The Quarterly Review of Economics and Finance 87 (2023) 181–190

Contents lists available at ScienceDirect

The Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

Impact of Covid-19 on corporate solvency and possible policy responses in the EU

Nawazish Mirza[a,*], Birjees Rahat[a], Bushra Naqvi[b], Syed Kumail Abbas Rizvi[c]

[a] Excelia Business School, La Rochelle, France
[b] Lahore University of Management Sciences Lahore, Pakistan
[c] Lahore School of Economics Lahore, Pakistan

ARTICLE INFO

Article history:
Received 26 May 2020
Received in revised form 23 August 2020
Accepted 19 September 2020
Available online 22 September 2020

JEL classification:
G30
G33
G38

Keywords:
Solvency
Coronavirus
Probability of default
Cash flows

ABSTRACT

The massive contagion of new coronavirus (Covid-19) has disrupted many businesses across the European Union. This has resulted in an immense drag on the revenues and cash flows that may lead to a significant increase in corporate bankruptcies. In this paper, we investigate the impact of Covid-19 on the solvency profile of the firms in the EU member states. We introduce multiple stress scenarios on the non-financial listed firms and report a progressive increase in the probability of default, an increase of debt payback, and declining coverages. Our results indicate that the solvency profile of all firms deteriorates. The manufacturing, mining, and retail sector are most vulnerable to a decline in market capitalization and a reduction in sales revenues. The paper also examines the possible policy interventions to sustain solvency at a pre Covid-19 level. Our findings suggest that for a moderate deterioration in economic conditions, a tax deferral is sufficient. However, in the event of exacerbating business shocks, there should be hybrid support through debt and equity to avoid a meltdown. This study has important implications for policymakers, corporate managers, and creditors.

1. Introduction

The new coronavirus (Covid-19) has exposed vulnerabilities in the corporate sector and brought forward new sets of challenges. The policymakers are facing a daunting task of supporting health care and unemployment along with interventions in economic and financial systems to prevent an economic shutdown. The businesses are trying to adjust to the changing paradigm of customers and suppliers while attempting to resist the operational and financial challenges. However, despite this agility from the public and private sector, Covid-19 is putting pressure on revenues, earnings, cash flows, and solvency position of the companies.

The European Union (EU) has been severely affected by the outbreak of Covid-19, with around 15 out of 27 member countries reporting more than ten thousand infected cases.[1] The reported mortality count of four member states (Spain, Italy, France, and Germany) is 31 % of the global death toll.[2] There have been stringent lockdowns with restrictive movements and business closures across the EU for weeks. This has led to stalled production, drag on-demand, and ultimately revenue contraction for the companies. Consequently, the EU has experienced unprecedented economic costs compared to any other region (Chen, Igan, Pierri, & Presbitero, 2020). There has been a growing literature that has documented the implications of Covid-19 on financial markets and participants. Corbet, Larkin & Lucey (2020) provided evidence on the contagion effect on cryptocurrency and gold. Sharif, Aloui, & Yarovaya (2020) focused on the nexus of policy uncertainty, geopolitical risk, and oil prices. Rizvi, Mirza, Naqvi & Rahat (2020) and Mirza, Naqvi, Rahat & Rizvi (2020) documented the investment styles and volatility timing of funds managers during the pandemic. Schell, Wang & Huynh (2020) explored the market reaction towards the outbreak of Covid-19, while Goodell & Huynh (2020) highlighted industry-wise response to the spread of new coronavirus.

Such a rapidly deteriorating situation poses severe challenges for liquidity and solvency of the businesses and warrants interventions by sponsors or policymakers. The impact of Covid-19 on

* Corresponding author.
E-mail addresses: elahimn@excelia-group.com (N. Mirza), rahatb@excelia-group.com (B. Rahat), bushra.naqvi@lums.edu.pk (B. Naqvi), kumail@lahoreschool.edu.pk (S.K.A. Rizvi).

[1] This includes Spain, Italy, France, Germany, Belgium, Netherlands, Switzerland, Portugal, Sweden, Ireland, Poland, Romania, Austria, Denmark and Serbia.

[2] As on May 14th, 2020

https://doi.org/10.1016/j.qref.2020.09.002
1062-9769/

liquidity and possible policy intervention was recently studied by De Vito & Gómez (2020). They suggested that in distressed scenarios, the average firm in their global sample will need to seek a liquidity recourse. However, the study's focus was entirely on short term liquidity management, and it did not examine the possible influence on the long term solvency of these firms, which is at least equally likely if not more and even more damaging. Given this context, it is timely to investigate how this pandemic may impair the financial soundness of the corporate sector and what could be the impact of possible responses on the solvency position.

In this paper, we attempt to assess the impact of Covid-19 on the solvency of 12,387 non-financial listed companies in the 15 EU member states where the infection count is more than ten thousand. We carry out this assessment by considering various distress scenarios related to the possible decline in sales and market value of these companies. To gauge the impact of these distressed scenarios, we employ three constructs for solvency. This includes a market-based assessment of default, an accounting-based discriminant specification for the likelihood of default, and cash flow sufficiency. Furthermore, we also analyze if a policy response in the form of capital injection or deferment of taxes may help in improving the solvency and what type of intervention will be optimal. Various sectoral specifications are possible to classify the sample firms. Goodell & Huynh (2020) assessed 46 industries, including financial services in the US, for abnormal returns. However, unlike their study, which employs industry-wide data, our assessment is based on firm-level. Hence, we consolidate our sample into six broader sectors similar to that of (De Vito & Gómez, 2020).

Our study has multiple contributions. This is the first one to assess the impact of Covid-19 on the solvency of European firms. Just like (De Vito & Gómez, 2020), we focus on a micro viewpoint of a specific risk. However, our methodology is much broader that incorporates both market and accounting based estimates of default. Moreover, most of the prior distress assessments using stress testing like (Busch, Koziol, & Mitrovic, 2018; Khan, Rizvi, & Sadiq, 2018; Naqvi, Rizvi, Uqaili, & Chaudhry, 2018; Grundke & Kühn, 2020; Soula, 2017) are in the context of banks. Therefore, our perspective of stress testing for the solvency of non-financial firms is a unique and significant value addition in the body of related literature. The rest of the paper is organized as follows. Section 2 outlines our empirical strategy. Section 3 will highlight data and stress scenarios, Section 4 will present results and discussion, while Section 5 will conclude.

2. Empirical strategy for solvency assessment and policy response

Solvency refers to a company's ability to settle its financial obligations. The financial obligations in the capital structure could differ based on the seniority, and this impacts the probability of default (Attaoui & Poncet, 2013). Therefore, in this paper, we define solvency as a business' ability to pay its senior debt (secured and unsecured). Specifically, we exclude the subordinate debt from the sponsors as policy interventions that we consider later are usually targeted to safeguard senior claims.

To stress-test the solvency of firms, we use three principle constructs related to the probability of default and cash flow sufficiency. Initially, we calculate the actual position of each firm based on these constructs and then compare them with distress scenario estimates. Finally, we will introduce the possible interventions and observe the impact of such interventions on the distressed estimates. To ensure that financial disclosures are available, we consider the base case scenario to be 2019. The details on the estimation framework for solvency measures are presented below.

2.1. Market based probability of default model

The structured or market-based models of default are used to estimate an ex-ante likelihood of default (probability of default) based on the market-based variables. These models stem from the theoretical foundations of (Merton, 1974) that relate corporate default to an option pricing framework. In a structured default model, observation of market value and standard deviation of assets is challenging as all assets are not marked to market. However, (Vassalou & Xing, 2004) introduced an iterative methodology of using equity prices to derive market value and volatility in assets at the firm level. This has been used by many studies like (Afzal & Mirza, 2012; Cherkasova & Kurlyanova, 2019; Denzler, Dacorogna, Müller, & McNeil, 2006; Mirza, Rahat, & Reddy, 2016). Although various extensions of (Merton, 1974) have been proposed, but recent comparative studies like (Afik, Arad, & Galil, 2016) demonstrate that the original model still outperforms its common variants.

