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Credit risk modelling within the euro area in the COVID-19 period: Evidence from an ICAS framework

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Abstract

This paper develops a logistic regression model in an in-house credit assessment system (ICAS) framework for predicting corporate defaults in the Greek economy. We consider the impact of the COVID-19 pandemic and the associated government financial support schemes, aiming to protect against financial vulnerabilities, on the probability of default of non-financial firms, as well as the relevant sectoral and firm-size effects. In developing the ICAS framework, we address methodological issues such as the predictive performance of statistical versus machine learning approaches and the imbalanced dataset problem, indicating ways to evaluate such models with strong predictive power. Our findings suggest that the effect of the financial support measures dominates the pandemic shocks, thus substantially reducing the probability of firms' default, while the size- and industry-based models show that firms in the micro and services sectors benefited the most. Furthermore, using a random forest model, our findings highlight the trade-off between the transparency of traditional statistical models and the predictive value of machine learning models.

KEYWORDS

COVID-19, credit risk, default, government financial support measures, in-house credit assessment system, machine learning

1 | INTRODUCTION

Several central banks within the Eurosystem have developed internal models for assessing the creditworthiness of non-financial corporations. These in-house credit assessment system (ICAS)[1] models produce internal assessment scores, informing the Eurosystem's collateral framework, which is central to monetary policy implementation (Schirmer, 2014; Deutsche Bundesbank, 2015; Antunes et al., 2016; Levy et al., 2020; Auria et al., 2021) and protects against financial vulnerabilities. Moreover, the ICAS can inform or affect financial stability policies (e.g., Bindseil et al., 2017; Cahn et al., 2018; Calza et al., 2021; Liikanen, 2017). Currently seven Eurosystem national central banks (NCBs) have developed fully-fledged ICASs, and several others are pursuing a similar task at various stages of development. The Bank of Greece started developing its ICAS framework for credit risk assessment in 2020, while the COVID-19 global health crisis was unfolding, with direct implications for financial risks, deteriorating credit quality across certain sectors, credit ratings, risk-weighted assets, credit limits, etc.

During the COVID-19 pandemic period, the Eurosystem's collateral rules were temporarily broadened by introducing temporary collateral easing measures in

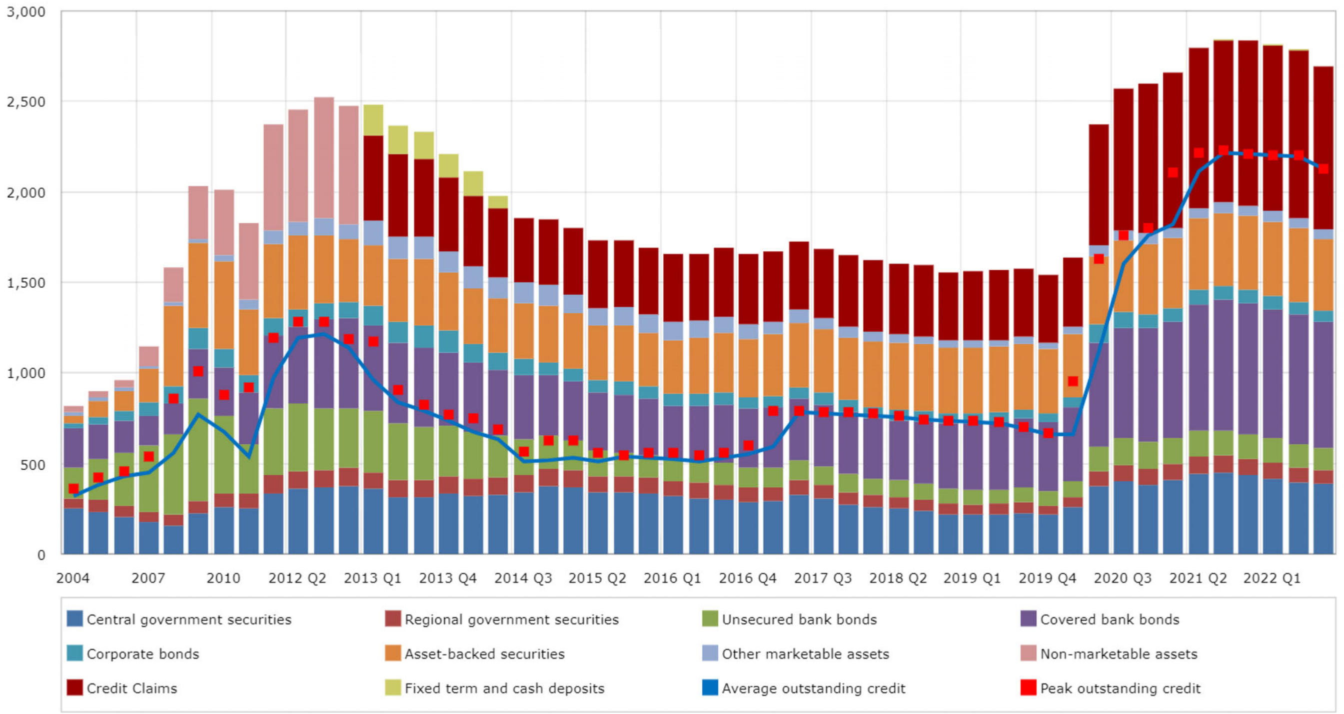

FIGURE 1 Use of collateral and outstanding credit across the Eurosystem. *Source*: ECB website, https://www.ecb.europa.eu/paym/coll/charts/html/index.en.html. [Colour figure can be viewed at wileyonlinelibrary.com]

April 2020, which were further extended from December 2020 to June 2022. Among others, the measures included an increase in the types of credit claims that were eligible as collateral (including loans benefiting from the guarantee schemes adopted in euro area Member States in response to the pandemic), for which companies' creditworthiness is assessed by ICASs. Hence, the development of default forecasting models with high predictive power is of foremost importance for facilitating the availability of eligible collateral for Eurosystem counterparties in order to participate in liquidity-providing operations, such as the TLTRO III series, and to increase their bank funding against loans to corporates and households.

Indeed, according to the ECB (Figure 1), since the start of the pandemic, mobilized collateral increased considerably, from €1.636 trillion in the first quarter of 2020 to €2.838 trillion at the end of 2021 due to the collateral easing measures. Credit claims (including additional credit claims (ACCs)) accounted for the largest share of the increase during the review period (around 44%), mostly due to the expansion of the ACC frameworks. This increase was also driven by the expansion of ACC frameworks (€162 billion). Overall, mobilized credit claims more than doubled in amount, from €384.9 billion in the first quarter of 2020 to €914.9 billion at the end of 2021. In addition, the revised framework has allowed NCBs to accept loans to small and medium-sized enterprises or self-employed individuals as collateral if COVID-19-related government and other public sector guarantee schemes cover them.

This paper examines the insights that can be provided by an ICAS modelling approach, such as that of the Bank of Greece, for policy analysis and assessment. We also consider the optimal design of ICAS models. A key policy issue that we address in the context of ICAS models is whether and how the government financial support measures in response to the COVID-19 pandemic affected the default probability of non-financial firms and how these effects may vary across different industries or firms of different sizes. By addressing issues that emerge in developing our ICAS model, our study can inform the current process of ICAS development in other Euro area NCBs, including the structure of the models, the predictive power of explanatory variables (which may vary across countries), and the differences between statistical models (e.g., logistic regression models) and machine learning models in terms of predictive efficacy.

This paper makes several contributions to the literature on NCBs' ICASs. First, a recent strand of this literature highlights the need to adjust credit risk models in response to the COVID-19 crisis (Caporale et al., 2022; Gavilá Alcalá et al., 2020; Levy et al., 2020; Zhai et al., 2024). Responding to these calls, we investigate the economic impact of COVID-19-related government

TABLE 1 COVID-19 measures in Greece.

	EUR million				% GDP			
	2020	2021	2022	2023	2020	2021	2022	2023
1 = 1a + 1b COVID-19 measures	−14,735	−15,791	−3784	308	−8.9%	−8.6%	−1.9%	0.1%
1a with effect on the budget balance	−11,898	−15,129	−4018	−18	−7.2%	−8.3%	−2.0%	0.0%
1b deficit-debt adjustment	−2837	−662	234	327	−1.7%	−0.4%	0.1%	0.2%
2 Guarantees	−2548	−220	0	0	−1.5%	−0.1%	0.0%	0.0%
3 Guarantees with leverage	−8241	−450	0	0	−5.0%	−0.2%	0.0%	0.0%
4 = 1 + 2 COVID-19 measures + guarantees	−17,283	−16,011	−3784	308	−10.5%	−8.8%	−1.9%	0.1%
5 = 1 + 3 COVID-19 measures + guarantees with leverage	−22,976	−16,241	−3784	308	−13.9%	−8.9%	−1.9%	0.1%

Source: Annual budget, various years.

supportive measures on Greek firms' default probabilities. As part of its emergency response to the pandemic, the Greek government adopted a series of temporal measures worth more than 10 billion euros (please see Table 1), aiming to provide financial support and bankruptcy protection to firms affected by the COVID-19 crisis. Recently, several research papers and policy analyses have emerged considering the implications of the COVID-19 pandemic for corporate default probabilities and credit risk, considering the impact of governments' financial support measures (Altman, 2020; Serra-Garcia & Szech, 2023). However, to our knowledge, the present study is the first to address this impact in the context of an ICAS framework. Specifically, we employ an ICAS framework using the AnaCredit (Analytical Credit Datasets) database of the European Central Bank (ECB).

Second, whereas the extant literature discusses the sectoral effects of the pandemic and government's responses (Canton et al., 2021; Das et al., 2021; Klein & Smith, 2021; Turkson et al., 2021), there is limited research on the default probabilities across sectors, particularly in the context of ICAS frameworks. All industries have suffered from the consequences of the pandemic and most benefited from government support measures. These government measures were designed to effectively mitigate the impact of COVID-19 on firms that were more threatened by the pandemic. We characterize the impact of the pandemic-cum-policy measures on corporate default risk across sectors. In addition, we explore the heterogeneous economic impacts of COVID-19 support measures between micro-sized firms and small, medium, and large (SML) firms.

Third, we provide insights into the impact of class imbalance on classification performance metrics. Traditional logit models employed by the majority of NCBs in their ICASs use imbalanced datasets (Auria et al., 2021). We show that it is essential to also consider balanced accuracy, in contrast to normal accuracy, because it is considered a better measure of classifier performance when classes are highly imbalanced.

Fourth, we explore the trade-off between the transparency of traditional models and the predictive performance of machine learning models and show that combining the features of a pure logistic approach with a suitable machine learning technique for classification problems, such as random forest (Breiman, 2001), can improve credit risk estimation.

Finally, we contribute to the open research question of whether specialization in the models might improve their predictive ability. Specifically, we consider whether multiple industry- or size-based equations yield better results than a single equation using the entire sample (Fernandes, 2005). Whereas a general model exploits the advantage of a large sample, specialized models do not force the same variables and parameters on all firms across industries and firm sizes.

Since no data on the exact amount of financial support per firm are available, we use a dummy variable equal to 1 if the firm received financial support due to COVID-19, and 0 otherwise. This variable practically captures the net effect of two opposing forces affecting the probability of default; the COVID-19 pandemic shock and the macroeconomic policy measures in response to it. Our findings suggest that the government's extraordinary COVID-19 financial support measures overcome pandemic shocks, thus substantially reducing the probability of default of Greek firms. Moreover, our empirical findings reveal that micro firms and firms in the services sector have benefited the most from government support measures. Indeed, the services sector was one of the sectors of the Greek economy most severely affected by the pandemic, and hence was the sector that received the most funding. This argument is enhanced by the fact that the COVID-19 crisis led to spillovers into multiple sectors of the global economy. Ozili and Arun (2023) explore the global spillover effect of the coronavirus outbreak in multiple sectors and highlight its severe impact on the services sector due to the spillover to the travel, hospitality and entertainment industries. In addition, compared to SML firms, micro firms were hit harder by the pandemic, and the Greek government provided targeted support to these firms to reduce their probability of default. The fact that the positive impact of supportive measures is stronger for firms that were most affected by the COVID-19 pandemic indicates that government interventions have been effective in helping the most vulnerable firms to respond to the coronavirus crisis and cope with instability in the global economy.

Our analysis also has direct policy implications for financial stability-oriented policies. During times of increased stress, such as the COVID-19 period, default risk increases for firms and their counterparts, that is, the banking system. A reliable gauge of default risk is an integral part of the process of designing financial policies and supervisory measures to prevent a wave of insolvencies that would threaten financial stability. Being the in-house assessment of credit risk, the ICAS steadily gains ground as the main tool for credit risk assessment that informs monetary policy and macroprudential/financial stability policy decisions in the Eurosystem (e.g., see Auria et al., 2021). The ICAS can serve as complement and/or an alternative to the assessments of credit rating agencies and internal ratings-based systems. Indeed, the Financial Stability Board (2014) suggested reducing reliance on credit rating agency ratings. The US Securities and Exchange Commission (2020) has expressed concern about whether credit rating agency assessment and downgrades can contribute to negative procyclicality in certain circumstances with implications for financial stability.

The remainder of this study is organized as follows. Section 2 reviews the policy background and related literature and outlines the existing national credit assessment systems within the Eurosystem. Section 3 describes our data set and Section 4 discusses our models and methodology. Section 5 reports and discusses our empirical results. Finally, Section 6 concludes.

