BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers
No 1014

A shot in the arm: stimulus packages and firm performance during Covid-19

by Deniz Igan, Ali Mirzaei and Tomoe Moore

Monetary and Economic Department

May 2022

JEL classification: G01, G14, G28, E65

Keywords: Economic stimulus, pandemic-prone, COVID-19, policy effectiveness

BIS Working Papers are written by members of the Monetary and Economic Department of the Bank for International Settlements, and from time to time by other economists, and are published by the Bank. The papers are on subjects of topical interest and are technical in character. The views expressed in them are those of their authors and not necessarily the views of the BIS.

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

A Shot in the Arm: Stimulus Packages and Firm Performance during COVID-19[†]

by

Deniz Igan[a*^], Ali Mirzaei[b] and Tomoe Moore[c]

[a] Monetary and Economic Department, Bank for International Settlements,
Basel, Switzerland, Tel: + 41 612808640, deniz.igan@bis.org
[*] CEPR Centre for Economic Policy Research,
33 Great Sutton Street, London, EC1V 0DX, UK

[b] Finance Department, School of Business Administration,
American University of Sharjah, PO Box 26666,
Sharjah, United Arab Emirates, Tel: + 97 165154645, amirzaei@aus.edu

[c] Department of Economics and Finance, Brunel University London,
Uxbridge, Middlesex, UB8 3PH, UK,
Tel: + 44 1895274000, tomoe.moore@brunel.ac.uk

[†] Awais Khuhro and Manzoor Gill provided valuable research assistance. We are grateful to Jana Bricco, Federico Diez, Christian Ebeke, Pierre Guerin, Kristine Hankins, Sole Martinez Peria, Manasa Patnam, and two anonymous referees for useful comments.

^ The views expressed here are those of the authors and not necessarily the views of the BIS.

A Shot in the Arm: Stimulus Packages and Firm Performance during COVID-19

Abstract

We use firm-level data to provide some early evidence on the effectiveness of COVID-19 economic policy packages. Our empirical strategy relies on the varying degree of vulnerability to the pandemic across industries. We find a robust association of fiscal stimulus with changes in firm performance indicators (as measured by sales-to-assets ratio, profit margin, interest coverage ratio as well as probability of default) in pandemic-prone sectors. We also observe marginal effects of monetary policy on the sales-to-assets ratio and of foreign exchange intervention on the interest coverage ratio in the hardest-hit firms. These results broadly survive a battery of exercises to address endogeneity. Additionally, we show that firms with a better financial position are more likely to take advantage of the stimulus packages to withstand the pandemic shock. Overall, these provide preliminary evidence suggesting that policy interventions have bought time for the hardest-hit industries, by supporting turnover and improving liquidity.

JEL Classification Numbers: G01, G14, G28, E65

Keywords: Economic stimulus, pandemic-prone, COVID-19, policy effectiveness

I. INTRODUCTION

COVID-19 prompted authorization and implementation of large economic policy packages around the world, understandably so since a crisis like no other necessitated a response like no other. These packages involved a combination of fiscal, monetary, financial, and capital-account policies. An important question for academics and policymakers alike is how effective these measures have been, especially by helping those sectors most in need.

In this paper, we use firm-level data to provide some answers to this question. Our empirical strategy relies on the varying degree of vulnerability to the pandemic across industries. Firms operating in sectors that rely more on face-to-face interactions when producing goods or providing services are contact-intensive, and thus have a larger portion of jobs that cannot be done at home. As a result, they are more vulnerable to non-pharmaceutical interventions (such as social distancing or lockdown measures) that aim to stop or slow the spread of virus. With the same token, economic policy support would aim to target these worst-hit industries. Contrary to standard economic crises, stimulating real activity in a crisis like COVID-19 is not only more challenging – given the complex nature of the shock combining supply, demand and uncertainty factors – but could also be undesirable, in particular for the contact-intensive sectors as this would go against the needed public health containment measures. That said, economic policies would try to curb the Keynesian feedback loop triggered by the abrupt and substantial loss of income in firms due to the shock, i.e. to minimize spillovers and dislocation costs associated with business failures as well to ensure that liquidity is sufficient enough to avoid unnecessary bankruptcies. One yardstick of success then is whether policy actions have given more of a lift to these sectors relative to others, especially with respect to supporting firms' liquidity and capital.

To measure how prone different firms are to non-pharmaceutical interventions, we rely on a proxy, namely, "distancing" measures that have been recently developed (Kóren and Petö 2020; Dingel and Neiman 2020; Hensvik et al. 2020) and utilized also by other researchers (e.g., Pagano et al. 2020; Laeven 2020). These measures capture the degree to which jobs require customer contact, teamwork, etc. at the sectoral level, as the share of workers in contact-intensive occupations. We first confirm that firms in sectors with higher distancing indices performed worse than the others in the same country, and especially so when the pandemic hit to their country was more severe (as captured by the stringency of the lockdown measures, which is highly correlated with the reported number of COVID-19 cases and deaths).

We then examine whether performance metrics (efficiency, profitability, liquidity, survival) in firms operating in more pandemic-prone sectors have fared better during the first year of the pandemic (2020), if they are located in countries that deployed more comprehensive economic stimulus packages (covering fiscal, monetary and foreign exchange). In other words, if economic policies during the COVID-19 crisis portray an effective action in response to the pandemic, we would expect this to be reflected in relatively better performance by firms that are more pandemic-prone compared to those that are less so. Our main specification, thus, focuses on the cross-sectional differences in firm performance depending on how sensitive to distancing a sector is, controlling for sector and country fixed effects as well as firm observables such as size, age and cash flow.

We find a robust positive association of fiscal stimulus with efficiency and profitability (proxied by asset turnover, that is, the change in the sales-to-assets ratio and profit margin, respectively) in pandemic-prone sectors: sales and profitability in firms that are more sensitive to distancing have grown faster when the fiscal stimulus is larger. Furthermore, we observe positive effects of fiscal packages on firm liquidity and survival (as measured by interest coverage ratio and probability of default): interest coverage ratio increased while probability of default decreased disproportionately more in pandemic-prone sectors.

Economically, moving from a country at the 10th percentile of the distribution of fiscal stimulus (for example, Sri Lanka) to a country at the 90th percentile (for example, Germany), the change in sales-to-asset ratio of firms in more pandemic-prone sectors is about 2 percent more than their less pandemic-sensitive counterparts from 2019 to 2020. This is consistent with Laeven and Valencia (2013), who report that fiscal policy disproportionately boosted the growth of firms that were more dependent on external financing in the context of the global financial crisis. Aghion et al. (2009) also find that counter-cyclical fiscal policy supported the growth of manufacturing industries across 17 OECD countries over the period 1980–2005.

Additionally, we find that monetary stimulus is marginally associated with an improvement in the sales-to-assets ratio. Prior to the COVID-19 outbreak, monetary policy stance in major economies was already accommodative, raising questions about central banks' ability to confront the next shock (Gagnon and Collins 2019). It appears that further easing has proved to be still effective in improving revenues for firms that were hit hardest by the pandemic. In this respect, the monetary policy transmission mechanism seems to have remained functional during the pandemic, as opposed to the case of the global financial crisis when banks were capital constrained and the lending channel was substantially weakened (Laeven and Valencia 2013).

By contrast, we do not find a robust significant relationship between monetary policy easing and the other firm performance indicators such as liquidity and probability of default. This is in line with the argument that monetary policy may not be particularly well-suited to deal with the implications of COVID-19 because of unsuitability of monetary policy in addressing supply-side shocks and the difficulty to target stimulus to specific sectors that are affected first and foremost by non-pharmaceutical interventions (Chen et al. 2020).

Foreign exchange interventions appear to arrest the decline of interest coverage ratio during the pandemic for the hardest-hit (although this finding is not as robust as those on fiscal and monetary policy measures). One plausible explanation for this finding may be that liquidity in pandemic-prone sectors such as recreation services and tourism is highly responsive to changes in the value of the domestic currency against foreign currencies.

Our findings are robust to a battery of checks, including different strategies to address endogeneity issues and using alternative measures of distancing. We also verify that the results remain broadly the same when we remove certain sectors or industries from the sample. Additional analysis suggests that stimulus packages are generally more effective in larger firms and firms entering the crisis with better liquidity, profitability and capital positions. The latter finding provides some comfort that policy interventions in response to this entirely exogenous shock may not have been distortive.

Our paper is linked to two strands of the literature. Firstly, it relates to those studies investigating the effect of a crisis on corporate performance. Many recent additions to this strand examine the real impact of the 2008–09 global financial crisis (see, among others, Duchin et al. 2010; González 2015; Demirgüç-Kunt et al. 2020), adding to studies that look more broadly at banking crises and sudden stops. Given that the COVID-19 crisis is still unfolding, researchers have so far mostly examined the impact of the pandemic on stock market performance (e.g., Alfaro et al. 2020; Fahlenbrach et al. 2020; Remelli and Wagner 2020). Rather closely related to our analysis, Pagano et al. (2020) find that the impact of COVID-19 on stock performance was more severe for firms that operate in sectors that are more vulnerable to social distancing. Ding et al. (2020) report that the adverse impact of the pandemic on stock returns is more pronounced for those firms that have more anti-takeover devices, lower social and corporate responsibility scores, and that depend more heavily on global supply chains.

Papanikolaou and Schmidt (2020) reveal that expected revenue growth of those sectors in which a higher fraction of the workforce is not able to work remotely declined significantly during the COVID-19 pandemic. Glover et al. (2020) document that the impact of the COVID-19 pandemic is more serious amongst younger generations working in vulnerable sectors. Our analysis adds to these studies by providing early evidence that balance sheet and income indicators also show that the pandemic has taken a heavier toll on firms operating in sectors that are more sensitive to distancing.

Secondly, we contribute to the literature that assesses the effectiveness of government policy measures during a crisis (see, for instance in the context of the global financial crisis, Laeven and Valencia 2013; Norden et al. 2013). By focusing on the differences across sectors, we also build on studies investigating the channel through which the real effect of a crisis materializes. See, for example, Claessens et al. (2012), Chaney et al. (2012), Chodorow-Reich (2014) and Giroud and Mueller (2017) with regard to the global financial crisis, and Laeven (2020) and Leibovici et al. (2020) with regard to COVID-19. Our study differs from these papers since it focuses on the effectiveness of government economic policies during the COVID-19 pandemic, rather than the transmission of the shock itself, by testing whether firms in pandemic-prone sectors performed disproportionately better if they are domiciled in countries with more comprehensive or larger stimulus packages. Closely related to our analysis, Demirgüç-Kunt et al. (2021) examine the impact of policy measures taken in response to the COVID-19 pandemic but only on the performance of the banking sector. They find that, while policy interventions in the form of liquidity support, borrower assistance and monetary easing, in general, mitigate the adverse impact of the crisis, this is not the case for all banks, nor in all circumstances.

The rest of the paper is organized as follows. Section II summarizes the potential channels through which policy stimulus could help firm performance in the hardest-hit sectors. Section III lays out the methodology and the data. Section IV presents the findings. Section V concludes.

II. Potential Transmission Channels

A. Fiscal Stimulus

Fiscal stimulus packages implemented during the pandemic aimed to support businesses and households at a time economic activity was intentionally curtailed to slow the spread of the virus and allay the burden on public health systems. Specific measures included tax cuts, cash handouts and social welfare payments on the demand side and tax relief measures and guarantees for access to credit on the supply side (Padhan and Prabheesh 2021).

There are various ways such measures could help firms. Firstly, corporate tax breaks could lessen the decline of profitability. Tax payment deferral is the common type of measure, in particular, in less developed countries (OECD 2000a). Yet, this has a limited benefit to the pandemic-prone sectors, as they have hardly generated profits and rather suffered from losses during the crisis. In this instance, alternative measures such as loss carry-back tax provisions can be more effective (OECD 2000a; Makin and Layton 2021). This allows firms to claim the losses against taxable profits in previous years, which potentially reduces the losses incurred during the COVID crisis. Such provisions have been introduced in some countries for the 2020 tax year.

Secondly, temporary increases in thresholds for low-value asset write-offs and depreciation allowances could mitigate the decline of investment, since they effectively reduce the tax liability of firms. The benefit should be felt across all sectors. However, if the contact-intensive sectors have to alter their business structure in order to survive the pandemic and if this requires investment, then this support should be more advantageous to these sectors. For instance, restaurants may adapt their services away from in-person dining and towards takeaway and delivery of food, or redesign the layout of the premises to maintain distance among customers. Such changes necessitate new investment and could be supported by investment incentives through temporary changes in the tax code. They would help maintain sales and profitability.

Thirdly, direct government subsidies such as furlough schemes curb the massive employment loss due to lockdowns. Many countries have helped the hardest-hit sectors retain their workers by providing income support to employees whose working hours have been curtailed or who have been temporarily laid off (OECD 2020b). The scheme enables firms to maintain the contract with them and to preserve workers' talent and experience. It also deters the decline of production side of the firms, since firms are able to quickly resume operations when the lockdown is eased.

Fourthly, many heavily affected businesses have been experiencing a sharp decline in liquidity. To deal with the liquidity shortage, the most common instrument among developed countries has been loan guarantee schemes, where the government guarantees all or part of the bank loans granted to eligible businesses (OECD 2020a). Other measures have included interest-free loans and cash grants. These measures are typically able to target or prioritize those businesses adversely affected by the pandemic, alleviating cash flow difficulties, enabling firms pay suppliers or creditors and, hence, avoid default or bankruptcy.

Finally, subsidies to consumers for consumption of certain goods and services could also help the suppliers of such goods and services. This can target the hardest-hit sectors, for example, some governments provided subsidies for eating out or domestic travel.

In general, the delivery speed of stimulus should be a key consideration. For instance, countries may find it timelier to provide loan guarantees, business grants or wage subsidies rather than tax measures. The effect of the latter is only felt at the end of the tax year. In order to achieve prompt delivery, fiscal aid may also be provided broadly across all sectors rather than targeting certain sectors, but then this is subject to taxation of regular profit. This would imply that adversely affected firms are able to keep the full amount of support by documenting the hit to their profits, while the firms whose economic circumstances have been affected the least would return some of the support via the tax system (Mankiw 2020; Marron 2020).

There is, however, potentially an unintended side effect of fiscal stimulus. Higher public debt fueled by the pandemic may harm business and household confidence, creating uncertainty about how public debt would be repaid (OECD 2020a). To the extent that firms perceive higher public debt to imply higher corporate taxes in the future, it would be reflected as a negative repercussion on the firms' performance. Note also that wage subsidy programs implemented in some countries may prove to be an innovative yet extremely costly way of sustaining business activities and employment, accelerating government debt. Besides, this support may simply delay the inevitable re-deployment of labor away from unviable firms and may not bring about a particular benefit to the vulnerable firms.

B. **Other Policy Stimulus**

With other stimulus actions such as monetary policy and foreign exchange intervention, unlike fiscal stimulus, the channels of transmission are not as clear. This is partly because it is difficult to target or prioritize specific sectors or firms that have been bruised by the pandemic. Nevertheless, there is some scope for these measures to alleviate the adverse effect of COVID on these sectors.

During the pandemic period, most economies have experienced exchange rate volatility and often intervened in the foreign exchange market. Vulnerable firms engaged in tourism or international trade may disproportionately benefit from such intervention, mitigating a decline of profits and strengthening ability to meet debt obligations.

Expansionary monetary policy may mitigate the effects of COVID-19 on the hardest-hit sectors if firms in these sectors come under pressure from a tightening of credit conditions. For instance, a fall in interest rates may enable vulnerable sectors to ease liquidity concerns and reduce the probability of default.