In a contingent claim setting, the probability of default for firm i ($\mathrm{PD_i}$) is presented as

$$PD_i = 1 - N\left[\frac{\ln\left(V_{Ai}/Xi\right) + \left(\mu_i + 0.5\sigma_{Ai}^2\right)T}{\sigma_{Ai}\sqrt{T}}\right] \tag{1}$$

where V_A is the market value of assets for each firm in the sample; μ is expected growth in assets subject to a standard deviation of σ_A. X represents financial commitments that will mature in time T and a density function N. To consider an extreme case, for each of our sample firms, we consider X as entire long term and short term financial debt (excluding subordinate) and T as the weighted maturity of these obligations. To account for two unknowns, (Vassalou & Xing, 2004) suggested using the system of simultaneous equations from the options pricing framework with V_E as the value of firm equity and r as the risk-free rate.

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{1.1}$$

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \tag{1.2}$$

$$\text{with } d_1 = \frac{\ln\left(V_A/X\right) + \left(\mu + 0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}}, \text{ and } d_2 = d_1 - \sigma_A\sqrt{T} \tag{1.3}$$

The sample firms are listed, so we initiate by calculating the daily standard deviation of equity using returns data for trailing twelve months. This is used as a pseudo standard deviation of assets that helps in determining the intraday market value of assets. Once the pseudo market value of assets is calculated, we reassess the standard deviation of assets. This process will be iterated until our first pass standard deviation of equity and second, pass standard deviation of assets converge (within 0.0001). The converged value will be used as the final input for estimation of the market value of assets and probability of default. This process will be used to compute historical as well as ex-ante distressed scenario PDs to examine the impact of Covid-19.

2.2. Accounting based discriminant models of default

The discriminant models of default that were pioneered by (Altman, 1968) use accounting data to determine a firm's financial soundness. The strength of these models stems from the fact that they are based on fundamental strengths and weaknesses and are not subject to equity market conditions. The discriminant models help in predicting a score that helps in distinguishing between distressed and non-distressed firms. These scores can be transformed into a probability of default. For this paper, we will use two important measures of discriminant analysis. These are the *Altman Z" score* that is advocated by Altman, Iwanicz-Drozdowska, Laitinen & Suvas (2017) and is a modified version of (Altman, 1968), and *O score* as suggested by Ohlson (1980). There are many studies like (Hillegeist, Keating, Cram, & Lundstedt, 2004; Kwak, Shi, Cheh, & Lee, 2004; Lin, Lo, & Wu, 2016; Merkevicius, Garšva, & Girdzijauskas, 2006; Xu & Zhang, 2009) that support the effectiveness of Z" and *O score* in predicting the distress of non-financial firms. Similar to (Altman et al., 2017), we estimate the Altman Z" score for each firm as follows

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (2)$$

where X_1 is working capital to total assets, X_2 is retained earnings to total assets, X_3 is operating earnings to total assets, and X_4 is the market value of equity to book value of debt. The calculated Z" score can then be transformed into the probability of default ($p_{z''}$) as

$$p_{z''} \left\langle Y = 1 \middle| X \right\rangle = \frac{1}{1 + e^{-Z''}} \quad (3)$$

It is worth mentioning that studies like (Hernandez Tinoco & Wilson, 2013; Hillegeist et al., 2004; Korol, 2013) and more recently (Altman, 2018) advocated the use of coefficients from the original Altman model. Their findings suggest that bankruptcy predictions from the original coefficients are more robust compared to the predictions that are based on re-estimated factor loadings. Therefore, in this study, we employ the original coefficients from Altman's proposition.

The estimation of (Ohlson, 1980) O score for each of the sample firms will take the following form.

$$O = -1.32 - 0.407 log \frac{TA_t}{GNP_t} + 6.03 \frac{TL_t}{TA_t} - 1.43 \frac{WC_t}{TA_t} + 0.0757 \frac{CL_t}{CA_t} - 1.72 D_1 - 2.37 \frac{NI_t}{TA_t} - 1.83 \frac{FFO_t}{TL_t} + 0.285 D_2 - 0.521 \frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|} \quad (4)$$

where TA = total assets, GNP = gross national product price index level, TL = total liabilities, WC = working capital, CL = Current Liabilities, CA = current assets, NI = net income, FFO = funds from operations, D_1 is a dummy that takes a value of 1 if TL > TA and D_2 is a dummy that takes a value of 1 if there is a net loss in the last two years. The suffix t is for the period. The associated probability of default (p_O) can be estimated as

$$p_O = \frac{e^{O\,Score}}{1 + e^{O\,Score}} \quad (5)$$

The $p_{z''}$ and p_o will be calculated for the historical period as well as the distressed scenarios.

2.3. Cash flow sufficiency

We also consider some conventional cash flows to leverage ratios to understand the current as well as distressed solvency position of all the firms in our sample. This is because the sufficiency of a firm's cash flows in comparison to the cash obligations is often an appropriate indicator of financial risk. We classify these ratios into two categories, namely debt payback and coverages. The payback ratios include funds from operations (FFO) to debt and free operating cash flows (FOCF) to debt. For coverage ratios, we consider FFO to cash interest and EBITDA to interest.

The free operating cash flows adjust cash flows from operations by taking into account the capital expenditures that include the financing of tangible and intangible assets. In a distressed scenario, the weakening fundamentals will result in a drag on cash flows that leads to an increase in debt payback and insufficient coverage (Keefe & Yaghoubi, 2016). This is plausible because cash flows sensitivity plays a vital role in capital structure optimization (Harris & Roark, 2019; Park, 2019) and financial flexibility (Drobetz, Haller, Meier, & Tarhan, 2017).

2.4. Policy interventions

The spread of Covid-19 has resulted in socio-economic fallout for EU member states. The lockdowns have resulted in significant losses of income for individuals and businesses. There have been some interventions that are aimed at minimizing the impact and getting back on track of sustainable growth. The union has committed funding of Euro 540 billion towards public welfare, while the European Investment bank is injecting up to 40 billion Euros as liquidity support for small and medium enterprises. The ECB has planned for 870 billion Euros for the purchase of private and public securities during the pandemic. On top of this, the EU is preparing a recovery plan that is expected in the next long term budget of the union[3] . As the crisis is suspected to be persisting for an extended period, this will warrant more fiscal support to avoid mass defaults. Regulatory forbearance and moratoriums on debt can ease the solvency situation, but they will create long term risks as it may not help in improving the structural issues. Therefore, a more robust long term fiscal intervention will be needed.

To assess the impact of support that businesses may get, we consider three policy interventions. These include a deferral of payable taxes, inclusion through a subordinate bridge loan, and equity injection. While tax deferral is essentially state-level support, subordinate loans and equity enhancements can be provided from sponsors as well. Uchida et al. (2015) and Brei, Mohan, & Strobl (2019) found out that state-level and sponsors' interventions reduce the likelihood of default during natural disasters. The tax deferrals can increase the internally generated cash flows, while subordinated debt and equity can ease the stress on the capital structure through external cash flows. We will assess the impact of these three possibilities during a distressed scenario to examine which intervention could optimize the solvency position and retain it at the level of the base year.

3. Stress scenarios and data

In principle, we consider two stress scenarios that may impair the solvency position of companies across the EU. These include attrition in market capitalization and a decline in sales due to the stressed operating environment for the businesses in the EU. Brogaard, Li & Xia (2017) suggested that a decrease in the market value of a firm and stock price illiquidity increases the likelihood of default. Similarly, Mselmi, Hamza, Lahiani & Shahbaz (2019) and Li & Luo (2019) provided evidence on the pricing of financial distress. In this context, we consider three possible shocks to market capitalization. These will be a 15 %, 30 %, and 45 % decline in the market capitalization from December 2019 level. Using these three scenarios, we will calculate the stressed probability of default using a market based model. The market-based specification directly incorporates market values and hence can explicitly capture the impact.