2 | LITERATURE REVIEW

2.1 | Background

In the Eurosystem, both ICASs—operated by almost half of the NCBs—and internal ratings-based (IRB) systems—developed by several external financial institutions—play crucial roles in the smooth funding of the banking sector. These tools are used to evaluate the credit quality of companies that have loans from commercial banks, in order for their bank loans to be accepted as collateral in monetary policy credit operations (Grandia et al., 2019). Although the primary task of ICAS credit ratings is the assessment of collateral, central banks can also use them for financial stability analysis. In particular, the ICAS can inform or directly affect financial stability policies. For example, Calza et al. (2021) show that ICAS credit ratings play a significant role in ensuring financial stability of the banking system by weaning central banks off their reliance on external credit ratings. Cahn et al. (2018) study how credit ratings issued by the Banque de France influence the stability of the banking system, including firms' access to bank credit and corporate policies. Liikanen (2017) and Bindseil et al. (2017) highlight the comparative advantage of central banks to stem liquidity crises, thus strengthening the soundness of the international banking system.

2.2 | Credit rating literature

Since the early work of Altman (1968), in which a discriminant analysis is implemented for the problem of predicting corporate bankruptcy, the academic literature has devoted considerable effort to studying the assessment of credit risk for both banks and non-financial firms. In general, the related literature can be distinguished into five major categories: (1) theoretical studies on credit scoring; (2) research papers that apply statistical models to predict credit ratings, such as regression, multivariate discriminant analysis, probit, and logit models; (3) studies focusing on the predictive accuracy of credit assessment criteria; (4) extensive research on credit rating evaluation procedures, focusing on different kinds of crises including the COVID-19 pandemic; and (5) machine learning literature modelling the probability of default.

The extensive theoretical literature develops several models for various credit management techniques. First, Altman (1968) uses simple error rates for credit model validation, whereas Savery (1976) and Galitz (1983) implement scoring systems using information related to the borrower. Greer (1967, 1968) presents the optimal cutoff score for determining the maximum allowable probability of default, and Eisenbeis (1977, 1978) identifies seven types of statistical problems in credit scoring models that apply discriminant analysis. Since these studies were published, several other approaches have been used for credit risk measurement, including dynamic models (Bierman & Hausman, 1970), artificial neural networks (Gallant, 1988), decision trees (Sparks, 1979), and integral programming (Showers & Chakrin, 1981).

The second strand of literature discusses statistical models applied in order to predict credit ratings, such as regression (Ang & Patel, 1975), multivariate discriminant analysis (Belkaoui, 1980; Bhandari et al., 1979; McAdams, 1980; Poon et al., 1999), probit (Pagratis & Stringa, 2009), and logit models (Kamstra et al., 2001). Among other studies, McQuown (1997), Sobehart et al. (2000), and Korablev and Dwyer (2007) verified the applicability of the KMV model in the global financial markets. In this context, several studies attempt to understand both qualitatively and quantitatively the impact of financial and macroeconomic frictions on corporate default rates. Analyses that estimate different credit risk models with macroeconomic variables for the corporate sector include, among others, Wilson (1997a, 1997b), Virolainen (2004), and Khan et al. (2020). Jiang et al. (2020) show that deregulation decreases corporate risk by focusing on the period from 1975 to 1994. In a similar spirit, Pozo and Rojas (2023) study the connection between bank competition and credit risk. Cathcart et al. (2020) examine how financial leverage impacts default risk depending on the size of the firms. Moreover, some recent papers examine the importance of relationships in the default risk definition such as relationship banking (Yildirim, 2020) and personal connections (Khatami et al., 2016).

Another group of research papers assess the criteria used to evaluate credit risk. Sobehart et al. (2000), Blochwitz et al. (2000), and Carey and Hrycay (2001) introduce accuracy and entropy ratios to measure the accuracy of six different scoring and rating models, based on balance sheet and market information from public companies. Dollery and Wallis (2001) evaluate the future loan performance of the customer, and Grunert et al. (2005) find that qualitative factors significantly increase the performance of internal credit rating systems.

Another strand of literature examines credit market distortions caused by different kinds of shocks and crises, including the COVID-19 pandemic. Several studies examine the role of financial crises in credit shocks (Acharya et al., 2018; Amiti & Weinstein, 2018; Dungey et al., 2022). More recently, several studies investigate the impact of the COVID-19 pandemic on debt markets; see, for instance, Liu et al. (2021), Augustin et al. (2022) and Beck and Keil (2020), as well as Hawley and Wang (2021) who concentrate on the COVID-19 pandemic's impacts on pricing and liquidity. Furthermore, Goodman et al. (2021) and Wang and Ku (2021) examine the widely observed increases in households' credit scores and the drivers behind this increase since the onset of the pandemic, and Telg et al. (2023) investigate the effects of COVID-19 on corporate rating migrations and defaults, with a particular focus on a risk management modelling perspective. Interestingly, Brzoza-Brzezina et al. (2022) study the trade-off between economic stabilization and the prevention of the epidemic, and the implications for monetary policy.

Finally, use of the machine learning approach is gaining momentum in credit risk modelling. Several studies on credit scoring show that machine learning models outperform statistical models, on average, due to their ability to capture nonlinear relationships between predictor variables and defaults. For example, Brown and Mues (2012) and Barboza et al. (2017) show that machine learning methodologies related to random forest and gradient-boosting classifiers are better at assessing default risk than traditional models, because they do not impose linearity assumptions on the structure of the data. Toward this direction, Amini et al. (2021)) highlight the superiority of random forest models over traditional models in predicting capital structure dynamics. Stevenson et al. (2021) develop a deep learning model that incorporates textual information to predict the credit risk of small businesses. Similarly, Tsai et al. (2016) find that textual information derived from newspapers and corporate filings includes crucial information on firms' credit risk assessments. Dumitrescu et al. (2022) combine traditional logistic regression with decision trees, with the aim of improving credit scoring efficacy. As established in several studies (Baesens et al., 2003; West, 2000), artificial neural networks are another popular machine learning methodology that has been frequently implemented in corporate credit rating prediction and performs better than statistical models. Similarly, Wang and Ku (2021) suggest an innovative approach in which a plethora of artificial neural networks are created in parallel to take into account historical financial data. Nevertheless, machine learning models lack transparency—for which reason why they are referred to as black boxes—and statistical models are preferred by financial analysts due to their ease of implementation and interpretation. The present study uses logistic regression to benefit from the dual advantages of simplicity and readability while conducting a comparative analysis of its predictive performance with random forest, a popular machine learning technique for classification and regression problems.

2.3 | National ICASs

According to the ECB, all countries in the Eurosystem are obliged to create their own ICASs, which are considered the lever for the collateral process to implement monetary policy. More specifically, ICASs have a two-step procedure. First, a statistical model estimates the probability of default for each firm. This predicted probability is then mapped to the corresponding rating grade, calibrated with respect to the Eurosystem requirements. Second, an expert assesses the creditworthiness of the firm and determines the final rating. Expert evaluation is a vital part of the ICAS, because it takes into account up-to-date data that the econometric model has not included. Based on this new information, the analyst will either confirm or amend (downgrade or upgrade) the statistical output. The present study focuses only on the statistical part of national ICASs.

In the development of the statistical model, there are two main approaches. First, the most popular among ICASs is the logistic regression approach, which is followed by the majority of NCBs, including the Banco de Espaňa, the Banque de France, the Banca d'Italia, the Banka Slovenije, and the Banco de Portugal. Second is the common proprietary approach (CoCAS), adopted by the Oesterreichische bank (OeNB) and the Deutsche Bundesbank (BBk). The CoCAS modelling approach is based on a novel consensus methodology that estimates a consensus rating for each financial statement based on various credit sources from external credit assessment institutions and IRB assessments, in addition to using default information. There are two steps in the process. First, CoCAS employs a mixed-effects model to purify the consensus rating produced from errors propagated when combining the various rating data. Next, in the second step, a linear regression model explains the consensus rating produced from the previous step using financial variables derived from the balance sheet information.

2.4 | The Greek ICAS

The Greek ICAS provides an overview of the creditworthiness assessment of Greek non-financial corporations that report under generally accepted accounting principles (GAAP). The present paper builds on the methodology used for the development of the Greek statistical ICAS model to study the net impact of the COVID-19 pandemic on the probability of default of Greek firms. The magnitude of financial support provided by the Greek government to firms due to the pandemic was around 14% of GDP, which demonstrates the importance of our analysis. This application is more than a proof of concept because it is an ideal case to study the impact of credit frictions during a pandemic crisis. Given the widely accepted use of logistic regression in credit rating models, we discuss to what extent its predictive performance could be improved using a balanced dataset and machine learning methodologies.

The development of the Greek ICAS followed common rules and procedures, which are defined by the Eurosystem Credit Assessment Framework, ensuring high credit quality standards for all eligible Greek assets. Its rating process is based on a two-stage design that calculates the firm's probability of default at 1 year using financial and accounting information and then identifies the corresponding credit rating class.

Using information on firm-level credit characteristics from the AnaCredit database for the period 2019–2021 and accounting data from the Bank of Greece's Central Balance Sheet Office (CBSO) for the period 2018–2020, a forward variable selection is adopted to determine the best subset among a large pool of explanatory variables to include in the prediction model.

Our case study of Greece is of particular interest because Greece is probably the country worst-affected by the financial crisis, with the percentage of non-performing loans (NPLs) in total loans close to 35% in March 2020, arguably the highest in Europe. The outbreak of the COVID-19 pandemic occurred while Greece was still recovering from the prolonged economic crisis. As a result of significant government measures to help firms cope with the COVID-19 pandemic, the ratio of NPLs to total loans has decreased substantially, but it remains the highest in Europe (see Figure 2). According to European Banking Authority data, in December 2022 the proportion of NPLs in Greece was approximately 2.8% higher than the European average.

2.5 | Greece's response to the COVID-19 crisis

Greece was faced with the spread of SARS-CoV-2 in early 2020. More precisely, on February 26, a person who had just returned from Italy was reported as Greece's first confirmed case of COVID-19 infection. In response to the pandemic threat, several containment measures were implemented, including long periods of lockdowns and restrictions on numerous activities. These measures were considered among the strictest imposed by any European country. In view of the dramatic impact of containment measures on economic activity, the Greek government adopted a series of protective measures providing financial support to firms affected by the COVID-19 crisis, including postponing the payment of loan instalments, VAT, taxes, state fees, and social security contributions, and increasing liquidity. According to Alogoskoufis (2021), the Greek economy suffered a deep recession in 2020 that, in combination with the cost of protective government measures to mitigate it, resulted in a further increase in the already high debt-to-GDP ratio of Greece. The study discusses three alternative methods to address the sharp increase in public debt after the end of the

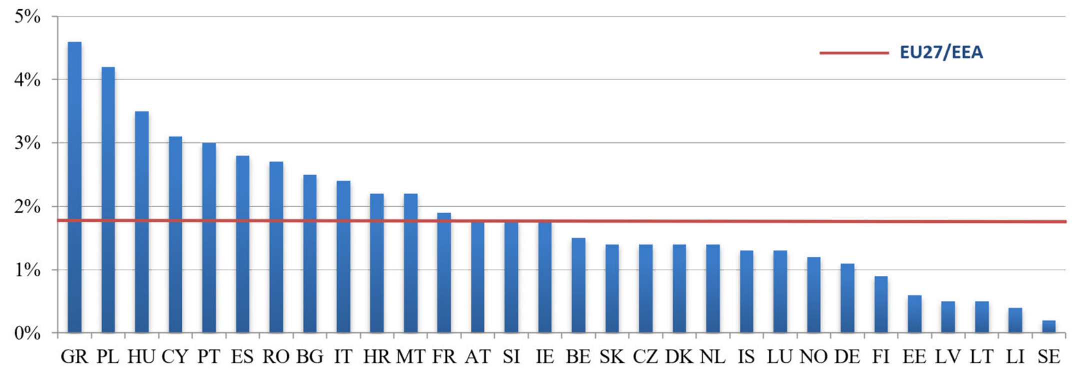

FIGURE 2 Percentage of non-performing loans in relation to total loans (countries of EU27/EEA – December 2022). *Source*: European Banking Authority (risk dashboard, data as of Q4 2022), https://www.eba.europa.eu/risk-analysis-and-data/risk-dashboard. [Colour figure can be viewed at wileyonlinelibrary.com]

pandemic, austerity measures, debt restructuring, and a 'gradual adjustment' policy.

Comunale and Nguyen (2023) create a new measure to capture MacroEconomic Uncertainty (MEU) in the euro area. MEU appears to be the largest spike at the time of the COVID-19 outbreak, where public debt increased in response to this uncertainty shock, and mostly emerging European countries, including Greece, were negatively affected by declining their economic activity.

Because the tourism sector was severely affected by the pandemic, the Greek government announced that more measures will be adopted for firms in this sector. Indeed, the latest OECD Economic Survey of Greece (2023) underlines the effectiveness of government interventions to support the revival and stability of the tourism sector by strengthening the economic and employment growth performance. Despite the financial risks associated with the COVID-19 pandemic, default rates in 2020 were substantially lower than in the pre-COVID-19 period. This finding is in agreement with the evidence provided by Eckert and Mikosch (2022) regarding firm defaults in Switzerland during the pandemic. Our study reports that the observed decrease in average default rates across most industries during the COVID-19 crisis can be attributed to the extraordinary government measures adopted to support the Greek economy, as shown in Table 1.

