Early Warning Systems for financial crises prediction in private companies: Evidence from the Italian context

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Abstract

Purpose: This study compares models for predicting business financial crises, focusing on which are most effective. In light of the new European Directive on business failure, it highlights a trade-off between predictive accuracy and timeliness in static models and offers an alternative approach.
Design/methodology/approach: This study examines the Italian early warning system (EWS), testing static alert indicators' predictive ability on a large sample of private companies. It then proposes a dynamic version of the EWS.
Findings: The results show a trade-off between predictive ability and timeliness for static models. In contrast, a dynamic system is more accurate in predicting crisis events, allowing managers to take corrective actions.
Originality: The results highlight the limitations of static prediction models and emphasize the potential of a simple dynamic model that is specifically designed for small- and medium-sized entities (SMEs).
Practical implications: This study proposes a dynamic model tailored for SMEs, which are particularly vulnerable to financial crises. This insight can help managers and policymakers balance accurate predictions with timely interventions, especially in European countries implementing crisis prediction models.

Keywords: corporate failure; early warning systems; crisis; crisis prediction

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1. Introduction

Private companies represent the core of developed economies, making up over 99% of commercial firms in the European Union (EU; European Commission, 2023). Compared with listed companies, private firms face less market pressure, and they usually rely on limited human and financial resources. Accordingly, they are more exposed to bankruptcy events (Charalambakis & Garrett, 2019). Despite their limited market value, private firm bankruptcies impose significant economic and social costs on various stakeholders. Banks, the primary financing source for these firms (Lin et al., 2012), face risks; employees experience income reductions (Bauweraerts, 2016); and auditors contend with potential legal disputes (De Meyst et al., 2020; Laitinen & Kankaanpaa, 1999). Within this context, the availability of reliable predictive models of financial crisis events, such as Early Warning Systems[1] (EWSs), which enable the proactive implementation of preventive and corrective measures, is essential for safeguarding stakeholders' interests and ensuring the long-term viability of businesses.

From the seminal studies of Beaver (1966) and Altman (1968), a wide stream of literature has studied EWSs for company crisis events, which have been classified based on their statistical methods. The classical methods are based on the selected ratios and cutoff values identified by univariate prediction models, which assume a linear relationship between failure probability and the selected values. These indicators are referred to as *static* (Jones, 2023) and are based only on the short term. These limitations are overcome via the use of multivariate statistical models built on longitudinal data, which are referred to as *dynamic* (Jones, 2023). These predictors offer higher reliability and adaptability over time.

European countries are now implementing new regulations on financial crisis and insolvency following the European Directive (European Union,

[1] Early Warning System (EWS) includes all methods used to early predict (detect) potential financial difficulties, aiming to identify problems before they fully materialize into a crisis. The goal is to provide timely alerts that allow managers or regulators to intervene and take corrective actions to prevent financial downturn. They differ from Financial Distress Prediction (FDP) models that focus on assessing the likelihood that a company will experience financial distress within a specific time frame, typically leading to insolvency, bankruptcy, or significant financial restructuring. The goal is to quantify the risk of financial failure.

2019), which introduces EWSs (country by country) to increase restructuring options for companies' survival. However, Directive prescriptions are minimal, and European countries are moving forward with the implementation of EWSs via different methods and approaches, often creating frictions among countries without, currently, the definition of the best system.

This study capitalizes on Italy's adoption of the new Code of Business Default and Crisis (CBDC) (Italian Republic, 2019)[2]. The Code aimed to align Italian insolvency law with the European Directive by focusing on early detection of financial distress and providing mechanisms for restructuring viable business before insolvency occurs. Italy's reform introduces new tools for early crisis detection, making it one of the leading countries in implementing EU standards. Specifically, the CBDC alert system uses a set of indicators to predict impending crises and insolvency.

The CBDC alert system is the core of this research, with a focus on its accuracy – intended at the ability to signal crisis status – and lowering the number of false positives in predicting a serious financial crisis.

Therefore, this leads to the following research questions: (*i*) Are static EWSs based on alert indicators accurate in predicting the crisis status of private companies? (*ii*) *Ceteris paribus*, do dynamic EWSs built on the same indicators present greater accuracy than static EWSs do?

The empirical analysis is conducted on panel data composed of 18,863 Italian limited liability private companies that published financial statements over the period 2010-2019 (140,469 firm-year observations).

