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Studying corporate liquidity and regulatory responses for economic recovery in COVID-19 crises

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ABSTRACT

Many enterprises across the European Union (EU) have been hampered by the massive spread of COVID-19. It has severely impacted revenues and financial flows, potentially leading to an increase in corporate insolvency. This study investigates the influence of this new coronavirus on the solvency status of businesses in EU Member States. Several stress scenarios were constructed for non-financial listed enterprises. The results reveal a gradual surge in the possibility of default, a rise in loan repayment, and coverage being refused. According to our findings, the solvency profiles of all firms are deteriorating. Industries, such as mining, mass production, and retail, are the most susceptible to a drop in sales income and market capitalization. Before COVID-19, previous research had looked at policy options for maintaining solvency. Our data imply that a tax delay is adequate if there is a slight deterioration in the economic outlook. There should be hybrid assistance through loans and equity for even a slight deterioration in the state of an economy. This research will benefit policymakers, corporate executives, and creditors.

1. Introduction

COVID-19 has revealed business weaknesses and introduced new challenges. Policymakers are attempting to adapt to changing customer and supplier paradigms while overcoming threats to work and their respective economies. Regardless of this, flexibility from the current pandemic is impacting companies' incomes, profitability, cash flows, and liquidity in the public and private sectors. With over 10,000 infected cases reported in 15 of the European Union (EU)'s 27 member countries, the COVID-19 outbreak has wreaked havoc on the EU. The death toll in member countries accounts for 32% of worldwide deaths. For weeks, there were strict lockdowns with limited movement and business closures. As a result, production and on-demand activities have slowed, whilst companies' revenues have shrunk. The EU is, therefore, facing unprecedented economic costs (Cheng et al., 2021). The impression of the coronavirus pandemic on financial markets and their participants is being recognized in an increasing number of studies. Iannaccone (1998) showed evidence of the cryptocurrency and gold contagion effect. Sovacool et al. (2016) looked at how policy uncertainty, geopolitical risk, and oil prices interact. Ellison (1991) studied fund managers' investment methods and the timing of volatility during the pandemic. Herrero (2017) looked at how the market reacted to the COVID-19 outbreak, while Rahman et al. (1999) looked at how the industry responded to the emergence of COVID-19.

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Such a fast-deteriorating position poses severe risks to enterprises' liquidity and solvency, necessitating action by sponsors and policymakers. Bhatia and Angelou (2015) looked into the effect of COVID-19 on liquidity and various government interventions (Iqbal and Bilal, 2021b). They claimed that a typical business in their worldwide sample would be forced to pursue solvency in a crisis. However, their research was solely focused on short-term liquidity management. It ignored the impact on these companies' long-term liquidity, which is likely, if not more so, and potentially more destructive than short-term liquidity problems (Mohsin et al., 2020, 2021a). In light of this, it is necessary to look into how the pandemic might affect the corporate sector's economic strength and what influence different solutions might have on the state of solvency (Li et al., 2021b). We are attempting to evaluate the impact of the COVID-19 pandemic on the liquidity of 12,387 non-financial businesses registered in 15 EU Member States, infecting over 10,000 people. We determined this impact by analyzing numerous distress scenarios involving prospective sales and market value declines for these businesses. Three theories are used to assess the impact of various distressed circumstances. These include cash flow sufficiency, a market-based default evaluation, and an accounting-based discriminant requirement for the possibility of failure to pay. We also looked at whether a strategic reaction of adding capital or deferring tax would be beneficial. The most effective intervention could help to strengthen solvency (Yang et al., 2022). So, we wanted to investigate this. The sample enterprises can be classified using a variety of sectoral criteria. Waddams Price et al. (2012) examined 46 industries for abnormal returns, including financial services in the United States. Our analysis, unlike theirs, is based on firm-level data rather than industry-wide statistics. As a result, we group our data into six main categories, similar to Day et al. (2016).

There are numerous contributions to our research. To the best of our knowledge, this is the first study that looks at the influence of COVID-19 on European corporate solvency. We focus on a micro perspective of a single measure, similar to Urbanucci (2018). Nonetheless, our model is far more thorough and includes market-based accounting and nonpayment forecasting. Furthermore, previous maximum stress evaluations utilizing stress testing are in a bank setting. Therefore, our approach to stress testing for non-financial firm solvency makes a unique and considerable contribution to a body of work on the subject. The remainder of this article follows a set structure. Section 2 contains the outline of the empirical strategy. The data and stressful situations are explained in Section 3. Section 4 provides the results and discussion, and Section 5 presents the conclusion.

2. Empirical strategy for solvency assessment and policy response

Our research makes numerous contributions. This study is the first to look at the influence of the COVID-19 pandemic on European business liquidity. We focus on a micro perspective of a single risk, similar to Gruber (2005). On the other hand, our research model is substantially larger, incorporating both accounting-based and market nonpayment default predictions. Additionally, the previous stress evaluations utilizing stress testing were in bank settings (Awaworyi Churchill, 2017; Wu et al., 2012). We employ three main components concerning the risk of default and cash flow adequacy for stress-testing a company's solvency. Firstly, each firm's actual situation is calculated using these components and compared to distress scenario projections. Finally, the various interventions that could be used and how they might affect the distressed estimations are determined. 2019 is set as the base case scenario to ensure that financial reports are provided. The specifics of the framework for estimating the solvency measures are given below.