3 | DATA AND SAMPLE CONSTRUCTION

3.1 | Sample

We obtain data from two different basic sources. First, we use the AnaCredit database of the ECB to construct the variables that capture default risk. AnaCredit comprises the collection of default and credit risk data at borrower-by-borrower and loan-by-loan levels. We note that because central banks preserve data confidentiality, the AnaCredit data used in this study are not publicly available, highlighting the uniqueness of our dataset.

Second, we obtain firm-level data from the unique database of the Bank of Greece known as the CBSO. In particular, the CBSO collects the annual accounts of Greek legal entities, which contain data from the balance sheet and income statements. Greek legislation requires four kinds of firm to provide data to the CBSO, namely Société anonyme (S.A.) companies, limited liability companies, private capital companies, and limited partnerships. CBSO data constitute the main data source for calculating financial ratios, which are used as inputs for predictive models.

Our sample size is constrained by the AnaCredit data, which are available from 2019 to 2021. Because financial data are used to predict the probability of default in the period (fiscal year) after their release date, we utilize CBSO data from 2018 to 2020. As a result, our sample includes 15,815 firm-year observations for 7405 unique firms.

3.2 | Default

Before describing how we construct the annual default variable, it is necessary to define some variables that are used in the calculations. First, we define the variable *Exposure*, which is determined at the level of the debtor, reporting agent (lender), and reporting period (1 month) by the following calculation:

$$\begin{aligned}\text{Exposure} = {} & \text{Outstanding nominal amount} \\ & + \text{Off balance sheet amount} \\ & + \text{Accrued interest} - \text{Transferred amount}\end{aligned}$$

Second, we employ a monthly default indicator, which is a binary variable at the level of debtor, reporting agent (lender), and reporting period (1 month). The monthly default indicator is equal to 1 if at least one of the following three conditions is met: first, the debtor firm is under judicial administration, receivership or similar measures, or bankruptcy/insolvency proceedings; second, the default status of the debtor firm implies default, that is, 'default because unlikely to pay' or 'default because more than 90/180 days past due' or 'default because both unlikely to pay and more than 90/180 days past due'; third, the default status of the instrument implies default, that is, 'default because unlikely to pay' or 'default because more than 90/180 days past due' or 'default because both unlikely to pay and more than 90/180 days past due'.

Considering the default indicators that have been determined using data on the borrower-lender level and the exposure on the borrower's level for a given reporting period, we calculate the current materiality at the borrower level and then apply a materiality threshold for three consecutive months (persistency condition). More precisely, if materiality is greater than 2.5% (materiality condition) within a 3-month period, we assign positive materiality to the entity and we call last-month materiality the fractional materiality. Otherwise, the materiality is set to 0. The monthly default dummy is set equal to 1 if the borrower is in the status of legal proceedings or if the fractional materiality is greater than 2.5%, and 0 otherwise. Finally, as in Aussenegg et al. (2011), the one-year default dummy (Default) equals 1 if the borrower-lender-month default indicator described above is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise.

3.3 | Variables engineering

Our empirical analysis employs a set of 58 financial, auditing, and macroeconomic/institutional variables as inputs in the predictive models, comprising our initial pool of variables. As is typical in the relevant literature, most explanatory variables are financial variables. We obtain these from the CBSO database, and we ensure that we have a sufficient number of variables in each of the following vital categories: activity (5 variables); asset structure (2 variables); capital structure (13 variables); capital structure, liquidity (2 variables); cash flow (1 variable); expense structure (5 variables); liquidity (7 variables); profitability (9 variables); revenue (2 variables); revenue, liquidity (1 variable); and size (6 variables). The initial list of 53 financial variables is summarized in Table 2.

TABLE 2 Categories of financial ratios.

Categories	Ratios
Activity	Trade payables/Current liabilities; Inventories × 360/Cost of sales; (Earnings − Dividends)/(Financial debt + Equity); Profit before tax/EBIT; Revenue/(Equity + Long term liabilities)
Asset structure	Current assets/Total assets; Tangible assets/Total assets
Capital structure	Equity/Total assets; Total liabilities/Total assets; Current liabilities/Total assets; Financial debt/(Financial debt + Equity); Equity/Non-current assets; Current financial liabilities/Total liabilities; Financial debt/Total assets; Net financial debt/Total assets; Retained earnings/ Total assets; Current liabilities/Total liabilities; Total liabilities/Tangible assets; Financial debt/EBITDA; Long term liabilities/Total assets
Capital structure, Liquidity	Current financial liabilities/Total assets; (Current liabilities − Cash)/Total assets
Cash flow	Operating cash flow/(Total liabilities − Provisions)
Expense structure	Interest expense/Total assets; Interest paid/ Financial debt; EBITDA/Interest expense; (Interest earned − Interest expense)/Revenue; Wages/Total assets
Liquidity	Cash/Total assets; Cash/Current assets; Cash/Current liabilities; Current assets/ Current liabilities; Reserves/Total assets; Current assets/Total liabilities; (Current assets − Inventories)/Current liabilities
Profitability	Earnings/Total assets; Earnings/Equity; EBITDA/Revenue; Trade payables/Total assets; EBIT/Total assets; Gross profit/Revenue; EBIT adjusted/Revenue; (Earnings + abs(Depreciation))/Total assets; EBIT/ (Equity + Long term liabilities)
Revenue	Trade payables × 360/Revenue; Revenue/ Total assets
Revenue, Liquidity	Trade receivables × 360/Revenue
Size	ln(Total assets); ln(Revenue); ln(Earnings); ln(EBIT); ln(EBITDA); ln(Profit before tax)

Note: This table summarizes the initial list of financial variables used in the empirical analysis. ln(·) denotes the natural logarithm of the variable.

Our models also include a variable that controls for the validity of financial statements. From the CBSO database, we obtain the auditor's evaluation for each firm (whereby an auditor offers an opinion with reasonable assurance that the financial statements report a true and fair view of the financial position and financial performance of the firm). We use this information to create the dummy variable *Auditor_opinion*, which is set to 1 if there is an unqualified opinion or unqualified opinion with an emphasis of matter paragraph, and 0 otherwise (i.e., unaudited financial statements, a qualified opinion, an adverse opinion, or a disclaimer of opinion). The expected sign of the coefficient on this variable is negative because a dummy value of 1 shows that the auditors did not find evidence of reporting problems in the firm's financial statements', thus decreasing the probability of default.

A key task in this paper is to characterize the effects of the COVID-19 pandemic on firm default. We therefore use a dummy variable that captures the net effect of the COVID-19 pandemic shock and the macroeconomic policy measures in response to it, *Net_COVID-19_effect*. This dummy variable equals 1 if the firm received financial support due to COVID-19, and 0 otherwise.

To control for the macroeconomic environment, we use *Credit_growth* in the private sector and *Nominal_GDP_growth*. The source of these data is the World Bank's database. To capture the institutional environment within which firm activity and economic policy responses take place, we use the institutional quality variable *Rule_of_law* index, which is well-established in the literature. The data for this variable are obtained from the World Justice Project (WJP). This is a multidimensional variable that considers eight components: (1) government power, (2) corruption, (3) openness of government, (4) fundamental rights, (5) order and security, (6) regulatory enforcement, (7) civil justice, and (8) criminal justice.

In addition to financial and macroeconomic variables, we use industry variables to capture credit risk and default patterns across different industries/sectors, as well as possible differential effects of the pandemic and policy measures attributable to each firm's industry. We follow the classification of Antunes et al. (2016) to split the firms into five basic industry categories. Notably, this selection satisfies the availability and homogeneity of the data in each category. The industry of economic activity is classified using the NACE code from the AnaCredit database, which denotes the economic activity sector and two, three, and four-digit subsectors according to the Eurostat methodology.[2] Our analysis maps each firm to one of the following five industry categories according to their 2-digit code: (i) wholesale and retail trade and the primary sector; (ii) processing, mining, and quarries; (iii) utilities, transport, and storage; (iv) construction and real estate activities; (v) services. Finally, we include a size dummy variable that accounts for the effect of firm size. The size dummy equals 1 if the firm is considered very small (micro), and 0 otherwise (small, medium, and large).[3]

4 | MODELS AND METHODOLOGY

4.1 | Feature selection process

Feature selection is a process that enhances the parsimony and interpretability of the model, and thus the efficiency and robustness of the predictions. Feature selection refers to the choice of the best subset of variables that are the most important drivers of the predictive model results. Because this choice of variables is based on the adopted model design approach, feature selection can be a challenging task. However, there are several advantages to adopting such a process to critically select variables (see, e.g., Ladha & Deepa, 2011; Khalid et al., 2014). First, it decreases the dimensionality of the feature space, thereby limiting the curse of dimensionality to some extent. Second, it purifies the sample of irrelevant or noisy data, thus leading to an overall improvement in data quality. Third, it means learning algorithms will need less running time for data analysis. Fourth, it reduces storage requirements, and finally, the predictive efficacy of the models is substantially increased.

Determining the optimal subset of variables would require consideration of all possible combinations, but this is unfeasible due to the resulting combinatorial explosion. Therefore, heuristic procedures should be adopted. Feature selection methods can be classified into three major pillars (categories): filter, wrapper, and embedded methods, based on their relationship with learning methods (Vergara & Estévez, 2014), and the wrapper procedure consists of three families of methods (forward selection, backward elimination, and bi-directional stepwise elimination) that generate a set of possible solutions by exploring a subspace of all possible combinations. Collectively, the existence of various approaches based on multi-criteria systems of variable selection highlights the importance of adopting a carefully chosen and stable variable selection method. We mainly utilize heuristic methods, employing a forward search, which starts with an empty set of variables and adds variables sequentially (e.g., Antunes et al., 2016). The fundamental advantage of these methods is that they are readily implemented and produce results quickly. After a search procedure is selected, an appropriate evaluation criterion must be adopted to evaluate the subset of potential variables and choose the best. The evaluation criterion cannot be selected independently of the modelling approach; the Wilk's Lambda or another variance criterion is suitable for discriminant analysis, whereas a likelihood criterion is suitable for logistic regression. Consequently, for the purposes of our analysis, the most relevant criteria are identified through maximum likelihood estimation (Imbens & Rubin, 2015).

The process starts with the estimation of a base model with fixed effects for firm size and activity sector. For each variable in the initial pool of variables, the model is estimated with the fixed effects plus that variable. The variable associated with the model with the highest likelihood statistic is selected under the condition that it is above the initial likelihood at a significance level of 5%. This corresponds to a likelihood ratio of at least 3.84. The process is repeated, with the base model as the model with the fixed effects plus the variable picked in the previous step (the forward approach). The second variable is chosen from the remaining $N-1$ variables. Beginning at this stage of the analysis, however, we impose certain conditions in addition to the likelihood ratio requirement for each candidate variable included in the model. These restrictions include: (a) Absence of multicollinearity. The selected variable must have linear and non-linear correlation coefficients with all variables already present in the model lower than the absolute value of 0.5. (b) In addition to statistical significance at the 5% level, the selected variable must have a rational coefficient sign based on economic theory and the literature, and all previously included variables must remain statistically significant. (c) Improvement in the AUROC criterion and in the Akaike information criterion (AIC), which are based on balancing the model's fitness and complexity by addressing the potential problem of over-fitting the model. (d) Improvement in the Brier score to further assess the predictive ability of the model.

The selection process terminates when none of the remaining variables in the set of potential variables meets all the aforementioned criteria. Table 3 presents the definitions of all selected variables, as well as the number of models for which each variable is chosen by the feature selection process. Table 4 reports the summary statistics of the dependent and the variables chosen by the feature selection process.

TABLE 3 Description of selected variables.

Variable	# times selected
Equity/Total assets	2
Total liabilities/Total assets	5
Current financial liabilities/Total liabilities	2
Current financial liabilities/Total assets	2
Cash/Total assets	1
(Current liabilities − Cash)/Total assets	1
Cash/Current assets	5
Current assets/Total assets	4
Reserves/Total assets	1
Earnings/Equity	6
(Interest earned − Interest expense)/ Revenue	1
Trade payables/Current liabilities	1
Trade receivables*360/Revenue	7
Revenue/Total assets	8
Gross profit/Revenue	3
EBIT/(Equity + Non-current liabilities)	1
ln(Revenue)	1
Auditor opinion	6
Rule of law	5
Net COVID-19 effect	8

Note: This table summarizes the variables chosen by the feature selection algorithm. The second column contains the number of models for which each variable is chosen by the feature selection process. ln(·) denotes the natural logarithm of the variable.

4.2 | Econometric model

Following the majority of national ICASs, we adopt a logistic regression model (Antunes et al., 2016; Auria et al., 2021). The logistic regression model is among the most popular models in finance (Durango-Gutiérrez et al., 2023; Espahbodi & Espahbodi, 2003; Katsafados et al., 2021; Mai et al., 2019; Veganzones & Séverin, 2018). Logistic regression estimates a non-linear sigmoid function between the binary output (default status) and the independent variables. The parameters of the model are learned by maximizing the conditional log-likelihood via the popular maximum likelihood estimation, typically using stochastic gradient ascent or variants. The mathematical formula for this model is as follows:

$$log\left(\frac{PD_{i,t}}{1-PD_{i,t}}\right)=b_0+\sum_{j=1}^{J}X_{i,j,t-1}+\text{Net\_COVID\_effect}_{t-1}+\varepsilon_{i,t} \tag{1}$$

where $PD_{i,t}$ represents the probability of default of firm i at time t within the next 12 months after the release of accounting data, $X_{i,j,t-1}$ is the set of J explanatory variables and $\varepsilon_{i,t}$ is the stochastic term. This implies that the probability of default is given by:

TABLE 4 Summary statistics.

