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Global Corporate Stress Tests—Impact of the COVID-19 Pandemic and Policy Responses

By Thierry Tressel and Xiaodan Ding

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Global Corporate Stress Tests—Impact of the COVID-19 Pandemic and Policy Responses

by Thierry Tressel and Xiaodan Ding[1]

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Abstract

Corporate sector vulnerabilities have been a central policy topic since the outset of the COVID-19 pandemic. In this paper, we analyze some 17,000 publicly listed firms in a sample of 24 countries, and assess their ability to withstand shocks induced by the pandemic to their liquidity, viability and solvency. For this purpose, we develop novel multi-factor sensitivity analysis and dynamic scenario-based stress test techniques to assess the impact of shocks on firm's ability to service their debt, and on their liquidity and solvency positions. Applying the October 2020 WEO baseline and adverse scenarios, we find that a large share of publicly-listed firms become vulnerable as a result of the pandemic shock and additional borrowing needs to overcome cash shortfalls are large, while firm behavioral responses and policies substantially help overcome the impact of the shock in the near term. Looking forward, while interest coverage ratios tend to improve over time after the initial shock as earnings recover in line with projected macroeconomic conditions, liquidity needs remain substantial in many firms across countries and across industries, while insolvencies rise over time in specific industries. To inform policy debates, we offer an approach to a triage between viable and unviable firms, and find that the needs for liquidity support of viable firms remain important beyond 2020, and that medium-term debt restructuring needs and liquidations of firms may be substantial in the medium-term.

JEL Classification Numbers: G3, G21, G01, G17, E65

Keywords: Covid-19 pandemic, corporate sector vulnerabilities, stress tests, debt restructuring, viability of firms, solvency and liquidity support policies.

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I. INTRODUCTION

The ongoing Covid-19 pandemic has focused the attention of policy-makers on the acute risks to the balance sheets of the non-financial private sectors, and on the necessity of strong monetary, fiscal and regulatory policy responses to avoid an economic collapse, credit crunch and bankruptcies in the near term, and potential lasting scarring effects on economic structures. In this context, it is critical to assess the dynamic impact of the pandemic on the financial soundness of non-financial corporates (NFCs), in particular regarding risks and viability concerns that may emerge going forward. Fragilities of NFCs could reverberate in the financial system through waves of defaults which may in turn impede the intermediation capacity of banks and markets.

This paper assesses the stress to NFCs resulting from the Covid-19 pandemic and develops forward-looking stress test projections of its impact on individual firms' balance sheets. We construct a large panel dataset of more than 17,000 publicly listed companies in a group of 12 Advanced Economies (AEs) and 12 Emerging Markets (EMs) and covering the period 2003-2019. We first document vulnerabilities of NFCs at the end of 2019, based on a battery of indicators related to debt leverage, profitability, liquidity buffers, and capacity to service debt, and benchmark these indicators aggregated at the country level to their values at the peak of the Global Financial Crisis (GFC) in 2009. We find that, while there is substantial cross-country variability of corporate health indicators, NFCs in general displayed better ratios at the end of 2019. However, in several countries, publicly listed firms on average appear to be have been more vulnerable from a leverage and liquidity perspectives at the end of 2019 than they were in 2009. Hence, many publicly listed firms around the world entered the pandemic with already stretched balance sheets - a stylized fact that echoes the findings of Banerjee and Hofman (2020).

Next, we develop firm level stress testing models to assess the impact of pandemic shock on the balance sheet of NFCs. The models are organized in two modules. We make use of these tools to assess both the near-term impact and the medium-term impact of the pandemic on the financial health of publicly-listed NFCs to inform the policy debate.[2]

The first module is a *multi-factor sensitivity analysis tool* allowing to assess the short-term liquidity impact on individual firms of a variety of shocks, and flexible enough to allow for firm behavioral responses and policies. Several other examples of sensitivity analysis can be found in recent papers described in section II. Specifically, the tool generates the impact of shocks on the interest coverage ratio (henceforth ICR), and on the cash balance of individual firms, and allows various policy analysis. The key difference between the ICR indicator and the cash balance indicator is that the latter approach allows to consider the use of cash buffers

[2] Our analysis relies upon pre-pandemic 2019 balance sheets and financial statements of firms. An interesting analysis left for future work would be to update our simulations with actual balance sheets for 2020 when they are fully available and more recent macroeconomic scenarios. While keeping in mind the caveat of model uncertainty, our simulations do not include the direct impact of policies on individual firms, only their indirect impact through macroeconomic variables. In contrast actual 2020 balance sheets will reflect the direct impact of policies.

that firms had in place before the shocks while the former assesses whether a firm's earnings are sufficient to cover interest charges.

With this sensitivity analysis tool at hand, we simulate the near-term impact on 2020 balance sheets and financial statements of shocks to sales caused by the pandemic. The shocks are calibrated by country and industry on the basis of the changes in annual sales forecasts by financial analysts between January 2020 and June 2020 and aggregated at the country-industry level. We allow for different behavioral responses of firms regarding the extent to which production costs are cut in response to the shocks. We find that the impact of the shocks to sales on the cash balance and capacity to service debt of firms are very substantial, even when firms can partially offset the shocks by cutting production costs (which could be achieved by laying-off workers, and/or by policies such as labor subsidies). As a result, both in AEs and in EMs, very high shares of firms see their interest-coverage-ratio (ICR) fall below one and have a cash deficit (in absence of additional borrowing), resulting in very high shares of debt at risk based on each of these two metrics.[3] We also perform several counterfactual illustrative policy analysis and find that policies that subsidize production costs and facilitate an increase in borrowing seem to be the most effective in alleviating liquidity shortfalls, while policies subsidizing borrowing costs and repayment moratoria have relatively smaller beneficial effects on liquidity needs (in absence of an increase in borrowing). Some caveats are in order. This illustrative analysis applies the same policies across countries, while in practice the intensity and duration of these policies varied across countries. Moreover, the sensitivity analysis focuses exclusively on the short-term impact of policies and does not include general equilibrium effects.[4]

The second module is a multi-year *dynamic scenario-based stress test tool* simulating over time the evolution of each firm's financial indicators, including their profitability, leverage, solvency, liquidity needs, and their ability to service their debt. The tool enhances significantly the existing literature which has usually simulated only one variable (the ICR, or a default rate), based on a regression analysis (see section II).[5] The tool is based on firm level OLS and Probit panel regressions that relate firm level indicators to past firm level structural and cyclical characteristics, industry fixed effects, and macro-financial conditions.[6] Regressions are to a large extent estimated country-by-country, hence ensuring that the estimated relationships between firm level indicators and macro-financial conditions are specific to each country, reflecting past statistical relationships.[7] The tool ensures consistency

[3] Debt at risk is defined as share of debt of firms below the required thresholds (either ICR below one or cash available below zero or solvency ratio below zero) out of total debt. Firm at risk is defined as share of number of firms below the required thresholds out of total number of firms.

[4] For example, while it may be optimal for individual firms to offset the impact of the shock by cutting costs and laying off workers, in the general equilibrium, such responses would cause an increase in employment and an additional decline in demand.

[5] An exception is Caceres et al. (2020) which jointly simulates liquidity and solvency ratios of US firms. However, Caceres et al. (2020) do not perform a triage of firms as we do for firms across 24 countries.

[6] Regressions pooling firms from various countries together also include country fixed effects.

[7] Stress testing models rely on parameters estimated econometrically. A potential caveat (to be explored in future research) would be that the COVID-19 pandemic caused a structural break in historical relationships.

across firm level indicators projected under a specific macroeconomic scenario, based on accounting identities. We also embody the possibility of an industry differentiation of shocks in each country, by making use of financial analysts' calendar year forecasts of earnings and sales of publicly listed firms, while ensuring country level consistency with the macroeconomic scenarios selected for the projections.

We make use of this novel dynamic stress testing tool and the published baseline projections and adverse scenarios of the October 2020 World Economic Outlook and Global Financial Stability Report to perform forward looking scenario-based stress test projections of NFCs' balance sheets and financial statements for the period 2020–2022.[8] We report the annual projections of three firm-level ratios, aggregated at country levels: the ICR, the cash balance at the end of the year (before any increase in debt), and the solvency position. The key findings are the following:

1. The share of firms (and the share of NFC debt) unable to meet interest payments from their earnings (e.g., an ICR below one) reach very high levels in 2020 and tends to decline relatively quickly in 2021 and 2022 in the baseline scenario, and at a somewhat slower pace in the adverse scenario, as earnings recover from the Covid shock in line with macroeconomic conditions. Firms in industries relatively more exposed to the pandemic are more likely to experience earning shortfalls to cover interest payments, and for a longer period of time.
2. The share of firms (or the share of debt) with cash balance shortfalls (in absence of additional borrowing) is even larger and also peaks to high levels in 2020, but it declines at a much slower pace over time than the share of firms (or of debt) with ICRs below one, even in the baseline scenario.[9] This implies that the need for additional borrowing to close the cash shortfall (which determines the debt dynamic) was very important during 2020 to avoid a liquidity crisis and would remain important even during the recovery period. Cash shortfalls tend to be relatively more widespread across industries than is the case with the ICR indicator, pointing at broad-based borrowing needs and exhaustion of cash buffers.
3. Solvency concerns tend to rise over time and tend to be very concentrated in specific industries very exposed to the pandemic shock.
4. Differences of results between the baseline scenario and the adverse scenario are not very large. This reflects the fact that the largest macroeconomic shock occurs in 2020 and is broadly the same across the two scenarios in all countries. Even if they can be notable in some countries, differences across scenarios in 2021 and 2022 are, in relative terms, much smaller on average than the 2020 shock itself.

[8] A caveat for the analysis in this paper is that the simulations are not updated with more recent forecasts. Such forecasts such as those of the Spring 2021 WEO are in general more optimistic on the speed of the recovery from the pandemic. Using these forecasts would result in more sanguine results. Moreover, our analysis does not include the direct impact of specific policies on individual firms.

[9] The findings reflect the fact that in the simulation, a very large share of firms will increase their borrowing as a result of the shock. The size of the liquidity needs, as a share of debt, are quantitively of the same order of magnitude as those found in the paper by Ebeke et al. (2021).

Third, we assess financial stability implications of the scenario-based forward-looking projected corporate vulnerabilities. For this purpose, we develop a methodology to construct firm level *probabilities of defaults* (PDs) from the vulnerability indicators, making use of past mapping between US firm's health indicators, their ratings and historical default frequencies. The firm level PDs are next aggregated at the country level based on each firms' debt stock. Next we perform two rescaling for each country: (i) to quantify default risks of publicly-listed firms and compare them across countries, we rescale the 2019 aggregated PD with each country's Moody's KMV one year forward Expected Default Frequencies (EDFs); (ii) to quantify default risks on bank exposures to NFCs, we rescale the 2019 value with PDs for bank loans obtained from publicly available sources or derived from NPL ratios. In the second case, we next multiply the PDs with total NFCs exposures of banking systems relative to Tier 1 capital to obtain estimates of the projected flows of new non-performing loans (NPLs) relative to bank capital. We find that, while there is important cross-country heterogeneity, the potential rise in NPLs as a share of bank capital would be important in general both in the baseline and the adverse scenario, but would decline over time broadly back to initial conditions at the end of 2019.

In the last part of the paper, we turn to a medium-term analysis to inform the policy debate regarding the triage of firms between viable and non-viable firms, the need for continued liquidity support, debt restructuring, and liquidation of firms. A firm is viable if it has the capacity to generate positive profits net of debt service (ICR>1) or has a high price-to-book ratio above the country average, under "normal economic conditions.[10] The assessment of a viable business model is based on the simplifying assumption that there will be a return to pre-pandemic "normal" (e.g., 2019) economic conditions. There is of course high uncertainty regarding the future economic structures in a post-pandemic world and addressing this question is beyond the scope of this paper. With this caveat in mind, firms are classified into: (i) "survivors" that generate positive profits net of debt service during the recovery from the pandemic (ICR>1); (ii) "viable" but distressed firms that have an ICR<1 during the recovery from the pandemic but that were viable or had a high price-to-book ratio pre-pandemic; and: (iii) "ghosts" that have an ICR below one during the recovery from the pandemic and also were already considered non-viable pre-pandemic.[11] We also offer a mapping between these categories of firms and potential policy actions regarding needs of liquidity support (needed both for "survivors" and "viable" firms), debt restructuring (required for "viable" firms), and liquidations (of "ghost" firms). Making use of our forward-looking stress test simulations, we offer quantifications of this triage of firms under the baseline and the adverse scenario. We show that, while by and large, firms will overcome the pandemic shock well under the scenarios considered, the stock of debt requiring some restructuring or among firms to be liquidated may be quantitatively significant in the medium-term. Moreover, needs for continued liquidity support, while declining, will remain very large in 2021 and 2022.

[10] The condition of a high price-to-book ratio (above country average) captures unicorn/growth firms which may have had low current profitability pre-pandemic, but are seen by the market as having high growth potential.

[11] Our estimates of the share of ghost firms is consistent with the findings of Banerjee and Hofmann (2020) who find that the share of zombie firms among publicly listed firms at the onset of the pandemic may have reached 15 percent.

The paper is organized as follows. Section II presents an overview of the literature. Section III offers descriptive statistics. The two modules of our stress testing tool are described in section IV. Section V conducts the sensitivity and policy analysis to assess the short-term liquidity impacts of the pandemic. In section VI, we present the regression results underlying the solvency and liquidity forward-looking stress tests, the two scenarios, and the results of the forward-looking stress tests including the impact on banking systems. Section VII is devoted to the viability triage of firms and medium-term policy analysis. Section VIII concludes.

II. LITERATURE

Our methodologies build on a growing literature that proposes various approaches to stress test NFCs. IMF (2019) develops a probabilistic scenario-based ICR-stress test model of non-financial corporates and applies it to a large sample of French large firms and SMEs, as well as to a cross-country sample of publicly listed firms. A similar approach applied to Korean firms can be found in IMF (2020a). Almeida and Tressel (2020) and Chow (2015) perform sensitivity analysis stress tests of non-financial corporates respectively among firms from AEs and among firms from large EMs, while Almeida and Tressel (202) also characterize the evolution and drivers of non-financial corporate debt in AEs after the Global Financial Crisis. Our paper builds upon and improves the techniques developed in these papers which typically focused only on one variable (the ICR), by developing fully consistent scenario-based dynamic simulation models for firm level balance sheets, and a sensitivity analysis that also simulates shocks to cash balances while allowing policy responses.

Various publications have assessed corporate stress resulting from the ongoing Covid-19 pandemic. Close to our work, Caceres et al. (2020) stress test the liquidity and solvency of US publicly listed corporates in a Covid-19 pandemic forward looking macroeconomic scenario, but they do not assess medium-term viability. IMF (2020d) makes use of a structural model to assess liquidity and solvency risks of European NFCs during the 2020 pandemic shock and the role of policy support, while Bank of England (2020) quantifies the cash balances of large firms and SMEs under a central scenario while allowing for behavioral responses, and assesses the extent to which policies in place may suffice to close cash deficits. Ebeke et al (2020) perform a sensitivity analysis and find that the COVID pandemic shock created large liquidity needs among European firms, quantitatively broadly similar to our findings. Button et al,. (2020) estimate that mid-size and large U.K. companies will face large cash shortfalls during 2021. ECB (2020) assesses liquidity challenges of NFCs and their refinancing needs going forward. With the exception of Caceres et al. (2020), these papers mostly focus on a sensitivity analysis with limited dynamics, and do not perform multi-year scenario-based simulations of balance sheets.

Various papers have shown that, during the onset of the pandemic, cash shortages may have been severe and that firms built precautionary cash buffers through higher leverage, thanks to a combination of increase reliance on credit lines, access to market borrowing and strong policy interventions.[12] Firms with greater financial flexibility—e.g., better able to fund

[12] For evidence on the sharp increase in corporate borrowing during the onset of the pandemic, see various Financial Stability Reviews of Central Banks as well as Chapter 3 of the October 2020 Global Financial

(continued…)

externally their cash flow shortfalls—stronger fundamentals, or less exposed to COVID-19 shocks experienced significantly lower stock price drops compared to other firms in the same industry (Fahlenbrach et al., 2020; Ding et al., 2020). Acharya and Steffen (2020) show that, following the stabilization once policies were in place, only the highest-rated firms switched to capital markets from banks to raise cash. Granja et al. (2020) find that many US firms used the loans of the Paycheck Protection Program (PPP) to make non-payroll fixed payments and build up savings buffers, reflecting precautionary motives in the face of heightened uncertainty.

