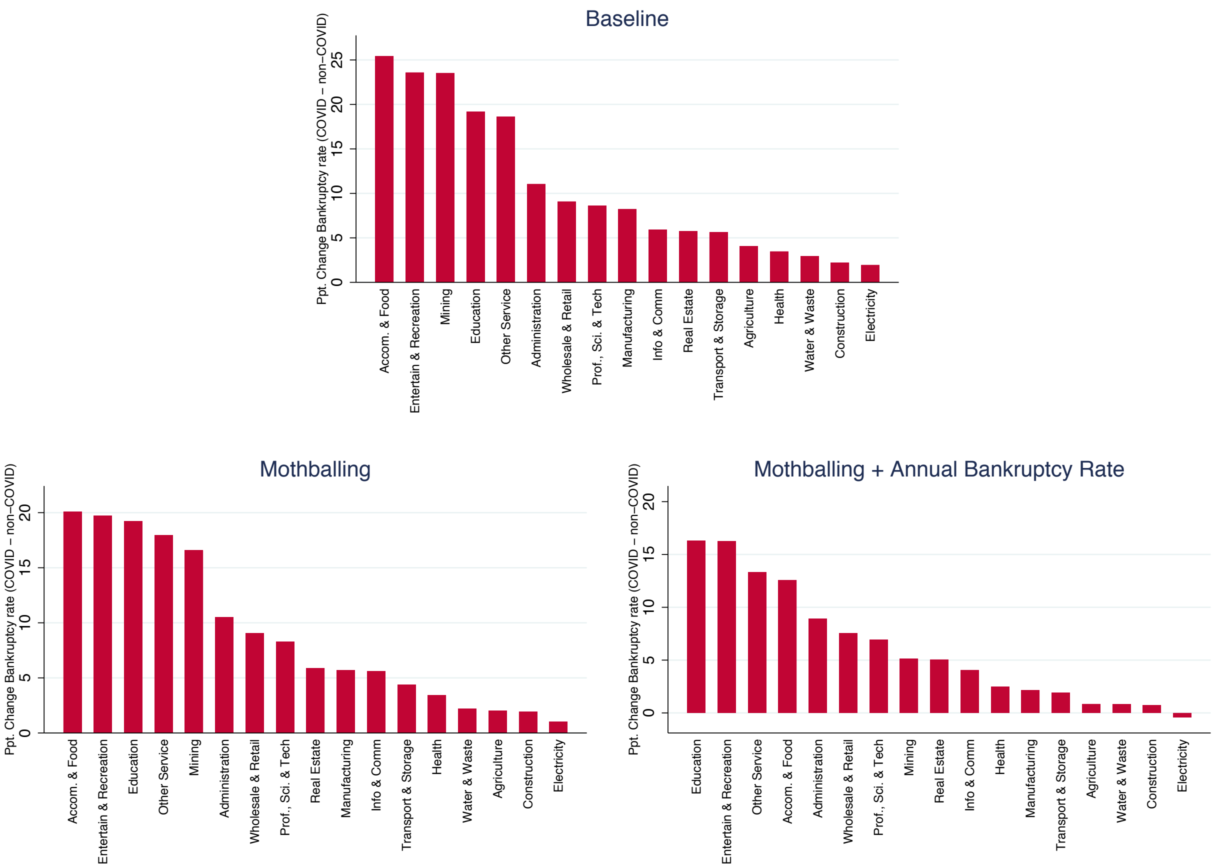
Notes: This table shows Bankruptcy Rate changes by sector by including two changes to our baseline: firstly allowing firms to "mothball" – shutting down temporarily when unprofitable to operate and re-opening later – and allowing firms to potentially smooth their cash position over 2020 by assessing our bankruptcy condition only at the end of 2020. Sector bankruptcy rates are first calculated at the 1-digit NACE level for each country, and then aggregated across countries using (country x sector) gross value added from the OECD as weights. The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Sloveian, and Spain.