Variable	Mean	Median	St. dev.
Default dummy	0.150	0.000	0.357
Equity/Total assets	0.392	0.396	0.290
Total liabilities/Total assets	0.599	0.593	0.291
Current financial liabilities/Total liabilities	0.208	0.134	0.223
Current financial liabilities/Total assets	0.126	0.068	0.154
Cash/Total assets	0.145	0.096	0.142
(Current liabilities − Cash)/Total assets	0.319	0.297	0.316
Cash/Current assets	0.239	0.165	0.223
Current assets/Total assets	0.668	0.727	0.267
Reserves/Total assets	0.115	0.129	0.328
Earnings/Equity	0.099	0.065	0.303
(Interest earned − Interest expense)/Revenue	−0.026	−0.011	0.045
Trade payables/Current liabilities	0.417	0.395	0.260
Trade receivables*360/Revenue	144.970	94.612	191.164
Revenue/Total assets	1.046	0.854	0.831
Gross profit/Revenue	0.294	0.259	0.212
EBIT/(Equity + Non-current liabilities)	0.166	0.086	0.289
ln(Revenue)	14.695	14.649	1.368
Auditor opinion	0.077	0.000	0.267
Rule of law	0.610	0.610	0.008
Net COVID-19 effect	0.293	0.000	0.455

Note: This table reports the summary statistics of dependent variable and explanatory variables chosen by the feature selection process. Default dummy equals 1 if the borrower-lender-month default indicator is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise. ln(·) denotes the natural logarithm of the variable.

$$PD_{i,t} = \frac{1}{1+e^{-\left(b_0+\sum_{j=1}^{J} X_{i,j,t-1}+\text{Net\_COVID\_effect}_{t-1}+\varepsilon_{i,t}\right)}} \quad (2)$$

5 | RESULTS

5.1 | Econometric estimation (logistic regression)

5.1.1 | Baseline models

Table 5 reports the results of the estimations of logistic regression models, where column 1 is attributed to the general model, columns 2 and 3 to the size-based models, and columns 4–8 to the industry-based models. As the results of Table 5 reveal, the *Net_COVID-19_effect* variable is highly statistically significant in each of the logistic regression models and has a negative sign.

Panel A of Table 6 presents the results of economic significance for the variables of interest. The variable *Net_COVID-19_effect* is highly economically significant in the general model, suggesting that, given the pandemic, the government financial support response measures reduce the probability of default by 11.83%. The impact of *Net_COVID-19_effect* is stronger for the micro companies (15.83%) than for SML firms (9.98%). Comparison of the industry-based models shows that the *Net_COVID-19_effect* has by far the greatest economic significance in industry group 5, services.

Panel B of Table 6 reports results for the order of selection of variables from the feature selection process. The rationale for this process is to prioritize the choice of the most important variables. In general, *Net_COVID-19_effect* is selected relatively early compared to the financial variables, which confirms the high importance of this variable in affecting default risk. Consistent with the results in Panel A, we show that *Net_COVID-19_effect* has its best positions for the micro firms and industry group 5 models (3rd position), thus indicating the robustness of this finding.

TABLE 5 Econometric estimation of models.

		Size-based		Industry-based				
Variables	General	Micro	SML	Industry 1	Industry 2	Industry 3	Industry 4	Industry 5
Equity/Total assets		−2.317*** (−11.33)					−2.758*** (−7.89)	
Total liabilities/Total assets	3.673*** (34.20)		3.826*** (26.79)	4.178*** (22.93)	4.515*** (17.02)			2.766*** (13.79)
Current financial liabilities/Total liabilities		0.839*** (2.96)		0.551*** (2.82)				
Current financial liabilities/Total assets							3.175*** (4.76)	1.243*** (3.21)
Cash/Total assets	−1.364*** (−4.96)							
(Current liabilities − Cash)/Total assets						2.596*** (4.75)		
Cash/Current assets		−0.837** (−2.56)	−1.100*** (−5.44)		−1.203*** (−2.62)		−2.302*** (−4.71)	−0.758*** (−3.20)
Current assets/Total assets	−0.535*** (−3.97)		−1.066*** (−6.26)	−1.919*** (−8.46)	−1.124*** (−3.56)			
Reserves/Total assets						−1.639*** (−3.17)		
Earnings/Equity	−0.301*** (−3.79)	−0.487*** (−2.74)	−0.286*** (−2.94)	−0.237** (−1.98)			−0.792** (−2.23)	−0.358*** (−3.11)
(Interest earned − Interest expense)/Revenue			−2.984*** (−4.04)					
Trade payables/Current liabilities						1.079** (2.27)		
Trade receivables × 360/Revenue	0.002*** (11.42)	0.000*** (4.00)	0.002*** (7.51)	0.002*** (8.43)	0.002*** (6.16)		0.001*** (3.23)	0.001*** (3.11)
Revenue/Total assets	−1.311*** (−18.59)	−1.990*** (−10.12)	−1.022*** (−11.87)	−1.031*** (−10.89)	−1.887*** (−9.27)	−1.622*** (−5.51)	−1.695*** (−7.13)	−1.595*** (−11.27)
Gross profit/Revenue	−0.437*** (−3.40)		−0.420** (−2.58)	−1.121*** (−3.68)				
EBIT/(Equity + Non-current liabilities)						−1.389** (−2.49)		
ln(Revenue)			−0.088*** (−2.80)					
Rule of law	−15.217*** (−4.72)		−15.637*** (−4.00)	−14.888*** (−2.76)	−17.315** (−2.45)			−16.057** (−2.44)
Auditor opinion	−0.983*** (−6.22)		−0.955*** (−5.33)	−0.660** (−2.54)	−1.255*** (−3.31)		−1.646*** (−3.57)	−0.680** (−2.14)
Net COVID-19 effect	**−0.631***** (−9.35)	**−1.085***** (−5.34)	**−0.521***** (−6.61)	**−0.440***** (−4.24)	**−0.577***** (−4.05)	**−0.658**** (−2.04)	**−0.429*** (−1.91)	**−1.000***** (−6.45)

TABLE 5 (Continued)

		Size-based		Industry-based				
Variables	**General**	**Micro**	**SML**	**Industry 1**	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Constant	6.815*** (3.46)	0.602*** (2.74)	8.252*** (3.39)	6.763** (2.06)	8.084* (1.88)	−1.623*** (−6.07)	1.079*** (3.86)	7.346* (1.83)
Size FE	YES	NO	NO	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO	NO	NO
Observations	14,549	1681	11,239	5958	3133	845	973	3226
R-pseudo	0.401	0.464	0.384	0.432	0.476	0.249	0.475	0.327
Brier score	0.086	0.100	0.079	0.078	0.086	0.070	0.117	0.090
AIC improvement	−3612.6	−543.4	−2505.1	−1616.7	−1021.8	−88.2	−356.0	−615.2

Note: This table reports the results of the estimations of logistic regression models, where column 1 is attributed to the general model, columns 2 and 3 to the size-based models, and columns 4–8 to the industry-based models. The dependent variable is the default dummy that equals 1 if the borrower-lender-month default indicator is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Heteroskedasticity-robust z-statistics are reported in parentheses. The bold shows the scores of the variables that are of the main interest and explained in the text.

TABLE 6 Economic significance, the order in feature selection and R-pseudo model improvement for the variables of interest.

		Size-based		Industry-based				
	General	**Micro**	**SML**	**Industry 1**	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Panel A: Economic significance								
Rule of law	5.83%	-	5.87%	5.36%	6.40%	-	-	6.72%
Auditor opinion	8.54%	-	8.98%	5.83%	10.28%	-	**16.28**%	6.85%
Net COVID-19 effect	11.83%	**15.83**%	9.98%	8.26%	10.86%	12.80%	9.27%	**17.65**%
Panel B: Order in feature selection								
Rule of law	7	-	9	7	8	-	-	7
Auditor opinion	6	-	5	9	5	-	5	9
Net COVID-19 effect	4	**3**	6	5	4	6	8	**3**
Panel C: R-pseudo improvement								
Rule of law	0.0021	-	0.0021	0.0017	0.0023	-	-	0.0027
Auditor opinion	0.0045	-	0.0045	0.0017	0.0057	-	0.0185	0.0025
Net COVID-19 effect	0.0086	**0.0215**	0.0060	0.0042	0.0066	0.0105	0.0039	**0.0216**

Note: Panel A reports the results of economic significance for the variables of interest. Panel B reports the results for the order of selection of variables from the feature selection process. Panel C reports the increase in the R-pseudo of a model that includes all variables compared to a model without the variable under examination. The bold shows the scores of the variables that are of the main interest and explained in the text.

To further enhance the robustness of our results, we perform another test of the importance of each variable, based on their effects on the R-pseudo. Specifically, we use a model with all variables included and a model without the variable under examination and determine the increase in the R-pseudo of the first model compared to the second model. Again, we show that the inclusion of *Net_COVID-19_effect* causes a larger increase at the R-pseudo for the micro and industry 5 models (both approximately 2%) than other models.

5.1.2 | The effects across industries and different-sized firms

Table 7 presents results for logistic regression models that include interdependence terms between the *Net_COVID-19_effect* dummy and industry or firm size dummies. The results reveal that in each case *Net_COVID-19_effect* is statistically significant at the 1% level. Further, the sign of the variable's coefficient is negative, which means that firms receiving financial support during 2020 appear to

TABLE 7 Interdependence between *Net_COVID-19 effect* and industry or firm size.

		Size-based	Industry-based				
Variables	**General**	**Micro**	**Industry 1**	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Total liabilities/Total assets	3.673*** (34.20)	3.674*** (34.18)	3.560*** (33.78)	3.601*** (34.02)	3.582*** (34.06)	3.614*** (34.19)	3.636*** (34.21)
Cash/Total assets	−1.364*** (−4.96)	−1.371*** (−4.98)	−1.686*** (−6.21)	−1.705*** (−6.30)	−1.693*** (−6.28)	−1.789*** (−6.63)	−1.422*** (−5.19)
Current assets/Total assets	−0.535*** (−3.97)	−0.541*** (−4.01)	−0.250* (−1.94)	−0.174 (−1.41)	−0.268** (−2.16)	−0.151 (−1.23)	−0.387*** (−2.99)
Earnings/Equity	−0.301*** (−3.79)	−0.303*** (−3.82)	−0.305*** (−3.89)	−0.308*** (−3.92)	−0.292*** (−3.70)	−0.312*** (−3.97)	−0.324*** (−4.09)
Trade receivables × 360/Revenue	0.002*** (11.42)	0.002*** (11.42)	0.002*** (11.64)	0.002*** (11.49)	0.002*** (11.53)	0.002*** (11.36)	0.002*** (11.67)
Revenue/Total assets	−1.311*** (−18.59)	−1.306*** (−18.53)	−1.328*** (−19.09)	−1.312*** (−18.93)	−1.310*** (−18.89)	−1.285*** (−18.69)	−1.343*** (−19.16)
Gross profit/Revenue	−0.437*** (−3.40)	−0.430*** (−3.35)	−0.530*** (−4.19)	−0.482*** (−3.82)	−0.489*** (−3.88)	−0.502*** (−4.00)	−0.527*** (−4.08)
Rule of law	−15.217*** (−4.72)	−15.273*** (−4.73)	−14.626*** (−4.57)	−14.618*** (−4.57)	−15.113*** (−4.71)	−14.747*** (−4.60)	−14.570*** (−4.53)
Auditor opinion	−0.983*** (−6.22)	−0.985*** (−6.22)	−0.943*** (−6.00)	−0.954*** (−6.09)	−0.948*** (−6.03)	−1.007*** (−6.38)	−0.946*** (−6.38)
Net COVID-19 effect	**−0.631***** (−9.35)	**−0.578***** (−8.11)	**−0.774***** (−8.82)	**−0.647***** (−8.28)	**−0.633***** (−9.21)	**−0.618***** (−8.76)	**−0.504***** (−6.83)
Micro		−0.119 (−1.24)					
Net COVID-19 effect × Micro		**−0.469**** (−2.19)					
Industry 1			0.060 (0.85)				
Net COVID-19 effect × Industry 1			**0.352***** (2.64)				
Industry 2				0.154** (2.10)			
Net COVID-19 effect × Industry 2				**0.087** (0.59)			
Industry 3					−0.828*** (−5.19)		
Net COVID-19 effect × Industry 3					**0.100** (0.30)		
Industry 4						0.602*** (5.44)	
Net COVID-19 effect × Industry 4						**0.015** (0.07)	
Industry 5							−0.293*** (−3.63)
Net COVID-19 effect × Industry 5							**−0.643***** (−3.82)
Constant	6.815*** (3.46)	6.833*** (3.47)	6.286*** (3.22)	6.168*** (3.16)	6.618*** (3.39)	6.217*** (3.18)	6.355*** (3.24)
Size FE	YES	NO	YES	YES	YES	YES	YES
Industry FE	YES	YES	NO	NO	NO	NO	NO

Note: The micro dummy variable takes the value 1 for micro firms, and 0 otherwise. The industry 1, 2, 3, 4, and 5 dummy variables take the value 1 for firms within the corresponding industry codes, and 0 otherwise. The dependent variable is the default dummy that equals 1 if the borrower-lender-month default indicator is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Heteroskedasticity-robust z-statistics are reported in parentheses. The bold shows the scores of the variables that are of the main interest and explained in the text.