III. Methodology and Data

A. Empirical Strategy

Our main empirical strategy is to examine whether firms in industries that are more pandemic-prone (that is, industries in which a significant share of employment is affected by social distancing) perform disproportionately better during the COVID-19 outbreak, if they happen to be located in countries that have larger government stimulus packages. In other words, if policy measures are to help firms during the pandemic, with regard to their real performance, then one would expect them to have a larger effect on sectors that are more vulnerable to social distancing measures. This inference can be empirically tested by estimating an econometric model in which the effect of government policies on firms is allowed to differ depending on how pandemic-prone is the industry to which the firm belongs.[1] Thus, our model specification is given by:

$$\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset . Distancing_j \times Policy_c + \tau . X_{ic,Pre} + \varepsilon_{ic,COVID} \quad (1)$$

where i stands for firm, j for sector, and c for country. This is a cross-sectional regression where $\Delta y_{ic,COVID}$ is the measure of change in performance indicators for firm i in country c between 2020—the latest data available—and 2019—a year prior. Following Claessens et al. (2012), we use the changes in firm-level performance. Given that COVID-19 began to spread in many countries and was declared a pandemic in 2020Q1, the pattern of change in performance indicators is deemed to be due to the pandemic.

We employ four response variables to test the impact of government policy interventions. Specifically, we use, in respective regressions, (i) change in the asset turnover ratio [$\Delta(SaleA)$], as measured by sales to total assets ratio; (ii) change in profit margin

[1] This approach is an augmentation of the literature that examines the relationship between government intervention and firm performance during a (financial) crisis (see, for example, Norden et al. 2013 and Laeven and Valencia 2013).

[$\Delta(ProfM)$], as measured by the net profit to total revenue ratio; (iii) change in the interest coverage ratio [$\Delta(IntrC)$], as measured by earnings before interest and tax divided by interest expenses; and (iv) change in the probability of default [$\Delta(ProbD)$], as measured by the default risk of publicly listed firms by quantitatively analyzing numerous covariates (see Section III.B for the detail of this data).

Following Claessens et al. (2012), we employ the changes in sales to asset ratio and profit margin to investigate the impact of economic stimulus packages on firm efficiency and profitability. In addition, crises have severe effects on firms' financial health in two aspects (Carletti et al. 2020): draining cash generation and liquidity that is necessary for functioning of firms and evaporating capital. Since during the public health crisis firms find it difficult to generate cash and thus could be expected to default on some obligations, we use the interest coverage ratio to determine whether policy measures help a company to pay interest on its outstanding debt. Also, following Ganganis et al. (2020) and Igan et al. (2022), we use an indicator for the probability that a firm will continue operations, which is the probability of default. It captures the likelihood of a default over a particular time horizon, reflecting not only the borrower's characteristics but also the economic environment. Overall, the first three response variables intend, in the main, to gauge whether government policies help firms in maintaining their cash flow and, hence, improving liquidity, and the fourth variable aims to capture the impact on firms' survival.

$Policy_c$ is a vector of variables that represent the economic stimulus package in country c. We employ three policy variables as follows: (i) cumulative fiscal stimulus expressed in percentage of GDP, (ii) cumulative change in the monetary policy rate expressed in basis points, and (iii) interventions in foreign exchange markets (0 for no intervention, 1 for intervention). All policy measures are computed over the period January 31st, 2020 (week 1) to December 4th, 2020 (week 43). We investigate the change in the performance of firms over the period 2019–2020 in response to government polices during the period from January to December 2020. We believe that this period represents the most important initial stage of the spread of the crisis, when countries declared the bulk of their policy packages. This is also the period of the collapse of international trade due to non-pharmaceutical public health interventions such as full (or partial) lockdowns and turmoil in financial markets as expectations were quickly revised to take the impact of the pandemic fallout on the global economy into account.

$Distancing_j$ is industry j's degree of sensitivity to a pandemic, computed as the share of industry employment affected by social distancing at the three-digit NAICS level (created by Kóren and Petö 2020, and also used by Laeven 2020 and Pagano et al. 2020; we describe this proxy further in the following subsection).

$X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. Note that, because of the pure cross-sectional nature of our empirical strategy, we enter all firm-level control variables as pre-determined (as do Laeven and Valencia 2013). We first consider the following five variables: (i) size ($Size$), measured as the natural log of total assets; (ii) age (Age), calculated by subtracting the firm's incorporation year from 2020; (iii) cash holdings ($CashA$), computed as the ratio of cash and cash equivalents to total assets; (iv) investment in R&D (RD_A), measured by R&D investment to total assets ratio; and (v) a dummy for private firms ($Private$). These controls are informed by the literature on the determinants of firm performance. Small firms tend to perform worse than their larger counterparts during a crisis (Gandhi and Lusting 2015). Younger firms face more constraints (Beck et al. 2006; D'Souza et al. 2017). Firms with larger cash holdings tend to be more resilient during a crisis while firms with better growth potential tend to invest more in R&D (Bates et al. 2009). Finally, privately-held firms may be different from their listed counterparts along the dimensions we investigate. For instance, Hall et al. (2014) document that public companies hold less cash given their greater access to capital markets as compared to privately-held firms. In addition to these five variables, we also include lags of the following variables as additional regressors: (vi) $SaleA$, to control for efficiency in generating revenue for a given level of assets; (vii) ROA, to control for pre-crisis differences in levels of profitability; (viii) $IntrC$, to control for ability to cover current interest payments with available earnings; and (ix) $EqitA$, to control for leverage given that more highly leveraged firms may face difficulty raising funds during a crisis (Giroud and Mueller 2019). Overall, all these nine firm-level control variables are rather common in the literature (e.g., Burns et al. 2017; Barbiero et al. 2020; Demirgüç-Kunt et al. 2020).

The main variable of interest is the interaction term $Distancing_j \times Policy_c$. The coefficient $\emptyset$ measures the difference between performance in pandemic-prone sectors in countries with high and low economic stimulus packages. A positive and significant point estimate of $\emptyset$ indicates that the vulnerable industries in countries with higher levels of government economic response do not suffer as much from the pandemic (we expect a negative $\emptyset$ for the probability of default).

ϑ_j refers to a vector of sectoral dummies (at three-digit NAICS level) to control for sector-specific factors that could affect cross-sector performance differentials. ϑ_c are country dummies that account for time-invariant country-specific features that might drive cross-country differences in firm activity, such as the institutional environment. This set of fixed effects absorbs all observable and unobservable time-invariant variations across sectors and countries. Also, they subsume the direct level effects of social distancing and economic policies, namely the $Distancing$ and $Policy$ variables in Eq. (1). By including this set of fixed effects, our identification is obtained by looking at the differential performance of two otherwise identical firms operating in more and less pandemic-prone sectors.

Eq. (1) is estimated with ordinary least squares (OLS). Residuals from OLS estimations may be correlated across countries, resulting in biased standard errors. Thus, following Demirgüç-Kunt et al. (2020), we cluster standard errors at the country level. An advantage of our empirical strategy is that it incorporates information about heterogeneity across countries in initiating and implementing economic stimulus packages.

One concern is that Eq. (1) is subject to the problem of endogeneity. Firstly, any association between government policies and firm performance may be attributable to omitted variables. Or, it could be that the effect of a particular policy is attributed to another because of their simultaneous implementation. Secondly, firm performance during a crisis may affect policy responses to the crisis, indicating the possibility of reverse causality.

Our empirical setup provides some leeway in alleviating these two endogeneity issues. By including all policy measures at once, we reduce the issue of simultaneity while our use of sector and country fixed effects mitigates the issue of omitted variable bias. In addition, we control for other potential channels through which policy measures may affect firm performance so as to gain more confidence that distancing remains a relevant channel for policy measures to influence firm performance. Also noteworthy is that endogeneity may even play against the chances to reject the null hypothesis: countries that are affected more by COVID-19 — that is, where pandemic-prone sectors are large and fare particularly bad — may be more likely to deploy large policy packages, giving rise to a negative correlation (which is the opposite of what we find). Nevertheless, we admit that the issue of endogeneity may continue to exist, hence we address this point by conducting several exercises in Section IV.B.[2]

[2] Arguably, our use of firm-level data, with distancing measured at the sectoral level, also introduces some degree of separation. While it is plausible that policies are more likely to be enacted where pandemic-prone sectors make up a larger portion of the economy, it is unlikely that government policy responds only to the performance of a

B. Data Sources

Applying the empirical strategy laid out in Section III.A requires measures of firm performance, sectoral pandemic sensitivity, and economic policy actions. This subsection describes the process of compiling these data.

Firm Performance

Firm-level data come from the ORBIS database by Bureau Van Dijk, which provides information on balance sheets and income statements for more than 40 million listed and private companies from more than 100 countries worldwide. As one of the most comprehensive databases of firm-level information, it has been increasingly used in academic research (e.g. Frijns et al. 2016; Baumohl et al. 2019; Demirgüç-Kunt et al. 2020; Barbiero et al. 2020; Cathcart et al. 2020).

We obtain data for 2019 and the latest year available, 2020 (at the time of conducting this analysis). This enables us to calculate the change in firm performance during the COVID-19 pandemic. We initially select all firms that belong to the nonfinancial corporate sector, excluding financial firms (identified as firms with NAICS2017 code of 52). We drop firms in sectors with no data on the distancing variable, which are "management of companies and corporations," "public administration," and "unclassified establishments" (NAICS2017 codes of 55, 92 and 99, respectively). Also, countries with no data on policy measures are excluded. In addition, we drop offshore financial centers. Following Demirgüç-Kunt et al. (2020), we further restrict our sample to countries with a minimum of 20 firms (with available information for 2020). Last but not least, we drop the United States since data on U.S. sectors are used to construct the distancing variable to avoid any mechanical endogeneity between this variable and firm performance.[3] Given our interest in evaluating the effectiveness of policy measures in improving firm performance during the COVID-19 crisis, we focus our baseline analysis on firms that are present in both before and during the crisis. We thus clean the dataset further by

particular firm in a pandemic-prone sector. Indeed, the correlation between policies and average distancing of firms in a given country is at most 7 percent (between distancing proxy and fiscal policy variable; for other policies, the correlation is less than 3 percent).

[3] In order to establish the benchmark of an industry's pandemic sensitivity, Kóren and Petö (2020) use U.S. data. Hence, one may argue that this proxy could be endogenous to the performance of U.S. firms. Therefore, following other studies that apply the Rajan and Zingales (1998) approach such as Igan and Mirzaei (2020), we drop U.S. firms from all regressions. Yet, for completeness, we check the robustness of the findings and present the results obtained with U.S. firms. See Section IV.B.

excluding all firms with no data available on sales as well as on our main firm-level control variables. This means we focus on the effects of policy measures on the intensive margin only.

As a result, 28,915 firms from 80 countries survive the filtering criteria.[4] Note that, after imposing such additional criteria, we end up with one country (Mongolia) with less than 20 firms. We confirm the robustness of our results to excluding this country. The number of firms in our dataset varies by country. On average, each country has about 361 firms with available data. We reduce the influence of outliers by winsorizing all dependent variables at the 1st and 99th percentiles.

Following Ganganis et al. (2020) and Igan et al. (2022), the data on probability of default measure is from the Credit Research Initiative (CRI) of the National University of Singapore. The probability of default estimates the default risk of publicly listed firms by quantitatively analyzing numerous covariates that cover market-based and accounting-based firm-specific attributes, as well as macro-financial factors (Duan et al. 2012). We use a prediction horizon of 1 month. Note that the data on probability of default is not available for all 80 countries and/or 28,915 firms. We have data only for 10,023 firms.

Pandemic Sensitivity

We now define our index for a sector's relative sensitivity to social distancing ($Distancing$). As already stated, the impact of the COVID-19 shock on firms is likely to vary by the sector in which they operate. More specifically, some sectors—for example, accommodation and food services—are more vulnerable to pandemic-induced social distancing measures.

Kóren and Petö (2020) estimate each sector's contact intensity, using pre-pandemic data from the Occupational Information Network (O*NET) survey. Specifically, they use information for 809 occupations from the 2010 Standard Occupational Classification System to compute, for each NAICS three-digit code, the share of workers whose job requires a high level of three occupational characteristics: customer contact, teamwork and physical presence.[5] They end up reporting two proxies. The first one is a measure of "communication" intensity

[4] We acknowledge that the sample of firms we study is biased toward larger firms as almost all firms (about 95 percent) reporting 2020 data are listed firms. Thus, we are conservative when interpreting our results, as we cannot analyze the overall effect of policy measures on the performance of small and medium-sized enterprises during COVID-19.

[5] Some industries will have high scores in all three dimensions while others may have high scores only in one. For instance, most manufacturing requires physical presence but not necessarily face-to-face customer contact.

that incorporates teamwork-intensive and customer-facing activities. The second proxy, "overall" incorporates the physical presence dimension to the first.

In our baseline, we use communication intensity as the metric for distancing. This arguably captures the nature of non-pharmaceutical interventions put in place in response to COVID-19 due to the fact that shelter-in-place or stay-at-home orders were gradually lifted allowing industries that primarily rely on physical presence (e.g., construction, factories) to get back to work whilst travel restrictions, bans on public gatherings and specific business closures (e.g., gyms and restaurants) remained. We confirm the robustness of our results to the use of "overall" index. We assume that distancing is an intrinsic characteristic of a sector and, thus, indices derived using U.S. data can be used for the same sector across all countries.

Policy Measures

The data source for policy response is the IMF's Policy Tracker.[6] Launched right around the time COVID-19 was declared a pandemic by the WHO on March 11, 2020, this tracker relies on responses by individual country teams to a survey designed by IMF staff. The teams are asked to fill the survey on a weekly basis in order to capture any new announcements and changes to previously implemented measures. The survey seeks responses on all policy actions taken by the authorities in a country covering fiscal, monetary, external and financial policies. The survey asks about not only whether a fiscal or monetary policy action has been taken but also the size of the intervention. For external and financial policies, information is gathered in a categorical manner with 0 denoting no action and +1 an intervention for foreign exchange market.[7]

In our analysis, we use three policy measures: (i) $FisStim$, cumulative fiscal stimulus expressed in percentage of GDP, (ii) MP_BP, cumulative change in the monetary policy rate expressed in basis points, and (iii) FXI, the interventions in foreign exchange markets. All policy measures are computed over the period January 31, 2020 (week 1) to December 4, 2020 (week 43) to overlap with the firm-level data we have.

The intensity of economic stimulus packages varies considerably (see Section III.C for more details). By including countries with no or less strong policy responses as well as those

[6] Available at https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

[7] The survey also gathers information on capital flow management measures and broader financial market policy measures such as loan forbearance and debt moratoria. We do not include these in our analysis given that there is not enough variation across countries to tease out any differential effects.

with proactive intervention in our dataset, we reduce concerns that the results may be driven by selection bias.

One shortcoming of this database is the lack of granularity as to the exact measures implemented, in particular, under the fiscal stimulus packages. While a more in-depth analysis would be desirable, it would be better conducted in a set of relatively homogeneous country sample (if not, within a single country). We leave this for future research. That said, we do confirm the robustness of our findings using policy measures from alternative source (see Section IV.C)

Other Variables

Additional data are retrieved from standard databases such as the World Bank's World Development Indicators (WDI).

Appendix Table A1 details the construction of the main variables that we employ in the analysis. Note also that Appendix Table A2 shows the number of firms by country.

