COVID-19 AND SME FAILURES

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ABSTRACT

We estimate the impact of COVID-19 on business failures for small and medium sized enterprises (SMEs) using firm-level data in seventeen countries. Absent government support, the failure rate of SMEs would have increased by 9.1 percentage points, representing 4.6 percent of private sector employment. Resulting non-performing loans are modest, decreasing the risk-weighted common equity Tier-1 capital ratio from 14.1 to 12 percent. Government support limited to "at-risk" firms would have low fiscal costs (0.8% of GDP). Less targeted policies such as government guaranteed loans are similarly effective, but substantially more expensive, with disbursed funds representing up to 5.8% of GDP.

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1 Introduction

The COVID-19 economic shock was unprecedented both in its complexity and severity. Globally, nationwide lockdowns, in conjunction with behavioral changes due to 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. The severity of the crisis and the uncertainty surrounding the recovery raised fears that a large number of businesses, especially small ones, would fail. In the midst of the rapidly evolving economic situation, governments rushed to mitigate the fallout. Ultimately, policy design was complicated by limited real-time information on which firms and which sectors were most vulnerable to and most impacted by the COVID-19 shock.

In this paper we develop a flexible framework that combines a model of firm cost minimization with rich firm level financial data to estimate the impact of the COVID-19 crisis on business failures among some of the most at-risk firms in the economy, small and medium-sized enterprises (SMEs). In the European Union, SMEs 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] At the same time, SMEs tend to have small cash buffers, higher dependence on bank financing, and limited access to new credit lines during crises. These factors, coupled with plummeting revenues due to COVID-19, could trigger liquidity shortages that eventually turn into solvency problems.

The potential vulnerability of SMEs to the COVID-19 shock was a primary concern for policymakers everywhere. Should a wave of SME failures occur, the efforts to contain the economic consequences of the pandemic would have failed – furloughed workers or those on temporary layoff would become unemployed; banks would experience large losses on their C&I loan books, raising the risk of a financial crisis; and fiscal costs of containing the crisis would continue to rise. Government policies to address SMEs' liquidity shortages were thus seen as essential to ensure a smooth economic recovery. Our framework enables us to assess the extent to which concerns about the vulnerability of SMEs were warranted, to estimate the impact of various policies aimed at mitigating SME failures, and to quantify their fiscal costs.

We first 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 that represent COVID-19. The total demand for a firm's output in each sector is affected both by an aggregate and a sector-specific demand shock. The former captures the size of the slowdown in aggregate expenditures due to COVID-19. It af-

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[1]SMEs are defined as firms with less than 250 employees. These statistics are derived from EUROSTAT's Structural Business Statistics.

fects all firms proportionately. The latter reflects the change in relative demand in that sector, as a result of changes in household behavior or government lockdown policies. 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 (such as online deliveries) rises during the same period.

On the supply side, we also make a distinction between essential and non-essential sectors. Essential sectors are assumed to be unconstrained while 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 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 it faces. Importantly, firms face no costs to adjusting labor, either because they can fire workers, or because of short-term work programs that shift the costs of non-working employees onto the government.

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] Our analysis focuses on the following 17 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.

Our approach has the advantage of being simple, flexible and easily mapped into available firm-level data. It can potentially be used to analyze any combination of firm/sector/aggregate supply and demand shocks. 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 overall rate of business failures. A possible interpretation is that we focus on the first-round impact of the COVID-19 crisis. 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-19 related output losses, due to demand and/or supply shocks (Baqaee and Farhi, 2020a; Barrot, Grassi and Sauvagnat,

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[2]Orbis reports firm level balance sheet data with a two year lag. We use 2018 as our benchmark.

2020; Çakmaklı, Demiralp, Kalemli-Özcan, Yesiltas and Yildirim, 2020; Çakmaklı, Demiralp, Kalemli-Özcan, Yeşiltaş and Yıldırım, 2021). Third, our approach is static and keeps prices unchanged. Reality is more complex, with evidence of 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 the ability to draw on credit lines. For instance, although Orbis balance sheet data provides information on the stock of short and long term debt, it does not contain data on undrawn credit lines (Chodorow-Reich, Darmouni, Luck and Plosser, 2020). Fifth, our analysis focuses on liquidity, not solvency. A complementary approach, followed for instance by Carletti, Oliviero, Pagano, Pelizzon and Subrahmanyam (2020) for Italy and by Díez, Duval, Fan, Garrido, Kalemli-Özcan, Maggi, Martinez-Peria and Pierri (2020) for a larger set of countries, would be to estimate equity shortfalls and focus on insolvency. To defend our approach, we note that the focus of our analysis is on SMEs, where book-value equity may be severely mismeasured, especially for illiquid and unlisted businesses.

We define a baseline scenario in which the COVID-19 shocks hit in week 9 of the year (end of February 2020) and the subsequent lockdown and stringent social distancing period lasts 8 weeks. This timing coincides with the lockdown period imposed in many of our sample countries.[3] During these 8 weeks, the economy is affected by the sectoral and aggregate supply and demand shocks described above. After the lockdown ends, sectoral labor supply and productivity shocks return to their pre-COVID levels, while aggregate demand evolves according to IMF quarterly projections, and sector-specific demand reverts back to normal at a quarterly rate of 0.5. We also assume that while firms continue to rollover existing debt, as is common practice, they are unable to obtain new credit. We evaluate our liquidity shortfall condition each week through the end of the year, and assume that firms that become illiquid in any week of the year fail at that point in time.

Our initial analysis abstracts from any government policies in order to illustrate how severe the COVID-19 crisis could have been had governments failed to intervene. This provides a counterfactual against which various support policies can then be evaluated. We estimate a quasi-doubling of business failures due to COVID-19 in our sample of countries: the SME failure rate rises by 9.1 percentage points, from 9.6 percent in the absence of the COVID-19 shocks to 18.7 percent under COVID-19. We find a great deal of sectoral heterogeneity in failure rates, with customer-oriented sectors heavily affected, including Accommodation &

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

Food Service and Arts, Entertainment & Recreation. While high failure rates in a sector often arise from high exposure to COVID-19 shocks, we also find that sectors containing many firms with pre-existing financial vulnerabilities can have high rises in failure rates even when faced with modest COVID-19 shocks. These factors also drive cross-country heterogeneity through differences in sectoral composition and initial firm cash/debt levels, with increases in failure rates ranging from 4.8 percentage points in the Czech Republic to 13.2 percentage points in Italy.

An increase in business failures can also pose a risk to the banking sector through a rise in non-performing loans (NPLs). We estimate an average increase in the fraction of SME NPLs of 9.0 percentage points. Moreover, the average increase in NPLs puts 1.01 percent of banks' total assets and 17.41 percent of their common equity Tier-1 (CET1) capital at risk, and results in a 2.12 percentage point decline in the ratio of CET1 capital to risk-weighted assets. As a point of comparison, the European Banking Authority's (EBA) 2018 EU-wide stress tests considered an adverse scenario with a decline in the risk-weighted CET1 capital ratio of around 4 percentage points.[4] We therefore conclude that despite that large rise in SME failures, the impact of COVID-19 on the health of the financial sector is likely to remain moderate.

We consider extensions that relax several of our assumptions. First, we allow for some relaxation of the labor supply constraint. Firms in our analysis face a tension between desired labor demand and available labor supply. When the labor supply constraint binds, firms try to meet demand by substituting away from labor, which drives up variable costs and drains cash flow. Some businesses may fail because they must meet demand in this constrained environment. In reality, some firms may prefer to temporarily shut down than produce, or implement costly workplace adjustments that would allow them to retain more employees. In the first extension, we allow firms to *'mothball'* as in Bresnahan and Raff (1991) for the duration of the lockdown. In a second extension, we allow firms to relax their labor supply constraint, provided they pay a quadratic cost. This extension captures the idea that firms may be able to retain more workers on-site safely during a lockdown by making workplace adjustments, such as rearranging the workplace layout to allow more distancing. Each of these two extensions dampen the increase in SME failures by less than two percentage points, but the main conclusions remain unchanged.

We also introduce two extensions that relax our assumption about credit conditions. By evaluating the failure criteria week-by-week throughout 2020, we assume that firms cannot borrow within the year to smooth the drop in cash flow during the weeks of confinement. We relax this assumption by evaluating the liquidity condition once at the end of the year. This is equivalent to allowing firms smooth cash flow within the calendar year. This extension lowers failure rates by 2.3 percentage points. Our final extension considers the effects of a hypothetical

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

credit crunch where banks decline to roll over firms' maturing debt. In our baseline, firms are allowed to roll over their maturing pre-COVID debts, even if they are unable to borrow additional funds. Forcing firms to cover both their financial expenses and principal payments due during COVID-19 leads to a 11.9 percentage point increase in SME failures, underscoring that the capacity to rollover debt is vital for many SMEs to survive.

Taken together, these results suggest that many SMEs would have failed in the absence of policy support. Governments, however, did not sit idly by. Around the world, they implemented an array of measures, such as tax deferrals, direct cash transfers, government guaranteed loans, and equity-like injections to provide support to struggling firms. The combined effect of these policies could significantly alleviate the direct impact of the COVID-19 shock on firms' cash flows and failure rates. Although we lack accurate data on firms' failures, early available estimates indicate that 2020 corporate failures are broadly comparable, and possibly lower, than their pre-COVID levels.[5]

We use our framework to explore the cost and effectiveness of various government interventions. First, we consider a hypothetical policy that bails out all firms that fail due to the COVID-19 shock but that would have survived under normal circumstances. While this policy may be hard to implement in practice, it is informative about the minimum resources needed to save all of these viable, at-risk firms. This benchmark policy is extremely cost-effective: at a cost of 0.78 percent of GDP, it lowers failure rates back to their pre-COVID level and helps preserve 4.64 percent of private sector jobs. These findings illustrate that properly directed policies to viable firms can efficiently provide relief to firms at a modest fiscal cost.

Next, we compare this benchmark policy to several interventions that mimic many of the policies implemented in practice. The first set of policies are rebates offered to *all* SMEs: waiving financial expenses, taxes, or rent from the beginning of the lockdown through the rest of the year.[6] We find that, while the fiscal cost of waiving financial expenses for the whole year is moderate, at 1.29 percent of GDP, it saves a mere 1.28 percent of businesses. Similarly, the taxation and rent waivers save few firms.

We also consider two policies that provide firms with fresh funds during the lockdown – a cash grant covering part of the firms' pre-pandemic labor costs and a government-guaranteed

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[5] 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 (Benassy-Quéré, 2020). Estimates of 2020 bankruptcies are still scarce due to reporting lags in firm filings and congested courts with regulatory freezes on proceedings. See the U.S. Small Business Pulse Survey, Crane, Decker, Flaaen, Hamins-Puertolas, Kruz and Christopher (2020) and Wang, Jeyul, Iverson and Kluender (2020) for information on temporary closures and alternative measures of failure in the U.S. and "German insolvencies continue to fall despite phasing out of virus-waiver," *Financial Times, Dec. 18, 2020* for recent information for Germany.

[6] 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. According to the same source tax deferrals have been one of the most common policy support measures used by governments and 22 countries have implemented some form of rent deferral or waiver scheme.

pandemic loan. Similar policies have been implemented in some countries, with the pandemic loan guarantee program widely adopted in the Euro Area.[7] We consider a cash grant that covers 100 percent of a firm's pre-COVID wage bill for the duration of the 8-week lockdown, amounting to 15.4 percent of the firm's pre-COVID annual wage bill. In line with European Commission guidelines, we assume that the pandemic loan is a zero interest loan that covers the maximum of 25 percent of pre-COVID average weekly revenues or twice the pre-COVID average weekly wage bill during the 8-week lockdown. Consequently, because our analysis focuses on 2020, the funding provided by the pandemic loan can be implemented in our framework as a lump-sum payment to firms, similar to the cash grant.[8]

In contrast to the rebate policies, we find that both the cash grant and pandemic loan provide significant relief, but require considerable funds be committed. The cash grant costs 2.38 percent of GDP, lowers failure rates by 5.60 percentage point, and saves 3.26 percent of jobs. Meanwhile, the pandemic loan saves 8.56 percent of firms and 4.59 percent of jobs, bringing both almost back to their pre-pandemic levels. The pandemic loan policy mobilizes 5.82 percent of GDP in government-guaranteed funding.

Both the cash grant and pandemic loan mobilize substantially more funds than the benchmark policy. We find that this is because these policies are poorly targeted and provide substantial support to strong firms that do not need it, and some support to weak firms that would have failed regardless of COVID-19. Under the cash grant policy, we find that only 0.24 percent of GDP (out of a total 2.38 percent) is channeled to the viable firms that fail under COVID-19 but would have survived otherwise. Meanwhile, 1.96 percent of GDP is wasted on strong firms that do not need the support, and another 0.19 percent on weak firms that would have failed even in the absence of COVID-19. Ultimately, the policy preserves 70 percent as many jobs as the benchmark policy (3.26 percent vs. 4.64 percent). Yet, while 100 percent of the jobs saved under the benchmark belong to viable firms, only 73 percent do under the cash grant. The remaining 27 percent of jobs are in weak firms and are likely to disappear as soon as government assistance ends. Under the pandemic loan policy, only 0.63 percent of GDP (out of a total 5.82 percent) is channeled to 'viable' firms while 4.75 percent of GDP is disbursed to strong firms and 0.44 percent of GDP on weak firms.

Our analysis of government policies yields two important lessons. First, the broad support policies that governments rushed to put in place in 2020 were quite effective at saving many SMEs made vulnerable by COVID-19, as intended. The preliminary evidence that failure rates

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[7]See ECB Economic Bulletin 6/2020 Focus. Should a firm find itself unable to repay its pandemic loan, the government bears between 70 percent and 90 percent of the principal losses.

[8]Loans differ from grants in that some firms who do not need the support may decide not to apply. Moreover, the amounts disbursed differ from the true fiscal cost to the extent that loans are subsequently reimbursed. Neither of these has any effects on our estimates of firms and jobs saved in 2020 by offering these loans. We take up the question of repayment on government-guaranteed loans in 2021 in our companion paper (Gourinchas, Kalemli-Özcan, Penciakova and Sander, 2021).

did not increase in 2020 is consistent with our findings. Second, while these policies were poorly targeted, they did not create many 'zombie' firms, i.e. firms that can survive only with continued support. Instead, they benefited strong firms that did not need support. This finding has important implications for the future, which we explore in our companion paper, Gourinchas et al. (2021).

Literature Review and Our Contribution

The literature on the economic impact of the COVID-19 pandemic is rapidly expanding. 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 COVID-19 on mobility and consumption patterns. Third, papers such as Baqaee and Farhi (2020a,b); Barrot et al. (2020); Woodford (2020); Gottlieb, Grobovsek, Poschke and Saltiel (2020); Çakmaklı et al. (2020); Çakmaklı et al. (2021) explore the importance of networks and linkages for sectoral shocks and their aggregate consequences. Although we do not consider a network structure, our analysis is very detailed at the firm and sectoral levels. Fourth, we are similar, in spirit, to papers such as Barrero, Bloom and Davis (2020); Guerrieri, Lorenzoni, Straub and Werning (2020); Krueger, Uhlig and Xie (2020), as they explore the distinction between the demand and supply component of the COVID-19 shock, and the sectoral reallocation it induces.