2.1. Market-based model

Market-based or structured bankruptcy frameworks used market forces to control the likelihood of bankruptcy (probability of default) in the past (Goldemberg et al., 1985; Benjaminsen, 1993; Fragiacomo and Genovese, 2020). These frameworks are based on Merton's (1974) theoretical foundations. They connect corporate bankruptcy with a pricing framework for options. As not all assets in a structured default model are marked to market, it is difficult to observe standard deviation and market values of support (Falchetta and Mistry, 2021; Rosenthal et al., 2018; González-Eguino, 2015). However, Healy and Clinch (2004) proposed an iterative process for calculating volatility and asset market values at the business stage using share prices (Iqbal and Bilal, 2021a). Many studies have employed this method (Zhou et al., 2010; Ozawa et al., 2019). Although several additions to Cnaan et al. (2003) have already been offered, current comparative research, such as Bouzarovski and Petrova (2015) and Clauser and Ewert (2018), show that the initial framework is superior to all versions.

The possibility of default for business I in a contingent claim scenario is shown by:

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

where V_A represents the individual business market values (in the sample) and μ is anticipated asset progression with a standard deviation of σA. X signifies monetary obligations that will be settled in time T and have a density function N.

To examine an extreme case, we consider X to be each of our sample firms' total shorter and more extended period of financial liability (without subordinate). T is the weighted maturity of these debts. Khanna et al. (2019) and Butler et al. (2013) proposed that *VE* is the value of a company's equity and r is the risk-free rate. The system of simultaneous equations from the options pricing framework accounts for two unknowns.

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{2}$$

$$V_E = V_A N\left(d_1\right) - Xe^{-rT} N(d_2) \tag{3}$$

$$\text{when } d_1 = \frac{\ln(\frac{V_A}{X}) + (\mu + 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}}, \text{ and } d_2 = d_1 - \sigma_A \sqrt{T} \tag{4}$$

Representative companies start utilizing return data for 12 months, measuring the daily standard equity variation. This is applied to determine the intra-day market value of assets as a pseudo-standard deviation of assets. After calculating the pseudo market value of property, this is complete unless the normal equity variation first pass and the standard asset variation second pass converge (within 0.0001). The convergent value is the last parameter for calculating the market price and the likelihood of defaults (Zhang et al., 2022).

2.2. Accounting-based discriminant models of default

Wang et al. (2019) pioneered discriminant models of default, which use accounting information to define the economic stability of a company. These models are effective because they are grounded in essential strengths and weaknesses. Also, the models are not influenced by market circumstances (Decancq and Lugo, 2013; Kahouli and Okushima, 2021). Discriminant prototypes support the prediction of scores that can be used to distinguish between stressed and non-stressed companies. These scores can be used to calculate the likelihood of default. This study uses two crucial discriminant analysis performance measures. One is the "Altman Z" score that Altman proposed (Howlett, 1995), which is a modified version of Goldemberg and Johansson (1995) and Pachauri and Spreng (2004). For example, many studies support the effectiveness of the Z″ and O scores in predicting non-financial firm distress (Molenaar et al., 1992; Harvey, 1990; Boardman, 1991). For each firm, the Altman Z″ score was calculated in the same way as by (Green and Gilbertson, 2008).

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \tag{5}$$

In the above equation, X_1 and X_2 refer to networking capitals as net worth total assets and earnings surplus to net worth total assets. Similarly, X_3 and X_4 signify operating profit as a proportion of total assets and market value of equity as a percentage of liabilities' carrying value, respectively. The possibility of bankruptcy or default (Pz'') can be shown using the approximate Z″ as:

$$P_{z''}\left\langle Y = 1|X\right\rangle = \frac{1}{1 + e^{-Z''}} \tag{6}$$

It is worth noting that research by Churchill and Smyth (2017) and, more recently, Chase (2013) recommended adopting the coefficients of the original Altman model. Their findings suggest that predicting insolvency using actual coefficient values is more reliable than re-estimated factor loadings. As a result, the original coefficients from Altman's argument were studied.

For each sample firm, the estimation by Hassan et al. (2017) using the O score was calculated using the following equation:

$$\begin{aligned} O = & -1.32 - 0.407 \log \frac{TA_t}{GNP_t} + 6.03 \frac{TL_t}{TA_t} - 1.43 \frac{WC_t}{TA_t} + 0.0757 \frac{CL_t}{CA_t} - 1.72D_1 - 2.37 \frac{NI_t}{TA_t} \\ & - 1.83 \frac{FFO_t}{TL_t} + 0.285D_2 - 0.521 \frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|} \end{aligned} \tag{7}$$

where FFO = funds from operations, CL = current liabilities, WC = working capital, NI = net income, TL = total liabilities, CA = current assets, GNP = gross national product price index level, TA = total assets, NI = D1, which is a dummy that equals 1 if TL > TA, and D2 is a dummy that equals 1 if the previous two years have resulted in a net loss. The suffix t is used to represent time. The following formula is used to calculate the probability of default (P_O):

$$p_o = \frac{e^{OScore}}{1 + e^{OScore}} \tag{8}$$

For the past timeframe, pz'' and po are determined, and distressed situations are generated.

2.3. Cash flow sufficiency

Research further indicated using traditional liquid asset use ratios to analyze the present and stressed solvency positions for all the companies in our sample. Due to the sufficiency of a company's cash flows, these are often a more suitable measure of financial risk than cash commitments. The above comparisons are divided into two classes: debt repayment and coverage. The reimbursement ratios comprise operational funds for liability and free functioning liquid assets for liability (FOCFs). We regard the FFO as cash interest and the EBITDA as interest for the coverage ratios (Pachauri and Spreng, 2011). The free cash flow adjusts cash flows from activities by considering capital costs, including tangible and intellectual assets financing. In a troubled environment, the decreasing basics cause cash flow drags, raising debt reimbursement and contributing to insufficient coverage. This is feasible given that cash flows play a critical role in optimizing the capital composition and financial flexibility of a company (Awan et al., 2013; Welsch and Biermann, 2017).