C. Descriptive Statistics

Insert Table 1 (Panels A and B) around here

Table 1 shows the summary statistics of change in the asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in the interest coverage ratio [$\Delta(IntrC)$ and change in the probability of default [$\Delta(ProbD)$] over the period from 2019 to 2020. The relation between firm performance and *Distancing* at the sector level is presented in Panel A. *Retail Trade* (NAICS 44-45) and *Health Care and Social Assistance* (NAICS 62) have the highest share of communication-intensive jobs, exceeding or around 60 percent. This is followed by *Art, Entertainment, and Recreation* (NAICS 71) and *Accommodation and Food Services* (NAICS 72) at around 40 to 44 percent. These two sectors suffered from the largest decline in sales to asset by around 20 to 24 percent and also in profit margin, dropping by around 18 to 24 percent. We observe the same pattern for the other two indicators of firm performance, change in interest coverage ratio and probability of default, for these two sectors. This heterogeneity across sectors is important to understand the effect of the pandemic and associated policy measures. The summary statistics for the main variables used in the regression analysis are shown in Table 1, Panel B. The sectors are classified as more pandemic-prone (greater than cross-country median) and less pandemic-prone (less than median) for the four dependent variables capturing firm performance. Amongst others, the mean values clearly indicate lower sales and profit margin, negative interest coverage and higher probability of default for sectors that are more vulnerable.

Insert Figures 1a and 1b around here

Figure 1a presents the cumulative fiscal stimulus from January to December 2020 for individual countries. Three advanced economies (Italy, Germany and Japan) top the chart spending more than 30 percent of GDP. The cumulative change in monetary policy from January to December 2020 by country is shown in Figure 1b. Emerging market economies appear to utilize monetary policy more. These patterns are in line with perceived policy space: ability to run budget deficits and increase in public debt being limited in developing countries, whereas interest rates being already historically low and close to the effective lower bound in advanced economies.

IV. EMPIRICAL FINDINGS

Using data for a maximum of 28,915 non-financial firms in 80 countries, we examine how the COVID-19 crisis has propagated across industries and how policy actions have helped alleviate the impact on firm performance.

Insert Table 2 around here

Before presenting our baseline results, we first show that the adverse impact of the COVID-19 outbreak on firm performance is indeed more pronounced on pandemic-prone sectors. This is to validate our main hypothesis that, if economic stimulus packages are effective, then pandemic-sensitive sectors benefit more. Applying a form of Eq. (1), Table 2 shows the impact of the pandemic. Column 1 displays a negative significant sign on the coefficient of $Distancing$ when the dependent variable is $\Delta(SaleA)$. It implies that a decline in the sales to be more noticeable for those sectors that are intrinsically more sensitive to social distancing. This result suggests that there is indeed a significant channel captured by $Distancing$, consistent with Kóren and Petö (2020). The change in in profit margin, $\Delta(ProM)$, in column 2 is also negative and significant. It is a plausible result in that firms in pandemic-prone sectors are unable to generate profit, whilst experiencing a drop in sales, possibly being forced to cut profit margins in order to survive the pandemic. We observe a negative significant sign on the coefficients of $\Delta(IntC)$ (change in the ratio of earnings to interest expenses) in column 3 and a positive sign on the coefficient of probability of default, $\Delta(ProD)$ in column 4. The crisis has not only drained liquidity, but has also increased the probability of default in vulnerable firms.

In columns 5–8, $Distancing_j$ is interacted with $COVID\_Severity_c$, that is, the country-level severity of the lockdown measures in response to the pandemic. This is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 with the score 100 being the strictest (Hale et al. 2020). Although the reported results suggest that there is still the same sign in all cases, they are less significant both statistically and in terms of magnitude when compared with those in columns 1–4.[8] The implication is that more weight is placed on the vulnerability of the specific sectors, rather than the exposure to the pandemic at the country level when explaining firm performance. Indeed, this is a reasonable outcome: sectors such as tourism and airlines are severely affected, whereas others such as information technology markedly benefit from social distancing. This phenomenon is common across countries.

As a separate exercise, we first run a regression of policy measures without interacting them with $Distancing$ and then with the interactions. This is to check the overall impact of policy measures on firm performance. As shown in Table A3 in the Appendix, almost all coefficients on stimulus variables are insignificant at conventional levels except for one in column 4. But when interacted with $Distancing$, we find significant coefficients in many cases for pandemic-prone sectors.

Collectively, the results in Table 2 and Table A3 suggest that pandemic-prone sectors were affected more severely by the COVID-19 pandemic, and that economic stimulus packages have disproportionately benefited these sectors. However, we cannot make any conclusions yet because these specifications do not employ a full set of fixed effects (though $COVID\_Severity_c$ and several other country characteristics are included as controls). We now turn to our baseline results using the full version of Eq. (1).

A. Baseline Results

Having observed the negative performance of pandemic-prone sectors in Table 2, we explore whether these industries are the ones that benefited more from economic stimulus measures. We specifically examine whether the stimulus measures alleviate the severity of the pandemic's impact on firm performance by interacting the policy measures with the distancing proxy. In Table 3, all policy measures are simultaneously included.

[8] Note that, in the specifications in columns 5–8, we include sector fixed effects. Hence, the coefficient on distancing itself may be absorbed in the fixed effects.

Insert Table 3 around here

Overall, we find evidence of positive impact of fiscal policy during the pandemic for vulnerable sectors, and indeed, the various types of fiscal stimulus appear to be working as intended by policy makers.[9] Fiscal policy is statistically significant in all four cases (columns 1-4) at the 5% or 1% levels, improving the sales, profit margin and liquidity position (proxied by interest coverage) and, at the same time, decreasing the probability of insolvency for vulnerable sectors, holding other policy variables constant. This is consistent with the findings in Aghion et al. (2009), Claessens et al. (2012), and Laeven and Valencia (2013).

Monetary policy easing appears to have been effective in supporting sales revenue, though at the marginal significance level of 10% (column 1). Note that the various robustness tests conducted in the subsequent subsections reveal a clearer effect of monetary policy on firm performance. In this respect, the functioning of monetary policy transmission appears to be, at least, preserved during the pandemic. This is in contrast with the case of the global financial crisis in 2008, when bank balance sheet constraints substantially weakened monetary policy transmission (Van den Heuvel 2009), and attests to the importance of advances in prudential regulation and deleveraging that allowed banks face the pandemic shock in much better shape than they did the subprime mortgage shock.

Foreign exchange intervention seems to have mitigated the decline of interest coverage (the ratio of earnings to interest expenses) during the pandemic (column 3). One of the possible explanations of this outcome may be due to the fact that the earnings of pandemic-prone sectors such as tourism are receptive to changes in the value of the domestic currency against foreign currencies. By limiting excessive volatility in the exchange rate, FXI may have protected earnings and kept interest expenses in check (especially if part of the debt is denominated in foreign currency). In this respect, the positive sign on the coefficient of profit margin ($\Delta(ProfM)$) is consistent, though it is insignificant.

Note that sales and interest coverage seem to be more responsive to policy measures, whereas the performance indicators of profit margin and the probability of default respond only to fiscal measures. This may be explained as follows: during the pandemic, there is little scope

[9] As a separate exercise, we run a regression of policy measures with two indicators of real activity as dependent variables: change in 'the number of employees' and change in 'value added'. The result is shown in Appendix Table A4, where we find a highly significant effect of fiscal stimulus for both cases, supporting the baseline result in Table 3. Given the limited sample size in this instance, we leave further exploration of real effects to the future when more data become available.

for raising margins for those vulnerable firms, culminating in smaller response to other policy stimulus than to specific fiscal instruments such as tax payment deferral or loss carry-back tax provisions that may have a direct impact on the profit margin. Similarly, default is not an unlikely outcome for vulnerable firms, in particular, for those with high levels of debt that were accumulated before the pandemic. Fiscal measures such as loan guarantee schemes, interest-free loans or cash grants may have effectively mitigated the risk of default.[10]

The effect of fiscal stimulus is economically meaningful. Focusing on the sales-to-assets ratio, the estimation results in column 1 of Table 3 suggest that a firm from an industry at the 90th percentile of distancing would have change in sales-to-asset that is 2.05 percentage points higher than a firm from a sector that is at the 10th percentile of distancing, if it were located in a country that is at the 90th percentile compared to a country at the 10th percentile of fiscal stimulus. Similarly, the estimation results in column 4 of Table 3 suggest that, relative to less pandemic-prone sectors (in the 10th percentile level), the probability of default in more pandemic-sensitive sectors (in the 90th percentile level) is around 0.68 percent less in a country that launched significant fiscal stimulus packages (in the 90th percentile) than in a country with a limited adoption of economic support in the form of fiscal stimulus (in the 10th percentile). Note that both differentials in changes in sales-to-asset ratio and the probability of default are substantial, compared to the average rates of change in $SalesA$ and $ProbD$ (which are –8.26 percent and 0.22 percent, respectively).

B. Endogeneity Issues

The key challenges for our identification strategy are the two conventional endogeneity problems – omitted variable bias and reverse causality. In this section, we present several exercises to address these issues.

Omitted variable bias

The established positive correlation between stimulus packages and firm performance is in line with our hypothesis, which suggests that government policies during the pandemic have provided life support for hardest-hit firms. Yet, the stimulus packages may have been automatically picking up the effects of some country-level and/or sectoral-level omitted variables that are also likely to affect firm performance. In fact, latent omitted variables that

[10] Due to differences in number of observations across our four dependent variables, it is worth confirming the validity of the findings in the restricted sample (that is, only the firms with non-missing observations for all response variables). Results reported in Appendix Table A5 columns 1-4 indicate that our main findings remain broadly unchanged, except for the case where profit margin is the dependent variable.

are correlated with both firm activities and stimulus policies may raise the issue of endogeneity (Hyytinen and Toivanen, 2005). For instance, countries more open to trade and cross-border capital flows may launch more economic support given their larger exposure to the negative shocks and the broader lift to the economy cushions firms' performance, and this may, in turn, lead to a spurious positive association between stimulus packages and firm performance. To address the omitted variable bias, we employ two approaches to evaluate the significance of such variables. Firstly, we control for observable characteristics – especially at the country/industry level – that may affect firms' performance. Secondly, we make selection on these observable factors to determine the likelihood that our estimates are being driven by unobserved heterogeneity across countries/sectors.

Following the existing literature, the first approach involves including a set of country- and sector-level control variables. We rely on two sets of characteristics. The first set includes those that are related to firm activities through country characteristics (*Other country characteristics*). These include five variables classified into four groups of a) pandemic resilience, b) channels of transmission, c) bank stability, and d) macroeconomic stability (see, for example, Claessens et al., 2010; Martin and Nagler, 2020; Igan et al., 2022).

a) ***Pandemic resilience***: We consider the vulnerability of a country to the pandemic by utilizing the variable of private health expenditure per capita ($HealE$). When people in a country are able to obtain health services without suffering financial hardship, the country can reasonably be expected to be more resilient to a pandemic such as COVID-19. Data are collected from the World Health Organisation as reported by the World Bank.
b) ***Channels of transmission***: Previous research has highlighted the role of real and financial channels through which a crisis can spread across countries. While arguably less applicable to the case of COVID-19 given the different nature of the shock, these channels may still matter in the transmission of the economic effects. For instance, given restrictions imposed on movement across and within borders, supply can be disrupted and countries that are more connected to global value chains may feel the effects more profoundly. We consider two variables: (i) foreign direct investment (FDI), as a proxy for financial interconnectedness, and (ii) total exports and imports in % of GDP ($Trade$), as a proxy for a country's economic integration with the rest of the world. Data are retrieved from the World Bank.

c) ***Bank stability***: The health of bank balance sheets could be an amplifier of the economic shocks. In order to capture bank health, we include the ratio of non-performing loans to total loans (NPL). Data come from the World Bank.

d) ***Macroeconomic stability***: We capture the general macroeconomic stability of a country by including inflation ($Inflation$). Data are collected from the WDI.[11]

These country-specific features are interacted with *Distancing*. Estimates of equation (1) controlling for these controls are reported in Table 4A.

Insert Tables 4A, 4B, 4C and 4D around here

We find almost identical estimated coefficients of the interaction terms between distancing and policy variables in terms of direction, significance and magnitude. This highlights that pandemic-prone firms disproportionately benefit from fiscal stimulus in firms' performance, in general. Expansionary monetary policy continues to raise sales, and mitigates the risk of default. The latter result is new relative to the baseline in Table 3 and a plausible outcome as monetary policy easing can relieve debt service pressures. As before, the liquidity position in vulnerable sectors improves when there is government intervention in the foreign exchange market.

Other channels of propagation emphasized in the literature involve liquidity constraints and sensitivity to consumer demand in non-financial firms.[12] Hence, as a second set of characteristics, we consider the effect of these two sectoral characteristics, which may interact particularly with financial policy measures. It follows that we control for sectoral characteristics by interacting the variables of external financial dependence ($FinDep$) and demand sensitivity ($DemSen$) of individual sectors, respectively, with the stimulus variables. We use the Rajan and Zingales (1998) index for external finance dependence and an index of

[11] One of the important country-level variables that may affect firm performance is the debt-to-GDP ratio. The ability of a country in diminishing the adverse impact of a crisis on corporate activity and risk may be related to its level of debt (Martin and Nagler, 2020). However, Benmelech and Tzur-Ilan (2020) show that debt-to-GDP is positively related to fiscal spending during COVID-19. Indeed, we face a high correlation with more than 0.8 between the sovereign debt ratio and the size of the fiscal response to the crisis. The correlation further increases to 0.9 when interacted with distancing. There are other likely control variables one could consider, such as share of population aged 65+ and number of hospital beds. However, due to the problem of multicollinearity as indicated by a large variance inflation factor (VIF), we have to be selective and exclude all these potential control variables from the baseline model.

[12] See, for instance, Tong and Wei (2008), who examine how the subprime crisis spilled over to the real economy and find that these two channels indeed explain the negative impact on stock prices during the global financial crisis.

sensitivity to demand shocks based on the stock price response to the September 11 shock, as computed by Tong and Wei (2008). We examine the extent to which policy measures affect firm performance through these two potential channels.

Table 4B presents the results.[13] With consistently high statistical significance at the 1 or 5% level, we continue to find that fiscal policy gives a boost to firm performance in sectors hit hard by the pandemic. Contrary to previous studies (e.g. Aghion et al. 2009; Laeven and Valencia 2013), we do not find much significant effect of fiscal stimulus on firms that are more dependent on external finance and firms that are more demand sensitive. A plausible interpretation of this result is that, in the context of the COVID-19 shock on firm performance and survival, the main channel through which fiscal stimulus helped is the alleviation of the impact of non-pharmaceutical interventions. The impact of monetary policy on sales growth of pandemic-prone firms remains significant, though still marginally at the 10% level (see the coefficient on $Distancing \times MP\_BP$ in column 1). There appears to be a similar link to profit margins (see column 2). The impact of FXI on $\Delta(IntrC)$ is still attributable to differences across sectors in terms of how vulnerable they are to distancing rather than other sectoral characteristics (column 3). Note that there seems to be a marginally significant negative impact of FXI on the probability of default (column 4). On balance, the key findings for the interaction terms between distancing and policy variables appear to be consistent with the baseline results in Table 3.

In Table 4C, we further estimate the model by controlling for interactions of both country and sector characteristics simultaneously. The results are close to those in the baseline reported in Table 3 in terms of the sign, magnitude and significance of the coefficients (or even better with more significant coefficients).

While the above control variables provide a reasonable amount of country- and sectoral specific information, they may not entirely account for all relevant factors and thus, the likelihood of some omitted variable bias continues to be present. In fact, while we control for observable factors, our result may still be biased due to unobservable variables that may be correlated with government stimulus packages and subsequently with firm performance.

[13] Note that since $FinDep$ and $DemSen$ are at the SIC 3-digit level whilst $Distancing$ is at the NAICS 3-digit level, NAICS 4-digit-level fixed effects are utilized in order to cover both SIC 3-digit levels and NAICS 3-digit levels in Table 4B. In Appendix Table A5 Columns 5-8, we use $FinDep$ at the NAICS 3-digit level from Bilir et al. (2019), and also impose sector fixed effects at the 3-digit level to be consistent with the specifications in Table 3. The main results are supportive to those in Table 4B.

