ESTIMATING SME FAILURES IN REAL TIME:
AN APPLICATION TO THE COVID-19 CRISIS

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NBER Working Paper No. 27877
September 2020, Revised January 2022
JEL No. D2,E65,G33

ABSTRACT

We develop a flexible framework for tracking business failures during economic downturns. Our framework combines firm-level data with a model of cost-minimization where firms react to a rich set of shocks and fail if illiquid. After verifying that our methodology approximates past official failure rates, we apply it to the COVID-19 crisis in 11 countries. Absent government support, SME failures would have increased by 6.15 percentage points, representing 3.15 percent of employment. We find little threat to financial stability. Commonly implemented COVID-19 policies saved firms but were costly because funds were directed to firms that could survive without support.

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1 Introduction

Tracking business exits in the midst of economic downturns, such as the recent COVID-19 crisis, is of interest to both researchers and policymakers who seek to better understand sources of economic vulnerability and to explore the costs and impacts of policy response options. Yet, measuring firm failures in real time and evaluating counterfactual scenarios during an evolving crisis remains challenging. Official data on business exits is only available with a lag of several years through administrative sources, such as bankruptcy filings and/or firms' own reporting to business registries and national census surveys, where the latter comes with even a longer lag. Non-traditional data on business exits from business services client databases, customer-tracking data sets, or ad-hoc surveys are available at high frequency. However, they cannot be used to evaluate counterfactual policy scenarios, or to study sources of vulnerabilities and aggregate implications because these data are generally only available for a select sample of firms.

We introduce a tractable, flexible framework that combines a model of cost-minimization with recent firm-level accounting data (ie: that predates the shock), to estimate business exits. Our framework incorporates both a rich set of economic shocks that impact firm cash flow and a range of modeling options that enable firms to adapt to these shocks. By mapping the model to detailed firm-level data, we can predict individual firm exits and study sources of firm, sectoral, and aggregate vulnerability to shocks. The framework can also be used to study macroeconomic concerns—such as financial sector risk through non-performing loans (NPLs)—and to evaluate counterfactual scenarios to study the costs and benefits of policy alternatives.

In our model, the total demand for a firm's output in each sector is affected both by an aggregate and a sector-specific demand shock. Assuming a negative shock, the former captures the size of the slowdown in aggregate expenditures. It affects all firms proportionately. The latter reflects the change in relative demand in that sector, as a result of changes in household preferences for certain goods. On the supply side, we consider an environment where prices are fixed and output is demand determined. Each firm adjusts variable inputs to meet demand, subject to possible input constraints it faces as a result of either labor shocks or supply-chain disruptions. Firms face a tension between desired input demand and available input supply. When the input constraint binds for one input, firms try to meet demand by substituting away to unconstrained inputs, 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, so our model allows firms to *mothball* temporarily, as in Bresnahan and Raff (1991).

From the solution to this cost-minimization problem, we project a firm's cash flow under

the shocks. Because the vast majority of firms are Small and Medium-Sized Enterprises (SMEs) and these firms tend to be liquidity constrained,[1] we estimate whether a firm has failed based on a liquidity criterion (as opposed to solvency).[2] In our model, a firm experiences a liquidity shortfall if available cash and projected cash flow are insufficient to cover fixed costs, taxes and financial expenses. This liquidity criteria can be evaluated at any frequency. We choose to evaluate this criterion at the end of the year to captures the many (non-modelled) options available to SMEs to prevent a temporary cash deficit leading to failure.[3]

We operationalize our framework by linking the model to detailed firm-level accounting data. Specifically, we use Orbis balance sheet and income statement data for a sample of 11 European countries.[4] We show how this recent data on firm revenue and costs can be combined with estimates of aggregate and sectoral shocks to predict firm level cash flows and liquidity shortfalls.

Our first application of the methodology compares official failure rates in 2018 for our sample of 11 countries to those simulated by our framework. This application is a validation exercise to confirm that we can match the most recently available failure rate data. To predict 2018 exit rates, we start with 2017 balance sheet data from Orbis and measure shocks using Eurostat data on quarterly aggregate GDP growth, sectoral revenue growth, and sectoral labor productivity growth between 2017 and 2018. Across the 11 countries, the difference between estimated and official failure rates is 0.70 percentage points on average.[5] Our framework also does well in matching the cross-sector variation in failure rates, with a correlation of 0.58.

While our framework can be used to predict exits in any year (with estimates of the relevant shocks) it is a particularly useful tool for real-time analysis of economic downturns. We showcase this by applying our framework to the recent COVID-19 crisis. This crisis was both unexpected and unprecedented. In particular, it featured massive heterogeneity in the severity of demand and supply shocks across sectors. Nationwide lockdowns, in conjunction with behavioral changes due to fear of the pandemic caused disruptions in production and led to the largest collapse in demand for firms' output since the Great Depression. Policymakers were faced with substantial uncertainty about the evolution of the crisis and needed to weigh alter-

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[1]See Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez (2017)

[2]SMEs are defined as firms with less than 250 employees. In the European Union, for example, SMEs account for 99.8 percent of all employer firms. They also account 65 percent of private sector employment, and 54 percent of private sector gross output. Output statistics are from Eurostat's Structural Business Statistics for a select set of sectors. SMEs account a large share of output (over 50 percent) when all the sectors of the aggregate economy are considered, as shown in Kalemli-Özcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas (2019). Note that for SMEs book-value equity may be more severely mismeasured, since most of the SMEs are unlisted.

[3]Examples include delaying the payment of receivables, not replenishing input inventories, utilizing credit lines or other very short term debt instruments.

[4]The countries in our sample are Czech Republic, Finland, France, Hungary, Italy, Poland, Portugal, Romania, Slovak Republic, Slovenia, and Spain.

[5]We first calculate the difference between simulated and official failure rates at the country level, and then aggregate across countries using GDP as weights to arrive at the 0.70 percentage point average difference.

native policy options in real-time. It is precisely in this type of scenario that our framework can provide insight on the underlying sources of economic vulnerability and on the costs and potential impacts of various policy alternatives.

To study how vulnerable economies were to the COVID-19 crisis, we first formulate a baseline scenario absent government intervention. We assume that shocks hit at the end of February 2020 and the subsequent lockdown and stringent social distancing period lasts 8 weeks.[6] During these 8 weeks, the economy is affected by the sectoral supply and demand and aggregate demand shocks, measured by ability to shift to remote work, reliance on face-to-face interactions, and quarterly IMF GDP growth forecasts, respectively. At the end of lockdown, 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 slowly. We allow firms to mothball temporarily, and evaluate our liquidity shortfall condition at the end of the year. Firms that are illiquid at that time fail.

Under the baseline COVID-19 scenario, we find that SME failure rates would have been 6.15 percentage points higher than in the absence of the crisis (a "non-COVID" 2020 scenario). Our baseline estimate is partly influenced by two modelling assumptions—annual evaluation of the liquidity criteria and temporary mothballing. Our framework allows us to easily modify these assumptions. If we evaluate the liquidity criteria weekly (i.e. other than changing production, firms cannot smooth through any temporary cash deficits) and assume that firms cannot mothball, we estimate a much higher SME failure rate of 9.38 percentage points above the non-COVID scenario.

Our framework also allows us to decompose the aggregate SME failure rates to study sources of cross-sector and cross-country heterogeneity. By adding different shocks sequentially, we document that exposure to sector-specific shocks and firm financial health explain observed differences. For example, while severe sector-specific demand shocks drove failure rates in Arts, Entertainment & Recreation, labor supply shocks drove failure rates in Accommodation & Food Service. Further, despite facing similar shocks Italy's failure rate (10.35 pp) exceeded France's (5.51) due to lower cash buffers and higher financial expenses of Italian firms at the onset of the COVID-19 crisis.

We also use the COVID-19 application to show how firm level outcomes can be linked to aggregate outcomes and to run policy counterfactuals. First, we address the macroeconomic concern of policymakers that non-performing loans (NPLs) of failing SMEs could spillover and lead to instability in the financial sector. Using our baseline scenario, we estimate that even in the absence of government intervention the increase in SME NPLs would have resulted in only a 1.20 percentage point decline in the ratio of CET1 capital to risk-weighted assets. As a

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[6]This timing coincides with the lockdown period imposed in many of our sample countries.

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.[7] We therefore conclude that despite the rise in SME failures, the impact of COVID-19 on financial sector stability is likely to remain moderate.

Next, we evaluate the cost and impact of various policy interventions considered by policymakers in response to the COVID-19 downturn through a series of counterfactuals. We start with a hypothetical benchmark policy that bails out all firms that fail due to the COVID-19 crisis but that would have survived under a non-COVID scenario. The policy costs only 0.65 percent of GDP, lowers failure rates back to their pre-COVID level, and helps preserve 3.15 percent of private sector employment. We compare this benchmark to several interventions that mimic polices implemented in practice, including interest, tax and rent rebates, cash grants, and government guaranteed loans (or pandemic loans).[8] We find that cash grants and pandemic loans provide the most relief, but require considerable funds be committed. For example, the pandemic loan mobilizes 5.78 percent of GDP in government-guaranteed funding and saves 7.95 percent of firms and 4.11 percent of jobs, bringing failure rates *below* their pre-pandemic level.