TABLE 8 Transition table.

Panel A	**CQS in 2020**						
CQS in 2019	**1 & 2**	**3**	**4**	**5**	**6**	**7**	**8**
1 & 2	**64.3**	14.3	14.3		7.1		
3	16.2	**60.8**	16.2		1.4	1.4	4.0
4	1.8	26.9	**55.6**	6.4	2.9	2.3	4.1
5		4.7	**43.4**	25.6	15.5	5.4	5.4
6	0.5	2.0	14.6	**36.7**	24.1	18.6	3.5
7		0.5	2.9	9.8	27.7	**49.0**	10.1
8		0.1	0.4	0.7	1.4	13.7	**83.7**
Panel B	**CQS in 2021**						
CQS in 2020	**1 & 2**	**3**	**4**	**5**	**6**	**7**	**8**
1 & 2	**46.2**	23.1	7.7	3.8		7.7	11.5
3	13.1	**39.3**	19.3	4.2	4.8	8.3	11.0
4	0.4	13.8	**42.2**	13.8	13.8	10.4	5.6
5	0.5	3.2	**27.0**	21.9	20.9	16.3	10.2
6		2.7	14.1	**28.5**	22.0	22.0	10.7
7		0.4	2.4	8.4	20.6	**47.7**	20.5
8		0.1	0.3	0.5	1.7	15.6	**81.8**

Note: Predicted probabilities of default are mapped to the appropriate credit quality step (CQS) of the Eurosystem's harmonized rating scale, which has eight categories. A higher CQS indicates that the predicted probability of default is greater, denoting a worse credit rating for the firm. Panel A presents the transition table for the general model conditional on firms being in the sample in 2018 and 2019. Panel B presents the transition table of the general model conditional on firms being in the sample in 2019 and 2020. All values are in percentages and each row adds up to 100%. The bold shows the scores of the variables that are of the main interest and explained in the text.

have a lower probability of default, corroborating the evidence reported in Table 5.

Notably, we observe that the interdependence terms for *Net_COVID-19_effect* with both the micro dummy (column 2) and the industry group 5 dummy (column 7) are statistically significant and negative. This suggests that micro firms and service-industry firms ("industry 5") experienced the most pronounced decreases in their probability of default. Given the large share of services and micro firms in the Greek economy and the policymakers' stated intention to support them in the face of the pandemic, this finding suggests that the financial support measures have been effective in mitigating credit risk by reducing the probability of these firms' default.

5.2 | Robustness checks

To further enhance the validity of our results, we evaluate the models' performance using three alternative methods. Namely, we consider: (1) transition matrix analysis, (2) benchmarking, and (3) out-of-sample evaluation.

5.2.1 | Transition matrix analysis

Our approach encompasses a two-step design. First, the econometric model predicts the probability of default, and second, we correspond the result to the European Credit Quality Step (CQS). Specifically, we map the probability of default to the appropriate CQS of the Eurosystem's harmonized credit rating scale. In addition to enhanced efficiency, another criterion for assessing the quality of credit rating prediction models is the stability of the results. To investigate this, we perform a transition matrix analysis. This approach is considered useful for characterizing the dynamics of firms' predicted credit ratings. Transition tables typically represent the probability of a firm moving to a specific credit rating class or default, always in relation to the current rating class. We construct the tables by comparing the predicted credit ratings for a given year compared to the following year. Table 8 reports probabilities for transitions from 2019 to 2020 (Panel A) and from 2020 to 2021 (Panel B).

As the results reveal, the transition matrix from 2019 to 2020 is more stable than the transition matrix from 2020 to 2021. In other words, during the pandemic period, firms were more likely to transition to different credit quality ratings. The critical questions here are whether the *Net_COVID-19_effect* dummy can deal with this instability condition, and if so, to what extent.

Next, we proceed to a z-test in order to verify the monotonicity of off-diagonal transition frequencies in the migration matrix. As a result, except for remaining in the same CQS, we find that it is more possible for the shift to be upward. In other words, it means that the CQS of 2021 has a statistically significant positive difference compared to the CQS of 2020. This is logical if we take into account the effects of the COVID-19 pandemic.

5.2.2 | Benchmarking

The benchmarking process consists of comparing the predicted credit ratings based on the CQS (as in the previous subsection) with ratings from other external sources such as the IRB ratings. We use Eurobank IRB predictions retrieved from AnaCredit to compare our results with valid benchmarks. Table 9 presents the results of this comparison.

According to Table 9, the deviation between predicted CQS and IRB CQS is smaller for micro firms than for SML firms. This finding is consistent with results reported in Table 6 showing that the *Net_COVID-19_effect* is stronger for micro firms. That is, financial support provided to micro firms enhances the stability of their credit quality. Unsurprisingly, the services sector group ("industry 5") appears highly stable. Interestingly, "construction and real estate activities" ("industry 4") is also found to be very stable in this analysis.

Next, we use the Wilcoxon signed-rank test, which examines whether the median difference between the paired data can be zero. However, differently from the previous analysis, the test is executed by computing a statistic after discarding all the pairs with the same values from the process of computing the statistic. In other words, it ignores observations with zero difference, thereby identifying possible patterns. According to the results, the median of the differences is zero in the case of "industry 3" and "industry 4". In the rest of the models, the predicted CQS rating exceeds the IRB rating, which is consistent with the more conservative approach to an ICAS model as a tool of the ECB.

5.2.3 | Out-of-sample evaluation

In this section, we check whether our developed models display strong predictability features. To ensure proper evaluation of the models, it is typical to assess them with respect to their out-of-sample performance (Doumpos et al., 2017; Geng et al., 2015). To do this, the models are trained on a subset of the sample called the training set. The trained model is then used to make predictions for the remaining sample, called the testing set, and these predictions are compared to actual results to evaluate the models' performance. There are several possible approaches to dividing a sample into training and testing sets. Here, we first adopt the random split method, whereby an algorithm randomly defines whether each observation in the sample belongs to the training or testing set. We choose to use 80% of the sample for training and the remaining 20% for testing (e.g., Pasiouras et al., 2010).

However, we also use an additional approach to split the training and test sets, known as out-of-time evaluation of the models. Specifically, we select the testing set

TABLE 9 Comparison with IRB ratings (rating grade deviation).

Predicted vs. IRB CQS	−6	−5	−4	−3	−2	−1	0	+1	+2	+3	+4	+5	+6
General	0.06	0.82	1.94	3.01	4.71	8.37	**43.70**	21.02	7.47	3.65	2.99	1.61	0.65
Micro	1.16	1.65	2.64	1.65	3.64	8.60	**52.89**	19.67	5.95	0.33	0.50	0.33	0.99
SML	0.02	0.39	2.08	3.56	4.88	9.78	**41.71**	20.40	8.09	3.92	3.15	1.54	0.48
Industry 1	0.10	0.69	1.95	3.26	4.28	9.88	**41.12**	22.54	7.78	3.72	2.90	1.65	0.13
Industry 2	0	0.26	1.47	2.68	3.77	8.37	**43.26**	18.79	9.07	5.05	4.22	2.36	0.70
Industry 3	0.97	0.32	6.13	8.06	7.42	10.65	**35.48**	16.45	6.13	3.23	1.61	1.29	2.26
Industry 4	0.26	0.52	1.84	3.67	3.15	9.19	**56.96**	14.96	5.25	0.26	0.79	0.79	2.36
Industry 5	0.48	0.72	2.56	2.56	3.36	8.24	**49.36**	21.28	5.84	2.48	1.36	1.28	0.48

Note: The benchmarking of the models was performed by comparing the assignment to CQSs using the output of the general model with the assignment to CQSs based on IRB. A positive number implies that the benchmark, that is, the CQS assigned based on the IRB, is less conservative than the CQS assignment from the general model. Eurosystem's credit quality steps (CQSs) are divided into eight grades. A higher CQS indicates a greater predicted probability of default, denoting a worse credit rating for the firm. All values are in percentages and each row adds up to 100%. The bold shows the scores of the variables that are of the main interest and explained in the text.

TABLE 10 Out-of-sample prediction (unbalanced sample).

		Size-based		Industry-based				
Logistic regression	**General**	**Micro**	**SML**	**Industry 1**	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Random split								
Accuracy score	0.885	0.864	0.895	0.897	0.885	0.915	0.821	0.878
AUROC	0.858	0.873	0.854	0.864	0.878	0.814	0.858	0.832
Balanced accuracy	0.675	0.724	0.657	0.696	0.723	0.543	0.699	0.615
Out-of-time								
Accuracy score	0.902	0.911	0.907	0.911	0.900	0.935	0.841	0.896
AUROC	0.774	0.859	0.756	0.756	0.838	0.591	0.757	0.755
Balanced accuracy	0.607	0.639	0.602	0.634	0.645	0.485	0.690	0.553
Split by year								
Accuracy score	0.889	0.887	0.890	0.903	0.890	0.923	0.855	0.837
AUROC	0.805	0.852	0.795	0.804	0.847	0.746	0.817	0.749
Balanced accuracy	0.680	0.713	0.660	0.682	0.703	0.521	0.684	0.610

Note: This table reports out-of-sample performance measures, namely the accuracy ratio, the AUROC and the balanced accuracy. In fact, we use three different train-test splits including random, out-of-time and yearly split. The results refer to an unbalanced sample when estimating logistic regression.

based on the time sequence of the observations. We proceed in two simple steps. First, we sort the sample starting from the most recent. Second, we apply train-test split rules. We implement two different rules: (1) a sample threshold (80% training and 20% testing with out-of-time order), and (2) a time-period threshold (2018 and 2019 are used for training, and 2020 for testing). This out-of-time approach has the advantage of examining the ability of the model to correctly classify future objects based on past information, which gives a realistic perspective to the model (Espahbodi & Espahbodi, 2003; Katsafados et al., 2023, 2024; Pasiouras et al., 2007).

Out-of-sample evaluation (logistic regression)

Table 10 presents the results of the prediction of the eight logistic regression models. We use three alternative evaluation measures, namely: accuracy score (Pasiouras et al., 2010), AUROC (Schechtman, 2017), and balanced accuracy. The use of alternative evaluation measures is motivated by one of the objectives of this paper, which is to indicate the proper use of evaluation measures. In particular, we observe that in some cases, including the industry 3 model, the accuracy score is extremely high, but the AUROC and balanced accuracy measures display poor performance. This demonstrates that when the dataset is unbalanced, one should be careful when interpreting the results of the accuracy measure. This finding is robust to use of the three different train-test splits.

Moreover, given that whether to use specialized models instead of generic ones is an open research question, the above analysis has important value. On the one hand, our industry- and size-based models have the advantage of better reflecting their data due to homogeneity. Their performance, however, depends greatly on the sub-sample size in each case. On the other hand, the generic model utilizes the entire dataset and exploits the existence of a larger training set. Based on the results in Table 10, we conclude that it is preferable for the micro and industry 2 (processing, mining, and quarries) models to be specialized, because their AUROC and balanced accuracy measures are better than those of the generic model. This finding is consistent for each of the train/test splits, indicating the robustness of this result. For the other cases, the generic model is the best choice.

Class imbalance is a serious issue in classification tasks in finance, such as forecasting acquisitions or bankruptcy (Barnes, 1999; Laitinen & Kankaanpaa, 1999; Neophytou & Molinero, 2004; Pasiouras et al., 2010). The problem of a severely imbalanced dataset could potentially worsen the performance of predictive models. Therefore, inspired by previous literature, we address this issue by implementing the under-sampling approach (Veganzones & Séverin, 2018). This method creates a balanced subsample from our original dataset by removing observations from the majority category (in this case, non-default observations).

Following Pasiouras et al. (2010), we adopt the time-based matching strategy, whereby each observation in the minority class is matched with an observation in the majority class, with the condition that they are in the same calendar year. Table 11 reports the results of this analysis. In general, when comparing the results for

TABLE 11 Out-of-sample prediction (balanced sample).

Logistic regression	General	Size-based: Micro	Size-based: SML	Industry-based: Industry 1	Industry 2	Industry 3	Industry 4	Industry 5
Random split								
Accuracy score	0.793	0.760	0.803	0.802	0.802	0.741	0.767	0.769
AUROC	0.875	0.844	0.879	0.874	0.891	0.796	0.865	0.844
Out-of-time								
Accuracy score	0.730	0.739	0.721	0.741	0.749	0.774	0.784	0.700
AUROC	0.813	0.792	0.786	0.798	0.860	0.750	0.834	0.763
Split by year								
Accuracy score	0.735	0.745	0.738	0.757	0.776	0.767	0.787	0.699
AUROC	0.818	0.818	0.808	0.813	0.861	0.733	0.833	0.760

Note: This table reports out-of-sample performance measures, namely the accuracy ratio, the AUROC and the balanced accuracy. In fact, we use three different train-test splits including random, out-of-time and yearly split. The results refer to a balanced sample when estimating logistic regression.

the AUROC scores between the two tables, and when comparing the balanced accuracy in Table 10 with the accuracy scores in Table 11, the results in Table 11 show a substantial improvement in predictive outcome. In particular, we have to pay attention to the fact that scores are fundamentally stochastic measures. During the comparisons, it could be checked if a difference between the two scores is statistically significant or not. However, in our comparisons, the differences are large enough in most of the cases to enhance the argument without requiring the computation of the statistical significance.