Henceforth, following Altonji et al. (2005), as a second approach, we measure the relative significance of omitted variable bias by testing to what extent the coefficients of interest are altered by the inclusion of more regressors (unobservable factors). This approach quantifies how much greater the influence of unobservable factors would be required to be, relative to observables, to completely explain away the positive association between the economic stimulus packages and the performance of firms that operate in pandemic-prone sectors. If such influence is substantial, inclusion of more controls (i.e., unobservable factors) would reduce the estimated effect even further. If it is trivial, we can be more assured in proposing a causal interpretation to the estimated relationship. We utilize the method proposed by Oster (2019), who argues that one should scale the coefficient movements by the observed increase in R^2 as the measurement of the change. In this set-up, we need to have two types of regressions: restricted regression (the one with a restricted set of control variables – those in baseline Table 3) and full regression (the one with a full set of country and sector controls – those in Table 4C).

Table 4D reports the coefficients of the interaction term between government stimulus packages and distancing (those that are significant in Table 3), along with the associated R^2 obtained by estimating Eq. (1) in a restricted version and in a full model. We find that the full model increases the magnitude of the coefficient, while R^2 increases from about 8% to 16%, depending on the proxy used for stimulus policy. This result indicates that, holding other factors constant, unobservable factors generally bias our coefficient toward zero (similar to the case in Claessens et al. 2021). Therefore, the estimated effects are likely to be conservative, resulting in negative figures for Oster delta as presented in columns 9-12, except for the one case for $\Delta(IntrC)$ that is just above the threshold unity.

Reverse causality

Besides omitted variables, reverse causality could be another challenge. Receiving government economic support may be endogenous to a firm's activities. Even if the COVID-19 shock is exogenous, the reaction of policy makers may not be random (Demirgüç-Kunt et al. 2021). For instance, companies, especially large ones, that were adversely affected by the COVID-19 pandemic and its associated lockdown measures could be more likely to be supported by the government.

To deal with reverse causality concerns, we apply three different strategies. Firstly, we drop the top 3 pandemic-prone industries in each country from our sample. The underlying idea is that the most vulnerable sectors in a country may be the ones to influence government policies. Secondly, we exclude large firms (firms with revenue greater than USD 5 billion) from the dataset. If activities of firms may determine the degree of government intervention, then this would be more likely to be the case with large influential firms. By contrast, one may expect that smaller firms are more vulnerable to COVID-19 and, thus, may benefit more from government policies, rather than the other way round. Finally, we remove countries with a high share of pandemic-prone sectors to the GDP. This is because the reverse causality effect should be in tandem with the size of vulnerable industries relative to the overall size of the economy (Levintal, 2013). In other words, one would expect a larger reverse causality bias in countries where the pandemic-prone sectors constitute a significant portion of GDP. We measure this share as $Share_c = \sum_{j=1}^{n} Distancing_j \times ValuA_j \ / \ GDP_c$ where $ValuA$ is value added of sector j computed as the sum of earnings before taxes, depreciation and labor expense (Laeven and Valencia, 2013). $ValAdd_j \ / \ GDP_c$ is measured for year 2019. We then remove countries in the 75th percentile of $Share$.

Insert Table 5 around here

The results are reported in Table 5 and resonate with those in the baseline reported in Table 3. Removing the top 3 pandemic-prone sectors (columns 1-4), largest firms (columns 5-8) or countries with a high share of pandemic-prone sectors (columns 9-12) do not alter the findings and, actually, in some cases deliver larger and more statistically significant coefficients.

To address any remaining endogeneity issue, our final attempt is to utilize the shock components for each policy as instruments. Specially, we follow Biljanovska et al (2021) to construct the shocks for year 2020 as residuals of the following regressions:

- **Fiscal policy**: the shock for fiscal policy is the residuals obtained from regressing the primary balance on its lag, output gap and a dummy for positive output gap.
- **Monetary policy**: the shock for monetary policy is the residuals obtained from regressing the policy rate on real output gap, inflation, one quarter lagged policy rate and the log difference of the real effective exchange rate (in the case of emerging economies).
- **FXI**: the shock for foreign exchange intervention is the residuals obtained from regressing the FXI (as calculated by Adler et al. 2021) on the change in the real effective exchange rate, change in portfolio flows, inflation, change in credit-to-GDP, the VIX,

change in commodity price index, interest rate differential to the US policy rate, foreign reserves and a dummy variable for floating exchange rate regime.

The regressions are run by country for fiscal and monetary policies. For FXI, they are run separately for emerging market economies and advanced economies. Additional information is available in Biljanovska (2021). We instrument our variable of interest (that is, $Distancing_j \times Policy_c$) with the estimated policy shocks interacted with distancing (that is, $Distancing_j \times Shock_c$). Due to data availability, we do not have estimates of the FXI shock for Japan and some EU countries, although FXI shocks in these cases can arguably be assumed to be zero. Thus, we choose to report the IV results for two cases: (i) FXI is not included and (ii) FXI is included (and instrumented).

In addition to policy shocks, we also use a proxy for the quality of the institutional environment to further orthogonalize the policy response. The structure and timely launch of an economic stimulus package when a country faces an external shock could depend on its overall institutional quality. Hence, we complement the shock data with data on institutional quality retrieved from the World Bank's World Governance Indicators Database, as of 2020, the so-called KKZ institution. It measures different dimensions of governance, which include government effectiveness, political stability, regulatory quality, rule of law, voice and accountability, and control of corruption. Again, we interact this variable with the sectoral distancing proxy.

Insert Table 6 around here

We report the IV estimates in Table 6, Panel A for fiscal and monetary stimuli and Panel B for all three policies. The F-test of the excluded instruments rejects the null hypothesis of weak instruments, and Hansen's J-test does not reject the null hypothesis that the over-identifying restrictions are valid. This indicates that our two instruments, policy shocks and institutional quality, are valid. We find that fiscal stimulus relates positively and statistically significantly to the performance of pandemic-prone sectors, with a magnitude which is even larger than that reported in Table 3 for the OLS case. We find no impact on the profit margin when FXI is included. Overall, the IV estimator confirms our baseline results.

To sum up, in this section, we have conducted a number of exercises to verify that the association we unveiled in Table 3 between stimulus packages and firm performance during COVID-19 can reasonably be considered to not suffer from omitted variable bias and reverse causality.[14] Yet, the above strategies may not entirely address such problems. Thus, we conduct several additional robustness tests in the next subsection.

C. Robustness Tests

Several robustness tests are conducted in order to ascertain the baseline results in Table 3. First, an alternative proxy for pandemic sensitivity is examined in Table 7A. Recall that, in the previous estimations, the proxy for *Distancing* is based on communication-intensive jobs. In this table, we employ Kóren and Petö (2020)'s overall index that incorporates not only communication intensity but also the need for physical presence. Note the interpretation of the Kóren-Petö index is as follows: a *higher* share of jobs that cannot be done at home indicates *higher* sensitivity to non-pharmaceutical interventions, which is captured by a *higher* level of reliance on face-to-face communication and physical presence. The results appear to be somewhat mixed, however, the effectiveness of fiscal policy remains as the main driver of differences in firm performance. With the alternative measure of *Distancing*, profit margin and interest coverage become more responsive to expansionary monetary policy as compared with the baseline results.

Insert Tables 7A, 7B, 7C and 7D around here

Another concern could be the composition of our dataset. Since firms in our dataset may be unequally distributed across countries, one issue could be that the results are driven by the unbalanced nature of the dataset. To alleviate such a concern, we re-estimate our baseline regressions in Table 7B using weighted least squares where observations are weighted by the inverse of the number of firm observations in each country (following Laeven and Valencia, 2013), which allows the covariance matrix of errors to be different from an identity matrix (in columns 1–4). In a related exercise, we remove 'critical' or 'essential' sectors in columns 5–8. The concern in this case is that some sectors may be mandated to stay open even under full lockdown and receive (direct) policy support in order to do so. Such sectors include: utilities, infrastructure, food and agriculture, critical manufacturing, healthcare and public health services, security and emergency services. We drop 36 three-digit industries as informed by Papanikolaou and Schmidt (2020). In both cases, the main findings are qualitatively unaltered. Fiscal stimulus, in general, help hardest-hit sectors weather the COVID-19 shock. The effect

[14] Recall that we excluded the United States in conducting the empirical analysis due to the concern of reverse causality. The estimates obtained when we include the US data are in Appendix Table A5 Columns 9-12. The results are almost identical to those in Table 3.

of monetary policy to profit margin becomes more pronounced. The boost provided by foreign exchange intervention to interest coverage remains robust. In fact, the coefficient on $Distancing \times FXI$ is highly significant in probability of default (column 8) by excluding 36 critical sectors, though it is still marginally significant with weighted least squares (column 4). This hints that FXI could be more instrumental than revealed in the baseline results.

It is possible that omitted variable bias could stem not only from country and sector characteristics (studied in Table 4), but also from differences at the firm level. Note that we already control for a battery of firm characteristics in the baseline, Table 7C extends the set of controls to include overhead costs and cash flow, both deflated by total assets. Tobin's Q (defined as the market value of common stocks plus the book value of total liabilities divided by the book value of total assets) is also specified in order to control for the market value of firms. Our sample includes both non-listed and listed firms, hence columns 1–4 are for all firms without Tobin's Q and columns 5–8 are for listed firms with Tobin's Q. The resonance of the baseline results in Table 3 is also apparent in Table 7C: fiscal policy is an effective tool to mitigate the decline in overall firm performance, whereas monetary policy seems to support revenue and foreign exchange intervention to improve interest coverage. An interesting observation is that, either listed or unlisted, hardest-hit firms disproportionately gain from stimulus packages implemented during the pandemic.

There are many databases that have been tracking what governments across the world are doing in response to the COVID-19 pandemic. They vary in terms of coverage in terms of country, frequency, and type of policy measures. There is often a trade-off between how many countries such databases can cover and how granular they can go in categorizing policy measures. While our dataset on stimulus packages from IMF policy tracker used in the baseline analysis is comprehensive, we, as a final sensitivity test, also check the robustness of our findings to two alternative sources: (i) ESCAP Policy Responses to COVID-19 in Asia and the Pacific Database, (ii) Yale COVID-19 Financial Response Tracker (CFRT) by the Yale Program on Financial Stability Database.[15] The advantage of these alternative sources over some others is that the data are reported for most countries in our main dataset. Since our analysis so far mainly produced robust results for fiscal stimulus policy, we focus only on this

[15] We do not utilize other stimulus policy databases because either their coverage is limited to a specific region and/or a small number of countries or they do not include sufficient quantitative information. For instance, the OECD provides a database with qualitative information on COVID policy measures in a narrative format but transforming this information into numerical values is not straightforward given lack of direct comparability.

policy dimension. The results reported in Table 7D with alternative stimulus policy data appear to affirm, generally, the effectiveness of fiscal policies during the pandemic, notably firms in pandemic-prone sectors performed better if they are located in countries that adopted larger fiscal stimulus packages.

D. Additional Analyses

In this subsection, we investigate the relationship between pre-COVID firm size and basic financial conditions and their performance during the crisis. More specifically, we test whether pre-crisis firm characteristics influence the link between government policies and firm performance during the COVID-19 crisis.

Insert Tables 8A, 8B, 8C and 8D around here

We focus on four characteristics commonly-studied in the literature (Giroud and Mueller 2017). The first one is size, and the other three relate to liquidity constraints and leverage. Because of the adverse impact of the COVID-19 crisis on revenues and free cash flow, one may expect that smaller firms and firms with less cash, more leverage and less profitability to be more vulnerable and, thus, more favorably affected by government economic stimulus policies. In this vein, Ding et al. (2020) find that firms entering the COVID-19 crisis with a better position in terms of cash holdings, leverage and profitability performed relatively better during the crisis, with respect to stock prices. Fahlenbrach et al. (2020) find that financial flexibility (proxied, for example, by cash holdings) is one of the factors explaining why some firms performed better during the COVID-19 crisis. Laeven (2020) finds that large firms and firms with cash buffers are better able to absorb the pandemic shock. Carletti et al. (2020) also report that distress in terms of book value of equity is more frequent for small and medium-sized enterprises and for firms with high pre-COVID-19 leverage, using a sample of 80,972 Italian firms. Although the nature of the initial shock is very different, these findings are in line with those reported in studies looking at the 2008 financial crisis (e.g., Duchin et al. 2010 find that the decline in investment is greatest for firms that have low cash reserves and are financially more constrained). Thus, we re-estimate the baseline specifications in Table 3, by considering the role of pre-crisis firm conditions with respect to size (Table 8A), cash holdings (Table 8B), profitability (Table 8C) and leverage (Table 8D). Columns 1–4 in all four tables include only the firms that are below the median values and columns 5–8 above the median values, respectively.

Larger pandemic-prone firms predominantly benefit more in all cases except for profit margin from fiscal stimulus (see the significant coefficient on the interaction for $FisStim$ in column 5, 7 and 8 of Table 8A). On the other hand, smaller firms benefit more from foreign exchange intervention (see the significant coefficient on the interaction for FXI in columns 3 and 4). Expansionary monetary policy seems to exert a preferable effect regardless of the firm size by easing the cost of borrowing which is raising profit in smaller firms (column 2), whereas increasing sales in larger firms (column 5).

Firms with operations in a pandemic-prone industry and a low level of cash holdings appear to have been protected from insolvency by the fiscal stimulus, given the significant coefficient on the interaction for $FisStim$ in column 4 of Table 8B. The benefit from the fiscal intervention tends to extend when it comes to meeting their debt obligations (column 3). For those firms with more cash holdings, the result appears to echo that for larger firms in Table 8A: both fiscal and monetary stimuli are, in general, suitable to their needs with highly significant coefficients found on the interaction terms for *FisStim* (column 5, 7 and 8) and MP_BP (column 5).

By distinguishing between higher and lower profitability amongst vulnerable firms in Table 8C, the effectiveness is not well determined with only 5 coefficients on the interaction terms are significant. Yet, interestingly, firms in the higher profitability group seem to benefit from fiscal and, to a lesser degree, from monetary stimuli more than their lower-profitability counterparts do (see column 5 and 7, where the interaction terms are highly significant). A somewhat speculative interpretation could be that fiscal and monetary policy stimuli provide a lifeline to even to those that were not doing well before the pandemic hit, but only firms of a certain level of profitability are then able to lever this lifeline to weather the blow to their profitability.

Looking at the results in Table 8D, there is clear distinction between higher debt-holding companies (columns 1-4) and lower debt-holding companies (columns 5-8). Predominantly, economic policy packages favor the latter, in particular both fiscal and monetary policy have shown to be operative to all types of firm performance, ranging from sales revenue, profit margin, interest coverage and probability of default. On the other hand, low leveraged firms appear to only receive the benefit of an improved interest coverage ratio from foreign exchange intervention (column 3) and of a decline in probability of default from fiscal stimulus (column 4). These results seem to support the argument in that firms with a better financial position are more likely to take advantage of the stimulus packages to withstand the pandemic shock.

V. CONCLUSION

In this paper, we use firm-level data to provide some early evidence on the effectiveness of COVID-19 economic policy packages. Our empirical strategy relies on the varying degree of vulnerability to the pandemic across industries. If policy actions have been targeted enough, they would give a lift to pandemic-prone sectors.