2.4. Policy interventions

The proliferation of the Covid-19 pandemic has affected the social and economic aspects of European countries. The lockdowns led to significant economic damage for citizens and companies. Various actions have been implemented to limit the effect of this and return to sustained development. The EU has promised to finance social welfare by EUR 540 billion, while the EIB is providing additional liquidity for small and medium-sized firms with up to EUR 40 billion. The ECB plans to buy private and public securities of EUR 870 billion where there is an outbreak. In addition, the EU is preparing a rescue strategy in its forthcoming long-term budget. Given that the economic emergency will last for a long time, additional financial assistance will be needed to prevent massive shortfalls. Administrative abstention and debt prohibitions may alleviate the state of liquidity, but they generate long-term risks because they do not alleviate the underlying problems. Thus, more vital fiscal involvement will be necessary in the long term. Some solutions include tax deferral, incorporation, and cash infusion through subprime mortgages. Sponsors can also offer subprime mortgages and capital upgrades in addition to tax deferrals, which are largely a form of government assistance (Karpinska and Śmiech, 2021; Sovacool, 2017; Nussbaumer et al., 2012).

3. Stress scenarios and data

Structural issues may go unaddressed. As a result, additional budgetary action on a long-term basis will be required. Three policy measures were evaluated to determine the impact of potential business assistance (Mohsin et al., 2021b, 2020). Several solutions include deferred taxation, a subordinated loan facility, and capital infusion (Biermann, 2016). A fall in a firm's market value and financial distress on the stock market increase the likelihood of default. Legendre and Ricci (2015), Sadath and Acharya (2017), and Koomson and Danquah (2021) provide evidence on financial distress pricing. In this framework, we look at three potential market capitalization shocks (Heynen et al., 2019; Sellitto et al., 2020; Thomson et al., 2017). Here, market capitalization will drop by 15%, 30%, and 45%, respectively from its December 2019 level. A market-based model was used to compute the stressed chance of default based on these three situations. Market-based requirements include direct market value and may, therefore, transparently represent impact (Bridge et al., 2016; Barnes et al., 2011; Desai and Vanneman, 2010). There is a well-established link between long-term solvency and revenue.

The relationship between previous and recent analyses indicates that the company's long-term liquidity and earnings generation are well established (Hitchcock and Wesner, 2008; Sanusi and Owoyele, 2016; Mirza and Szirmai, 2010). We follow the method of Kadlec and Gabrys (2009) to construct the sensitivities for stress testing solvency in the face of a reduction. All essential inputs include Altman Z, Ohlson O, and liquid asset sufficiency. The sum of the stressed variables is calculated using these sensitivities and is based on a 25%, 50%, and 75% drop in sales due to COVID-19. The equations are as follows (from A1 to F1):

$$\partial NI = \frac{\partial Sales}{Sales} \times (Sales - opex \times E_{opex}) \times (1 - t) \tag{9}$$

$$\partial FFO = \partial NI + \partial Dep + \partial DT \tag{10}$$

$$\partial CFO = \partial FFO - \Delta CA \times E_{\Delta CA} + \Delta CL \times E_{\Delta CL} \tag{11}$$

$$\partial FOCF = \partial CFO - \Delta FA\,|E_{\Delta FA} \tag{12}$$

$$WC = CA + (\Delta CA|E_{\Delta CA}) - CL + (\Delta CL|E_{\Delta CL}) \tag{13}$$

$$\partial TA = \Delta CA\,|E_{\Delta CA} + \Delta FA\,|E_{\Delta FA} + OA = \Delta CL\,|E_{\Delta CL} + OL + FD + Eq + \Delta RE\,|\partial NI \tag{14}$$

Operational costs (opex), deferred taxes (DT), the applicable tax rate (t), other liabilities (OL), other assets (OA), financial debt (FD), fixed assets (FA), retained earnings (RE), and equity (Eq) are all included. Our review found that OA and OL were stable in the year before our study. We are going to assume that no acquisitions have been completed and no profits have been distributed. As a consequence, the stock price is fluctuating due to changes in financial stability and the economy (Okushima, 2016; Charlier and Kahouli, 2019; Suganthi, 2018). Similarly, FD is expected to remain steady in the basic scenario at 2019 levels. Many aspects of sales are sensitive to the enterprise (E)'s specific consumers. We make use of panel evaluations in the way described above to arrive at these sensitivity levels.

$$\Delta X_{it} = \alpha + \beta_X \Delta Sales_{it} + \beta_\omega \omega_t + \varepsilon_{it} \tag{15}$$

In the above equation, β_X is the factor's sensitivity and X denotes the variable factor for firm I at time t (i.e., opex, CA, CL, FA). Y represents firm I's fixed element at time t (i.e., opex, CA, CL, FA). All macroeconomic control factors [estimated based on a company's turnover relative to gross domestic product (GDP)] include GDP growth, industry concentration (Herfindahl–Hirschmann index), inflation, and system size. These calculations can be carried out to aid a firm in the event of a sales distress scenario. We can determine a firm's overall solvency for Z'', O score, and cash flow sufficiency. The firm-level and macroeconomic data used to estimate Eq. (6) spans 19 years, from 2001 to 2019. As a result, to ensure adequate estimate data, we only evaluated non-financial listed companies that have been in operation since 1998. COVID-19 has a long and illustrious history, which negatively impacts tourism and related businesses (for example, aviation). Companies, such as hotels, holding companies, and airlines, were excluded from this study because we believe their inclusion could skew the overall results. Thorough research is required to understand the solvency dynamics of tourism-related businesses. Thus, we created a balanced panel of 12,387 enterprises. We did not have company or time-fixed effects due to the extensive size of our dataset, which includes a large number of firms and a time series spanning several years. According to Moore (2012), adding unit effects to large datasets makes causal inference difficult. Similar methodologies have been used when researching green finance (Taghizadeh-Hesary and Yoshino, 2019, 2020; Taghizadeh-Hesary and Taghizadeh-Hesary, 2020; Taghizadeh-Hesary et al., 2021).