In addition to assessing corporate stress during the pandemic, several papers have also proposed approaches to categorize firms and assess the extent to which recapitalizations, debt restructuring and liquidations of firms may be required when the pandemic is over (Appendix table). Blanchard et al. (2020) categorize firms in 3 groups: (i) privately viable firms (present value of profits exceeds recovery of assets) that are solvent (present value of profits exceeds current debt); (ii) firms that are not viable and not solvent; and: (iii) viable firms that have been made insolvent by the shock and need debt restructuring. Our approach also makes a distinction between solvency and viability (while also differentiating firms with and without liquidity needs). A difference with Blanchard et al. (2020) is that we also provide a quantification of this triage of firms in the medium-term, and the related liquidation and debt restructuring needs. Gourinchas et al. (2020) develop a structural model to assess liquidity risks affecting SMEs during the 2020 pandemic and estimate the fiscal cost of providing cash injections to SMEs to ensure they can survive the pandemic shock. To do so, they classify SMEs into three groups based on estimates of their cash balance in absence of direct policy support and with no additional borrowing: (i) 'survivor' firms that don't need support to weather the COVID-19 shock; (ii) 'viable' firms that would survive in normal times, but fail under COVID-19; and (iii) 'ghost' firms that would fail regardless of COVID-19. In contrast to our work, they do not model the dynamics of balance sheets over several periods. As we do, Greenwood et al. (2020) develop forward-looking projections but they focus only on corporate loan defaults in the US resulting from the pandemic, by relying on a regression of loan charge-off rates on unemployment rates, and predict a large increase in defaults.[13] Philippon (2020) compares the social value of a firm to the recovery value of assets as the criteria for continuation of a firm, and designs incentive compatible government participation and guarantees. Carletti et al. (2020) perform a sensitivity analysis to assess the impact on Italian firms' equity of a 3 months lockdown; they note that a recapitalization of firms facing equity shortfall as a result of the pandemic may not suffice to restore viability because many firms had weak pre-pandemic balance sheets.

Banerjee and Hofman (2020) assess the empirical relevance of "zombie" firms and their characteristics, across countries before the pandemic in a sample of publicly listed companies. They define as "zombies" firms with an ICR below one and with a market-to-book value below median. They find that the share of these firms has risen over time, and

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Stability Report. OECD (2020) notes the importance of emergency liquidity support policies to avoid firms' failures in 2020.

[13] Building on Crozet and Gourio (2020, they also simulate the impact of earning' shocks on firm leverage, based on market analysts' forecasts and assumptions on costs of producing goods.

empirically represent a significant share of firms, in particular in Anglo-Saxon countries. More generally, the "zombie" firm literature (see for instance Caballero, Hoshi and Kashyap (2008)) has defined such non-viable firms based on their capacity to generate "adequate" profits and productivity, and their high reliance on subsidized lending. Banerjee and Kharroubi (2020) present empirical evidence that there is a two-year lag from a rise in vulnerabilities to the peak in firm exit.

Several papers have proposed principles for short-term and medium-term policy interventions (see Appendix table). Blanchard et al. (2020) explain that solvency and liquidity policy support of firms has been crucial at the onset of the pandemic, and should continue in the post-lockdown period, aiming at protection and reallocation, in the form of temporary wage subsidies and loan guarantees. They note that dealing with legacy debt will be complex (and expensive) and that restructuring plans for viable but insolvent firms will be needed, together with temporary wage subsidies. Brunnermeier and Krishnamurthy (2020) assess financial conditions and the US policy response at the onset of the pandemic and propose a framework to guide policy interventions in credit markets to avoid medium-term scarring. They consider as criteria a combination of post-pandemic solvency condition and profitability. They note that, for large firms, the case for liquidity injections is less clear cut than for SMEs which can be credit constrained and face high social costs of bankruptcy. For large firms, debt overhang could distort employment and investment decisions, requiring a nuanced approach toward bankruptcy and debt restructuring. They note that bankruptcies should be made more efficient while policies supporting funding costs are socially desirable only if the pandemic is short-lived and bankruptcy is costly. Stein (2020) offers an evaluation of the Fed-Treasury credit programs, suggesting a "staged-finance approach" and dynamically adjusting intervention, with the government playing the role of a venture capitalist of last resort. He suggests assessing firms based on their solvency position, as well as their ability to generate profits and service their debt post-pandemic. Boot et al. (2020) suggest to rely on "equity-like" policy instruments offering risk sharing without impinging on ownership structures. Bauer et al. (2020) discuss forward looking policy options to facilitate the efficient restructuring of viable firms while allowing non-viable firms to exit in a post-pandemic world. Greenwood et al. (2020) argue that the triage of firms will raise substantial challenges post-pandemic, including court congestion and excess liquidation and failure of small firms. Jorda et al. (2020) find that economic costs of corporate debt booms rise when inefficient debt restructuring and liquidation impede the resolution of corporate distress. Diez et al. (2021) rely on the methodology of analyze policy options to address insolvencies of SMEs.

In sum, our paper upgrades existing stress testing approaches for non-financial corporates and integrates a full spectrum of topics related to COVID-19 across advanced economies and emerging markets to assesses short-term and medium-term risks. Findings from the analysis are broadly consistent with other existing studies pointing at the sizeable liquidity needs and future default risks going forward.

III. DATA AND DESCRIPTIVE STATISTICS

A. Data Sources

Data used in the analysis consist of two main categories: firm level data and macroeconomic indicators. Firm level data mainly consists of historical balance sheet and financial statements information from which we constructed various key variables including vulnerabilities indicators (such as ICR and leverage ratio) sourced from Datastream and Capital IQ.[14] Furthermore, we collected firm specific analyst forecast on total sales and earnings before interest and taxes (EBIT) from the Institutional Broker's Estimate System (IBES) for the same sample of firms in order to produce firm specific shocks, which were further aggregated to country-industry shocks applied in both the sensitivity and scenario based stress tests. The historical firm level dataset covers some 17,000 publicly listed firms for 24 major countries from both advanced economies and emerging markets (Table 1) covering 10 industries at both annual and monthly frequency over the period of 2003-2019. The analyst forecast horizon spans the period 2020-2022. A detailed list of variables used in the analysis and their corresponding data sources, frequency and time horizon can be found in Table 2.

For the scenario-based analysis, additional macroeconomic variables were collected to conduct panel regressions and produce scenario-based projections. Two main macroeconomic variables used in the analysis are real GDP growth and a financial condition index, which were collected at the country level at annual frequency over period of 2003-2022 (including projections over period of 2020-2022). For historical time series, country specific financial condition index was generated using a group of macro-financial indicators under the principle component analysis approach.[15] The historical series for GDP and other macro-financial variables were collected from the IMF WEO databases and the October 2020 GFSR. For projections, GDP baseline forecasts and the adverse scenario were sourced from the October 2020 published IMF WEO databases, and the financial condition indices were projected from IMF baseline projections and adverse scenarios (see more detailed description in section VI.B).

The analysis used SIC industry classification for industry related assessment (Table 3). The 4-digit SIC industry code for each individual firm were downloaded from Datastream and Capital IQ and then grouped into 10 major industries deemed to be relevant for this analysis. The classification allows clear separation into energy and transportation intensive industries, as well as industries that require more physical interactions in the production and sales process such as hotel and restaurant as well as tourism industry. Our industry classification is thus highly relevant in the context of COVID-19 pandemic as it allows differentiation and comparison on the severity of impact on highly COVID-19 impacted sectors vis-a-vis less

[14] For large economies in our sample, we did a careful comparison between Datastream and Capital IQ coverage and selected the database with the best firm coverage for each country to maximize representativeness of the analysis.

[15] The index of financial conditions is constructed from short-term and long-term interest rates, corporate spreads, equity market returns and volatility, exchange rates, and real house prices. For more details, see Chapter 3 of the IMF's October 2017 Global Financial Stability Report.

impacted sectors, and is relevant to design of targeted policy measures to alleviate those impacted the most and mitigate the impact caused by the pandemic.

B. Descriptive Statistics

Our sample of around 17,000 publicly-listed firms across 24 countries as of 2019 are very significant as a group from a macro-financial point of view at the country level. For a subset of countries which report country level NFC statistics to the OECD, we are able to assess that our sample accounts for a very large share of aggregate NFC debt and output; specifically our sample of firms represent on average around 40 percent of total NFC output and 36 percent of total NFC debt (Table 4 and Table 5).[16]

Figure 1 reports key country level summary statistics for 2019 and a comparison with 2009. It reveals that firms in a notable share of countries in AEs (in particular the U.S. and Canada) has already vulnerable financial health indicators in 2019, and in some cases their balance sheet leverage was even more stretched that at the height of the GFC in 2009. [17] This is reflected in various firm level vulnerability indicators, such as leverage ratio, liquidity positions proxied by cash and cash equivalent to total assets, and cash available defined as cash and equivalent net of working capital commitments, and the standard ICR indicator.[18] On a positive note, firms in several European countries exhibited reduced leverage while some countries (such as the United States, Canada, Germany, and Japan) exhibit improved return on asset and better ICR profiles over time. It is also important to note the large variations across countries as some countries in the same group may outperform the others.

IV. Conceptual Framework

A. Firm Level Vulnerability Indicators

We focus on a set of firm level indicators to assess: (i) external borrowing needs based on the cash balance estimated at constant debt level; (ii) the ability to service debt (the ICR), and: (iii) the solvency position. Each of these indicators are related to vulnerability assessments of firms: (1) having protracted external borrowing needs indicates that a firm has to increase its leverage to finance cash outflows, and may in some cases indicate a risk of illiquidity that would materialize if banks and/or markets become reluctant to provide financing to that

[16] Coverage of total output and of NFC debt is generally good in our sample but it may vary across countries. It may be lower in countries with large SME and privately held large firm sectors. For more details on SMEs based on data availability, see forthcoming IMF Staff Discussion Note "Insolvency Prospects Among Small-and-Medium-Sized Enterprises in Advanced Economies: Assessment and Policy Options".

[17] The heightened vulnerabilities associated with Canadian firms reflect the fact that a disproportionate number of publicly traded Canadian firms are in the oil and mining sectors which were negatively impacted from the fall in oil prices in 2014 and the fall in other commodity prices in 2012, and have high leverage and low ICRs.

[18] Cash available is defined as cash and equivalent plus receivables minus short-term liabilities (excluding short-term debt and the current portion of long-term debt). It is a measure of the cash stock that is truly available for debt payments and not already tied to other accrued short-term liabilities. In this definition we assume that inventories cannot be easily transformed into cash.

particular firm at a "reasonable" cost;[19] (2) generating insufficient earnings to service the debt, if it is not related to a temporary shock, indicates that the firm has insufficient capacity to generate profits compatible with its indebtedness and may not be viable going forward; (3) having insufficient equity indicates that either the firm is not viable and should be liquidated or that its business may be viable going forward but that its debt should be restructured and equity should be injected.

B. Multi-Factor Sensitivity Analysis

The impact on individual firms' ICR and cash flows of shocks to their sales, allowing for a range of behavioral responses, is assessed as follows:

$$EBIT_{post\_shock} = EBIT_{Pre\_shock} - x\% \times [Net\_sales - y\% \times Costs\_Goods\_Sold]$$

Where: $EBIT_{post\_shock}$ is the earnings before interest and taxes after the shock, $EBIT_{Pre\_shock}$ the earnings before interest and taxes before the shock, x is the share of sales lost as a result of the shock, and y is the share of productions costs adjusted for each unit of sales lost as a result of the shock. This parameter y reflects both firm level decisions (such as to fire workers or keep them on the payroll) and policies (such as labor subsidies). With this simple indicator, we assess the impact of the shock on the ability to service debt as follows:

$$ICR_{post\_shock} = \frac{EBIT_{post\_shock}}{Interest\ expenses}$$

The impact of the shock on the end of period cash balance of firms is derived from initial cash buffers and cash inflows and cash outflows during the period:

$$Cash\_Balance_{post\_shock} = Initial\_Cash\_Balance + EBIT_{post\_shock} - \left[z\% \times \frac{STD}{TD} \times Interest\_Payments + \left(1 - \frac{STD}{TD}\right) \times Interest\_Payments\right] + (z - 100)\% \times Short\_Term\_Debt + (Depreciation + Amortization) - CAPEX$$

Where, the initial cash balance, $Initial\_Cash\_Balance$, is adjusted for working capital commitments, $\frac{STD}{TD}$ is the share of short-term debt and long-term debt maturing during the year in total debt, z represents the issuance of new debt during the year expressed as a share of the short-term debt and long-term debt maturing during the year , $Interest\_Payments$ are total interest payment on the initial debt of the firm. Specifically, z>100% means that short-term debt increases by (z-100)%; z=100% means that the short-term debt and long-term debt maturing are rolled-over; and z<100% means that new debt issued during the year is smaller than the maturing stock of short-term debt and long-term debt. We assume that, under a stress scenario, firms do not initiate new fixed capital investments and invest only to maintain their initial stock of capital (depreciation+amortization=CAPEX). The initial stock

[19] Having external financing needs does not imply that a firm is subject to liquidity stress or that it is illiquid. In fact, unless they are credit-constrained or are flush with cash, most firms typically rely on external finance for their operations and for investment purposes. However, having external financing needs will indicate a need to increase leverage and is a necessary condition for a firm to be at risk of illiquidity.

of cash is defined as: cash & equivalents + short-term investments + receivables – (accrued payables+ accrued payrolls and other short-term liabilities).[20] [21]

We calibrate the shock *x%* industry by industry for each country. Specifically, we consider, for each firm for which it is available, market analyst's 12 month forward forecasts of firm sales at the end of January 2020 (pre-pandemic) and in June 2020 (after the initial shock of the pandemic) and compute the shock parameter as the percent change in the sales' forecasts.[22] The shock is next aggregated at the country-industry level using each firm 2019 total asset as weight. The country-industry shock is then used as the shock parameter in the sensitivity analysis and is applied to end-2019 sales of each firms. Ebeke et al. (2020) perform a sensitivity analysis broadly conceptually similar for a sample of European firms with a focus on the cash balance and the equity position.

C. Dynamic Scenario-Based Stress Tests

The scenario-based stress tests models are built from a battery of firm level regressions estimated as much as possible country by country, combined with accounting identities allowing to derive remaining firm level variables in a consistent manner if these are not predicted from firm level regressions. The methodology builds upon work done in recent FSAPs for France and Korea and enhances these approaches that were focused on projecting the ICR based on a probit regression. After a careful specification search based on regression performance (in particular the sign of coefficients and the R2), we rely on country level regressions for sales growth and for ICR Probit models, and cross-country regressions for ROA, leverage and for the cash balance Probit model (see below).[23]

The dependent variables of the fixed effect panel OLS regressions include: the ROA, leverage and sales growth. The dependent variable of the Probit panel regressions are indicator variables (i) equal to 1 if the ICR is below one and 0 otherwise; (ii) equal to 1 if cash available is zero or negative, and 0 otherwise. The dependent variables are projected dynamically from firm level variables in the previous year, including time varying and time invariant structural characteristics, and macro-financial variables.

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[20] Not including short-term debt and the current portion of long-term debt.

[21] The initial stock of cash and equivalents and accrued receivables are net of accrued short-term liabilities (such as payables and accrued payroll and other short-term liabilities excluding debt). This means that (i) the initial stock of cash and equivalents is not fully free cash and part of it may already be tied to working capital; (ii) accrued receivables are collected and accrued short-term liabilities are paid out. A similar adjustment is applied to the initial 2019 cash balances in the scenario-based stress test.

[22] The IBES (The institutional broker's estimate system) dataset provides rich information on the historical evolution and forward-looking projections of company balance sheet and risk indicators, sourced from over 18, 000 analysts.

[23] The results presented in the paper are based on the ROA and sales growth projected from regressions, while other variables are derived from accounting relationships. Our tool allows for alternative models making use of regressions with the debt-to-asset ratio as dependent variable, and Probit regressions of ICR and cash balance to directly estimate the aggregate share of firms and/or debt at risk for each of these two indicators without relying on accounting relationships. Regression results from the Probit models are presented in the paper, but corresponding scenario-based projections are omitted.

The basic firm level regression specification is a dynamic OLS regression including a set of industry level fixed effects if the regression is estimated country-by-country:

$Y_{i,s,t} = \alpha \cdot Y_{i,s,t-1} + \Delta \cdot firm\_char_{ist-1} + \Phi \cdot Macro\_financial_t + d_s + \nu_{ist}$ (1a)
Where $Y_{i,s,t}$ is the variable to be projected for firm i, in industry s and year t, $firm\_char_{ist-1}$ is a set of firm level explanatory variables, $Macro\_financial_t$ is a set of macro variables for year t, d_s is a full set of industry fixed effects and ν_{ist} is a residual which is clustered at the country-year level. Our key criteria for the selection of the empirical models, in line with Basel guidance on IRB modeling of credit risk models, is their forecasting power which turn out to be good. In addition, because we do not include firm level fixed effects (but industry fixed effects) in the models we selected, our coefficients are less likely to biased from the dynamic panel correlation between the lagged dependent variable and the fixed effect (Nickell, 1981).[24] Year fixed effects cannot be included in the regressions because they would absorb the effect of macro-financial variables that are needed for the scenario simulations.

In a variant, the firm level specification is estimated by pooling all countries together:

$Y_{i,s,j,t} = \alpha \cdot Y_{i,s,j,t-1} + \Delta \cdot firm\_char_{ijst-1} + \Phi \cdot Macro\_financial_{jt} + c_j + d_s + \nu_{ijst}$ (1b)

Where j is the country indicator, c_j is a set of country fixed effects and the residual terms ν_{ijst} are allowed to be correlated across firms within each country and year.