The relation between long term solvency and revenues is long-established and recent studies like (Cui & Kaas, 2020; Duan, Kim, Kim, & Shin, 2018; Ghulam & Derber, 2018) have validated this link. To stress-test the solvency vis-à-vis a drop in sales, we follow De Vito & Gómez (2020) to devise the sensitivities. This is repeated for all fundamental inputs of Altman Z", Ohlson O, and cash flow sufficiency. These sensitivities are employed to recalculate the stressed variables based on an assumed decline in sales of 25 %, 50 %, and

[3] Source : The common EU response to COVID-19, https://europa.eu/european-union/coronavirus-response_en

75 % due to Covid-19. The functional forms are as follows (from a to f):

$$\partial NI = \frac{\partial Sales}{Sales} \times (Sales - opex \times E_{opex}) \times (1 - t) \quad (a)$$

$$\partial FFO = \partial NI + \partial Dep + \partial DT \quad (b)$$

$$\partial CFO = \partial FFO - \Delta CA \times E_{\Delta CA} + \Delta CL \times E_{\Delta CL} \quad (c)$$

$$\partial FOCF = \partial CFO - \Delta FA \left| E_{\Delta FA} \right. \quad (d)$$

$$WC = CA + (\Delta CA \left| E_{\Delta CA} \right.) - CL + (\Delta CL \left| E_{\Delta CL} \right.) \quad (e)$$

$$\partial TA = \Delta CA \left| E_{\Delta CA} \right. + \Delta FA \left| E_{\Delta FA} \right. + OA = \Delta CL \left| E_{\Delta CL} \right. + OL + FD + Eq + \Delta RE \left| \partial NI \right. \quad (f)$$

where opex refers to operating expenses (including the cost of goods sold), t is the applicable tax rate, DT is deferred taxes, OA corresponds to other assets, FA is fixed assets, OL represents other liabilities, FD is financial debt, Eq corresponds to equity and RE represents retained earnings. In our assessment, we keep OA and OL as constant at the base year. We assume that there are no buybacks, and no dividends are paid. Therefore, equity will change due to changes in retained earnings. Similarly, FD will also remain constant at the level of 2019 for the base case. The sensitivities of various fundamentals to sales are captured by E with their respective subscripts. To calculate these sensitivities, we use panel estimates of the following form.

$$\Delta X_{it} = \alpha + \beta_X \Delta Sales_{it} + \beta_\omega \omega_t + \varepsilon_{it} \quad (6)$$

where X represents the variable factor for firm i at time t (i.e., *opex*, *CA*, *CL*, *FA*), β_X is the sensitivity of factor X (i.e. E_{opex}, $E_{\Delta CA}$, $E_{\Delta CL}$, $E_{\Delta FA}$). The ω_t is a matrix of macro-level control variables of GDP growth, sector concentration (Herfindahl–Hirschman Index), inflation rate, and systemic importance (calculated as firms revenue to GDP). These estimations will help us in calibrating the firmwide solvency for Z", O score, and cash flow sufficiency under the sales distress scenario.

The firm-level and macroeconomic data to estimate equation six spans over 19 years from 2001 to 2019. Therefore, to ensure sufficient estimating data, we consider non-financial listed firms that are in existence since 1998. The Covid-19 has very severely impacted tourism and related firms (for example, Aviation). We also exclude such firms (hotels and their holding companies, aviation, etc.) as we believe that their inclusion can bias the overall results. A thorough investigation is explicitly required for tourism-related firms to understand their solvency dynamics. This results in a balanced panel of 12,387 firms. We do not include firm or time fixed effects due to the exhaustive nature of our dataset owing to a large number of firms and the time series that spans over many years. Imai & Kim (2019) noted that for comprehensive datasets adding unit effects makes causal inference very difficult[4] . The firm-level data, macroeconomic factors, and market-based price information is extracted from Datastream and trending economics. As we only include firms that are operating since 1998, it is interesting to note that all these firms survived the global financial crisis of 2007–08.

4. Results and discussion

The descriptive statistics for firm-specific variables are presented in Table 1. The representation is the weighted average (as per total assets) for each sector from 2001 to 2019. The WC/TA is maximum (25 % of total assets) in the wholesale and retail industry which is plausible primarily because of the inventory requirements. The mining and construction firms, followed by manufacturing, have an average of 18 % and 15 % investment in working capital compared to their total assets. As we may expect a lot of inventory for the manufacturing sector, their higher payables compared to retail requires them to have a lower proportionate investment in working capital. The wholesale and retail sector depicts maximum risk absorption capacity with RE/TA of 30.2 %, while manufacturing has the lowest ratio of 12.4 %. With an EBIT/TA of 21.5 %, services sectors show maximum operating returns on assets and retail having a minimum of 4.1 %. The mining, construction, and chemical firms are most leveraged with an average TL/TA of 61 %, followed by 54 % of the manufacturing sector. In terms of funds from operations, wholesale and retail has the minimum debt payback with FFO/Debt of 48 %. The agriculture, forestry, and the fishing sector have the maximum debt payback with FFO/Debt of 20 %. The wholesale and retail firms also dominate the coverages with FFO/Cash interest of 5 times and EBITDA/Interest of 7 times. The correlation matrix of these variables is presented in Table 2.

The sensitivities of sales to expenses, current assets, current liabilities, and fixed assets estimated from Eq. 6 are presented in Panel A of Table 3. The fixed effects regression results demonstrate that all sensitivities are significant at 95 % to 99 % across all sectors. The expenses for wholesale and retail have an 85.1 % variation with sales followed by manufacturing (75.1 %), while services sensitivity is lowest with a 56.1 % change vis-à-vis total revenues. For current assets, we have similar estimates with wholesale and retail and manufacturing, depicting the maximum sensitivity of 91.45 % and 85.1 %, respectively. This is logical because of both manufacturing and wholesale and invests a lot in inventories that vary directly with sales.

Furthermore, the manufacturing sector also has sizeable accounts receivables. The sensitivity for current liabilities is maximum for manufacturing firms owing to their higher trade payables. The coefficient for the services sector is minimum, with a variation of 41.2 %. The elasticity of fixed assets is maximum for manufacturing firms, which is understandable as these firms have capacity constraints and need incremental investments to support their sales. On average, there will be a 2 % change in fixed assets of manufacturing firms to cope up with the revenues. The within-sample forecast accuracy results are presented in Panel B through Panel E. We employed root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) to test the precision of our sensitivities. The estimated values for all four measures represent robust forecast accuracy for the four elasticities. The out of sample forecast statistics are presented in Panel F through Panel I. Similar to the within-sample forecast, out of sample statistics also confirm the robustness of our estimates.

A probable caveat of our analysis is the possibility of a structural break in the data due to the changing business dynamics from Covid-19. The studies like (Naeem, Tiwari, Mubashra, & Shahbaz, 2019; Nasir, Al-Emadi, Shahbaz, & Hammoudeh, 2019; Omay, Shahbaz, & Hasanov, 2020; Shahbaz, Rehman, & Afza, 2016; Solarin, Shahbaz, & Stewart, 2018) and (Shahbaz, Tahir, Ali, & Rehman, 2014) have extensively documented the role of structural stability in model estimation during changing business cycles. The limitation of this study to apply a comprehensive structural break analysis is the post Covid-19 firm-level data, which is only available for two quarters (till end June 2020). However, to ensure the robustness of this preliminary assessment, we follow the methodology of (Emirmahmutoglu, Gupta, Miller, & Omay, 2020) and (Omay et al., 2020) to test for stationarity in our estimates. This approach builds on (Ucar & Omay, 2009) and (Emirmahmutoglu & Omay, 2014). It

[4] The Chow test results in a p value of 0.0803 so we accept the null hypothesis of data poolability.

Table 1
Descriptive Statistics (Weighted Average 2001–2019).