The papers closest to us are the ones studying the effects of COVID-19 on business failures. The key challenge in this literature is the lack of timely and granular data on financial positions of SMEs. This problem is most serious for the U.S., where only large listed firms are required to report. Hence, many papers focusing on the U.S. use data on large publicly listed firms (e.g. Acharya and Steffen (2020), Greenwood, Iverson and Thesmar (forthcoming), Crouzet and Gourio (2020)). These studies find that large firms could smooth out the COVID-19 shock by drawing on their credit lines (e.g. Greenwald, Krainer and Paul (2020)). Greenwood et al. (forthcoming) and Hanson, Stein, Sunderman and Zwick (forthcoming) conjecture that extensive government support is needed for SMEs, as liquidity shortfalls and court congestion will lead to excess liquidation. We are not aware of any study estimating the extent of such bankruptcies for U.S. SMEs. Studies that use data on small firms for European countries (e.g. Demmou, Franco, Sara and Dlugosch (2020), Carletti et al. (2020), Schivardi

and Romano (2020)) do not rely on a structural model of the firm and often consider a simple empirical rule to project cash flow under COVID-19. Some studies also explore the question of solvency related bankruptcies, while we limit our focus to liquidity related bankruptcies.[9]

Finally, 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, such as the Paycheck Protection Program in the United States. Greenwood et al. (forthcoming), Blanchard, Philippon and Pisani-Ferry (2020) and Hanson et al. (forthcoming) suggest that the government could subsidize debt restructuring, provide tax credit to lenders, or take an equity stake in the private sector. Brunnermeier and Krishnamurthy (forthcoming) caution that these type of government policies may create a debt overhang effect. Drechsel and Kalemli-Özcan (2020) propose a negative tax on SMEs which can be clawed back later, via an excess profits tax. In a similar vein, Landais, Saez and Zucman (2020) support direct government support to firms via grants and not loans. After providing our baseline estimates of SME bankruptcies from 17 countries, we evaluate the effect of some of these policy proposals on SMEs failure rates.

2 A Simple Theoretical Framework

The objective of our exercise is to develop a flexible framework that leverages existing firm level data to estimate the impact of the COVID-19 crisis on SME failures; first under a baseline scenario without policy support, and then under various policy scenarios and extensions. 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 flow. 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.

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[9]Two exceptions are Guerini, Nesta, Ragot and Schiavo (2020) and Díez et al. (2020). These papers - subsequent to ours- borrow and build on our methodology. The former uses a comprehensive database of firms but is limited to France. The latter uses data similar to ours and extends our analysis to other countries.

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. 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:

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

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 is 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 adopt a nested CES demand structure, for both final and intermediate uses, of the form:

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

In Eq. (2), D denotes aggregate demand, D_s is sectoral demand, ζ_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 $\mathcal{N}_s\zeta_s = 1, \forall s$. We denote with a "prime" the value of variables during COVID-19, so that ζ_s' is the sectoral demand shifter during COVID-19. For many sectors, we expect $\zeta_s' < \zeta_s$, 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 in-

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[10]This is an important simplification. See Jaravel and O'Connell (forth.); Cavallo (2020); Baqaee and Farhi (2020b) for evidence on sectoral price adjustment.

stance, 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. $\xi'_s > \xi_s$. For instance, the demand for some online services or home delivery may increase during confinement.

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 "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 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:

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

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

[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 $\sum_s \mathcal{N}_s P_s D_s$.

Putting the two previous equations together, we obtain a very simple expression for the change in demand under COVID-19:

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

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 $\hat{\zeta}_s$ 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 $\hat{\zeta}_s < \hat{\zeta}_{s'}$, 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 $\hat{\zeta}$: 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 $\hat{\zeta}_s = \hat{\zeta}, \forall s$, then Eq. (7) indicates that total demand in all sectors is affected uniformly with $\hat{d}_{is} = \widehat{PD}$. Define $\tilde{\zeta}_s^\eta \equiv \hat{\zeta}_s^\eta / (\sum_\sigma \hat{\zeta}_\sigma^\eta / \mathcal{S})$. $\tilde{\zeta}_s^\eta$ succinctly summarizes the impact of sector-specific demand shocks on total demand and satisfies $\sum_s \tilde{\zeta}_s^\eta / \mathcal{S} = 1$. With this notation, we can rewrite total demand as:

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

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.[13] 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, etc.) 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, remote workers may perform their duties less efficiently than on-site. Some workers may face adjustment costs, others may face additional constraints, or need to take 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 ζ_s to ζ'_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 $\zeta'_s = 0$ 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 $\{\zeta'_s\}$ 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 con-

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[13]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.

sumption or investment. Second, as explored by Guerrieri et al. (2020) and Baqaee and Farhi (2020b), the supply shock itself could generate an even larger decline in aggregate demand, when markets are incomplete and goods are complements in demand or production. 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 cash flow.[14]

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 $f(.)$ is Cobb Douglas:

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

with the (sector-specific) exponents α, β and γ summing to one.[15]

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

$$\min_{m',n'} \quad wn' + p_m m' \tag{11}$$

$$zk^\alpha (A'n')^\beta m'^\gamma \geq d'$$

$$n' \leq x'n,$$

where d' is the level of demand faced by the firm, obtained from Eq. (8). The second line

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[14]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.

[15]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. $\beta + \gamma < 1$.

indicates that, if the firm produces, it must meet the demand. The third line is the labor supply 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 $\hat{n} \le \hat{x}$, that is, as long as $\hat{x}^{c} \le \hat{x}$. We can rewrite Eq. (12) and impose that the labor supply constraint does not bind ($\hat{x}^{c} \le \hat{x}$) to get the following expression:

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

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 inequality tells us for which firms the demand or supply side is the binding force on employment and output – demand constrains output and employment decisions if the demand terms are lower than the supply terms and the labor supply constraint binds in the opposite case. 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.[16]

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[16]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:

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

Compared to the unconstrained case, a binding labor supply reduces labor input and increases 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 cash flow 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, $r_s k_{i,s}$, 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.[17] Since the predicted cash flows 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 cash flow during COVID-19 (compared to the non-COVID scenario) can be expressed using Eq. (13) as:

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

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

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

Our business failure rule states that the firm closes if there isn't enough cash, $\mathcal{Z}_{is}$, and operating cash flow, CF'_{is}, to cover 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 payments due on the firm's debts. 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 cash flow 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 failure 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 instead evaluate the business failure condition at the end of the calendar year, even if the

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[17]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. 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.

We focus on a liquidity criterion for three additional reasons. First, we cannot hope to construct estimates of future revenues and costs at the firm level, which would be important for a solvency criterion. It is also 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. Finally, we do not have direct information on 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. SMEs typically have more limited and costlier access to credit (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 construct empirical counterparts to the sector-specific $(\tilde{\xi}_s^\eta)$ and aggregate $(\widehat{PD})$ demand shocks, and 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, we construct a counterfactual change in cash flows 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 cash flow (CF_{is}), we evaluate Eq. (20) to determine which businesses fail.

3.1 Firm-Level Data

We use Orbis, a firm level data set from BvD-Moody's, covering both private and publicly listed firms. Orbis data are collected by BvD from various sources, including national business registries, and are harmonized into an internationally comparable format. The Orbis database covers more than 200 countries and over 200 million private and publicly listed firms. The longitudinal dimension and representativeness of Orbis data vary 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 2018 as our base year. 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 described in Table A.1 in the appendix, we have good coverage of aggregate revenues for the countries in our sample, both for all firms and SMEs. We define a high-coverage subset of thirteen countries where revenue coverage for our *analysis* sample exceeds one-third (Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain).[18]

To evaluate failure rates, our analysis requires data on firm revenue, wage bill, material cost, number of employees, net income, depreciation, cash stock and financial expenses.[19] Cash flow is calculated as the sum of net income and depreciation, less financial profits. The analysis focuses on private, non-financial SMEs.[20] Table A.2 in the appendix reports cross-country summary statistics for key variables of interest.

An important feature of most economies is the over-sized role SMEs – defined as firms with less than 250 employees – play in the economy. We show in Fig. 1, using our Orbis data, that SMEs account for 62.3 percent of employment and 60.7 percent of payroll, 65.2 percent of revenue, and 64.7 percent of total assets across our high-coverage European countries.[21] It

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[18]Although *raw* data coverage for these countries is close to 60 percent of the aggregate economy, our *analysis* sample drops firm observations for which data is not available for any one of the variables needed to evaluate firm liquidity, including number of employees, revenue, labor and material costs (or cost of goods sold), net income, depreciation, cash stock, and financial expenses. Employment is the most critical variable in this regard as in general this is not an item reported on balance sheets.

[19]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 divide the costs of materials sold between labor and materials using 2-digit industry cost shares derived from the high-coverage countries in the sample where labor and material costs are reported separately.

[20]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 failure rates and cash shortfalls.

[21]The contribution of SMEs to the aggregate economy in the official data mimics the numbers here based on Orbis as shown in detail in Kalemli-Özcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas (2015). The

Figure 1: Share of SMEs in Employment, Payroll, Revenue, and Total Assets
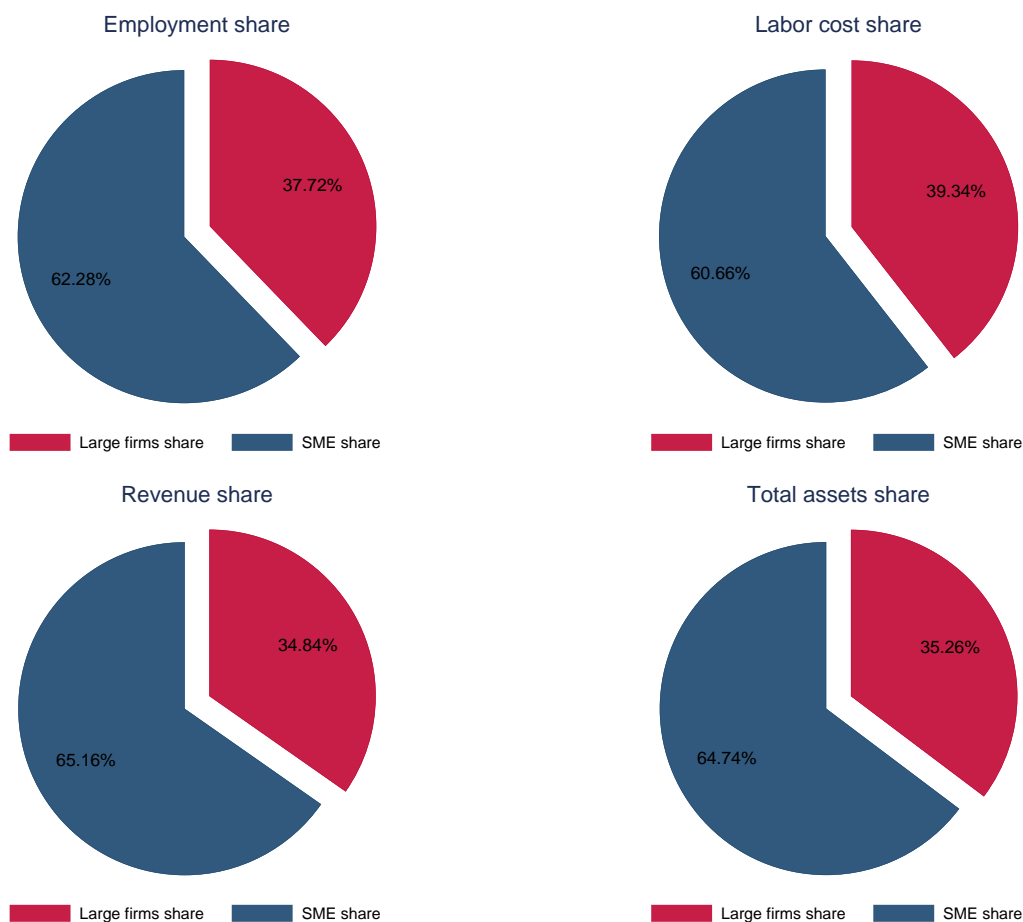
Notes: Figures depict the SME share of employment (top-left), payroll (top-right), revenue (bottom-left), and total assets (bottom-right). The aggregation is done over the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. The SME shares are first calculated at the country level and aggregated across countries using country GDP for weighting.

is precisely these SMEs that are most vulnerable to the COVID-19 shock because they tend to have lower cash buffers, be bank-dependent, and have limited ability to draw on credit lines. These features make them vulnerable to solvency problems that can follow the liquidity shortage.

Table 1 compares the failure rate of all enterprises reported by the OECD with a failure rate based on our liquidity criteria applied to Orbis data (henceforth referred to as "Orbis Failure rates"). Column (1) reports the latest (2017) official OECD failure rate for all firms. Column (2) uses Orbis data to calculate the fraction of all firms that face a liquidity shortfall in 2018 (ie: in the absence of COVID-19). Because the OECD data is not available for all sectors (notably Agriculture) and does not separate large firms from SMEs, the failure rate comparison in columns (1) and (2) is made for all firms, across the subset of Orbis sectors where OECD data

shares are based on the cleaned Orbis data used in the analysis.

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Table 1: Pre-COVID Business Failure Rates

	(1) OECD	(2) Orbis (All)
Belgium	3.0	8.8
Czech Republic	7.9	8.7
Finland	5.4	9.7
France	4.7	8.8
Germany	6.7	11.3
Greece	4.1	8.3
Hungary	8.8	9.4
Italy	6.7	9.3
Portugal	11.5	12.7
Romania	8.6	13.8
Slovak Republic	10.0	10.7
Slovenia	3.9	7.5
Spain	7.4	8.7
United Kingdom	13.8	11.3

Notes: Column (1) reports official OECD 2017 failure rates among all firms; column (2) failure rates are calculated by evaluating the fraction of all firms that face a liquidity shortfall in the Orbis data in 2018 using our procedure. Columns (1) and (2) report failure rates aggregated across sectors covered in both OECD and Orbis data. Official data on firm failure rates (all firms) 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. Sector-level gross value added (GVA) shares in 2018 (OECD) are used for aggregation of both Orbis and OECD data to the country level. The failure rate comparison is only done for the subset of countries covered in the OECD data. We use the latest data available in SDBS (2017) and Orbis (2018) to calculate the failure rates. Highlighted in grey are countries with lower coverage.

are available.[22]

It is reassuring that the OECD and Orbis failure rates are broadly comparable for many of the high-coverage countries. However, we observe that the overall Orbis failure rates are typically higher than those reported by the OECD. This is to be expected since our failure rate calculation assumes that all illiquid firms fail, not taking into account how access to credit or a possible debt restructuring might allow firms – especially large ones – to continue operating when faced with a liquidity shortfall. Because of these differences, we emphasize *changes* in the business failure rates before and after COVID-19 instead of levels.