We also estimate a set of firm level Probit regressions country-by-country (or a variant pooling all countries together, as for OLS regressions). The specification for country-by-country regressions is as follows:

$P[Risk_{i,s,t} = 1] = A \cdot firm\_char_{ist-1} + \delta \cdot macro\_financial_t + d_s + \varepsilon_{ist}$ (2a)

Where the indicator $Risk_{i,s,t} = 1$ if the firm is assessed to be risky if the variable considered is below the risk threshold, or $= 0$ if it is above the threshold. We consider two variables: the ICR, with the standard threshold of 1, and the balance of cash available, with a threshold of zero. We also consider a specification (2b) with all countries pooled together and including country fixed effects.
Firm level explanatory variables are lagged by one period and include profitability (return on assets), leverage (the debt-to-asset ratio), size (measured by total assets, relative to the average of all firms in a country in a given year), tangibility of assets (the ratio of fixed assets to total assets), ability to generate cash flows (the ratio of sales to total assets), and growth

[24] Moreover, panel GMM methods often relied upon to correct the panel fixed effect bias can also be subject to weak instrument or invalid instrument biases and can result in imprecisely estimated parameters.

opportunities (the annual growth rate of sales). These variables are considered standard determinants of firms' indebtedness and maturity structure.[25]

To construct firm level projections of the dependent variables considered, we will assume that some of these explanatory variables reflect structural characteristics of firms and will be time invariant. Specifically, we will consider the size indicator, the tangibility ratio and the cash flow generation ratio as structural and set them at their 2019 value. Variables such as the ratio of fixed assets to total assets or the turnover ratio tend to be related with industry characteristics and structural while the size of the firm is also unlikely to vary with the cycle.[26] Other variables (ROA, sales growth and leverage) will be projected in a consistent manner and will vary over time given the macro-scenarios considered.

Macro-financial determinants of firm level profitability, sales' growth and leverage are the annual real GDP growth and an index of financial conditions. To generate firm level vectors of consistent projected variables $\hat{Y}_{i,s,t}$, we will also make use of the following accounting identities:

Cash/borrowing needs are given by: EBIT – Taxes – Interest Expense + Initial Cash and eq. under the assumption that firms do not pay dividends and invest to maintain the existing stock of capital (depreciation+amortization=CAPEX). A negative value means that the firm has to increase its indebtedness to be able to honor cash outflows.[27] [28]

The increase in debt is defined as "minus" borrowing needs if cash needs <0 and zero otherwise.[29] [30]

The evolution of a firm's net worth is determined by the equation: equity(t+1)=equity(t)+retained earnings (t) where retained earnings are income net of taxes and interest expenses, assuming that firms do not or cannot issue equity on the stock market and do not pay dividends, and assuming that firms invest to maintain the existing stock of capital.

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[25] See, for instance, A. Demirguc-Kunt, M. Martinez-Peria, and T. Tressel, 2015. *"The Impact of the Global Financial Crisis on Firms' Capital Structure,"* World Bank Policy Research Working Paper No. 7522.

[26] See the discussion in Demirguc-Kunt et al. (2015).

[27] We assume that under a stress scenario, the traditional corporate finance "pecking order" theory holds: firms first rely on internal sources of funds, and second borrowing, and third issue equity on the stock market. In addition, we assume that the cost of issuance equity is significantly higher than the cost of borrowing, and therefore firms do not issue equity.

[28] EBIT is related to ROA = (EBIT-taxes)/Total Assets *100. Since we directly project ROA, we do not need to estimate taxes.

[29] Note that because we also have a regression model for leverage, we actually have two methods of deriving a projection for leverage once we have a projection for EBIT. We will make use of the average of the two models of projecting leverage.

[30] The analysis does not directly capture firm vulnerabilities towards FX risks as granular information on currency decomposition of corporate balance sheet is not publicly available.

Interest expenses reflects incremental macro shocks to interest rates in each scenario, and firm level base effects reflecting each firm's 2019 effective interest rates and debt levels in each period. Specifically, they are projected according to the equation:

Interest expense(i,t) = {2019 effective interest rate(i) + [LTD/TD(i) * Δscenario LT rate(t) + STD/TD(i)*Δscenario ST rate(t)]}× TD(i,t-1).

where: "2019 effective interest rate(i)" is the effective interest rate paid by firm i on its stock of debt in 2019, "TD(i,t)" is the firms' debt stock in period t, "LTD/TD(i)" is the firm's 2019 ratio of long-term debt to total debt in 2019, "STD/TD(i)" is the 2019 ratio of short-term debt to total debt, "Δscenario LT rate(t)" is the change in the long-term interest rate for corporates in the scenario considered between 2019 and year t, and "Δscenario ST rate(t)" is the change in the short-term interest rates for corporates between 2019 and period t. The long-term (respectively short-term) interest rate for corporates, in turn, are computed as the sum of the long-term risk-free rate (respectively short-term risk-free rate) and of the corporate spread provided in the macroeconomic scenarios of the October 2019 GFSR. [31]

Projections are constructed as follow:

For the year 2020, the projection of the variable $Y_{i,s,t}$ is constructed from the actual 2019 firm level variables both for structural and non-structural characteristics, the projected macro-financial indicators for 2020 and the regression estimated coefficients $\tilde{\alpha}$, $\tilde{\Delta}$, $\tilde{\Phi}$, and fixed effects $\tilde{d}_s$ (and $\tilde{c}_j$ for pooled cross-country regressions):

$$\hat{Y}_{i,s,j,2020} = \tilde{\alpha} \cdot Y_{i,s,j,2019} + \tilde{\Delta} \cdot firm\_char_{i,s,j,2019} + \tilde{\Phi} \cdot Macro\_financial_{2020} + \tilde{d}_s \quad (3a)$$

Variables always projected from regressions are the ROA, and sales growth. [32] Other, non-structural firm characteristics can then be derived from the regression-based projected firm characteristics of ROA and sales growth and the accounting identities above. Note that leverage can also be directly projected from a regression, and we can also project from the Probit regressions probabilities of ICR<1 and of cash balances<0. This implies that some variables are overdetermined in the sense that we can choose between several projection methodologies. Given this, our preference in the rest of the paper will be to report results from accounting based derived values of ICR, cash balances and leverage from borrowing needs (and consistently equity). However, we will be able to some extent address modeling uncertainty and ascertain robustness of our main results by considering alternative models which will be available in the toolset.

For years 2021 and 2022, the firm level projection $\hat{Y}_{i,s,t}$ is constructed from the regression estimated coefficients, the 2020 projections of the variables $Y_{i,s,j,t}$ and the 2019 values of the structural firm characteristics (size, tangibility ratio and turnover ratio):

[31] We assume that the change in corporate spreads plus risk free rates is a good proxy for the change in funding costs of firms, both for market finance and for bank loans.

[32] The firm level growth rate of sales projected from the regression model is not *directly* used in the construction of firm level variables from accounting identity. Instead, it is used *indirectly* as one of the lagged cyclical determinants of ROA and of leverage in the regression-based models.

$$\hat{Y}_{i,s,j,t} = \tilde{\alpha} \cdot \hat{Y}_{i,s,j,t-1} + \tilde{\Delta} \cdot \left[firm\_struct\_char_{i,s,j,2019}, \widehat{firm\_other\_char}_{i,s,t-1}\right] + \tilde{\Phi} \cdot Macro\_financial_t + \tilde{d}_s \quad (3b)$$

We next introduce an industry-differentiation of firm-level projections of ROA and sales' growth by making use of financial market analysts' calendar year projections of individual firms' EBIT and sales for each calendar year 2020, 2021 and 2022. This information is obtained from Datastream for a subset of firms in our sample. The firm level market forecasts are then aggregated using each firm's total asset as weight: (i) at the industry level in each country as variable $\tilde{Y}_{sjt}$, and: (ii) at the country level as variable $\tilde{Y}_{jt}$. We next adjust each calendar year's predicted values of ROA and sales growth sequentially to introduce a differential across industries in each country.

The adjustment is done as follows:
First, we obtain the year 2020 projection $\hat{Y}_{i,s,j,2020}$ of ROA and sales' growth from equation (3a).
Second, we aggregate the firm level variable at the industry level in each country, using each firm's total asset as weight: $\hat{Y}_{s,j,2020}$.
Third, we adjust the firm level projection as follows to construct an adjusted projection that accounts for relative levels across industries in each country:

$$\hat{Y}_{scaled,isjt} = \frac{\hat{Y}_{jt} / \tilde{Y}_{jt}}{\hat{Y}_{sjt} / \tilde{Y}_{sjt}} \times \hat{Y}_{isjt} \quad (4)$$

This adjustment based on relative industry performance in the market analysts' forecasts is consistent with the condition that the country level projections of ROA and sales remain unchanged after industry differentiation and is robust to the sign of each variable:

$$\hat{Y}_{scaled,jt} = \hat{Y}_{jt}$$

Fourth, once the adjustment is done for the calendar year 2020 for ROA and sales growth, we recompute other variables' 2020 projections that are generated from accounting relationships described above.
Fifth, we feed the new adjusted 2020 projections into the regression-based models to generate 2021 projections and repeat steps 2 to 4 above.

D. Financial Stability Implications

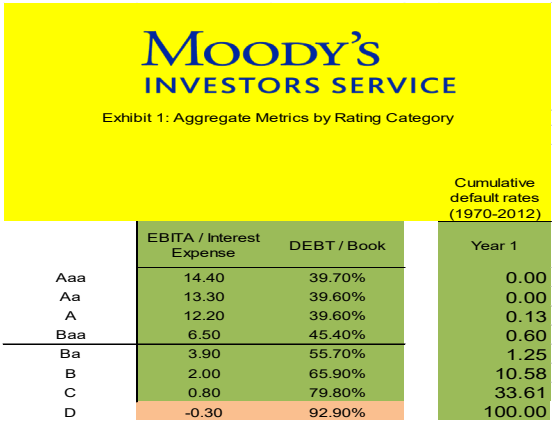
To assess the stability implications for the financial system at large and for the banking system in particular, we map firm level vulnerability indicators into a probability that a firm would default on its debt, and aggregate these PDs at the country level.

For this purpose, we use of a two-step approach. First, we map our firm level predicted ICR and leverage with annual default rates which were constructed for the period 1970–2012 in the United States based on a matrix from Moody's Investor Services (see Figure 1). This matrix maps ICR and debt to equity ratios of individual firms into buckets of annual default rates.

Second, we benchmark our aggregated predicted default rates in each country with 2019 annual corporate EDFs from Moody's KMV. This ensures that the aggregate predicted default rates are aligned with Moody's default rates in each country. The adjustment to match 2019 values with aggregate EDFs is needed because (i) historical relationships from the mapping matrix tend to overstate recent probabilities of default in the US, reflecting a lower propensity to default in recent years at high leverage in the context of very low interest rates and QE since the GFC; (ii) there could be structural difference between a US-based mapping and a mapping for publicly-listed firms in other countries.

The country-level adjustment is reported both for the mean value and the median value of the 2019 EDF from Moody's KMV. This is because the average values of EDFs could appear to be high due to a fat upper tail of the distribution in several countries.[33] The set of PDs obtained from this procedure provides, for each scenario, a simulation of default rates among large firms with market access in each country.

Figure 1. Moody's Aggregate Matrices by Rating Category



MOODY'S INVESTORS SERVICE

Exhibit 1: Aggregate Metrics by Rating Category

	EBITA / Interest Expense	DEBT / Book	Cumulative default rates (1970-2012) Year 1
Aaa	14.40	39.70%	0.00
Aa	13.30	39.60%	0.00
A	12.20	39.60%	0.13
Baa	6.50	45.40%	0.60
Ba	3.90	55.70%	1.25
B	2.00	65.90%	10.58
C	0.80	79.80%	33.61
D	-0.30	92.90%	100.00

Source: Moody's Analytics.

We next assess the impact on banking systems. For this purpose, we do not rely on Moody's KMV EDFs to benchmark the model predicted PDs to actual default rates on bank loans for 2019. This is because, by and large, banks are exposed to a much broader set of firms than only large firms with market access, and as a result, default rates may be quite different. Instead, for the second step we rely on actual (or derived) default rates on bank corporate loans for the end of 2019 to benchmark our model prediction for 2019. The reason is that the aggregate default risk on bank corporate loans could be quite different than the market-based estimates of default frequencies on a sample of publicly listed firms. For a number of countries, we collected actual PDs/default rates on bank loans for 2019. For the European sample, we obtained PDs at the banking system level published by the European Banking Authority.[34] For the US, PDs for 2019 are set equal to the delinquency rates on commercial and industrial loans published by the US Fed. For remaining countries, PDs are estimated from NPL ratios and bank credit growth for 2019 published in the Financial Stability Indicators and International Financial Statistics of the IMF based on the formula:

$$PD_t = \frac{NPL_t - (1-\alpha)NPL_{t-1}}{Perf\ Loans_{t-1}}$$

[33] Moody's KMV expected default frequencies are calculated on a set of large firms with market access, and are benchmarked to actual default rates. The set of firms may differ from ours, and may not necessarily be representative of the industry composition at the country level.

[34] The EBA Risk Dashboard can be found at: Risk Dashboard | European Banking Authority (europa.eu)

Where α is the annual outflow rate from the non-performing state (corresponding to non-performing loans returning to the performing state or maturing during the period).[35]
Last, as a measure of credit risk, the share of banks' exposures to non-financial corporations expected to default are reported as a ratio of Tier 1 capital, based on the formula:

$$Impact_{it} = PD_{it} * \frac{Loans\_to\_NFCs_{i,2019}}{Tier1_{i,2019}}$$

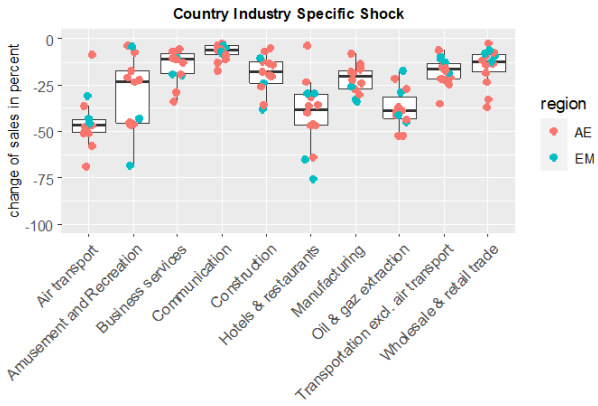
Where for each country $Loans\_to\_NFCs_{2019}$ is the stock of loans to NFCs and $Tier1_{i,2019}$ is the banking system's Tier 1 capital in 2019, both obtained from the International Financial Statistics.[36] [37]

V. Sensitivity Analysis

A. Main Results

Figure 2 shows the asset-weighted shock parameter applied to sales in each industry and its cross-country dispersion.[38] Not surprisingly, industries such as Air Transportation, Hotels and Restaurants, and Oil and Gas extraction are perceived to be the most impacted by the pandemic. Next we consider, four possible behavioral responses of firms: (i) no reduction in the cost of goods sold (y=0%); (ii) 50 percent reduction in the cost of producing goods (y=50%); (iii) 75 percent reduction in the cost of producing goods (y=75%); and: (iv) full offset and reduction in the cost of production (y=100%). The sensitivity analysis assumes that all short-term debt and long-term debt maturing during the year is rolled over.

Figure 2. Country Industry Specific Shocks
(In percent)



Sources: Datastream, Capital IQ and IMF staff estimates.

Aggregated results of the sensitivity analysis of the ICR and of cash balances, each performed separately, are reported in

[35] We considered different values of this parameter, and the main findings are not significantly affected. We consider an outflow rate of 35 percent.

[36] A fuller measure of credit risk would be to estimate expected losses. To do so, we would need country level estimates of Loss Given Default (LGDs) that we would multiply with the "Impact" measure to obtain an estimate of expected losses as a share of bank capital.

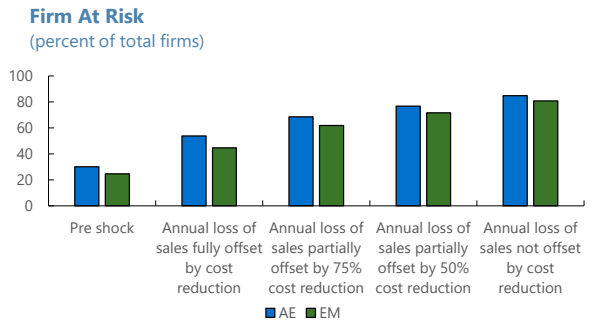
[37] Banks' stock of loans to NFCs, as informed by the FSI concept and definition capture loans to both resident and non-resident corporates. Information on country specific banking sector are compiled from FSI on a consolidated group basis which includes coverage of domestic banks' own activities as well as those of its branches and subsidiaries (both domestic and foreign). Detailed information can be found in FSI compilation guide in https://data.imf.org/?sk=51B096FA-2CD2-40C2-8D09-0699CC1764DA&sId=1390288795525.

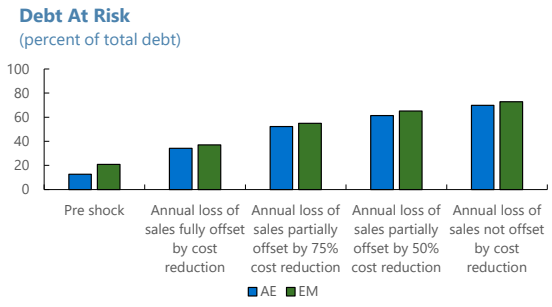
[38] The differences of shocks across industries likely reflect characteristics that shape how they have been affected by the pandemics, such as the extent to which they are contact-intensive or can adjust thanks to working from home arrangements (see for instance, Bloom, 2020).