Machine learning versus logistic regression

We perform a horse race between a typical logistic regression approach and a machine learning approach. We implement random forest (RF), which is a novel machine learning model. Random forest creates several uncorrelated decision tree classifiers, and for that reason, it belongs to the ensemble category of machine learning. It was initially introduced by Breiman (2001) as a variant of bagging (Breiman, 1996). The created decision trees are typically trained on bootstrap copies of original samples by randomly choosing a subset of independent variables. The prediction process is then conducted with each individual tree predicting a class. The class with the most votes is considered the output of the model. We choose random forest from all machine learning models because it has demonstrated high performance in several recent prediction tasks in finance, including initial public offerings and deposit flow prediction. Across the Eurosystem, ICASs are either in development or under continuous improvement. Thus, experimenting with novel predictive models, including machine learning, can inform the ICASs construction project. For example, the Bank of France adopts a decision tree model. The random forest approach, however, is considered an improved version of the decision tree, as previously explained, and limits the decision tree's problem of overfitting to the training sample (Mai et al., 2019).

As a robustness check, we examine the added value of an alternative machine learning model belonging to the artificial neural networks. In particular, we adopt the Multilayer perceptron (MLP) which is frequently used in several tasks in finance. The results in Table 12 (Panel A) show that random forest generally performs better than the logistic regression reported in Table 10. Notably, in line with the discussion in previous subsections, we primarily focus on the balanced accuracy measure. Furthermore, when the focus goes on the MLP model (Panel B), we conclude that machine learning is still a better predictive model than logistic regression. In general, the machine learning approach, in the form of a representative random forest model, emerges as a winner in this horserace. This finding is in line with the literature that utilizes random forest approaches in several prediction tasks with extraordinary efficacy, such as the IPO literature and deposit flow prediction literature.

Next, we attempt to shed light on the black box of machine learning models to increase the transparency and interpretability of the random forest results. More precisely, we illustrate the importance scores based on the SHapley Additive exPlanations (SHAP) methodology (see Figures 3–10). The SHAP values denote how important each independent variable is in the prediction process of the machine learning model. The critical inference here is that *Net_COVID-19_effect* has the greatest impact in "industry 5" (services), exceeding 0.03 (see Figure 10), among the industry-specific models (Figures 6–10). Furthermore, when we shift attention to size-specific models, we observe that the SHAP value is

TABLE 12 Machine learning prediction.

		Size-based		Industry-based				
Balanced accuracy	**General**	**Micro**	**SML**	**Industry 1**	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Panel A: Random forest								
Random split	0.701	0.726	0.671	0.698	0.699	0.557	0.785	0.617
Out-of-time	0.622	0.718	0.613	0.656	0.675	0.494	0.713	0.603
Split by year	0.686	0.738	0.687	0.716	0.708	0.492	0.714	0.660
Panel B: MLP								
Random split	0.695	0.746	0.673	0.695	0.729	0.500	0.761	0.643
Out-of-time	0.653	0.750	0.619	0.641	0.659	0.500	0.714	0.557
Split by year	0.677	0.728	0.674	0.602	0.714	0.500	0.729	0.659

Note: This table reports the out-of-sample balanced accuracy scores for a random forest and a MLP machine learning model, using three different train-test splits including random, out-of-time and yearly split.

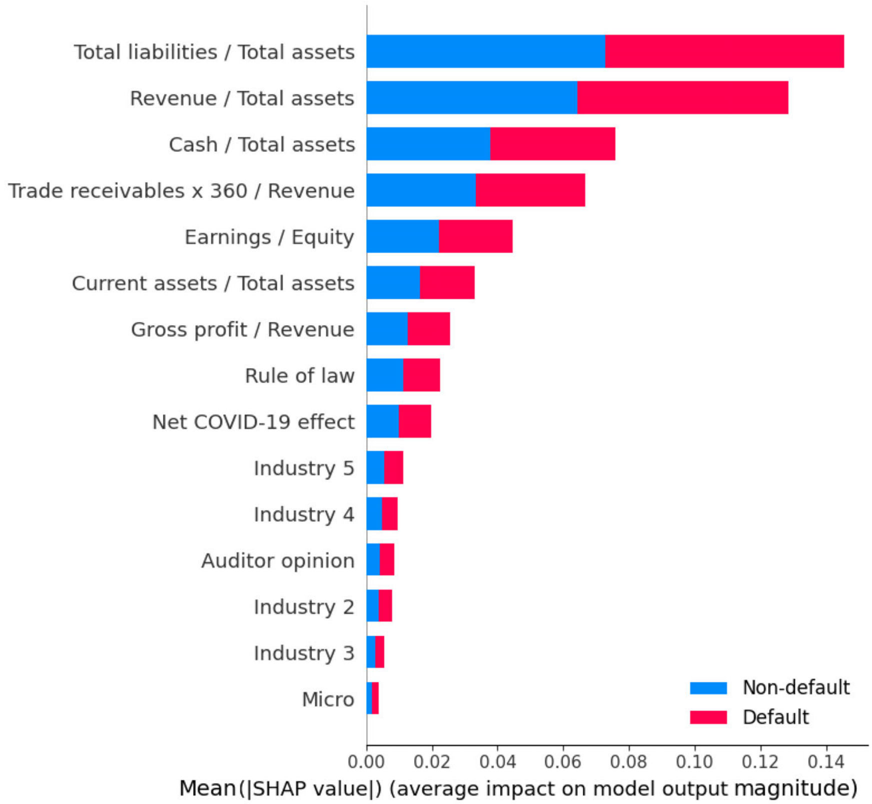

FIGURE 3 General model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

larger for micro firms compared to SML firms, as expected (see Figures 4 and 5). Both findings further enhance the main result of the paper regarding the *Net_COVID-19_effect* on credit risk.

5.3 | Further robustness analysis

To test our main finding that the Greek government's financial support measures have reduced firms' probability of default, we repeat the analysis without considering the *Net_COVID-19_effect*. More specifically, we exclude the *Net_COVID-19_effect* from the initial pool of variables and select the best subset of explanatory variables for the general, industry-based, and size-based models in our analysis. Appendix A (Table A1) presents a summary of the results for the prediction models of interest. After mapping the estimated probabilities of default to the corresponding CQS, we computed the divergence of these ratings from those initially estimated. Notably, the divergence is defined as the CQS rating estimated with the *Net_COVID-19_effect* minus the rating estimated without

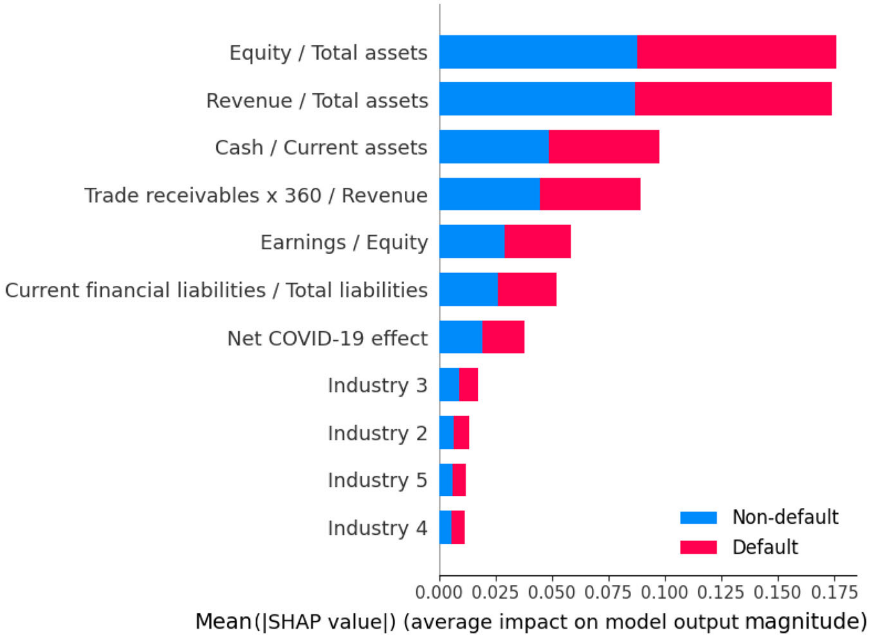

FIGURE 4 Micro firms model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

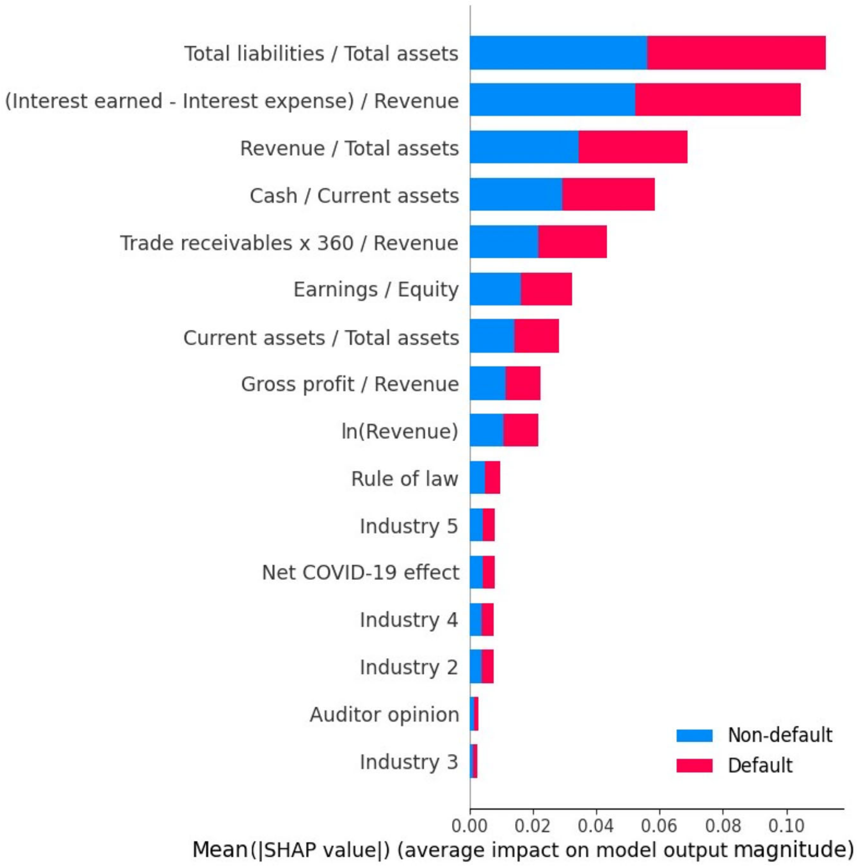

FIGURE 5 SML firms model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

this variable. For example, a divergence of 0 means that the COVID-19 measures have no impact on the estimated probability of default, whereas a divergence of −1 implies that the inclusion of *Net_COVID-19_effect* results in a better rating with a difference of one point on the scale. Table 13 reports the percentage of observations moving to a specific credit rating class, as a difference in CQSs, when the *Net_COVID-19_effect* is not taken into consideration for each model. In 2021, we observe that on average around 31% and 1% of the ratings for the general model

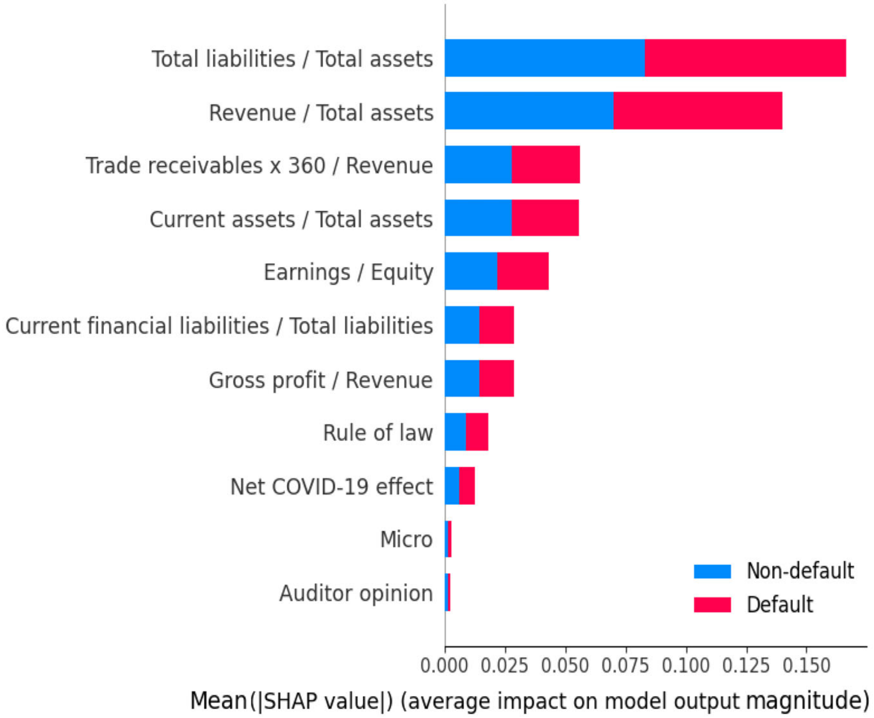

FIGURE 6 Industry 1 model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

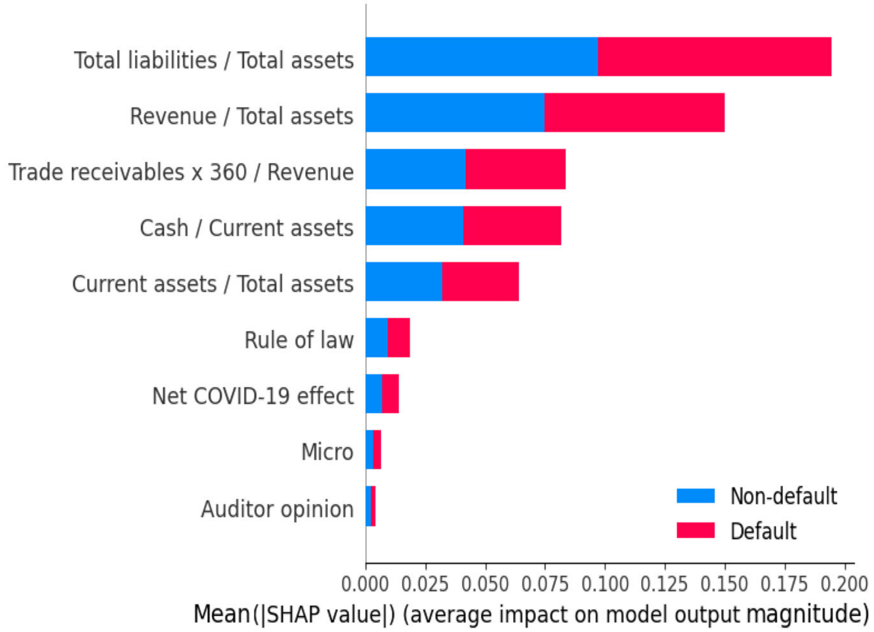

FIGURE 7 Industry 2 model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

have a divergence of −1 and −2, respectively, confirming our main finding. Consistent with the baseline analysis, the greatest negative divergences, even of three points on the scale, are reported for micro firms and firms in the services sector.