		Manufacturing	Utilities	Mining, Construction and Chemicals	Wholesale and Retail	Agriculture, Forestry and Fishing	Services
WC/TA	Mean	0,152	0,105	0,181	0,250	0,141	0,098
	Std Dev	0,025	0,014	0,024	0,040	0,019	0,016
	Skewness	0,373	0,454	0,454	0,373	0,454	0,373
	Kurtosis	0,043	0,199	0,091	0,080	0,038	0,043
	JB Stats	48,091	74,443	71,746	48,485	71,151	48,090
RE/TA	Mean	0,124	0,154	0,210	0,302	0,151	0,126
	Std Dev	0,015	0,035	0,048	0,036	0,020	0,015
	Skewness	0,509	0,263	0,263	0,509	0,454	0,509
	Kurtosis	0,096	0,085	0,024	0,023	0,080	0,012
	JB Stats	89,996	24,429	23,861	89,252	71,579	89,221
EBIT/TA	Mean	0,094	0,059	0,065	0,041	0,075	0,215
	Std Dev	0,025	0,042	0,017	0,005	0,053	0,025
	Skewness	0,228	0,085	0,228	0,509	0,085	0,509
	Kurtosis	0,059	0,004	0,057	0,003	0,009	0,095
	JB Stats	18,173	2,486	18,155	89,209	2,491	89,983
MVE/BD	Mean	2,158	4,202	5,120	6,093	3,105	5,078
	Std Dev	0,146	0,305	0,372	0,412	0,817	0,520
	Skewness	0,443	0,413	0,413	0,443	0,114	0,293
	Kurtosis	0,007	0,000	0,002	0,002	0,006	0,000
	JB Stats	67,678	58,779	58,779	67,675	4,471	29,575
NI/TA	Mean	0,051	0,031	0,035	0,022	0,031	0,160
	Std Dev	0,010	0,005	0,006	0,005	0,002	0,026
	Skewness	0,318	0,367	0,367	0,263	0,827	0,367
	Kurtosis	0,001	0,008	0,010	0,000	0,000	0,010
	JB Stats	34,733	46,375	46,379	23,812	235,114	46,379
TL/TA	Mean	0,540	0,420	0,610	0,518	0,541	0,402
	Std Dev	0,018	0,027	0,041	0,038	0,018	0,029
	Skewness	0,890	0,467	0,443	0,413	0,890	0,413
	Kurtosis	0,003	0,035	0,054	0,060	0,003	0,002
	JB Stats	272,617	75,040	67,927	59,085	272,616	58,779
FFO/Debt	Mean	0,317	0,403	0,320	0,484	0,201	0,320
	Std Dev	0,035	0,081	0,035	0,110	0,038	0,073
	Skewness	0,551	0,298	0,551	0,263	0,318	0,263
	Kurtosis	0,008	0,009	0,002	0,006	0,000	0,005
	JB Stats	104,585	30,623	104,580	23,815	34,733	23,814
FOCF to Debt	Mean	0,252	0,301	0,240	0,410	0,150	0,280
	Std Dev	0,039	0,011	0,009	0,063	0,025	0,046
	Skewness	0,390	1,596	1,596	0,390	0,367	0,367
	Kurtosis	0,000	0,001	0,002	0,010	0,010	0,007
	JB Stats	52,412	875,988	875,988	52,420	46,379	46,375
FFO/Cash Interest	Mean	3,954	4,102	2,701	5,051	2,101	4,501
	Std Dev	1,292	2,120	0,883	1,781	0,479	2,327
	Skewness	0,184	0,116	0,184	0,170	0,263	0,116
	Kurtosis	0,002	0,002	0,031	0,004	0,006	0,002
	JB Stats	11,602	4,636	11,685	9,968	23,816	4,636
EBITDA/Interest	Mean	5,026	6,805	3,121	7,016	3,901	6,003
	Std Dev	1,362	2,058	0,944	1,411	0,890	1,816
	Skewness	0,221	0,198	0,198	0,298	0,263	0,198
	Kurtosis	0,003	0,006	0,003	0,003	0,001	0,002
	JB Stats	16,867	13,543	13,540	30,618	23,812	13,540

Std Dev is standard deviation, Kurtosis is excess kurtosis, JB represent Jarque Bera Stats.

Table 2
Correlation Matrix of Selected Financial Ratios.

	WC/TA	RE/TA	EBIT/TA	MVE/BD	NI/TA	TL/TA	FFO/Debt	FOCF to Debt	FFO/Cash Interest
RE/TA	0,1042								
EBIT/TA	0,0604	0,0755							
MVE/BD	0,2739	0,0784	0,0678						
NI/TA	0,1745	0,0658	0,0775	0,0692					
TL/TA	0,0275	0,0181	0,0254	0,0955	0,2557				
FFO/Debt	0,1571	0,0781	0,0351	0,2157	0,1741	0,1305			
FOCF to Debt	0,0569	0,0909	0,0497	0,1030	0,2483	0,1589	0,0423		
FFO/Cash Interest	0,2726	0,0811	0,0722	0,2030	0,1569	0,1603	0,1061	0,0463	
EBITDA/Interest	0,0178	0,0339	0,0232	0,0384	0,0592	0,0536	0,1357	0,1286	0,0138

is considered robust compared to other propositions [for example (Romero-Ávila, 2012)] because it incorporates non-linearity, asymmetry, and cross-sectional dependence in panel data. The results on the estimates from Ucar & Omay (2009) and Emirmahmutoglu & Omay (2014) using the sequential panel selection method (SPSM) are reported in Table X that suggests stationarity across our elasticity coefficients. While this may signify that there is no significant impact of the structural break, we would again like to caution

Table 3
Variable Sensitivities with Sales and Forecast Accuracy.

	Manufacturing	Utilities	Mining, Construction and Chemicals	Wholesale and Retail	Agriculture, Forestry and Fishing	Services
Panel A						
Eopex	0,7512**	0,71235**	0,65125***	0,85144**	0,6914***	0,56147***
ECA	0,85123**	0,712548**	0,68455***	0,91452***	0,5124**	0,41254**
ECL	0,84124**	0,75415**	0,7176**	0,817***	0,5819**	0,4508***
EFA	0,0214***	0,01425**	0,0247**	0,0197***	0,0124***	0,0024**
Within Sample Forecast Accuracy						
Panel B - RMSE						
Eopex	0,00707 %	0,00523 %	0,00387 %	0,00286 %	0,00212 %	0,00157 %
ECA	0,00116 %	0,00387 %	0,00286 %	0,00212 %	0,00157 %	0,00116 %
ECL	0,00086 %	0,00064 %	0,00047 %	0,00035 %	0,00026 %	0,00019 %
EFA	0,00059 %	0,00044 %	0,00032 %	0,00024 %	0,00018 %	0,00013 %
Panel C - MSE						
Eopex	0,00335 %	0,00248 %	0,00183 %	0,00136 %	0,00100 %	0,00074 %
ECA	0,00055 %	0,00183 %	0,00136 %	0,00100 %	0,00074 %	0,00055 %
ECL	0,00041 %	0,00030 %	0,00022 %	0,00016 %	0,00012 %	0,00009 %
EFA	0,00028 %	0,00073 %	0,00053 %	0,00011 %	0,00040 %	0,00006 %
Panel D - MAE						
Eopex	0,00272 %	0,00201 %	0,00149 %	0,00110 %	0,00082 %	0,00060 %
ECA	0,00045 %	0,00149 %	0,00110 %	0,00082 %	0,00060 %	0,00045 %
ECL	0,00033 %	0,00024 %	0,00018 %	0,00013 %	0,00010 %	0,00007 %
EFA	0,00023 %	0,00059 %	0,00043 %	0,00009 %	0,00032 %	0,00005 %
Panel E - MAPE						
Eopex	0,00502 %	0,00372 %	0,00275 %	0,00203 %	0,00151 %	0,00111 %
ECA	0,00082 %	0,00275 %	0,00203 %	0,00151 %	0,00111 %	0,00082 %
ECL	0,00061 %	0,00045 %	0,00033 %	0,00025 %	0,00018 %	0,00014 %
EFA	0,00042 %	0,00031 %	0,00023 %	0,00017 %	0,00013 %	0,00009 %
Panel F - RMSE						
Eopex	0,00236 %	0,00205 %	0,00201 %	0,00191 %	0,00100 %	0,00077 %
ECA	0,00039 %	0,00152 %	0,00149 %	0,00141 %	0,00074 %	0,00057 %
ECL	0,00029 %	0,00025 %	0,00024 %	0,00023 %	0,00012 %	0,00009 %
EFA	0,00020 %	0,00017 %	0,00017 %	0,00016 %	0,00008 %	0,00006 %
Panel G - MSE						
Eopex	0,00112 %	0,00097 %	0,00095 %	0,00090 %	0,00047 %	0,00037 %
ECA	0,00018 %	0,00072 %	0,00071 %	0,00067 %	0,00035 %	0,00027 %
ECL	0,00014 %	0,00012 %	0,00012 %	0,00011 %	0,00006 %	0,00004 %
EFA	0,00009 %	0,00029 %	0,00028 %	0,00008 %	0,00019 %	0,00003 %
Panel H - MAE						
Eopex	0,00091 %	0,00079 %	0,00077 %	0,00073 %	0,00038 %	0,00030 %
ECA	0,00015 %	0,00059 %	0,00057 %	0,00054 %	0,00028 %	0,00022 %
ECL	0,00011 %	0,00010 %	0,00009 %	0,00009 %	0,00005 %	0,00004 %
EFA	0,00008 %	0,00023 %	0,00023 %	0,00006 %	0,00015 %	0,00002 %
Panel I - MAPE						
Eopex	0,00167 %	0,00146 %	0,00143 %	0,00135 %	0,00071 %	0,00055 %
ECA	0,00027 %	0,00108 %	0,00106 %	0,00100 %	0,00052 %	0,00041 %
ECL	0,00020 %	0,00018 %	0,00017 %	0,00016 %	0,00009 %	0,00007 %
EFA	0,00014 %	0,00012 %	0,00012 %	0,00011 %	0,00006 %	0,00005 %