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[22]Table A.3 in the appendix provides further details, including a comparison of Orbis failure rates for all firms and SMEs.

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 based on the U.S. Department of Homeland Security Guidance on the Essential Critical Infrastructure Workforce.[23] 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 labors 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 characteristics 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. Using a cross-walk between NAICS and NACE codes, we arrive at the fraction of employees that cannot perform their work remotely by 4-digit NACE code.

In constructing the COVID-19 sectoral labor supply shock ($\hat{x}_s$), we assume that firms in non-essential sectors can produce with at most the fraction of workers they can shift to remote work, and that firms in essential sectors face no such restriction. Fig. 2 illustrates the severity of the labor supply shock at the 1-digit NACE level.[24] As expected, the Accommodation & Food Service and Arts, Entertainment & Recreation sectors are among the most affected, while essential infrastructure sectors, including Electricity and Water & Waste, remain largely unaffected.

We follow a similar approach in constructing sector-specific demand, and use the same O*NET surveys to classify occupations based upon 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

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[23]See CISA's Guidance on the Essential Critical Infrastructure Workforce.

[24]We aggregate to the 1-digit 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.

Figure 2: Supply Shock by Sector
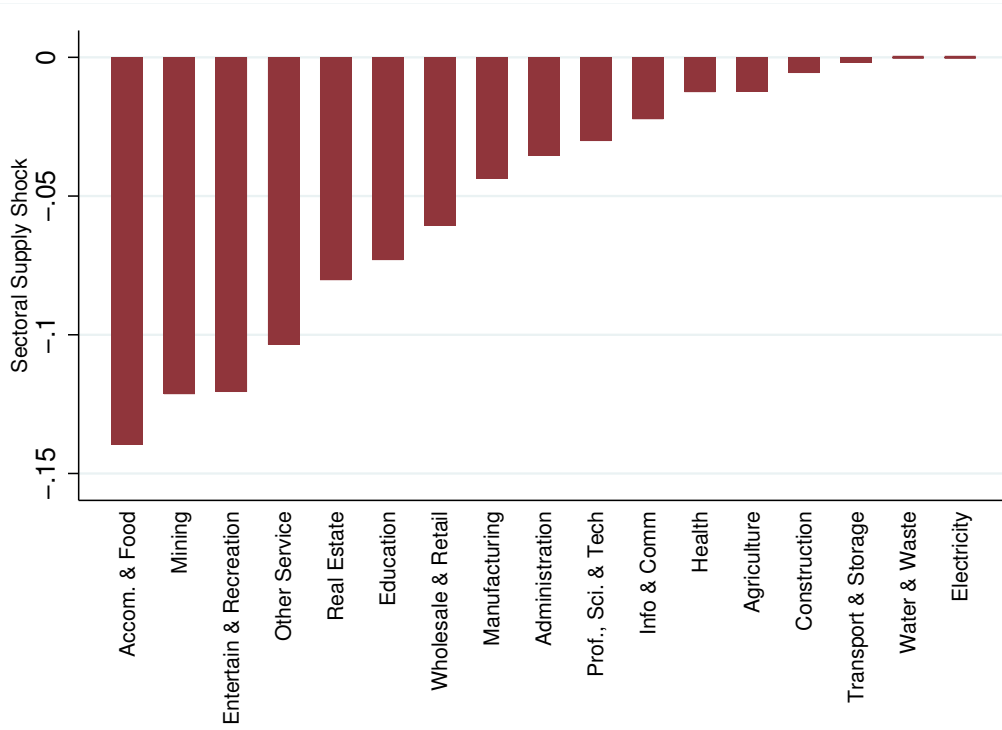
Notes: Depicts the COVID-19 labor supply shock by 1-digit NACE sector, as the percent change relative to the non-COVID scenario. Supply shocks are first aggregate from the 4-digit NACE to 1-digit NACE by taking a simple average across 4-digit sectors within each country. The gross value added sector 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.

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 under COVID-19 the demand shifter (ξ'_s) is one in essential sectors and is one minus the "interaction share" in non-essential industries. We interpret the resulting estimate as a measure of $\hat{\varsigma}_s^\eta$.[25] We then normalize the sectoral demand shocks to be consistent with aggregate demand Eq. (7) by constructing $\tilde{\varsigma}_s^\eta = \hat{\varsigma}_s^\eta / (\sum_\sigma \hat{\varsigma}_\sigma^\eta / \mathcal{S})$. Fig. 3 illustrates the size of the sector-specific demand shock ($\tilde{\varsigma}_s^\eta$) 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, & Recreation to non-affected essential sectors including Water & Waste.[26]

In addition to sector-specific demand shocks, we also measure changes in aggregate de-

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

[26]Within each country $\sum_s \tilde{\varsigma}_s^\eta / \mathcal{S} = 1$ 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 do not sum to one.

Figure 3: Demand Shock by Sector
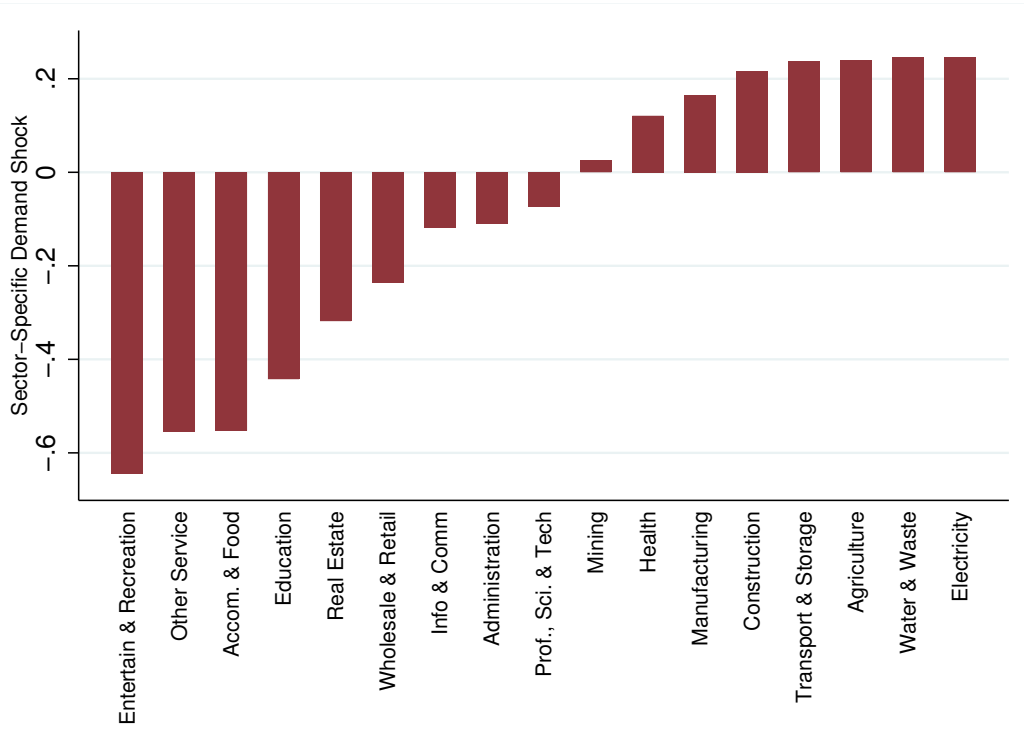
Notes: Depicts the COVID-19 demand shock by 1-digit NACE sector, as the percent change relative to the non-COVID scenario. Demand shocks are first aggregated from the 4-digit NACE to 1-digit NACE by taking a simple average across 4-digit sectors within each country. The gross value added sector share 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.

mand ($\widehat{PD}$) using projections of quarterly changes in GDP from the International Monetary Fund (IMF).[27] What matters for the estimation of failure 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

The sectoral productivity shock ($\hat{A}_s$) captures possible declines in productivity due to shifts to remote work. We first assume sectoral productivity is a weighted average of the productivity of on-site and remote workers:

$$A_s = A_s^{work}\omega_s + A_s^{home}(1 - \omega_s) \qquad \text{Before COVID,} \qquad (21)$$
$$A_s' = A_s^{work'}\omega_s' + A_s^{home'}(1 - \omega_s') \qquad \text{COVID-19,}$$

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

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

If we assume that A_s^{work} and A_s^{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 do not 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 the relative productivity of onsite and remote workers, we opt to calibrate $A_s^{home}/A_s^{work} = 0.8$. This implies that $\hat{A} = 0.8$ (i.e. a 20 percent decline) is the maximum reduction in productivity possible, which would occur in a sector with no remote work before COVID-19 and 100 percent remote work 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.[28] 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.[29] Due to the lack of price data, the elasticities we estimate are revenue, rather than output, elasticities.

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[28]Calculating country $\times$ 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 – do not report labor and material costs separately. The elasticities for these 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 percent (Belgium, Czech Republic, Finland, France, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain).

[29]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).

4 Failure Rates Absent Government Action

Our initial analysis sheds light on how severe the COVID-19 crisis could have been had governments failed to intervene. Investigating how vulnerable SMEs were to the COVID-19 shock in the absence of government support provides a useful baseline against which we can then evaluate the impacts and costs of various government policies aimed at alleviating or delaying business failures. In this section, we first define a baseline COVID-19 scenario and report aggregate SME failure rates. We then examine the importance of sector-specific shocks and firm financial vulnerability in explaining cross-sector and cross-county heterogeneity in these failure rates.

4.1 Evaluating Baseline Aggregate SME Failure Rates

To arrive at an estimate of the aggregate SME failure rate, we define a baseline COVID-19 scenario, calculate Eqs. (17) and (18) with our shocks and firm level data, and evaluate the failure condition given by Eq (20). Our baseline scenario assumes that the COVID-19 crisis begins in week 9 of the year (end of February), triggering a lockdown period that lasts 8 weeks. The 8 week lockdown lowers sectoral labor supply ($\hat{x}_s$), demand ($\hat{d}_s = \tilde{\zeta}_s^\eta \widehat{PD}$), and labor productivity ($\hat{A}_s$). Once the lockdown ends, the sectoral labor supply and productivity shocks return to pre-COVID levels. The total demand shock remains active, with the aggregate demand component ($\widehat{PD}$) evolving according to IMF projections, and the sector-specific demand shocks ($\tilde{\zeta}_s^\eta$) evolving according to an AR(1) process with persistence of 0.5 at quarterly frequency. Persistence in the total demand shock captures how continued uncertainty and fear of infection have subdued demand even after stay-at-home orders were lifted.

We also assume that there are no disruptions to the credit market, but firms are unable to access fresh credit to smooth the COVID-19 shock. As is the case under normal credit market conditions, firms are still able to rollover existing loans that come due within the next 12-months. Consequently, our liquidity criteria requires firms to make interest payments, but not pay down principal, on their existing pre-COVID debt. SMEs tend to have limited access to finance in normal times (Gopinath et al., 2017) and to new credit lines during crises (Greenwald et al., 2020; Chodorow-Reich et al., 2020). We therefore limit firms' ability to access fresh credit to help weather the COVID-19 shock by evaluating the failure condition at a weekly frequency.[30]

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[30]Section 6 relaxes this assumption by doing an annual calculation which will allow firms to smooth their cash flow to stay afloat during the worst of the crisis. Note also that to map our annual balance sheet data to a weekly frequency we assumed that revenue is earned 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.

Table 2 reports that the COVID-19 shock leads to a large increase in SME failure rates. Column (1) reports the overall non-COVID failure rate as the fraction of SMEs in 2018 that face a liquidity shortage. The non-COVID failure rate is a useful benchmark because it accounts for the firms that would have failed even in the absence of COVID-19. Column (2) reports the end of 2020 estimated SME failure rate under the baseline COVID-19 scenario. Column (3) reports the difference between the two and represents the *additional* effect COVID-19 has on SME failures in 2020. This is our preferred metric for business failures.[31] The COVID-19 crisis results in a 9.1 percentage point increase in SME failure rates relative to normal times, putting 4.64 percent of private sector jobs at risk (see Table 8). In the following subsections, we unpackage these aggregate numbers by investigating sources of cross-sector and cross-country heterogeneity in SME failure rates.

Table 2: Aggregate SME Failure Rate

	(1) Non-COVID	(2) COVID	(3) Δ
High coverage	9.61	18.66	9.06
All	9.43	18.41	8.98

Notes: Failure rates are first calculated at the 1-digit NACE level and aggregated to the country level using 2018 sector gross value added as weights (the exceptions, due to data availability, are Korea and Japan where Orbis sector gross value added weights are used). Failure 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.

4.2 Cross-Sector Heterogeneity

Underlying the 9.1 percentage point increase in the aggregate SME failure rate under our baseline COVID-19 scenario is a substantial amount of cross-sector heterogeneity in firm financial health and exposure to shocks. In our model, the rise in failure rates under COVID-19 is driven by a deterioration in firms' cash flow that results in a liquidity shortage. This cash flow deterioration is largely driven by the COVID-19 total demand, supply, and productivity shocks. In turn, liquidity shortages arise when firms cannot withstand the fall in cash flow due to a combination of low cash buffers and high financial expenses.

Table 3 confirms considerable variation in failure rates across sectors. Columns (1) and (2) report the non-COVID and COVID-19 SME failure rates, respectively. Column (3) reports the difference between the two (Δ). Given their customer orientation and limited scope of remote work, some service sectors, such as Accommodation & Food Service or Arts, Entertainment & Recreation, experience an increase in failure rates (Δ) under COVID-19 exceeding 20 per-

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[31]In appendix Table A.4 we report summary statistics on key variables of interest for surviving and failing firms under the non-COVID and baseline COVID scenarios.

Table 3: Sector SME Failure Rates

	(1) Non-COVID	(2) COVID	(3) Δ
Agriculture	9.39	13.97	4.58
Mining	10.17	34.56	24.39
Manufacturing	8.64	16.94	8.30
Electric, Gas & Air Con	10.41	11.79	1.38
Water & Waste	6.96	10.32	3.36
Construction	7.26	9.38	2.12
Wholesale & Retail	9.20	19.42	10.22
Transport & Storage	8.25	14.17	5.92
Accom. & Food Service	12.81	38.54	25.72
Info. & Comms	9.98	15.83	5.85
Real Estate	11.31	18.10	6.79
Prof., Sci., & Technical	10.17	18.89	8.73
Administration	8.55	20.62	12.08
Education	10.56	29.54	18.98
Health & Social Work	8.51	11.78	3.27
Arts, Ent., & Recreation	12.98	39.18	26.20
Other Services	13.38	33.89	20.51

Notes: Sector failure 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, Slovenian, and Spain.

centage points.[32] In stark contrast, majority essential 1-digit sectors (henceforth referred to as "essential sectors") that face small sectoral supply shocks and higher sector-specific demand, including Construction and Health, experience a less than 5 percentage point rise in SME failure rates. Finally, sectors with fewer essential workers, but relatively low total demand shocks (Manufacturing) and/or high scope for remote work (Information & Communications) are moderately affected, experiencing a rise in failure rates under 10 percentage points.