To further assess the robustness of our empirical results, we adopt an alternative measure to explore the government response during the pandemic crisis. More specifically, since our *Net_COVID-19_effect* dummy captures the net effect of the COVID-19 pandemic and the financial support measures taken by the Greek government, the Oxford COVID-19 Government Response Tracker (OxCGRT), the government response index, is used instead. The OxCGRT dataset was collected by a team of more than 1500 volunteers and published in real-time to understand the variations in government responses to the pandemic. Table 14 reports the results of the estimations of logistic regression models after having replaced the *Net_COVID-19_effect* variable with the *Government_response_index* in Greece (dataset last revised in

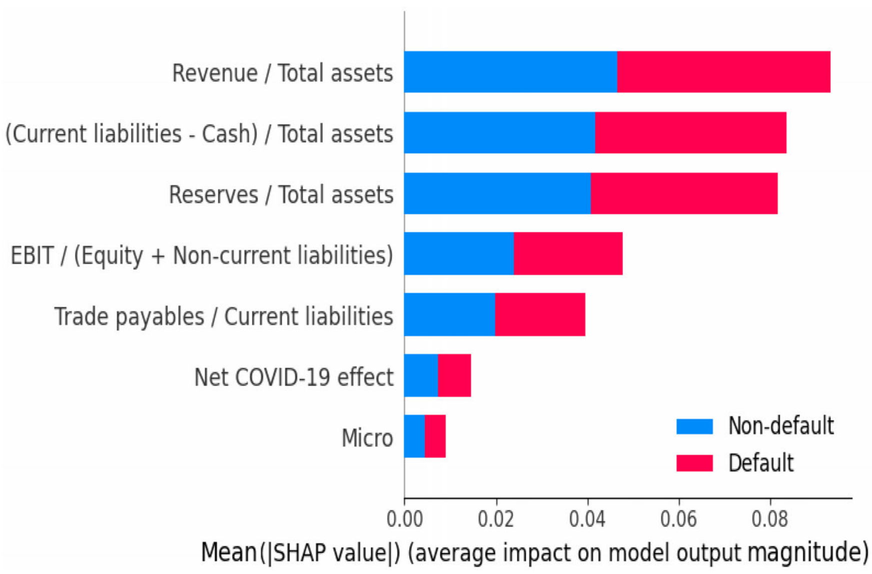

FIGURE 8 Industry 3 model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

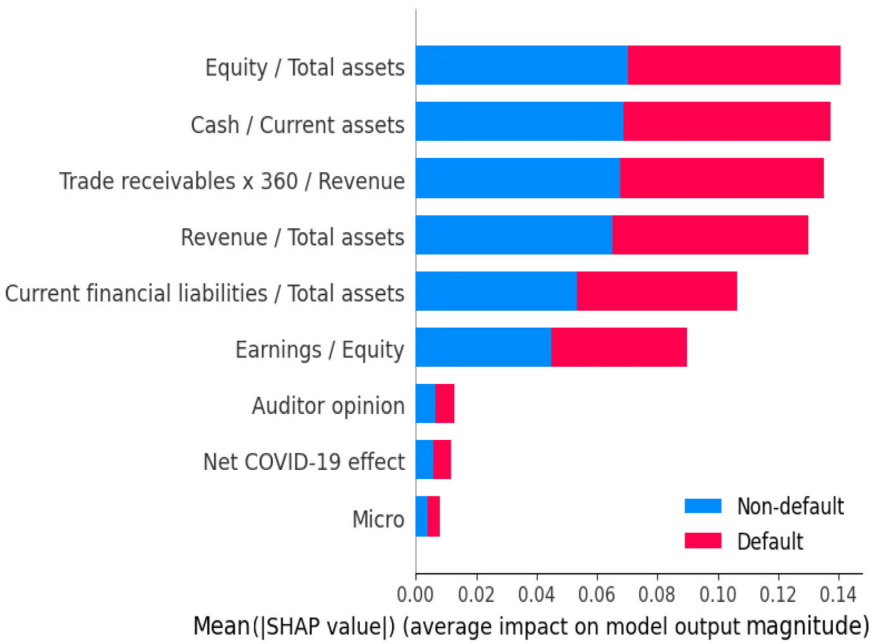

FIGURE 9 Industry 4 model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

June 2023), where column 1 is attributed to the general model, columns 2 and 3 to the size-based models, and columns 4–8 to the industry-based models. As the results of Table 14 reveal, the *Government_response_index* variable is highly statistically significant in each of the logistic regression models and has a negative sign. In addition, the value of the coefficient on the *Governement_response_index* is the highest for micro firms and firms in the services sector, confirming our study findings.

Finally, to examine all possible determinants that can potentially influence the probability of default of Greek firms, we have also included in our econometric setting, as a control variable, the type of company with a special focus on 'Société Anonyme' (SA). In Table 15, we perform the same regressions as in Table 5, the only difference being the addition of SA dummy. More specifically, we consider the SA dummy variable that takes the value of 1, if the legal form of the entity is public limited liability company ('Société Anonyme') and 0 if the entity can take any of the following forms: limited liability company, private capital company, and limited partnership. Based on the results in Table 15, we find that the legal form of SA has a positive and highly statistically significant impact on the probability of default of Greek firms, except for firms in the utilities, transport, and storage sector and firms in the services sector. Since private firms depend more on trade credit than public companies (Abdulla et al., 2017), our findings are in line with those

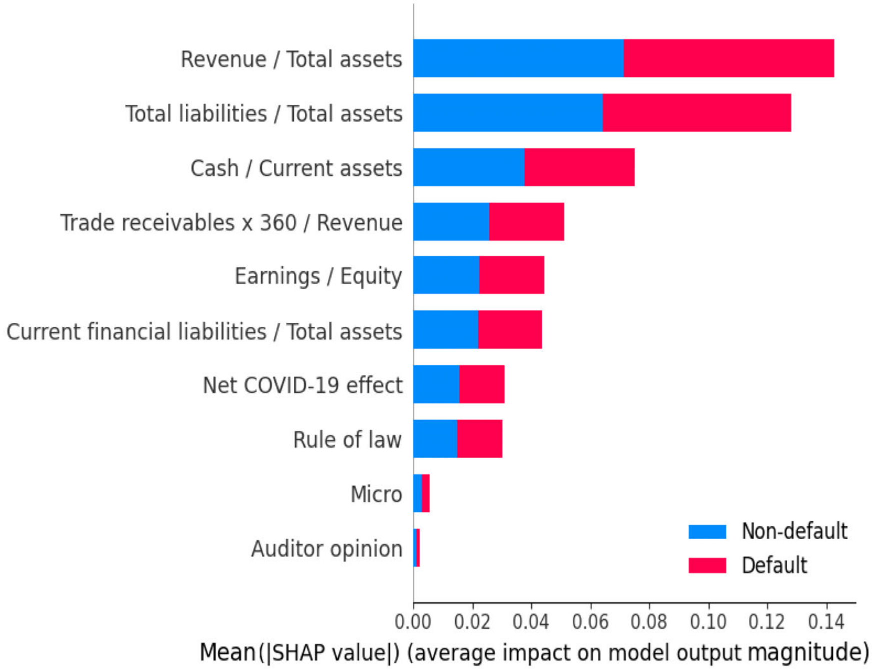

FIGURE 10 Industry 5 model. Feature importance computed with SHAP values from the random forest. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 13 Robustness check: transition matrix analysis with and without the COVID-19 effect.

2021—Rating grade deviation				
CQS with COVID-19—CQS without COVID-19	**−3**	**−2**	**−1**	**0**
General model	0	1.10	30.90	68.00
Micro	0.44	11.09	35.03	53.44
SML	0	0.18	29.80	70.02
Industry 1	0	0	26.41	73.59
Industry 2	0	0.73	32.64	66.63
Industry 3	0	4.60	43.29	52.11
Industry 4	0	0	17.82	82.18
Industry 5	0.24	9.80	34.46	55.50

Note: The assignment to CQSs estimated with *Net COVID-19 effect* is compared to the assignment to CQSs without this effect. The table reports the percentage of observations moving to a different credit rating class, by the difference in credit quality steps (CQSs), when *Net COVID-19 effect* is not included. Eurosystem's credit quality steps (CQSs) are divided into eight grades. A higher CQS indicates a greater predicted probability of default, denoting a worse credit rating for the firm. All values are in percentages and each row adds up to 100%.

of McGuinness et al. (2018), suggesting that trade financing is negatively related to default risk.

6 | CONCLUSION

The main motivation of this study emerges from the need to effectively estimate the credit ratings of Greek firms in an ICAS framework, consistent with that of the Bank of Greece. In pursuing this objective, we contribute to the literature in two ways. First, we consider the effects of the COVID-19 pandemic and the policy responses on credit risk at the aggregate level and across industries and different-sized firms. Second, we address several aspects of ICASs' development, including the class imbalance problem and the relative predictive ability of traditional versus machine learning approaches.

To do this, we create several industry- and size-based models, in addition to the general/baseline model, using the logistic regression approach. Our sample size is determined by the availability of AnaCredit data and includes the start of the COVID-19 pandemic. We examine how the probability of default of Greek firms changes during the pandemic period, using a dummy to capture the net

TABLE 14 Econometric estimation of models with Government response index.

Variables	General	Size-based Micro	 SML	Industry-based Industry 1	 Industry 2	 Industry 3	 Industry 4	 Industry 5
Equity/Total assets		−2.317*** (−11.33)					−2.758*** (−7.89)	
Total liabilities/Total assets	3.673*** (34.20)		3.826*** (26.79)	4.178*** (22.93)	4.515*** (17.02)			2.766*** (13.79)
Current financial liabilities/Total liabilities		0.839*** (2.96)		0.551*** (2.82)				
Current financial liabilities/Total assets							3.175*** (4.76)	1.243*** (3.21)
Cash/Total assets	−1.364*** (−4.96)							
(Current liabilities − Cash)/Total assets						2.596*** (4.75)		
Cash/Current assets		−0.837** (−2.56)	−1.100*** (−5.44)		−1.203*** (−2.62)		−2.302*** (−4.71)	−0.758*** (−3.20)
Current assets/Total assets	−0.535*** (−3.97)		−1.066*** (−6.26)	−1.919*** (−8.46)	−1.124*** (−3.57)			
Reserves/Total assets						−1.639*** (−3.17)		
Earnings/Equity	−0.301*** (−3.79)	−0.487*** (−2.74)	−0.286*** (−2.94)	−0.237** (−1.98)			−0.792** (−2.23)	−0.359*** (−3.11)
(Interest earned − Interest expense)/Revenue			−2.984*** (−4.04)					
Trade payables/Current liabilities						1.079** (2.27)		
Trade receivables × 360/Revenue	0.002*** (11.42)	0.000*** (4.00)	0.002*** (7.51)	0.002*** (8.43)	0.002*** (6.16)		0.001*** (3.23)	0.001*** (3.11)
Revenue/Total assets	−1.311*** (−18.59)	−1.990*** (−10.12)	−1.022*** (−11.87)	−1.031*** (−10.89)	−1.887*** (−9.27)	−1.622*** (−5.51)	−1.695*** (−7.13)	−1.595*** (−11.27)
Gross profit/Revenue	−0.437*** (−3.40)		−0.420** (−2.58)	−1.121*** (−3.68)				
EBIT/(Equity + Non-current liabilities)						−1.389** (−2.49)		
ln(Revenue)			−0.088*** (−2.80)					
Rule of law	−15.217*** (−4.72)		−15.637*** (−4.00)	−14.888*** (−2.76)	−17.315** (−2.45)			−16.057** (−2.44)
Auditor opinion	−0.983*** (−6.22)		−0.955*** (−5.33)	−0.660** (−2.54)	−1.255*** (−3.31)		−1.646*** (−3.57)	−0.680** (−2.14)
	−0.012* (−9.35)**	**−0.020*** (−5.34)**	**−0.010*** (−6.61)**	**−0.008*** (−4.24)**	**−0.011*** (−4.05)**	**−0.012** (−2.04)**	**−0.008* (−1.91)**	**−0.019*** (−6.45)**

