1. INSOLVENCY PROSPECTS FOR THE LUXEMBOURG NON-FINANCIAL CORPORATION SECTOR

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ABSTRACT

The Covid-19 pandemic has increased the importance of the topic of insolvencies of non-financial corporations (NFCs) and the potential implications for the real economy and the banking sector. This study examines the potential effects of increased insolvencies in the Luxembourg NFC sector and provides three main contributions. First, we investigate the macro-financial drivers of NFCs insolvencies in Luxembourg. Second, we directly assess the effect of the Covid-19 pandemic on different segments of the NFC sector. Third, we assess the link between NFC insolvencies and the Luxembourg banking sector. The results suggest that at the sectoral level, variables that measure sectoral activity are among the key drivers of NFC insolvencies in Luxembourg. At the macroeconomic level, GDP growth and interest rate are also found to be significant determinants of corporate insolvencies in Luxembourg. In relation to the impact of the Covid-19 pandemic on NFCs, we find that the decline in the number of insolvencies cannot be explained with pre-Covid data. These findings are consistent with the view that the supportive effects of the exceptional policy measures exceeded the adverse impact on NFC insolvencies resulting from the pandemic-related crisis. Finally, we show that NFC insolvencies are strong predictors of the number of banks' non-performing loans.

1. INTRODUCTION

This research investigates the drivers of non-financial corporation (NFC) bankruptcies in Luxembourg against the background of the Covid-19 pandemic. Understanding the key determinants of corporate bankruptcies is important from a financial stability perspective, particularly in view of a less accommodative monetary policy stance. Moreover, corporate bankruptcy has long been recognized as a macroeconomic issue, which could have adverse consequences for the broader economy. Indeed, an increase in insolvencies could potentially result in higher levels of banking stress if non-performing loans (NPL) were to increase. In addition, the increase in unemployment resulting from higher insolvencies can reduce income streams for affected households while forgone taxes and government support schemes for the unemployed can weaken sovereign balance sheets.

In view of the significant shock resulting from the Covid-19 pandemic and the subsequent effects of the lockdown measures on the non-financial corporate sector, this study looks at the potential drivers of NFC insolvencies in Luxembourg. The analysis proceeds in three steps. First, this study attempts to provide a better understanding of the main macroeconomic and financial drivers of NFC insolvencies in Luxembourg and it provides forecasts of the number of aggregate corporate insolvencies as well as by sector. Second, we investigate the effectiveness of the government support measures that were implemented during the pandemic in order to mitigate the adverse effects of the lockdown measures on the corporate sector. Finally, we look at the impact of NFC insolvencies on the Luxembourg banking sector. This is done via a model linking forecasted NFC insolvencies with the non-performing loan levels of Luxembourg banks.

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In terms of the drivers of insolvencies, we follow the literature and adopt sectoral and macroeconomic variables such as gross value added, production and employment growth, the ratio of employees' compensation to gross value added, consumption of fixed capital growth, GDP growth, the interest rate, the credit-to-GDP gap and inflation. However, to identify potential issues related to the reverse causality between these variables as drivers of insolvencies, we adopt the feasible generalized least squares (FGLS) approach and include the first lag of the dependent variable along with the first lag of the drivers as explanatory variables. This approach allows us to address the serial correlation across the variables. Our results suggest that, at the sectoral level, variables that measure sectoral activity such as growth in gross value added or production growth and the ratio of employees' compensation to gross value added are among the key drivers of NFC insolvencies in Luxembourg. Employee compensation provides insights on the cost structure of firms as it measures the degree to which employment costs translate into the production of a given output. With respect to macroeconomic variables, GDP growth and interest rate are also found to be significant determinants of corporate insolvencies in Luxembourg, while inflation is not. To further assess corporate insolvencies, we also construct the Z-score using firms' balance sheet data and the principal component analysis (PCA) to extract the appropriate weightings for the Z-score calculation. When included as an explanatory variable, we find that the Z-score is a statistically significant predictor of NFC insolvencies for firms operating in Luxembourg.

In addition, we show that forecasts which are based on the identified sectoral and macroeconomic drivers can replicate the evolution of insolvencies over time reasonably accurately. Specifically, our models forecast that 31 percent of all insolvencies occurred in the wholesale segment, followed by the construction, and accommodation and food sectors, which represented 17 and 15 percent of all insolvencies, respectively. To better assess the accuracy of our models, we apply a moving window to predict the number of insolvencies over a one-year horizon and compare the corresponding results with a random walk (RW) model.

In relation to the impact of the Covid-19 pandemic on NFC insolvencies, we compare the out-of-sample forecasts from our models with the actual number of insolvencies observed during the pandemic for the years 2020 and 2021. In comparison to the pre-pandemic period, the number of insolvencies declined by 18% in 2020 and 7% in 2021, respectively. These declines are likely attributable to the extraordinary public support measures. We find that these declines cannot be predicted using pre-crisis data. A more granular perspective suggests that those sectors most affected by the lockdown measures, such as accommodation and food services, are also the sectors with disproportionately low levels of insolvencies. These findings are consistent with the view that the supportive effects of the exceptional policy measures exceeded the adverse impact on insolvencies resulting from the pandemic-related crisis.

Finally, we look at how NFC insolvencies could impact the banking sector in Luxembourg. NFC insolvencies may have an adverse effect on banks' balance sheets through an increase in non-performing loans (NPLs). To conduct the analysis, we combine the number of insolvencies forecasted from our econometric models with the number of sectoral NPLs at the bank level. We show that NFC insolvencies are strong predictors of the amount of NPLs. Specifically, we find that an increase of one unit of insolvency in a sector is associated with a 0.84 percent increase (per number of firms in a given sector) in NPL.

The remainder of this study is organized as follows. Section 2 surveys the literature on the determinants of NFC insolvencies, their impact on the banking sector, as well as the role of the Covid-19 pandemic in driving corporate insolvencies. Section 3 introduces the data used in our analysis, and Section 4 describes the methodology. Section 5 discusses the results while Sections 6 and 7 focus on the Covid-19 pandemic and the role of the banking sector, respectively. Section 8 concludes.

2. LITERATURE REVIEW

Understanding the drivers of NFC insolvencies, particularly during times of stress, remains an important question for policy-makers as NFCs are major contributors to employment and growth. Altman (1968) introduced the first multivariate bankruptcy model using five financial indicators as predictors. These financial indicators include working capital, retained earnings, earnings before interest and tax (EBIT), the ratio of sales to total assets, and the ratio of market capitalization to total liabilities. With these financial ratios, he was then able to construct an indicator of bankruptcy called the Z-score. Moreover, Altman (2000) shows that the Z-score had an accuracy for forecasting insolvencies of 82% (94%) for the periods of 1969-1975 and 1976-1995, respectively. From the 1990s onwards, and following rapid technological innovations, more complex models emerged, including for example, neural networks for improving the logit prediction model (Fletcher and Goss (1993)). These models offer promising results by providing more accurate simulations of corporate bankruptcies compared to logit models and they offer additional options for assessing causal relationships in data (Ahn *et al.* (2000), Tseng and Hu (2010), Callejón *et al.* (2013)).

On the underlying macroeconomic factors of insolvency, Altman (1983) focuses on the determinants of corporate failure. He found that business failure is negatively affected by aggregate economic activity (measured by the gross national product i.e., GNP), money market conditions and investor expectations. Similarly, Wadhwani (1986) focuses on inflation and other macroeconomic variables for UK firms over the period 1964-1981. He shows that real wages, real prices, capital gearing, and the level of interest (both nominal and real) have statistically significant effects on NFC insolvency.