After confirming that firms in sectors with higher distancing indices performed worse than the others in the same country, we find a robust positive association of fiscal stimulus with growth in the sales-to-assets ratio, profit margin, and interest coverage ratio, and negative association with probability of default in pandemic-prone sectors. Put differently, firms that are more sensitive to distancing have performed better when the fiscal stimulus is larger. There is also some evidence that monetary stimulus has been associated with improved sales and foreign exchange intervention with increased interest coverage ratio for the hardest-hit firms. Overall though, the evidence indicates that fiscal stimulus packages are more effective than other policies during the COVID-19 pandemic. Thus, this early evidence seems to suggest that policy interventions have bought time for the hardest-hit industries, by supporting sales and improving liquidity.

References

Aghion, P., Hémous, D., Kharroubi, E., 2014. Cyclical fiscal policy, credit constraints, and industry growth, *Journal of Monetary Economics* 62, 41-58.

Alfaro, L., Chari, A., Greenland, A.N., Schott, P.K., 2020. Aggregate and Firm-Level Stock Returns during Pandemics, in Real Time, NBER Working Paper No. 26950.

Altonji, J.G., Todd E. E., and Christopher R. T., 2005. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, 113(1): 151–84.

Barbiero, F., Popov, A., Wolski, M., 2020. Debt overhang, global growth opportunities, and investment, *Journal of Banking & Finance* 120.

Bates, T.W., Kahle, K.M., Stulz, R.M., 2009. Why Do U.S. Firms Hold So Much More Cash than They Used to? *Journal of Finance* 64(5), 1985–2021.

Baumohl, E., Iwasaki, I., Kočenda, E., 2019. Institutions and determinants of firm survival in European emerging markets. *Journal of Corporate Finance* 60, 431–453.

Beck, T., Demirgüç-Kunt, A., Laeven, L., Maksimovic, V., 2006. The determinants of financing obstacles. *Journal of International Money and Finance* 25(6), 932–952.

Benmelech, E., and Tzur-Ilan, N., 2020. The determinants of fiscal and monetary policies during the Covid-19 crisis, NBER Working Papers 27461.

Bilir, L.K., Chor, D., Manova, K., 2019. Host-country financial development and multinational activity. *European Economic Review* 115, 192–220.

Biljanovska, N., Chen, S., Igan, D., Martinez Peria, M.S., 2021. Exploring the Interactions of Macroprudential Regulation with Other Policies, forthcoming IMF Working Paper.

Carletti, E., Oliviero, T., Pagano, M., Pelizzon, L., Subrahmanyam, M.G., 2020. The COVID-19 shock and equity shortfall: Firm-level evidence from Italy, *Review of Corporate Finance Studies* 9, 534–568.

Cathcart, L., Dufour, A., Rossi, L., Varotto, S., 2020. The differential impact of leverage on the default risk of small and large firms, *Journal of Corporate Finance* 60.

Chaney, T., Sraer, D., and Thesmar, D., 2012. The Collateral Channel: How Real Estate Shocks Affect Corporate Investment, *American Economic Review* 102(6), 2381–2409.

Chen, S., Igan, D., Pierri, N., Presbitero, A.F., 2020. Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States, *CEPR Covid Economics* 36.

Chodorow-Reich, G., 2014. The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008–09 Financial Crisis, *Quarterly Journal of Economics* 129(1), 1–59.

Claessens, S., Dell'Ariccia, G., Igan, D., Laeven, L., 2010. Cross-country experiences and policy implications from the global financial crisis, *Economic Policy* 25(62), 267–293.

Claessens, S., Tong, H., Wei, S. J., 2012. From the financial crisis to the real economy: Using firm-level data to identify transmission channels. *Journal of International Economics* 88(2), 375–387.

Claessens, S., Cornelli, G., Gambacorta, L. et al., 2021. Do macroprudential policies affect non-bank financial intermediation? *BIS Working Papers* 27.

Demirgüç-Kunt, A, Pedraza, A., Ruiz-Ortega, C., 2021. Banking sector performance during the COVID-19 Crisis, *Journal of Banking and Finance* 133.

Demirgüç-Kunt, A., Peria, M.S.M., Tressel, T. 2020. The global financial crisis and the capital structure of firms: Was the impact more severe among SMEs and nonlisted firms? *Journal of Corporate Finance 60*.

Ding, W., Levine, R., Lin, C., 2020. Corporate immunity to the COVID-19 pandemic, NBER Working Paper No. 27055.

Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? *Journal of Public Economics* 189, 1–8.

D'Souza, J., Megginson, W.L., Ullah, B., Wei, Z., 2017. Growth and growth obstacles in transition economies: Privatized versus de novo private firms, *Journal of Corporate Finance* 42, 422–438.

Duan, J.C., Sun, J., Wang, T., 2012. Multiperiod corporate default prediction –a forward intensity approach, *Journal of Econometrics* 170 (1), 191–209.

Duchin, R., Ozbas, O., Sensoy, B., 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis, *Journal of Financial Economics* 97, 418–435.

Fahlenbrach, R., Rageth, K., Stulz, R.M., 2020. How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis, NBER Working Papers 27106.

Frijns, B., Dodd, O., Cimerova, H., 2016. The impact of cultural diversity in corporate boards on firm performance, *Journal of Corporate Finance* 41, 521–541.

Gaganis, C., Lozano-Vivas, A., Paradimitri, P., Pasiouras, F., 2020. Macroprudential policies, corporate governance and bank risk: cross-country evidence. *Journal of Economic Behavior and Organization* 169, 126–142.

Gagnon, J.E., Collins, C.G., 2019. Are Central Banks Out of Ammunition to Fight a Recession? Not Quite, Peterson Institute for International Economics Policy Brief 19–18.

Gandhi, P., Lustig, H., 2015. Size anomalies in U.S. bank stock returns. *Journal of Finance* 70, 733–768.

Giroud, X., Mueller, H.M., 2017. Firm leverage, Consumer Demand, and Employment Losses during the Great Recession, *Quarterly Journal of Economics* 132, 271–316.

Giroud, X., Mueller, H.M., 2019. Firms' Internal Networks and Local Economic Shocks, *American Economic Review* 109(10), 3617–49.

Glover, A., Heathcote, J., Krueger, D., Ríos-Rull, J.V., 2020. Health versus Wealth: On the Distributional Effects of Controlling a Pandemic, mimeo, University of Pennsylvania.

González, V.M., 2015. The financial crisis and corporate debt maturity: the role of banking structure, *Journal of Corporate Finance* 35, 310–328.

Hale, T., Webster, S., Petherick, A., Phillips, T., Kira, B., 2020. Oxford Covid-19 government response tracker, Blavatnik School of Government.

Hall, T., Mateus, C., Mateus, I.B., 2014. What determines cash holdings at privately held and publicly traded firms? Evidence from 20 emerging markets, *International Review of Financial Analysis* 33(3), 104–116.

Hensvik, L., Le Barbanchon, T., Rathelot, R., 2020. Which jobs are done from home? Evidence from the American Time Use Survey, CEPR Discussion Paper No. 14611.

Hyytinen, A., Toivanen, O., 2005. Do financial constraints hold back innovation and growth? Evidence on the role of public policy. *Research Policy* 34 (9), 1385–1403.

Igan, D., Mirzaei, A., 2020. Does going tough on banks make the going get tough? Bank liquidity regulations, capital requirements, and sectoral activity. *Journal of Economic Behavior & Organization* 177, 688–726.

Igan, D., Mirzaei, A., Moore, T., 2022. Does macroprudential policy alleviate the adverse impact of COVID-19 on the resilience of banks? *Journal of Banking and Finance*, (in press).

Kóren, M., Petö, R., 2020. Business disruptions from social distancing, *PLoS ONE* 15(9): e0239113.

Laeven, L., 2020. Pandemics, Intermediate Goods, and Corporate Valuation. CEPR Discussion Paper No. 15022.

Laeven, R., Valencia, F., 2013. The real effects of financial sector interventions during crises, *Journal of Money, Credit and Banking* 45 (1), 147–177.

Leibovici, F., Santacreu, A.M., Famiglietti, M., 2020. How the Impact of Social Distancing Ripples through the Economy, St. Louis Fed On the Economy Blog, April 7.

Levintal, O., 2013. The real effects of banking shocks: evidence from OECD countries. *Journal of International Money and Finance* 32, 556–578.

Makin, A.J., Layton, A., 2021. The global fiscal response to COVID-19: Risks and repercussions, *Economic Analysis and Policy* 69, 340-349.

Mankiw, G., 2020. A Proposal for Social Insurance During the Pandemic, http://gregmankiw.blogspot.com/2020/03/a-proposal-for-social-insurance-during.html

Marron, D., 2020. If We Give Everybody Cash To Boost The Coronavirus Economy, Let's Tax It | Tax Policy Center, https://www.taxpolicycenter.org/taxvox/if-we-give-everybody-cash-boostcoronavirus-economy-lets-tax-it

Martin, T., Nagler, F., 2020. Sovereign Debt and Equity Returns in the Face of Disaster (September 15, 2020). Available at SSRN: https://ssrn.com/abstract=3572839 or http://dx.doi.org/10.2139/ssrn.3572839

Norden, L., Roosenboom, P., Wang, T., 2013. The impact of government intervention in banks on corporate borrowers' stock returns, *Journal of Financial and Quantitative Analysis* 48 (5), 1635–1662.

OECD, 2020a. Tax and Fiscal Policy in Response to the Coronavirus Crisis: Strengthening Confidence and Resilience, https://www.oecd.org/coronavirus/policy-responses/tax-and-fiscal-policy-in-response-to-the-coronavirus-crisis-strengthening-confidence-and-resilience-60f640a8/.

OECD, 2020b. Supporting people and companies to deal with the COVID-19 virus: Options for an immediate employment and social-policy response, https://read.oecdilibrary.org/view/?ref=119_119686-962r78x4do&title=Supporting_people_and_companies_to_deal_with_the_Covid-19_virus.

Oster, E., 2019. Unobservable Selection and Coefficient Stability: Theory and Evidence, *Journal of Business & Economic Statistics* 37(2), 187–204.

Padhan, R., Prabheesh, K.P., 2021. The economics of COVID-19 pandemic: A survey, *Economic Analysis and Policy* 70, 220-237.

Pagano, M., Wagner, C., Zechner, J., 2020. Disaster Resilience and Asset Prices, CEPR Discussion Paper No. 14773.

Papanikolaou, D., Schmidt, L.D.W., 2020. Working Remotely and the Supply-side Impact of COVID-19, NBER Working Paper No. 27330.

Rajan, R., Zingales, L., 1998. Financial dependence and growth. *American Economic Review* 88(3), 559–586.

Ramelli, S., Wagner A.F., 2020. Feverish Stock Price Reactions to COVID-19, CEPR Discussion Paper No. 14511.

Tong, H., Wei, S. J., 2008. Real effects of the subprime mortgage crisis: Is it a demand or a finance shock? IMF Working Paper No. 08/186.

Van den Heuvel, S., 2009. The bank capital channel of monetary policy, mimeo, Federal Reserve Board.

Table 1. Summary statistics

Panel A: Change in firm performance and distancing by sector

NAICS (2d)	NAICS (3d)	Sub sector	Sector	Obs	Change in firm performance				Distancing
					Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	
11	113-115	3	Agriculture, Forestry, Fishing and Hunting	178	-0.042	-0.020	-3.054	-0.011	0.147
21	211-213	3	Mining, Quarrying, and Oil and Gas Extraction	1012	-0.060	-0.030	-2.146	0.004	0.196
22	221	1	Utilities	1013	-0.044	-0.003	1.548	0.002	0.200
23	236-238	3	Construction	1022	-0.065	-0.021	-1.966	0.002	0.164
31-33	311-339	20	Manufacturing	14504	-0.073	-0.006	1.188	0.002	0.100
42	423-425	3	Wholesale Trade	2039	-0.108	-0.009	-3.900	0.002	0.154
44-45	441-454	12	Retail Trade	978	-0.152	-0.020	1.016	0.007	0.642
48-49	481-493	9	Transportation and Warehousing	1038	-0.106	-0.050	1.427	0.003	0.134
51	511-519	6	Information	1683	-0.071	-0.022	-3.334	0.002	0.146
53	531-533	3	Real Estate and Rental and Leasing	1293	-0.029	-0.088	-0.952	0.005	0.216
54	541	1	Professional, Scientific, and Technical Services	2016	-0.091	-0.009	-2.038	-0.0001	0.120
56	561-562	2	Administrative and Support and Waste Management …	901	-0.150	-0.042	-6.801	0.008	0.264
61	611	1	Educational Services	126	-0.149	-0.056	-7.885	0.0004	0.190
62	621-624	4	Health Care and Social Assistance	298	-0.084	-0.018	-3.995	0.005	0.596
71	711-713	3	Arts, Entertainment, and Recreation	234	-0.200	-0.179	-14.364	0.003	0.405
72	721-722	2	Accommodation and Food Services	458	-0.239	-0.238	-17.783	0.011	0.440
81	811-813	3	Other Services (except Public Administration)	122	-0.119	-0.064	-11.221	0.005	0.351

Panel B: Summary statistics of main variables

Variable	Obs	Mean	Std	p25	Median	p75	Min	Max
Change in firm performance ($\Delta y_{ic,COVID}$)								
Δ(SaleA)	28915	-0.08	0.25	-0.16	-0.05	0.02	-1.15	0.68
sectors more pandemic prone	13694	-0.10	0.27	-0.17	-0.05	0.01	-1.15	0.68
sectors less pandemic prone	15221	-0.07	0.22	-0.15	-0.05	0.03	-1.15	0.68
Δ(ProfM)	26993	-0.02	0.17	-0.05	-0.001	0.03	-0.76	0.56
sectors more pandemic prone	12484	-0.04	0.20	-0.07	-0.01	0.03	-0.76	0.56
sectors less pandemic prone	14509	-0.01	0.15	-0.04	-0.01	0.04	-0.76	0.56
Δ(IntrC)	27845	-0.73	63.94	-4.55	0.02	4.62	-327.34	292.72
sectors more pandemic prone	13099	-3.29	61.04	-5.59	-0.33	3.17	-327.34	292.72
sectors less pandemic prone	14746	1.54	66.33	-3.76	0.39	5.92	-327.34	292.72
Δ(ProbD)	10023	0.002	0.04	-0.002	0.001	0.01	-0.16	0.18
sectors more pandemic prone	4748	0.004	0.03	-0.001	0.001	0.01	-0.16	0.18
sectors less pandemic prone	5275	0.001	0.04	-0.003	0.0003	0.01	-0.16	0.18
Pandemic-prone $_j$								
Distancing	79	0.16	0.13	0.09	0.11	0.16	0.04	0.9
Policy $_c$								
FisStim (% of GDP)	80	11.62	10.29	6.1	6.1	14.6	0	40.9
MP_BP (-1*basis pint/100)	80	0.71	1.09	0.15	0.3	1.15	-3	10
FXI	80	0.24	0.43	0	0	0	0	1
Controls ($X_{ic,Pre}$)								
Size (log)	28915	11.64	2.25	9.98	11.5	13.13	1.66	20.12
Age (log)	28915	3.17	0.77	2.71	3.09	3.66	0	5.9
CashA	28915	0.13	0.14	0.03	0.09	0.18	0	1
RD_A	28915	0.02	0.04	0	0	0.02	-0.18	1.27
Private (dummy)	28915	0.05	0.22	0	0	0	0	1
SaleA	28915	0.87	0.85	0.41	0.71	1.09	-0.62	30.13
ROA (%)	28915	2.70	13.62	0.31	3.84	8.31	-99.64	97.34
IntrC	28915	38.09	117.42	0.81	4.49	19.89	-99.83	999.84
EqitA	28915	0.49	0.37	0.35	0.52	0.68	-27.29	1