With trillions of dollars spent on slowing the tide of firms failures, policymakers began questioning whether fiscal policies reached vulnerable firms or helped prevent the natural failure of weak firms. Because our framework generates failures at the firm level, we can decompose the cost and impact of policies across different types of firms. To evaluate whether fiscal support was adequately targeted, we group firms into: "strong firms" that are able to survive COVID-19; "weak firms" that would not survive 2020 even in the absence of COVID-19; and "viable firms" that only fail 2020 if COVID-19 occurs. We find that both cash grants and pandemic loans provided substantial funding to "strong" firms, and little support to "weak" firms. Under the pandemic loan policy, for example, 0.46 percent of GDP (out of a total of 5.78 percent) is channeled to "viable" firms. An additional 0.41 percent of GDP goes to weak firms, while the majority of the money (4.92 percent of GDP) is disbursed to "strong" firms. Therefore, our results suggest that the trade-off between a policy's effectiveness at saving viable firms versus the fiscal burden facing governments can best be handled by designing policies to clawback some of the support directed towards strong firms.

This COVID-19 application of our framework highlights the value of integrating a tractable model of firm decision making with detailed firm level data. The framework is a tool that researchers and policymakers can use to generate real-time, nuanced insights during an economic downturn. For instance, early in the COVID-19 crisis, policymakers feared that many

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

[8]According to OECD (2020) tax deferrals have been one of the most common policy support measures used by OECD governments and 22 OECD countries have implemented some form of rent deferral or waiver scheme. Cash grants and government guaranteed loans are also widely used. See ECB Economic Bulletin 6/2020 Focus

SMEs would fail. Our framework suggests that without policy support, the rise in failure rates would have been severe in certain country-sectors, but manageable in others, underlying the importance of the targeted polices. More importantly, there were concerns that weak firms saved by policy support would slow economic recovery. Our framework suggests instead that resources were wasted on strong firms. These types of insights can help policymakers design more efficient policies.

Literature Review and Our Contribution

The theoretical literature on endogenous firm failures in the short-run due to bad shocks is very limited. The New Keynesian strand of the literature tends to model short-run exit exogenously. Recently, Bilbiie and Melitz (2021) study short-run entry-exit dynamics during COVID-19. Because firms are homogeneous in their framework, they cannot capture the heterogeneity in firm exits emphasized in this paper. The most closely related papers to our paper are Clementi and Palazzo (2016) and Lee and Mukoyama (2015). Both generate short-run exits endogenously through negative aggregate productivity shocks. Heterogeneity in exits arises from heterogeneous, sector-specific operating costs, with firms facing higher costs being more likely to exit in response to negative shocks.

Given our COVID-19 application, we also relate to rapidly expanding literature on the impact of COVID-19 on business failures. Some papers focus on tracking business exits at high frequency using non-traditional data such as business services client databases or customer-tracking data sets (e.g. Crane, Decker, Flaaen, Hamins-Puertolas, Kruz and Christopher (2020), Kurman, Lale and Lien (2021)). This approach is useful for documenting failures in real-time, but cannot be used to evaluate counterfactual scenarios. Others use firm-level data to project cash flow under COVID-19 using a simple empirical rule, without a model (e.g. Demmou, Franco, Sara and Dlugosch (2020), Carletti, Oliviero, Pagano, Pelizzon and Subrahmanyam (2020), Schivardi and Romano (2020)). A couple of papers combine firm-level data with a structural model to explore the question of solvency related bankruptcies, while we focus on liquidity related bankruptcies (e.g. Guerini, Nesta, Ragot and Schiavo (2020) and Díez, Duval, Fan, Garrido, Kalemli-Özcan, Maggi, Martinez-Peria and Pierri (2020)).[9] These papers tend to focus on estimating firm failures, but do not delve into sources of vulnerabilities or the evaluation of alternative policy scenarios.

We also relate to papers that study the optimal design of COVID-19 firm support policies. Some papers focus on how firms access the credit market to smooth shocks and whether or not government policies are needed (e.g. Acharya and Steffen (2020), Greenwood, Iverson and

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[9]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.

Thesmar (forthcoming)). Others evaluate the need for and targeting and effectiveness of various government support programs, such as the Paycheck Protection Program in the United States (e.g. Granja, Makridis, Yannelis and Zwick (2020); Elenev, Landvoigt and Van Nieuwerburgh (2020); Core and De Marco (2020)). Papers such as Greenwood et al. (forthcoming), Blanchard, Philippon and Pisani-Ferry (2020) and Hanson, Stein, Sunderman and Zwick (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. In this paper, we evaluate the effect of some of these policy proposals on SMEs failure rates.

2 A Simple Theoretical Framework

In this section we introduce a simple and tractable model that can be combined with firm-level data to investigate the effects of an economic downturn on firms. The model allows for a rich set of sectoral and aggregate demand and supply shocks, which impact firm earnings, cash flow, and liquidity position. The modeller therefore has considerable flexibility in deciding which shocks firms face. For the sake of tractability, our model relies on a number of important simplifying assumptions, which we discuss in more detail after the exposition of the general framework. We focus here on the first-round partial equilibrium effects of the shocks, insofar as we do not estimate their general equilibrium effects, nor do we incorporate an input-output structure. The evolution of aggregate demand is taken as given.

In the model, firms solve a cost-minimization problem, subject to shocks. Optimal production decisions are expressed as (non-linear) "perturbations" from their decisions in a benchmark year. This benchmark year can, for example, be the most recent available year of data prior to an economic downturn. The use of firm data allows for a more nuanced analysis. For instance, in our framework two firms facing the same shocks—perhaps because they operate in the same sector—may have different outcomes depending on their pre-downturn profitability or cash buffers.

In Section 3.2 we show in a validation exercise that, despite its simplicity and tractability, our approach is able to reasonably approximate firm failures under observed business conditions, even without a significant downturn or crisis. In our COVID-19 application in Section 4, we show that our framework allows policymakers to obtain useful "quasi real-time" estimates of business failures and to evaluate the impact of policies.

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 take the initial 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:

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

In Eq. (1), y_{is} denotes gross output, k_{is} represents any fixed factor, including capital, entrepreneurial talent etc.., n_{is} is a 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 denote p_{is} as the price of output of firm i in sector s, w_s the wage rate per effective unit of labor, r_s the user cost for fixed factors and p_{ms} 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.

Some shocks can impose short run constraints on firms' production sets either in terms of inputs combinations available or in terms of productivity (A_s). For instance, in a natural disaster, some materials may be rationed, or workers may be unable to travel to work. Or as we investigate in our COVID-19 application, firms may be forced to reduce the size of their labor force, due to health-mandated lockdowns and supply chain constraints or delays may reduce the intermediate inputs a firm has access to. We model such constraint at the firm level as follows:

$$h_{is}(n_{is}, m_{is}) \leq 0,$$ (2)

where we assume that the constraint $h_{is}(., .)$ satisfies regularity conditions such that the problem of the firm is well-defined and convex.

2.2 Demand

Each firm within a given sector sells a differentiated variety. We assume that total demand has a nested-CES structure of the form:

$$D = \left[\sum_s \mathcal{N}_s \xi_s D_s^{(\eta-1)/\eta}\right]^{\eta/(\eta-1)}.$$ (3)

In Eq. (3), D denotes aggregate (real) demand, D_s is sectoral demand, ζ_s is a sectoral demand shock, and η is the elasticity of substitution between sectors. For simplicity, we assume that sectors are initially symmetric, and set $\mathcal{N}_s \zeta_s = 1, \forall s$. We also denote with a "prime" the value of variables in the target period (or year), so that ζ_s is the value of the sectoral demand shifter in sector s in the reference period and ζ'_s is the value in the target period (or period experiencing shocks), with $\zeta'_s < \zeta_s$ when demand for sector s falls and $\zeta'_s > \zeta_s$ when it increases.

In turn, sectoral demand D_s satisfies:

$$D_s = \left(\frac{1}{\mathcal{N}_s} \int_0^{\mathcal{N}_s} d_{is}^{(\rho_s-1)/\rho_s} \mathrm{d}i \right)^{\rho_s/(\rho_s-1)} , \tag{4}$$

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

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

$$d_{is} = \zeta_s^\eta \left(\frac{p_{is}}{P_s} \right)^{-\rho_s} \left(\frac{P_s}{P} \right)^{-\eta} D, \tag{5}$$

where P_s denotes the average sectoral price index per unit of expenditure, and P the overall price level. They satisfy:[10]

$$P_s = \left(\frac{1}{\mathcal{N}_s} \int_0^{\mathcal{N}_s} p_{is}^{1-\rho_s} \mathrm{d}i \right)^{1/(1-\rho_s)} \quad ; \quad P = \left(\sum_s \zeta_s^\eta \mathcal{N}_s P_s^{1-\eta} \right)^{1/(1-\eta)} . \tag{6}$$

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. (6) are also constant. The aggregate price index P, however, can change because of the demand shifters ζ_s.