Datastream and trending economics extracted firm-level data, macroeconomic parameters, and market-based price information. As we only included businesses that have been in operation since 1998, it is worth noting that all of these businesses had survived the global financial crisis of 2007–2008.

4. Results and discussion

Table 1 shows the descriptive statistics for factors unique to a company — the weighted average (as the ratio of an asset) for each sector from 2001 to 2019. Due to inventory requirements, the percentage of working capital (WC) to total assets (TA) in the wholesale and retail industries is a maximum 25% of total assets. Mining and construction firms are the most common, followed by manufacturing companies. Companies invest 18% and 15% of their total assets in working capital, respectively. As the industrial sector is likely to have much inventory, their more outstanding payables relative to retail necessitate a smaller proportionate investment in working capital. With an RE/TA of 30.2%, the wholesale and retail sectors have the highest risk absorption capacity, while manufacturing has the lowest at 12.4%. Services industries have the highest operational returns on assets at 21.5%, while retail has the lowest at 4.1%. With an average TL/TA of 61%, mining, construction, and chemical companies in the manufacturing sector account for 54% of the total. With an FFO/debt ratio of 48%, wholesale and retail have the lowest debt payback in terms of funds from operations. With FFO/debt ratios of 20%, agriculture, forestry, and fisheries have the highest debt payback rates. Wholesale and retail companies also dominate the coverages, with FFO/cash interest of five times and EBITDA/interest of seven times. The correlation between these factors is shown in Table 1.

In Panel A of Table 3, the sensitivity of sales to expenses, current assets, current liabilities, and fixed assets were calculated using Eq. (6). According to the fixed effects regression results, all sensitivities are significant at 95% to 99% across all sectors. Wholesale and retail expenses are 85.1% sensitive to sales, followed by manufacturing at 75.1%. Services are the least sensitive, with a 56.1% fluctuation in total revenues. We have similar estimations for current assets with wholesale, retail, and manufacturing, with a maximum sensitivity of 91.5% and 85.1%, respectively. This is understandable given that these companies invest much in inventory that fluctuates with sales in manufacturing and wholesale.

Table 2 shows the correlation matrix. In addition, the industrial sector has a large number of receivable accounts. Manufacturing enterprises have the highest sensitivity to current liabilities due to their higher trade payables. With a fluctuation of 41.2%, the coefficient for the services sector is the smallest. Manufacturing enterprises have the highest elasticity of fixed assets, which is unsurprising given their capacity restrictions and requirement for incremental investments to sustain their sales. To cope with their increased revenues, the fixed assets of manufacturing enterprises will vary by 2% on average. Panels B through E show the results of the within-sample forecast accuracy. To assess the precision of our sensitivities, we used the root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), which carry the same meaning. The expected values for all four measures necessarily mean rigorous forecast accuracy for the four elasticities. The out-of-sample forecast statistics are shown in Panels F through I. Out-of-sample statistics, such as within-sample forecasting, bolster the validity of our findings. A potential caveat of our analysis is the possibility of a structural break in the data due to COVID-19's changing business dynamics. Structural stability in model estimation during changing market cycles has been well documented in similar studies (Solangi et al., 2019; Kumar, 2020; Hou et al., 2021).

Table 3 shows variable sensitivities with sales and forecast accuracy. The post-COVID-19 firm-level data, which is only available for two quarters, limits this study's ability to conduct a comprehensive structural break analysis (Li et al., 2021a). We used the strategy of Jamali et al. (2021) and Njiru and Letema (2018) to ensure this same solidity for our quick evaluation by testing for serial correlation in our estimates. This strategy is based on Bradshaw et al. (2008) and Wu and Lee (2007). It is considered robust compared to other propositions, incorporating non-linearity, opacity, and bridge dependence in panel data (Sailer et al., 2020). Table 4 shows the results of the sequential panel selection method (SPSM) estimates from Sanchez-Guevara et al. (2019), indicating that our elasticity coefficients are rationalized. While this may imply that the structural break has had no significant impact, we must reiterate the limitations of post-COVID-19 firm data (Table 4).

Table 1
Descriptive statistics.

		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
	SD	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
	SD	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
	SD	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
	SD	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
	SD	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
	SD	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
	SD	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
	SD	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
	SD	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
	SD	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

Standard deviation is represented by SD, excess kurtosis is represented by kurtosis, and JB represents Jarque–Bera Stats. Authors' calculation.

Table 5 presents the likelihood of market-based variables as the basis for default calculations for various situations and stressful scenarios, calculated using Eq. (1). The PDs used in the base case scenario are current (in 2019) before COVID-19 had any significant impact. The average mining, construction, and chemical company, according to our calculations, has a 12.5% chance of default, followed by manufacturing with a 12% chance of default. The manufacturing company with the highest default risk had a 31.8% chance of failing. Wholesale and retail markets are noncyclical. These sectors have a default chance of 5.1% on average. Agriculture, forestry, and fishing are the safest businesses, with a PD of 3.15%.

4.1. Impact of Covid-19 utility effects

The impact of COVID-19 creates a significant increase in the probability of default throughout all sectors in the stress scenarios. The average mining company's PD rises to 24.7%, despite a 15% drop in market cap, while the retail sector's PD rises to 12.5%. Productivity in manufacturing firms has increased slightly, with an average PD of 12%. A further reduction

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		

Authors' calculation.