Following Wadhwani (1986), Davis (1987) studied the predictors of NFC insolvencies in the U.S., Canada and Germany. His results suggest that nominal interest rates, real input prices, real GNP and the debt to GNP ratios are significant determinants of corporate insolvency. Platt and Platt (1994) show that strong economic activity reduces the likelihood of corporate failure. According to Young (1995), real interest rate shocks, changes in the number of companies, aggregate demand, real input prices, and the nominal interest rate are the most important predictors of NFC insolvency.

Using data for Australia over the period 1974-1990, Everett and Watson (1998) find that the corporate failure rate is positively correlated with interest rates and the rate of unemployment. In a similar vein, Vlieghe (2001) analyses UK data for the period 1975-1999, and observes that the real interest rate is a significant long-run determinant of corporate bankruptcies. Virolainen (2004) argues in favor of the use of GDP, interest rates[121] and corporate sector indebtedness as explanatory variables for the default rate by emphasizing the significant and fairly robust relationship between this rate and key macroeconomic factors. Focusing on Sweden, Salman *et al.* (2011) analyze the influence of macroeconomic variables on the failure of small companies using quarterly data for the period 1986-2006. The authors find that the bankruptcy rate is negatively affected by the level of industrial activity, while the money supply, changes in GNP and the economic openness rate are positively related to the real wage.

121 The interest rate appears as the less powerful indicator. This result is justified by the sampling period being large, including two different inflation regimes.

Zikovic (2016) examines the macroeconomic elements of bankruptcies in Croatia for the period 2000-2011, concluding that interest rates, as well as industrial production, have a short-term effect on insolvencies while unemployment has a long-run effect. More recently, Anghel *et al.* (2020) investigates the response of the insolvency rate to various shocks in the economies of Romania and Spain through a structural autoregressive model using quarterly data for 2008-2016. It was found that future values of the insolvency rate are explained by past values of the interest rate in both countries as well as the retail trade index. In contrast, the influence of the investment rate on insolvency was not significant. Finally, Bellone *et al*. (2006) and Blanchard *et al.* (2012) also show that productivity has a negative and significant impact on firm exit probability.

At the sectoral level, Aleksanyan and Huiban (2016) focus on the economic and financial determinants of firm exit due to bankruptcy in the French food sector and compare them with those of other manufacturing sectors during the period 2001-2012. They demonstrate that bankruptcy risk patterns differ across food industry firms and other manufacturing firms, and that productivity and the cost of credit are important determinants of a firm's probability of going bankrupt. Mackevicius *et al.* (2018) present a cross-country analysis on the dynamics of Latvian and Lithuanian firm bankruptcy using data on more than 40,000 firms. Their work highlights that bankruptcies may materialize in larger waves during certain periods and they also outline the driving factors. In Latvia and Lithuania, the wholesale and retail repair of motor vehicles and motorcycles sector has the largest bankruptcy rate (30% on average), followed by construction firms (13% on average). They also find that private companies are more likely to initiate bankruptcy proceedings than public firms (81% versus 19%), respectively.

In the context of the Covid-19 crisis, work on the effect of government support measures has gained additional momentum. Gourinchas *et al*. (2021) and Diez *et al.* (2021) assess the role of government support in avoiding failures for small and medium sized enterprises (SMEs). Acharya and Steffen (2020) study corporate behavior by investigating the significant impact of credit risk on corporate cash holdings. Carletti *et al*. (2020) forecast the drop in profit and equity shortfall triggered by the lockdown by using a representative sample of Italian firms. They investigate the impact of the lockdown on firms' profits and estimate that a 3-month lockdown generates an aggregate yearly drop in profits of around 10% of GDP, and that 17% of firms become financially distressed.

Greenwald *et al.* (2020) show the central role of credit lines in the transmission of macroeconomic shocks and spillover effects. While credit lines increase total credit growth and have a positive impact on less constrained firms, the draw on credit by large firms leads to the tightening of lending conditions. Schivardi and Romano (2020) emphasize the high speed at which firms face liquidity shortages during the Covid-19 pandemic but argue that under the current schemes of liquidity provision, firms' liquidity remains manageable. Pagano *et al.* (2021) measure stock return response according to companies' resilience to social distancing and show that stocks of more pandemic resilient firms reflect lower exposure to disaster risk. Hanson *et al*. (2020) show that the combination of the high uncertainty with aggregate demand externalities highlights a "social value" in keeping firms alive and maintaining government support. Nevertheless, liquidity shortages may impair the long-term viability of firms.

While corporates had to adapt to be profitable during the pandemic, determining the persistence of the economic effects of Covid-19 remains important (Schivardi *et al*., 2020). In addition, the recovery of the economy to its pre-crisis level depends on its capacity to reabsorb the decline in output. The long-lasting effects of bankruptcy, also known as the spillover effect, can amplify financial contagion to other companies, which can then affect the entire economy through its adverse impact on employment, productivity and growth.

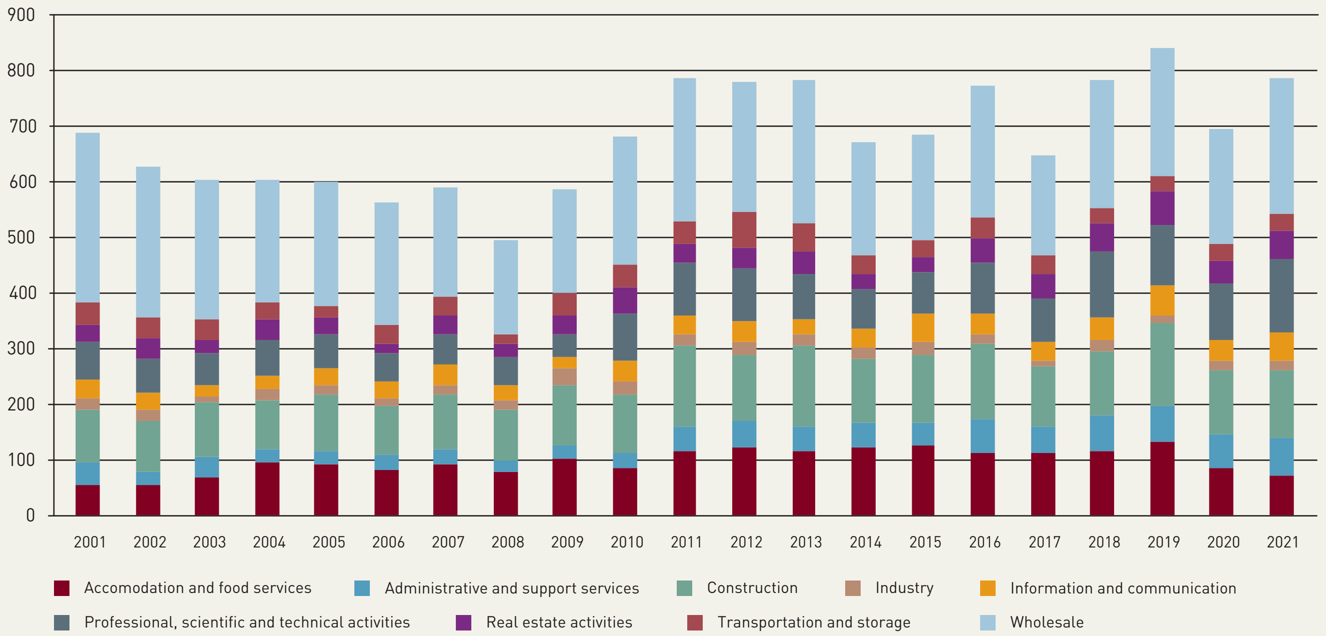
Indeed, the exceptional and unanticipated nature of the COVID-19 shock is unique for two main reasons, according to Hanson *et al*. (2020). First firms' long-run post-pandemic viability is at risk as the economic and financial recovery is linked to public health interventions in the context of an ongoing pandemic. Second, the extreme macroeconomic uncertainty due to the lack of knowledge surrounding the future path of the pandemic itself is also a unique challenge. The study highlighted different rationales behind governments' interventions. Keeping firms viable in the current environment of high macro-financial uncertainty with aggregate demand externalities has a social option value such that surviving firms exert positive spillovers on other surviving firms.