Table 4 further decomposes the role of firm financial health and sector-specific shocks in driving cross-sector heterogeneity by evaluating changes in failure rates 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 the total demand shock ($\widehat{PD}\tilde{\varsigma}_s^\eta$), which is composed of both aggregate demand and sector-specific demand shocks. The third includes both aggregate demand and sectoral labor supply shocks ($\widehat{PD}, \hat{x}_s$). The fourth includes total demand and sectoral labor supply shocks ($\widehat{PD}\tilde{\varsigma}_s^\eta, \hat{x}_s$). The last is our baseline, which adds sectoral productivity shocks to column (4).

Including only the aggregate demand shock (col. 1) is informative about the heterogeneity in firm financial health across sectors because it is the only shock that applies equally to all sectors. We see modest variation in failure rate changes in response to the aggregate demand

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[32]Mining, a non-service sector, also experiences a large increase in failure 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 cash flow. See the extensions in Section 6 that introduces labor adjustment costs or a shut down option that mitigate the pressure on this sector.

shock varying from a rise of 0.16 percentage points in Other Services to 7.29 percentage points in Transport & Storage. Given all firms face the same proportional decline in revenue, this heterogeneity in failure rates indicates that sectors like Transport & Storage or Water & Waste contain many financially vulnerable firms. This vulnerability can arise from, for example, low cash buffers and/or high debt levels, which increase the likelihood that declines in cash flow lead to liquidity shortages.

The addition of sector-specific demand shocks to the aggregate demand shock (col. 2) either exacerbates or mitigates underlying sectoral vulnerability, thus resulting in higher failure rates in some sectors and lower failure rates in others. In an already vulnerable sector, like Administration, even a modest negative sector-specific demand shock leads to a large rise in failure rates. Meanwhile, according to column (1) Transport & Storage is the most vulnerable sector and Other Services the least vulnerable. Yet, because sector specific demand falls most in customer-oriented service sectors, like Other Services, and increases in essential sectors, like Transport & Storage, SME failure rates in column (2) rise in Other Services far above those in Transport & Storage.

Adding the sectoral labor supply shock to the *aggregate* demand shock (col. 3) heavily impacts non-essential, labor-intensive sectors that cannot easily transition to remote work, such as Other Services. The pronounced rise in SME failure rates in these sectors occurs because a small aggregate demand shock relative to a more severe 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 cash flow and leads to a liquidity shortage. Meanwhile, labor-intensive sectors with higher scope for remote work, such as Administration, experience a smaller rise in failure rates. Sectors composed of essential subsectors, such as Water & Waste and Transport & Storage, are exposed to small labor supply shocks and therefore experience only a small rise in failure rates.

The addition of sectoral labor supply shocks to the *total* demand shock (col. 4) has a negligible impact on SME failure rates in sectors with high scope for remote work (Administration) and essential sectors that are largely exempt from the shock (Water & Waste and Transport & Storage). By contrast, failure rates in labor intensive and customer oriented sectors – such as Other Services – tend to react strongly to the labor supply shock when demand is high (col. 3) but only modestly when demand is low (col. 2). This occurs because lower demand reduces firms' optimal labor demand, leading to fewer firms becoming labor constrained. The last column shows that in most sectors, the inclusion of the labor productivity shock has little effect on failure rates. Overall, Table 4 highlights the importance of firm financial health (col. 1) and sector-specific demand (col. 2) and labor supply (col. 3) shocks, and their interaction (col. 4), in explaining heterogeneity in cross-sector vulnerability to the COVID-19 crisis.

Table 4: Δ Failure Rate Comparison (Alternative Shock Combinations)

	(1) $\widehat{PD}$	(2) $(\widehat{PD}\tilde{\varsigma_s})$	(3) $\widehat{PD}, \hat{x}_s$	(4) $(\widehat{PD}\tilde{\varsigma_s}), \hat{x}_s$	(5) Baseline
Agriculture	0.67	0.99	3.12	4.28	4.58
Mining	0.46	0.83	21.15	20.17	24.39
Manufacturing	1.17	1.01	6.25	6.64	8.30
Electric, Gas & Air Con	0.77	1.38	0.77	1.38	1.38
Water & Waste	3.33	3.36	3.33	3.36	3.36
Construction	2.02	2.09	2.33	2.10	2.12
Wholesale & Retail	2.35	10.03	5.68	9.91	10.22
Transport & Storage	7.29	5.89	7.42	5.92	5.92
Accom. & Food Service	0.22	10.11	74.93	20.47	25.72
Info. & Comms	2.11	5.44	3.84	5.44	5.85
Real Estate	1.78	6.71	2.23	6.68	6.79
Prof., Sci., & Technical	3.80	8.06	4.40	8.22	8.73
Administration	4.66	11.74	6.92	11.84	12.08
Education	2.29	18.46	49.62	18.46	18.98
Health & Social Work	2.30	3.12	11.73	3.12	3.27
Arts, Ent., & Recreation	2.22	21.75	52.74	24.37	26.20
Other Services	0.16	18.81	45.81	19.57	20.51
Average	2.36	6.77	12.03	8.34	9.06

Notes: The table reports the change in failure rates (COVID-19 - non-COVID) under 5 alternative scenarios – aggregate demand shock only $(\widehat{PD})$; both aggregate demand and sector-specific demand shocks $(\widehat{PD}\tilde{\varsigma}_s^{\eta})$; both aggregate demand and sectoral supply shocks $(\widehat{PD}, \hat{x}_s)$; total demand and supply shocks $(\widehat{PD}\tilde{\varsigma}_s^{\eta}, \hat{x}_s)$; and the baseline $(\widehat{PD}\tilde{\varsigma}_s^{\eta}, \hat{x}_s, \hat{A}_s)$. Sector changes in failure 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.

4.3 Cross-Country Results

The vulnerability of individual firms at the onset of the crisis and uneven impact of the COVID-19 shocks across sectors contributes to cross-country heterogeneity in failure rates. Table 5 highlights the heterogeneity in SME failure rate changes (Δ, col. 3) across our sample of high-coverage countries, ranging from 4.8 percentage points in the Czech Republic to 13.2 percentage points in Italy.[33]

A comparison of France and Italy in Fig. 4 makes clear the importance of both industrial composition and overall firm financial health in explaining the differential impact of COVID-19 across countries. The figure depicts the weekly evolution of the change in failure 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). Under our baseline scenario, Italy's SME failure rate rises by 4.6 percentage points more than France's. Total demand evolves similarly in both countries, despite France's production being less concentrated in sectors heavily impacted by the sector-specific demand shock. Due to higher cross-sector heterogeneity in labor supply and demand shocks, more Italian firms became labor supply constrained and

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[33]We provide in the online appendix the full set of results for each country × sector, without and with policy support.

Table 5: Country-Level SME Failure Rates

	(1) Non-COVID	(2) COVID	(3) Δ
Belgium	8.16	15.11	6.96
Czech Republic	8.25	13.04	4.78
Finland	9.20	17.55	8.35
France	9.87	18.46	8.59
Greece	9.86	15.22	5.37
Hungary	8.64	15.30	6.66
Italy	9.39	22.59	13.20
Poland	11.53	21.19	9.66
Portugal	11.99	19.59	7.61
Romania	14.08	21.90	7.82
Slovak Republic	10.12	15.38	5.25
Slovenia	7.27	17.26	9.99
Spain	8.50	15.32	6.82

Notes: Country-level failure rates under non-COVID evaluate the fraction of firms facing a liquidity shortfall in 2018, and under COVID are evaluated under our baseline scenario. Country level results represent the weighted average of 1-digit NACE failure rates, where weights are given by 2018 sector gross value added.

therefore faced higher costs during the lockdown than French firms. Additionally, Italian firms were more vulnerable to declining cash flows triggering liquidity shortages because they entered the COVID-19 crisis with a lower average cash balance than French firms.

4.4 Financial Stability Implications of SME Bankruptcies

We investigate whether the non-performing loans (NPLs) that result from the large rise in SME failures due to COVID-19 pose a risk to the banking system.[34] Table 6 reports that under our baseline scenario the share of SME NPLs rose, on average, by 8.97 percentage points due to COVID-19. Columns (1) and (2) show the fraction of loans that belong to illiquid firms under non-COVID and COVID-19, respectively. Column (3) reports the difference between the two (Δ).[35] The increase in the share of non-performing loans ranges from 4.84 pp in Belgium to 11.82 pp in Italy.

Table 7 shows that despite COVID-19's large impact on SME failures, the crisis poses only a moderate risk to the banking sector.[36] Specifically, Table 7 reports the change (relative to non-COVID) in SME NPLs under COVID-19 as a fraction of the banking sector's total assets (col. 1) and common equity Tier-1 capital (CET1) (col. 2). The table also reports the initial risk-

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[34]A loan is classified as non-performing for firms that fail, either under normal times or COVID-19.

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

[36]Note that Table 7 reports results for only the 11 countries for which data were available from both the EBA's 2018 country level bank stress test and the ECB's Consolidated Banking Database.

Figure 4: Weekly Evolution (Country)
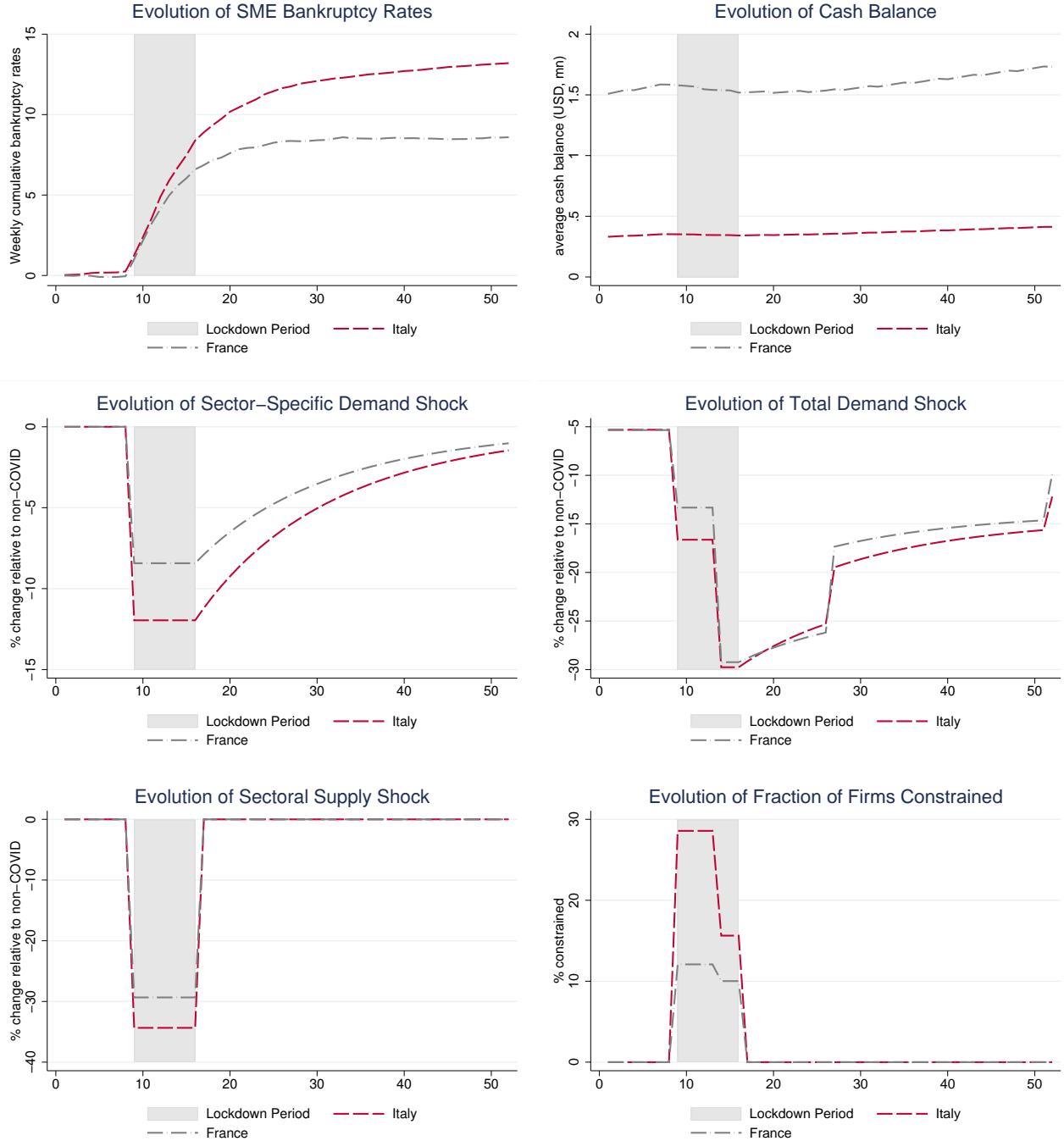
Notes: Figures show the weekly evolution of six key variables: increase in failure rates due to COVID-19 (top left), average firm cash balance (top right), sector-specific demand shock (middle left), total demand shock (interaction between sector-specific demand and aggregate demand shock, middle right), 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 2018 sector gross value added.

weighted CET1 capital ratio (col 3.) and the change in risk-weighted CET1 capital ratio due to COVID-19 (col. 4).[37] The change in the SME NPL share of total assets averages 1.01 percentage points, and ranges from 0.40 pp in Belgium to 1.84 pp in Italy. Meanwhile, the change in SME NPL share of CET1 capital averages 17.41 pp across countries, ranging from 5.10 pp in Poland to 31.60 pp in Italy.

Finally, we estimate a moderate decline in the risk-weighted CET1 capital ratio (CET1R) of 2.12 percentage points, ranging from a decline of 0.72 pp (Poland) to 3.75 pp (Italy). Given that the initial level of the risk-weighted CET1 capital ratio is on average 14.14 percent, we conclude that the direct impact of SME failures due to COVID-19 on the banking system remains manageable. 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).[38]

5   Impact of Government Intervention

Our findings thus far suggest that, in the absence of government action, firm failures would rise considerably. However, in reality governments provided sizeable and generous support to SMEs. In this section we try to mimic the most common policy interventions enacted by governments in response to the COVID-19 shock by analyzing the effect of various types of cash injections.

We find that policies tend to fall into two groups: those with moderate cost but moderate reductions in firm failures and those with high cost but a large reductions in firm failures. We show that high policy costs arise when support is inefficiently directed towards all firms, including ones who do not face liquidity shortages. While more costly than necessary, these policies still save many failing firms.