We denote with a "hat" the ratio of variables relative to the reference period, e.g. $\hat{\zeta}_s \equiv \zeta'_s / \zeta_s$. From Eq. (5), we can use hat algebra to express the change in demand relative to a reference period as:

$$\hat{d}_{is} = \hat{\zeta}_s^\eta \hat{P}^{\eta-1} \widehat{PD}. \tag{7}$$

Under the assumption that the equilibrium is symmetric in the reference period, $P_s \mathcal{N}_s =$

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

$P\mathcal{S}^{1/(\eta-1)}$, and we can write:

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

Putting the two previous equations together, we obtain a very simple expression for the change in demand relative to a reference period:

$$\hat{d}_{is} = \frac{\hat{\xi}_s^\eta}{\sum_\sigma \hat{\xi}_\sigma^\eta/\mathcal{S}}\widehat{PD}. \tag{8}$$

Eq. (8) indicates that the total change in sectoral demand is a function of two drivers: a relative and an aggregate one. First, sector-specific demand shocks $\hat{\xi}_s$ reallocate a given level of aggregate expenditure *across* sectors. Importantly, it is the relative pattern of sector-specific demand shocks that matters, not their absolute level. For instance, suppose there is no change in aggregate demand so $\widehat{PD} = 1$ and the economy consists of two sectors with $\hat{\xi}_s < \hat{\xi}_{s'}$, then $\hat{d}_s < 1 < \hat{d}_{s'}$: one sector is in recession, and the other is in a boom. The elasticity of substitution across sectors η modulates the intensity of the sectoral demand shocks $\hat{\xi}$: when goods are very substitutable (high η), small sectoral demand shocks lead to large demand responses. Conversely when demand is very inelastic (low η) demand responses become more similar across sectors (in the limit of $\eta = 0$, we obtain $\hat{d} = \widehat{PD}$). Second, for a given pattern of sector-specific demand shocks, all sectors respond proportionately to changes in aggregate demand. For instance, if all sectors are affected uniformly so that $\hat{\xi}_s = \hat{\xi}, \forall s$, then Eq. (8) indicates that total demand in all sectors is affected uniformly with $\hat{d}_{is} = \widehat{PD}$.

Define $\tilde{\xi}_s^\eta \equiv \hat{\xi}_s^\eta/(\sum_\sigma \hat{\xi}_\sigma^\eta/\mathcal{S})$. $\tilde{\xi}_s^\eta$ succinctly summarizes the impact of sector-specific demand shocks on total demand and satisfies $\sum_s \tilde{\xi}_s^\eta/\mathcal{S} = 1$. With this notation, each firm i in sector s experiences the same proportional change in demand relative to a reference period, given by:

$$\hat{d}_s = \tilde{\xi}_s^\eta \widehat{PD}. \tag{9}$$

2.3   The Firm's Cost Minimization Problem

We are interested in evaluating our scenarios over a sufficiently short horizon that the prices of goods and factors can be taken as given and firms can be assumed to meet the demand they face. We further assume that labor cannot reallocate across firms or sectors in the short run, so workers who cannot work for their original place of employment are laid off and do not generate a drain on the firm's cash-flow.

Each firm aims to minimize variable costs by solving the following problem:

$$\min_{m'_{is}, n'_{is}} \quad w_s n'_{is} + p_{ms} m'_{is} \tag{10}$$

$$z_{is} f(k_{is}, A'_s n'_{is}, m'_{is}) \geq d'_{is}$$

$$h_{is}(n'_{is}, m'_{is}) \leq 0,$$

where the level of demand d'_{is} is given by Eq. (5).

We specialize the problem further by assuming that the production function $f_s(.)$ is Cobb-Douglas:

$$y_{is} = z_{is} k_{is}^{\alpha_s} (A_s n_{is})^{\beta_s} m_{is}^{\gamma_s}, \tag{11}$$

where the (sector-specific) exponents α_s, β_s and γ_s sum to one.[11]

We also specialize the supply constraint as follows:

$$h_{is}(n'_{is}, m'_{is}) = \omega_s(n'_{is} - x_{ns} n_{is}) + (1 - \omega_s)(m'_{is} - x_{ms} m_{is}) \leq 0. \tag{12}$$

In this expression, n_{is} and m_{is} denote the level of employment and materials before the shocks, x_{ns} and x_{ms} denote the tightness of the labor and intermediate input constraint, defined at the sector level, while ω_s captures the relative importance of the labor and intermediate input constraints for firms in sector s. To illustrate, Eq. (12) can capture the notion that firms in some sectors can only employ a fraction x_{ns} of their normal time employment level by setting $\omega_s = 1$. In that case the constraint becomes $n'_{is} \leq x_{ns} n_{is}$. Alternatively, Eq. (12) can capture the notion that firms in some sectors face supply-chain constraints and can only purchase a fraction x_{ms} of their reference period material usage m_{is} by setting $\omega_s = 0$. In that case, the constrained becomes $m'_{is} \leq x_{ms} m_{is}$. Policymakers may have information on which sectors are constrained and on what inputs, i.e. data on ω_s, x_{ns} and x_{ms}. We assume that the supply constraint can bind only on one of the factors for any given sector, that is $\omega_s \in \{0, 1\}$.

It follows that we have three cases to consider: (a) when the supply constraint doesn't bind; (b) when it binds on labor supply and (c) when it binds on materials.

2.3.1 When Supply is Not Constrained

When the supply constraint Eq. (12) does not bind, we can solve the above program for the demand for labor and materials. Ignoring for simplicity the sector and firm subscript and

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[11]Because we assume that capital k_{is} is fixed, the relevant part of this assumption is that production exhibits decreasing returns to labor and intermediate jointly, i.e. $\beta_s + \gamma_s < 1$.

manipulating the first-order conditions yields:

$$\hat{m} = \hat{n} = \hat{d}^{1/(\beta+\gamma)} \hat{A}^{-\beta/(\beta+\gamma)} = \left(\tilde{\xi}^{\eta}\widehat{PD}\right)^{1/(\beta+\gamma)} \hat{A}^{-\beta/(\beta+\gamma)} \equiv \hat{x}^c. \tag{13}$$

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 the supply constraint does not bind, $\hat{n} \leq \hat{x}_n$ and $\hat{m} \leq \hat{x}_m$. Since only one of the constraints binds for any firms in any sector, inputs are unconstrained as long as $\hat{x}^c \leq \hat{x} \equiv \omega_s \hat{x}_n + (1 - \omega_s)\hat{x}_m$.

We can rewrite Eq. (13) and impose that the supply constraint does not bind to get the following expression:

$$\hat{x}^{(\beta+\gamma)} \hat{A}^{\beta} \geq \hat{\xi}^{\eta}\widehat{PD}. \tag{14}$$

The left hand side of this expression captures the *supply side* of the model – the supply constraints as well as the productivity shock. The exponent on the supply shocks is $\beta + \gamma < 1$ because adjustment in one variable input forces also an adjustment in the other one, with a total exponent $\beta + \gamma$. The right hand side captures the *demand side* of the model, i.e. the change in demand coming from sectoral or aggregate demand shifts. The inequality tells us for which firms the demand or supply side is the binding factor—demand constrains output and input use if the demand terms are lower than the supply terms, while supply constraints bind in the opposite case. Since all the variables in this expression are defined at the sectoral level, the threshold for binding supply vs. demand factors is also defined at the sectoral level.

Variable profits for unconstrained firms can be expressed as:

$$\pi' \equiv pd' - wn' - p_m m' = pd\left(\tilde{\xi}^{\eta}\widehat{PD} - (s_n + s_m)\hat{x}^c\right), \tag{15}$$

where $s_n = wn/py$ and $s_m = p_m m/py$ denote respectively the firm's wage and material bill in the period prior to the shock.[12]

2.3.2 When Labor Input is Constrained

Labor is constrained when $\omega = 1$ and $\hat{x} \equiv \hat{x}_n < \hat{x}^c$. Following similar steps, we obtain:

$$\hat{n} = \hat{x} \quad ; \quad \hat{m} = \left(\tilde{\xi}^{\eta}\widehat{PD}\right)^{1/\gamma} (\hat{A}\hat{x})^{-\beta/\gamma} = \hat{x}^{-\beta/\gamma} \hat{x}^{c(\beta+\gamma)/\gamma} > \hat{x}. \tag{16}$$

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[12]If the firm is behaving competitively and optimizing over its level of output prior to the shocks, $s_n = \beta$ and $s_m = \gamma$, but we don't need to impose these conditions. The firm may have market power or be demand determined prior. Our framework only imposes cost-minimization during the target period (e.g. period experiencing shocks).

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

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

$$\pi' = pd \left(\tilde{\xi}^\eta \widehat{PD} - \hat{x}^c \left(s_n \left(\frac{\hat{x}}{\hat{x}^c} \right) + s_m \left(\frac{\hat{x}}{\hat{x}^c} \right)^{-\beta/\gamma} \right) \right). \tag{17}$$

Comparing this expression to Eq. (15) when labor is unconstrained, we observe that the lower use of labor tends to increase variable profits (the term $s_n \hat{x}_n / \hat{x}^c$ decreases since $\hat{x}_n < \hat{x}^c$), while the extra reliance on materials tends to lower profits (the term $s_m (\hat{x}_n / \hat{x}^c)^{-\beta/\gamma}$ 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).

2.3.3 When Materials Input is Constrained

The case of constrained materials is entirely symmetric and described here for completeness. This case arises when $\omega = 0$ and $\hat{x} \equiv \hat{x}_m < \hat{x}^c$. In that case:

$$\hat{m} = \hat{x} \quad ; \quad \hat{n} = \left(\tilde{\xi}^\eta \widehat{PD} \right)^{1/\beta} (\hat{A}\hat{x})^{-\gamma/\beta} = \hat{x}^{-\gamma/\beta} \hat{x}^{c(\beta+\gamma)/\beta} > \hat{x}, \tag{18}$$

while variable profits are given by:

$$\pi' = pd \left(\tilde{\xi}^\eta \widehat{PD} - \hat{x}^c \left(s_n \left(\frac{\hat{x}}{\hat{x}^c} \right)^{-\gamma/\beta} + s_m \left(\frac{\hat{x}}{\hat{x}^c} \right) \right) \right). \tag{19}$$

2.4 Business Failures and Mothballing

To evaluate business failure, we assume that firms follow a simple decision rule—they remain in business as long as their initial cash balances and cumulated operating cash flow over a given horizon are sufficient to cover their financial expenses. Otherwise, they are forced to close. If the horizon were a week, this would mean that firms are forced to close as soon as they are unable to cover current financial expenses. This would impose an excessively strict and unrealistic failure constraint on businesses, preventing them from common strategies such as delaying the payment of receivables, running down input inventories or accessing very short term debt or credit lines to limit temporary cash deficits leading to failure. In our baseline implementation, we consider instead an annual horizon. This captures the availability of these

options for SMEs without needing to explicitly model them, while also capturing that they cannot be utilized indefinitely.