3. DATA

We first identify variables that are relevant for the solvency of firms in Luxembourg. Once these variables have been identified, we then forecast the total number of insolvencies in a given segment of the corporate sector. Hence, our main variable of interest is the total number of insolvent firms per year and sector which we obtain from STATEC.

Figure (1) displays the evolution of the number of insolvent firms in Luxembourg from 2001 until 2021. While the number of insolvent firms in Luxembourg was relatively stable until 2008, insolvencies increased following the global financial crisis and the subsequent European debt crisis. Insolvencies declined after 2013, with some fluctuation, before eventually increasing after 2017. Interestingly, the number of insolvent firms declined by 18% during the first year of the Covid-crisis. However, compared to 2020, corporate insolvencies increased by 13% in 2021. Nevertheless, they remain below the level observed in 2019.

Figure 1
Number of Insolvent Firms in Luxembourg from 2001 until 2021



Source: STATEC

To conduct the analysis, we first identify a baseline model, which we subsequently expand. The explanatory variables consist of macro variables and sector-specific variables based on the relevant literature. In the baseline model, the year-on-year (yoy) real GDP growth rate and the interest rate on NFC loans are the main macro variables that we consider. For the interest rate, we rely on a floating rate with an initial rate fixation up to one year[122]. We apply a weighted average of loans up to one million Euro and over one million Euro, respectively[123]. Using other NFC loan interest rates leads to very similar results. We take the GDP series from STATEC and the interest rate data from the BCL database.

At the sectoral level, we control for the total number of firms, the yoy growth rate of the gross value added and the ratio between the compensation of employees and the gross value added. While the first two variables are straightforward to interpret, the latter need further explanation. Compensation of employees can, to a large extent, be interpreted as fixed costs in a short-term perspective. Ideally, we would like to have these fixed costs as a share of total costs. However, as total costs are not available, we consider these fixed costs in relation to the gross value added. This variable not only allows us to identify the role of fixed costs, it also helps to estimate the effects of the government support measures, such as short-time work programs, during the Covid-crisis. The data for all three sectoral variables are taken from STATEC.

For the baseline model, we include nine sectors[124]. The number of firms is the limiting factor, so that the model covers the period from 2005 to 2021. Moreover, the number of firms is only available until 2019. For 2020 and 2021, we assume that the total number of firms per sector has not changed in comparison to 2019. This is a relatively mild assumption as the number of firms does not change significantly year on year. Indeed, the autocorrelation of the number of insolvencies per sector is 0.96.

In the non-baseline models, we analyze the effects of additional macro and sectoral variables. These macro variables include government surplus relative to GDP, yoy inflation[125], the NFC credit-to-GDP gap and two shadow short rates for the Euro area. The government surplus over GDP and the HICP inflation are directly taken from STATEC and the BCL, respectively. The BCL's narrow measure of the credit-to-GDP gap also used. The shadow short rate[126] is intended to capture the impact of the cost of financing. We focus on the shadow rates used by Wu and Xia (2017; 2019) and Krippner (2012), respectively. For additional sectoral variables, we use production growth, employment growth, and the share of micro and small firms, the share of large firms and the yoy growth rate of the consumption of fixed capital.

Finally, in terms of robustness checks, we consider balance sheet information obtained from the Bank for the Accounts of Companies Harmonized (BACH) dataset provided by the Banque de France. The BACH data contains firm information at the sector level and spans the period from 2011 to 2020 for Luxembourg. The Altman (1968) Z-score captures the most important balance sheet information that would help to forecast insolvencies. The relevant variables are working capital over total assets, retained earnings over total assets, earnings before interest and taxes (EBIT) over total assets, equity over total liabilities and sales over total assets. However, rather than applying the pre-specified weights, we use the first principal component of these five variables as an alternative weighting for the Z-score.

122 The corresponding data is taken from the BCL Website and can be accessed via https://www.bcl.lu/en/statistics/series_statistiques_luxembourg/03_Capital_markets/index.html
123 Specifically, we weight by the total number of loans.
124 The nine sectors are: Accommodation and food services, construction, information and communication, real estate activities, wholesale, administrative and support services, industry, professional scientific and technical activities, and transportation and storage.
125 Inflation levels are based on the Harmonised Index of Consumer Prices.
126 According to Krippner (2012), the shadow rate is defined as a metric for the stance of monetary policy in a zero lower bond environment.

Our approach has several advantages over the pre-specified Z-score weights. Most importantly, our weights are entirely data driven.[127] Moreover, the pre-specified weights by Altman (1968) are based on the US over the period from 1946 to 1965. In contrast, we analyze Luxembourg sectoral data over the period 2011 to 2020.

The loadings for the principal components are displayed in Table (1). Similar to Altman's (1968) Z-score that only has positive coefficients, the first principal component loads all five variables with a positive coefficient. Consequently, it can be interpreted as a variable that measures the overall health of a given sector in a given period.

Table 1:

Principal Component Weights for the Z-score calculation

VARIABLE	COMP1	COMP2	COMP3	COMP4	COMP5
EBIT/Tot. Assets	0.6727	-0.0224	0.0558	-0.1786	-0.7156
Equity/Tot. Liabilities	0.4379	-0.3403	-0.2	0.7793	0.2123
Working Capital/Tot. Assets	0.0083	0.6773	0.5682	0.4596	-0.0838
Sales/Tot. Assets	0.1367	-0.5185	0.7889	-0.1684	0.2483
Retained Earnings/Tot. Assets	0.5805	0.3951	-0.1077	-0.348	0.6117

Source: Authors' own calculations based on the BACH dataset.

4. METHODOLOGY

We first forecast the number of insolvent firms. In the analysis, we rely on two distinct models. This allows us to evaluate the robustness of our results. In its simplest form, we forecast the number of insolvencies $Insolv_{i,t}$ at time *t* and for sector *i* with sector-specific and macroeconomic variables $\boldsymbol{X}_{i,t-1}^{sector}$ and $\boldsymbol{X}_{t-1}^{macro}$, respectively, see Equation (1). We use the first lag of all variables. In the baseline model, growth in gross value added and the compensation of employees in relation to gross value added are the sector-specific variables and GDP growth and the interest rate on NFC loans are the macroeconomic variables, while the lag of the dependent variable and the lag of the number of firms are the remaining exogenous variables. Finally, the error term is given by $\varepsilon_{i,t}$.

$$Insolv_{i,t} = c + \beta_1 X_{i,t-1}^{sector} + \beta_2 X_{t-1}^{macro} + \beta_3 Insolv_{i,t-1} + \beta_4 No.Firms_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

The second model is given by Equation (2). It uses the relative number of insolvent firms as the dependent variable. Thus, the number of firms in a sector is excluded from the list of exogenous variables. To obtain a forecast in terms of absolute insolvencies $\frac{\widehat{Insolv_{i,t}}}{No.Firms_{i,t}}$ is multiplied by the corresponding number of firms.

$$\frac{Insolv_{i,t}}{No.Firms_{i,t}} = c + \beta_1 X_{i,t-1}^{sector} + \beta_2 X_{i,t-1}^{macro} + \beta_3 \frac{Insolv_{i,t-1}}{No.Firms_{i,t-1}} + \varepsilon_{i,t} \qquad (2)$$

127 In order to calculate the five financial ratios, we use data taken from the BACH dataset and the ratios provided within. For example, the first ratio, namely EBIT/Total assets is calculated by using ratio 35 defined as the ratio between EBIT, net turnover combined with total assets. Equity/total liabilities is determined by taking the inverse of ratio 12, which is liabilities to equity ratios. Working capital/total assets is also calculated using ratio 54, defined as operating working capital and net turnover, combined with total assets. Sales/total assets is proxied by ratio 41, defined as asset turnover ratio. Retained earnings/total assets is determined by using ratio 34, defined as the ratio between net operating profit and net turnover, combined with total assets. We then use the first principal component of these five ratios as a measure of the firm solvency captured by the Z-score. However, the Z-score with the original weights proposed by Altman (1968) leads to similar results.