Table 4
SPSM Results based on (Emirmahmutoglu & Omay, 2014) and (Ucar & Omay, 2009).

	(Emirmahmutoglu & Omay, 2014)				(Ucar & Omay, 2009)	
I(0) Series	F_{AE}		t^{as}_{AE}		t_{NL}	
Eopex	7,1315	**	2,9125	**	4,1325	**
ECA	10,1855	***	4,2056	***	3,2940	**
ECL	5,1256	**	3,3660	***	3,1015	**
EFA	8,0125	***	3,1255	***	2,7050	***

*** represents significance at 1 %, ** represents significance at 5 % based on bootstrapped values.
The coefficients are tested for the null hypothesis of non stationarity.

about the limited firm-level data for the post Covid-19 period (Table 4).

Table 5 shows the probability of default estimations from the market-based variables for both cases and stressed scenarios. This is estimated from Eq. 1. The base case scenario PDs are actual as of 2019 and before any significant impact of Covid-19. Our calculation shows that an average firm in mining, construction, and chemical has a 12.5 % chance of default, followed by manufacturing where PD is 12 %. The worst firm in manufacturing was having a 31.8 % likelihood of default. The noncyclical wholesale and retail show an average 5.1 % probability of default. The firms in agriculture, forestry, and fishing are safest with an estimated PD of 3.15 %.

In the stress scenarios as a probable outcome of Covid-19, we see a significant increase in the probability of default across all sectors. For a decline of market cap by 15 %, the PD of average mining firm increases to 24.7 % while that of the retail sector increases to 12.5 %. The manufacturing firms also experience a marginal increase to an average PD of 12 %. A further decline to 30 % in market capitalization results in a higher drag on the solvency. The PD for firms in mining, manufacturing, retail, and services augments to 38.7 %, 27.9 %, 19.8 %, and 15.2 %, respectively. Finally, a drop of market cap to 45 % from current levels results in a PD of 56.8 % for mining, 37.7 % for manufacturing, 28.7 % for retail, and 19.7 % for utilities. These results identify manufacturing, mining, and retail firms to be more susceptive to solvency issues owing to a decline in market capitalization. The utilities and services' firms depict modest problems for the base case as well as stress scenarios of a 15 % and 30 % reduction in market capitalization. However, in the extreme case, these firms demonstrate significant vulnerabilities towards default.

The accounting-based PD estimates from Eq. 2 to 5 are presented in Table 6. The results are consistent for Altman Z" as well as Ohlson O score. Owing to the estimation procedure, the magnitude of PDs of Ohlson O is higher than that of Z" (Altman et al., 2017). In the base case scenario, we observe mining, construction, and chemical firms have a Z" based PD of 13 % (15 % from Ohloson O) and manufacturing firms' PD is 11.5 %. Similar to market-based default estimates, wholesale and retail demonstrates a lower PD of 5.7 %. As we impose the Covid-19 stress by considering declining sales and using the sensitivities reported in Table 2, the likelihood of default across all sectors increases significantly. The average manufacturing firm will have a PD of 17 % for a sales decline of 25 %. In case the sales decline by 50 % and 75 %, the PD will increase to 22.4 % and 43.4 %, respectively. The mining sector will have a similar fate with average PDs rising to 17 %, 28 %, and 40 % for the three sales scenarios. This is followed by utilities, agriculture, forestry, and fishing, serviced and wholesale and retail. There is an interesting contrast in our PD based analysis using market and accounting-based measures. The wholesale and retail sector appeared to be more turbulent in market-based PD compared to the accounting counterpart. We believe that, in part, this difference represents a strong fundamental position that is possibly not priced adequately by the equity market.[5] Nonetheless, the results demonstrate a declining solvency profile across all sectors.

We present the results on cash flow sufficiency in Table 7. Given the sizeable cash flows emanating from a lower cash cycle, it is not surprising to see the wholesale and retail sector dominating both leverage payback and coverages in the base case. The utilities, manufacturing, and services sectors also depict adequate solvency ratios in the base case. Once the Covid-19 scenarios are introduced, we observe a significant decline in cash flow sufficiency. The FOCF to debt for the manufacturing sector regresses to 9.5 % in case of sales decline by 75 % (base case 35.1 %). The utility sector would experience a FOCF to debt of 9.7 % down from 42.1 % in the base case. The mining firms observe a decline to 6 % from 29 %. The wholesale and retail firms will also experience a notable drop from a base case FOCF to debt of 42.8 % to a worst-case scenario based FOCF to debt of 9 %. A similar impact is observable across coverages, where we see a significant decline in FFO to cash interest and EBITDA to interest for all stress scenarios.

Our results show important issues related to solvency and cash flow sufficiency across major sectors in the EU. Therefore, to avoid a global meltdown, a policy response is needed to mitigate the impact of Covid-19. The country-wise results for three proposed interventions are summarized in Table 8. We evaluate the impact of these interventions and their efficacy to sustain the probability of default (accounting base), debt payback, and coverage similar to the pre-covid-19 level of 2019. If the sales revenue decline is limited to 25 %, the optimal response across the EU is a tax deferral. This will enable 74 % (maximum) of the firms in Ireland to sustain their PDs at the pre-Covid-19 level. In Serbia, 52 % (minimum) of the firms will be able to maintain their default profiles with the tax break. The significant equity injection is not warranted if the revenues decline is limited to 25 %.

However, if the expected revenue decline is 50 % and 75 %, the subordinated loans and equity injections are more optimal. The subordinated loans will restore up to 50 % of firms in Spain (maximum) and 21 % in Austria (minimum) for a decline of 50 % in revenues. The majority of Austrian firms (51.3 % and 67 %) will require equity support for a 50 %–75 % decrease in revenues. The proportion of Spanish firms looking for equity participation will be as high as 70 % for the extreme case impact on sales. For other EU countries, a hybrid response of subordinated debt and equity will be needed if revenues are expected to regress by 50 %–75 %. A similar trend can be observed for debt payback and coverages, where a downside of 25 % in sales can be mitigated by tax deferral. At the same time, any further reduction will warrant a hybrid response.