Figure 3. For each country in our sample, we first compute the share of firms or share of debt meeting the relevant ICR<1 or cash balance<0 criteria; second, we compute the averages of each country's results among AEs and EMs, weighted by each firms' debt. [39] In the bottom two panels, we show industry-by-industry country results of the shares of firms at risk, and their dispersion across countries.

We find that the pandemic annual shock to sales as reflected by financial analysts' in their forecasts after the first quarter of 2020 is very severe: from an ICR perspective, and even if firms could entirely offset the decline in sales by cutting production costs, the shares of firms at risk would broadly double relative to pre-pandemic level, from about 20 percent in AEs and in EMs, to 54 percent in AEs and 45 in EMs. If firms were unable to cut production costs, the shares of firms at risk would rise to about 83 percent on average both in AEs and in EMs. From a debt-at-risk perspective, with a full pass-through of the sales shock to cost reduction, the increase in corporate vulnerabilities would also be very substantial to some 34 percent in AEs and 37 percent in EMs. If firms are unable to cut production costs, debt-at-risk would rise to 70 percent in AEs, and 73 percent in EMs. Turning to the impact of the shock on cash balances, we also observe a sharp increase in the share of firms unable to maintain positive cash balances in absence of new borrowing, to about 37 percent in AEs and 44 percent in EMs assuming firms can fully offset the shocks to sales by cutting production costs. [40] In absence of adjustments to production costs, 60 percent in AEs (respectively 65 percent in EMs) of firms would have negative cash balances in absence of an increase in borrowing. Last, industry level results show that both from an ICR and a cash balance perspective, three industries appear particularly impacted by the initial pandemic shock: Air Transport, Amusement and Recreation and Hotels and Restaurants.

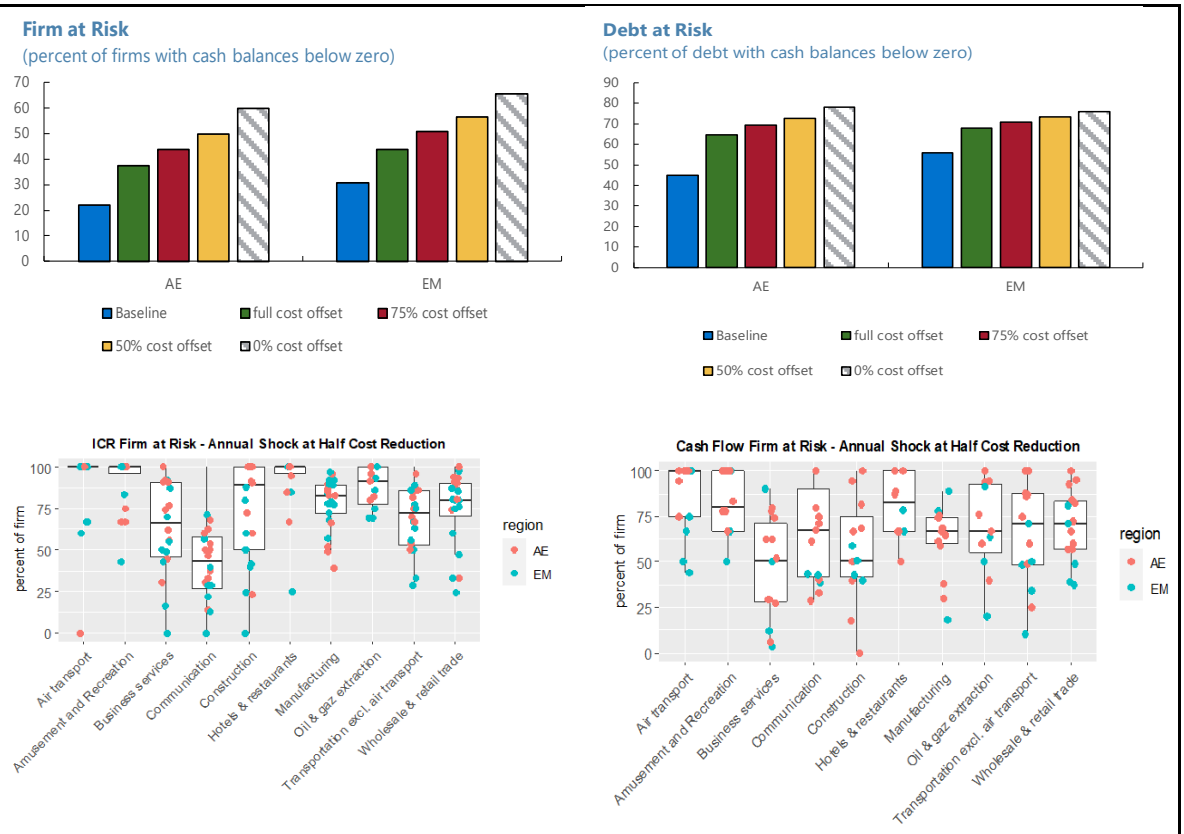
Figure 3. Sensitivity Analysis: Shocks to ICR and to Cash Balance





[39] In absence of granular information on industry and country specific ICR thresholds, the analysis considers 1 as a homogenous ICR threshold to ensure comparability across countries and industries.

[40] The baseline is computed from 2019 balance sheets by netting out from cash balances payables and other short-term liabilities (other than short-term debt) and adding receivables.



Sources: Datastream, Capital IQ and IMF staff estimates.

B. Counterfactual Policy Analysis

In this section, we perform several relevant counterfactual short-term policy analyses to quantify how policies may have helped provide support to non-financial corporates during the initial phase of the pandemic in 2020.

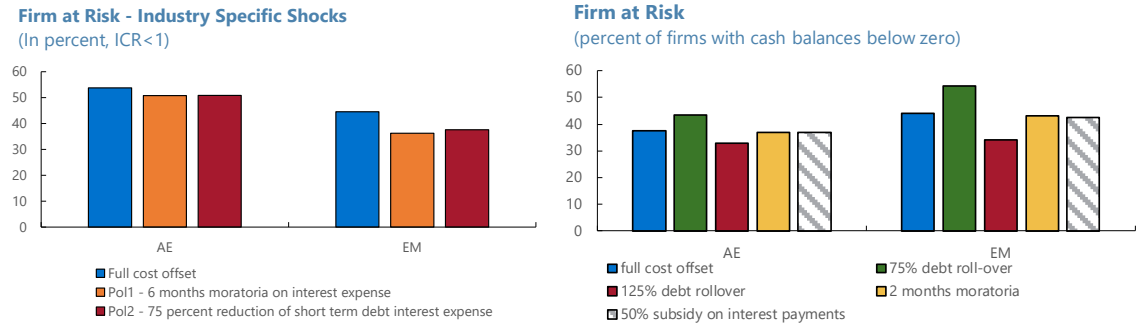
We consider the following policies: (i) a baseline which is a policy subsidizing 100 percent of production costs (corresponding to the scenario reported in section A with a complete offset reduction in production costs); (ii) baseline + temporary guarantees on new corporate debt issued (modelled as a 50 or 75 percent subsidy on short-term debt rolled-over during the year); (iii) baseline + a 2 or 6 months moratoria on debt service. To these scenarios, we add, for the cash balance analysis, the following scenarios: (iv) baseline + 25 percent increase in total debt; and: (v) baseline + 25 percent decline in total debt (which could correspond to a situation where firms face credit constraints and are unable to fully roll-over their debt).[41]

Aggregated results of the shares of firms at risk are reported in Figure 4. We find that, both from an ICR perspective or from a cash balance perspective, relative to policies that help

[41] Debt moratoria is modeled as a reduction in annual interest expenses, and debt reduction and debt increase are simulated as a direct corresponding reduction or increase in cash inflows, respectively. For detailed formulas see section IV.B.

subsidize production costs (such as wage subsidies, grants, or cuts to payroll and other production taxes), policies that help temporarily lower borrowing costs or temporary moratoria on interest payments may have smaller effects as long as debt is rolled-over. In contrast, policies that support firms' ability to increase their leverage or that alleviate credit constraints also tend to have a significant impact on firms' liquidity position. Nonetheless, the analysis on policy offset should be treated with caution as the results are largely driven by initial assumptions and may not be fully reflective of actual policies taken place, which can be continuously evolving. For instance, the analysis assumes a blanket moratoria whereas in reality the duration could vary among jurisdictions with possible extensions.[42] Moreover, although policies that provide firms with additional funding may alleviate liquidity shortage in the short term, it may also lead to debt overhang problem in the long term.

Figure 4. Policy Analysis



Sources: Datastream, Capital IQ and IMF staff estimates.

VI. Dynamic Scenario-Based Liquidity and Solvency Stress Test

A. Regression Results

Table 6 reports the cross-country firm level regressions. The regressions are estimated separately for AEs and for EMs. Columns 1-4 of the table report OLS fixed effects regressions and columns 5-8 report Probit regressions. All specifications include country fixed effects and industry fixed effects (based on 2 digit SIC industry classifications), and standard errors are clustered by country-year to correct for potential correlation across firms of unobserved shocks. After careful specification search based on sign and statistical significance of the two macro-financial variables, we chose specification with either real GDP growth or the FCI as the explanatory variable.

In OLS regressions, we find that there exists a good persistence of leverage (with a coefficient of close to 0.9 on the lagged dependent variable both for AEs and EMs). This implies that shocks to the capital structure of a firm tend to be persistent over time and feed-through over time, with medium-term impacts significantly larger than the contemporaneous effects. ROA is also persistent over time, but with a much smaller autocorrelation coefficient

[42] Detailed information on the duration of the moratoria for each country would be needed to conduct a more in-depth analysis, which is outside the scope of this paper.

both for AEs and EMs, implying that the impact of shocks on profits is more immediate than the impact on leverage. Consistent with the existing literature, we find that, after controlling for country and industry fixed characteristics and persistence of the dependent variable, firms that are less profitable, larger in size, and have a higher proportion of fixed assets to total assets, lower turnover, and higher growth opportunities tend to be more indebted. Firms that have higher turnover and larger share of fixed assets tend to be more profitable. Larger firms are more profitable in AEs, but there is no clear correlation between size and profitability in EMs. More indebted firms are less profitable in EMs, but they are more profitable in AEs, conditional on other control variables. The R2 is high for leverage, and also very good for ROA, which suggests that we have good specifications for the purpose of out-of-sample projections. In these specifications, we also find that, after controlling for country and industry fixed characteristics and firms' characteristics, profitability is strongly positively correlated with real GDP growth and leverage strongly positively with an index of financial conditions.[43] The estimated coefficients imply that the impact of macroeconomic shocks is economically quite significant: a one standard deviation decline of real GDP growth imply a decline in ROA of 0.17 percentage points in AE (respectively 0.09 percentage points in EMs) during the year of the shock, everything else equal. This compares to an average ROA of 1.6 percentage points in 2019 in AE and 4.6 percentage points in EMs). But because of the persistence in ROA embedded in the lagged dependent variable, the impact of the shock will be larger over time. The impact of an FCI shock to the debt-to-asset ratio is smaller, but it is still quite large: over time, a one standard deviation increase in the FCI will increase leverage by 1.38 percentage points on average in AEs and by 1.5 percentage points on average in EMs.[44]

Probit regressions reported in columns 5 and 6 show that, both in AEs and in EMs, the likelihood that a firm does not generate enough earnings to pay for expenses without additional net borrowing is negatively correlated with profitability, and positively correlated with leverage, tangibility of assets, the turnover ratio and size. The sign of the coefficients for profitability and leverage are as expected: higher profits before interest payments generate higher retained earnings, everything else equal, and therefore higher cash buffers, while higher leverage being associated with higher interest expenses may result in lower cash buffers. Firms with more tangible assets, that are larger and generate more sales, may have easier access to external borrowing, or may generate higher gross cash inflows and as a result may not need to accumulate cash buffers to fund their operations. After controlling for firm characteristics, country and industry fixed effects, we uncover that a tightening of financial conditions, everything else equal, tend to increase the likelihood that firms may lack sufficient cash buffers and so may have to resort to external borrowing to fund their operations.

Regressions in columns 7 and 8 show that, both in AEs and in EMs, the probability that a firm is unable to pay for its interest expenses from earnings is negatively correlated with

[43] We note that the real GDP growth coefficient is smaller for the sample of EM firms than it is for the sample of AE firms. Finding an explanation for this result is beyond the scope of this paper.

[44] Note that the average increase in the FCI in the baseline scenario for 2020 amount to about a 2 standard deviation shock.

profitability, size and the tangibility ratio and is positively correlated with leverage, as expected. Thus, vulnerabilities of a firm related to its ICR, if they are sustained, may reflect both viability consideration (ability to generate profits) and capital structure considerations (excessive leverage). The likelihood of having a low ICR is not clearly related to the tangibility ratio or the growth rate of sales, conditional on other explanatory variables. We find that, both in AEs and in EMs, after controlling for firm characteristics and country and industry fixed effects, the likelihood that a firm does not generate sufficient earnings to pay for interest expenses is negatively correlated with macro-economic performance (proxied by real GDP growth). Once again, the size of the coefficient tends to be lower (and exhibit greater variability as seen in the country-by-country regressions) in EMs than in AEs.

Summaries of country-by-country firm level regressions are reported in Tables 7 and Table 8. Each table shows the country-specific coefficient for the financial condition index (for the ICR-probit regressions) or for real GDP growth (for the sales growth regression). These regressions will be used instead of cross-country regressions to generate projections for the likelihood of having an ICR below one, and for the projections of sales. We make two exceptions for the ICR-probit, for China and Poland. Given the very small coefficient for these two countries and their high standard errors, we prefer to use the coefficients of the EM cross-country regression.[45] For the sales growth models, we also use the coefficient of the EM cross-country regressions for Argentina and India because of the counter-intuitive coefficient estimated for these two countries.[46]

B. Scenarios

The scenario-based stress test involves simulating the evolution of key firm level variables such as profitability, interest-coverage ratio, cash position, leverage and solvency position for 2020, 2021 and 2022, using end of 2019 balance sheet and financial statement data as the starting point of the exercise. The firm level variables are next aggregated at the country level as simple averages (to assess the share of firms from our sample being at risk) or as weighted averages, using each firm's debt as weight, to assess aggregate corporate vulnerabilities and potential spillovers to the banking system.

We consider two scenarios in the forward-looking stress-tests. The first scenario is based on the published baseline projections from the October 2020 World Economic Outlook, and the second one involves the adverse scenario of the World Economic Outlook which is also presented in chapter 4 of the October 2020 Global Financial Stability Report. For each scenario, we construct a projection of the financial condition index constructed from the methodology of the 2017 Global Financial Stability Report, which includes the following variables: stock market return, short-term interest rate, long-term interest rates, corporate spreads, and the VIX, as explained in section III. We also construct macro projections of the change in interest rates on corporates, adding to risk-free short-term and long-term interest rates a spread for corporates.

[45] The small coefficient for China and Poland may be explained by unique country characteristics, such as the effect of state ownership in firms' capital structure and other types of public subsidization in the case of China.

[46] These regressions are not reported but are available upon request.

As shown in Figure 5, the baseline scenario involves a strong rebound of real GDP growth in 2021 and a stabilization in 2022, while the adverse scenario assuming slower progress in the fight against the coronavirus is based upon a slower recovery on average, in particular among EMs. Financial conditions tighten on average in 2020, despite the strong policy actions to keep interest rates and spreads low, and rapidly loosen in 2021, in particular in AEs. Under the adverse scenario, financial conditions remain elevated in AEs in 2021 and 2022 and continue to tighten in EMs.

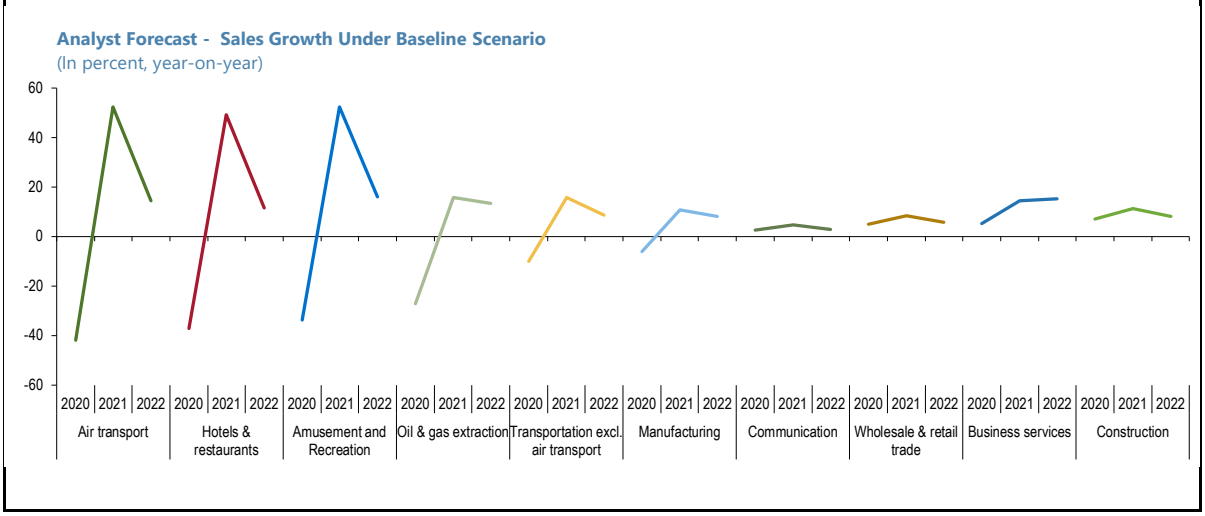
These macro scenarios implicitly incorporate the effects of broad macroeconomic and monetary policy interventions, including interest rate cuts, unconventional monetary policies, fiscal measures, social safety net packages, and other policies that support real economic activity and financial markets, and contain corporate borrowing costs. However, they do not incorporate the impact of specific liquidity and solvency support policies on *individual* firms (see October 2020 GFSR, chapter four, for a similar approach on the analysis of banking stress).