Further, if production costs are excessive, we allow firms to prevent these falls in their cash flows by shutting down temporarily, i.e. mothballing their operations (see Bresnahan and Raff (1991)). In that case, $y_{is} = n_{is} = m_{is} = \pi_{is} = 0$. While the firm still has to cover its fixed costs and financial expenses, this option is particularly relevant for firms that face severe supply constraints – either on labor or materials – that would force them to substitute – at excessively high cost – with the other available inputs. Direct inspection of the variable profits for constrained firms, Eqs. (17) and (19) reveal that mothballing is more likely when labor supply is constrained and firms have a low materials output elasticity γ, or conversely when material supply is constrained and firms have a low labor output elasticity β.

Weekly operating cash flow of the firm is defined as:

$$CF_{is} \equiv p_{is}d_{is} - wn_{is} - p_{ms}m_{is} - F_{is} - T_{is} = \pi_{is} - F_{is} - T_{is} \tag{20}$$

where the first term represents revenues, 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 π_{is}, minus payments to fixed factors and taxes. As long as fixed costs and taxes are unchanged, 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.[13]

The predicted cash flow CF'_{is} is then obtained by substituting our constructed measure of variable profits π'_{is} using Eqs. (15), (17) and (19) depending on whether the firm is unconstrained, labor constrained, or material constrained.

Formally, denote initial cash balances $\mathcal{Z}_{is,0}$ in week 0, weekly operating cash flow $CF'_{is,t}$ in week t, and annual financial expenses defined as interest payments due on the firms' debt, ιL_{is}, then a firm fails when :

$$\mathcal{Z}_{is,0} + \sum_t CF'_{is,t} - \iota L_{is} < 0, \tag{21}$$

where the summation takes place over the calendar year.

The business failure condition Eq. (21) calls for a number of observations. First, while this rule has the advantage of simplicity it assumes that firms with a cash flow shortfall at the end

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[13]Many business taxes are paid in the following calendar year. Therefore, from a liquidity perspective the taxes a business needs to pay in year t are likely determined in year $t-1$ and will not change if an unexpected shock occurs in year t.

of a calendar year cannot access credit markets to borrow new funds.[14] This is not unrealistic for SMEs as shown in Caglio, Darst and Kalemli-Ozcan (2021).

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. In the U.S. for example, there is automatic stay and lenders lend based on future cash flow during the restructuring process. However, this is mostly for the larger corporations – for instance, over the years, many airlines 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 large downturn 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 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 equity shortfalls is a difficult exercise. Finally, policymakers often do not have direct information on firms' continued access to credit – particularly in a typical or severe downturns. For instance, during COVID-19, mounting evidence suggests that only very large firms responded to the early phase of the crisis by borrowing (Acharya and Steffen, 2020), (Chodorow-Reich, Darmouni, Luck and Plosser, forthcoming), 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 et al., 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 input shocks ($\{\hat{x}_{ns}, \hat{x}_{ms}, \omega_s\}$) and productivity ($\hat{A}_s$) shocks. Together with firm level factor shares ($s_{n,is}, s_{m,is}$) and sales ($p_{is}d_{is}$), we construct a counterfactual change in cash flows. With data on the firm's cash balances ($\mathcal{Z}_{is}$), financial expenses (ιL_{is}) and cash flow (CF_{is}), we then evaluate Eq. (21) to determine which businesses fail.

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[14]Note however, that this criterion also assumes that existing debt levels can be maintained. This assumes that firms may rollover their *existing* principal payments due in the calendar year, but are constrained when it comes to obtaining *additional* funds beyond covering *within-year* cash shortfalls.

3.1 Firm Level Data

To operationalize our framework, 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 eleven countries. The countries included are Czech Republic, Finland, France, Hungary, Italy, Poland, Portugal, Romania, Slovak Republic, Slovenia, and Spain. 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. For this sample of countries, our *analysis* sample exceeds 30 percent.[15]

We use data on firm revenue, wage bill, material cost, number of employees, net income, depreciation, cash stock and financial expenses.[16] Cash flow is calculated as the sum of net income and depreciation, less financial profits. The analysis focuses on non-financial SMEs.[17]

An important feature of most economies is the over-sized role SMEs – defined as firms with less than 250 employees – play in the economy. In the Orbis data SMEs account for 62.68 percent of employment and 61.31 percent of payroll, 65.50 percent of revenue, and 65.48 percent of total assets across our sample of countries.[18] It is precisely these SMEs that are most vulnerable to economic shocks 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 failure that can follow the liquidity shortage.

We also use Orbis data to estimate labor and material elasticities (β_s and γ_s) at the 2-digit

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[15] Although *raw* data coverage for these countries exceeds 50 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.

[16] We winsorize all of the level variables used for analysis at the 99.9th percentile.

[17] 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.

[18] The SME shares are calculated using Orbis data. Aggregation is done over our sample of countries: Czech Republic, Finland, France, 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. 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 et al. (2019). The shares are based on the cleaned Orbis data used in the analysis.

NACE level for each country. 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.[19] Due to the lack of price data, the elasticities we estimate are revenue, rather than output, elasticities.

3.2 Framework Validation

In this section we use Orbis data to show that our framework replicates both country and sectoral patterns of official Eurostat failure rates. We use Orbis firm level data in 2017 and construct shocks from Eurostat data. We then estimate firm cash flow week-by-week and evaluate our liquidity criterion at the end of the year. We compare these estimated failure rates to the corresponding Eurostat failure rates in the most recent year available (2018).

We make modeling assumptions that are consistent with market conditions in a typical year, and measure shocks as changes in aggregate and sectoral conditions between 2017 and 2018. We assume that firms rollover existing debt, and only make interest payments on that debt. We also assume that during periods when production costs are high, firms can mothball temporarily. We evaluate the liquidity condition at the end of the year to capture additional (non-modelled) tools available for SMEs to smooth their cashflow over the year. Because we we do not expect any supply bottlenecks or constraints in a typical year, we assume the input constraints are inactive ($\hat{x}_{ns} = \hat{x}_{ms} = \infty$). We measure the productivity shock ($\hat{A}_s$) as the growth in output per worker (2017 to 2018) for each country at the 1-digit NACE level. The aggregate demand shock ($\widehat{PD}$) is the cumulative quarterly change in real GDP over 2018. We measure the sector-specific demand shocks by sector revenue growth for each county at the 1-digit NACE level.[20]

Table Table 1 shows that our validation exercise matches the official failure rate data well. Column (1) shows the official failure rate data from Eurostat, column (2) shows the estimated failure rate from our validation exercise, and column (3) shows the difference. On average, over our set of countries, the bias is only 0.7 percentage points and the mean absolute error is only 1.45 percentage points. Moreover, Fig. 1 compares official failure rates by 1-digit sector to our estimated failure rates. We are able to match fairly well which sectors have high failure rates and which sectors have low failure rates.

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[19]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).

[20]Using our equation for ($\tilde{\xi}_{\varsigma s}^{\eta}$), we normalize the average revenue growth in each country to have $\tilde{\xi}_{\varsigma s}^{\eta} = 1$.

Our validation exercise shows that our framework is a reasonable approximation of reality—despite the shocks being defined at the one-digit level and, except for the aggregate demand shock, not varying within the year. It further reinforces liquidity conditions as an important cause of SME failures (given that the bulk of firms that fail are SMEs).

Table 1: Eurostat versus Estimated Failure Rates (2018)

	(1)	(2)	(3)
	Eurostat Failure Rate	Estimated Failure Rate	Δ (Estimated - Eurostat)
Czech Republic	7.96	6.82	-1.14
Finland	10.26	8.30	-1.96
France	9.60	8.90	-0.70
Hungary	11.26	9.58	-1.68
Italy	7.48	9.88	2.39
Poland	12.75	12.67	-0.09
Portugal	8.11	12.44	4.33
Romania	8.16	15.46	7.30
Slovak Republic	9.35	9.99	0.64
Slovenia	8.05	8.26	0.21
Spain	8.34	8.97	0.63
Weighted Average	8.96	9.66	0.70
Weighted Absolute Average	8.96	9.66	1.45

Notes: Eurostat failure rates are obtained from the Structural Business Statistics data for employer businesses at the 1-digit NACE level. Simulated failure rates are obtained by using Orbis balance sheet data, Eurostat national accounts data at the 1-digit NACE level to calculate sectoral demand and labor productivity shocks, the OECD's quarterly GDP growth data to calculate aggregate demand. The liquidity criteria is evaluated for each firm at the end of the year. Eurostat and simulated failure rates are aggregated to the country level using sectoral gross value added weights, and are aggregated across countries using GDP for weighting. The sample covers countries in our high coverage sample of countries that have reliable failure rate data.

4 COVID-19 Application

To demonstrate how our framework is a useful tool for real-time analysis of economic downturns, we apply it to the COVID-19 crisis. First, we discuss the calibration of sectoral and aggregate shocks. Second, we evaluate how vulnerable economies were to the COVID-19 shock in the absence of government support policies. We then shed light on several important concerns facing policymakers during the crisis: the risk to the financial sector from SME failures; and the cost and impact of alternative fiscal policy proposals. Finally, we assess how our conclusions are impacted by more recent data.