TABLE 14 (Continued)

Variables	General	Size-based Micro	 SML	Industry-based Industry 1	 Industry 2	 Industry 3	 Industry 4	 Industry 5
Government response index								
Constant	6.815*** (3.46)	0.602*** (2.74)	8.252*** (3.39)	6.763** (2.06)	8.084* (1.88)	−1.623*** (−6.07)	1.079*** (3.86)	7.346* (1.83)
Size FE	YES	NO	NO	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO	NO	NO
Observations	14,549	1681	11,239	5958	3133	845	973	3226
R-pseudo	0.401	0.464	0.384	0.432	0.476	0.249	0.475	0.327
Brier score	0.086	0.100	0.079	0.078	0.086	0.070	0.117	0.090
AIC improvement	−3612.6	−543.4	−2505.1	−1616.7	−1021.8	−88.2	−356.0	−615.2

Note: This table reports the results of the estimations of logistic regression models, where column 1 is attributed to the general model, columns 2 and 3 to the size-based models, and columns 4–8 to the industry-based models. The Government response index refers to the Oxford COVID-19 Government Response Tracker (OxCGRT) for Greece (dataset last revised in June 2023). The dependent variable is the default dummy that equals 1 if the borrower-lender-month default indicator is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Heteroskedasticity-robust z-statistics are reported in parentheses. The bold shows the scores of the variables that are of the main interest and explained in the text.

effect of the COVID-19 pandemic and the financial support measures taken by the Greek government. Our empirical findings indicate a strong negative relationship between the *Net_COVID-19_effect* variable and firms' probability of default. The findings of the size-based and sectoral analyses reveal that micro firms and firms in the “services” industries benefited the most from government support. This finding is consistent with the government's stated policy objectives because the services sector was among the sectors of the Greek economy that was most directly affected by the pandemic, and thus the sector that received the most funding.

On the methodological front, and given that all ICASs have imbalanced datasets, we address the class imbalance problem. We show that the accuracy score measure may be insufficient to fully reflect the actual performance of the predictive models. In this regard, we show that it is vital to evaluate the models using balanced accuracy instead of normal accuracy, because it is considered a better measure of classifier performance when the classes are highly imbalanced. Finally, we use our ICAS model to evaluate the trade-offs that emerge between the transparency features of traditional models—specifically logistic regression—and the high predictive power of machine learning models. We show that the combination of features of a pure logistic approach with a suitable machine learning technique for classification problems such as random forest may be the best option for this task.

Several NCBs within the Eurosystem are currently in the process of developing ICAS frameworks. The findings of this study could inform this process by demonstrating how to efficiently assess credit ratings through an ICAS, especially in demanding environments such as the COVID-19 pandemic. Moreover, commercial banks may be interested in the development of such models to augment their IRB methodologies, whereby banks decide whether to lend to firms based on credit rating estimations. From an economic policy perspective, the proposed models may prove useful to government policymakers who are interested in a decision tool that guides them to financially support firms in a crisis period, aiming to reduce firms' probability of default. Finally, the successful use of government financial measures to support non-financial firms can inform policy debates concerning potential future shocks. In general, the construction of an effective in-house credit assessment system can constitute an integral part of central banks' monetary and financial stability policies, reducing reliance on external sources of default risk assessment.

Credit risk modelling through ICAS constitutes an important pillar of the Eurosystem's collateral framework and the Euro area central banks will be developing them further in the years to come as a basis for designing monetary and financial stability policies. ICASs also offer other advantages for the Eurosystem as they promote the transmission of monetary policy measures to the real

TABLE 15 Econometric estimation of models with SA dummy.

		Size-based		Industry-based				
Variables	**General**	**Micro**	**SML**	**Industry 1**	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Equity/Total assets		−2.405*** (−11.49)					−2.855*** (−8.06)	
Total liabilities/Total assets	3.743*** (34.41)		3.881*** (26.96)	4.245*** (23.06)	4.567*** (17.08)			2.766*** (13.75)
Current financial liabilities/Total liabilities		0.864*** (3.03)		0.466** (2.36)				
Current financial liabilities/Total assets							3.195*** (4.76)	1.243*** (3.21)
Cash/Total assets	−1.178*** (−4.25)							
(Current liabilities − Cash)/Total assets						2.718*** (4.87)		
Cash/Current assets		−0.774** (−2.35)	−1.044*** (−5.14)		−1.064** (−2.30)		−2.135*** (−4.32)	−0.758*** (−3.20)
Current assets/Total assets	−0.473*** (−3.49)		−1.001*** (−5.84)	−1.757*** (−7.60)	−1.052*** (−3.31)			
Reserves/Total assets						−1.733*** (−3.30)		
Earnings/Equity	−0.281*** (−3.51)	−0.454*** (−2.52)	−0.259*** (−2.64)	−0.202* (−1.67)			−0.803** (−2.23)	−0.359*** (−3.11)
(Interest earned − Interest expense)/Revenue			−2.848*** (−3.84)					
Trade payables/Current liabilities						1.133** (2.36)		
Trade receivables × 360/Revenue	0.002*** (11.19)	0.000*** (3.93)	0.002*** (7.23)	0.002*** (7.98)	0.003*** (6.15)		0.001*** (3.24)	0.001*** (3.11)
Revenue/Total assets	−1.275*** (−18.02)	−1.860*** (−9.33)	−0.974*** (−11.23)	−1.014*** (−10.69)	−1.814*** (−8.81)	−1.582*** (−5.43)	−1.561*** (−6.43)	−1.595*** (−11.05)
Gross profit/Revenue	−0.410*** (−3.18)		−0.395** (−2.41)	−1.065*** (−3.48)				
EBIT/(Equity + Non-current liabilities)						−1.300** (−2.30)		
ln(Revenue)			−0.119*** (−3.66)					
Rule of law	−15.091*** (−4.67)		−15.559*** (−3.98)	−14.883*** (−2.75)	−17.040** (−2.41)			−16.057** (−2.44)
Auditor opinion	−1.026*** (−6.48)		−0.960*** (−5.36)	−0.730*** (−2.81)	−1.300*** (−3.43)		−1.718*** (−3.73)	−0.680** (−2.14)
Net COVID-19 effect	−0.635*** (−9.39)	−1.077*** (−5.29)	−0.522*** (−6.61)	−0.440*** (−4.23)	−0.588*** (−4.12)	−0.668** (−2.07)	−0.413* (−1.83)	−1.000*** (−6.44)

TABLE 15 (Continued)

Variables	General	Size-based: Micro	Size-based: SML	Industry-based: Industry 1	Industry 2	Industry 3	Industry 4	Industry 5
SA dummy	**0.497*** (5.87)**	**0.563*** (2.93)**	**0.453*** (4.25)**	**0.490*** (4.01)**	**0.702*** (3.03)**	**0.567 (1.46)**	**0.936** (2.46)**	**−0.000 (−0.00)**
Constant	6.189*** (3.13)	0.177 (0.67)	8.151*** (3.34)	6.205* (1.88)	7.129* (1.65)	−2.193*** (−4.61)	0.150 (0.32)	7.347* (1.83)
Size FE	YES	NO	NO	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO	NO	NO
Observations	14,549	1681	11,239	5958	3133	845	973	3226
R-pseudo	0.404	0.470	0.387	0.436	0.480	0.254	0.482	0.327
Brier score	0.086	0.099	0.079	0.077	0.085	0.069	0.116	0.090
AIC improvement	−3646.9	−550.3	−2522.1	−1631.5	−1030.0	−88.5	−360.8	−613.2

Note: This table reports the results of the estimations of logistic regression models, where column 1 is attributed to the general model, columns 2 and 3 to the size-based models, and columns 4–8 to the industry-based models. SA dummy equals 1 if the legal form of the entity is public limited liability company ('Société Anonyme'), and 0 otherwise. The dependent variable is the default dummy that equals 1 if the borrower-lender-month default indicator is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Heteroskedasticity-robust z-statistics are reported in parentheses. The bold shows the scores of the variables that are of the main interest and explained in the text.

economy, especially to small and medium-sized enterprises (SMEs) that do not issue marketable securities. Furthermore, helping the pledge of credit claims contributes to diversifying risk in the Eurosystem area. The research challenges that emerge include (i) considering environmental, social, and governance (ESG) variables as potential factors in predicting credit risk, (ii) using soft information (e.g., textual information from annual reports), and (iii) utilizing the potential of other machine learning models, such as support vector machines and recurrent neural networks.

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CONFLICT OF INTEREST STATEMENT

The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Bank of Greece. No conflict of interest exists in the submission of this manuscript, and this manuscript is approved by all authors for publication.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Bank of Greece. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of Bank of Greece.

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ENDNOTES

[1] Abbreviations: AIC, Akaike information criterion; CBSO, Central Balance Sheet Office; CQS, Credit quality step; ICAS, In-house credit assessment system; IRB, internal ratings-based; NCB, national central bank; SHAP, SHapley Additive exPlanations; SML firms, small, medium, and large firms.

[2] NACE Rev.2 – European Commission.

[3] Micro entities are entities which at the balance sheet date do not exceed the limits of at least two of the following three criteria: (a) Total assets: 350.000 euros, (b) Net turnover: 700.000 euros, (c) Average number of employees during the reporting period: 10 people.

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APPENDIX A

TABLE A1 Econometric estimation of models without the *Net COVID-19 effect*.

Variables	General	Size-based: Micro	Size-based: SML	Industry-based: Industry 1	Industry 2	Industry 3	Industry 4	Industry 5
Equity/Total assets		−2.284*** (−11.30)					−2.730*** (−7.85)	
Total liabilities/Total assets	3.641*** (33.98)		3.787*** (26.63)	4.189*** (23.01)	4.476*** (16.97)			2.587*** (13.29)
Current financial liabilities/Total liabilities	0.455*** (3.72)	0.884*** (3.15)		0.599*** (3.07)				
Current financial liabilities/Total assets							3.237*** (4.86)	1.301*** (3.44)
Cash/Total assets	−1.809*** (−6.64)				−2.082*** (−2.86)			
(Current liabilities − Cash)/Total assets						2.651*** (4.91)		
Cash/Current assets		−1.078*** (−3.33)	−1.386*** (−6.96)				−2.440*** (−5.00)	−1.257*** (−5.72)
Current assets/Total assets	−0.582*** (−4.32)		−1.155*** (−6.82)	−1.978*** (−8.75)	−0.911*** (−2.78)			
Reserves/Total assets						−1.660*** (−3.23)		
Earnings/Equity	−0.277*** (−3.52)	−0.404*** (−2.33)	−0.279*** (−2.90)	−0.233* (−1.96)			−0.777** (−2.19)	−0.283** (−2.56)
(Interest earned − Interest expense)/Revenue			−2.885*** (−3.94)					
Trade payables/Current liabilities						1.019** (2.16)		
Trade receivables × 360/Revenue	0.002*** (11.24)	0.000*** (3.78)	0.002*** (7.31)	0.002*** (8.63)	0.003*** (6.43)		0.001*** (3.14)	
Revenue/Total assets	−1.239*** (−17.80)	−1.985*** (−10.19)	−0.973*** (−11.45)	−0.998*** (−10.67)	−1.826*** (−9.09)	−1.617*** (−5.48)	−1.709*** (−7.21)	−1.575*** (−11.80)
Gross profit/Revenue	−0.335*** (−2.64)		−0.323** (−2.01)	−1.107*** (−3.64)				
EBIT/(Equity + Non-current liabilities)						−1.316** (−2.44)		

(Continues)

TABLE A1 (Continued)

Variables	General	Size-based: Micro	Size-based: SML	Industry-based: Industry 1	Industry 2	Industry 3	Industry 4	Industry 5
ln(Revenue)			−0.090*** (−2.86)					
Rule of law	−16.645*** (−4.99)		−17.166*** (−4.26)	−16.208*** (−2.92)	−18.989*** (−2.62)			−18.042*** (−2.63)
Auditor opinion	−1.020*** (−6.46)		−0.981*** (−5.47)	−0.653** (−2.53)	−1.263*** (−3.34)		−1.642*** (−3.58)	−0.811** (−2.56)
Constant	7.405*** (3.64)	0.410* (1.91)	9.129*** (3.64)	7.415** (2.19)	8.789** (1.99)	−1.799*** (−7.01)	0.992*** (3.60)	8.710** (2.08)
Size FE	YES	NO	NO	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	NO	NO	NO	NO	NO

Note: This table reports the summary of results after excluding the *Net COVID-19 effect* from the variable selection process. The dependent variable is the default dummy that equals 1 if the borrower-lender-month default indicator is 1 for at least 1 month within a 12-month period after the CBSO date (fiscal year), and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Heteroskedasticity-robust z-statistics are reported in parentheses.