Panel logistic regression results reveal structural issues with the CBDC alert system, indicating that the predictive ability of static models is limited to the short term, with accuracy diminishing over time. This pattern holds for the Altman Z score, adjusted for private firms, which serves as a control model. To improve accuracy, this study proposes a dynamic EWS based on the same CBDC indicators. The results show that the dynamic model significantly outperforms the static models, especially in terms of medium-term predictions.

Our analysis provides several contributions.

This study contributes to the literature on small- and medium-sized enterprises (SMEs) by proposing an alternative methodological approach to implement a dynamic EWS based on a set of alert indicators.

Traditional financial crisis prediction models, such as Altman's Z score, use static financial ratios at a single point in time. Although these models have been studied for their predictive abilities, they face criticism because

[2] The Italian CBDC was issued in 2019 and become fully enforced in December 2023.

they do not capture ongoing financial changes (Agarwal & Taffler, 2008; Hillegeist et al., 2004; Shumway, 2001). This paper introduces a dynamic model using time series data and compares it to static models. The analysis uses panel logistic regression (LR) on a wide sample, testing medium-term financial crisis predictors and addressing the research gaps highlighted by Munoz-Izquierdo et al. (2019).

Additionally, most research has focused on large firms (Campbell et al., 2008; Charitou et al., 2004; Tinoco & Wilson, 2013), with fewer studies on SMEs (Bava et al., 2020; Ciampi et al., 2021). This study replicates existing methodologies on a large sample of SMEs, recognizing their unique financial dynamics and specifically contributing to the ongoing debate about the enforcement of EWSs in Italy (Bava et al., 2020). More specifically, to test the accuracy of the proposed Italian EWS, we replicate the approach suggested by Jemovic and Marinkovic (2019), which analyzed 64 crisis events in the banking industry, on a large sample of private firms involved in 1,528 crisis events.

Situating the study within the context of Italy's CBDC reform also highlights the role of legal frameworks in shaping financial distress models. The findings provide insights for all European countries that will implement the Directive in the coming years.

Finally, the study contributes to practitioners, since the alternative dynamic model proposed in this study provides evidence of the real signs of crisis status, helping reduce the socioeconomic costs related to false positives signaled by EWSs based on static models.

The remainder of this paper proceeds as follows. Section 2 presents the literature, theoretical framework, and hypotheses. Section 3 illustrates the methodology, including sample selection and the explanatory variables. Section 4 presents descriptive statistics and results, while in Section 5, robustness checks and additional analyses are presented. Finally, Section 6 draws conclusions.

2. Literature review and hypotheses development

2.1. Financial distress and bankruptcy

Since Altman's (1968) pioneering research, company failure has often been classified as either failed or nonfailed. Despite researchers considering different perspectives (juridical, financial, economic and econometric), a universally accepted definition of company crises is still lacking (Veganzones & Severin, 2020). Although the legal bankruptcy perspective has been predominant, it is characterized by a relevant drawback, as it cannot differentiate whether a bankruptcy declaration emerges due to financial issues or other reasons (Balcaen & Ooghe, 2006). It also overlooks the time between a company's financial troubles and the eventual declaration of bankruptcy, which may occur long after actual insolvency.

Sun et al. (2014) provide both theoretical and empirical perspectives. Theoretically, financial distress can range from temporary cash flow shortages to severe insolvency, potentially leading to bankruptcy. Empirically, it is useful to identify clear and indisputable criteria to define distressed companies. From this perspective, financial distress can be identified by bankruptcy or arrangements with creditors. In the same stream of research, Platt and Platt (2006) emphasize that while financial distress often precedes bankruptcy, it does not inevitably result in bankruptcy. Financial distress occurs when a company struggles to meet its financial commitments, typically due to issues such as insufficient cash flow, falling profitability, or high levels of debt. Nevertheless, numerous companies experiencing financial distress manage to avert bankruptcy by pursuing strategies such as restructuring, selling off assets, or implementing other corrective measures. Finally, Habib et al. (2020) further explore the internal (e.g., poor financial management, high debt) and external (e.g., economic downturns, industry disruptions) factors that increase financial distress risk, highlighting the need to differentiate between distress and bankruptcy for effective risk management.