Figure 5a. Baseline and Adverse Scenarios

Sources: World Economic Outlook and IMF staff estimates.

Analysts' average forecasts aggregated by industries are reported in Figure 5b. These forecasts of sales growth (and similarly for EBIT) are relied upon to bring about a sectoral differentiation of projections based on formula (4). According to financial market analysts,' the top five industries in term of the shock experienced in 2020 are Air Transport, Hotels and Restaurants, Amusement and Recreation, and Oil and Gas extraction, which then experience a mechanical rebound in 2021. In contrast, sectors such as Wholesale & Retail Sale, Business Services and Construction still experience positive growth of sales in 2020 on average according to market analysts.[47] These aggregated market forecasts are then rescaled so that the aggregated projections of firm level variables remain consistent with those resulting from the WEO baseline and adverse scenarios.

Figure 5b. Country Industry Specific Shocks by Calendar Year
(In percent)



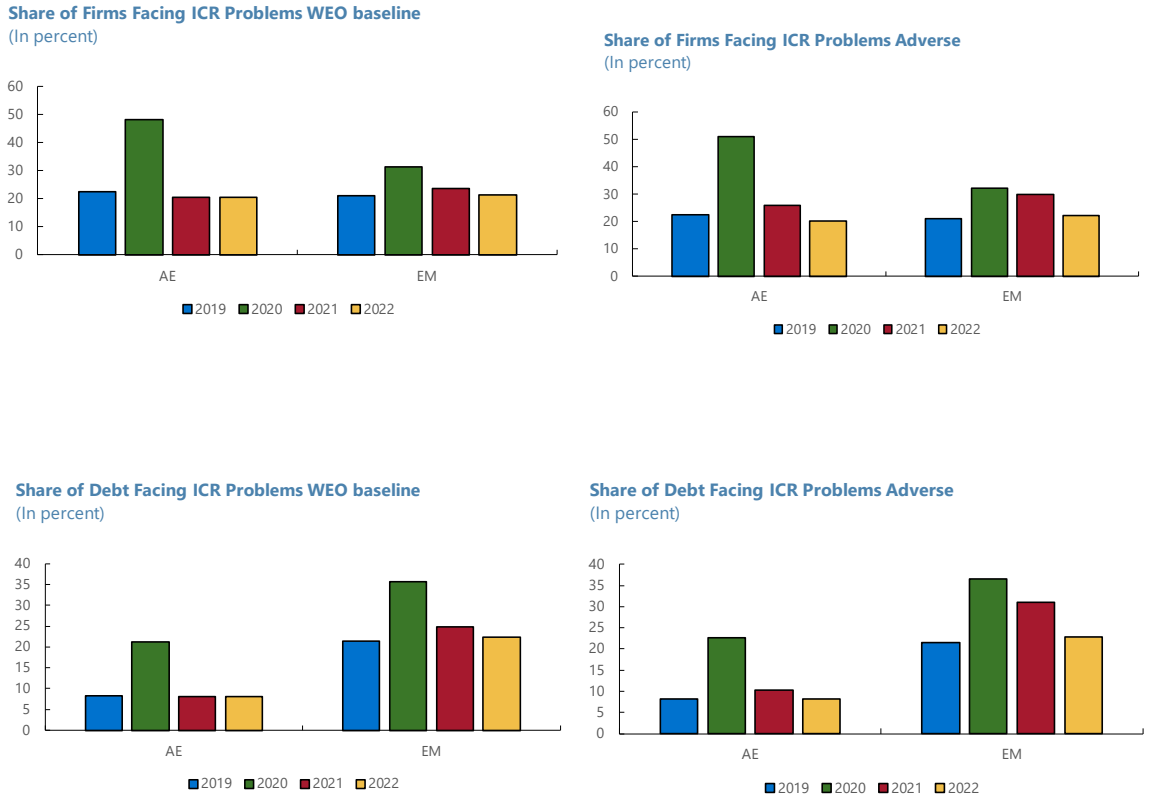
C. Results of Scenarios-Based NFC Stress Tests

Figures 6 to 8 reports the firm level results of the scenario-based stress test. The results are first aggregated at the country level, and second averaged across countries for AEs and EMs. Two metrics are presented: the shares of firms meeting a vulnerability criterion and the share of total country NFC debt accounted for by these firms. Given that our analysis only includes publicly listed companies, our findings may not be necessarily representative of what would happen to all NFCs' balance sheets in a particular country. However, to the extent that publicly listed firms account for a very large share of total NFC debt, it is reasonable to consider that the scenario-based analysis provides a good benchmark for a forward-looking analysis at the country level.

[47] Landier and Thesmar (2020) show that downward revisions in analysts' forecasts for 2020-2022 following the pandemic shock were sharp and explain all of the decrease in equity values between mid-January and mid-May 2020.

Figure 6 presents the scenario results regarding firms' ability to service their debt. The top two charts of Figure 6 show that, both under the baseline scenario and the adverse scenario, the share of firms facing difficulties to service their debt rises to very high levels in 2020, in particular among AEs where this share reaches 50 percent of firms on average, and subsequently declines. The decline is very fast in AEs on average, as the shares of firms with ICR<1 returns to the pre-Covid pandemic levels in the baseline scenario, and remain moderately above the pre-pandemic levels in the adverse scenario. Among EMs, the increase in the share of firms at risk is more moderate in 2020 but tends to remain above pre-pandemic levels in the adverse scenario. Turning to the aggregate debt at risk, the picture is similar for advanced economies where the share of debt at risk tends to fall back to pre-crisis levels on average after the peak in 2020. In contrast, in EMs, the aggregate debt-at-risk reaches on average a higher level in 2020 than in AEs and remains on average above pre-crisis levels in 2021 and 2022 if the adverse scenario materializes.

Figure 6. Debt servicing problems rise sharply in 2020 and decline in 2021–2022 as profitability recovers

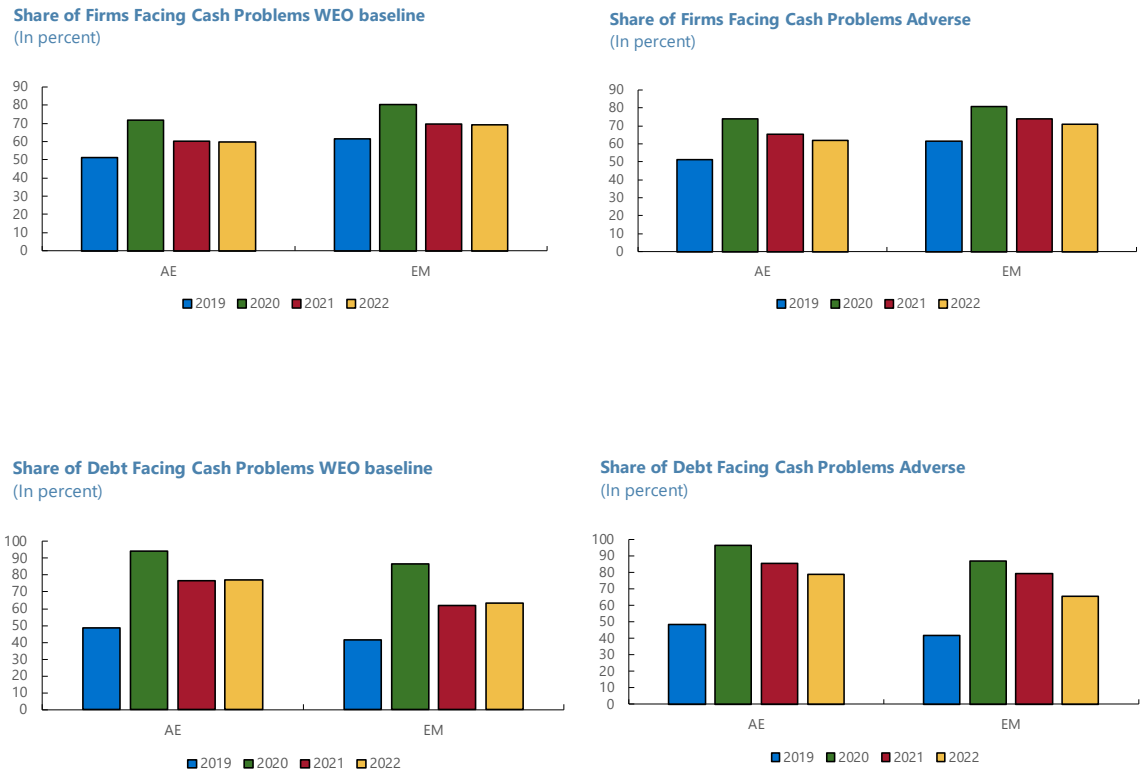


Sources: Datastream, Capital IQ, World Eocnomic Outlook and IMF staff estimates.
Note: WEO baseline corresponds to October 2020 WEO baseline. ICR problem refers to cases where ICR is less than one.

We next turn to the assessment of firms' borrowing needs summarized in Figure 7. For each year 2020 to 2022, we assess the end of year cash position of firms *based on constant*

indebtedness. A negative cash position implies that a firm has to increase its indebtedness to ensure that projected cash inflows are at least sufficient to cover projected cash outflows. If the cash balance is positive, we assume that indebtedness remains constant. In the scenario, firms with positive end of period cash balances do not increase their debt and simply accumulate some cash into the following year. We find that, as a result of the pandemic, the share of firms with borrowing needs increases very sharply in 2020 to very high levels of some 80 percent or above, both in AEs and in EMs. A difference with the assessment of the ICR is that, on average, we do not observe a sharp reversal back to pre-pandemic levels of the share of firms with liquidity needs after 2020, and a large share of firms still continue to increase their leverage in the medium-term, even in the baseline scenario, both in AEs and in EMs. The intuition for this finding is that, even if many firms returns to profitability in 2021 after the large shock experienced this year, the cash inflows resulting from these profits are not sufficient to restore cash balances depleted in 2020, and the dynamics of leverage tend to persist for a significant amount of time even if the macro-economic situation improves. The continued increase in leveraging is even more pronounced in the adverse scenario.

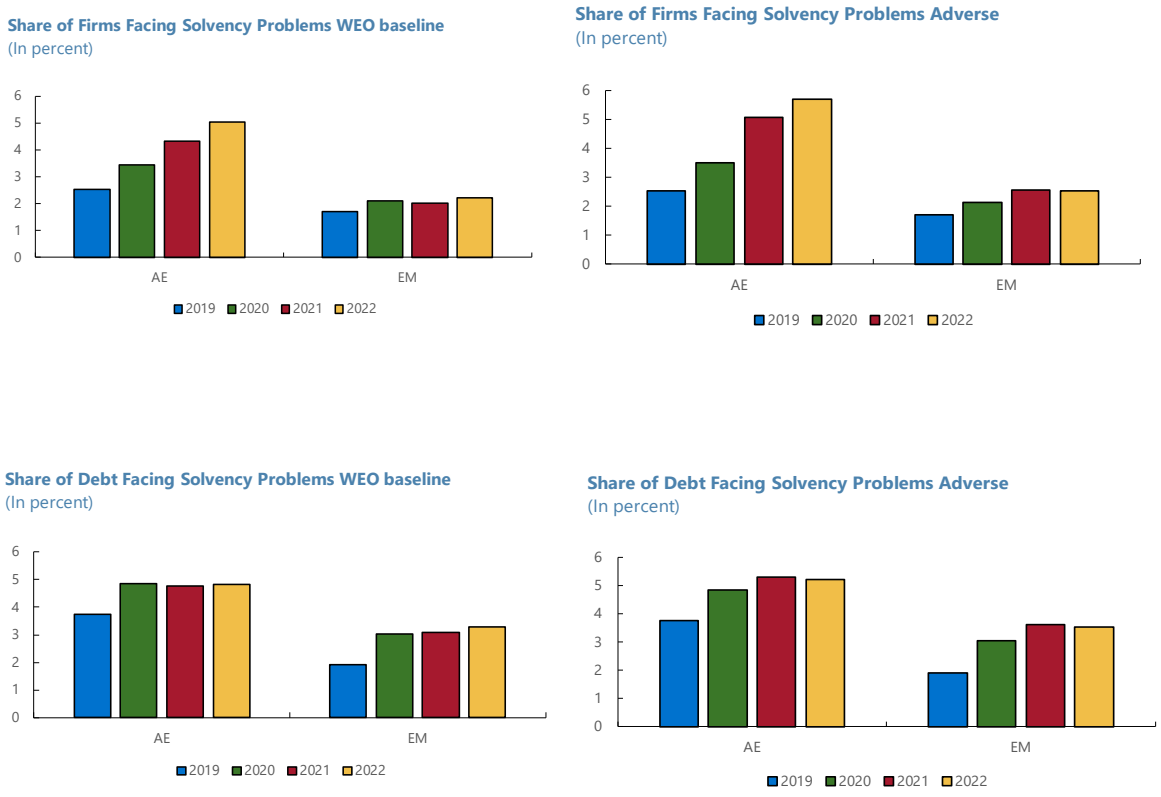
Figure 7. Borrowing needs remains elevated 2020–2022



Sources: Datastream, Capital IQ, World Eocnomic Outlook and IMF staff estimates.
Note: WEO baseline corresponds to October 2020 WEO baseline. Cash problem refers to cases where cash balance is below 0.

An increasing number of publicly listed firms experience a negative solvency position over time in the baseline and in the adverse scenario (Figure 8). The share of publicly listed firms and the amounts of debt at risk increase to respectively some 8-10 percent and some 15–20 percent in AEs. Insolvencies also increase among EMs but to a smaller extent than in AEs. What this analysis reveals is that solvency risks tend to increase over time on average, even in a baseline scenario involving a sharp economic recovery in 2021. A reason for this evolution is that equity tends to be depleted over time as a result of accumulated operating losses and the debt overhang and that for some firms the economic rebound is not sufficient to overcome the adverse 2020 shock.

Figure 8. Firms Solvency Position under Baseline and Adverse Scenario

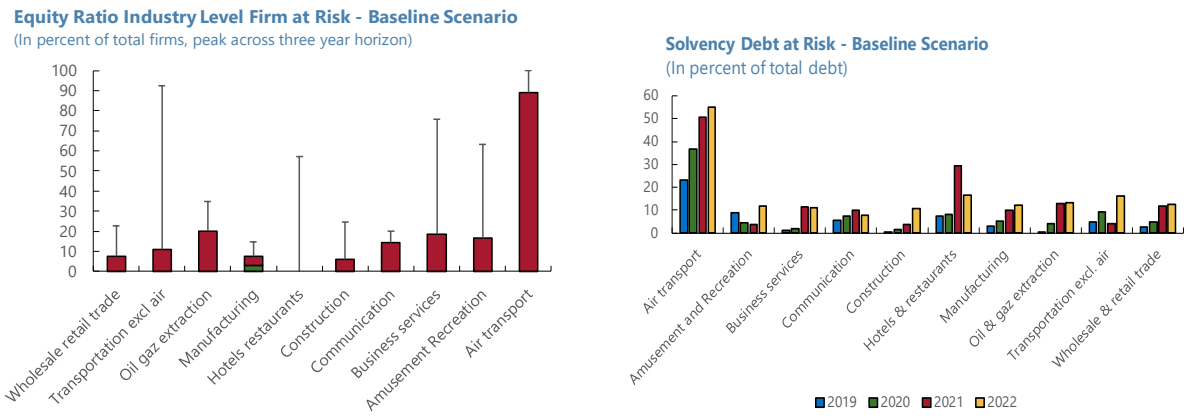


Sources: Datastream, Capital IQ, World Eocnomic Outlook and IMF staff estimates.
Note: WEO baseline corresponds to October 2020 WEO baseline. Solvency problem refers to cases where firm equity is below zero.

The sectoral scenario analysis shows that vulnerabilities are to a large extent concentrated in economic sectors that are more vulnerable to the shock of the Covid pandemic (Figure 9). Debt servicing capacity worsens in many sectors and becomes particularly difficult as profits decline in sectors such as Air Transport, Hotels and Restaurants and Oil Extraction (top panel charts). The recovery in debt servicing capacity also appears to be uneven across sectors, reflecting how lasting the shocks to each sector are. Interestingly, the impact of the pandemic on firms' liquidity needs appears widespread and impacts many sectors (middle panel

charts), despite differences across sectors in the severity and duration of the shocks experienced. This finding suggests that cash buffers get depleted relatively easily in many sectors, and that the 2020 shock is sufficient to achieve that for many firms. In contrast, solvency concerns resulting from the pandemic appear to a large extent to be very concentrated in specific sectors, in particular Air Transport, Oil Extraction, Amusement and Recreation and Hotels and Restaurants.