4.1 Shocks

In order to highlight how our framework can be deployed in real-time, we calibrate our shocks using information available at the early stages of the COVID-19 crisis – May 2020. As a first step, we separate sectors, at the 4-digit NACE level, into essential and non-essential based on

Figure 1: Eurostat versus Simulated Failure Rates (cross-country weighted average, 2018)
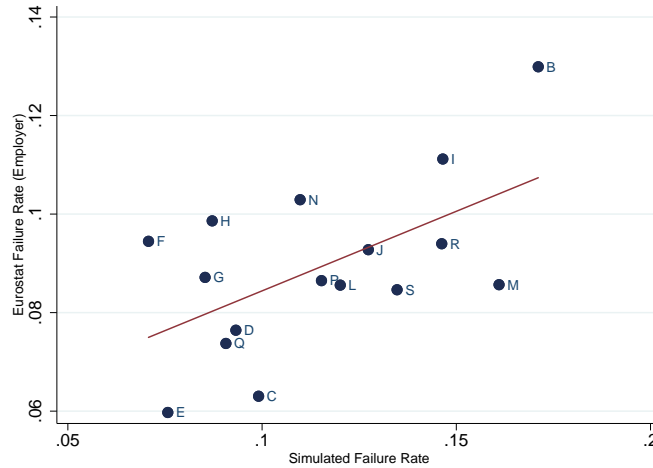
Notes: Eurostat failure rates are obtained from the Structural Business Statistics data for employer businesses at the 1-digit NACE level. Simulated failure rates are obtained by using Orbis balance sheet data, Eurostat national accounts data at the 1-digit NACE level to calculate sectoral demand and labor productivity shocks, the OECD's quarterly GDP growth data to calculate aggregate demand. The liquidity criteria is evaluated for each firm at the end of the year. Sectoral Eurostat and simulated failure rates are aggregated across countries using GDP for weighting. The sample covers countries in our high coverage sample of countries that have reliable failure rate data.

the U.S. Department of Homeland Security Guidance on the Essential Critical Infrastructure Workforce.[21] 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.

Sector-Specific Input Shock: in the context of COVID-19, an important constraint facing firms was that workplace restrictions limited the number of workers that could be used on site. We therefore focus on a labor supply constraint where in Eq. (12) we set $\omega_s = 1$ and $\hat{x}_s \equiv \hat{x}_{ns}$:

$$n'_{is} - \hat{x}_s n_{is} \leq 0$$

To measure this sectoral labor constraint, $\hat{x}_s$, 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, 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. The left panel of Fig. 2 illustrates the severity of the labor supply shock at the 1-digit NACE level.[22] The figure depicts 1-digit sectors composed mainly of non-essential 4-digit industries in blue and those composed mainly of essential 4-digit industries in orange. 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.

Sector-Specific Demand Shock: We follow a similar approach in constructing sector-specific demand shocks. Using the same O*NET surveys, we 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, caring for others, working with the public, and selling to others are deemed important. Using the BLS data and NAICS-NACE crosswalks, we aggregate these occupation-level data to arrive at an estimate of the fraction of employees reliant on face-to-face interactions at the 4-digit NACE level.

We assume that under COVID-19 the sector-specific 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 $\hat{\xi}_s^{\eta}$.[23] We then normalize the sectoral demand shocks to be consistent with aggregate demand Eq. (8) by constructing $\tilde{\xi}_s^{\eta} = \hat{\xi}_s^{\eta} / (\sum_\sigma \hat{\xi}_\sigma^{\eta} / \mathcal{S})$. The right panel of Fig. 2 illustrates the size of the sector-specific demand shock ($\tilde{\xi}_s^{\eta}$) at the 1-digit NACE level. The figure illustrates that COVID-19 reallocates aggregate expenditure from highly affected non-essential sectors such as Arts, Entertainment, & Recreation to non-affected essential sectors including Water & Waste.[24]

Aggregate Demand Shock: In addition to sector-specific demand shocks, we also measure changes in aggregate demand ($\widehat{PD}$) using projections of quarterly changes in GDP from the International Monetary Fund (IMF).[25] What matters for the estimation of failure rates is the

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[22]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.

[23]Note that because we directly assess the change in sectoral demand according to Eq. (8), and not the underlying shock to preferences $\hat{\xi}_s$, we do not need to make an assumption about the elasticity of substitution η. This is already encoded in our measure of $\hat{\xi}_s^{\eta}$.

[24]Within each country $\sum_s \tilde{\xi}_s^{\eta} / \mathcal{S} = 1$ holds. However, Fig. 2 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.

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

Figure 2: Shocks by Sector

(a) Supply Shock
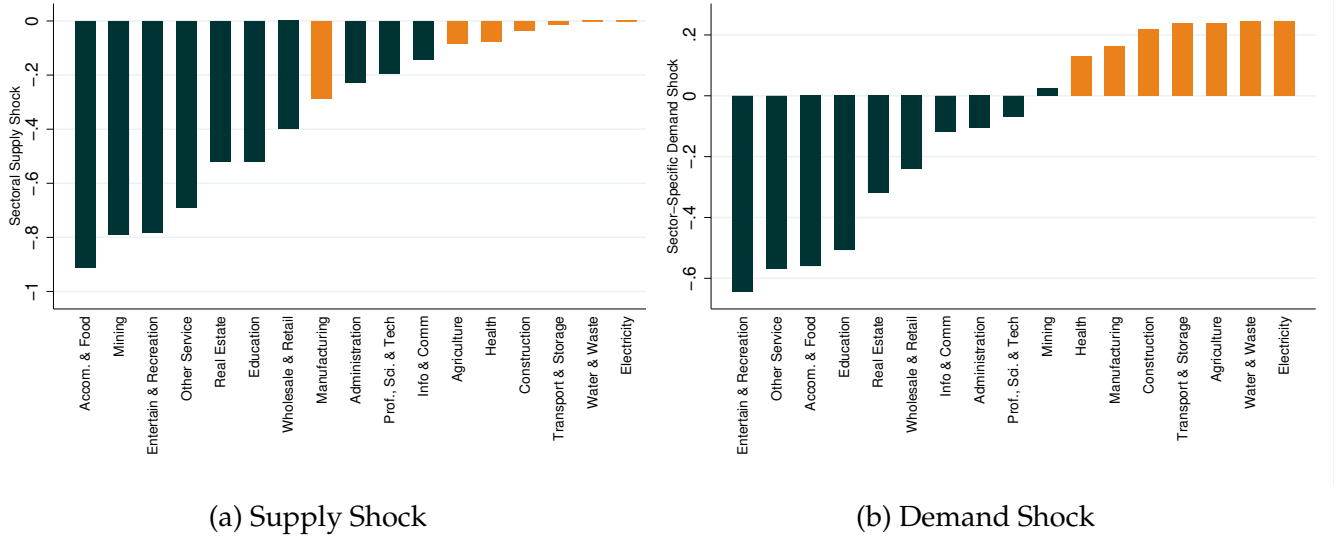
(b) Demand Shock

Notes: Depicts the COVID-19 labor supply shock (L) and demand shock (R) by 1-digit NACE sector, as the percent change relative to the non-COVID scenario. 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. Sectors composed mainly of non-essential industries are depicted in blue and those composed mainly of essential industries are depicted in orange

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.

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:

$$A_s = A_s^{work}\omega_s + A_s^{home}(1 - \omega_s) \qquad \text{Before COVID,} \qquad (22)$$
$$A_s' = A_s^{work'}\omega_s' + A_s^{home'}(1 - \omega_s') \qquad \text{COVID-19,}$$

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:

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

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

$$\hat{A}_s = \frac{\frac{A_s^{home}}{A_s^{work}}}{\omega_s + \frac{A_s^{home}}{A_s^{work}}(1 - \omega_s)}. \tag{24}$$

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, which would occur in a sector with no remote work before COVID-19 and 100 percent remote work during COVID-19.

4.2 Evaluating Vulnerability to COVID-19

Our initial analysis sheds light on how severe the COVID-19 crisis could have been had governments failed to intervene. Through this exercise, we explore sources of firm-level, sectoral, and country vulnerabilities to the shock. In doing so, we shed light on an early concern of policymakers—that COVID-related lockdowns would force many otherwise healthy SMEs into failure.[26] We find that, on average, the rise in failure rates is moderate. However, the aggregate failure rate mask substantial heterogeneity. Some country-sectors experienced pronounced increases in failure rates, while others experienced more manageable increases. We show how these differences in failure rates stem from differences in exposure to shocks and financial health of firms at the onset of the crisis.

4.2.1 Baseline Aggregate SME Failure Rates

To arrive at an estimate of the aggregate SME failure rate, we need to first define a baseline COVID-19 scenario. To mimic how the framework might have been deployed in real-time, we define our baseline scenario based on the information available during the initial stages of the crisis. In the model, we assume that pre-COVID and during COVID-19 there are no disruptions to the credit market, that firms have until the end of the year to recover from any negative cash balances, and that firms can temporarily shut down operations via mothballing. In calibrating shocks, we assume that the crisis begin 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 ($\hat{d}_s = \tilde{\varsigma}_s^\eta \widehat{PD}$), and 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

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[26]Bartik, Bertrand, Cullen, Glaeser, Luca and Stanton (2020) conducted a survey of U.S. firms at the onset of COVID-19 and found that 28% of firms worried they would fail after a 1 month lockdown and that the median firm had only enough cash on hand for 2 weeks of expenses.

projections, and the sector-specific demand shocks ($\tilde{\varsigma}_s^\eta$) 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 subdued demand even after stay-at-home orders were lifted.