To estimate models (1) and (2), we face two main issues. First, our time dimension (T) is greater than the cross-sectional dimension (N). Therefore, we cannot apply the widely used Arellano-Bond/Blundell-Bover (GMM) estimators. Second, we use the Pesaran test for cross-sectional dependence, finding that the residuals are correlated across segments of the corporate sector using the fixed effects models. To address these issues, we apply the feasible generalized least squares (GLS) approach to estimating our model following Greene (2018), Maddala and Lahiri (2006), Davidson and McKinnon (1993). This method is appropriate for panel-data linear models, in which there is the presence of AR(1) autocorrelation.

5. RESULTS

As outlined above, we base our findings on the two previous regressions. The estimates using equation 2 are shown in Table (2) while the estimates for equation 1 are shown in Table (3). Both models lead to similar results. Table (2) displays the results for all model specifications based on the share of insolvent firms as the endogenous variable and Table (3) presents the findings of the different specifications using the total number of firm insolvencies as the dependent variable.

In total, 26 different models are estimated, with different specifications for the explanatory variables as shown in the columns of Tables (2) and (3). The baseline regressions are given by column 1 in Table (2) and column 14 in Table (3), respectively. As expected, the lag of the dependent variable positively affects its current value; its coefficient is significant at one percent across all columns in both tables. The two sectoral variables, namely growth in gross value added and the ratio of compensation of employees to gross value added have the expected signs and are found to be statistically significant predictors of corporate insolvencies at the ten percent level in most specifications. While growth in gross value added is significant in 15 out of 22 cases, the ratio of compensation of employees in relation to gross value added is significant in 17 out of 26 specifications.

The macro variables also have the expected signs. GDP growth has a negative and significant impact at the one percent level, the positive coefficient of the interest rate is statistically significant at the ten percent level in 12 out of 20 specifications. Only specifications (11), (19), (20) and (24) display a negative coefficient for the interest rate, so that a positive coefficient can be found in 16 out of 20 specifications, meaning that higher funding costs make it more difficult for stressed firms to "survive".

Overall, the results of the baseline models also hold when other variables are added, see specifications (2) to (13) and (15) to (26) in Tables (2) and (3), respectively. In addition, the total number of firms is highly significant across most models that predict the number of insolvencies. The significance of the macroeconomic and sectoral variables is in line with the literature on NFC insolvencies.

Replacing the growth rate of gross value added with production growth as another variable that captures economic activity in a sector still leads to significant negative coefficients, see columns (2) and (15), respectively. Employment growth shows positive not significant coefficients in columns (3) and (16). This might be attributed to the labor stickiness (Granger 1989). Including shadow rates rather than the interest rate for NFC loans does not lead to significant parameters. However, in specification (5), the shadow rate is statistically significant at the five percent level.

In order to account for the types of firms, namely micro, small and large; specifications (6), (7), (19) and (20) of Tables (2) and (3), respectively, adjust the findings for the share of micro and small, and large firms across sectors. The coefficients associated with these variables enter insignificantly in all of the specifications.

The NFC credit-to-GDP gap and government surplus in relation to GDP have a positive, but non-statistically significant coefficient as shown for specifications (8), (12), (13), (21), (25) and (26), respectively. Nevertheless, the signs of the coefficients match expectations. An increase in credit as well as stronger government support through public spending makes insolvencies less likely. The effect of inflation is unclear from a theoretical point of view. While higher inflation levels increase the cost of input factors, it also reduces the accumulated real debt of firms. Furthermore, inflation and economic activity are positively correlated. Empirically, we observe that the latter of the two effects dominates, see columns (9) and (22). Finally, we find that the Z-score is statistically significant, in specification (11).

Table 2:

Regression coefficient estimates using Share of Insolvencies as the Dependent Variable

	1	2	3	4	5	6	7	8	9	10	11	12	13
Sector-Specific Variables													
Share of insolvent firms (lag)	0.8174*** (0.0000)	0.8046*** (0.0000)	0.8268*** (0.0000)	0.8185*** (0.0000)	0.8134*** (0.0000)	0.7452*** (0.0000)	0.7618*** (0.0000)	0.8158*** (0.0000)	0.8129*** (0.0000)	0.7906*** (0.0000)	0.8056*** (0.0000)	0.8240*** (0.0000)	0.8250*** (0.0000)
Gross value added growth (lag)	-0.0001*** (0.0062)			-0.0001*** (0.0064)	-0.0001*** (0.0091)	-0.0001*** (0.0002)	-0.0001*** (0.0000)	-0.0001*** (0.0072)	-0.0001*** (0.0052)	-0.0001** (0.0119)	-0.0001*** (0.0000)	-0.0001*** (0.0073)	-0.0001*** (0.0054)
Comp. of empl. to value added (lag)	0.0000*** (0.0014)	0.0001*** (0.0003)	0.0000*** (0.0014)	0.0000*** (0.0019)	0.0000*** (0.0011)	0.0001*** (0.0001)	0.0001*** (0.0004)	0.0000*** (0.0016)	0.0000*** (0.0013)	0.0001*** (0.0002)	0.0001*** (0.0000)	0.0000*** (0.0026)	0.0000*** (0.0031)
Production growth (lag)		-0.0001*** (0.0000)											
Employment growth (lag)			0 (0.7610)										
Share micro & small firms (lag)						0,0002 (0.1328)							
Share large firms (lag)							-0,0193 (0.6173)						
Consumption of fixed capital gr. (lag)										-0.0001*** (0.0000)			
Z-score principal component (lag)											-0.0007*** (0.0000)		
Macroeconomic Variables													
GDP growth (lag)	-0.0005*** (0.0002)	-0.0006*** (0.0000)	-0.0008*** (0.0000)	-0.0004*** (0.0025)	-0.0004*** (0.0006)	-0.0005*** (0.0012)	-0.0004*** (0.0025)	-0.0005*** (0.0007)	-0.0005*** (0.0006)	-0.0005*** (0.0000)	-0.0018*** (0.0000)	-0.0005*** (0.0003)	-0.0005*** (0.0014)
Interest Rate (lag)	0.0006** (0.0195)	0.0006*** (0.0055)	0.0006*** (0.0084)			0.0010*** (0.0057)	0.0012*** (0.0008)	0,0005 (0.1323)	0,0006 (0.1028)	0.0006*** (0.0096)	-0.0009*** (0.0000)	0.0005* (0.0508)	
Shadow Rate WU Xia (lag)				0,0001 (0.2499)									0 (0,729)
Shadow Rate Wu Krippner (lag)					0.0002** (0.0229)								
NFC Credit-to-GDP gap (lag)								0 (0.8589)					
Inflation (lag)									0,0001 (0.8254)				
Government surplus to GDP (lag)												0,0001 (0.8263)	0,0001 (0.6413)
Constant	0.0020*** (0.0071)	0.0025*** (0.0005)	0.0021** (0.0115)	0.0032*** (0.0000)	0.0035*** (0.0000)	-0,0142 (0.1826)	0.0019* (0.0992)	0.0021** (0.0166)	0.0020** (0.0147)	0.0028*** (0.0002)	0.0078*** (0.0000)	0.0020** (0.0100)	0.0030*** (0.0000)