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[37]Three 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). (3) The European Central Bank's Consolidated Banking Data is used to calculate total loans (total loans CBD), total assets (total assets CBD) of depository institutions, common equity tier 1 capital (CET1), and the risk-weighted CET1 capital ratio as the ratio of CET1 capital to risk-weighted asset (CET1R). 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 CBD × (share of SME loans from EBA) × (Δ SME NPL share from Orbis)]/[total assets from CBD]. 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 CBD × (share of SME loans from EBA) × (Δ SME NPL share from Orbis)]/[CET1 from CBD]. The country CET1 capital ratio (risk-weighted) from the ECB's CBD is reported in column 3, and the change in the CET1 capital ratio (risk-weighted) due to COVID, calculated as [CET1R × SME NPLs % CET1 × [CET1R-1]/[1-(SME NPLs % CET1 × CET1R)], is reported in column 4.

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

Table 6: Country-Level Fraction of Non-Performing Loans

	(1) Non-COVID	(2) COVID	(3) Δ
Belgium	16.16	21.00	4.84
Czech Republic	7.92	14.18	6.27
Finland	9.65	19.43	9.78
France	14.30	23.93	9.63
Greece	16.59	23.13	6.53
Hungary	12.98	21.71	8.73
Italy	9.78	21.60	11.82
Poland	13.47	20.16	6.68
Portugal	10.70	19.64	8.94
Romania	14.39	20.53	6.14
Slovak Republic	9.89	16.80	6.91
Slovenia	8.43	18.79	10.36
Spain	11.42	18.72	7.31
Average	12.37	21.34	8.97

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 illiquid firms to the country level. The last row is the country GDP weighted average.

Table 7: Country-Level COVID-19 Risk to the Banking Sector

	SME NPLs Due to COVID-19			
	(1) % Total Assets	(2) % CET1 Capital	(3) CET1R	(4) Δ CET1R
Belgium	0.40	7.53	15.82	-1.01
Finland	0.73	13.50	17.10	-1.96
France	0.85	16.73	14.37	-2.11
Greece	1.14	10.66	15.29	-1.40
Hungary	0.68	6.65	16.22	-0.91
Italy	1.84	31.60	13.08	-3.75
Poland	0.51	5.10	16.93	-0.72
Portugal	1.37	18.49	12.95	-2.14
Romania	0.49	5.28	16.37	-0.73
Slovenia	1.38	12.09	18.97	-1.90
Spain	0.62	11.60	12.20	-1.26
Average	1.01	17.41	14.14	-2.12

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 Common Equity Tier-1 (CET1) capital (2). The 2018 risk-weighted CET1 capital ratio (3); and the change in the risk-weighted CET1 capital ratio due to COVID-19 (4). 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 CBD × (share of SME loans from EBA) × (Δ SME NPL share from Orbis)]/[total assets from CBD]. The change in the NPL value of SMEs under COVID-19 as a fraction of CET1 (column 2) is calculated as [(total loans from CBD × (share of SME loans from EBA) × (Δ SME NPL share from Orbis)]/[CET1 from CBD]. Column 3 reports the 2018 country CET1 ratio (risk-weighted) from the ECB CBD (CET1R). Column 5 reports the change in the CET1 capital ratio (risk-weighted) due to COVID-19, calculated as [CET1R × SME NPLs % CET1 × [CET1R-1]/[1-(SME NPLs % CET1 × CET1R)]. The last row is the country GDP weighted average.

5.1 Evaluating Policy Interventions

Government support that prevents firm failures also saves jobs and wages, preserves economic output, and limits the rise in non-performing loans. For each policy we consider, Table 8 shows the costs and benefits of saving SMEs. Column (1) shows the reduction in the COVID-19 failure rate from each policy, in percentage points. This is calculated as the difference between the COVID-19 failure rate when each policy is implemented, less the baseline COVID-19 failure rate absent policy support. The second column shows jobs saved under each policy, as a fraction of total employment. The third column reports 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 failure may choose to operate at lower scale – employing fewer workers and paying less in labor compensation – than in pre-COVID.[39] The fourth columns reports the fraction of SME loans saved. Finally, the fifth column reports the funds disbursed to firms by each policy, expressed as a fraction of GDP.

To benchmark the performance of policies implemented in practice, we first consider a hypothetical policy that bails out every firm that fails due to the COVID-19 crisis. By design, this benchmark policy directs support only towards firms that we classify as viable, i.e. firms that would fail under COVID-19, but would survive otherwise. Under this policy, each viable firm receives the minimum amount required to leave it with a zero cash balance at the end of 2020. The identity of viable firms and their cash deficits are not observable in practice, but this benchmark policy highlights the approximate minimum level of resources needed to fully mitigate the impact of the COVID-19 crisis on SME failures. This policy is shown in the first row of Table 8.

Our benchmark policy illustrates that, provided sufficient information, the overall fiscal cost of saving SMEs that fail due to the COVID-19 crisis remains quite modest. With overall disbursements of 0.78 percent of GDP, the benchmark policy saves 1.12 percent of GDP in wages, 9.06 percent of businesses and 4.64 percent of jobs.[40] Moreover, each dollar disbursed by this policy generates 1.44 dollars in direct aggregate demand (1.12/0.78) in the form of wages saved. We call this ratio the *fiscal-bankruptcy multiplier*. This multiplier is not a traditional Keynesian multiplier: it reflects the fact that businesses may be inefficiently shut down as a consequence of the pandemic, and that fiscal resources deployed to preserve viable businesses help increase overall output and employment.[41]

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[39]While these jobs and wages saved numbers pertain to jobs and wages saved in 2020 by preventing these firms' failure, they may understate the long-run jobs and wages saved should these saved firms after 2020 return to their previous scale as they recover from the COVID-19 shock.

[40]Note that Orbis does not cover the full universe of firms, so to compute columns (2), (3) and (5) in Table 8 we compute sectoral coverage rates by comparing 1-digit sectoral Orbis employment and labor costs the the equivalent OECD data for each country. We then scale by the inverse of the coverage ratio to get representative numbers for each country by sector pair.

[41]Traditional fiscal multipliers could add to that, so that one dollar in fiscal resources used to preserve vi-

Table 8: The Impact and Costs of Various Policy Options

	(1)	(2)	(3)	(4)	(5)
	Firms Saved (% Firms)	Jobs Saved (% Employed)	Wages Saved (% GDP)	Loans Saved (% Loans)	Funds Disbursed* (% GDP)
Benchmark Policy	9.06	4.64	1.12	8.40	0.78
Financial Expenses Waived	1.28	0.52	0.14	4.54	1.29
Tax Waiver	1.90	0.65	0.10	2.63	1.44
Rent Waiver	3.05	1.63	0.40	2.15	3.13
Cash Grant	5.60	3.26	0.74	3.28	2.38
Pandemic Loans	8.56	4.59	1.06	5.79	5.82

Notes: The scenarios considered are as follows: Targeted Bailouts closes the cash shortfall of business we estimate would have survived in the absence of COVID-19. The next 3 scenarios waive financial expenses (interest costs), tax payments and rent starting from the 1st week of lockdown until the end of 2020. Then row 5 represents a cash grant covering 8 weeks of pre-COVID labor costs. The final scenario reflects pandemic loans backed with government guarantees mirroring those implemented in the Euro Area. 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 2018 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. The policy cost (column 10) for the Euro Area Loan Guarantee represents the funds disbursed under this policy and not the actual fiscal cost which depends on the rate of repayment and the distribution of losses between the government and the banking sector.
* For policies that are grants funds disbursed are exactly equal to the fiscal cost. For policies in the form of a loan, repayments may lower the cost substantially below the funds disbursed numbers.

The next five rows of Table 8 show a set of alternative policies that better reflect the policy responses implemented by countries. Policy responses have varied considerably by countries but have tended to take the form of cheaper debt refinancing, loan guarantees, expense rebates, and size-based grants. Rather than focus on the policies of any particular country, we focus on some simple policy interventions that together span most types of policies implemented by governments. Notice that the method by which resources are transferred to firms (i.e. government guaranteed loans or direct government grants) is irrelevant to firms in 2020, the period which our exercise covers: to avoid failure, all that matters to a firm is the injection of additional resources (or reduction in expenses due) it receives (or owes).

The first of these policies (row 2 of Table 8) rebates to firms their financial expenses starting at the beginning of the lockdown until the end of 2020. This policy is an extreme version of policies that guarantee existing firm loans or refinance them at lower interest rates. As can be seen, this policy has moderate costs but also modest effects – the failure rate is estimated to fall by 1.28 percentage points at a cost of 1.29 percent of GDP. The fiscal bankruptcy multiplier is $0.14/1.29 = 0.11$.

Next, rows (3) and (4) detail two other types of rebates offered to firms based on their taxes or rent paid (again starting during the lockdown and continuing until the end of 2020). While

able businesses may increase overall output by more (or less) than 1.44 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.

Orbis contains data on firm tax payments, it does not include any information on firm rents. Therefore, we estimate firm rent expenses by assuming that the ratio of rent to cost-of-goods-sold is constant within 1-digit sectors and use data from Compustat to calculate these ratios. We find that similar to waiving financial expenses, waiving taxes due has moderate costs, but also moderate benefits. Waiving rent however, saves 3.05 percent of firms at a cost of 3.13 percent of GDP – a fairly expensive intervention – with a low fiscal-bankruptcy multiplier of $0.40/3.13 = 0.13$.

The final two policies considered are injections of new funds rather than rebates of upcoming expenses. The first is a cash grant indexed to each firm's wage bill in the reference year, 2018. The second is a program of public loan guarantees for SMEs, broadly similar to that implemented by several Euro-area countries.

The cash grant disburses to firms their average 2018 weekly wage bill during the 8 weeks of lockdown.[42] 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 decisions. We observe that these cash grants have a much larger impact than the rebate policies on business failures, jobs and wages saved; but, other than the rent waiver, at a substantially higher fiscal cost. This grant halves the rise in the failure rate (failure rates decline of 5.60 percentage points relative to the no-policy benchmark), saves 3.26 percent of jobs and 0.74 percent of GDP in wages, but at an overall fiscal cost of 2.38 percent of GDP.[43] The fiscal-bankruptcy multiplier is now only 0.31: each dollar of fiscal resources only saves 0.31 cents in direct aggregate demand.

The final policy we consider is a program of public loan guarantees for SMEs – pandemic loans – broadly similar to that implemented by several Euro-area countries. Since most of the countries in our high coverage group do belong to the Euro-area, this policy is especially relevant. To remain consistent with how the policy was designed in Europe, we assume that zero interest and principal is due in 2020. Consequently, from the perspective of 2020 outcomes, the relevant aspects of the loan guarantees are the new funds provided: they immediately provide resources to SMEs, allowing them to survive the year. Other than affecting the policy's net cost and firm take-up, repayment terms and interest beyond 2020 have no effect on our analysis.[44]

Under the terms of this program, firms are eligible to borrow up to the larger of 25 percent of their 2018 revenues, or twice their 2018 wage-bill, during each week of lockdown and

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[42]This grant therefore equals 8/52=15.4 percent of the 2018 wage bill of the firm. Cash transfers of this form are discussed in an early policy note in April 2020, by one of the authors, Drechsel and Kalemli-Özcan (2020).

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

[44]Our companion paper, Gourinchas et al. (2021) explores the implications of repayment of this program on firm failures in 2021.

Table 9: The distribution of policy support by firm type

| | Firms that Survive COVID (Strong Firms) (1) | Firms Bankrupt Regardless of COVID (Weak Firms) | | Firms Bankrupt Only in COVID Scenario (Viable Firms) | | Total |
| | | (2) | (3) | (4) | (5) | (6) |
	Funds Disbursed* (% GDP)	Failure Rate (% Firms)	Funds Disbursed* (% GDP)	Failure Rate (% Firms)	Funds Disbursed* (% GDP)	Funds Disbursed* (% GDP)
Benchmark Policy	0.00	8.93	0.00	0.00	0.78	0.78
Cash Grant	1.96	7.44	0.19	5.62	0.24	2.38
Pandemic Loans	4.75	6.51	0.44	3.59	0.63	5.82

Notes: The scenarios considered are as follows: the benchmark policy closes the cash shortfall of business we estimate could have survived a non-COVID 2020; the cash grant is a lump-sum payment equal to 8 weeks worth of wages paid in 2018 and is disbursed week-by-week during the 8 week lockdown; and the final scenario is a pandemic loan based on Euro Area loan guarantees (see paper for details). For all policies, the policy cost is presented as a percent of overall economy-wide GDP. 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.
* For policies that are grants funds disbursed are exactly equal to the fiscal cost. For policies in the form of a loan, repayments may lower the cost substantially below the funds disbursed numbers.

neither pay interest nor repay any principal in 2020.[45] This policy turns out to be the most generous, providing 5.82 percent of GDP in funding for SMEs.[46] It has a dramatic impact on failure rates, bringing them back almost to their pre-COVID levels (failure rates become 9.06-8.56=0.50 pp) and saving 4.59 percent of jobs.[47] This result is consistent with early anecdotal estimates from few countries that suggest 2020 corporate failure rates will be broadly comparable and possibly lower than pre-COVID failure rates, suggesting our simulation of this policy may come close to actual outcomes.[48] At first glance, the fiscal bankruptcy multiplier in terms of wages saved relative to funds disbursed appears relatively low at 1.06/5.82=0.18. However, as we will discuss later in this section, because this policy is a loan, the fiscal bankruptcy multiplier once repayment is accounted for could easily be much higher.

Our analysis shows that policies that are as effective as the benchmark disburse considerably more resources. To investigate the reasons for this we partition our firms into three policy-independent groups: 'strong firms' that are able to remain liquid during our baseline COVID-19 crisis scenario; 'weak firms' that fail both with or without COVID; and 'viable firms' that survive without COVID but would fail when COVID hits if no support were provided.[49]

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[45] See ECB Economic Bulletin 6/2020 Focus for details.

[46] This amount represents funds disbursed by the banking sector and not a policy cost. The ultimate policy cost will depend on the repayment rate and the distribution of losses between the government and the banking sector.

[47] Note that we assume funds directly go through from banks to firms, whereas in real-life these type of programs suffered several setbacks and delays due to frictions in banking intermediation.

[48] As noted earlier, real-life bankruptcies will not be available for some time for SMEs given the lags in filings and official freezes on bankruptcies. However firm surveys, including the U.S. Census Bureau Pulse Survey, report that many SMEs suggested that they would have failed without the government support.