Table 2: Aggregate SME Failure Rate

	(1) Non-COVID	(2) COVID	(3) Δ
Average	9.61	15.77	6.15

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. Failure rates are aggregated across countries using GDP as weights.

In Table 2, we show the estimates of average increase in SME failure rates due to the COVID-19 shock. Column (1) reports our estimate of the 2020 failure rate in the absence of COVID-19 (our "Non-COVID" scenario) and serves as a useful benchmark. The non-COVID failure rate is calculated using the same approach as the validation exercise. We estimate firm liquidity at the end of 2020 with 2018 firm level data (the most recent year this data was available at the onset of COVID) and shocks that are calibrated using realized quarterly GDP growth (aggregate demand), growth in sector-specific revenue (sector-specific demand), and growth in labor productivity between 2018 and 2019. In constructing this estimate we assume that the distribution of firm variables in 2018 and 2019 are similar and that our shocks approximate what would have occurred in 2020 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. The COVID-19 crisis results in a 6.15 percentage point increase in SME failure rates relative to non-COVID, putting 3.15 percent of private sector jobs at risk (see Table 8).

Table 3: Failure Rates (COVID - non-COVID) under Extensions

	(1) Baseline	(2) Annual + No Mothballing	(3) Weekly + Mothball	(4) Weekly + No Mothball
Average	6.15	7.10	8.21	9.38

Notes: Reports the change in failure rates (COVID - non-COVID) under – (1) baseline scenario: annual liquidity criteria evaluation and firms are allowed to temporarily shut down (mothball); (2) annual liquidity criteria, but firms not allowed to mothball; (3); weekly evaluation of the liquidity criteria and firms are allowed to mothball; (4) liquidity criteria evaluated weekly and no mothballing. 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. Failure rates are aggregated across countries using GDP as weights.

Next, table Table 3 shows how different modeling assumptions about production and funding affect our baseline results. Column (1) repeats our baseline failure rate and Columns (2) through (4) show how removing the ability to mothball or to take a year to correct cash deficits

affects failure rates. First, in column (2) we no longer allow firms to mothball—instead they must stay open and meet demand regardless of the cost. Many firms may have faced this constraint, having signed contracts prior to the pandemic that committed them to deliver output by a certain date. In this case, failure rates increase by almost one percentage point above our baseline. Column (3) shows failure rates in when firms must have enough cash on hand to meet expenses in every week. This scenario raises failure rates by two percentage points above the baseline. Finally, Column (4) shows the effects of *both* not allowing firms to shut down and requiring them to be liquid in every week of 2020. The results suggest that even under stringent production and funding assumption, failure rate would rise by around 9.38 percentage points—nearly double the non-COVID scenario and 3.2 percentage points above our baseline estimates.

4.2.2 Heterogeneity and Exploring Sources of Vulnerability

A massive amount of heterogeneity underlies our average estimate of a 6.15 percentage point increase in SME failure rates—the excess failures were much higher in some country-sectors and much lower in others. Our framework estimates failure rates at the firm level. Consequently, we can study how individual firms with different initial financial conditions respond to shocks, such as COVID-19. This allows us to evaluate, at a granular level, sources of heterogeneity in sector and country outcomes during economic downturns.

Sectoral Exposure to Shocks: Table 4 confirms that there is considerable variation across sectors underlying our baseline 6.15 percentage point aggregate excess failure rate. 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 10 percentage points. 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.[27] Finally, sectors with fewer essential workers, but relatively low total demand shocks and/or high scope for remote work (Professional, Scenitific & Technical Services) are moderately affected, experiencing a rise in failure rates between 5 and 10 percentage points.

To better understand which shocks drive the observed cross-sector variation, Table 5 evaluates 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

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[27]Note that in some essential sectors total demand (sectoral and aggregate) can *rise* in COVID-19 and this can lead to lower failure rates than in a normal year —see Electric, Gas, & Air Conditioning or Water & Waste.

Table 4: Sector SME Failure Rates

	(1) Non-COVID	(2) COVID	(3) Δ
Agriculture	8.89	9.83	0.94
Mining	11.10	15.70	4.60
Manufacturing	8.72	10.63	1.91
Electric, Gas & Air Con	10.20	9.68	-0.52
Water & Waste	8.23	7.90	-0.33
Construction	7.29	7.81	0.52
Wholesale & Retail	8.89	17.81	8.92
Transport & Storage	8.70	10.71	2.01
Accom. & Food Service	12.88	26.26	13.37
Info. & Comms	9.86	14.12	4.26
Real Estate	11.35	17.54	6.19
Prof., Sci., & Technical	10.34	17.42	7.08
Administration	8.02	19.24	11.22
Education	11.03	30.61	19.58
Health & Social Work	8.40	10.96	2.56
Arts, Ent., & Recreation	12.39	31.55	19.16
Other Services	13.85	28.59	14.74

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. 1-digit sectors where the majority of 4-digit sectors are classified as essential are highlighted in grey.

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) implies that all sectors face identical shocks. Yet, Column (1) shows that excess failure rates range from 0.11 percentage points in Accommodation & Food Services to 7.59 percentage points in Transportation & Storage. This heterogeneity stems from differences in firm financial health across sectors. By this metric, Transport & Storage was ex-ante one of the most vulnerable sectors. 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 Arts, Entertainment & Recreation among the least vulnerable. Yet, because sector specific demand falls most in customer-oriented service sectors, like Art, Entertainment & Recreation, and increases in essential sectors, like Transport & Storage, SME failure rates in column (2) rise in Arts, Entertainment, & Recreation 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 Accommodation & Food Service. 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.[28] Meanwhile, labor-intensive sectors with higher scope for remote work, such as Other Services, experience a smaller rise in failure rates. Sectors composed of essential sub-sectors, 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 sector-specific demand shocks to aggregate demand and sectoral labor supply shocks (col. 4) is informative about which shock—labor supply or sector-specific demand—is more binding for sectors. In some sectors, like Accommodation and Food Service, the addition of the sector-specific demand shock does not raise failure rates much above those in in column 3, pointing to the importance of sectoral labor supply shocks. In contrast, the sector-specific demand shock appears more important than the sectoral labor supply shock in a sector like Arts, Entertainment, & Recreation. Comparing columns (4) to (5) shows the effects of the productivity shock on sectoral failure rates, which in this case is modest.

Overall, Table 5 shows a useful decomposition that can provide insights into how pre-existing firm financial health interacts with each shock and how these combine to explain the heterogeneity in cross-sector outcomes.

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

	(1) $\widehat{PC}$	(2) $(\widehat{PC}\tilde{\varsigma}_s)$	(3) $\widehat{PC}+\hat{x}_s$	(4) $(\widehat{PC}\tilde{\varsigma}_s),\hat{x}_s$	(5) Baseline
Agriculture	0.70	0.36	1.21	0.94	0.94
Mining	0.24	1.02	4.76	5.15	4.60
Manufacturing	1.17	0.74	2.22	1.90	1.91
Electric, Gas & Air Con	0.79	-0.68	0.79	-0.68	-0.52
Water & Waste	3.55	0.39	3.55	0.39	-0.33
Construction	2.00	0.13	2.03	0.12	0.52
Wholesale & Retail	2.41	8.82	3.04	8.63	8.92
Transport & Storage	7.59	1.60	7.60	1.61	2.01
Accom. & Food Service	0.11	7.89	10.33	11.85	13.37
Info. & Comms	2.29	3.69	2.39	3.69	4.26
Real Estate	1.80	6.20	1.16	6.18	6.19
Prof., Sci., & Technical	3.73	7.09	3.48	7.00	7.08
Administration	4.54	9.77	4.71	9.77	11.22
Education	2.54	19.22	12.80	19.22	19.58
Health & Social Work	2.26	2.49	3.62	2.49	2.56
Arts, Ent., & Recreation	2.22	18.41	11.15	18.65	19.16
Other Services	-0.03	14.43	7.31	14.68	14.74
Average	2.37	5.50	3.91	5.86	6.15

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 last row is the sector GVA weighted average. 1-digit sectors where the majority of 4-digit sectors are classified as essential are highlighted in grey.

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[28]While the worst affected can shutdown during the lockdown, they still face cash flow reductions.

Table 6: Country-Level SME Failure Rates

|	(1) Non-COVID	(2) COVID	(3) Δ
Czech Republic	7.17	9.93	2.75
Finland	9.02	13.41	4.38
France	9.94	15.46	5.51
Hungary	9.44	12.19	2.75
Italy	9.39	19.73	10.35
Poland	11.64	18.06	6.42
Portugal	12.04	16.32	4.28
Romania	13.23	16.00	2.77
Slovak Republic	9.17	12.25	3.08
Slovenia	8.49	12.18	3.69
Spain	8.12	11.77	3.65

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.

Country-Specific Factors: Other than the evolution of $\widehat{PD}$, our baseline scenario features identical shocks for all firms that operate in the same sector, irrespective of country. Nonetheless, as Table 6 documents, there is considerable cross-country heterogeneity in excess SME failure rates (Δ, col. 3), ranging from 2.75 percentage points in the Czech Republic and Hungary to 10.35 percentage points in Italy.

To better understand the sources of heterogeneity, we compare France and Italy in Fig. 3. The figures 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 average firm cash balances (top left), total demand shocks (top right), sectoral supply shocks (bottom left), and fraction of firms that are labor constrained (bottom right). While firms in a given sector face the same sectoral shocks regardless of the country they are in, the country *averages* of these shocks can vary based on differences in the industrial composition.