*Note: The dependent variable is the share of insolvencies in terms of number of firms at the sectoral level. The explanatory variables include the first lag of the share of insolvencies, gross value added, production and employment growth, ratio of employees' compensation to value added, consumption of fixed capital growth, the Z-score, share of micro and small and large firms all at the sectoral level. At the macroeconomic level, the first lag of GDP growth, interest rate, shadow rate, credit to GDP gap and government surplus to GDP are used. ***, **, * indicate statistical significance at the 1, 5, and 10% levels, respectively. Standard errors are displayed in parentheses.*

Table.3:

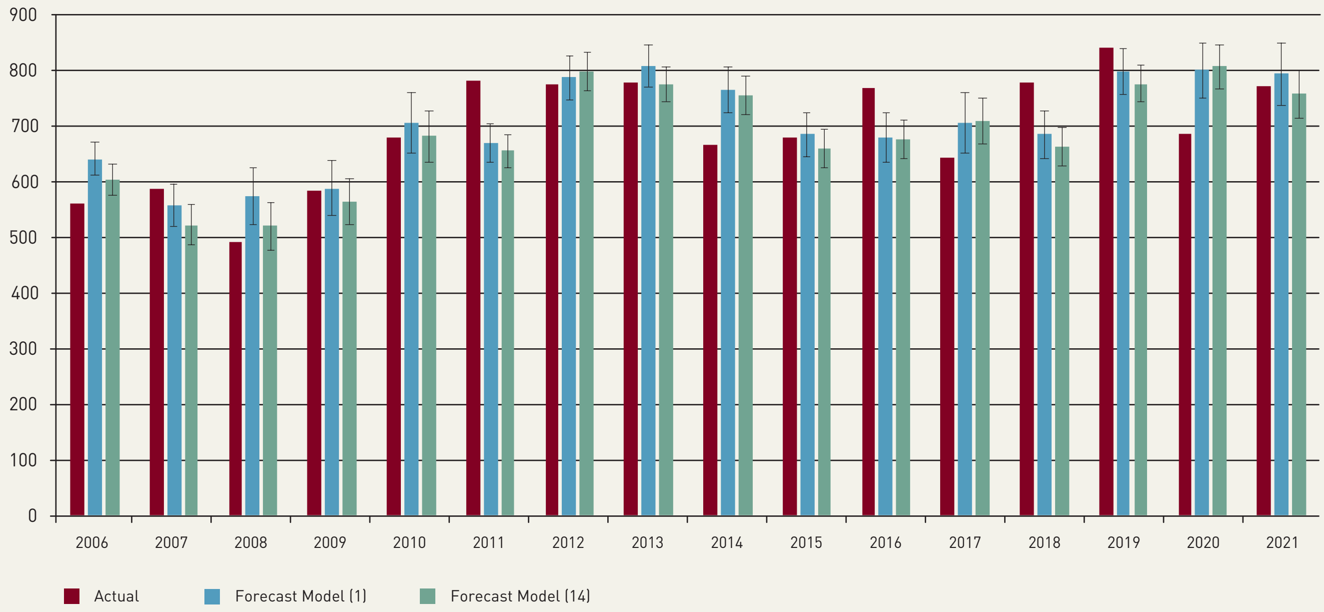
Regression coefficient estimates using No. of Insolvencies as the Dependent Variable

	14	15	16	17	18	19	20	21	22	23	24	25	26
Sector-Specific Variables													
No. of Insolvencies (lag)	0.9098*** (0.0000)	0.8920*** (0.0000)	0.9169*** (0.0000)	0.9152*** (0.0000)	0.9128*** (0.0000)	0.9258*** (0.0000)	0.9221*** (0.0000)	0.9097*** (0.0000)	0.9095*** (0.0000)	0.8996*** (0.0000)	0.9189*** (0.0000)	0.9105*** (0.0000)	0.9158*** (0.0000)
No. of firms (lag)	0.0015*** (0.0071)	0.0021*** (0.0003)	0.0013** (0.0217)	0.0014** (0.0188)	0.0015** (0.0155)	0,0011 (0.1046)	0,0011 (0.1399)	0.0016*** (0.0091)	0.0015*** (0.0071)	0.0017*** (0.0011)	0.0017*** (0.0077)	0.0015*** (0.0008)	0.0014** (0.0201)
Gross value added growth (lag)	-0,0227 (0.7740)			-0.1387* (0.0840)	-0,1313 (0.1058)	-0.1702** (0.0345)	-0.1656** (0.0462)	-0,0057 (0.9436)	-0,0186 (0.8146)	0,0335 (0.6516)	-0,0077 (0.9231)	-0,0174 (0.8265)	-0.1348* (0.0965)
Comp. of empl. to value added (lag)	0,0309 (0.1534)	0,0329 (0.1049)	0,0308 (0.1546)	0.0448** (0.0451)	0.0450** (0.0488)	0.0568* (0.0792)	0.0588* (0.0781)	0,0333 (0.1280)	0,0311 (0.1525)	0,0303 (0.1606)	-0,0003 (0.9910)	0,0306 (0.1558)	0.0449** (0.0447)
Production growth (lag)		-0.2036*** (0.0001)											
Employment growth (lag)			0,078 (0.6688)										
Share micro & small firms (lag)						0,2659 (0.2212)							
Share large firms (lag)							-798.679 (0.2983)						
Consumption of fixed capital gr. (lag)										-0.2874*** (0.0001)			
Z-score principal component (lag)											-0,4447 (0.3562)		
Macroeconomic Variables													
GDP growth (lag)	-1.8308*** (0.0000)	-1.6907*** (0.0000)	-1.9443*** (0.0000)	-1.5830*** (0.0000)	-1.6547*** (0.0000)	-2.7000*** (0.0000)	-2.6819*** (0.0000)	-1.7867*** (0.0000)	-1.7943*** (0.0000)	-1.8962*** (0.0000)	-3.8072*** (0.0000)	-1.9635*** (0.0000)	-1.6458*** -0,0001
Interest Rate (lag)	0.9847* (0.0999)	1.1974** (0.0232)	1.0293* (0.0818)			-14.512 (0.2796)	-12.885 (0.3346)	0,7183 (0.3821)	0,4124 (0.6256)	0.9114* (0.0735)	-15.932 (0.2177)	0,9423 (0.1187)	
Shadow Rate WU Xia (lag)				0,2443 (0.3954)									0,0189 (0.9445)
Shadow Rate Wu Krippner (lag)					0,4081 (0.1283)								
NFC Credit-to-GDP gap (lag)								0,0752 (0.6606)					
Inflation (lag)									0,7438 (0.3468)				
Government surplus to GDP (lag)												0,4447 (0.3562)	0,237 (0.7653)
Constant	22.838 (0.1994)	20.565 (0.1713)	23.378 (0.2031)	4.3963*** (0.0075)	4.7825*** (0.0051)	-174.404 (0.3853)	8.3470** (0.0385)	26.046 (0.2054)	20.892 (0.2483)	3.9206** (0.0128)	11.1574*** (0.0002)	21.535 (0.2218)	4.2004** (0.0178)

*Note: The dependent variable is the number of insolvencies at the sectoral level. The explanatory variables include the first lag of the share of insolvencies, gross value added, production and employment growth, ratio of employees' compensation to value added, consumption of fixed capital growth, the Z-score, share of micro and small and large firms all at the sectoral level. At the macroeconomic level, the first lag of GDP growth, interest rate, shadow rate, credit to GDP gap and government surplus to GDP are used. ***, **, * Indicate statistical significance at the 1, 5, and 10% levels, respectively. Standard errors are displayed in parentheses.*

Figure (2) shows the absolute number of forecasted insolvencies according to the baseline model and compares the out-of-sample forecast insolvencies with actual observed insolvencies. The model is unable to accurately forecast the number of insolvencies during the pandemic. In fact, 2020 marks the year with the highest overestimation of the predicted values from the actual levels. This is not surprising since the forecasts are based on pre-covid data. The fact that we forecast a high number of insolvencies in 2020 could signal that the government support measures play an important role and lead to less insolvent firms.