2.2. Early warning system and financial distress prediction model in the literature

Within the business crisis research area, a broad body of literature has been developed to predict companies' financial distress via their current financial information. These prediction models are typically divided into three categories: artificial intelligence methods, ensemble techniques and statistical methods. In recent decades, artificial intelligence methods have gained popularity (Atiya, 2001; Kim & Upneja, 2014; Li & Sun, 2008; Liang et al., 2015; Min & Lee, 2005; Wang et al., 2015) since they are not based on causality assumptions but rather on learning from data.

In parallel, the use of ensemble models has also increased in financial distress prediction studies (Chuang, 2013; Sun et al., 2011). Compared with any individual learning algorithm, an ensemble system integrates multiple algorithms to increase the predictive accuracy. Ensemble techniques are generally categorized into two groups: "hybrid methods" and "ensemble-based techniques". Balcaen and Ooghe (2006) provide one of the most comprehensive reviews of statistical prediction techniques in this domain.

According to the CBDC alert system requirements, previous methodological approaches are not suitable for capturing the phenomenon under investigation. Statistical methods that rely on causality assumptions are considered more appropriate. The use of single statistical methods, including univariate analysis, linear discriminant analysis (DA), multivariate discriminant analysis (MDA), quadratic discriminant analysis, linear regression and factor analysis, is prominent in empirical studies of financial distress prediction (Sun et al., 2014).

The univariate prediction model, for example, estimates a threshold for selected financial ratios, applying a classifier to assess a company's likelihood of failure based on these ratios. These methods, however, use static systems, relying on fixed financial data snapshots (typically the most recent financial statement). While easy to implement, they fail to account for evolving trends or risks over time. This static nature introduces several limitations.

First, they cannot embody both the effect of (*i*) structural changes over time and (*ii*) the interactions among predictors, as they are not necessarily based on regression models. Second, such approaches do not consider the time frame between the occurrence of crisis signs and crisis events. Among multivariate models, DA is still popular (Canbas et al., 2005; Serrano-Cinca & Gutiérrez-Nieto, 2013), although linear regression is the prevailing method used (Barniv et al., 2000; Foreman, 2003; Munoz-Izquierdo et al., 2019; Tseng & Lin, 2005), as it requires fewer statistical constraints than does DA.

Altman (1968) was one of the first to apply MDA for financial distress prediction, developing the well-known Z score model, which demonstrated increased predictive ability compared with univariate models, especially in the year before company failure.

The earliest use of a logistic probability model for predicting company distress was by Ohlson (1980), who reported that it is more accurate than the MDA model. The logit model is favored for its ability to handle a noncontinuous dependent variable (financial distress probability) and does not require normally distributed covariates. Binomial logit models are standard but face crisis duration bias, as they assume that all crises last the same time (Jemović & Marinković, 2019). To address this, a multinomial approach can specify the year a crisis begins (Bussiere & Fratzscher, 2006; Caggiano et al., 2014, 2016; Hamdaoui, 2016). Studies also suggest the use of lagged dependent variables and logistic panel regression to develop a dynamic EWS (Candelon et al., 2014).

Assuming that an accurate model must balance both predictive ability (the likelihood of correctly identifying a crisis event) and timeliness (issuing early warnings that allow for corrective actions), the following hypothesis is proposed:

H1a: For a ***static*** *EWS, there is a tradeoff between its predictive ability and timeliness.*

Static models, regardless of how crisis signs are defined, use a fixed set of variables to predict crises. For example, the CBDC alert system sets thresholds via static data, ignoring changes in a company's financial condition over time. In contrast, dynamic models capture interactions among variables and account for time lags. The literature suggests that dynamic systems are more accurate than static systems because they use regression models (Atiya, 2001). To test the predictive ability of the dynamic EWS, the following hypothesis is proposed:

H1b: Ceteris paribus, a ***dynamic*** *EWS presents a greater level of accuracy than does a static EWS.*

Dynamic systems, by definition, use time series data to track how financial indicators change over time. This flexibility allows them to adjust to new information continuously, capturing short-term fluctuations and offering more timely warnings. Although more complex, dynamic systems allow for tracking the trajectory of a company's financial health, detecting early signs of deterioration or improvement, and thus providing more accurate predictions.

3. Methodology

3.1. Research setting

In line with CBDC regulation, the empirical analysis is based on the following selected indicators: (*i*) negative net equity, (*ii*) a six-month debt service coverage ratio (DSCR) less than 1, and (*iii*) joint exceedance of the thresholds of five industry-specific indicators. The system is hierarchical and thus is applied based on a preselected pattern. If the first indicator (*i*) is not exceeded, the second (*ii*) is verified. If the threshold is exceeded, a crisis is hypothesized, which places the company in an alert status. If the first two indicators are not available, the analysis is conducted on a set of industry-specific indicators that have been identified by the National Council of Chartered Accountants.