[49] Note that these group definitions are independent of the policy implemented. We therefore choose not to use the term "zombie", which tends to refer to policy-induced changes in the composition of firms where many

Table 10: Wages, Jobs and Loans Saved by firm type

	Firms Bankrupt Regardless of COVID (Weak Firms)				Firms Bankrupt Only in COVID Scenario (Viable Firms)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Jobs Saved (% Emp)	Wages Saved (% GDP)	Loans Saved (% Loans)	Policy Cost* (% GDP)	Jobs Saved (% Emp)	Wages Saved (% GDP)	Loans Saved (% Loans)	Policy Cost* (% GDP)
Benchmark Policy	0.00	0.00	0.00	0.00	4.64	1.12	8.40	0.78
Cash Grant	0.87	0.20	0.67	0.19	2.39	0.55	2.61	0.24
Pandemic Loans	1.27	0.30	1.42	0.44	3.32	0.76	4.37	0.63

Notes: The scenarios considered are as follows: the benchmark policy closes the cash shortfall of business we estimate could have survived a non-COVID 2020; the cash grant is a lump-sum payment equal to 8 weeks worth of wages paid in 2018 and is disbursed week-by-week during the 8 week lockdown; and the final scenario is a pandemic loan based on Euro Area loan guarantees (see paper for details). For all policies, the policy cost is presented as a percent of overall economy-wide GDP. For all policies, the policy cost is presented as a percent of overall economy-wide GDP. Jobs saved 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. 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 2018 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.
* For policies that are grants funds disbursed are exactly equal to the fiscal cost. For policies in the form of a loan, repayments may lower the cost substantially below the funds disbursed numbers.

We discuss the effects of each policy on these firm groups in Table 9.

Column (1) of Table 9 relates to strong firms, columns (2) and (3) to weak firms and columns (4) and (5) to viable firms. Columns (2) and (4) show the failure rates under each policy for the weak and viable firm groups.[50] For instance under our benchmark policy the all weak firms still fail since they do not receive any support, while the failure rate of viable firms falls to 0.[51] Columns (1), (3) and (5) show the funds disbursed to each group from each intervention and column (6) the total amounts disbursed, all as a percent of GDP.

By construction, the benchmark policy does not waste any resources on strong firms (they don't need it), or weak firms (the support merely delays their exit). By contrast, the cash grants and pandemic loan disbursements prove to be poorly directed. Under each policy 40-60 percent of all viable firms are saved, at a cost of 0.24-0.63 percent of GDP. The policies also devotes a small amount of resources (0.19-0.44 percent of GDP) to inefficiently saving 15-30 percent of all weak firms. The cost of bailing out these weak firms is small because there are few such firms to start with, but this remains inefficient since these firms are likely to struggle and fail after fiscal support ends.

Table 10 further breaks down the jobs, wages and non-performing loans saved by weak firms and viable firms. Approximately 25 percent of the jobs saved (0.87/3.39) and wages saved (0.20/0.78), and 20 percent of loans saved (0.71/3.37) from the cash grants can be at-

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low value-added firms are survive due to policy.

[50]Note we do not show a column for failure rates of strong firms since these are 0 by definition of this group.

[51]Weak firms comprise 8.93 percent of all firms. Note that this is less than the 9.61 percent of firms we estimate that would fail in a non-COVID 2020 scenario (Table 2). The remaining 0.66 percent of firms that fail in our non-COVID scenario *survive* COVID because some sectors faced rises in demand due to COVID. These positive demand shocks helped save these firms from otherwise failing in 2020. These firms are classified as strong firms.

tributed to retaining workers at 'weak firms'. The same figures for the pandemic loans are 28, 28, and 25 percent respectively.

From a fiscal cost-efficiency perspective, however, both tables reveal clearly that the major defect of the cash grant and pandemic loan policies is that they "waste" fiscal resources on surviving firms that don't need it. The cash grants directs almost 2 percent of GDP to these firms. While the pandemic loan is even less efficient in terms of disbursements, providing funds equal to 4.75 percent of GDP to survivor firms, one potential advantage is that these funds may be recovered in the future. If the 4.75 percent of GDP distributed to strong firms were to be fully recovered by repayments, the overall cost of the policy would fall to 1.07 percent of GDP and the fiscal bankruptcy multiplier would rise to 1.06/1.07= 0.99 – a fairly effective policy. However, because loans require repayment from all firms (not merely strong firms) there is the risk that, even after the COVID shock subsides, viable firms may not be in a strong enough position to make repayments. Therefore, using loan repayment as a tool to limit the resources misdirected to strong firms may undo the benefits of supporting viable firms.

Rather than taking a debt position where repayment is required by all firms, policy support could instead take the form of an equity injection where repayments are only made by firms that are sufficiently profitable. This is obviously difficult to implement. An interesting alternative – with equity-like properties – is to couple immediate support with a mechanism by which fiscal authorities recoup some of the relief in future years, in case the firm survives. This could be implemented via a tax on future excess profits.[52]

With an appropriate claw-back mechanism, the pandemic loan disbursement formula then looks fairly cost-effective. It brings failure rates down to those in a typical year and has a fiscal bankruptcy multiplier just in excess of one. Furthermore, in Appendix B we show that the distribution of firms and jobs saved across sector and firm size mirrors closely our benchmark policy. This suggests that with the appropriate clawback mechanism, this loan policy can become equity-like and can disburse support fairly appropriately at a fairly modest fiscal cost.[53]

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[52]See Drechsel and Kalemli-Özcan (2020) and Blanchard et al. (2020) for similar recommendations.

[53]As reported in Financial Times, March 2021, " State takes stakes in UK start-ups under 1 billion convertible loan scheme," the UK government is converting smaller loans under the UK Future Fund into equity. Loans from 125,000 to 5 million pounds with a minimum of 8 percent interest rates will be either repaid or converted to government equity at a discount. The initiative was criticized by some as smaller loans might be taken out by low-productivity firms while high-productivity firms with larger loans cannot benefit from the program (Financial Times, March 2021, "UK strategy will create zombie companies that cannot grow.")

5.2 Policy Support Size, Timing and Additional Lockdowns

At the onset of the pandemic, governments felt pressure to enact generous policy support quickly to prevent firms failing. Moreover, as additional lockdowns were imposed, there was pressure to offer additional support. This section investigates the impact of varying the timing and size of policy disbursements on SME failure rates.

For each firm i in week w of 2020, we parameterize the pandemic loan policies according to:

$$\text{Support}_{i,w}(\kappa, s) = \kappa \frac{1}{52} \max \left\{ \frac{1}{4}\text{Revenue}_{i,2018}, 2\text{Labor Costs}_{i,2018} \right\} \mathbb{1}_{w \in [9,9+s)}. \qquad (24)$$

In this equation, κ controls the generosity of the pandemic loan and s controls the number of weeks covered by the program. Our original 8-week policy corresponds to $\kappa = 1$ and $s = 8$.

Fig. 5 reports the results. The original pandemic loan policy (blue line) prevents the entire rise in failure rates observed during lockdown under the no policy scenario (dashed black line), and subsequently maintains failure rates at typical levels even after lockdown ends.

Next, the red line considers the effect of changing the timing of policy disbursement – slowing the rate at which the pandemic loans are disbursed by half, but doubling the disbursement period to 16 weeks ($\kappa = 0.5$, $s = 16$). Note that firms that survive at least 16 weeks will receive the same amount of support as they do under the original policy ($\kappa = 1$ and $s = 8$). However, because we assume that once a firm runs out of cash, it cannot be saved by a subsequent cash injection, delayed policy disbursement risks arriving too late to be useful for some firms. A comparison of the 8-week 100% and 16-week 50% policies provides two insights. First, during the lockdown, slower disbursement (16-week 50% policy) results in a 1.03 pp rise in failure rates above a typical year. Yet, because disbursements continue even after lockdown ends, cumulative SME failure rates under the original and slower disbursement policies converge to similar levels by the end of 2020.

Finally, the green line in Fig. 5 shows the effects of extending disbursement of the pandemic loans by an additional 8 weeks after the lockdown ends ($\kappa = 1$, $s = 16$). As can be seen, this lowers the failure rate profile even after the support ends. Overall, the failure rate falls 1.47 percentage points below a typical year. Given that the firms do not begin failing after week 17 – once support ends – this suggests that the additional support continues to save mostly viable firms.

We confirm this in Table 11 where we show for each policy the failure rate for both weak (col. 1) and viable (col. 4) firms, the percent of firms that fail within each group (cols. 2 and 4, respectively), and the amount of support disbursed to each group of firms (cols. 3 and 6).

Figure 5: Timing and size of policy support.
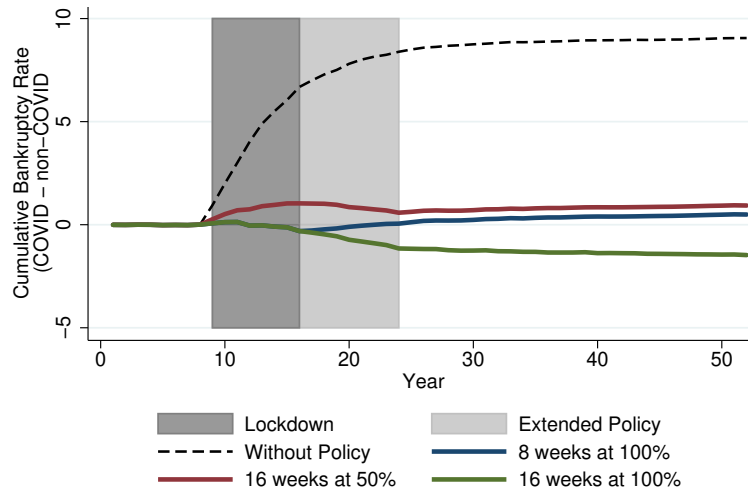
Notes: The results presented in these panels are aggregated across several countries using total revenue of firms in Orbis as weights. The aggregation is done over our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain. Each panel shows the failure rates over the year for each country in a variety of scenarios. The black dashed line shows the failure rates over time without any policy interventions. The navy line shows failure rates if policymakers give a pandemic during the 8 week lockdown. The red line shows failure rates under an extended pandemic loan for 16 weeks (ending 8 weeks after the lockdown ends) but at 50% of the previous weekly disbursement rate. The green line shows the failure rate with an extended pandemic loan for 16 weeks but paid out the full weekly disbursement rate during entire the period.

Comparing our original 8-week 100% pandemic loan policy (row 1) to the 16-weeks at 100% policy (row 3) shows that extending the loan guarantee saves an additional 10.69 percent of viable firms (col. 5) or 1.18 percent of all firms (col. 4). However, column (1) shows that extending policy also saves an additional 8.69 percent of weak firms (or 0.79 percent of all firms – col. 2). By contrast, varying the timing of policy (16-weeks at 50%) appears to affect only viable firms. Slowing the policy disbursement rate by half (row 2) affects barely any weak firms (an additional 0.44 percent of weak firms fail), but column (5) shows that an additional 4.10 percent of viable firms fail (comprising 0.4 percent of all firms – col 4). Though varying the timing of policy affects a very small subset of firms, it is striking that virtually all of them are viable firms. This lends support to the argument that initiating policy support early was important – delaying support tends to hurt viable firms. Moreover, continued support, even after a lockdown has ended, saves additional viable firms.

At the time of writing, many countries have faced second or even third waves of COVID-19 infections requiring additional temporary lockdowns. A natural question is whether additional policy support during each lockdown is needed or whether selection pressures or previous policy generosity will have left surviving firms with strong enough balance sheets to withstand additional lockdowns.

To answer this question, we consider a second 6-week lockdown in Fig. 6 that starts in week 32 of the year (mid-August). The black dashed line in this panel shows the weekly evolution

Table 11: The effect of timing and size of policy support by firm type

	Firms Bankrupt Regardless of COVID (Weak Firms)			Firms Bankrupt Only in COVID Scenario (Viable Firms)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Failure Rate (% Firms)	Failure Rate (% Group)	Funds Disbursed (% GDP)	Failure Rate (% Firms)	Failure Rate (% Group)	Funds Disbursed (% GDP)
8-weeks at 100%	6.51	72.18	0.44	3.59	32.65	0.63
16 weeks at 50%	6.55	72.54	0.44	3.99	36.75	0.63
16 weeks at 100%	5.72	63.49	0.88	2.41	21.96	1.26

Notes: All policies represent our Euro Area Loan Guarantees for different periods of time. The first allows firms to borrow half the usual amount for 16 weeks (the maximum of 1/8 of revenue or the wage bill of the firm), the second is the policy presented earlier – the maximum of 1/4 of revenue or double the wage bull – for 8 weeks and the final policy extends this for an additional 8 weeks (16 total). For all policies, funds disbursed is presented as a percent of overall economy-wide GDP. 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.

Figure 6: Policy responses to additional lockdowns
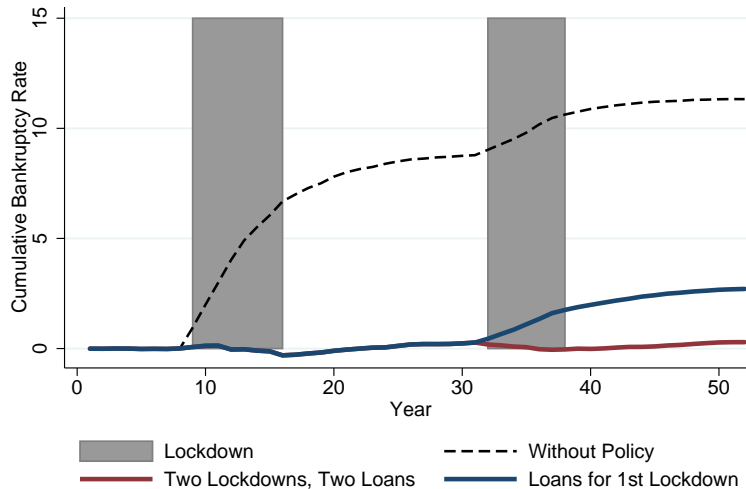
Notes: The results presented in these panels are aggregated across several countries using total revenue of firms in Orbis as weights. The aggregation is done over our high coverage group and is comprised of Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Spain. Each panel shows the failure rates over the year for each country in a variety of scenarios. The black dashed line shows the failure rates over time without any policy interventions with 2 lockdowns imposed. The navy blue line represents the effects on failure rate evolution if a pandemic loan is available during only the first lockdown and the red line represents the effects of also extending the pandemic loan into the second lockdown.

of failure rates under both lockdowns without any government support.

Absent any policy support, imposing a second lockdown raises failure rates by an additional 2.25 percent – much less than the effect of the first lockdown. This occurs for three reasons. First, 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 would have already been forced into failure by the first lockdown and remaining businesses would have considerably stronger cash positions.[54] 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 providing pandemic loan support on the cumulative failure rate over 2020. The blue line shows the effect of providing a pandemic loan facility only in the first lockdown and the red line shows the effect of re-opening the facility in the second 6-week lockdown. As can be seen, imposing a second lockdown without providing policy support (blue line) raises failure rates by around 2.7 percentage points relative to providing policy support during both lockdowns (red line). Furthermore, providing policy support in both lockdowns leads to an end-of-year failure rate level that is almost the same as the end-of-year failure rate from our single lockdown scenario with pandemic loans -and maintains failure rates close to standard levels. This suggests that, provided the government has the fiscal capacity to extend additional policy support, additional lockdowns may be imposed without necessarily raising firm bankruptcies.