Figure 2
Predicted Insolvencies over time



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations. Note: Error bars indicate two standard errors around the mean.

Figure (3) evaluates the cross-sectional dimension as it compares the forecasts of Model (1) and (14) with the actual results by looking at the average across the 2006 to 2020 sample. We observe that our forecasts match the actual number of insolvencies across sectors fairly well. For all three cases, the majority of NFC insolvencies occurs in the wholesale sector. Based on the actual data and Model specification (14), 31% of all insolvencies occur in this sector. This is not surprising as this is the largest sector in terms of the number of firms. The construction, and the accommodation and food sectors have the second and third highest share of insolvencies with 17% and 15%, respectively, as shown in Figure 3.

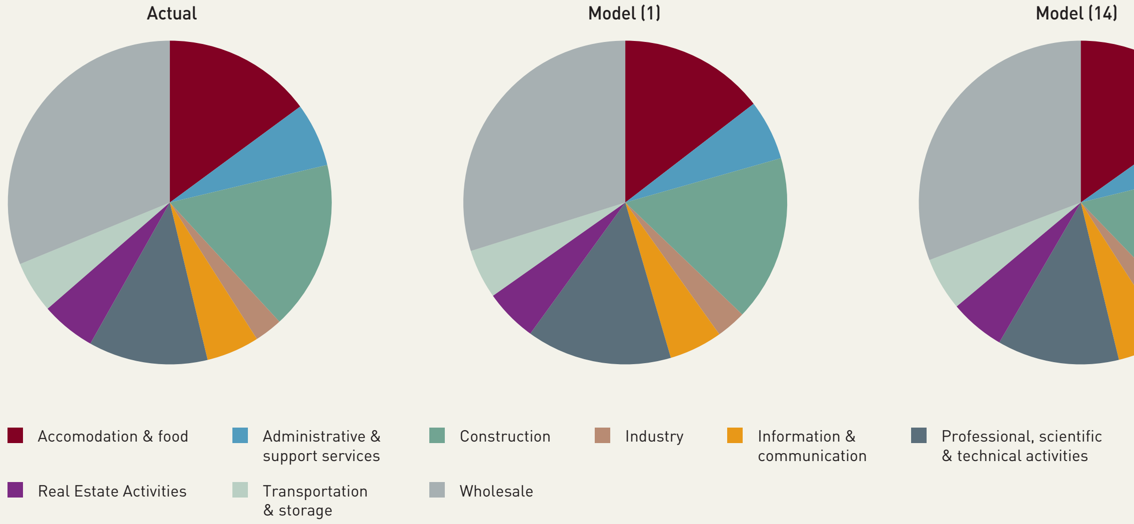
Similarly, Figure (4) shows the likelihood for a firm to become insolvent across the different sectors. The difference between Figure (4) and Figure (3) is that we now take the size of the sector into account. Again, we observe that both models forecast the share of insolvent firms quite accurately. Overall, accommodation and food services activities, followed by transportation and storage are the sectors with the highest likelihood for firms to become insolvent. These sectors are followed by construction and wholesale activities. However, firms in the real estate, as well as professional, scientific and communication sectors have the highest likelihood to remain viable.

To further assess the accuracy of our forecasting models, we evaluate them using moving window out of sample forecasts that we compare with a random walk (RW). For the moving window, we choose 2013 as the starting year for the forecast. We start by relying on the 2005 to 2012 period for forecasting insolvencies in 2013. We then add a period to forecast the dependent variable in the next year.

The benchmark that we compare our results to is a random walk. Specifically, for Model specifications (1) to (13), we assume that the share of insolvent firms has not changed in comparison to the previous

Figure 3

Year-on-Year Forecasts of Insolvencies across Sectors, Average over the period from 2006 to 2021



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations.

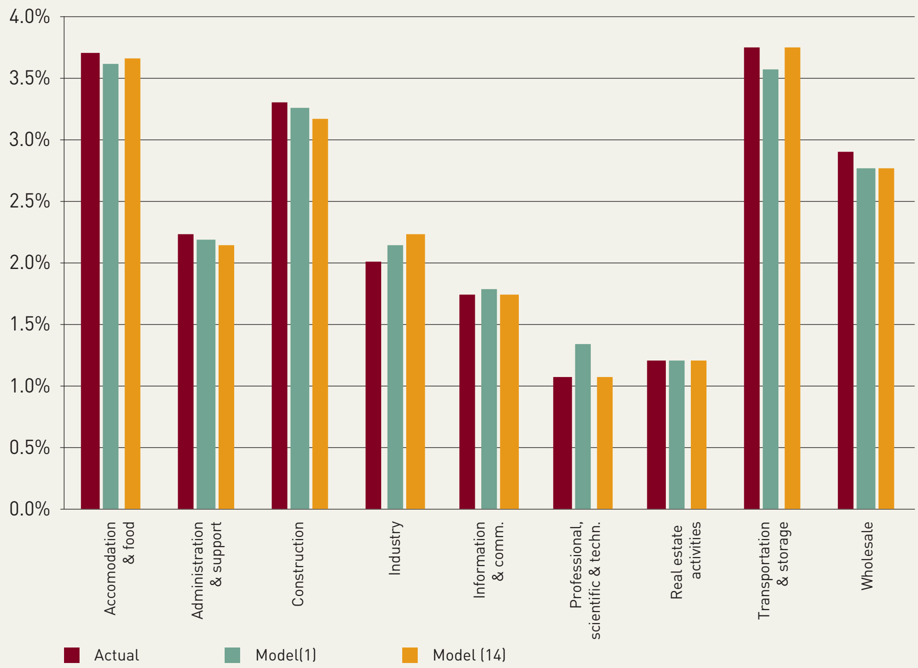
period[128]. For specifications (14) to (26), we assume that the number of insolvent firms has not changed in comparison to the previous year. We then assess our results with the root mean squared forecast error (RMSFE). We find that all models result in lower RMSFE in comparison to the random walk. According to the *t*-tests that evaluate whether the squared forecast error differs between the model and the random walk, this finding is statistically significant at the 5 percent level in 22 out of 24 models.

6. THE COVID CRISIS

During the pandemic, the relationship between economic fundamentals and NFC insolvencies may have been affected by three separate factors. First, the pandemic-related lockdown measures likely led to a decrease in sales.

Figure 4

Forecasted Share of Insolvent Firms across Sectors, Average over the period from 2006 to 2021

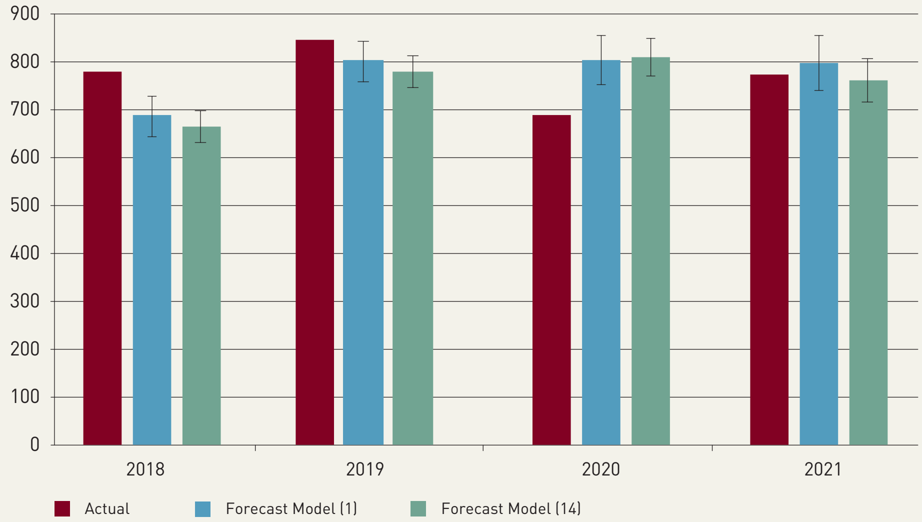


Source: The data is taken from STATEC, the forecasts are authors' own calculations