and annual bankruptcy calculations, results in a decline in the bankruptcy rate due to COVID-19 – across all sectors, ranging from a 0.7 percentage point decline in Real Estate to a 18.4 percentage point decline in Mining. As with mothballing, the most affected sectors are those with large labor supply shocks and a large fraction of firms that end up labor constrained during the crisis. Despite these numerical changes, as shown in Fig. 9, the most-to-least affected ranking is broadly similar to our baseline. One notable exception is Mining which is a unique sector which faces high demand but also strong workplace restrictions. Mothballing is particularly helpful for the solvency of firms in the mining sector by allowing them to avoid trying to operate to meet higher than normal demand with very few workers. Moreover, once workplace restrictions are loosened, the mining sector faces higher demand than pre-COVID which allows for a quick recovery in their cash balances.[48] Therefore, assessing the liquidity position of mining firms at the end of year particularly advantages them as they have the ideal conditions with which to recover their lost cash during lockdown.

Table 14 reports bankruptcy rates and their changes by country. With mothballing, the cross-country results yield a similar pattern as the cross-country results – declines in both non-COVID and COVID bankruptcy rates and a larger impact on COVID bankruptcy rates.

[48] Recall, we assume that our sector-specific demand shock $\tilde{\xi}_s^{\eta}$ slowly reverts to pre-COVID levels after the lockdown ends. For mining, this shock was above 1 in the lockdown which means it remains above 1 for the remainder of the year. Even when combined with the aggregate demand shock $\widehat{PD}$, for mining demand is above pre-COVID.

Figure 9: Cross-Sector Difference in SME Bankruptcy Rates (COVID - non-COVID)



Notes: This Figure shows Bankruptcy Rate difference between our COVID and non-COVID scenarios by sector including two changes to our baseline: firstly allowing firms to "mothball" (bottom left panel) – shutting down temporarily when unprofitable to operate and re-opening later – and by also allowing firms to potentially smooth their cash position over 2020 by assessing our bankruptcy condition only at the end of 2020 (bottom right panel). The top panel shows the differences between COVID and non-COVID bankruptcy rates in our baseline scenario. Sector bankruptcy rates are first calculated at the 1-digit NACE level for each country, and then aggregated across countries using (country x sector) gross value added from the OECD as weights. The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Sloveian, and Spain.

The impact of mothballing on the COVID – non-COVID bankruptcy rate change, relative to the baseline, varies across countries from just -0.58 percentage points in Italy to -1.95 percentage points in Romania. The impact of incorporating annual bankruptcy rate calculations varies across countries, ranging from a 1.7 percentage point decline in Greece to a 2.9 percentage point decline in Finland. Despite changes in country bankruptcy rates arising from both extensions, the ordering of most-to-least affected countries is similar to our baseline.

Table 14: Bankruptcy Rates under Extensions by Country

	Baseline			Mothballing			Mothballing + Annual		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Non-COVID	COVID	Δ	Non-COVID	COVID	Δ	Non-COVID	COVID	Δ
Belgium	7.75	14.18	6.42	7.73	12.89	5.16	7.73	11.19	3.46
Czech Republic	8.24	13.59	5.35	7.42	11.51	4.09	7.42	9.95	2.53
Finland	8.35	16.91	8.56	8.26	15.46	7.20	8.26	12.56	4.30
France	9.03	16.94	7.91	8.96	16.08	7.12	8.96	13.64	4.68
Greece	10.43	16.37	5.94	9.99	14.65	4.65	9.99	12.94	2.95
Hungary	8.22	14.01	5.79	8.13	12.92	4.79	8.13	11.23	3.11
Italy	9.91	22.68	12.77	9.73	21.92	12.19	9.73	19.65	9.92
Poland	11.68	20.45	8.77	11.61	19.62	8.01	11.61	17.23	5.62
Portugal	12.21	19.65	7.44	12.04	18.34	6.30	12.04	16.12	4.08
Romania	15.77	23.18	7.41	15.15	20.61	5.46	15.15	17.74	2.59
Slovak Republic	10.41	16.05	5.64	9.63	14.36	4.73	9.63	12.81	3.18
Slovenia	7.25	15.95	8.71	6.99	13.88	6.89	6.99	11.18	4.19
Spain	8.98	15.50	6.52	8.32	13.32	5.00	8.32	11.77	3.45