6   Extensions

The assumptions behind our baseline COVID-19 scenario generate an upper bound estimate of the impact of COVID-19 and associated lockdowns on economic activity under normal credit conditions. In particular, we assume firms meet demand even if workplace restrictions make that prohibitively expensive and that while firms are able to rollover existing debt, they cannot borrow fresh funds. In Table 12, we introduce extensions that relax these assumptions and report the resulting change in failure rates (COVID - non-COVID).

In columns (2) and (3) we consider two ways to relax our assumption that firms must always meet demand while simultaneously employing a potentially very limited workforce.[55] In column (2), we allow firms to temporarily shutdown operations if meeting demand under

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[54]Note that this finding is not a 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. Empirically, we do not find that this is the case.

[55]Details on how these extensions are introduced into our baseline model are provided in Appendix C and Appendix E.

workplace restrictions leads to negative profits (referred to as "mothballing" – see Bresnahan and Raff (1991)).[56] Mothballing captures firms, such as restaurants, that may prefer to remain closed rather than switch to curbside pickup or online delivery. In column (3) we introduce a quadratic labor adjustment cost that allows firms to pay in order to hire more workers than allowed by their labor supply constraint if doing so is more cost effective than switching from labor to materials to meet demand. This extension captures the options firms may have available to invest in additional workplace safety measures (e.g, regular COVID testing, screening and installing barriers) under COVID-19 in order to retain more workers than they would otherwise be able to during lockdown. Columns (2) and (3) of Table 12 show that each of these extensions lowers failure rates by under two percentage points relative to our baseline scenario.

In columns (4) and (5) we investigate two alternative assumptions about credit market conditions: first, we effectively allow firms to borrow within the year and second, we consider a credit market disruption that prevents firms from rolling over their loan obligations. In column (4) we adjust the frequency with which we assess the firm's liquidity conditions to approximate firms tapping into short-term credit facilities during the worst phase of the pandemic. Instead of evaluating the failure criteria at a weekly frequency, we only evaluate it once at the end of the calendar year. This different timing assumption is conceptually similar to allowing firms to access zero-interest loans during 2020 that must be repaid by the end of the year. In this way, firms are able to smooth cash deficits incurred during the earlier parts of 2020 over the remainder of the year, during which time workplace restrictions end and demand conditions improve. As shown in column (4), this extension lowers failure rates by over 2 percentage points relative to our baseline scenario.

Lastly, in column (5) we consider what might occur if credit conditions deteriorate, forcing banks to call in obligations due within the next 12 months. Under this "no rollover" scenario, we assume that in addition to meeting their financial expenses, firms now also have to repay the principal on short term and long term loans due within the course of the year. Though credit markets have generally weathered the COVID-19 crisis well in our sample of countries, this scenario is meant to capture the additional failure risk countries would have faced from credit market disruptions during COVID-19. If COVID-19 has been coupled with a financial crisis, the impact on failure rates would have been high, with failure rates rising by almost 11 percentage points above our baseline scenario.

Table 13 shows the impacts across sectors of our five extensions, with the no rollover and annual extensions having a similar effect across sectors and mothballing and labor adjust-

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[56]Note that during their temporary shutdown, firms still pay rent and other fixed costs but incur no variable costs. Once labor restrictions ease or demand rises sufficiently, firms may then choose to re-open and restart production.

Table 12: Failure Rates (COVID - non-COVID) under Extensions

	(1) Baseline	(2) Mothballing	(3) L Adjustment	(4) Annual	(5) No Rollover
High coverage	9.06	7.88	7.71	6.79	20.94
All	8.98	7.15	7.38	6.36	25.82

Notes: Reports the change in failure rates (COVID - non-COVID) under – (1) baseline scenario; (2) firms are allowed to temporarily shutdown (Mothballing); (3) firms can pay a quadratic adjustment cost to overcome their labor supply constraint (L Adjustment) (4); the failure criteria is evaluated at the end of the calendar year (Annual); and (5) scenario in which loan obligations due within the next 12 months must be repaid (No Rollover). Failure rates are first calculated at the 1-digit NACE level and aggregated to the country level using 2018 sector gross value added as weights (the exceptions, due to data availability, are Korea and Japan where Orbis sector gross value added weights are used). Failure 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, which have lower Orbis coverage of official aggregate SME revenue.

Table 13: Failure Rates by Sectors under Extensions

	(1) Baseline	(2) Mothballing	(3) L Adjustment	(4) Annual	(5) No Rollover
Agriculture	4.58	1.69	2.75	3.33	22.13
Mining	24.39	15.85	9.61	14.22	34.19
Manufacturing	8.30	5.45	4.39	4.52	24.26
Electric, Gas & Air Con	1.38	0.31	1.38	-0.51	12.70
Water & Waste	3.36	2.61	3.36	1.03	15.71
Construction	2.12	1.63	2.09	0.86	13.83
Wholesale & Retail	10.22	9.95	10.27	8.66	27.40
Transport & Storage	5.92	4.73	5.90	2.51	18.31
Accom. & Food Service	25.72	20.34	13.60	17.34	34.28
Info. & Comms	5.85	5.22	5.85	4.31	13.32
Real Estate	6.79	6.68	6.80	5.98	19.10
Prof., Sci., & Technical	8.73	8.37	8.54	7.51	17.45
Administration	12.08	11.39	11.87	10.32	20.86
Education	18.98	18.84	18.98	17.41	25.12
Health & Social Work	3.27	3.16	3.27	2.42	10.14
Arts, Ent., & Recreation	26.20	22.10	21.94	22.57	32.85
Other Services	20.51	19.57	19.25	14.91	27.11

Notes: Reports the change in failure rates (COVID - non-COVID) under – (1) baseline scenario; (2) firms are allowed to temporarily shutdown (Mothballing); (3) firms can pay a quadratic adjustment cost to overcome their labor supply constraint (L Adjustment) (4); the failure criteria is evaluated at the end of the calendar year (Annual); and (5) scenario in which loan obligations due within the next 12 months must be repaid (No Rollover). Failure rates are first calculated at the 1-digit NACE level and aggregated to the country level using 2018 sector gross value added as weights (the exceptions, due to data availability, are Korea and Japan where Orbis sector gross value added weights are used). Sector failure 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.

ment costs associated with more cross-sectoral heterogeneity. Allowing firms to smooth cash flow during the year lowers failure rates by 1 to 4 percentage points in most sectors (col. 4), while a credit market disruption (col. 5) drastically increases failure rates across all sectors. Meanwhile, there is more cross-sectoral heterogeneity associated with the introduction of mothballing (col. 2) and labor adjustment costs (col. 3). In many sectors the impact of these extensions is negligible – for example, lowering the change in failure rates by less than 0.15 percentage points in Health & Social Work. In other sectors the impact is large, including Mining (-14.8) and Accommodation & Food Service (-12.1) under the labor adjustment extension. The large impact is felt primarily in sectors with large labor supply shocks and high fraction of firms that are labor constrained during COVID-19. Despite these numerical changes, the most-to-least affected ranking is broadly similar to our baseline.[57]

7 Conclusion

COVID-19 could have seriously disrupted the world economy by pushing a large number of small and medium enterprises (SMEs) into failure. This paper attempts to assess the vulnerability of these firms to the crisis in the absence of any policy support and then analyze the effect of various realistic policy interventions. We combine a large firm-level dataset, covering SMEs' financial positions at the start of the pandemic, 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. The methodology introduced in this paper could be applied to a number of other shocks and associated policy responses. For instance, it could be used to evaluate the short-run impact of trade liberalization, credit disruptions, or natural disasters on SMEs.

Our baseline estimates for COVID-19 suggest that, absent government intervention, the rate of SME failures would have almost doubled, increasing by 9.1 percentage points in 2020. We document significant heterogeneity in the rate of SME failures both across sectors and across countries due to factors such as firm profitability and cash holdings and estimates of sectoral COVID-19 supply and demand shocks. These business failures would put a significant number of jobs at risk – about 4.64 percent of employment. Despite these large real effects, we estimate only a moderate impact on the financial sector, with a decline in the risk-weighted CET1 capital ratio of 2.12 percentage points, on average.

Our framework allows us to consider a number of policy interventions aimed at supporting

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[57]One notable exception is Mining which is a unique sector which faces high demand but also strong workplace restrictions. Mothballing and labor adjustment costs are particularly helpful for the liquidity 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.

SMEs and to measure their cost-effectiveness. Our benchmark policy saves only viable firms. It is both efficient and reasonably cheap, but the information required for its implementation is too granular. Other, more realistic policies, face significant trade-offs. Some policies, such as interest rate forgiveness, and tax and rent deferrals, have only a small impact on firm failures. Cash grants can significantly reduce the rate of business failures, but at a high fiscal cost. According to our estimates, a grant corresponding to 15 percent of the firm's annual wage bill in a normal year would reduce business failures by 5.60 percentage points, saving 3.26 percent of jobs, at a fiscal cost of 2.38 percent of GDP. Pandemic loans, i.e. bank loans with government guaranties, representing 5.82 percent of GDP, help bring the SME failure rate back to its pre-COVID level and save 4.59 percent of jobs. Both grants and pandemic loans, however, could significantly misallocate resources. Contrary to conventional wisdom, the "waste" does not come from creating future zombies or saving weak firms that would fail anyway. According to our estimates, cash grants or pandemic loans artificially save only a third of weak firms, which amounts to 1.5-2.5 percent of SMEs. Rather, the bulk of the support is disbursed towards strong firms that don't need it to survive the COVID-19 crisis.

Our results suggest that equity-like support best balances the tension between a policy's effectiveness at saving viable firms versus the fiscal burden (from the bulk of support going to strong firms). Existing loan policies could be turned into equity-like support with an appropriate clawback mechanism (i.e. an excess profit taxes for grants and for loans allowing equity conversions as repayment). With appropriate clawback mechanisms policy can fairly cheaply save a meaningful number of viable SMEs.

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Appendices

A Summary Tables and Figures

Table A.1 reports the aggregate revenue coverage for the countries in our sample, both for all firms and SMEs specifically in 2017.[58] SMEs are defined as firms with less than 250 employees in both data sources, OECD and Orbis. Using raw Orbis data, our coverage ranges from 27.7 percent in Germany to over 67 percent in Finland.[59] Even after imposing additional data requirements for analysis, such as availability of intermediate costs, our data cover over 50 percent of the aggregate revenue of SMEs for most countries – key exceptions are highlighted in grey, where our analysis sample covers under one-third of aggregate SME revenue.[60]

Table A.1: Orbis Coverage (2017)

	% of OECD Revenue	
	(1)	(2)
	All Firms	SMEs
Belgium	60.2	52.1
Czech Republic	61.0	62.5
Finland	66.5	68.4
France	47.0	47.1
Germany	27.7	18.1
Greece	48.1	48.8
Hungary	60.7	47.1
Italy	63.9	76.3
Japan	38.0	.
Korea	54.0	32.6
Poland	48.7	45.4
Portugal	65.7	75.3
Romania	60.2	39.7
Slovak Republic	52.6	73.6
Slovenia	50.0	60.9
Spain	59.0	71.0
United Kingdom	49.2	41.4

Notes: OECD revenue (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 for Japan 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 (all firms and SMEs) is summed and divided by the total revenue (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 failure condition. Highlighted in grey are countries where the coverage rate falls below one-third of SME revenue in the analysis sample. Japan is also highlighted in grey because revenue data on SMEs is not available to evaluate coverage. SMEs are defined as firms with less than 250 employees in both OECD and Orbis data.

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[58]While we use the 2018 ORBIS data for our analysis, we evaluate coverage based on 2017 data because the OECD Structural Business Statistics Database (SBSD) does not yet have all data available for 2018.

[59]To obtain coverage rates we sum up all 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.

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

Table A.2 reports summary statistics (means) of various variables of interest both at the country level and aggregated across all countries and our high coverage subsample of countries. Column (1) reports the average number of employees; (2) average number of years since incorporation (age); (3) average labor productivity, measured as the log of number of employees over revenue (in millions); (4) average of employment growth in 2016-2018; (5) average revenue growth in 2016-2018; (6) average financial leverage, measured as short term and long term debt over total assets; and (7) average short term leverage, measured as short term debt over total assets.

Table A.2: Country-level Summary Statistics (Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employees	Age	L Prod	Emp Growth	Rev Growth	Fin Leverage	ST Leverage
Belgium	49.0	32.2	0.77	0.04	0.06	0.23	0.08
Czech Republic	27.8	15.3	2.32	0.04	0.15	0.08	0.03
Finland	16.6	17.8	1.69	0.07	0.10	0.22	0.06
France	33.3	22.6	1.53	0.04	0.05	0.13	0.06
Germany	94.3	31.7	1.05	0.04	0.05	0.23	0.05
Greece	29.7	21.2	1.82	0.09	0.11	0.21	0.08
Hungary	51.7	18.2	1.98	0.05	0.14	0.12	0.06
Italy	11.2	15.3	1.96	0.09	0.11	0.09	0.04
Japan	78.5	44.4	0.94	0.03	0.06	0.29	0.11
Korea	33.7	13.9	1.19	0.05	0.20	0.35	0.17
Poland	35.8	14.3	2.13	0.29	0.16	0.22	0.10
Portugal	12.6	15.3	2.50	0.10	0.17	0.33	0.07
Romania	82.0	15.2	2.27	0.01	0.06	0.12	0.06
Slovak Republic	10.7	10.9	2.47	0.14	0.19	0.13	0.09
Slovenia	10.9	13.9	2.22	0.10	0.15	0.36	0.19
Spain	12.4	16.3	2.13	0.10	0.13	0.26	0.06
United Kingdom	62.5	22.2	1.49	0.04	0.10	0.57	0.41
High Coverage	25.8	18.9	1.82	0.08	0.10	0.16	0.06
All	55.5	27.3	1.38	0.06	0.09	0.27	0.12

Notes: Summary statistics (means) are first calculated at the 1-digit NACE level and aggregated to the country level using 2018 sector gross value added as weights (the exceptions, due to data availability, are Korea and Japan where Orbis sector gross value added weights are used). Summary statistics 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 analysis sample coverage in Orbis of official (OECD) aggregate SME revenue. Column (1) reports the average number of employees; (2) average number of years since incorporation (age); (3) average labor productivity, measured as the log of the number of employees over revenue (in millions); (4) average employment growth in 2016-2018; (5) average revenue growth in 2016-2018; (6) average financial leverage, measured as short term and long term debt over total assets; and (7) average short term leverage, measured as short term debt over total assets.