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	0.7614^{**}	0.71236^{**}	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%	

Authors' calculation.

Table 4
SPSM results.

I(0) Series	FAE	tAEas		NL	
Europe	71.315**	29.125	**	41.325	**
ECA	101.855**	42.056	***	32.940	**
ECL	51.256**	33.660	***	31.015	**
EFA	80.125***	31.255	***	27.050	***

Authors' calculation.

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

Authors' calculation.

in market capitalization to 30% causes more significant drag on solvency. Mining, manufacturing, retail, and service companies have PDs of 38.7%, 27.9%, 19.8%, and 15.2%, respectively. A 45% drop in market capitalization from 2019 levels results in 56.8% for mining, 37.7% for manufacturing, 28.7% for retail, and 19.7% for utilities. Manufacturing, mining, and retail businesses are particularly vulnerable. According to these findings, solvency is a concern as market capitalization declines. The utilities and service companies display minor issues in their primary case and stress scenarios with 15% and 30% market value reductions. However, these companies have significant vulnerabilities to default in the worst-case scenario.

Table 6 shows the PD estimations based on accounting from Eq. (2) to 5. The Altman Z″ and Ohlson O score results are consistent. The estimation process means that Ohlson O's PDs are more significant than those of Z″. Organizations in mining, construction, and chemical production have a Z″-based PD of 12%. In the base case scenario, manufacturing enterprises have a PD of 11.5%. The wholesale–retail price is 5.7%, comparable to market-based default projections. The COVID-19 stress model and the susceptibility mentioned in Table 6 indicate a high chance of failure in all industries. A typical manufacturer's PD is about 17%. This translates to a 25% decrease in sales. The PD will increase to 22.4% and 43.4% if sales fall by 50% and 75%, respectively. The mining industry experiences a similar trajectory for the three sales scenarios, with average PDs growing to 17%, 28%, and 40%. Service, agriculture, forestry, utilities, retail, and wholesale businesses follow. Market and accounting-based research was used in our PD-based study. There is a fascinating contrast here. The wholesale and retail areas are considered more efficient under market-based PD volatility than their accounting counterparts. This disparity reflects an underlying solid position that the equity market may not have fully priced in. However, the statistics show a deteriorating solvency profile in all industries.

4.2. Results regarding liquid asset or cash flow sufficiency

Table 7 illustrate the cash flow validation analysis findings. The shorter cash cycles create high quantities of cash flows. Therefore, the wholesale and retail sectors often dominate financial leverage recovery and coverage. Under normal conditions, the utilities, manufacturing, and service industries all have a good credit status. A big decrease in the working capital ratio has been observed since the Covid-19 strategy was implemented. While revenues plummeted by 75%, the FOCF's manufacturing debt ratio declined to 9.5% (35.1%). The FOCF debt-to-GDP ratio in the utilities sector will fall from 42.1% to 9.7%. In the most basic scenario, mining companies predict a decline in sales of between 29% and 6%. This identical debt ratio in FOCF declines from 42.8% in the base case to 9% in the worst-case scenario for wholesalers and retailers. All stress levels have similar impacts, such as a substantial drop in FFO cash interest and EBITDA obligations.

Our findings reveal significant difficulties with solvency and cash flow sufficiency in major EU sectors. Hence, a legislative reaction is required to reduce the impact of COVID-19 and avert a global collapse. Table 8 summarizes the country-by-country outcomes for three proposed strategies. We assessed the impact of these programs and their efficacy in reducing the likelihood of (money-based) bankruptcy, debt compensation, and coverage at levels similar to those seen

Table 6
Probabilities of Bankruptcy or default results of Z and O indicators.

		Production	Utilities	Mining	Retail	Agriculture	Services
	Base Cases as of 2019						
PD (Z″)	Max	0.3283	0.2284	0.2332	0.2034	0.2215	0.1374
	Mean	0.1143	0.0485	0.1293	0.0473	0.0432	0.0593
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 (Z″)	Max	0.6432	0.2498	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
	Sales Decline 50%						
PD (Z″)	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 (Z″)	Max	0.8574	0.5352	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	

Authors' calculation.

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	30.179	40.919	26.106	52.185	20.089	42.315
EBITDA/Interest	32.841	54.209	22.506	81.248	38.201	51.193
	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	11.947	31.397	18.965	22.303	15.812	35.226
EBITDA/Interest	12.090	38.575	17.820	51.193	15.496	42.315
	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	18.838	11.379	13.382	0.9487	21.136
EBITDA/Interest	10.881	34.718	16.038	46.074	13.946	38.084
	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	15.070	0.9103	10.705	0.7590	16.908
EBITDA/Interest	0.9793	31.246	14.434	41.466	12.552	3.42

Authors' calculation.

before COVID-19 in 2019. Deferring taxes within the EU is the best strategy if the loss of revenue is restricted to 25%. This will allow 74% of Irish businesses to maintain PD levels prior to COVID-19. Thanks to the tax decrease, Serbian businesses may preserve their (minimum) 52% default rate. Sales are down by less than 25% and no substantial capital investments are required.

4.3. The impact of the COVID-19 pandemic

According to preliminary results, the COVID-19 pandemic did not substantially influence hotel operations in the United States in January and February 2020, and critical performance metrics did not alter considerably. According to a careful statistical analysis, the demand and sales of OCC, ADR, RevPAR, and hotel rooms decreased as of March 1, 2020. In March 2020, the supply of hotel rooms remained constant, but the American hotel sector lost a significant number of rooms after April 1. In April 2020, the number of hotel rooms fell by around 12% compared to the previous year. OCC, ADR, RevPAR, demand, and income changed dramatically compared to hotel room sources. On April 11, the fall in demand and income for hotel rooms was 74%, 47%, 86%, and 77%, respectively. Since April 11, hotel performance indicators have improved, but as of May 31, 2020, they remained steady, but much lower than the previous year.