5. Conclusion

The new coronavirus (Covid-19) came as a surprise and has taken the world by a storm. The risk of a pandemic was ranked

[5] In our sample, we observed that wholesale and retail firms had the lowest trading volume.

Table 5
Market Based PD under Market Cap Scenarios.

	Manufacturing	Utilities	Mining, Construction and Chemicals	Wholesale and Retail	Agriculture, Forestry and Fishing	Services
Base Case End of 2019						
Max	0,3181	0,2103	0,2365	0,2598	0,2233	0,1845
Average	0,1208	0,0601	0,1252	0,0515	0,0315	0,0558
Decline in Market Cap by 15 %						
Max	0,5003	0,4172	0,3122	0,3384	0,3131	0,2310
Mean	0,1572	0,0790	0,2473	0,1252	0,0570	0,1082
Decline in Market Cap by 30 %						
Max	0,8042	0,7854	0,4353	0,5865	0,4952	0,2421
Mean	0,2792	0,1367	0,3872	0,1981	0,1058	0,1524
Decline in Market Cap by 45 %						
Max	0,9264	0,8641	0,6599	0,6281	0,7786	0,3656
Mean	0,3773	0,1969	0,5681	0,2875	0,1608	0,1862

Table 6
Probability of Default - Altman Zänd Ohlson O.

		Manufacturing	Utilities	Mining, Construction and Chemicals	Wholesale and Retail	Agriculture, Forestry and Fishing	Services
	Base Case as of 2019						
PD (Z̈)	Max	0,3375	0,2110	0,2452	0,2248	0,2130	0,1494
	Mean	0,1153	0,0519	0,1304	0,0571	0,0672	0,0418
PD(O)	Max	0,4469	0,2399	0,2940	0,2404	0,2813	0,1943
	Mean	0,1315	0,0767	0,1514	0,0871	0,0982	0,0659
	Sales Decline 25 %						
PD (Z̈)	Max	0,5794	0,2501	0,2635	0,2680	0,2656	0,1972
	Mean	0,1726	0,0955	0,1703	0,0961	0,0943	0,0864
PD(O)	Max	0,6517	0,3159	0,3558	0,3155	0,3144	0,2345
	Mean	0,1912	0,1032	0,1995	0,1160	0,1231	0,1089
	Sales Decline 50 %						
PD (Z̈)	Max	0,6489	0,3640	0,4226	0,2951	0,3092	0,2431
	Mean	0,2244	0,1284	0,2872	0,1369	0,1621	0,1372
PD(O)	Max	0,7829	0,4123	0,5276	0,3975	0,3746	0,3017
	Mean	0,2570	0,1661	0,2449	0,2078	0,1518	0,1489
	Sales Decline 75 %						
PD (Z̈)	Max	0,8588	0,4651	0,6405	0,3213	0,4771	0,3403
	Mean	0,4342	0,2504	0,4026	0,1798	0,2206	0,2152
PD(O)	Max	0,9202	0,5198	0,7161	0,4434	0,5094	0,3872
	Mean	0,5552	0,2670	0,5790	0,2415	0,2093	0,2329

Table 7
Cash Flow Sufficiency.

	Manufacturing	Utilities	Mining, Construction and Chemicals	Wholesale and Retail	Agriculture, Forestry and Fishing	Services
FFO/Debt	0,3513	0,4218	0,2974	0,5018	0,2012	0,3070
FOCF to Debt	0,2881	0,3564	0,2100	0,4286	0,1546	0,2403
FFO/Cash Interest	3,0179	4,0919	2,6106	5,2185	2,0089	4,2315
EBITDA/Interest	3,2841	5,4209	2,2506	8,1248	3,8201	5,1193
	Sales Decline by 25 %					
FFO/Debt	0,2450	0,3260	0,2403	0,3070	0,1789	0,2050
FOCF to Debt	0,1960	0,2007	0,1372	0,1853	0,1324	0,1883
FFO/Cash Interest	1,1947	3,1397	1,8965	2,2303	1,5812	3,5226
EBITDA/Interest	1,2090	3,8575	1,7820	5,1193	1,5496	4,2315
	Sales Decline by 50 %					
FFO/Debt	0,1715	0,2282	0,1682	0,2149	0,1252	0,1435
FOCF to Debt	0,1274	0,1304	0,0892	0,1204	0,0861	0,1224
FFO/Cash Interest	0,7168	1,8838	1,1379	1,3382	0,9487	2,1136
EBITDA/Interest	1,0881	3,4718	1,6038	4,6074	1,3946	3,8084
	Sales Decline by 75 %					
FFO/Debt	0,1029	0,1369	0,1009	0,1289	0,0751	0,0861
FOCF to Debt	0,0956	0,0978	0,0669	0,0903	0,0645	0,0857
FFO/Cash Interest	0,5735	1,5070	0,9103	1,0705	0,7590	1,6908
EBITDA/Interest	0,9793	3,1246	1,4434	4,1466	1,2552	3,4275

Table 8
Country wise Impact of Policy Interventions.

	Deferred Tax			Subordinated Loan			Equity Support		
	25 %	50 %	75 %	25 %	50 %	75 %	25 %	50 %	75 %
	Pd (Z̈) and Pd (O)								
Spain	0,6000	0,3000	0,1000	0,3000	0,5000	0,2000	0,1000	0,2000	0,7000
Italy	0,5300	0,2257	0,0945	0,3500	0,4989	0,5090	0,1200	0,2754	0,3965
France	0,6700	0,2853	0,1195	0,2800	0,3991	0,4072	0,0500	0,3156	0,4733
Germany	0,7000	0,2980	0,1248	0,2000	0,2851	0,2908	0,1000	0,4169	0,5843
Belgium	0,5500	0,2342	0,0981	0,3100	0,4419	0,4508	0,1400	0,3239	0,4511
Netherlands	0,6700	0,2853	0,1195	0,3000	0,4276	0,4363	0,0300	0,2871	0,4443
Switzerland	0,6300	0,2682	0,1123	0,2700	0,3849	0,3926	0,1000	0,3469	0,4950
Portugal	0,5800	0,2470	0,1034	0,3000	0,4276	0,4363	0,1200	0,3254	0,4603
Sweden	0,5300	0,2257	0,0945	0,2800	0,3991	0,4072	0,1900	0,3752	0,4983
Ireland	0,7400	0,3151	0,1320	0,2000	0,2851	0,2908	0,0600	0,3998	0,5772
Poland	0,6500	0,2768	0,1159	0,2000	0,2851	0,2908	0,1500	0,4381	0,5933
Romania	0,6100	0,2597	0,1088	0,2500	0,3564	0,3636	0,1400	0,3839	0,5277
Austria	0,6400	0,2725	0,1141	0,1500	0,2138	0,2181	0,2100	0,5137	0,6677
Denmark	0,6000	0,2555	0,1070	0,2600	0,3706	0,3781	0,1400	0,3739	0,5149
Serbia	0,5200	0,2214	0,0927	0,3400	0,4847	0,4944	0,1400	0,2939	0,4128
	Debt Payback and Coverage								
Spain	0,6307	0,1667	0,0922	0,3006	0,7828	0,1625	0,0686	0,0506	0,7453
Italy	0,5572	0,1254	0,0871	0,3508	0,7811	0,4136	0,0921	0,0936	0,4993
France	0,7043	0,1585	0,1101	0,2806	0,6249	0,3309	0,0151	0,2167	0,5590
Germany	0,7359	0,1656	0,1150	0,2004	0,4463	0,2363	0,0637	0,3881	0,6486
Belgium	0,5782	0,1301	0,0904	0,3107	0,6918	0,3663	0,1111	0,1781	0,5433
Netherlands	0,7043	0,1585	0,1101	0,3006	0,6695	0,3545	−0,0050	0,1720	0,5354
Switzerland	0,6623	0,1490	0,1035	0,2706	0,6025	0,3190	0,0671	0,2484	0,5774
Portugal	0,6097	0,1372	0,0953	0,3006	0,6695	0,3545	0,0896	0,1933	0,5502
Sweden	0,5572	0,1254	0,0871	0,2806	0,6249	0,3309	0,1622	0,2498	0,5821
Ireland	0,7779	0,1750	0,1216	0,2004	0,4463	0,2363	0,0216	0,3786	0,6421
Poland	0,6833	0,1538	0,1068	0,2004	0,4463	0,2363	0,1163	0,3999	0,6569
Romania	0,6413	0,1443	0,1002	0,2505	0,5579	0,2954	0,1082	0,2978	0,6044
Austria	0,6728	0,1514	0,1052	0,1503	0,3347	0,1772	0,1769	0,5139	0,7176
Denmark	0,6307	0,1419	0,0986	0,2606	0,5802	0,3072	0,1087	0,2778	0,5942
Serbia	0,5466	0,1230	0,0855	0,3407	0,7588	0,4018	0,1126	0,1182	0,5128