128 Other forms of random walks such as RWs with drift do not result in significantly lower RMSFE.

Figure 5

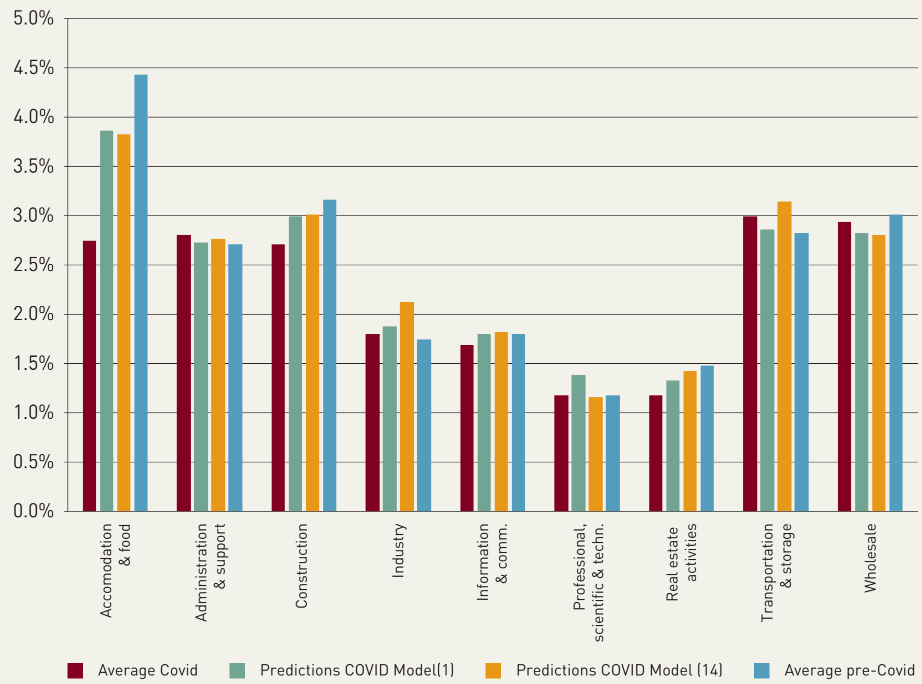
Actual and Predicted Insolvencies in the lead up to and during the COVID-Crisis



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations. Note: Error bars indicate the area within two standard errors around the mean

Figure 6

Share of Insolvent Firms across Sectors during the pandemic



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations. The pre-COVID period covers the years (2018 and 2019), while 2020 and 2021 are the Covid periods.

Second, the level of economic uncertainty increased significantly during the crisis[129], which could result in households experiencing less consumption choices and/or accumulating precautionary savings. Third, support schemes such as short-time work, moratoria or state-guaranteed loans were implemented. At the euro area level, the ECB launched its Pandemic Asset Purchase Programme. While the COVID-related shock may have led to an increase in the total number of insolvent firms, the exceptional support measures helped to lower insolvencies in the short to medium-term. Therefore, we analyze the impact of all these factors on the solvency of NFCs.

Figure (5) shows the evolution of insolvencies in the two years prior to the pandemic (2018, 2019) as well as the two years during the pandemic (2020, 2021). It compares these insolvencies with the forecasts from model specifications (1) and (14). Interestingly, the number of insolvent NFCs declined in 2020 by 18% relative to 2019. Although it increased by 13% in 2021 year-on-year, with the number of insolvencies remaining below pre-crisis levels.

While model specifications (1) and (14) underestimate the number of corporate insolvencies in 2018 and 2019, they overestimate the number of insolvencies during the first year of the pandemic. The relative difference between forecasted and observed data is particularly pronounced in 2020 reaching 17% for specification (1) and 18% for specification (14). The fact that the total number of insolvencies during the

129 For instance, the VSTOXX increased from 17.15 in end-January 2020 to 84.80 on 18 March 2020.

crisis is low in comparison to pre-crisis levels and model forecasts suggest that the pandemic-related policy support measures were effective in reducing the number of NFC insolvencies.

Figure (6) compares insolvencies during the pre-COVID periods 2018 and 2019 with the COVID periods 2020 and 2021, and the corresponding predictions from model specifications (1) and (14). However, in this case the focus is on the cross-sectional dimension. As shown in Figure (6), the actual number of insolvencies are relatively low across all sectors during the pandemic, namely 2020 and 2021. Using forecasts from specifications (1) and (14) during the pre-COVID periods (2018 and 2019), it is found that the accommodation and food sector has the most pronounced decline in insolvencies compared to the COVID periods (2020 and 2021). This is not surprising since this sector was one of the most affected by the lockdown measures and uncertainty. We therefore conclude that the public policy support measures were well targeted.

7. RISKS OF NON-PERFORMING LOANS FOR BANKS

In this section, we investigate the relationship between corporate insolvencies and banks' non-performing loans (NPLs). Specifically, we link forecasted insolvencies based on sectoral and macroeconomic variables obtained from model specifications (1) and (14) to sectoral non-performing loans at the bank level. This allows us to identify how banks may be exposed to NFC insolvencies due to their lending to those sectors that exhibit a higher number of insolvencies.

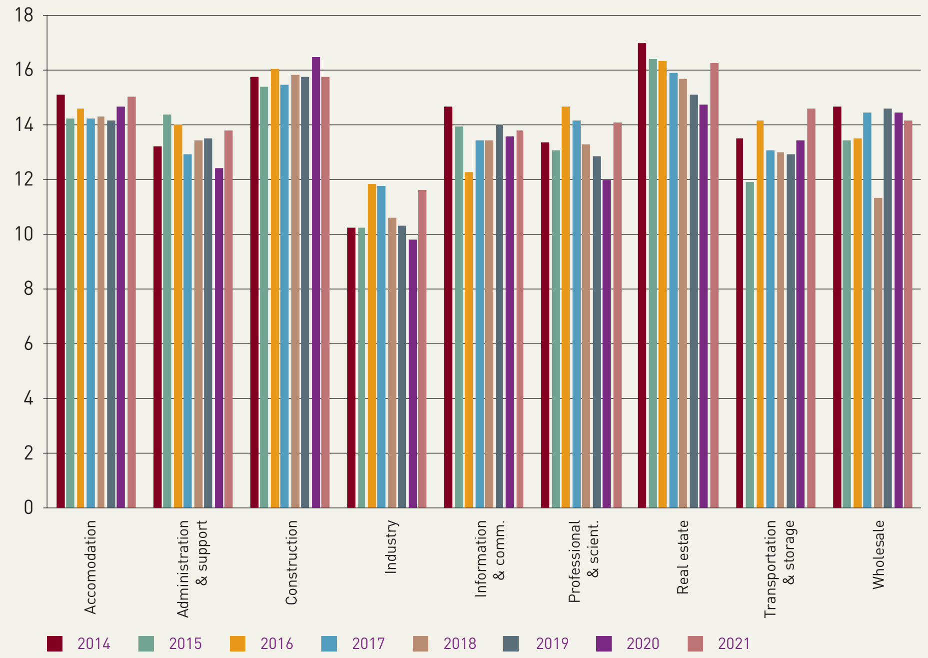
We estimate the following linear model, where *j*, *i*, and *t*, respectively refer to bank, economic sector and period.

$$\log\,(NPLs)_{j,i,t} = \mathrm{C} + \beta\, \widehat{Insolvencies}_{i,t} + \gamma_{j,t} + \varepsilon_t \qquad (3)$$

NPLs is the logarithm of the amounts of non-performing loans in sector *i* of bank *j* in period *t*. $\widehat{Insolvencies}_{i,t}$ is the forecasted sectoral NFC insolvencies in sector *i* during period *t*. $\gamma_{j,t}$, are bank-period fixed effects. The data used in this section cover the period 2014-2021. In Figure (7), the real estate and construction and accommodation sectors show higher levels of NPLs in logarithm during the period 2014-2021.