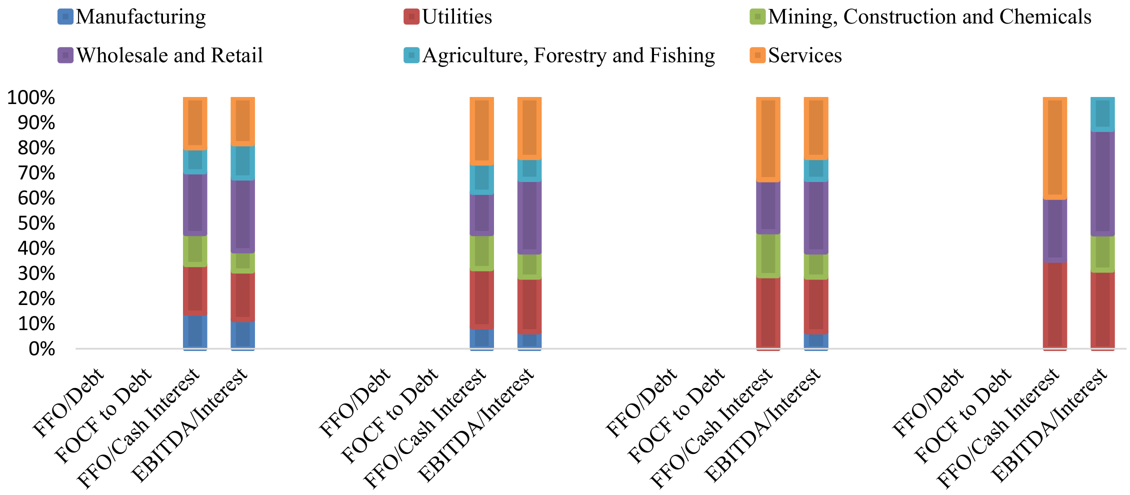

Fig. 1. Cash flow sufficiency with all model results.

Table 8
The average and difference score.

Hotel segments	Hotel performance measures					
	OCC	ADR	RevPAR	Supply	Demand	Revenue
Economy	−24.76	−12.48	−33.60	−0.59	−25.14	−33.90
	(11.29)	(5.94)	(13.84)	(1.40)	(11.77)	(14.29)
Midscale	−41.54	−15.41	−49.59	0.15	−41.24	−49.28
	(16.43)	(6.56)	(18.11)	(2.30)	(17.42)	(19.05)
Upper Midscale	−54.64	−20.77	−62.70	−0.71	−54.63	−62.57
	(20.19)	(8.13)	(21.30)	(3.14)	(21.36)	(22.43)
Upscale	−61.89	−25.20	−69.93	−3.90	−62.74	−70.35
	(20.79)	(9.91)	(21.48)	(6.35)	(22.43)	(23.15)
Upper Upscale	−74.79	−32.30	−80.35	−19.37	−77.88	−82.19
	(22.32)	(14.06)	(22.86)	(15.15)	(23.80)	(23.94)
Luxury	−78.88	−16.59	−80.76	−36.84	−83.85	−84.69
	(22.43)	(12.90)	(23.20)	(24.83)	(23.32)	(23.82)
Analysis of Variance						
F-test	1112.45[a]	54.87[a]	83.77[a]	141.31[a]	99.88[a]	80.43[a]

The letter a stands for one percent statistical significance. The standard deviation is shown in brackets. A number is used to denote the pace of change. All post-tests of mean differences are statistically significant at the one percent significance level, with a few outliers. Due to space limits, detailed analysis results are not presented, but are available on demand. Authors' calculation.

4.4. The impact of the COVID-19 pandemic on hotel sector

Preliminary data indicate a considerable reduction in key performance measures for hotels in the rate of change in the hotel segment's major daily performance parameters from January 1, 2020 to May 31, 2020, compared to the same period the previous year. The findings are consistent with general hotel sector trends in the United States. However, there are significant distinctions within the hospitality business. The COVID-19 pandemic appears to have had the most negligible economic impact on low- and middle-income earners, followed by middle- and high-income earners. COVID-19 will significantly impact high-end hotels more than budget, mid-range, and mid-to-high-end hotels. However, it will have a far more significant impact on luxury hotel categories and high-end luxury hotels. On April 11, occupancy rates in the economy, mid-range, mid-high-end, and high-end categories declined by 47%, 68%, and 80%, respectively. Hotel room occupancy declined by 90% and 92% in luxury hotels and standard hotels, respectively. Other hotel KPIs have shown similar lower trends in this sector, demonstrating that the larger the segment of the hotel chain, the greater the influence of COVID-19 on its KPIs. Preliminary data indicated the average variations in the performance metrics of significant hotels across hotel segments and we statistically quantified these discrepancies. These findings are presented in Table 8.

The variance of each group is equal according to the variance test. The Shapiro–Wilk test was performed to verify if the data are evenly distributed. Irrespective of whether certain variables are skewed to the left or right, one-way analysis of variance (ANOVA) produces accurate results unaffected by asymmetry. According to a single ANOVA test, the average difference of most KPIs supports the initial conclusion that the COVID-19 outbreak has severely affected premium hotels. Although all key performance metrics are less pronounced, budget and mid-sized hotels are also impacted. Budget hotel RevPAR declined by 33.6%.