Notes: This table shows bankruptcy rates at the country level for our baseline and two scenarios with alternative assumptions. The first allows for "mothballing" – shutting down temporarily when unprofitable to operate and re-opening later – and by also allowing firms to potentially smooth their cash position over 2020 by assessing our bankruptcy condition only at the end of 2020. Country-level bankruptcy rates under non-COVID evaluate the fraction of firms facing a liquidity shortfall in 2017, and under COVID are evaluated under our baseline scenario. Country level results represent the weighted average of 1-digit NACE bankruptcy rates, where weights are given by 2017 sector gross value added. Only countries who are in the high quality group are included in this table.

7 Conclusion

COVID-19 may seriously disrupt the economic fabric by pushing a large number of small and medium enterprises into bankruptcy. This paper attempts to assess the extent of the problem, and to analyze the effect of various policy interventions. To answer these questions, we combine a large firm-level dataset with a tractable structural framework. The framework allows for considerable firm level heterogeneity and provides a rich set of supply, demand, sectoral and aggregate shocks by which COVID-19 can affect firms.

Our baseline estimates suggest that – absent intervention and with impaired access to credit markets – the rate of businesses failures for SMEs would almost double, increasing by 8.8 percentage points in 2020. We document significant heterogeneity in the rate of SME failures both across sectors, and across countries based on both firm profitability and cash holdings and our estimates of COVID supply and demand shocks. These business failures would put a significant number of jobs at risk – about 3.1 percent of employment. Despite these large real effects, we estimate only a modest impact on the financial sector, with a decline of the CET1 capital ratio of 0.75 percentage points on average.

Our framework allows us to consider a number of policy interventions and to measure their cost-effectiveness at supporting the SMES. We find evidence of a significant trade-off. Direct support can significantly reduce the rate of business failures, but at a significant fiscal costs. According to our estimate, a subsidy corresponding to 15% of the firm's annual wage bill in a normal year would reduce business failures by 5.6 percentage points, saving 2.96 percent of employment, at a fiscal cost of 1.8 percent of GDP. However, we uncover evidence that such policies would significantly misallocate resources, with the bulk of the support going to firms that don't need it, and a smaller fraction going to firms that would fail anyway. These results highlights the importance of proper targeting of fiscal interventions.

Our modeling framework presents a number of limitations that we acknowledge. First, one would like to conduct a similar analysis in a general equilibrium environment. Second, while we model a rich sectoral environment, we do not incorporate input-output linkages that could amplify some of the results. Third, a more dynamic treatment, allowing for prices adjustment and capital reallocation would also be an interesting exercise. We view these as natural – but much more complex – extensions of our analysis. Yet even absent these features, our estimates can be interpreted as a capturing the "first-round" effects of COVID-19 and already suggest that the impacts, absent intervention, could be large, heterogenous and show that significant benefits could be reaped from appropriate policy support. While accounting for general equilibrium and firm-to-firm linkages is important, we believe they are unlikely to weaken these conclusions.

References

Acharya, Viral V. and Sascha Steffen, "The risk of being a fallen angel and the corporate dash for cash in the midst of COVID," *COVID Economics: A Real Time Journal*, April 2020, *10.*

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83*, 2411–2451.

Almeida, Heitor and Ander Ippollito Filippo ad Perez, "Credit Lines as Monitored Liquidity Insurance: Theory and Evidence," *Journal of Financial Economics*, 2014, *112*, 287–319.

_ **and Murillo Campello**, "Aggregate Risk and the Choice between Cash and Lines of Credit," *Journal of Finance*, 2013, *68*, 2059–2116.

Baqaee, David Rezza and Emmanuel Farhi, "Nonlinear Production Networks with an Application to the Covid-19 Crisis," May 2020. NBER Working Paper 27281.

_ **and** _ , "Supply and Demand in Disaggregated Keynesian Economies with an Application to the Covid-19 Crisis," May 2020. CEPR Discussion Paper DP14743.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis, "Covid-19 is also a reallocation shock," *Brookings Papers on Economic Activity*, June 2020.