Table (4) presents the results of the regression using bank and year fixed effects. As shown in Columns (1) and (2), the coefficient associated with forecasted insolvencies from the two baseline models enters positively and significantly at the one percent level. This suggests that insolvencies increase the number of banks' non-performing

Figure 7
Number of NPLS in logarithm across sectors and over time



Source: Authors' own calculation based on BCL data loans. Based on the coefficients in Column (1), an increase of one unit of insolvency in a sector is associated, on average, with a 0.84 percent increase per number of firms in that sector for a given bank.

Table 4:

The dependent variable is the logarithm of the amounts of non-performing loans

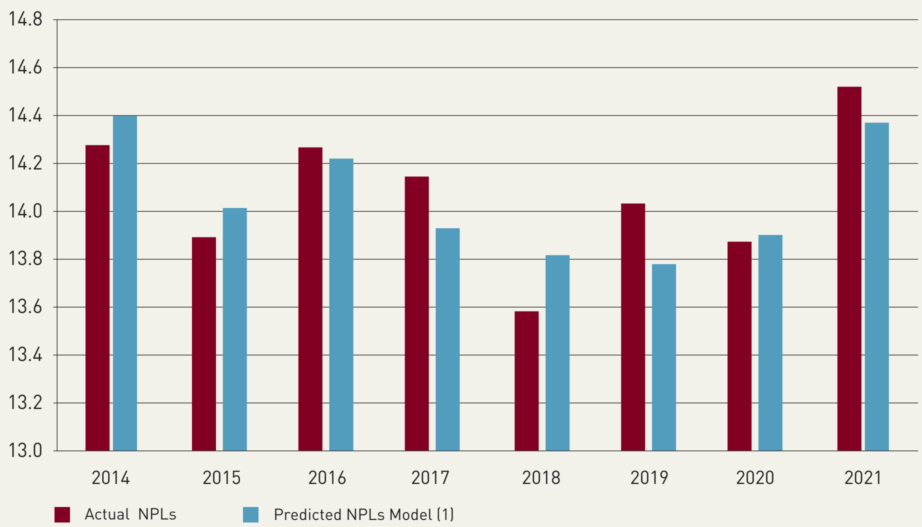
	(1)	(2)
Predicted insolvencies	0.0084*** (0.006) [0.0026]	0.0089*** (0.003) [0.0025]
Constant	13.693*** 0 [0.681]	13.653*** 0 [0.666]
Bank-fixed effects	Yes	Yes
Year Fixed effects	Yes	Yes
F-stat (p-value)	11.54*** (0.000)	13.653*** (0.000)

Source: Authors' own calculation based on BCL and STATEC data. Column (1) is based on predicted insolvencies obtained from the baseline model of equation (1) of Table (2), whereas Column (2) uses predicted insolvencies from the baseline model of equation (14) of Table (3). P-values and robust standard errors are in parentheses and brackets, respectively.

Accordingly, these two specifications can be used to estimate sectoral NPLs. As in Section 5, we use the year 2017 as the starting period for our forecasts. To assess the forecasting quality of the model, we then compare the root mean squared forecast error (RMSFE) with the random walk model RMSFE of the same years. Overall, one can see that NFC insolvencies are relatively good predictors of banks' non-performing loans in Luxembourg compared to a random walk model. Moreover, Figure (8) displays the actual annual amounts of NPLs versus those obtained using Column (1) of Table (4).

Figure 8

Predicted amounts of NPLs in logarithm based on Column (1) and Actual NPLs



Source: Authors' own calculation based on BCL and STATEC data.

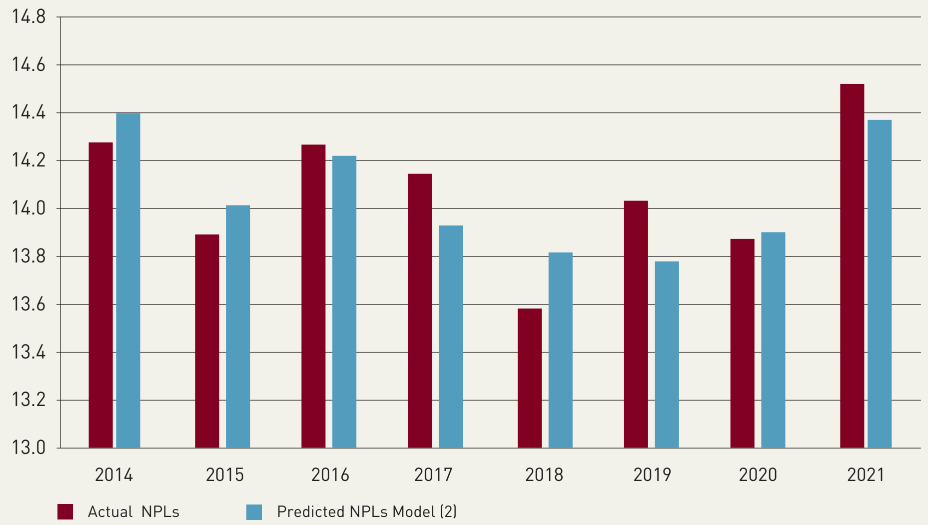
Similarly, Column (2) of Table (4) is also used to obtain predicted amounts of NPLs, which are then compared to actual amounts of NPLs as displayed in Figure (9). Finally, at the sectoral level, the forecasted NPLs obtained from the model are close to the observed data.

8. CONCLUSION

The recent and ongoing COVID-19 pandemic has generated a focus on NFCs and their role for the real economy, particularly due to the exceptional nature of the shock that affected both the supply and demand sides of the economy and the impact of the pandemic-related containment measures on the corporate sector. Moreover, significant uncertainty over developments in the NFC sector remains as the recovery still faces additional challenges including potentially higher interest rates as well as possible economic turmoil resulting from the high level of geopolitical risks.

Figure 9

Predicted amounts of NPLs in logarithm based on Column (2) and Actual NPLs in logarithm



Source: Authors' own calculation based on BCL and STATEC data

In this study, we assessed the effects of the pandemic and the related support measures on NFC insolvencies in Luxembourg and provided three contributions. First, we attempted to provide a better understanding of the main drivers of NFC bankruptcies in Luxembourg, and to forecast the number of insolvencies based on these drivers. Second, we investigated the role of the extraordinary pandemic-related support policies in mitigating corporate insolvencies in the Luxembourg NFC sector during the COVID-19 related crisis. Third, this study assesses the impact of NFC insolvencies on banks' non-performing loan levels.

The results suggest that growth in sectoral value added, employees' compensation in relation to value added, GDP growth and the Z-score are strong drivers of NFC insolvencies in Luxembourg. However, inflation, firm size and the credit gap are not found to be significant determinants of NFC insolvencies in Luxembourg. Additionally, our econometric models, based on these variables, are able to provide reasonable out-of-sample forecasts of the number of insolvencies when compared to actual observed data.

With respect to the COVID-19 related crisis, we compared the forecasts from our models with actual data, building on pre-Covid data and including the period following the initial Covid-related shock (during 2020-2021). The results suggest that the number of insolvencies during the COVID-19 pandemic is below the forecasted amount, possibly confirming the mitigating role of the Covid-related public support measures for NFCs in Luxembourg. In relation to the impact of NFC insolvencies on the banking sector, the model results suggest that an increase of one unit of insolvency in a sector is associated with a 0.84% increase in the amount banks' NPLs per number of firms in that sector.

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