For companies presenting negative net equity (*NEG_EQUITY*), the risk of a crisis is manifested; this parameter is used as a fundamental indicator in the CBDC alert system, although there are many doubts about its real usefulness in predicting crisis phenomena. By law (Civil Code), in fact, several automatic mechanisms already exist that are activated when excessive losses erode net equity, even well before net equity becomes negative. Consequently, the use of this parameter does not represent any significant novelty in the alert system.

The DSCR is calculated as the ratio of the expected free cash flow (six months) to the debts due within the same period. If the resulting value is greater than one, then the estimated capacity to sustain debts over a six-month period is verified; in contrast, if the value is lower than one, a relative inability to sustain debts is indicated. Hence, the DSCR may be unavailable or deemed unreliable due to poor prognostic data quality. This is common among small- and medium-sized companies lacking organization in forecasting future cash flows, reducing the applicability of the DSCR as an alert indicator. Given its reliance on future forecasts, DSCR is heavily influenced by subjective judgments, increasing managerial discretion.

Given the circumstances described, the subsequent alert indicators are implemented as an EWS, accounting for various thresholds tailored to industry specificity.

The five industry-specific indicators set by the Council are (*i*) the financial expense ratio (*FIN_EXP_RATIO*), which is calculated as the ratio of total financial expenses to turnover; (*ii*) the equity-to-debt (E/D) ratio (*ED_RATIO*), which is the book value of equity to total debt; (*iii*) the quick ratio (*QUICK_RATIO*), which is the total current assets (including cash and cash equivalents) to total current liabilities; (*iv*) the cash return on assets ratio (*CASH_RET_RATIO*), which is measured by dividing the operating cash flow over total assets; and (*v*) the social and tax debt ratio (*SOC_TAX_RATIO*), which is calculated as the ratio between the value of debts for taxes and social security (both current and noncurrent) to total assets. Without delving into the selection of indicators, it is crucial to emphasize that the pertinent thresholds are determined based on the average of a set of static panel data in accounting. This implies no adjustment over time to accommodate changes in companies' economic and financial conditions within the alert system. To detect crisis status, all the indicators must be considered simultaneously; each indicator that is considered standalone provides only a partial signal of a possible crisis. Consequently, the simultaneous exceeding of all 5 thresholds is required for the early warning of a potential crisis.

3.2. Data collection and empirical models

The empirical analysis focuses on Italian limited liability private companies that published at least one ordinary financial statement under generally accepted accounting principles (GAAPs) from 2010-2019. This period was chosen to avoid impacts from the 2008 global financial crisis and the COVID-19 pandemic. Owing to their limited disclosure levels, the sample excludes small and micro companies that opt for simplified accounting rules per the Italian Civil Code, which hinders the calculation of CBDC indicators. Hence, the sample companies are characterized by the following size requirements: more than € 4.4 million in total assets, more than € 8.8 million in total revenue, and more than 50 employees.

All financial data were collected from the Bureau van Dijk database (AIDA). The resulting sample was composed of 26,027 companies and 154,111 firm-year observations. Moreover, to solve issues related to missing values, companies that published fewer than three financial statements were excluded from the sample (6,583 companies). Finally, owing to their specific accounting regulations and financial statement structures, 581 financial companies were excluded. The final sample used for the empirical analysis is composed of 18,863 companies and 140,469 firm-year observations.

Financial crisis events were identified via a narrow definition: signaled by a public procedure (via a notice to the Chamber of Commerce) involving public authority intervention (judicial or administrative). Voluntary liquidation procedures, which lack identifiable determinants, were excluded. In total, 1,528 financial crisis events were identified during the observation period.

The methodological approach for testing the predictive ability of the alert indicator system is retrospective. Past financial information was used to estimate six alert indicators, whereas the DSCR was excluded because of its reliance on future cash flow forecasts. A company is considered “on alert status” if (i) it has negative net equity or (ii) if, despite having positive net equity, the other five industry-specific indicators exceed their thresholds. The alert status is represented by a binary variable, *ALERT*, equal to 1 if at least one condition is met and 0 otherwise. This status relates to financial crises through two binary variables: *LEAD1*, which equals 1 if the company entered a crisis in the year following observation, and *LEAD2*, which is equal to 1 if a crisis occurred between two and four years after the last observation.