Barrot, Jean-Noel, Basile Grassi, and Julien Sauvagnat, "Sectoral Effects of Social Distancing," April 2020. HEC Paris Research Paper No. FIN-2020-1371.

Benassy-Quéré, Agnes, "Equity gaps in the French corporate sector after the great lock-down," https://www.tresor.economie.gouv.fr/Articles/2020/08/25/equity-gaps-in-the-french-corporate-sector-after-the-great-lock-down August 2020. French Treasury.

Blackwood, G. Jacob, Lucia S. Foster, Cheryl A. Grim, John Haltiwanger, and Zoltan Wolf, "Macro and Micro Dynamics of Productivity: From Devilish Details to Insights," *AEJ: Macroeconomics*, forthcoming, 2020.

Bresnahan, Timothy F and Daniel MG Raff, "Intra-industry heterogeneity and the great depression: The american motor vehicles industry, 1929-1935," *Journal of Economic history*, 1991, pp. 317–331.

Carletti, Elena, Tommaso Oliviero, Marco Pagano, Loriana Pelizzon, and Marti Subrahmanyam, "The COVID-19 Shock and Equity Shortfall: Firm-level Evidence from Italy," June 2020. CEPR Discussion Paper DP14831.

Cavallo, Alberto, "Inflation with Covid Consumption Baskets," *Harvard Business School BGIE Unit Working Paper*, 2020, (20-124).

Çakmaklı, Cem, Selva Demiralp, Şebnem Kalemli-Özcan, Sevcan Yesiltas, and Muhammed A Yildirim, "COVID-19 and Emerging Markets: An Epidemiological Model with International Production Networks and Capital Flows," May 2020. NBER Working Paper 27191.

Chetty, Raj, John N Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team, "How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data," June 2020. NBER Working Paper 27431.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, "Labor markets during the covid-19 crisis: A preliminary view," April 2020. NBER Working Paper 27017.

Core, Fabrizio and Filippo De Marco, "Public Guarantees for Small Businesses in Italy during COVID-19," May 2020. SSRN 3604114.

Cox, Natalie, Peter Ganong, Pascal J Noel, Joseph S Vavra, Arlene Wong, Diana Farrell, and Fiona E Greig, "Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data," July 2020. NBER Working Paper 27617.

Demmou, Lilas, Guido Franco, Calligaris Sara, and Dennis Dlugosch, "Corporate Sector vulnerabilities during the Covid-19 outbreak: assessment and policy responses," OECD ECOSCOPE June 2020.

Dingel, Jonathan and Brent Neiman, "How Many Jobs Can be Done at Home?," June 2020. NBER Working Paper 26948.

Drechsel, Thomas and Şebnem Kalemli-Özcan, "Are standard macro and credit policies enough to deal with the economic fallout from a global pandemic? A proposal for a negative SME tax," March 2020. mimeo University of Maryland.

Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, "Can the Covid Bailouts Save the Economy?," May 2020. NBER Working Paper 27207.

Gandhi, Amit, Salvador Navarro, and David Rivers, "On the Identification of Production Functions: How Heterogeneous is Productivity?," *Society of Economic Dynamics Meeting Meeting Papers*, 2012.

Goolsbee, Austan and Chad Syverson, "Fear, Lockdown, and Diversion: Comparing Drivers of Pandemic Economic Decline 2020," June 2020. NBER Working Paper 27432.

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez, "Capital Allocation and Productivity in Southern Europe," *Quarterly Journal of Economics*, 2017, *132* (4), 1915–1967.

Gottlieb, Charles, Jan Grobovsek, Markus Poschke, and Fernando Saltiel, "Lockdown Accounting," 2020. IZA Discussion Paper.

Granja, João, Christos Makridis, Constantine Yannelis, and Eric Zwick, "Did the Paycheck Protection Program Hit the Target?," May 2020. NBER Working Paper 27095.