Under our baseline scenario, Italy's SME failure rate rises by 4.84 percentage points more than France's. Total demand evolves similarly in both countries, as does the sectoral supply shock. However, more Italian firms are in sectors facing both relatively modest demand shocks but stringent workplace restrictions which leads a higher fraction of them to became labor constrained. This meant Italian firms therefore faced higher costs during the lockdown than French firms. However, the largest difference between the two countries is the initial cash position of each country's firms. Italian firms began COVID with much less cash than French firms which meant they were considerably more vulnerable to failure in COVID.
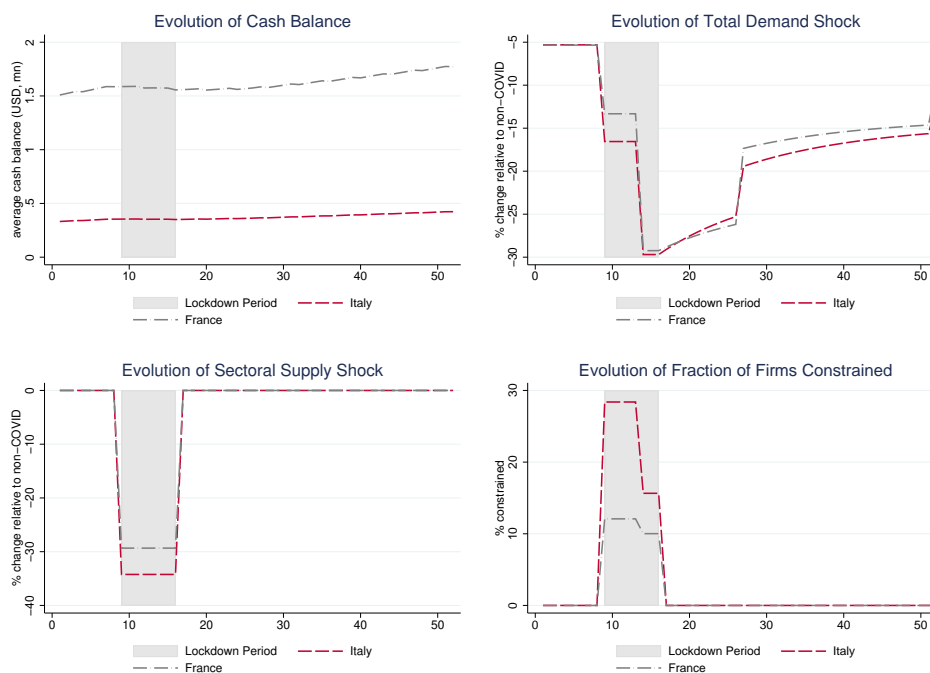
Notes: Figures show the weekly evolution of four key variables: caverage firm cash balance (top left), total demand shock (interaction between sector-specific demand and aggregate demand shock, top right), sectoral supply shock (bottom left), and fraction of firms constrained (bottom right). In each week, country-level variables represent the weighted average of 1-digit NACE variables, where weights are given by 2018 sector gross value added.

4.3 Addressing Macro Issues of Concern to Policymakers

We now shift from exploring how our framework provides insights on sources of vulnerabilities to shocks, to how our framework can inform policymaking. Specifically, we tackle three key areas of concern to policymakers during the early phases of COVID-19. First, would the COVID-induced rise in SME failures and resulting rise in NPLs pose a risk to the financial sector? Second, among a range of policy options, which would be most effective at saving firms and jobs, and at what cost? Third, how well targeted were these policies?

4.3.1 Evaluating Potential Spillovers to the Financial Sector

We investigate whether the non-performing loans (NPLs) that result from the excess SME failures due to COVID-19 pose a risk to the banking system.[29] Table 7 shows the effects of non-performing SME loans on the bank equity ratios by linking the share of non-performing loans in Orbis data with bank level aggregate data. We see that despite COVID-19's large

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

impact on SME failures, the crisis poses only a moderate risk to the banking sector.[30]

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).[31] The table also reports the initial risk-weighted CET1 capital ratio (col 3.) and the change in risk-weighted CET1 capital ratio coming from these COVID-related failures (col. 4).[32] The change in the SME NPL share of total assets averages 0.57 percentage points, and ranges from 0.28pp rise in Spain to a 1.01pp rise in Italy. Meanwhile, the change in SME NPL share of CET1 capital averages 10.04 pp across countries, ranging from a 2.91 pp rise in Slovenia to a 17.43 pp rise in Italy. We also estimate a moderate decline in the risk-weighted CET1 capital ratio (CET1R) of 1.20 percentage points, ranging from 0.40 pp decline in Poland to 2.03 pp in Italy. Given that the initial level of the risk-weighted CET1 capital ratio is on average 13.99 percent, we conclude that the direct impact of SME failures due to COVID-19 on the banking system remains manageable. [33]

4.3.2 Evaluating Fiscal Policy Options

At the onset of COVID policymakers rushed into action with fiscal support programs—all at unprecedented speed and cost. In this subsection, we analyze the effectiveness of a variety of measures that were considered. 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 firms from failure.

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[30]Note that Table 7 reports results for only the 9 countries in our sample for which data were available from both the EBA's 2018 country level bank stress test and the ECB's Consolidated Banking Database.

[31]In Orbis, we define loans as the sum of short-term and long-term loans and non-performing loans are calculated as the total Orbis loans outstanding in firms that fail.

[32]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 assets (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.

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

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

	% Total Assets	% Bank Tier-1 Capital	CET1R	Δ CET1R
Finland	0.32	5.87	17.10	-0.84
France	0.51	10.11	14.37	-1.26
Hungary	0.32	3.12	16.22	-0.43
Italy	1.01	17.43	13.08	-2.03
Poland	0.28	2.80	16.93	-0.40
Portugal	0.60	8.09	12.95	-0.92
Romania	0.31	3.29	16.37	-0.45
Slovenia	0.33	2.91	18.97	-0.45
Spain	0.28	5.24	12.20	-0.56
Average	0.57	10.04	13.99	-1.20

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.

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 SME. 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.[34] 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. While we can do this in our framework, the identity of viable firms and their cash deficits are not observable in practice. Nonetheless, 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.

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[34]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.

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	6.15	3.15	1.24	6.76	0.65
Financial Expenses Waived	1.59	0.66	0.28	6.76	1.25
Tax Waiver	2.28	0.83	0.26	2.74	1.44
Rent Waiver	4.16	2.31	0.87	2.78	3.08
Cash Grant	4.79	2.69	1.00	2.83	2.37
Pandemic Loans	7.95	4.11	1.57	5.23	5.78

Notes: To account for imperfect firm coverage in Orbis we obtain aggregate costs by scaling the total costs in Orbis 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). All data is based on 2018 numbers. The numbers presented here are GDP-weighted averages across countries. 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.

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 0.65 percent of GDP, the benchmark policy saves 1.24 percent of GDP in wages, 6.15 percent of businesses and 3.15 percent of jobs.[35] Moreover, each dollar disbursed by this policy generates 1.91 dollars in direct aggregate demand (1.24/0.65) 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.[36]

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 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 set of policies rebates to firms their financial expenses (row 2 of Table 8), taxes

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[35]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.

[36]Traditional fiscal multipliers could add to that, so that one dollar in fiscal resources used to preserve viable businesses may increase overall output by more (or less) than 0.65 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.

(row 3), or rent (row 4) at the beginning of lockdown through the end of 2020.[37] The financial expenses and tax rebates have in common that they can be implemented at moderate cost, but have modest benefits. For example, under the financial expenses rebate, the failure rate is estimated to fall by 1.59 percentage points at a cost of 1.25 percent of GDP. The fiscal bankruptcy multiplier is low at 0.28/1.25 = 0.22. Meanwhile waving rents is a bit more costly, at 3.08 percent of GDP and saves more firms, 4.16 percent. Yet, the fiscal-bankruptcy multiplier remains low at 0.87/3.08 = 0.28.

The last two policies considered are injections of new funds rather than rebates. The first of these is a cash grant that disburses to firms their average 2018 weekly wage bill during the 8 weeks of lockdown.[38] 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 reduces the rise in the failure rate by nearly one-third (failure rates decline 4.16 percentage points relative to the no-policy benchmark), saves 2.69 percent of jobs and 1.00 percent of GDP in wages, but at an overall fiscal cost of 2.37 percent of GDP.[39] The fiscal-bankruptcy multiplier is 0.42: each dollar of fiscal resources saves 0.42 cents in direct aggregate demand.

The final policy we consider is a program of public loan guarantees for SMEs (e.g. pandemic loans) broadly similar to those implemented by several Euro-area countries.[40] Because 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.[41]

This policy turns out to be the most generous, providing 5.78 percent of GDP in funding

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[37]Note that the financial expenses rebate is an extreme version of policies that guarantee existing firm loans or refinance them at lower interest rates. Note also that Orbis 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.

[38]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).

[39]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.

[40]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 neither pay interest nor repay any principal in 2020.See ECB Economic Bulletin 6/2020 Focus for details.