Table 2. Social distancing and firm performance during COVID-19

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_c + \emptyset.Distancing_j + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ and $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Covid\_Severity_c + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $Covid\_Severity_c$ is a proxy for severity of COVID-19 in country c, using the Oxford stringency index. $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) in Columns 5-8 at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Without interaction				Interacted with COVID-19 severity			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distancing_j	-0.122***	-0.124***	-1.190***	0.014*				
	(-6.499)	(-13.098)	(-8.142)	(1.900)				
Distancing_j x Covid_Severity_c					-0.002*	-0.002***	-0.015	0.001***
					(-1.771)	(-2.901)	(-1.427)	(3.334)
$\text{Controls}_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	0.019	-0.039***	0.365**	-0.016*	0.011	-0.061	-0.293	-0.025***
	(0.814)	(-3.009)	(2.561)	(-1.871)	(0.470)	(-1.327)	(-0.681)	(-2.744)
Sector FEs	N	N	N	N	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	28,915	26,993	27,841	10,023	28,860	26,941	27,791	10,023
Adj. R^2	0.154	0.096	0.080	0.024	0.175	0.142	0.093	0.035

Table 3. Social distancing and firm performance during COVID-19: Baseline results

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)
$Distancing_j$ x $FisStim_c$	0.003**	0.001**	0.030***	-0.001**
	(2.369)	(2.321)	(2.795)	(-2.500)
$Distancing_j$ x MP_BP_c	0.031*	0.023	0.169	-0.004
	(1.922)	(1.649)	(1.186)	(-0.813)
$Distancing_j$ x FXI_c	-0.011	0.026	0.736**	-0.010
	(-0.255)	(0.978)	(2.043)	(-1.518)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√
Constant	0.008	-0.067	-0.443	-0.022**
	(0.303)	(-1.446)	(-0.967)	(-2.493)
Sector FEs	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y
# Countries	80	80	80	80
# Sectors	79	79	79	79
N	28,915	26,993	27,841	10,023
Adj. R^2	0.175	0.142	0.093	0.035

Table 4. Addressing omitted variable bias

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \nabla.Z_{ijc,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. $Z_{ijc,Pre}$ is a vector of country-specific or sector-specific (interacted with Distancing or policy variables) new control variables. We include sector fixed effects (ϑ_j) at the three-digit NAICS level (or at the four-digit in Panel B) as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4A: Controlling for other (pre-crisis) country characteristics

	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)
$Distancing_j$ x $FisStim_c$	0.004**	0.002**	0.032***	-0.001**
	(2.128)	(2.176)	(3.642)	(-2.182)
$Distancing_j$ x MP_BP_c	0.037***	0.019	0.182	-0.008**
	(2.753)	(1.245)	(1.424)	(-2.170)
$Distancing_j$ x FXI_c	-0.023	0.025	0.639*	-0.009
	(-0.484)	(0.797)	(1.723)	(-1.003)
Other country characteristics				
$Distancing_j$ x $HealE_c$	0.018	0.003	0.256	-0.007
	(0.612)	(0.106)	(1.028)	(-1.279)
$Distancing_j$ x FDI_c	-0.003**	-0.004	-0.037*	-0.000
	(-2.458)	(-1.471)	(-1.980)	(-0.768)
$Distancing_j$ x $Trade_c$	0.001**	0.000	0.004**	-0.000
	(2.050)	(1.359)	(2.074)	(-0.669)
$Distancing_j$ x NPL_c	0.003	-0.001	0.001	-0.003*
	(1.243)	(-0.324)	(0.075)	(-1.851)
$Distancing_j$ x $Inflation_c$	0.005	0.004	0.088	0.006**
	(1.225)	(1.176)	(1.002)	(2.545)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√
Constant	-0.050	-0.071	-1.090**	-0.020**
	(-1.610)	(-1.525)	(-2.387)	(-2.172)
Sector FEs	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y
# Countries	80	80	80	80
# Sectors	79	79	79	79
N	28,502	26,603	27,452	10,020
Adj. R^2	0.176	0.141	0.093	0.035

4B: Controlling for other sector characteristics (other possible channels)

	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)
$Distancing_j$ x $FisStim_c$	0.003***	0.002***	0.029**	-0.001**
	(3.827)	(2.902)	(2.177)	(-2.517)
$Distancing_j$ x MP_BP_c	0.033*	0.024*	0.232	-0.005
	(1.947)	(1.849)	(1.658)	(-0.987)
$Distancing_j$ x FXI_c	0.002	0.034	0.791**	-0.013*
	(0.049)	(1.295)	(2.147)	(-1.717)
Other sector characteristics				
$FinDep_j$ x $FisStim_c$	-0.000	-0.000**	-0.001*	-0.000
	(-0.381)	(-2.570)	(-1.683)	(-0.870)
$FinDep_j$ x MP_BP_c	0.002	-0.000	-0.002	-0.000
	(0.914)	(-0.522)	(-0.180)	(-0.834)
FinDepj x FXI_c	0.002	0.001	0.043	-0.000
	(0.580)	(0.348)	(1.507)	(-0.100)
$DemSen_j$ x $FisStim_c$	-0.001	0.002	-0.022*	0.000
	(-0.774)	(1.516)	(-1.786)	(0.720)
$DemSen_j$ x MP_BP_c	-0.022	0.008	-0.229	0.002
	(-1.042)	(0.421)	(-1.260)	(0.341)
$DemSen_j$ x FXI_c	-0.097**	-0.012	-0.114	0.005
	(-2.545)	(-0.298)	(-0.247)	(0.442)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√
Constant	-0.060*	-0.183***	-1.065***	0.019
	(-1.767)	(-6.585)	(-4.419)	(1.031)
Sector FEs (4-digit level)	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y
# Countries	80	80	80	80
# Sectors	79	79	79	79
N	25,954	24,237	24,999	9,042
Adj. R^2	0.174	0.156	0.099	0.032

4C: Controlling for other country and sector characteristics

	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)
Distancing_j x FisStim_c	0.004***	0.002**	0.023**	-0.001**
	(3.116)	(2.144)	(2.026)	(-2.485)
Distancing_j x MP_BP_c	0.035**	0.020	0.246*	-0.013***
	(2.403)	(1.288)	(1.670)	(-3.078)
Distancing_j x FXI_c	0.001	0.042	0.894**	-0.013
	(0.015)	(1.337)	(2.157)	(-1.317)
Other country characteristics				
Distancing_j x HealE_c	-0.000	-0.000**	-0.001	-0.000
	(-0.445)	(-2.582)	(-1.523)	(-0.881)
Distancing_j x FDI_c	0.002	-0.001	-0.001	-0.000
	(0.901)	(-0.982)	(-0.098)	(-0.816)
Distancing_j x Trade_c	0.002	0.001	0.032	-0.000
	(0.658)	(0.320)	(1.074)	(-0.132)
Distancing_j x NPL_c	-0.001	0.002	-0.023*	0.000
	(-0.784)	(1.576)	(-1.850)	(0.703)
Distancing_j x Inflation_c	-0.014	0.008	-0.166	0.002
	(-0.619)	(0.353)	(-0.834)	(0.306)
Other sector characteristics	-0.098**	-0.028	-0.138	0.004
FinDep_j x FisStim_c	(-2.613)	(-0.686)	(-0.291)	(0.369)
FinDep_j x MP_BP_c	0.022	0.014	0.435	-0.009
	(0.668)	(0.511)	(1.641)	(-1.660)
FinDepj x FXI_c	-0.004***	-0.004	-0.042	-0.000
	(-2.844)	(-1.151)	(-1.494)	(-0.577)
DemSen_j x FisStim_c	0.001*	0.000	0.003	-0.000
	(1.815)	(0.982)	(1.228)	(-0.420)
DemSen_j x MP_BP_c	0.004	-0.002	-0.008	-0.003
	(1.500)	(-0.644)	(-0.408)	(-1.474)
DemSen_j x FXI_c	0.001	0.003	0.027	0.008***
	(0.291)	(0.822)	(0.322)	(3.045)
$\text{Controls}_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√
Constant	-0.145**	-0.199***	-2.160***	0.028
	(-2.541)	(-4.552)	(-4.890)	(1.482)
Sector FEs (4-digit level)	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y
# Countries	80	80	80	80
# Sectors	79	79	79	79
N	25,581	23,884	24,648	9,039
Adj. R^2	0.174	0.155	0.098	0.033

4D: Coefficient stability - test for omitted variable bias.

This table reports the results of the coefficient stability test of Oster (2019). $\emptyset$ is the coefficient of the policy variable, the one that is statistically significant in Table 3, along with the associated R-squared, obtained by estimating Eq. (1) in a restricted version (omitting all country-level and industry-level control variables) and in a full model (as presented in Table 4C). The Oster Delta statistic represents the degree of selection on unobserved variables relative to that on observed variables, where we set $R^{max} = 1.3 * R^{full}$. Note that R^{max} is described as the R-squared for a speculative regression that contains unobserved confounders.

	from restricted model (Table 3)				from full model (Table 4C)				Oster Delta			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Distancing_j$ x $FisStim_c$	0.0034	0.0014	0.0296	-0.0008	0.0035	0.0017	0.0227	-0.0006	-2.54	-2.16	1.01	-6.88
$Distancing_j$ x MP_BP_c	0.0314				0.0348				-0.67			
$Distancing_j$ x FXI_c			0.7362				0.8935				-1.74	
R^2	0.180	0.147	0.099	0.047	0.184	0.166	0.109	0.031				

Table 5. Addressing reverse causality

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Removing top 3 pandemic-prone sectors				Removing large firms				Removing countries with a high share of pandemic-prone sectors to GDP			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Distancing_j$ x $FisStim_c$	0.003*	0.002**	0.027***	-0.001**	0.003**	0.001**	0.031***	-0.001**	0.004**	0.001**	0.035***	-0.001***
	(1.794)	(2.561)	(2.692)	(-2.517)	(2.400)	(2.318)	(2.978)	(-2.513)	(2.571)	(2.025)	(4.473)	(-5.276)
$Distancing_j$ x MP_BP_c	0.033*	0.028*	0.193	-0.001	0.032*	0.023	0.171	-0.004	0.035*	0.029**	0.122	-0.007
	(1.761)	(1.981)	(1.391)	(-0.279)	(1.986)	(1.655)	(1.200)	(-0.826)	(1.810)	(2.064)	(0.864)	(-1.098)
$Distancing_j$ x FXI_c	-0.025	0.028	0.794**	-0.016**	-0.010	0.027	0.749**	-0.010	-0.001	0.019	1.302***	-0.015*
	(-0.572)	(1.000)	(2.010)	(-2.100)	(-0.243)	(0.995)	(2.076)	(-1.549)	(-0.014)	(0.636)	(4.523)	(-1.786)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√	√	√	√	√
Constant	0.011	-0.066	-0.451	-0.022**	0.006	-0.067	-0.434	-0.022**	0.021	-0.067	-0.629	-0.004
	(0.391)	(-1.415)	(-0.989)	(-2.570)	(0.214)	(-1.442)	(-0.950)	(-2.572)	(0.719)	(-1.428)	(-1.398)	(-0.445)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80	63	63	63	63
# Sectors	76	76	76	76	79	79	79	79	79	79	79	79
N	28,775	26,858	27,709	9,950	28,825	26,904	27,751	9,980	24,246	22,867	23,308	7,632
Adj. R^2	0.173	0.142	0.093	0.035	0.175	0.142	0.093	0.035	0.169	0.135	0.088	0.039

Table 6. IV strategy

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta ProbD)$]. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using IV approach where instrument variables are the policy shocks and a proxy for institutional quality. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.005***	0.001*	0.040**	-0.001***	0.005***	0.001	0.040**	-0.001***
	(3.351)	(1.647)	(2.278)	(-5.002)	(3.215)	(0.776)	(2.235)	(-4.358)
$Distancing_j$ x MP_BP_c	0.058**	0.014	0.210	-0.024*	0.070	0.051	0.379	-0.026*
	(2.443)	(0.604)	(0.704)	(-1.737)	(1.313)	(1.215)	(0.891)	(-1.807)
$Distancing_j$ x FXI_c					-0.034	-0.096	-0.368	0.008
					(-0.265)	(-0.952)	(-0.481)	(0.519)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	0.019	-0.075	-0.381	-0.008	0.026	-0.053	-0.355	-0.008
	(0.539)	(-1.327)	(-0.599)	(-1.000)	(0.560)	(-0.918)	(-0.556)	(-0.928)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	45	45	46	47	44	44	44	44
# Sectors	79	79	79	79	79	79	79	79
N	24,876	23,223	23,968	8,886	24,182	22,609	23,289	8,863
Adj. R^2	0.171	0.138	0.091	0.034	0.165	0.136	0.089	0.034
F-value (first stage)								
FisStim	8.12***	8.63***	7.80***	14.08***	6.02***	6.46***	5.76***	14.44***
MP_BP	3.31**	3.21**	3.31**	4.61***	3.20**	3.19**	3.16**	3.57**
FXI					6.37***	6.29***	6.38***	4.14***
Instruments relevance (LM χ2)	7.84**	7.51**	7.82**	3.32	6.83**	6.50**	6.77**	3.51
J-statistics (p-value)	0.97	0.15	0.40	0.57	0.54	0.27	0.66	0.73

Table 7. Other sensitivity tests

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset. Distancing_j \times Policy_c + \tau. X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic (labeled "overall") from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

7A: Robust to alternative distancing proxy

	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)
$Distancing_j$ x $FisStim_c$	0.002	0.001***	0.029***	-0.001*
	(1.546)	(2.813)	(2.737)	(-1.728)
$Distancing_j$ x MP_BP_c	0.023**	0.013**	0.190*	0.000
	(2.428)	(2.072)	(1.897)	(0.046)
$Distancing_j$ x FXI_c	-0.013	0.012	0.392	-0.007
	(-0.498)	(0.767)	(1.553)	(-0.926)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√
Constant	0.006	-0.071	-0.485	-0.021**
	(0.231)	(-1.499)	(-1.032)	(-2.298)
Sector FEs	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y
# Countries	80	80	80	80
# Sectors	79	79	79	79
N	28,915	26,993	27,841	10,023
Adj. R^2	0.175	0.142	0.093	0.034

7B: Robust to WLS estimation and to excluding critical sectors

	Weighted Least Square (WLS)				Excluding 36 critical sectors			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.003***	0.001**	0.025**	-0.001***	0.003**	0.001*	0.0001	-0.001***
	(3.043)	(2.058)	(2.387)	(-2.984)	(2.330)	(1.939)	(0.016)	(-3.096)
$Distancing_j$ x MP_BP_c	0.022**	0.024**	0.077	-0.002	0.049**	0.029*	0.168	-0.006
	(1.976)	(2.513)	(0.724)	(-0.568)	(2.184)	(1.676)	(0.845)	(-0.975)
$Distancing_j$ x FXI_c	-0.016	0.024	0.613**	-0.013*	-0.003	0.030	0.652*	-0.022***
	(-0.586)	(1.162)	(2.126)	(-1.738)	(-0.053)	(0.853)	(1.689)	(-2.782)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	-0.022	-0.065***	0.022	-0.016	-0.022	-0.034	-0.150	-0.027***
	(-0.971)	(-3.578)	(0.089)	(-0.441)	(-0.704)	(-0.671)	(-0.304)	(-3.023)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	43	43	43	43
N	28,915	26,993	27,841	10,023	21,343	19,924	20,533	7,358
Adj. R^2	0.179	0.138	0.099	0.046	0.189	0.157	0.099	0.039