Table A.3 provides a mapping from the OECD overall firm failure rate and the Orbis SMEs failure rate for the sectors in our analysis. Columns 1 and 2 reproduce Table A.3. Column (1) reports the latest (2017) official OECD failure rate among all firms. Column (2) reports the Orbis failure rate, calculated as the fraction of all firms that face a liquidity shortfall when we apply our procedure to the 2018 data (i.e. non-COVID). OECD failure rates do not cover all sectors (notably Agriculture). Accordingly, the comparison in columns (1) and (2) is made

Table A.3: Pre-COVID Business Failure Rates

| | Overlapping Sectors | | | All Sectors |
| | (1) | (2) | (3) | (4) |
	OECD	Orbis (All)	Orbis (SME)	Orbis (SME, analysis)
Belgium	3.0	8.8	8.8	8.2
Czech Republic	7.9	8.7	8.1	8.3
Finland	5.4	9.7	8.8	9.2
France	4.7	8.8	9.9	9.9
Germany	6.7	11.3	12.4	11.7
Greece	4.1	8.3	8.2	9.9
Hungary	8.8	9.4	8.8	8.6
Italy	6.7	9.3	9.3	9.4
Portugal	11.5	12.7	12.8	12.0
Romania	8.6	13.8	15.3	14.1
Slovak Republic	10.0	10.7	10.7	10.1
Slovenia	3.9	7.5	7.3	7.3
Spain	7.4	8.7	8.6	8.5
United Kingdom	13.8	11.3	11.2	13.5

Notes: Column (1) reports official OECD 2017 failure rates among all firms; column (2) failure rates are calculated by evaluating the fraction of all firms that face a liquidity shortfall in the Orbis data in 2018; column (3) and (4) report the fraction of SMEs that face a liquidity shortfall in Orbis data in 2018. Columns (1)-(3) report failure rates aggregated across sectors covered in both OECD and Orbis data, while column (4) includes all sectors used in our analysis. Official data on firm failure rates (all firms) 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. Sector-level gross value added (GVA) shares in 2018 (OECD) are used for aggregation of both Orbis and OECD data to the country level. The failure rate comparison is only done for the subset of countries covered in the OECD data. We use the latest data available in SDBS (2017) and Orbis (2018) to calculate the failure rates.

for the set of sectors present in both OECD and Orbis (overlapping sectors). Moreover, the comparison is made for all firms since the OECD failure rate does not provide a breakdown between SMEs and large firms. Column (3) shows the Orbis failure rate when we restrict the analysis to SMEs, but keeping the set of sectors for which OECD failure rates are available. The numbers barely change, since SMEs dominate the universe of firms. Column (4) reports the Orbis failure rate among SMEs for all the sectors we consider in our analysis. That last column corresponds to column 1 in Table 5.

Table A.4 reports the cross-country averages of variables of interest (ie: those Table A.2) by non-COVID and COVID survivor versus failing firms. Under both the non-COVID and COVID scenarios, failing firms are smaller, younger, and more highly leveraged than surviving firms. Relative to non-COVID, under COVID failing firms are slightly larger, less productive, faster growing, and less leveraged – though the differences are small.

Table A.4: Summary Statistics (Means): Surviving vs. Failing Firms in non-COVID and COVID

	Non-COVID		COVID	
	(1)	(2)	(3)	(4)
	Survive	Fail	Survive	Fail
Employees	26.13	23.18	26.17	24.50
Age	19.09	17.08	19.25	17.30
L Prod	1.77	2.30	1.80	1.96
Emp Growth	0.08	0.06	0.08	0.07
Rev Growth	0.10	0.05	0.10	0.08
Fin Leverage	0.15	0.29	0.14	0.23
ST Leverage	0.05	0.12	0.05	0.10

Notes: Summary statistics (means) are first calculated at the 1-digit NACE level, aggregated to the country level using 2018 sector gross value added as weights, and aggregated across countries using GDP as weights. The summary statistics are only aggregated across the high coverage group, which includes Belgium, Czech Republic, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia, Slovenia, and Spain. Row (1) reports the average number of employees; (2) average number of years since incorporation (age); (3) average labor productivity, measured as the log of the number of employees over revenue (in millions); (4) average employment growth in 2016-2018; (5) average revenue growth in 2016-2018; (6) average financial leverage, measured as short term and long term debt over total assets; and (7) average short term leverage, measured as short term debt over total assets.
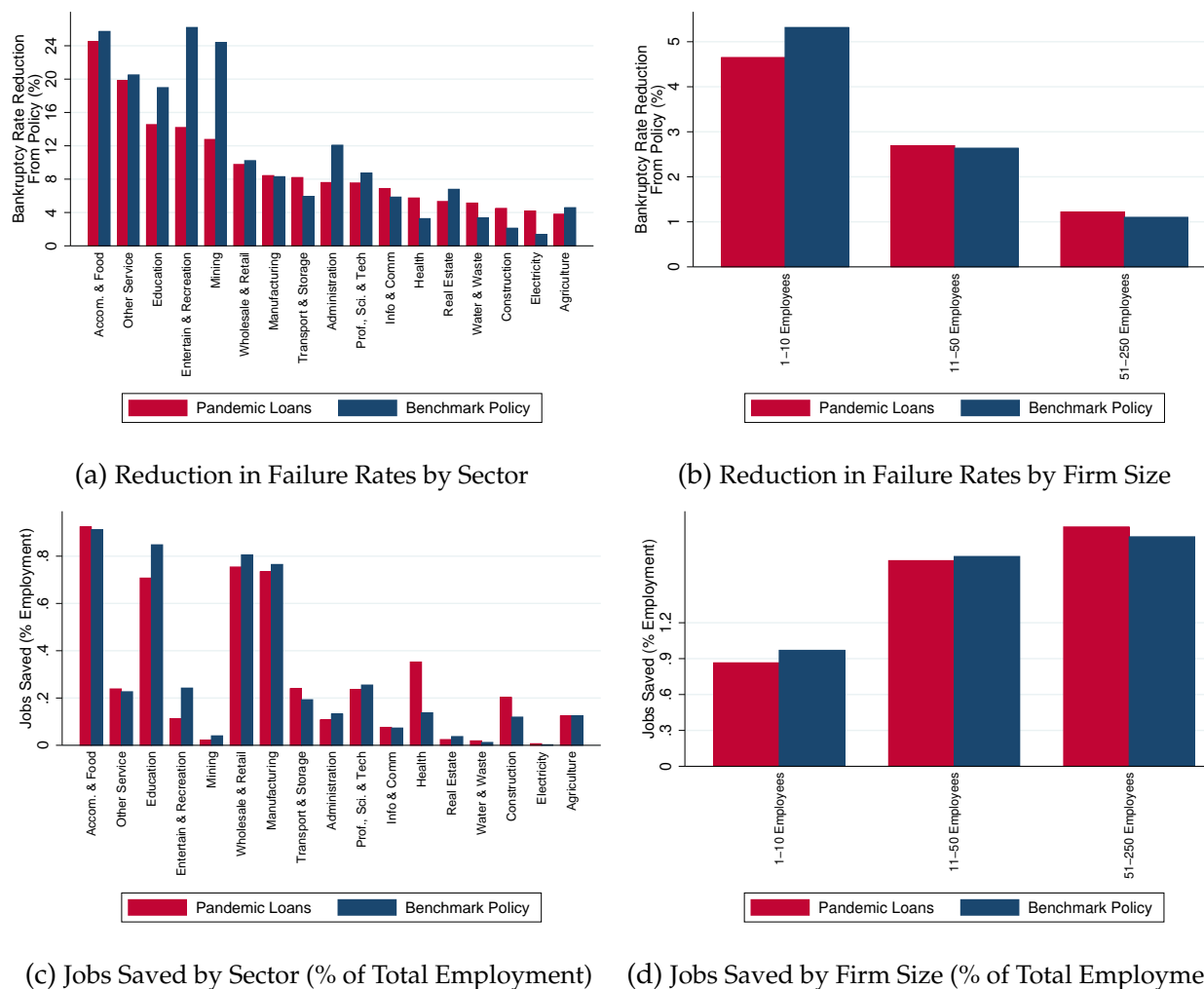
B   Targeting policy support with stricter criteria

Several policies implemented have opted to focus support with restricted eligibility criteria. For instance, France and Germany setup support directed at firms with fewer than 10 employees and Colombia, Austria and Brazil focused some of their support to restaurant and tourism sectors (see OECD (2020)). There is a case to opt to focus support if this characteristic helps focus support to viable firms.

We investigate the benefits of targeting policy support by comparing the variation in firms and jobs saved and disbursements for our benchmark (blue) and loan guarantee policies (red) by both sector (left panels) and size (right panels) in Figure B.1.

The top row shows the reduction in failure rates and the second row jobs saved. What is striking is that the benchmark policy and loan guarantees have very similar distributions of firms and jobs saved by sector. The main notable difference is that the targeted policy is better at supporting firms in the Education & Recreation and Mining sectors and for micro-enterprises (firms with fewer than 10 employees). There is modest evidence of many firms being saved in the Transport & Storage, Health, and Water & Waste, Construction and Electricity sectors, but this gap is relatively minor.

Figure B.1: Firms saved, jobs saved and funds disbursed by firm sector and size

(a) Reduction in Failure Rates by Sector

(b) Reduction in Failure Rates by Firm Size

(c) Jobs Saved by Sector (% of Total Employment)

(d) Jobs Saved by Firm Size (% 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% cash grant to SME firms during the 8 week lockdown. The first row shows the reduction in overall failure rates from the cash grant by sector (left) ordered from largest to smallest and size (right). The second row shows jobs saved by sector relative to overall employment.

These results suggest that there is not a strong case to target support among certain sectors or firm size groups if disbursing policy according to the criteria of our loan guarantee policy – the cross section of firms saved matches that of our benchmark policy.

C 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:

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

This expression indicates that mothballing is more likely when firms experience larger productivity shocks (a lower $\hat{A}$).[61]

For labor constrained firms the condition for mothballing is relaxed to

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

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. (C.1) and (C.2).

D Labor Adjustment Costs

If the labor constraint falls by more than demand, firms may need to increase materials utilization by excessive amounts in order to meet demand. In practice firms may be able to spend money avoiding having to send its workforce home in a lockdown – with for example, running its own testing regime, constructing enclosed individual areas for workers or improving building airflow. To model this, consider now a simple (static version) of the adjustment costs model, in the case where a firm is labor constrained.

We assume the adjustment costs take the following form (in the relevant range, i.e. $\hat{x}_s \leq \hat{n} \leq \hat{x}^c_s$):

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[61]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.

$$\Phi_s\left(n'\right) = wn\hat{x}_s \left(\frac{\hat{n}}{\hat{x}_s}\left(\frac{1}{2}\frac{\hat{n}}{\hat{x}_s} - 1\right) + \frac{1}{2}\right)\mathbf{1}_{\{\hat{x}_s < \hat{x}_s^c\}}$$

With this adjustment cost function, the cost minimization becomes:

$$\min_{n',m'} wn' + p_m m' + \Phi_s\left(n'\right)$$

$$zk^\alpha \left(A'n'\right)^\beta \left(m'\right)^\gamma \geq d'$$

and the first order conditions imply:

$$\hat{n}\left[1 + \frac{\Phi'_s\left(n'\right)}{w}\right] = \hat{m}$$

Notice from this expression that the adjustment costs already force some adjustment on materials instead of labor.

Substituting into the production function, we obtain

$$\hat{A}^\beta \hat{n}^{\beta+\gamma}\left[1 + \frac{\Phi'_s\left(n'\right)}{w}\right]^\gamma = \hat{d}$$

and given the adjustment cost function,

$$1 + \frac{\Phi'_s\left(n'\right)}{w} = \frac{\hat{n}}{\hat{x}_s}$$

so that we obtain

$$\hat{n} = \hat{x}^{c\frac{\beta+\gamma}{\gamma+2\gamma}}\hat{x}_s^{\frac{\gamma}{\beta+2\gamma}}$$

$$\hat{m} = \hat{x}_s^{-\frac{\beta}{\gamma}}\hat{x}^{c\frac{\beta+\gamma}{\gamma}}\left(\frac{\hat{x}_s}{\hat{x}^c}\right)^{\frac{\beta(\beta+\gamma)}{\gamma(\beta+2\gamma)}} < \hat{x}_s^{-\frac{\beta}{\gamma}}\hat{x}^{c\frac{\beta+\gamma}{\gamma}}$$

The first equation tells us that (log) employment is a weighted average of constrained and unconstrained (log) employment:

$$\ln\hat{n} = \frac{\beta+\gamma}{\gamma+2\gamma}\ln\hat{x}^c + \frac{\gamma}{\beta+2\gamma}\ln\hat{x}_s$$

so that it be somewhere in the interval $[\hat{x}_s, \hat{x}_s^c]$. As for materials, the second equation shows that firms adjust by less than in the case where the constraint on employment were tight.

E Labor Adjustment Costs

If the labor constraint falls by more than demand, firms may need to increase materials utilization by excessive amounts in order to meet demand. In practice firms may be able to spend money avoiding having to send its workforce home in a lockdown – with for example, running its own testing regime, constructing enclosed individual areas for workers or improving building airflow. To model this, consider now a simple (static version) of the adjustment costs model, in the case where a firm is labor constrained.

We assume the adjustment costs take the following form (in the relevant range, i.e. $\hat{x}_s \leq \hat{n} \leq \hat{x}_s^c$):

$$\Phi_s\left(n'\right) = wn\hat{x}_s\left(\frac{\hat{n}}{\hat{x}_s}\left(\frac{1}{2}\frac{\hat{n}}{\hat{x}_s} - 1\right) + \frac{1}{2}\right)\mathbf{1}_{\{\hat{x}_s < \hat{x}_s^c\}}$$

With this adjustment cost function, the cost minimization becomes:

$$\min_{n',m'} wn' + p_m m' + \Phi_s\left(n'\right)$$
$$zk^\alpha \left(A'n'\right)^\beta \left(m'\right)^\gamma \geq d'$$

and the first order conditions imply:

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Notice from this expression that the adjustment costs already force some adjustment on materials instead of labor.

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and given the adjustment cost function,

$$1 + \frac{\Phi'_s\left(n'\right)}{w} = \frac{\hat{n}}{\hat{x}_s}$$

so that we obtain

$$\hat{n} = \hat{x}^{c\frac{\beta+\gamma}{\gamma+2\gamma}}\hat{x}_s^{\frac{\gamma}{\beta+2\gamma}}$$

$$\hat{m} = \hat{x}_s^{-\frac{\beta}{\gamma}}\hat{x}^{c\frac{\beta+\gamma}{\gamma}}\left(\frac{\hat{x}_s}{\hat{x}^c}\right)^{\frac{\beta(\beta+\gamma)}{\gamma(\beta+2\gamma)}} < \hat{x}_s^{-\frac{\beta}{\gamma}}\hat{x}^{c\frac{\beta+\gamma}{\gamma}}$$

The first equation tells us that (log) employment is a weighted average of constrained and unconstrained (log) employment:

$$\ln \hat{n} = \frac{\beta + \gamma}{\gamma + 2\gamma} \ln \hat{x}^c + \frac{\gamma}{\beta + 2\gamma} \ln \hat{x}_s$$

so that it be somewhere in the interval $[\hat{x}_s, \hat{x}_s^c]$. As for materials, the second equation shows that firms adjust by less than in the case where the constraint on employment were tight.