[41]Our companion paper, Gourinchas, Kalemli-Özcan, Penciakova and Sander (2021) explores the implications of repayment of this program on firm failures in 2021.

for SMEs.[42] It has a dramatic impact on failure rates, bringing them *below* their pre-COVID levels (excess failure rates become 6.15-7.95=-1.8 pp) and saving 4.11 percent of jobs.[43] At first glance, the fiscal bankruptcy multiplier in terms of wages saved relative to funds disbursed appears low at 1.57/5.78=0.27. 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

Table 9: The distribution of policy support by firm type

	Firms that Survive COVID (Strong Firms)	Firms Bankrupt Regardless of COVID (Weak Firms)		Firms Bankrupt Only in COVID Scenario (Viable Firms)		Total
	(1)	(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	8.47	0.00	0.00	0.65	0.65
Cash Grant	2.02	6.48	0.18	4.50	0.17	2.37
Pandemic Loans	4.92	4.90	0.41	2.92	0.46	5.78

Notes: As firm coverage in Orbis is imperfect we obtain aggregate costs by scale the total costs in Orbis by the inverse of the coverage ratio of Orbis (based on 1-digit data on value added). The numbers presented here are GDP-weighted averages. * 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.

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	3.15	1.25	6.76	0.65
Cash Grant	1.12	0.42	1.03	0.18	1.58	0.58	1.79	0.17
Pandemic Loans	1.84	0.72	2.10	0.41	2.28	0.86	3.13	0.46

Notes: As firm coverage in Orbis is imperfect we obtain aggregate costs by scale the total costs in Orbis 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. * 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.

4.3.3 Evaluating which Firms Get Saved

After implementing fiscal policies, policymakers wanted to understand whether the support was reaching the right firms, with a major concern being the potential creation of zombie firms. Our analysis shows that policies that are as effective as the benchmark disburse considerably

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[42]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.

[43]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.

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 and without COVID; and 'viable firms' that survive without COVID but would fail under COVID without support.[44] 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.[45] For instance under our benchmark policy, all weak firms still fail because they do not receive any support, while the failure rate of viable firms falls to 0.[46] 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 would merely delays their exit). By contrast, the cash grants and pandemic loan disbursements prove to be poorly directed. Under each policy 25-50 percent of all viable firms are saved, at a cost of 0.17-0.46 percent of GDP. The policies also devotes a small amount of resources (0.18-0.41 percent of GDP) to inefficiently saving 20-45 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 because 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 42 percent of the jobs saved (1.12/2.69) and wages saved (0.42/1.00), and 36 percent of loans saved (1.03/2.83) from the cash grants can be attributed to retaining workers at 'weak firms'. The same figures for the pandemic loans are 45, 46, and 40 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 over 2 percent of GDP to these firms. While the pandemic loan is even less efficient in terms of disbursements, providing funds equal to 4.92 percent of GDP to survivor firms, one potential advantage is that these funds may be recovered in the future. If the 4.92 percent of GDP distributed to strong firms were to be fully recovered by repayments, the overall cost of the policy would fall to 0.86 percent of

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[44]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 low value-added firms are survive due to policy.

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

[46]Weak firms comprise 8.47 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 1.14 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.

GDP and the fiscal bankruptcy multiplier would rise to 1.57/0.86= 1.82—an effective policy.

The issues investigated in this section highlight how our framework can be used to provide nuanced insights to policymakers. While some were concerned about the possibility that SME NPLs would stress the financial system or that fiscal support would create large numbers of zombie firms, our framework underscores a different key challenge. During a crisis in which policymakers lack full information and are pressed to respond quickly, untargeted and costly policies were implemented. Importantly, we find that such policies did save many viable firms, and that most of the support went to strong, rather than weak firms. These findings suggest policy design is critical. Policymakers have several options that may help reduce their overall fiscal burden. In the case of pandemic loans, the fiscal burden is lessened because strong firms are likely to repay. However, because the loans require repayment from all firms (not merely strong ones) there is a risk, even after the COVID shock subsides, that viable firms may not be able to make repayments. Instead, policymakers could couple immediate support with a mechanism by which fiscal authorities recoup some of the relief in future years from the best performing survivors — for example., via an excess profit tax (see Blanchard et al. (2020), Drechsel and Kalemli-Özcan (2020), and Hanson et al. (forthcoming) for similar recommendations).

5 Evaluating Whether Additional Data Changes the Message

Our baseline calibration relies on information available at the early stages of the crisis. In this section, we evaluate how accurate our real time predication are by comparing our baseline failure rates to estimates derived when using data made available in later phases of the crisis to calibrate shocks, or more recent firm level data from Orbis. Table 11 compares the failure rates for each country where Column (1) represents our baseline and Columns (2)-(6) report failure rates estimated using more recent data that was not available early in the crisis.

During the pandemic two series were produced—the Oxford Government Response Tracker's (OxCGRT) stringency index and Google mobility data—which we can use to generate variable lockdown intensity over 2020 for each country.[47] Rather than have a single 8 week lockdown period, we now allow our supply and demand shocks to vary by country and week-by-week in 2020 based on the evolution of the appropriate country-specific intensity index. Given the OxCGRT index is constructed from data on of government containment measures, we apply this to our labor workplace restrictions shock $\hat{x}_s$ and productivity shock $\hat{A}_s$. The Google mobility data tracks shopping activity which maps nicely to our sectoral demand shocks $\tilde{\varsigma}_s$. We normalize both indexes to varies from 0 to 1 and interact this with our previous sectoral shock

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[47]The lockdown stringency index can be obtained at Oxford Government Response Tracker and the mobility data from Google's COVID-19 Mobility Reports.

Table 11: **Robustness Table**

	Baseline	Variable Lockdown Intensity	OECD GDP growth rates (2020)	Both Columns (2) and (3)	Updated Orbis (2018)	Updated Orbis (2019)
	(1)	(2)	(3)	(4)	(5)	(6)
Czech Republic	2.75	2.04	2.81	1.52	3.24	2.97
Finland	4.38	1.83	4.81	3.30	4.23	4.31
France	5.51	5.01	4.68	5.00	4.28	3.84
Hungary	2.75	1.91	2.75	2.01	2.84	2.33
Italy	10.35	9.94	8.45	8.67	10.19	10.13
Poland	6.42	4.74	6.95	4.40	6.39	6.55
Portugal	4.28	4.56	3.94	5.17	4.16	4.17
Romania	2.77	1.90	2.79	2.09	2.67	2.02
Slovak Republic	3.08	2.15	2.85	1.48	2.98	.
Slovenia	3.69	3.30	3.70	2.73	3.73	3.48
Spain	3.65	4.70	3.27	4.91	3.71	3.55
Average	6.15	5.79	5.36	5.53	5.71	5.53

series to get new shock series that vary by sector, country and week of 2020. Column (2) of Table 11 details the results with this new lockdown data. Average failure rates across all countries fall by only 0.26 percentage points, and for most countries the change in failure rate remain below 1 percentage point.

In Column (3) of 11 we show the effects of updating $\widehat{PD}$ with realized GDP data, instead of IMF forecasts.[48] Column (4) then shows the failure rates from using both the variable lockdown data and up-to-date GDP data. In both cases average failure rates fall to below our baseline by between 0.62 to 0.79 percentage points and for almost all countries, failure rates in our baseline and Column (4) remain quantitatively similar.

Finally, Orbis financial data is subject to reporting lags. Consequently, by late 2021, we could update our firm-level Orbis data in two ways – reevaluate 2018 data with a more complete set of reporting firms; and use available 2019 firm balance sheet data. The results are shown in Columns (5) and (6). In both cases, failure rates remain remarkably similar to our baseline for all countries. We conclude that our real-time results remain qualitatively unchanged as new data becomes available.

6   Conclusion

Tracking business failures and evaluating policy responses in real-time, in the midst of economic downturns is critical for researchers and policymakers. To this end, we develop a framework that combines a tractable, but flexible, model of firm cost minimization with detailed firm level accounting data. Our approach permits an array of aggregate and sectoral,

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[48]This data was made available for our full set of countries by the OECD at the end of 2021.

supply and demand shocks. It allows for a range of assumptions about how firms adapt to these shocks, and relies on data available for firms prior to the onset of crisis. Our methodology enables us to provide nuanced insights on the vulnerability of firms, sectors, and the aggregate economy to different types of shocks, as well as detailed evaluations of the costs and impacts of fiscal interventions across different types of firms.

We apply the framework to the COVID-19 crisis, and estimate an average 6.15 percentage point rise in SME failure rates due to COVID-19. Taking advantage of the detailed firm level data, we document the high degree of cross-sector and cross-country heterogeneity in these SME failures, and highlight the importance of exposure to sectoral shocks and firm financial weakness in explaining this observed heterogeneity. We also tackle some of the key questions that policymakers faced as the COVID-19 crisis evolved, showing that the rise in NPLs from failing SMEs did not pose a significant risk to the financial sector and that despite being costly, large infusions of cash saved many firms without propping up many weak ones. Our COVID-19 application highlights the usefulness of our framework in studying firm failures and policy responses in real time during economic downturns.

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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 2018. 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 39.5 percent in Poland to nearly 60 percent in Finland.[49] Focusing on SMEs, our coverage ranges from 36.0 percent in Poland to 70.1 percent in Italy. Even after imposing additional data requirements for analysis, such as availability of intermediate costs, our data cover at least 30 percent of the aggregate revenue of SMEs in our sample of countries.

Table A.1: Orbis Coverage (2018)

	% of OECD Revenue	
	(1)	(2)
	All Firms	SMEs
Czech Republic	49.6	36.6
Finland	59.5	61.8
France	41.1	40.6
Hungary	46.5	42.7
Italy	58.4	70.1
Poland	39.5	36.0
Portugal	57.9	68.2
Romania	57.1	39.7
Slovak Republic	47.7	66.3
Slovenia	44.7	52.2
Spain	51.3	68.6

Notes: OECD revenue (all firms and SMEs) in 2018 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. Only sectors covered in both the OECD 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. SMEs are defined as firms with less than 250 employees in both OECD and Orbis data.

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[49]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.