7C: Robust to other (pre-crisis) firm characteristics

	Controlling for firm efficiency and investment opportunities				Controlling for firm growth opportunities			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.004**	0.001**	0.028***	-0.001**	0.004**	0.002**	0.023**	-0.001**
	(2.591)	(2.039)	(2.778)	(-2.356)	(2.309)	(2.121)	(2.307)	(-2.585)
$Distancing_j$ x MP_BP_c	0.031*	0.020	0.123	-0.004	0.030	0.024	0.039	-0.005
	(1.835)	(1.430)	(0.857)	(-0.762)	(1.372)	(1.582)	(0.263)	(-0.812)
$Distancing_j$ x FXI_c	-0.002	0.022	0.678*	-0.010	0.013	0.022	0.674*	-0.009
	(-0.039)	(0.841)	(1.917)	(-1.433)	(0.286)	(0.856)	(1.779)	(-1.425)
Other firm characteristics (OverA, CashFlowA)	Y	Y	Y	Y	Y	Y	Y	Y
(Tobin's Q)	N	N	N	N	Y	Y	Y	Y
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	0.043	-0.070	-0.439	-0.020**	0.025	-0.149**	-0.777	-0.025**
	(1.425)	(-1.521)	(-0.959)	(-2.324)	(0.656)	(-2.629)	(-1.378)	(-2.618)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	28,335	26,519	27,310	9,942	18,320	17,076	17,811	9,562
Adj. R^2	0.183	0.145	0.096	0.035	0.193	0.171	0.099	0.038

7D: Robust to alternative policy stimulus databases

	Alternative policy stimulus databases: Policy response to COVID-19 in Asia and Pacific				Alternative policy stimulus databases: Yale dataset			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.004***	0.001*	0.024**	-0.001***	0.0003***	0.00002	0.001	-0.00004*
	(4.520)	(1.827)	(2.715)	(-4.720)	(4.080)	(0.454)	(0.716)	(-1.733)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	-0.061***	-0.084*	-1.157***	-0.023**	-0.001	-0.062	-0.341	-0.027***
	(-3.187)	(-1.829)	(-3.384)	(-2.919)	(-0.031)	(-1.378)	(-0.776)	(-2.898)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	22	22	22	22	60	60	60	60
# Sectors	79	79	79	79	79	79	79	79
N	20,900	19,844	20,070	8,482	25,528	23,846	24,565	9,736
Adj. R^2	0.165	0.121	0.090	0.035	0.176	0.141	0.094	0.028

Table 8. Heterogeneity in firms' size and financial positions entering the pandemic

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. Each panel displays the results obtained by running the regression in a subsample determined by the median value of various pre-crisis financial variables. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

8A: Size

	Size (<Mdn.)				Size (>Mdn.)			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.002	0.002	0.026	-0.001	0.004***	0.001	0.031***	-0.001***
	(1.020)	(1.446)	(1.507)	(-0.847)	(3.070)	(1.391)	(3.190)	(-3.379)
$Distancing_j$ x MP_BP_c	0.026	0.028***	0.108	-0.005	0.037**	0.023	0.253	-0.003
	(1.031)	(2.726)	(0.642)	(-0.688)	(2.127)	(1.024)	(1.412)	(-0.705)
$Distancing_j$ x FXI_c	-0.010	0.046	0.940**	-0.021**	-0.015	-0.002	0.418	0.003
	(-0.174)	(1.043)	(1.996)	(-2.040)	(-0.346)	(-0.037)	(1.271)	(0.321)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	-0.036	-0.095	-0.995**	-0.047***	0.033	-0.046	0.120	0.005
	(-0.577)	(-1.352)	(-2.203)	(-4.019)	(0.502)	(-0.777)	(0.159)	(0.708)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	14,440	13,237	13,630	2,361	14,475	13,756	14,211	7,662
Adj. R^2	0.155	0.122	0.096	0.080	0.231	0.183	0.091	0.045

8B: Cash holdings

	CashA (<Mdn.)				CashA (>Mdn.)			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.003	0.001	0.021*	-0.001**	0.004***	0.001	0.044***	-0.001***
	(1.016)	(1.362)	(1.937)	(-2.165)	(3.622)	(1.514)	(3.028)	(-2.793)
$Distancing_j$ x MP_BP_c	0.021	0.038**	0.178	-0.003	0.058**	-0.016	0.035	-0.005
	(1.077)	(2.535)	(1.053)	(-0.523)	(2.471)	(-0.763)	(0.136)	(-1.056)
$Distancing_j$ x FXI_c	0.009	-0.001	0.546	-0.018	-0.036	0.073*	0.892*	-0.001
	(0.217)	(-0.035)	(1.422)	(-1.533)	(-0.499)	(1.966)	(1.915)	(-0.128)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	0.080*	-0.103	-0.720	-0.037***	-0.155*	0.063	0.633*	0.005
	(1.774)	(-1.423)	(-1.089)	(-2.834)	(-1.803)	(0.866)	(1.670)	(0.284)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	14,446	13,162	14,065	3,903	14,469	13,831	13,776	6,120
Adj. R^2	0.168	0.158	0.088	0.059	0.181	0.134	0.100	0.012

8C: Profitability

	ROA (<Mdn.)				ROA (>Mdn.)			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.002	0.002	0.011	-0.001**	0.005***	0.001	0.046***	-0.0002
	(1.452)	(1.582)	(0.845)	(-2.703)	(2.666)	(1.216)	(3.536)	(-1.399)
$Distancing_j$ x MP_BP_c	0.031	0.027	0.010	-0.007	0.035	0.016	0.433**	-0.001
	(1.414)	(1.462)	(0.080)	(-0.721)	(1.198)	(1.223)	(2.171)	(-0.673)
$Distancing_j$ x FXI_c	0.010	0.014	0.661**	-0.019	-0.032	0.046	0.700	-0.003
	(0.240)	(0.342)	(2.389)	(-1.475)	(-0.526)	(1.498)	(1.248)	(-0.611)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	0.044	-0.021	0.020	-0.035***	0.046	-0.254**	-1.763**	-0.004
	(1.250)	(-0.399)	(0.045)	(-2.885)	(1.229)	(-2.553)	(-2.045)	(-0.634)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	14,471	12,929	13,904	4,798	14,444	14,064	13,937	5,225
Adj. R^2	0.162	0.158	0.095	0.052	0.190	0.140	0.097	0.040

8D: Leverage

	EqitA (<Mdn.)				EqitA (>Mdn.)			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Distancing_j$ x $FisStim_c$	0.002	0.000	0.003	-0.001**	0.007***	0.003***	0.090***	-0.001***
	(0.939)	(0.313)	(0.297)	(-2.128)	(8.007)	(2.933)	(4.885)	(-3.037)
$Distancing_j$ x MP_BP_c	0.028	0.018	0.020	0.003	0.054**	0.039**	0.526**	-0.009**
	(1.368)	(1.333)	(0.159)	(0.718)	(2.463)	(2.040)	(2.347)	(-2.086)
$Distancing_j$ x FXI_c	-0.030	0.003	0.758**	-0.016	0.012	0.031	0.431	-0.007*
	(-0.676)	(0.084)	(2.521)	(-1.214)	(0.200)	(1.061)	(0.685)	(-1.975)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	-0.026	-0.091	-0.628	-0.035***	0.056	-0.082	-0.708	0.004
	(-0.594)	(-1.389)	(-1.114)	(-4.121)	(0.751)	(-1.449)	(-0.732)	(0.622)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	14,708	13,739	14,467	4,913	14,207	13,254	13,374	5,110
Adj. R^2	0.179	0.166	0.095	0.052	0.181	0.128	0.100	0.021

Appendix

Table A1. Variable definitions and sources

Variable	Definition	Source
Change in firm performance ($\Delta y_{ic,COVID}$)		
Δ(SaleA)	The change in a bank sale to asset ratio (SaleA) between 2019 and 2020, calculated as Δ(SaleA)=(SaleA20-SaleA19). SaleA is an asset turnover ratio, which measures the efficiency of a company's assets to generate revenue or sales.	Bureau van Dijk, ORBIS, and own calculation.
Δ(ProfM)	The change in a bank profit margin (ProfM) between 2019 and 2020, calculated as Δ(ProfM)=(ProfM20-ProfM19). Profit margin is a measure of profitability where it is calculated as the net profit as a share of the revenue.	"
Δ(IntrC)	The change in a bank interest coverage ratio (IntrC) between 2019 and 2020, calculated as Δ(IntrC)=(IntrC20-IntrC19). Interest coverage ratio is a company's ability to meet its debt obligations. The interest coverage ratio is calculated by dividing a company's earnings before interest and taxes by its interest expense.	"
Δ(ProbD)	The change in indicator of probability of default (ProbD) between Dec. 2019 and Dec. 2020. ProbD reflects the default risk of publicly listed firms by quantitatively analyzing numerous covariates that cover market-based and accounting-based firm-specific attributes, as well as macro-financial factors. We use a prediction for horizon of 1 month. Higher figures denote higher risk.	Credit Research Initiative – CRI, National University of Singapore.
Pandemic-prone $_j$		
Distancing	Kóren and Petö' (2020) sectoral pandemic-prone proxy, using data from O*NETZ. It represents share of worker whose job requires a high level of teamwork and customer contact. Kóren and Petö document that US industries are different when it comes to reliance on teamwork and customer contact in their operations. This proxy suggests that firms in economic sectors with a high degree of such pandemic-prone proxy are particularly vulnerable to social distancing.	Kóren and Petö (2020)
Policy $_c$		
FisStim	Fiscal policy: Cumulative fiscal stimulus package (% of GDP) from January to December 2020 (week 1 to week 43).	IMF, and own calculation.
MP_BP	Monetary policy: cumulative change in basis points from January to December 2020 times (-1) divided by 100.	"
FXI	Foreign exchange intervention (0=No, 1=Yes): cumulative from January to December 2020.	"
Controls $_{ic,pre}$		
Size	Natural logarithm of a firm total assets in 2019.	Bureau van Dijk, ORBIS, and own calculation.
Age	Firm age measured by logarithm of subtracting the firm's year of incorporation from year 2020.	"
CashA	Firm cash assets to total assets ratio in 2019.	"
RD_A	Research and development expenditure divided by total assets in 2019.	"
Private (dummy)	A dummy variable that takes value 1 if the firm is a private firm, and 0 otherwise.	"
SaleA	Firm sales to total assets ratio in 2019.	"
ROA	Return on assets, which is defined as profit before tax as a percentage of average assets of a bank, in 2019.	"

Table A1: Continued …

IntrC	Interest coverage ratio is earnings before interest and taxes (EBIT) to interest expenses ratio in 2019. It determines how easily a company can pay interest on its outstanding debt.	"
EqitA	The ratio of shareholder fund (equity) to total assets of a firm in 2019.	"
Other variables		
Covid_Severity	The country-level severity of the lockdown measures in response to the pandemic. This is a composite measure of the scale of school closures, workplace closures and travel bans based on the data on the 31st December 2020. The indicator is normalised to be from 0 to 100 with the score100 being the strictest.	Hale et al. (2020).
HealE	Current private expenditures on health per capita expressed in international dollars at purchasing power parity in year 2019.	World Bank - WDI.
FDI	Foreign direct investment, which refers to direct investment equity flows in the reporting economy, as % of GDP in year 2019.	"
Trade	Total exports and imports as % of GDP in year 2019.	"
NPL	The ratio of a country bank nonperforming loans to total gross loans in year 2019.	"
Inflation	Inflation, measured by consumer price index, which is defined as the yearly change in the prices of a basket of goods and services in year 2019.	"
FinDep	External financial dependence of U.S. firms by 3-digit SIC codes. This is an industry-level median of the ratio of capital expenditures minus cash flow over capital expenditures. Cash flow is defined as the sum of funds from operations, decreases in inventories, decreases in receivables, and increases in payables. Capital expenditures include net acquisitions of fixed assets. Source: Rajan and Zingales (1998).	Tong and Wei (2008).
DemSen	Demand sensitivity is a sector-level index on the sensitivity to demand shocks, based on stocks' response to the 9/11/2001 shock.	"
OverA	The ratio of a company's overheads cost (other operating expenses) to its total assets in year 2019.	Bureau van Dijk, ORBIS, and own calculation.
CashFlowA	The ratio of a company's cash flow to its total assets in year 2019.	"
Tobin's Q	Total market value of common equity divided by total book value of assets in year 2019.	"

Table A2: Number of firms by country

ID	Country	Number of firms	ID	Country	Number of firms
1	Argentina	124	41	Malta	26
2	Australia	625	42	Mauritius	40
3	Austria	45	43	Mexico	109
4	Bangladesh	184	44	Mongolia	19
5	Belgium	99	45	Morocco	45
6	Bolivia	24	46	Netherlands	94
7	Bosnia and Herzegovina	84	47	New Zealand	95
8	Brazil	343	48	Nigeria	82
9	Bulgaria	82	49	North Macedonia	55
10	Canada	660	50	Norway	157
11	Chile	173	51	Oman	58
12	China	9804	52	Pakistan	303
13	Colombia	45	53	Panama	47
14	Côte d'Ivoire	21	54	Paraguay	24
15	Croatia	75	55	Peru	95
16	Cyprus	44	56	Philippines	160
17	Denmark	113	57	Poland	469
18	Ecuador	127	58	Portugal	37
19	Egypt	110	59	Qatar	20
20	Finland	129	60	Republic of Korea	1350
21	France	468	61	Romania	196
22	Germany	436	62	Russia	481
23	Greece	128	63	Saudi Arabia	112
24	Hong Kong	139	64	Serbia	147
25	Hungary	21	65	Singapore	426
26	India	1057	66	Slovakia	26
27	Indonesia	533	67	South Africa	146
28	Ireland	52	68	Spain	204
29	Iran	196	69	Sri Lanka	103
30	Israel	264	70	Sweden	549
31	Italy	271	71	Switzerland	148
32	Jamaica	40	72	Thailand	572
33	Japan	2724	73	Tunisia	35
34	Jordan	63	74	Turkey	171
35	Kazakhstan	48	75	Ukraine	129
36	Kenya	27	76	UAE	50
37	Kuwait	65	77	United Kingdom	694
38	Lithuania	20	78	Uzbekistan	82
39	Luxembourg	46	79	Vietnam	1134
40	Malaysia	694	80	Zimbabwe	22
				All	28915

Table A3. Social distancing and firm performance during COVID-19

This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \emptyset.Policy_c + \tau.X_{ic,Pre} + \nabla.Z_{c,Pre} + \varepsilon_{ic,COVID}$ and $\Delta y_{ic,COVID} = \vartheta_j + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \nabla.Z_{c,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in asset turnover ratio [$\Delta(SaleA)$], change in profit margin [$\Delta(ProfM)$], change in interest coverage ratio [$\Delta(IntrC)$], and change in probability of default [$\Delta(ProbD)$]. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $Policy_c$ is a vector of variables represent government stimulus packages in country c. $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. $Z_{ic,Pre}$ is a vector of country-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Without interaction				Interacted with distancing			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FisStim_c$	-0.001*	0.0001	-0.003	-0.0004***	-0.001***	-0.0002	-0.008**	-0.0002*
	(-1.744)	(0.426)	(-1.026)	(-2.832)	(-2.799)	(-0.769)	(-2.419)	(-1.862)
MP_BP_c	0.003	-0.004	-0.031	0.000	-0.003	-0.009**	-0.074	0.001
	(0.954)	(-1.326)	(-0.941)	(0.343)	(-0.594)	(-2.128)	(-1.544)	(0.850)
FXI_c	0.005	0.001	0.044	-0.001	0.011*	-0.000	-0.026	0.001
	(0.543)	(0.106)	(0.719)	(-0.628)	(1.677)	(-0.057)	(-0.327)	(0.258)
$Distancing_j$ x $FisStim_c$					0.004**	0.002***	0.031***	-0.001***
					(2.405)	(2.905)	(3.193)	(-2.875)
$Distancing_j$ x MP_BP_c					0.036**	0.030**	0.277*	-0.004
					(2.361)	(2.043)	(1.808)	(-0.845)
$Distancing_j$ x FXI_c					-0.041	0.009	0.476	-0.013**
					(-1.064)	(0.315)	(1.426)	(-2.114)
$Controls_{c,pre}$ (FDI, Trade, NPL, Covid_Severity, HDI, LOG_GDP)	√	√	√	√	√	√	√	√
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√
Constant	-0.182**	0.065	-1.274	-0.113***	-0.167*	0.072	-1.190	-0.118***
	(-2.147)	(0.802)	(-1.487)	(-3.833)	(-1.979)	(0.882)	(-1.388)	(-4.017)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	N	N	N	N	N	N	N	N
# Countries	80	80	80	80	80	80	80	80
# Sectors	79	79	79	79	79	79	79	79
N	28,860	26,941	27,791	10,023	28,860	26,941	27,791	10,023
Adj. R^2	0.168	0.131	0.089	0.028	0.169	0.132	0.089	0.029