Figure 9. Sectoral Results



Sources: Datastream, Capital IQ, World Eocnomic Outlook and IMF staff estimates.
Note: Firm at risk denotes share of firms with ICR less than one out of total sample firms and debt at riak denotes share of debt with ICR less than one out of total debt, respectively.

D. Impact on the Financial System

Figure 10 reports estimated aggregated annual PDs of corporate debt for publicly-listed firms, using the average and the median of each countries' Moody's KMV corporate EDF as scaling factors for the starting point. The reason for showing country level PDs for large publicly listed firms using both mean and median EDFs as benchmarking factors is because for several countries (notably the United States and Canada), the mean EDFs for 2019 appear to be high (7–8 percent). A distribution analysis of EDFs by ratings suggests that the US and Canada sample of Moody's KMV contains a tail of relatively large proportion of low rated firms which may drive up the average EDF for these samples of large firms. These estimated PD projections convey information for bank and nonbank financial institutions' exposures regarding the risk that large corporates with market access may default on loans or bonds.

We also report estimated PDs for each banking system using banking PDs on NFC loans as benchmarking factors, and estimated inflows of NPLs to assess direct risks to banking systems, as explained in section IV.D.

The following facts emerge from our analysis. First, as show in Figure 10, top panel, scaling by mean or median EDFs does make a difference for some countries regarding the absolute level of default risk for large corporates, in particular for the United States, Canada, several large EMs, as well as for France and United Kingdom (albeit to a smaller extent). Second, in spite of differences, the *relative* ranking of countries is broadly robust when using the mean or the median EDF from Moody's KMV as scaling factor: large firms from large EMs, the United States or Canada appear more vulnerable and more at risk of default than those of other countries.

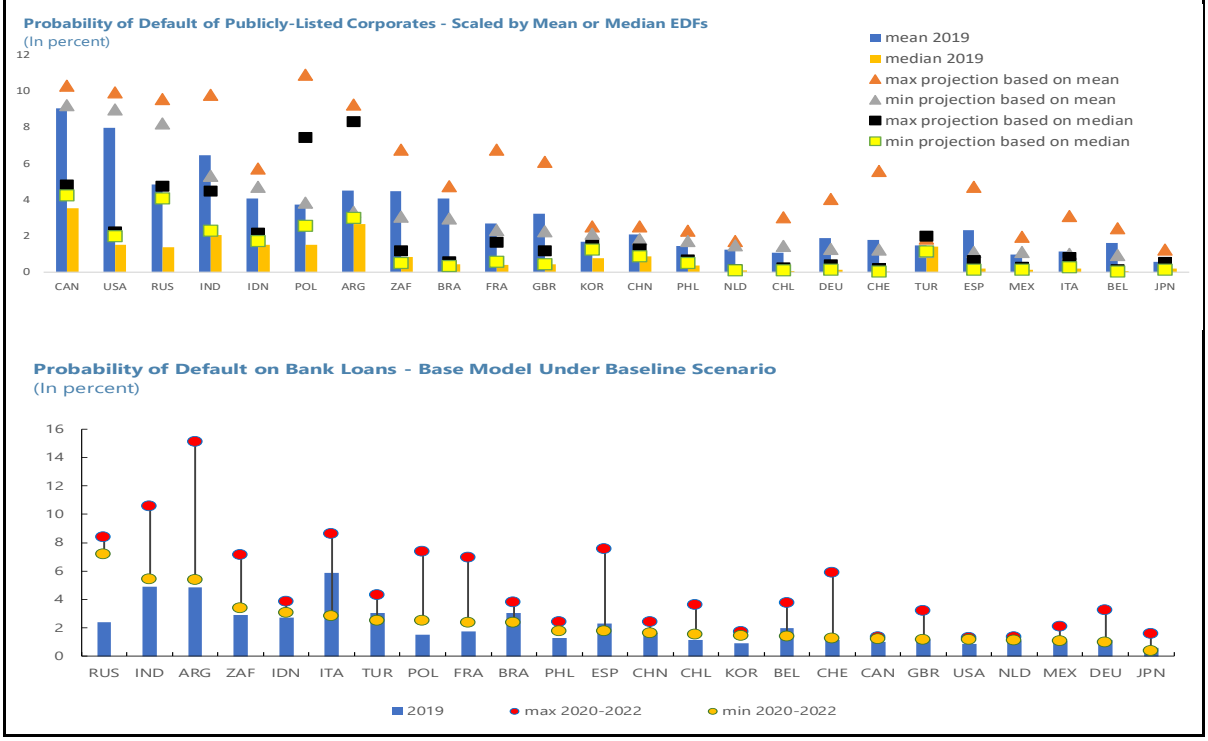
The second panel of Figure 10 reports projections of PDs on bank loans, with a benchmarking to 2019 bank loan PDs as explained in section IV.D. There are similarities with the analysis for large corporates: bank loans appear in general to be more at risk of default in EMs than in AEs. There are also notable differences with the previous results for

several large AEs: PDs for US and Canada are now very low, while those for Italy are quite high. These findings suggest there can be important differences of vulnerabilities within countries between large publicly listed corporates and the corporates to which banking systems are exposed. These differences of vulnerabilities are not necessarily in the same direction in all countries. This also suggests that nonbank financial institutions may in some cases be bearing risks arising from publicly listed firms.

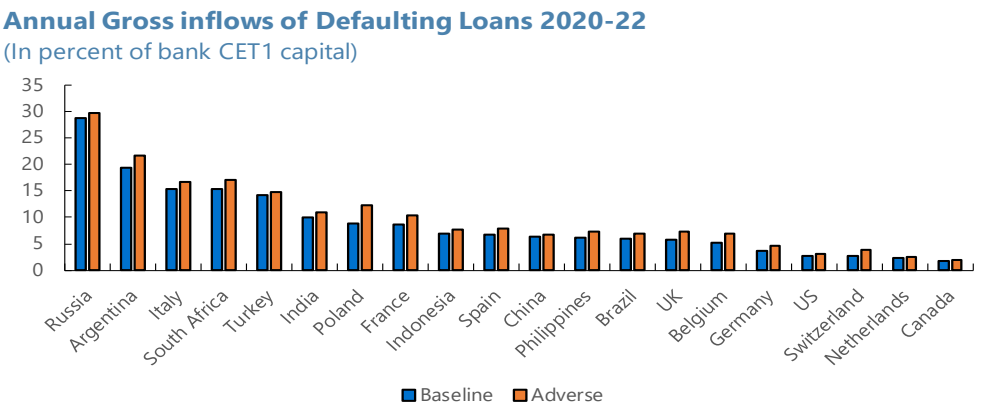
Last, there are also significant differences in the extent to which PDs increase as a result of the pandemic with PDs rising significantly in several EMs such as Argentina, India, Poland or Russia, but also in several AEs such as Canada, France, Switzerland, and the UK.

The impact on banking system is proxied by the ratio of the annual inflow of NPL to bank capital, and is computed by multiplying the aggregate bank corporate PDs by banks' total exposures to NFC and then scaled by aggregate T1 capital as explained in section IV.D (third panel). We find that the impact is the most severe among large EMs and for Italy where it would reach more than 10 percent of bank capital. Risks to banking system would also be relatively important for several other EMS and for France and Spain. For European countries, our findings can be compared to the stress test results of banks reported in Aiyar et al. (2021). Our ranking of credit risk impact appears similar to theirs among countries common to the two sample, with the largest impact concerning Italy, France and Spain in decreasing order, and the smallest credit risk impact concerning Germany.[48]

Figure 10. Probabilities of Default and Impact on the Banking System



[48] See Box Figure 1.3 in Aiyar et al. (2021).



Sources: Datastream, Capital IQ, World Eocnomic Outlook, Haver, European Banking Authority, US Federal Reserve, IMF Financial Soundness Indicators and IMF staff estimates.

VII. Medium-term Policies: Triage of Firms, Debt Restructuring and Liquidity Provision

In this section, we turn to the medium-term policy analysis. We propose a triage of firms and quantify the number of firms, amounts of NFC debt, and amounts of equity gaps for each category of firms. We highlight the time dimension of the analysis, which focuses on the onset of the pandemic and the post-pandemic recovery period 2021–2022. The simulations present a quantification under the two scenarios.

The viability of firms' business models emphasizes their capacity to sustainably generate positive profits net of interest payments on their debt, that is whether the benefits of continuing a business exceed its costs. In theory, the continuation value of a business should be assessed by comparing the present value of future net profits flows (if the firm is allowed to continue operating) to the net recovery value of assets (if the firm is liquidated). Due to the complexity of such an assessment under uncertainty regarding the recovery value of assets and future profit flows, in the literature, viability is often assessed in different ways, by combining different indicators, such as profitability (including the ICR), productivity and/or market indicators such as the market-to-book value of equity.[49]

Given the large uncertainties regarding the shape of the recovery post-pandemic, we consider the pre-pandemic (2019) net profits of firms or their price-to-book ratio as the two key criteria regarding the assessment of viability of a business model in a "normal" economic environment in absence of the Covid shock which has caused debt overhang problems. We consider as viable a firm that has an ICR>1 or a price-to-book ratio above the country average (to capture unicorns/growth firms). Note that, while it is related to solvency, the viability differs in important ways (Antoshin et al., 2021). In particular, while solvency refers

[49] The ICR is particularly informative: a ratio that is sustainably above one (respectively below one) indicates a business that can sustainably service its debt from current profits while rolling over its debt at the current level. Conversely, a ratio sustainably below one indicates a sustainably loss-making firm or a firm that makes positive profits but that are not sufficient to service its existing debt stock. When market indicators are also available, the market-to-book value of equity (a proxy for Tobin's marginal Q) provides a way to assess whether the net present value of future profits is positive (if the ratio is above one) or not (ratio below one).

to the residual value of a business (assets net of liabilities) at any point in time, viability refers to the continuation value of a business, e.g., its ability to generate profits going forward.

Among firms with a viable business model, we distinguish firms (i) that may still be viable after the pandemic but may suffer from debt overhang caused by the Covid shock from (ii) those that overcome the pandemic well, and (iii) those may not be viable and may not generate positive net profits even in normal time. Specifically, we consider the following three-way split reminiscent of Gourinchas et al. (2020) but based on the ICR criteria and the price-to-book ratio instead of a cash-balance criteria as they do, while adopting a medium-term perspective (Table 9):

(i) **Survivor firms** generate positive net profits both before the pandemic and during the recovery phase of the pandemic: pre-Covid ICR>1 and post-Covid ICR>1.

(ii) **Viable (but distressed) firms** do not generate positive net profits in the recovery phase of the pandemic because of debt overhang but generated positive net profits before the pandemic or had a high price-to-book ratio (above country average) and would therefore be viable as economies return to normal, potentially after some debt restructuring: pre-Covid ICR>1 or pre-Covid market-to-book ratio > country average, but post-Covid ICR<1.

(iii) **Ghost firms** did not generate positive net profits before and during the recovery phase of the pandemic: pre-Covid ICR<1 and pre-Covid price-to-book ratio < country average, and post-Covid ICR<1.

Table 9. Triage of Firms

The viability assessment is based on firms' pre-Covid ability to generate positive net profits and growth potential

Triage	Pre-Covid	Medium-term (2022)
Survivor	ICR>1 or price-to-book ratio > country average	ICR>1
Viable	ICR>1 or price-to-book ratio > country average	ICR<1
Ghosts	ICR<1 and price-to-book ratio < country average	ICR<1

Source: IMF staff.

Our classification of firms has three dimensions: viability (ICR based); solvency (equity position); and liquidity/borrowing needs (cash position in absence of additional borrowing).[50] The viability assessment determines whether a firm may continue to operate or not, and if it continues to operate, whether a debt restructuring may be needed to address the debt overhang problem. As Blanchard et al. (2020), we do not consider the post-pandemic equity position of a firm as the key criteria for the viability assessment because some firms may have experienced an erosion of their net worth during the pandemic as a result of a collapse of earnings, but may still have a viable business model once the pandemic is over and be able

[50] Stein (2020) argues that the ICR can be an adequate indicator of viability, especially in situations with high uncertainty. Banerjee and Kharroubi (2020) present evidence that the ICR is a good predictor of firm liquidation.

to generate positive profits over time. [51] However, the post-pandemic net worth of a firm is still an important indicator of how fragile the balance sheet is, in particular the extent to which a recapitalization may be needed to restore a firm with a viable business model on a sound financial footing when the pandemic is over.

An advantage of our approach to viability based on the ICR is that it is a conservative criteria in the sense that the group of firms deemed non-viable based on this criteria includes at least all firms that were not generating positive economic profits (e.g., firms with ROA <0) before the pandemic, as well as firms with positive ROA but with interest expenses exceeding gross profits. [52] On the other hand, a potential limitation of our approach that considers as a viable business model a firm with ICR<1 in 2022 (but with an ICR>1 in 2019), that is the assumption that economies will return to "normal" (pre-pandemic) conditions. Indeed, we could be over-estimating the number of firms that are truly viable post-pandemic: if the pandemic result in structural economic changes or if financial conditions tighten, there could be firms that had viable business models in the past but that may have become unviable post-pandemic. While it is beyond the scope of our paper to assess the extent of structural economic changes post-pandemic, we note that relying on 2022 as a medium-term horizon could, on the other hand, result in underestimating the number of firms that may actually be survivors because the effects of the pandemic on earnings could take more time to fully dissipate, in particular if an adverse scenario were to materialize or if borrowing costs rise.

In addition to the viability assessment, we will also consider an assessment of the extent to which survivor and viable firms may require some form of continued liquidity support as the economies recover from the pandemic. For this purpose, we continue considering the simulated cash balance position of each firm in absence of new borrowing to determine whether firms need to continue to increase their debt or not. The policy question is whether and to what extent it is critical to maintain liquidity support policies during the recovery that would continue to contain the borrowing costs of firms with a viable business model.

With this classification of firms at hand, we map policy interventions during the recovery phase to each category of firms as follows: (i) during the recovery period 2021-2022, continue some policies supporting corporate liquidity needs for "viable" and "survivor" firms; (ii) consider debt restructuring of "viable" firms in the recovery phase of the pandemic to address debt overhang problems; (iii) liquidate non-viable businesses ("ghost" firms); and: (iv) consider equity-like injection for viable and survivor firms if needed to bring them to a positive equity position. The triage and related taxonomy of medium-term policy interventions is summarized in Table 10.

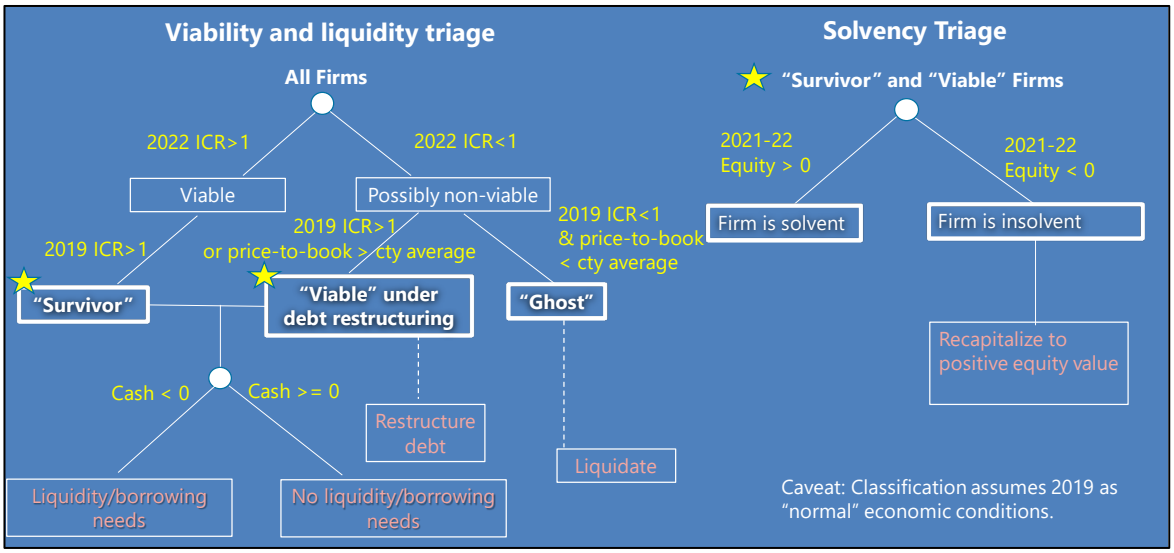
Figure 11 presents the results of the triage of firms into groups of "survivor," "viable" and "ghost" firms, and the aggregated estimates of corporate debt to restructure (viable firms) and of corporate debt to liquidate (ghost firms). We average the results over the period 2021–22, and we present results both for the baseline and for the adverse scenario. The estimates

[51] Blanchard et al. (2020) emphasizes the distinction between viability and solvency: some firms may be viable after the pandemic even if they have become insolvent as a result of a debt overhang problem.

[52] Indeed, an ROA < 0 implies an ICR<1.

suggest that: (i) debt restructuring needs would be significant by 2022; (ii) the debt of liquidated firms would also be quite large.