Table 9
Mean and difference scores.

Hotel operational structure	Hotel performance measures					
	OCC	ADR	RevPAR	Supply	Demand	Revenue
Chain-managed	−57.22	−48.58	−75.38	−19.06	−64.50	−78.44
	(17.16)	(17.76)	(20.91)	(14.36)	(19.54)	(22.29)
Franchise	−52.06	−27.87	−63.68	−1.91	−52.61	−63.93
	(18.53)	(10.47)	(20.79)	(3.77)	(19.75)	(21.92)
Independent	−47.14	−35.96	−63.91	−7.96	−50.88	−66.07
	(14.77)	(14.17)	(21.19)	(6.04)	(18.22)	(21.98)
Analysis of Variance						
F-test	35.87[a]	58.11[a]	10.76[a]	78.98[a]	22.87[a]	23.48[a]

Notes: An asterisk (*) denotes a statistical significance of 1%. The standard deviations are given in brackets.

4.5. The impact of the COVID-19 pandemic on business operations

We also looked at how COVID-19's influence differs based on a hotel's operational structure (for example whether a hotel is part of a chain, franchise, or independent). These findings are shown in Fig. 1. The influence of COVID-19 on key performance metrics for hotels is dependent on the hotel's operational structure. However, the overall pattern of outcomes is consistent with the whole of the United States' hotel sector. Chain hotels are the most susceptible to outbreaks, followed by franchise and independent hotels. The COVID-19 pandemic appears to affect both franchised and independent hotels; however, there are notable distinctions. Independent chains, franchises, and hotel RevPARs, for example, plummeted by roughly 89%, 84%, and 86%, respectively, on April 11. Hotel chains are shown to be immune to OCC volatility, and their occupancy rate is higher than that of franchised and independent hotels. The ADR and RevPAR have been cut. On April 11, the loss in room supply at chain hotels was over 31%. This was much higher than the reduction in room supply at franchised and independent hotels, at around 6%. The same findings are summarized in Table 9.

A number is used to denote the pace of change. The actual post-test findings have been withheld due to space limits. From March 1 to May 31, 2020, the sales structure was statistically significant, increasing by 1% over the year. These findings correspond with a preliminary study's conclusion that the COVID-19 pandemic has a more significant impact on chain hotels than on franchised or independent hotels. However, they are not as severely affected as chain hotels in all critical parameters. For instance, RevPAR plummeted by 63.93% and 66.07%, respectively, while hotel chains fell 78.44%. COVID-19 has a similar effect on franchised and independent hotels but with distinct OCC, ADR, and product changes. The OCC of franchised hotels declined even further, while the supply of ADRs and independent hotels decreased even more.

4.6. The economic impact of the COVID-19 pandemic during 2020

According to preliminary studies, the COVID-19 pandemic is expected to impact the European hotel industry significantly. The economic effect on the hotel industry as a whole and various hotel services and operational structures is quantified in this section. The total hotel room income in March, April, and May 2020 is the subject of this study. The future budget restrictions for hotels were evaluated by comparing this income to the income in 2017, 2018, and 2019. These findings are summarized in Tables 10 and 11.

Based on group 1 data in Table 11, total hotel revenues for March, April, and May 2020 declined by 50.6%, 82.2%, and 73.3%, respectively. Hotel room sales climbed to 5.8% and 3.0% over the year from March 1, 2018 to May 31, 2019. If hotel room sales had remained constant between March 1 and May 31, 2020, total revenues would have been around $ 43.9 billion. COVID-19's economic impact was further studied in hotels with different operating settings. These findings are summarized in Table 11 by groups 2, 3, and 4. Revenues at hotel chains plummeted by 78.60% over a year, while revenues at franchise and independent hotels fell 64.8% and 66.7%, respectively. In other words, the COVID-19 pandemic affected hotel chains most adversely between March 1 and May 31, 2020. Table 11 also outlines COVID-19's economic impact on the hotel industry. Hotel room revenues in the luxury and luxury market categories declined by 84.5% and 63.4%, and 50.9% and 35% from March 1 to May 31, 2020. The losses in the performance indicators of the leading hotels in these hotel sectors, as stated in Section 4.2, are consistent with these results (inversely proportional). Budget, midrange, mid-high-end, high-end, and luxury hotel revenue losses are estimated to be USD 1.1 bn, USD 5 bn, USD 1.5 bn, USD 7.1 bn, and USD 2.6 bn respectively between 2020 and 2019. If subprime mortgages and equity injections become more readily accepted, sales are expected to drop by 50%–75%. Subprime mortgages will rebuild up to 50% (maximum) of Catalan businesses and up to 21% (minimum) of Austrian businesses, resulting in a 50% reduction in sales. A reduction of 50% to 75% is proposed. Most Austrian businesses (51.3% or 67%) require capital to expand their sales. The number of Spanish companies requesting participation could reach 70% in the worst-case sales scenario. A hybrid subordinated debt and equity approach is required if payments to the other EU Member States are expected to decrease by 50%–75%. Debt repayment and insurance coverage follow a similar pattern, with tax deferral compensating for a 25% drop in sales. Further reductions, on the other hand, will necessitate a combined response.

Table 10
Revenues and operational structure.