very low and highly improbable till mid-January 2020. However, the massive spread of contagion, by the end of the first quarter of 2020, has disrupted many businesses across the EU. The member states adopted mandatory curfews and strict lockdowns that transpired into very challenging realities for the operating environment of the firms. With constrained supply chains, uncertain production, and restricted demand, the revenues and cash flows of firms across the EU are under immense pressure. Therefore, it is very timely to study the effect of Covid-19 on the solvency profile of firms and gauge the impact of possible interventions to promote business resilience.

In this paper, we stress test the solvency of non-financial firms in 15 EU member countries that have reported over 10,000 coronavirus cases. We use two broad measures of the probability of default based on market and accounting variables. Further, we also consider a cash flow sufficiency framework that includes debt payback and coverages. There are two types of stress situations that we consider. The first one is a progressive decline in market capitalization of 15 %, 30 %, and 45 %. The second one is the decline in sales revenues of 25 %, 50 %, and 75 %. Our results suggest that a reduction in market capitalization will increase the probability of default. We highlight that mining, construction and chemicals, manufacturing, and wholesale and retail are most vulnerable to market capitalization shock. The results remained robust for accounting based estimates as well as cash flow sufficiency. The average firms in these sectors are likely to experience a probability of default between 24 % and 57 % in the worst-case scenarios. The payback and coverages are likely to erode significantly for a 50 %–70 % decrease in revenues. To cope with these vulnerabilities, we analyze three policy interventions. These include tax deferrals, subordinated debt, and equity injection. Our results suggest that if revenues decline is up to 25 %, a tax deferral is optimal. However, if the revenues decline by 50 %–75 %, hybrid support of debt and equity will be needed to sustain the solvency profile at the pre-Covid-19 level.

These findings are not very encouraging for the EU as an economic zone for many reasons. In the case of extreme revenue shocks, we expect solvency to deteriorate and the probability of default to increase significantly. This will compromise the financial flexibility of firms across Europe and put business continuity under lots of stress. The policy interventions will further strain the tightening economic conditions due to rising healthcare costs and unemployment. The Covid-19 has put the EU in a catch-22 situation. The tax deferrals will reduce the exchequer collections, and providing subordinated loans and equity support will be a significant drag on public funds. However, if there is no intervention, it can trigger insolvencies at an unprecedented rate. The Covid-19 shall pass, but its daunting economic impact is here to stay.

Declaration of Competing Interest

The authors report no declarations of interest.

References

Afik, Z., Arad, O., & Galil, K. (2016). Using Merton model for default prediction: An empirical assessment of selected alternatives. *Journal of Empirical Finance*, http://dx.doi.org/10.1016/j.jempfin.2015.09.004

Afzal, A., & Mirza, N. (2012). Interest rate spreads in an emerging economy: The case of Pakistan's commercial banking sector. *Ekonomska Istrazivanja*, *25*(4) http://dx.doi.org/10.1080/1331677X.2012.11517543

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, http://dx.doi.org/10.2307/2978933

Altman, E. I. (2018). Applications of distress prediction models: What have we learned after 50 years from the Z-score models? *International Journal of Financial Studies*, *6*(3), 70. http://dx.doi.org/10.3390/ijfs6030070

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z- score model. *Journal of International Financial Management and Accounting*, *28*(2), 131–171. http://dx.doi.org/10.1111/jifm.12053

Attaoui, S., & Poncet, P. (2013). Capital structure and debt priority. *Financial Management*, http://dx.doi.org/10.1111/fima.12011

Brei, M., Mohan, P., & Strobl, E. (2019). The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean. *The Quarterly Review of Economics and Finance*, *72*, 232–239. http://dx.doi.org/10.1016/j.qref.2018.12.004

Brogaard, J., Li, D., & Xia, Y. (2017). Stock liquidity and default risk. *Journal of Financial Economics*, *124*(3), 486–502. http://dx.doi.org/10.1016/j.jfineco.2017.03.003

Busch, R., Koziol, P., & Mitrovic, M. (2018). Many a little makes a mickle: Stress testing small and medium-sized German banks. *The Quarterly Review of Economics and Finance*, *68*, 237–253. http://dx.doi.org/10.1016/j.qref.2017.08.001

Chen, S., Igan, D., Pierri, N., & Presbitero, A. (2020). *The economic impact of Covid-19 in Europe and the US (VOX, CEPR policy portal)*. https://voxeu.org/article/economic-impact-covid-19-europe-and-us

Cherkasova, V., & Kurlyanova, A. (2019). Does corporate R&D investment support to decrease of default probability of Asian firms? *Borsa Istanbul Review*, *19*(4), 344–356. http://dx.doi.org/10.1016/j.bir.2019.07.009

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from Gold and Cryptocurrencies. *Finance Research Letters*, 101554. http://dx.doi.org/10.1016/j.frl.2020.101554

Cui, W., & Kaas, L. (2020). Default cycles. *Journal of Monetary Economics*, http://dx.doi.org/10.1016/j.jmoneco.2020.02.001

De Vito, A., & Gómez, J. P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy*, *39*(2), 106741. http://dx.doi.org/10.1016/j.jaccpubpol.2020.106741

Denzler, S. M., Dacorogna, M. M., Müller, U. A., & McNeil, A. J. (2006). From default probabilities to credit spreads: Credit risk models do explain market prices. *Finance Research Letters*, *3*(2), 79–95. http://dx.doi.org/10.1016/j.frl.2006.01.004

Drobetz, W., Haller, R., Meier, I., & Tarhan, V. (2017). The impact of liquidity crises on cash flow sensitivities. *The Quarterly Review of Economics and Finance*, *66*, 225–239. http://dx.doi.org/10.1016/j.qref.2017.03.004

Duan, J. C., Kim, B., Kim, W., & Shin, D. (2018). Default probabilities of privately held firms. *Journal of Banking & Finance*, *94*, 235–250. http://dx.doi.org/10.1016/j.jbankfin.2018.08.006

Emirmahmutoglu, F., & Omay, T. (2014). Reexamining the PPP hypothesis: A nonlinear asymmetric heterogeneous panel unit root test. *Economic Modelling*, *40*, 184–190. http://dx.doi.org/10.1016/j.econmod.2014.03.028

Emirmahmutoglu, F., Gupta, R., Miller, S. M., & Omay, T. (2020). Is real per capita state personal income stationary? New nonlinear, asymmetric panel-data evidence. *Bulletin of Economic Research*, *72*(1), 50–62. http://dx.doi.org/10.1111/boer.12209

Ghulam, Y., & Derber, J. (2018). Determinants of sovereign defaults. *The Quarterly Review of Economics and Finance*, *69*, 43–55. http://dx.doi.org/10.1016/j.qref.2017.12.003

Goodell, J. W., & Huynh, T. L. D. (2020). Did Congress trade ahead? Considering the reaction of US industries to COVID-19. *Finance Research Letters*, 101578. http://dx.doi.org/10.1016/j.frl.2020.101578