Table 10. Triage and taxonomy of Policies during the Recovery from the Pandemic



Source: IMF staff.

As shown in the top two panels of Figure 11, in the baseline scenario, about 74 percent of firms in AEs and about 76 percent of firms in EMs are considered survivor firms on average, meaning that in the next two years, they would have returned to pre-pandemic positive net profits. In the adverse scenario with a weak recovery due to additional waves of the pandemic and policy response, the share of "survivor" firms would decline to about 67 percent on average both in AEs and in EMs. From the point of view of aggregate corporate debt, about 85 percent and 84 percent of this debt appears to be sound on average in AEs and in EMs respectively in the baseline scenario, and about 70-78 percent in the adverse scenario.

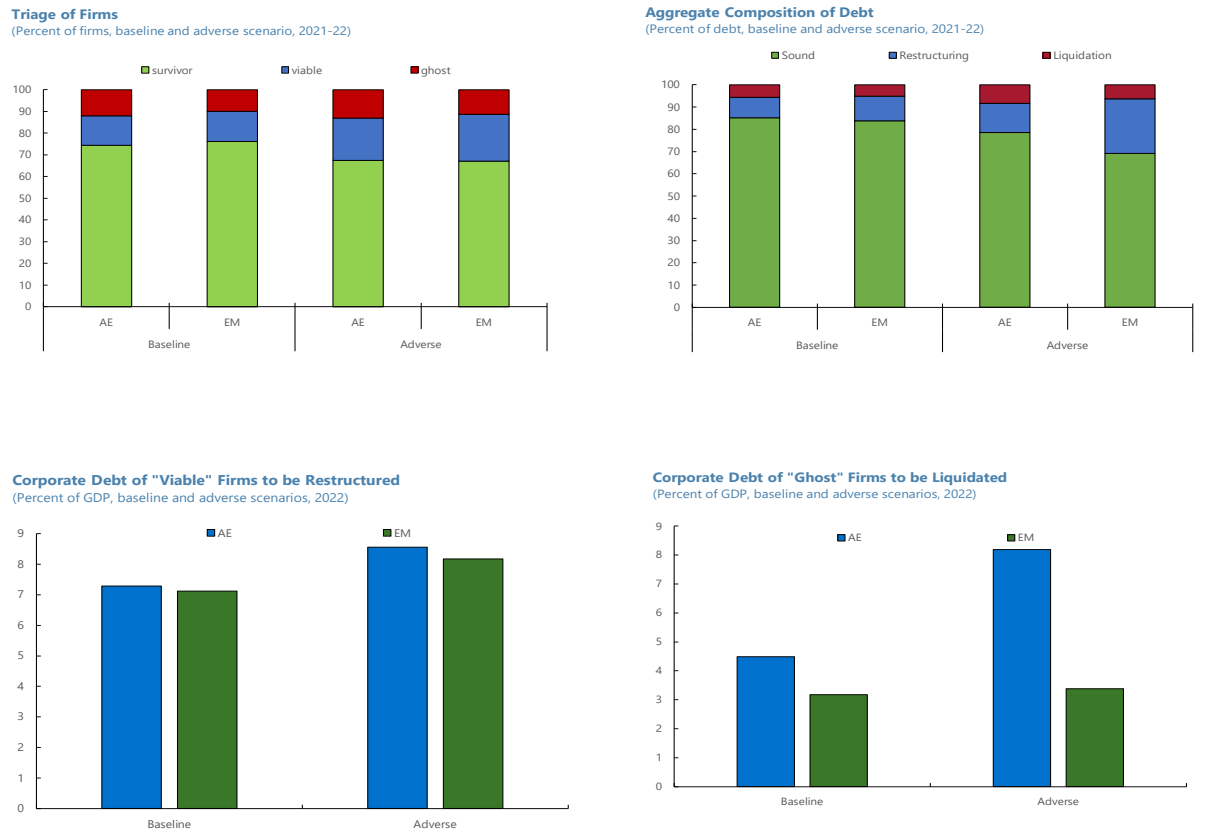
Turning to "viable" firms, in AEs, some 13 percent of firms on average, accounting for 9 percent of total NFC debt, would require a debt restructuring in the baseline scenario, and 19 percent of firms accounting for 13 percent of debt in the adverse scenario. In EMs, 14 percent (respectively 22 percent) of firms would require a debt restructuring in the baseline scenario (respectively in the adverse scenario), accounting respectively for 11 percent and 24 percent of NFC debt respectively in the baseline and the adverse scenario.

Extrapolating to the entire NFC sector, we find that corporate debt restructuring of viable but distressed firms need may be quite significant at the macroeconomic level. Indeed, extrapolating our results to privately held firms, these findings imply that in AEs, on average some 7.3 percent of GDP of NFC debt (respectively 8.6 percent of GDP) in the baseline scenario (respectively in the adverse scenario) would require some form of restructuring in 2022, either for viable but distressed firms or for "ghost" firms. In EMs, the same figures would reach about 7.1 percent of GDP in the baseline scenario, and 8.2 percent of GDP in the adverse scenario, reflecting the lower ratio of total NFC debt to GDP in EMs relative to AEs.

The extrapolation may be interpreted with caution because the sample of publicly-listed firms may not be representative of the entire NFC sector in each countries. [53]

Next, we find that a significant share of firms may need to be liquidated, about 12-13 (baseline-adverse) percent in AEs, and 9-11 percent in EMs. The amounts of debt to be liquidated would reach to some 5-8 percent of total NFC debt in AEs, and some 5-6 percent in EMs – amounts that would correspond to 4.5-8.2 and 3.2-3.4 percent of GDP in 2022 respectively in AEs and in EMs if projections for publicly listed firms are extrapolated to privately held firms.

Figure 11. Triage of Firms—Results



Sources: Datastream, Capital IQ, World Eocnomic Outlook and IMF staff estimates.

In Figure 12, we report the results of the cash balance analysis which provides information on the extent to which firms will continue to need to expand their borrowing, a proxy for liquidity needs. The main finding is that liquidity needs of viable and survivor NFCs, while declining, would remain substantial at an aggregate level in 2021–22, especially for survivor firms which account for a large share of total firms.

[53] The extrapolation is done in each country by assuming that the same shares of debt for category of firms for the entire stock of debt of the NFC sector. Caution may be required in interpreting the numbers since the sensitivity to shocks, P&L and capital structures, as well as sectors of activity may be different between listed and non-listed companies.

Borrowing needs of "survivor" and "viable" firms decline over time, but remain elevated in the medium-term. Indeed about 41 percent of these firms in AEs (47 percent in EMs) would still need to expand their borrowing in 2022, on average in the baseline and the adverse scenarios, accounting for 45 percent of these firms' debt in AEs (33 percent in EMs) on average across the two scenarios (top two panels of figure 12).

Extrapolating our results to the country level stock of corporate debt, we find that the stock of debt of survivor and viable firms requiring additional borrowing is high in percent of GDP. In AEs, the stock of debt of these firms requiring additional borrowing would stand on average at around 40 percent of GDP in 2022 in the two forward looking scenarios. In EMs, this stock of debt of these firms with borrowing needs would reach to about 16 percent of GDP in 2022. From a policy perspective, these findings of large borrowing needs in the medium-term do not *per se* imply that policy support would be required for *all firms*, but at least a very substantial share of them would need it to avoid or contain debt overhang problems.

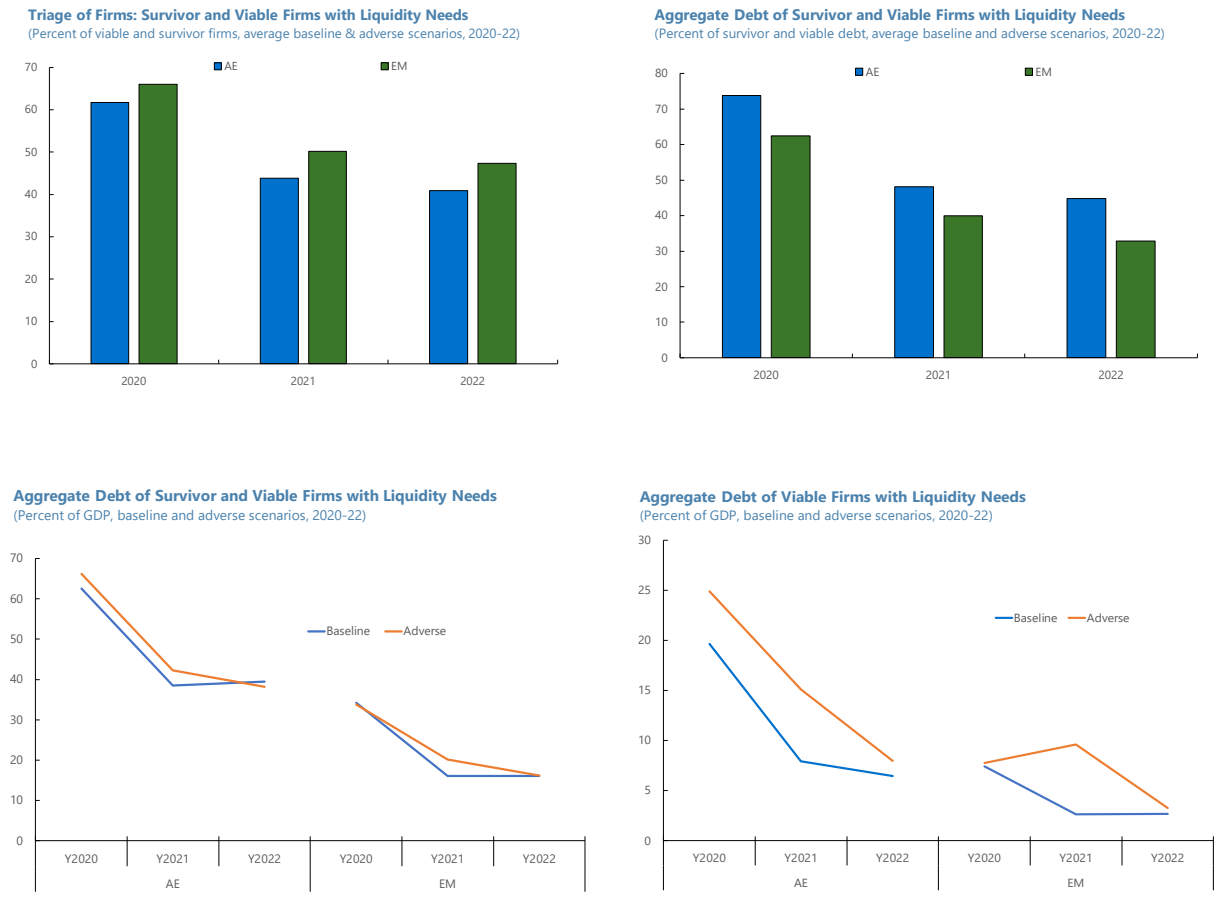
The bottom right panel shows the aggregate debt of viable firms with liquidity needs in the two scenarios. While their debt declines sharply over time, it would still reach about 6 percent of GDP on average in AEs, and about 3 ¼ percent of GDP for the EMs. This finding suggests that some targeted liquidity support, if feasible, would concern a smaller amount of corporate debt

There are some relevant qualifiers suggesting that liquidity support, if targeted only to viable firms with additional borrowing needs may be insufficient:

1. The scenario simulations are performed under the assumption that firms invest only to maintain their stock of capital and do not expand their stock of capital. New fixed investments to sustain real GDP growth would require additional cash.

2. There are viable firms that do not need to expand their borrowing but still would face debt overhang problems, which suggests that these firms may also benefit from liquidity support that contains borrowing costs only to rollover their stock of maturing debt.

Figure 12. Survivor and Viable Firms with Liquidity Needs



Sources: Datastream, Capital IQ, World Eocnomic Outlook and IMF staff estimates.

VIII. Conclusions

This paper analyzes the short-term and medium-term stress of publicly-listed NFCs resulting from the Covid-19 pandemic in a broad sample of AEs and in EMs. The study adopts a multi-dimensional approach, and to do so, constructs novel methodologies to undertake stress tests of NFCs incorporating both macro and sectoral shocks. Besides data availability considerations, a focus on publicly-listed NFCs is appropriate from a financial stability perspective given that these firms tend to account for a disproportionate share of NFC debt in many countries, but extending our results to the entire NFC sector may still result in some bias in specific cases where SME vulnerabilities differ from those of publicly-listed companies. We focus on indicators of liquidity risk (the cash balance), viability (the interest coverage ratio, which in the short-term is also an indicator of liquidity) and of solvency risk (the net worth).

We develop two new stress testing methodologies for NFCs. These new methodologies making use of firm level information could be used in the future to complement existing banking stress tests models by developing scenario-based assessments of corporate

vulnerabilities. Our models also allow to conduct policy assessments which could feed into banking stress test scenarios.

The first methodology is a multi-factor sensitivity tool that allows to assess the short-term response of the balance sheet and financial statement of NFCs to various stress factors, and provides the flexibility to consider combinations of shocks to sales, behavioral firm level responses, and policy actions encompassing fiscal, monetary and regulatory policies which can be tailored at the firm level and/or at the sectoral level. In addition, we offer a new approach making use of financial analysts' forecasts of firms' sales pre- and post-pandemic shock of 2020:Q1 to calibrate shocks at the country-industry level.

We apply this sensitivity analysis tool to the pandemic shock of 2020. We find that, both in AEs and in EMs, the short-term impact of the shock on firms' cash balances and on the capacity to pay interest expenses from operating profits is very severe as a very large share of firms accounting for a substantial portion of our sample of NFC debt would face liquidity difficulties, and would need to increase their debt to cover their cash outflows after exhausting their initial cash buffers. We also find that firms' behavioral responses to the shock, e.g. their capacity to offset it by cutting production costs, as well as policy responses (in particular such as those subsidizing the wage bill and facilitating an increase in borrowing) play a crucial role in mitigating the impact of the pandemic shock.[54]

The second methodology is a dynamic forward-looking scenario-based stress testing tool that permits to generate firm level internally consistent projections of standard balance sheet and financial statement ratios such as leverage, solvency, cash balance ratios and ROA by combining regressions with accounting identities. Very few papers have developed such a methodology, and, to the best of our knowledge, our paper is the first one to perform such a dynamic analysis for firms of several countries in the context of the COVID-19 pandemic. Firm level cyclical variables projected are linked to pre-determined firm level variables (including their own lagged values) and to macro-financial variables. The tool is further refined by developing a methodology allowing for a sectoral differentiation of country shocks to profits and the growth rate of sales of firms, again by making use of financial analysts' calendar year projections of sales and profits, while maintaining aggregate consistency of projections with the macroeconomic scenario.

Making use of the October 2020 World Economic Outlook published baseline projections and adverse scenario, and analysts' firm level projections for calendar years 2020-2022, and starting from the 2019 balance sheets and financial statements, we simulate the evolution of these firm level variables for the period 2020-22. We find that: (i) from an ICR perspective, vulnerabilities peak in 2020 and decline thereafter, especially in the baseline scenario, as profitability recovers in line with the macroeconomic rebound; (ii) solvency concerns tend to rise over time; and (iii) needs for additional borrowing (assessed from the simulated cash balance at constant debt level) increase significantly as a result of the shock and remain important in the medium-term while declining at a moderate pace, suggesting that many

[54] The analysis does not account for general equilibrium effects: would all firms cut labor costs, the rise in unemployment would depress demand and generate additional declines in sales.

firms still need to continue to increase their leverage to cover cash outflows. Solvency risks but also to some extent ICR-related risks tend to be concentrated in a few sectors. In contrast, liquidity/borrowing needs tend to be more widespread across industries. We also find that there is some notable cross-country heterogeneity in the evolution of NFC risks which also reflects initial conditions in each country, in addition to the severity of the shock. Of course, our findings are tied to specific macroeconomic scenarios, and considerations related to taking a stance on the extent of possible structural change are left to future work.

Next, given our interest in financial stability implications of NFC vulnerabilities, we offer an approach to map vulnerability indicators into firm level probabilities of default based on Moody's mapping between ratings and vulnerabilities indicators and benchmark them to Moody's KMV country-level EDFs. These market-based estimates suggest that the pandemic potential credit risks to financial systems from large corporates would be significant, in particular among several EMs and a few large AEs but would decline as economies recover from the shock. If instead we benchmark our simulated PDs to bank loans, we find that credit risks to banking systems are significant in particular for large EMs, but also for several AEs. Such findings raise the question of potential tightening of lending standards going forward, and decline in the provision of liquidity to firms that could occur if banks engage in a de-risking of their balance sheets. Note that our analysis does not account for cascading and second-round effects among firms through trade receivables and trade payables which are quantitatively important in the corporate sectors of many countries. Thus, the gross trade creditor positions of a firm would also indicate its susceptibility to receiving and/or transmitting shocks across firms which could cause cascades of defaults. Such effects could amplify financial stability risks.