Table A4. Social distancing and real firm performance during COVID-19

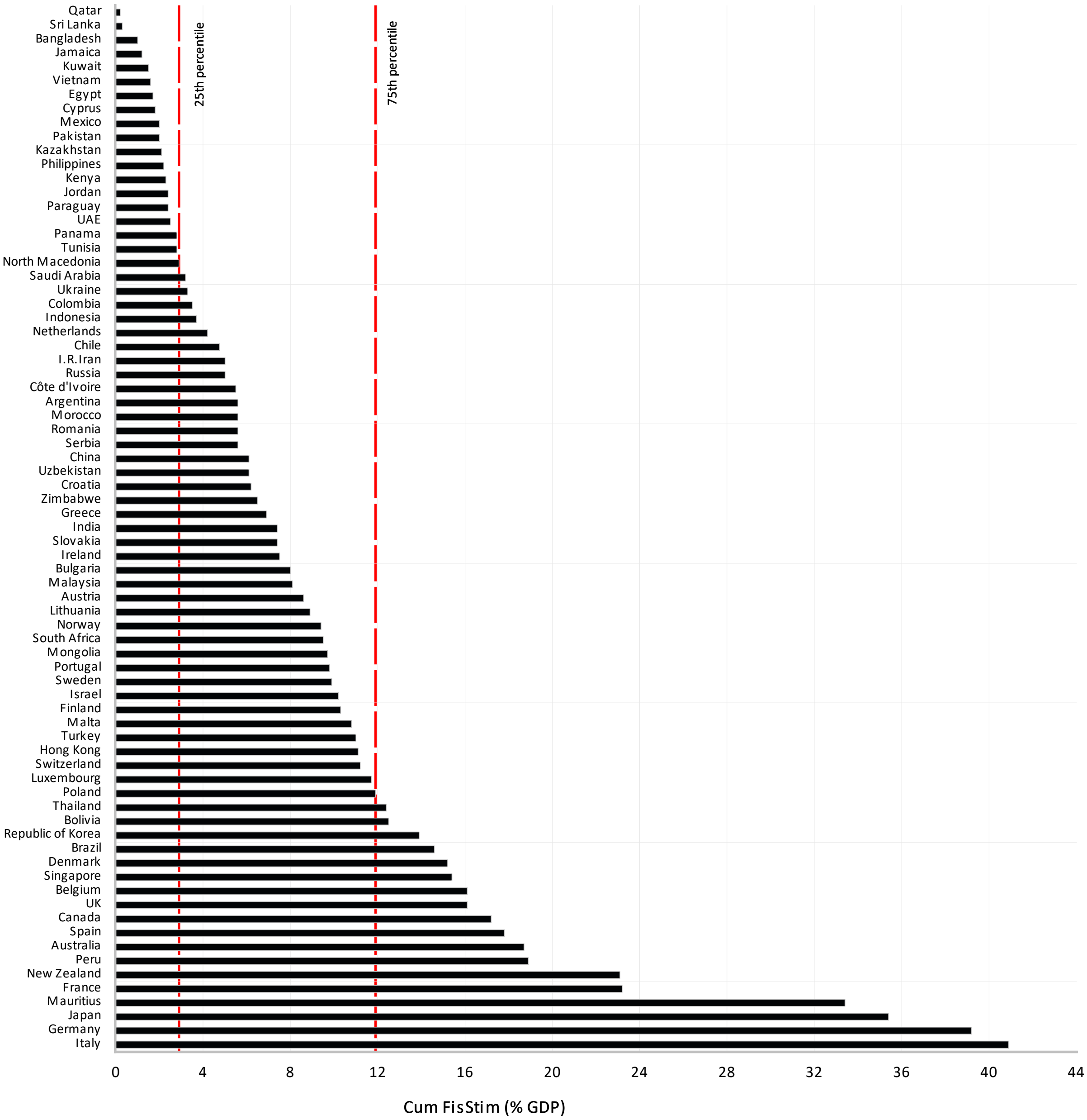
This table reports the results estimating $\Delta y_{ic,COVID} = \vartheta_j + \vartheta_c + \emptyset.Distancing_j \times Policy_c + \tau.X_{ic,Pre} + \varepsilon_{ic,COVID}$ where i stands for firm, j for sector, and c for country. $\Delta y_{ic,COVID}$ is the change in real performance ratios for firm i in country c between 2020 and 2019. We use, alternatively, change in number of employees [$\Delta(NumbE)$] and change in valued added [$\Delta(ValuA)$]. Value added is computed as the sum of earnings before taxes, depreciation and labor expense. $Policy_c$ is a vector of variables represent government stimulus packages in country c. $Distancing_j$ is industry j's degree of sensitivity to a pandemic from Kóren and Petö (2020). $X_{ic,Pre}$ is a vector of firm-level explanatory variables, computed as of 2019. We include sector fixed effects (ϑ_j) at the three-digit NAICS level as well as country fixed effects (ϑ_c) in all regressions. See Appendix, Table A1 for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on clustered standard errors at the country level (associated t-values reported in parentheses). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Number of Employees Δ(NumbE)	Value Added Δ(ValuA)
	(1)	(2)
$Distancing_j$ x $FisStim_c$	0.111***	0.192***
	(5.761)	(2.969)
$Distancing_j$ x MP_BP_c	0.015	0.264
	(0.042)	(0.436)
$Distancing_j$ x FXI_c	0.111	-1.486
	(0.222)	(-1.068)
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√
Constant	4.170***	0.618
	(4.578)	(0.300)
Sector FEs	Y	Y
Country FEs	Y	Y
# Countries	80	80
# Sectors	79	79
N	20,793	13,090
Adj. R^2	0.085	0.123

Table A5. Other robustness tests

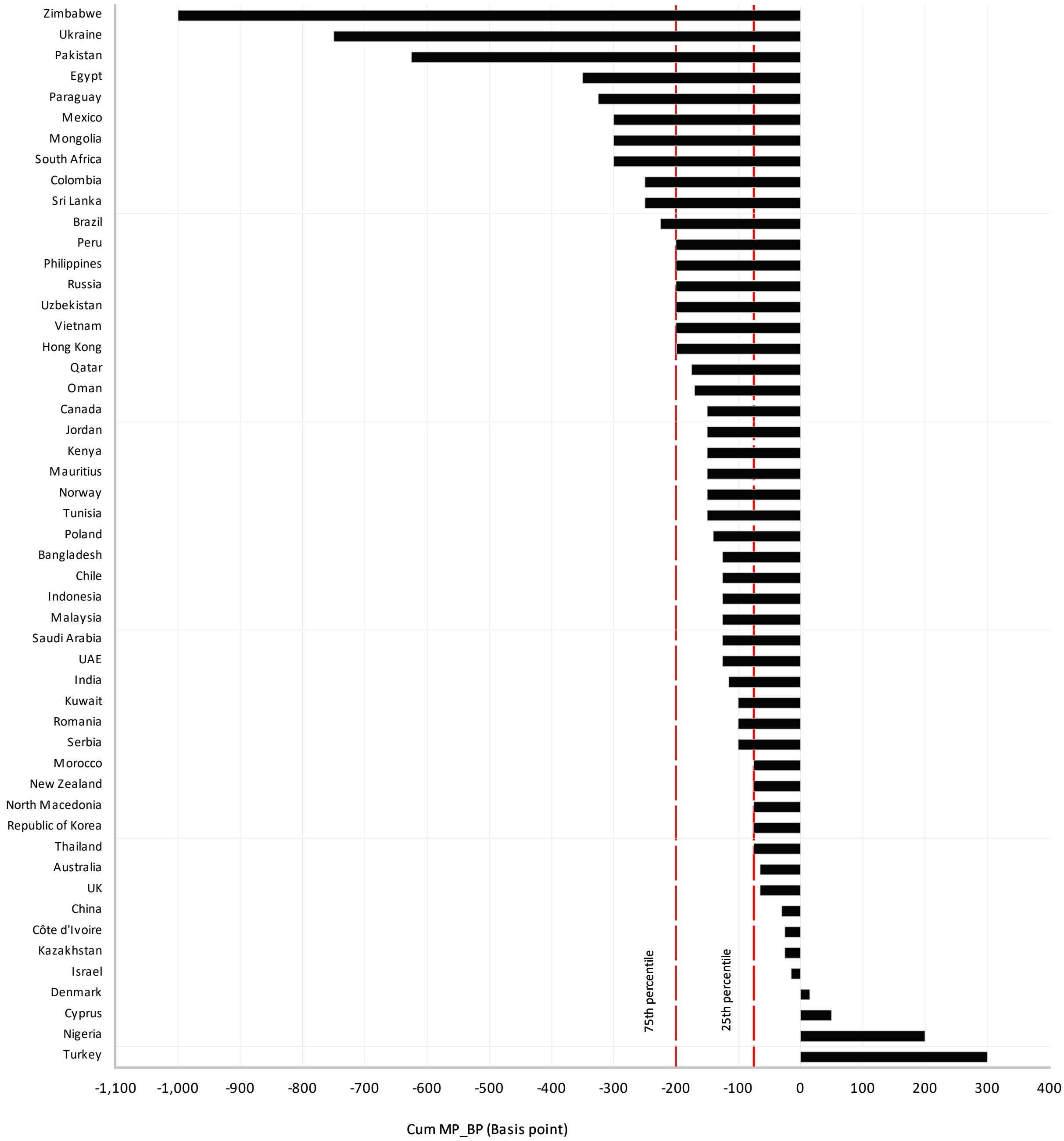
	Baseline results for restricted dataset				External finance dependence at the NAICS 3-digit level				Baseline results with the US data			
	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)	Δ(SaleA)	Δ(ProfM)	Δ(IntrC)	Δ(ProbD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Distancing_j$ x $FisStim_c$	0.007***	0.001	0.034***	-0.001**	0.003**	0.002**	0.041***	-0.001*	0.003**	0.001**	0.029***	-0.001**
	(6.368)	(1.552)	(3.039)	(-2.660)	(2.224)	(2.522)	(3.914)	(-1.937)	(2.294)	(2.109)	(2.648)	(-2.535)
$Distancing_j$ x MP_BP_c	0.033	0.010	0.311	-0.004	0.015	0.027*	0.208	-0.002	0.029*	0.020	0.184	-0.005
	(1.026)	(0.310)	(1.477)	(-0.864)	(0.923)	(1.665)	(1.258)	(-0.556)	(1.814)	(1.435)	(1.302)	(-1.036)
$Distancing_j$ x FXI_c	-0.070	-0.012	0.081	-0.008	-0.005	0.028	0.848**	-0.003	-0.007	0.031	0.724**	-0.008
	(-1.069)	(-0.354)	(0.095)	(-1.205)	(-0.131)	(1.000)	(2.104)	(-0.446)	(-0.170)	(1.159)	(2.026)	(-1.303)
Other sector characteristics												
$FinDep_j$ x $FisStim_c$					-0.000	-0.000	-0.000	0.000				
					(-1.342)	(-1.144)	(-0.615)	(0.209)				
$FinDep_j$ x MP_BP_c					0.001**	0.001**	0.014**	-0.000				
					(2.198)	(2.138)	(2.387)	(-0.517)				
FinDepj x FXI_c					0.001	0.000	-0.003	-0.000				
					(0.839)	(0.391)	(-0.192)	(-0.198)				
$Controls_{ic,pre}$ (Size, Age, CashA, RD_A, Private, SaleA, ROA, IntrC, EqitA)	√	√	√	√	√	√	√	√	√	√	√	√
Constant	-0.015	-0.021	-0.530	-0.015*	-0.037	-0.162***	-1.017***	0.018	0.003	-0.071	-0.439	-0.021**
	(-0.331)	(-0.328)	(-0.788)	(-1.944)	(-1.059)	(-5.851)	(-4.004)	(1.064)	(0.111)	(-1.530)	(-0.969)	(-2.547)
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	80	80	80	80	80	80	80	80	81	81	81	81
# Sectors	79	79	79	79	79	79	79	79	79	79	79	79
N	9,200	9,200	9,200	9,200	25,571	23,832	24,642	8,929	29,964	27,890	28,830	10,857
Adj. R^2	0.200	0.177	0.100	0.028	0.168	0.143	0.088	0.031	0.177	0.141	0.091	0.037

Figure 1a. Cumulative fiscal stimulus (% of GDP) from January to December 2020 by country



Sources: IMF and own calculations.

Figure 1b. Cumulative of change in monetary policy (basis point) from January to December 2020 by country



Sources: IMF and own calculations.

Previous volumes in this series

1013 May 2022	Banking in the shadow of Bitcoin? The institutional adoption of cryptocurrencies	Raphael Auer, Marc Farag, Ulf Lewrick, Lovrenc Orazem and Markus Zoss
1012 May 2022	It takes two: Fiscal and monetary policy in Mexico	Ana Aguilar, Carlos Cantú and Claudia Ramírez
1011 May 2022	Big techs, QR code payments and financial inclusion	Thorsten Beck, Leonardo Gambacorta, Yiping Huang, Zhenhua Li and Han Qiu
1010 March 2022	Financial openness and inequality	Tsvetana Spasova and Stefan Avdjiev
1009 March 2022	Quantitative forward guidance through interest rate projections	Boris Hofmann and Fan Dora Xia
1008 March 2022	Deconstructing ESG scores: How to invest with your own criteria	Torsten Ehlers, Ulrike Elsenhuber, Anandakumar Jegarasasingam and Eric Jondeau
1007 March 2022	Cross-border regulatory spillovers and macroprudential policy coordination	Pierre-Richard Agénor, Timothy P Jackson and Luiz A Pereira da Silva
1006 February 2022	Estimating conditional treatment effects of EIB lending to SMEs in Europe	Alessandro Barbera, Aron Gereben and Marcin Wolski
1005 February 2022	The NAIRU and informality in the Mexican labor market	Ana María Aguilar-Argaez, Carlo Alcaraz, Claudia Ramírez and Cid Alonso Rodríguez-Pérez
1004 February 2022	Original sin redux: a model-based evaluation	Boris Hofmann, Nikhil Patel and Steve Pak Yeung Wu
1003 February 2022	Global production linkages and stock market co-movement	Raphael Auer, Bruce Muneaki Iwadate, Andreas Schrimpf and Alexander Wagner
1002 February 2022	Exorbitant privilege? Quantitative easing and the bond market subsidy of prospective fallen angels	Viral V Acharya, Ryan Banerjee, Matteo Crosignani, Tim Eisert and Renée Spigt
1001 February 2022	Unequal expenditure switching: Evidence from Switzerland	Raphael Auer, Ariel Burstein, Sarah Lein and Jonathan Vogel
1000 February 2022	Dollar beta and stock returns	Valentina Bruno, Ilhyock Shim and Hyun Song Shin
999 February 2022	Shadow loans and regulatory arbitrage: evidence from China	Amanda Liu, Jing Liu and Ilhyock Shim

All volumes are available on our website www.bis.org.