Date	April	Change	May	Change	June	Change	Total 3 months	Change
Panel 1 EU hotels (Total)								
2017	11,574,293,781		12,778,773,788		18,473,485,372		40,337,113,484	
2018	14,467,946,268	5.40%	13,799,136,738	6.80%	14,400,259,707	5.20%	42,667,342,713	5.80%
2019	14,752,968,978	2.00%	14,247,532,797	3.20%	14,945,276,259	3.80%	43,945,778,034	3.00%
2020	7,290,803,160	−50.6%	2,533,490,422	−82.2%	3,995,028,655	−73.3%	13,819,322,237	−68.6%
Panel 2 Chain managed								
2017	3,365,121,278		3,205,907,931		3,259,197,115		9,887,220,426	
2018	3,625,850,081	6.00%	3,423,750,212	6.80%	3,381,233,710	3.70%	10,430,834,003	5.50%
2019	3,622,897,107	−0.1%	3,446,920,733	0.70%	3,477,239,576	2.80%	10,547,057,416	1.10%
2020	1,471,584,134	−59.4%	319,479,298	−90.7%	470,796,675	−86.5%	2,261,860,107	−78.6%
Panel 3 Franchise								
2017	6,582,386,319		6,283,011,306		6,764,808,040		19,630,205,665	
2018	6,999,766,884	6.30%	6,808,913,402	8.40%	7,178,437,581	6.10%	20,987,117,867	6.90%
2019	7,256,891,171	3.70%	7,057,965,274	3.70%	7,550,735,402	5.20%	21,865,591,847	4.20%
2020	3,859,535,526	−46.8%	1,520,749,682	−78.5%	2,325,883,838	−69.2%	7,706,169,046	−64.8%
Panel 4 Independent								
2017	3,726,478,450		3,433,673,742		3,658,883,024		10,819,035,216	
2018	3,842,329,300	3.10%	3,566,473,132	3.90%	3,840,588,414	5.00%	11,249,390,846	4.00%
2019	3,897,877,148	1.40%	3,683,677,532	3.30%	3,988,974,723	3.90%	11,570,529,403	2.90%
2020	1,959,683,501	−49.7%	693,261,442	−81.2%	1,198,346,452	−70.0%	3,851,291,395	−66.7%

Table 11
Hotel room revenues: Hotel segments.

Date	April	Change	May	Change	June	Change	Total 3 months	Change
Panel 1 Economy-scale								
2017	743,483,543		832,646,348		924,578,341		2,646,962,327	
2018	920,471,412	3.50%	856,351,303	2.80%	939,837,150	1.70%	2,716,659,865	2.60%
2019	910,443,031	−1.1%	853,481,641	−0.3%	943,121,048	0.30%	2,707,045,720	−0.4%
2020	661,932,262	−27.3%	470,770,797	−44.8%	614,565,827	−34.8%	1,747,268,886	−35.5%
Panel 2 Midscale								
2017	627,209,477		588,066,480		655,282,991		1,870,558,948	
2018	652,539,496	4.00%	623,567,050	6.00%	679,582,352	3.70%	1,955,688,898	4.60%
2019	664,959,165	1.90%	630,982,498	1.20%	703,266,092	3.50%	1,999,207,755	2.20%
2020	418,700,562	−37.0%	229,482,308	−63.6%	334,396,700	−52.5%	982,579,570	−50.9%
Panel 3 Upscale								
2017	2,355,638,276		2,265,828,862		2,387,531,165		7,008,998,303	
2018	2,554,061,412	8.40%	2,485,957,652	9.70%	2,572,573,839	7.80%	7,612,592,903	8.60%
2019	2,648,921,834	3.70%	2,587,740,437	4.10%	2,719,293,094	5.70%	7,955,955,365	4.50%
2020	1,285,059,338	−51.5%	406,668,022	−84.3%	614,537,708	−77.4%	2,306,265,068	−71.0%

N.B.: The figures above indicate the percentage of total change from the previous date.

5. Conclusion

The global spread of COVID-19 has caused shockwaves around the world. A pandemic was extremely unlikely to occur in mid-January 2020. However, it had affected many firms across the EU by the end of the first quarter of 2020. Member States implemented stringent curfews and closures, making it difficult to do business. Tight supply chains, variable output, and restricted demand significantly hindered EU enterprises' revenues and cash flows. As a result, it is critical to investigate the implications of these factors. To analyze the success of various steps to strengthen a business's resilience, COVID-19 can be used for the company's credit profile. The subject of this article is the credit status of non-financial firms that have reported over 10,000 COVID-19 cases in 15 EU Member States. We used two broad metrics of the probability of default based on market and balance sheet data. We are also proposing a methodology for calculating an optimal cash flow ratio that accounts for loan repayment and coverage. We can see two sorts of stressful circumstances. The first is that the market value steadily drops by 15%, 30%, or 45%. The second is a 25%, 50%, or 75% loss in income.

According to our analysis, a lower market value raises the risk of default. The mining, construction, chemical, manufacturing, wholesale, and retail sectors suffered the worst damage from the market value shock. The findings support the accounting and cash flow sufficiency projections. In the worst-case scenario, the weighted average of these sectors might range from 24% to 57%. As sales decrease by 50%–70%, depreciation and coverage are projected to deteriorate rapidly. Three policy solutions were proposed to overcome these flaws. Tax deferral, subordinated debt, and capital infusion are examples of these tactics. Our findings demonstrate that deferring taxes is the best option when income is cut by 25%. However, if revenues fall by 50% to 75%, a mix of debt and equity will be necessary to keep a company afloat beyond COVID-19.

We believe that, if earnings experience a significant decline, the credit status of a business will suffer and the risk of default will rise. This puts the financial flexibility and viability of all European firms in jeopardy. Consequently, this will exacerbate the economy's initial burden, with growing medical bills and unemployment compounding the problem. The EU is caught in a catch-22 situation with COVID-19. By providing subprime mortgages and financial support, cash flow has been considerably curtailed due to tax delays and lost income. However, if left uncontrolled, there might be an unprecedented number of bankruptcies. COVID-19 will phase out, but its disastrous economic impacts will persist.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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