Last, we propose an approach to achieve a medium-term triage and viability assessment of firms under our scenario-based stress tests. While sorting out which firms are viable or non-viable is in practice a complex endeavor, we argue that, in the context of the medium-term implications of the Covid-19 pandemic and given large uncertainties about the future, the pre-pandemic interest coverage ratio of a firm and the price-to-book ratio can be considered as reasonably good variables to analyze medium-term viability considerations, and may be better suited for that purpose than the solvency ratio. Our assumption is that the return to "normal" economic conditions at the firm level can be approximated by a combination of pre-pandemic (2019) ICR and price-to-book ratio. An important caveat is that post-pandemic "normal" medium-term conditions may turn out to be different, but assessing what the medium-term would look like after the pandemic is beyond the scope of our work. We compare our approach with several recent proposals in the literature and highlight differences and commonalities, in particular the importance of making a distinction between viability and solvency, as viable firms could become overindebted as a result of the pandemic shock, but still be viable, and so would require a debt restructuring.

We quantify the amounts of NFC debt of viable firms to be restructured in the medium-term, and the debt of unviable firms to be liquidated, and find that these amounts may be substantial at a macroeconomic level. We quantify needs for additional borrowing and find that these are very large for both survivor and viable firms. We also quantity the equity gaps to be filled as well as the share of firms (and debt) to be liquidated in the medium-term.

Table 1. Country Sample

Advance Economies	Number of Firms	Emerging Market	Number of Firms
Belgium	63	Argentina	53
Canada	663	Brazil	212
France	411	Chile	115
Germany	350	China	2819
Italy	223	India	2109
Japan	3032	Indonesia	308
Korea	2014	Mexico	81
Netherlands	67	Philippines	55
Spain	109	Poland	284
Switzerland	133	Russia	216
United Kingdom	601	South Africa	158
United States	2456	Turkey	243

Sources: Datastream and Capital IQ.

Table 2. Variable List

Variables	Sources	Frequency
Firm Level		
Total assets Cash and equivalents Short-term investments Receivables, net Property, plant and equipment, net Total currency liabilities Total currency assets Short-term debt and current portion of long-term debt Long-term debt Total liabilities Common equity Total liabilities and shareholders' Equity Total debt Net sales Cost of goods sold EBIT EBITDA Return on assets Income tax Operating income Operating expense Interest expenses on debt	Datastream and Capital IQ	2003-2019
Macro Level		
GDP growth Financial condition index	World Economic Outlook and IMF Staff Estimates	2003-2022
Analyst Forecast		
Sales EBIT	IBES (The institutional broker's estimate system)	January – May 2020, Calendar year 2020-2022

Table 3. Industry Classification

Industry	SIC code
Air transport	[4500, 6000)
Amusement and Recreation	[7900, 8000)
Business services	[7300, 7400)
Communication	[4800, 4900)
Construction	[1500, 1700)
Hotels & restaurants	[7000, 7100)
Manufacturing	[2000, 3900)
Oil & gas extraction	[1300, 1400)
Transportation excl. air transport	[4000, 4500), [4600, 4800)
Wholesale & retail trade	[5000, 5900)

Sources: SIC industry classification.

Table 4. Output Share of Sample Firms of Total Output

Country	Year	Benchmark	Share of Total NFC Output
Belgium	2018	Total NFC output	21.2
Brazil	2017	Total NFC output	19.0
Chile	2017	Total output	28.9
France	2018	Total NFC output	60.5
Germany	2018	Total NFC output	43.9
Italy	2019	Total NFC output	16.3
Japan	2017	Total output	58.1
Korea	2017	Total NFC output	66.3
Mexico	2018	Total NFC output	17.6
Netherland	2018	Total NFC output	62.9
Russia	2017	Total NFC output	31.0
South Africa	2017	Total NFC output	49.3
Spain	2018	Total NFC output	25.6
Switzerland	2018	Total NFC output	58.6
Turkey	2017	Total NFC output	14.4
United Kingdom	2018	Total NFC output	61.6
United States	2017	Total output	33.9
Poland	2018	Total NFC output	19.2
Total			39.9

Sources: Datastream, Capital IQ, OECD statistics and IMF staff estimates.

Table 5. Debt Share of Sample Firms of Total Debt
(In percent, unless otherwise noted)

Country	Year	Consolidation Level	Debt Share of Total NFC Debt
Argentina	2018	Conso	40.6
Belgium	2018	Conso	25.5
Brazil	2018	Conso	40.9
Canada	2019	Solo	29.5
Chile	2018	Conso	27.7
China	2018	Conso	28.8
France	2018	Conso	34.5
Germany	2018	Conso	54.1
India	2018	Conso	39.0
Indonesia	2018	Conso	40.0
Italy	2018	Conso	22.2
Japan	2018	Solo	41.4
Korea	2019	Solo	45.6
Mexico	2018	Conso	42.8
Netherlands	2018	Conso	19.0
Poland	2018	Conso	14.1
Russia	2018	Conso	40.8
South Africa	2018	Conso	70.5
Spain	2019	Conso	28.5
Switzerland	2018	Solo	22.5
Turkey	2018	Conso	14.4
United Kingdom	2018	Conso	30.6
United States	2019	Solo	40.4
Total			34.4

Figure 13. Selected Financial Indicators
(In percent, unless otherwise noted)

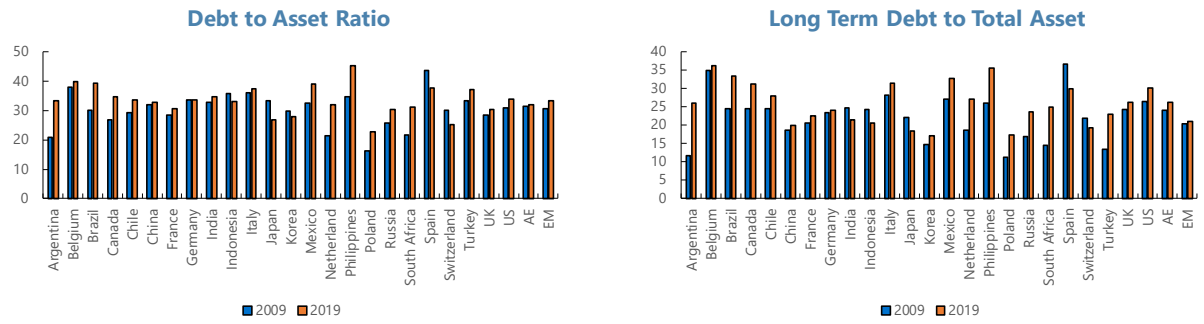
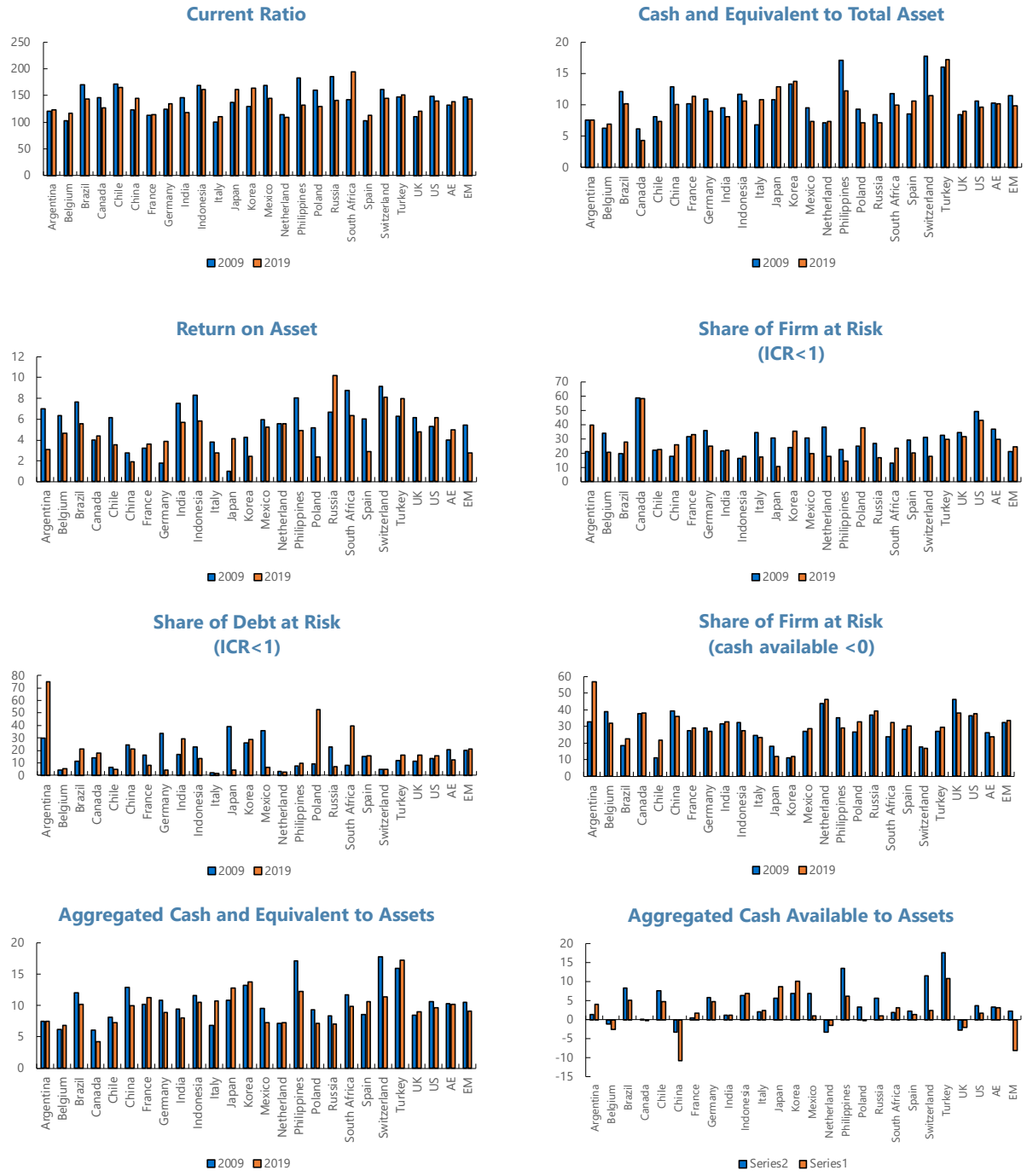


Figure 13. Selected Financial Indicators (continued)



Sources: Datastream, Capital IQ and IMF staff estimates.

Table 6. Pooled Panel Regressions

	OLS				Probit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	**ROA**		**Debt-to-asset ratio**		**Cash net of WC ≤ 0**		**ICR <1**	
Country sample	AEs	EMs	AEs	EMs	AEs	EMs	AEs	EMs
Firm level variables (t-1)								
Lagged dependent variable	0.606***	0.592***	0.882***	0.877***	.	.	.	.
ROA	.	.	0.000103	-0.0782***	-0.00785***	-0.0559***	-0.0820***	-0.168***
Debt-to-asset ratio	0.00929***	-0.00368***	.	.	0.0152***	0.0261***	0.00793***	0.0152***
growth rate of sales	-0.000373*	3.66e-07***	0.000408**	-2.27e-06***	4.71e-05	9.48e-07***	-1.56e-05	-5.52e-06
Fixed assets to total assets	0.0156***	0.00514***	0.0136***	0.00583	0.0141***	0.0116***	-0.00163***	0.000148
Sales to total assets	0.00672***	0.00678***	-0.00337***	-0.00800***	0.00386***	0.00470***	-0.00103***	-0.00280***
Size	0.0300***	-0.000717	0.0108***	0.0135***	0.0192***	0.00871***	-0.0116***	-0.0158***
Macro-financial variables (t)								
real GDP growth	24.08***	4.934**	.	.	.	.	-7.293***	-1.973
FCI	.	.	0.547**	0.446**	0.0781***	0.05**	.	.
Constant	-0.0420	0.975***	3.354***	4.668***	-1.819***	-0.498***	-0.345***	0.279*
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,341	51,085	73,341	51,464	72,915	44,360	73,341	51,685
R2	0.429	0.446	0.808	0.800	.	.	.	.

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by country-year.

Source: IMF staff estimates.

Table 7. Country level regressions I: Probit (ICR<1)

Advanced Economies		Emerging Markets	
Belgium		Argentina	
Real GDP growth	-11.72*	Real GDP growth	-5.618***
Observations	578	Observations	311
Canada		Brazil	
Real GDP growth	-5.965	Real GDP growth	-3.624**
Observations	4,177	Observations	1,413
France		Chile	
Real GDP growth	-10.41***	Real GDP growth	-2.329
Observations	3,914	Observations	945
Germany		China	
Real GDP growth	-7.615***	Real GDP growth	-0.726
Observations	3,204	Observations	24,418
Italy		India	
Real GDP growth	-10.18***	Real GDP growth	-1.207
Observations	1,451	Observations	13,708
Japan		Indonesia	
Real GDP growth	-11.82***	Real GDP growth	-1.701
Observations	24,087	Observations	2,294
Korea		Mexico	
Real GDP growth	-2.641	Real GDP growth	-3.778*
Observations	11,070	Observations	702
Netherlands		Philippines	
Real GDP growth	-13.74***	Real GDP growth	-7.295
Observations	546	Observations	780
Spain		Russia	
Real GDP growth	-10.82***	Real GDP growth	-2.183**
Observations	868	Observations	1,529
Switzerland		South Africa	
Real GDP growth	-28.43***	Real GDP growth	-11.75***
Observations	964	Observations	864
UK		Turkey	
Real GDP growth	-4.257***	Real GDP growth	-2.727
Observations	4,136	Observations	1,494
US		Poland	
Real GDP growth	-3.879	Real GDP growth	-0.313
Observations	17,366	Observations	1,957

Notes: *** p<0.01, ** p<0.05, * p<0.1. The Table reports the coefficient of real GDP growth and the number of observations for each country-by-country regression. Standard errors are clustered by year. Specifications include lagged firm control variables and industry fixed effects

Source: IMF staff estimates.

Table 8. Country level regressions II: OLS: Growth rate of sales

Advanced Economies			Emerging Markets		
Belgium			Argentina		
	Real GDP growth	3.882***		Real GDP growth	-0.463
	Observations	586		Observations	321
	R-squared	0.156		R-squared	0.084
Canada			Brazil		
	Real GDP growth	5.273***		Real GDP growth	1.969***
	Observations	4,165		Observations	1,416
	R-squared	0.068		R-squared	0.094
France			Chile		
	Real GDP growth	3.095***		Real GDP growth	2.415***
	Observations	3,940		Observations	955
	R-squared	0.104		R-squared	0.114
Germany			China		
	Real GDP growth	1.942***		Real GDP growth	1.995***
	Observations	3,207		Observations	24,789
	R-squared	0.107		R-squared	0.052
Italy			India		
	Real GDP growth	2.454***		Real GDP growth	-0.400
	Observations	1,502		Observations	13,699
	R-squared	0.142		R-squared	0.039
Japan			Indonesia		
	Real GDP growth	0.312		Real GDP growth	9.521***
	Observations	24,013		Observations	2,292
	R-squared	0.048		R-squared	0.107
Korea			Mexico		
	Real GDP growth	2.345***		Real GDP growth	1.035***
	Observations	11,025		Observations	705
	R-squared	0.047		R-squared	0.091
Netherlands			Philippines		
	Real GDP growth	2.060***		Real GDP growth	1.119
	Observations	554		Observations	833
	R-squared	0.191		R-squared	0.056
Spain			Russia		
	Real GDP growth	2.377***		Real GDP growth	1.870***
	Observations	865		Observations	1,581
	R-squared	0.197		R-squared	0.111
Switzerland			South Africa		
	Real GDP growth	4.166***		Real GDP growth	1.684**
	Observations	998		Observations	918
	R-squared	0.179		R-squared	0.133
UK			Turkey		
	Real GDP growth	0.598		Real GDP growth	1.245***
	Observations	4,132		Observations	1,496
	R-squared	0.074		R-squared	0.082
US			Poland		
	Real GDP growth	2.420**		Real GDP growth	3.516*
	Observations	17,360		Observations	1,978
	R-squared	0.076		R-squared	0.047

Notes: *** p<0.01, ** p<0.05, * p<0.1. The Table reports the coefficient of real GDP growth and the number of observations for each country-by-country regression. Standard errors are clustered by year. Specifications include lagged firm control variables and industry fixed effects

Source: IMF staff estimates.

Appendix Table. Triage of Firms in the Literature

Paper	Proposal / Criteria
Gourinchas, Kalemli-Ozcan, Penciakova and Sander (2020)	"Survivors", "viable", "ghost" firms Pre-Covid and post-Covid shock cash balance Funding stop prevents firms to increase borrowing
Blanchard, Philippon, Pisani-Ferry (2020)	3 categories of firms. Distinguish "viable" and "insolvent": some firms may be viable but made insolvent by the Covid shock and will need debt restructuring
Philippon (2020)	Liquidation condition: E[social value of the firms] > recovery value of assets; Debt restructuring condition: private value of equity; government guarantees.
Banerjee & Hofman (2020) **BIS Working Paper 882**	"zombies" and viable firms ICR<1 and market-to-book < sectoral median
Carletti et al. (2020) **CEPR WP 14831**	Viable/distressed firms Book value equity <0 post 3 months lockdown shock
Brunnermeier, Markus, and Arvind Krishnamurthy (2020)	Viable / non-viable firms Post Covid shock: E[Assets]<Debt & low ROA
Stein (2020)	Unviable firms: Assets<Debt] Or high uncertainty in pandemic environment: ICR<1 and revenues ≈ 0 Equity-like injections
Caballero et al. (2008), AER	ROA, productivity - Reliance on subsidized bank lending

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