Guerini, Mattia, Lionel Nesta, Xavier Ragot, and Stefano Schiavo, "Firm liquidity and solvency under the Covid-19 lockdown in France," *OFCE Policy Brief*, July 2020, (76).

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning, "Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?," April 2020. NBER Working Paper 26918.

Jaravel, Xavier and Martin O'Connell, "Inflation spike and falling product variety during the Great Lockdown," *Journal of Public Economics*, forth.

Kalemli-Özcan, Şebnem, Bent Sorensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yesiltas, "How to Construct Nationally Representative Firm Level Data from the ORBIS Global Database," September 2015. NBER Working Paper 21558.

Krueger, Dirk, Harald Uhlig, and Taojun Xie, "Macroeconomic dynamics and reallocation in an epidemic," April 2020. NBER Working Paper 27047.

Levinsohn, James A. and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 2003, *7* (2), 317–341.

Mongey, Simon, Laura Pilossoph, and Alex Weinberg, "Which workers bear the burden of social distancing policy?," BFI Working Paper 2020-51 2020.

OECD, "Coronavirus (COVID-19): SME Policy Responses," Note, OECD July 2020.

Schivardi, F and G Romano, "A simple method to estimate firms liquidity needs during the COVID-19 crisis with an application to Italy," *Covid Economics*, 2020, *35*, 51–69.

Shapiro, Adam Hale et al., "Monitoring the Inflationary Effects of COVID-19," *FRBSF Economic Letter*, 2020, *2020*, 24.

Woodford, Michael, "Effective Demand Failures and the Limits of Monetary Stabilization Policy," September 2020. NBER Working Paper 27768.

Wooldridge, Jeffrey M., "On estimating firm-level production functions using proxy variables to control for unobservables," *Economic Letters*, 2009, *104* (3), 112–114.

Appendices

Appendices

A Mothballing

If production costs are excessive, firms could have a higher cash-flow if they decide to shut down temporarily – i.e. to 'mothball' – during the COVID-19 period. In that case $y_{is} = n_{is} = m_{is} = 0$. The option to mothball will be particularly relevant for firms that face severe labor constraint and would be required to substitute – at excessively high cost – with intermediate inputs (see Bresnahan and Raff (1991)). Conditional on meeting demand, firms aim to minimize costs. They do so by re-optimizing over both labor n'_{is}, subject to the labor supply constrained Eq. (9), and other flexible input m'_{is}.

As Eqs. (13) and (15) illustrate, firms could make negative variable profits if trying to meet the demand d'. This is especially the case for firms that are labor constrained and have a low material output elasticity. These firms would prefer not to produce at all rather than generate large losses. We allow these firms to 'mothball' for the duration of COVID-19: by setting $n' = m' = 0$ then can avoid any variable losses $\pi' = 0$. Inspecting Eq. (13), and substituting $\hat{x}^c$ in terms of primitives, we see that non-constrained firms choose to mothball if and only if:

$$\hat{A}^{\beta} \leq \left(\tilde{\xi}^{\eta}\widehat{PD}\right)^{1-\beta-\gamma}(s_n + s_m)^{\beta+\gamma}. \tag{A.1}$$

This expression indicates that mothballing is more likely when firms experience larger productivity shocks (a lower $\hat{A}$).[49]

For labor constrained firms the condition for mothballing is relaxed to

$$\hat{A}^{\beta} \leq \left(\tilde{\xi}^{\eta}\widehat{PD}\right)^{1-\beta-\gamma}\left(s_n\frac{\hat{x}}{\hat{x}^c} + s_m\left(\frac{\hat{x}}{\hat{x}^c}\right)^{-\beta/\gamma}\right)^{\beta+\gamma}. \tag{A.2}$$

As expected, this expression illustrates that mothballing is more likely for labor constrained firms with low material elasticity. Because we measure the cost shares s_n and s_m at the firm level, the condition for mothballing applies to individual firms, according to Eqs. (A.1) and (A.2).

[49] There is also the possibility that unconstrained firms prefer to mothball rather then produce if they experience a large *increase* in sectoral demand ($\tilde{\xi}^{\eta}$). However in our estimation, this case is not empirically relevant.