Grundke, P., & Kühn, A. (2020). The impact of the Basel III liquidity ratios on banks: Evidence from a simulation study. *The Quarterly Review of Economics and Finance*, *75*, 167–190. http://dx.doi.org/10.1016/j.qref.2019.02.005

Harris, C., & Roark, S. (2019). Cash flow risk and capital structure decisions. *Finance Research Letters*, *29*, 393–397. http://dx.doi.org/10.1016/j.frl.2018.09.005

Hernandez Tinoco, M., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394–419. http://dx.doi.org/10.1016/j.irfa.2013.02.013

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, *9*(1), 5–34. http://dx.doi.org/10.1023/B:RAST.0000013627.90884.b7

Imai, K., & Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? *American Journal of Political Science*, *63*(2), 467–490. http://dx.doi.org/10.1111/ajps.12417

Keefe, M. O. C., & Yaghoubi, M. (2016). The influence of cash flow volatility on capital structure and the use of debt of different maturities. *Journal of Corporate Finance*, *38*, 18–36. http://dx.doi.org/10.1016/j.jcorpfin.2016.03.001

Khan, T. M., Rizvi, S. K. A., & Sadiq, R. (2018). Disintermediation of banks in a developing economy: Profitability and depositor protection in adverse economic conditions. *Managerial Finance*, http://dx.doi.org/10.1108/MF-11-2017-0493. MF-11-2017-0493

Korol, T. (2013). Early warning models against bankruptcy risk for Central European and Latin American enterprises. *Economic Modelling*, *31*(1), 22–30. http://dx.doi.org/10.1016/j.econmod.2012.11.017

Kwak, W., Shi, Y., Cheh, J. J., & Lee, H. (2004). Multiple criteria linear programming data mining approach: An application for bankruptcy prediction. *International Journal of Data Mining & Knowledge Management Process*, *3327*, 164–173. http://dx.doi.org/10.1007/978-3-540-30537-8_18

Li, X., & Luo, D. (2019). Financial constraints, stock liquidity, and stock returns. *Journal of International Financial Markets Institutions and Money*, *63*, Article 101139 http://dx.doi.org/10.1016/j.intfin.2019.101139

Lin, H. W. W., Lo, H. C., & Wu, R. S. (2016). Modeling default prediction with earnings management. *Pacific Basin Finance Journal*, *40*, 306–322. http://dx.doi.org/10.1016/j.pacfin.2016.01.005

Merkevicius, E., Garšva, G., & Girdzijauskas, S. (2006). A hybrid SOM-altman model for bankruptcy prediction. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 3994 LNCS-IV*, 364–371. http://dx.doi.org/10.1007/11758549_53

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, http://dx.doi.org/10.2307/2978814

Mirza, N., Naqvi, B., Rahat, B., & Rizvi, S. K. A. (2020). Price reaction, volatility timing and funds' performance during Covid-19. *Finance Research Letters*, 101657. http://dx.doi.org/10.1016/j.frl.2020.101657

Mirza, N., Rahat, B., & Reddy, K. (2016). Financial leverage and stock returns: Evidence from an emerging economy. *Economic Research-Ekonomska Istrazivanja*, http://dx.doi.org/10.1080/1331677X.2016.1160792

Mselmi, N., Hamza, T., Lahiani, A., & Shahbaz, M. (2019). Pricing corporate financial distress: Empirical evidence from the French stock market. *Journal of International Money and Finance*, *96*, 13–27. http://dx.doi.org/10.1016/j.jimonfin.2019.04.008

Naeem, M., Tiwari, A. K., Mubashra, S., & Shahbaz, M. (2019). Modeling volatility of precious metals markets by using regime-switching GARCH models. *Resources Policy*, *64*, Article 101497 http://dx.doi.org/10.1016/j.resourpol.2019.101497

Naqvi, B., Rizvi, S. K. A., Uqaili, H. A., & Chaudhry, S. M. (2018). What enables Islamic banks to contribute in global financial reintermediation? *Pacific Basin Finance Journal*, *52*, 5–25. http://dx.doi.org/10.1016/j.pacfin.2017.12.001

Nasir, M. A., Al-Emadi, A. A., Shahbaz, M., & Hammoudeh, S. (2019). Importance of oil shocks and the GCC macroeconomy: A structural VAR analysis. *Resources Policy*, *61*, 166–179. http://dx.doi.org/10.1016/j.resourpol.2019.01.019

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109. http://dx.doi.org/10.2307/2490395

Omay, T., Shahbaz, M., & Hasanov, M. (2020). Testing PPP hypothesis under temporary structural breaks and asymmetric dynamic adjustments. *Applied Economics*, *52*(32), 3479–3497. http://dx.doi.org/10.1080/00036846.2020.1713293

Park, J. (2019). Financial constraints and the cash flow sensitivities of external financing: Evidence from Korea. *Research in International Business and Finance*, *49*, 241–250. http://dx.doi.org/10.1016/j.ribaf.2019.03.007

Rizvi, S. K. A., Mirza, N., Naqvi, B., & Rahat, B. (2020). Covid-19 and asset management in EU: A preliminary assessment of performance and investment styles. *Journal of Asset Management*, 1–11. http://dx.doi.org/10.1057/s41260-020-00172-3

Romero-Ávila, D. (2012). Multiple trend shifts and unit roots in US state income levels: Implications for long-run growth. *The Annals of Regional Science*, *48*(3), 641–661. http://dx.doi.org/10.1007/s00168-010-0420-6

Schell, D., Wang, M., & Huynh, T. L. D. (2020). This time is indeed different: A study on global market reactions to public health crisis. *Journal of Behavioral and Experimental Finance*, *27*, Article 100349 http://dx.doi.org/10.1016/j.jbef.2020.100349

Shahbaz, M., Rehman, I. U., & Afza, T. (2016). Macroeconomic determinants of stock market capitalization in an emerging market: Fresh evidence from cointegration with unknown structural breaks. *Macroeconomics and Finance in Emerging Market Economies*, *9*(1), 75–99. http://dx.doi.org/10.1080/17520843.2015.1053820

Shahbaz, M., Tahir, M. I., Ali, I., & Rehman, I. U. (2014). Is gold investment a hedge against inflation in Pakistan? A co-integration and causality analysis in the presence of structural breaks. *The North American Journal of Economics and Finance*, *28*, 190–205. http://dx.doi.org/10.1016/j.najef.2014.03.012

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, Article 101496 http://dx.doi.org/10.1016/j.irfa.2020.101496

Solarin, S. A., Shahbaz, M., & Stewart, C. (2018). Is the consumption-income ratio stationary in African countries? Evidence from new time series tests that allow for structural breaks. *Applied Economics*, *50*(38), 4122–4136. http://dx.doi.org/10.1080/00036846.2018.1441515

Soula, J. L. (2017). Measuring heterogeneity in bank liquidity risk: Who are the winners and losers? *The Quarterly Review of Economics and Finance*, *66*, 302–313. http://dx.doi.org/10.1016/j.qref.2017.04.006

Ucar, N., & Omay, T. (2009). Testing for unit root in nonlinear heterogeneous panels. *Economics Letters*, *104*(1), 5–8. http://dx.doi.org/10.1016/j.econlet.2009.03.018

Uchida, H., Miyakawa, D., Hosono, K., Ono, A., Uchino, T., & Uesugi, I. (2015). Financial shocks, bankruptcy, and natural selection. *Japan and the World Economy*, *36*, 123–135. http://dx.doi.org/10.1016/j.japwor.2015.11.002

Vassalou, M., & Xing, Y. (2004). Default risk in equity returns. *The Journal of Finance*, *59*(2), 831–868. http://dx.doi.org/10.1111/j.1540-6261.2004.00650.x

Xu, M., & Zhang, C. (2009). Bankruptcy prediction: The case of Japanese listed companies. *Review of Accounting Studies*, http://dx.doi.org/10.1007/s11142-008-9080-5