To test the predictive ability of the alert system for companies entering crisis status from 2010 to 2019, a logistic regression (LR) model was used. This panel LR model assumes that the probability of a crisis is related to independent variables, including alert status and control variables, via a logistic cumulative distribution function (Ge & Whitmore, 2009). To evaluate different time spans between the observed year and crisis events, two models were used with *LEAD1* (short-term crisis) or *LEAD2* (medium-term crisis) as the dependent variable.

The independent variable (*ALERT*) is a dummy variable equal to 1 if the company results in an alert status and 0 otherwise. Following Balcaen and Ooghe (2006), we included the following controls: size, measured through the logarithm of a company's total assets of the (*TOT_ASS*); as startup companies have a greater probability of entering a financial crisis, *AGE*, calculated as the difference between the year of observation and the setting-up year, was included. Since the Italian socioeconomic context is strongly influenced by geographic-contextual factors (Putnam et al., 1993), two binary variables (*DUMMY_CENTRE* and *DUMMY_SOUTH*) reflecting the region of settlement of companies (northern Italy is omitted) were included.

To monitor the reliability of financial indicators (Laitinen, 1991; Liou & Yang, 2008), the models also control for accounting quality. Specifically, two dummy variables were included in the analysis: (*i*) *MISSING_FS*, which is equal to 1 if the company has at least one missing financial statement between the first and last statements available in the time frame of observation, and (*ii*) *SPOS_SNEG*, which is equal to 1 if the ratio of net profit/net loss to total assets is between 0% and 2.5%. *MISSING_FS* is used as a proxy for the commitment of the company to publishing reliable financial information, whereas *SPOS_SNEG* is generally recognized as an indicator of earnings management (Burgstahler & Dichev, 1997).

Finally, industry dummies ($SECTOR_n$) were considered (Balcaen & Ooghe, 2006). The indicator system is based on ten industries that are represented through a set of nine dummy variables (industry 1, agriculture, is omitted).

Thus, the empirical model used to test H1a is the following[3]:

[3] Our model includes year fixed effects to consider the impact of other exogenous events (e.g., 2012 sovereign debt crisis) that could affect the occurrence of a crisis event over the observation period.

$$LEAD\ n_{it} = \beta_0 + \beta_1 ALERT_{it} + \beta_2 TOT\_ASS_{it} + \beta_3 AGE_{it} + \beta_4 DUMMY\_CENTRE_i + \beta_5 DUMMY\_SOUTH_i + \beta_6 MISSING\_FS_{it} + \beta_7 SPOSSNEG_{it} + \beta_i SECTOR_n + YEAR_i + \varepsilon_{it}. \quad \text{(i)}$$

To increase the robustness of our findings, we assessed the predictive ability of another established alert indicator system from the literature, Altman's Z score (Altman, 1993)[4] adjusted for private companies, as a control model. Therefore, a dummy variable (*ALTMAN*) to identify distress was built. To test the control model's predictive ability in the short term (*LEAD1*) and medium term (*LEAD2*), the following models were estimated:

$$LEAD\ n_{it} = \beta_0 + \beta_1 ALTMAN_{it} + \beta_2 TOT\_ASS_{it} + \beta_3 AGE_{it} + \beta_4 DUMMY\_CENTRE_i + \beta_5 DUMMY\_SOUTH_i + \beta_6 MISSING\_FS_{it,} + \beta_7 SPOSSNEG_{it} + \beta_i SECTOR_n + YEAR_i + \varepsilon_{it}. \quad \text{(ii)}$$

Aligned with Jemović and Marinković (2019), a dynamic early warning index was constructed using panel LR coefficients. The subsample of companies in crisis status was used to estimate the coefficients of the six alert indicators. The control model includes *LEAD2* as the dependent variable, with independent variables represented by *NEG_EQUITY* (equal to 1 if equity is negative) and the raw values of the five indicators. The dynamic index (representing the logits of the medium-term crisis probability) was derived from significant coefficients across the sample.

Finally, to compare the accuracy of those three models, receiver operating characteristic (ROC) regression was conducted, in which *ALERT* was used as a proxy for the static CBDC alert system, *ALTMAN* was used as a control model, and *INDEX* was used as a proxy for the dynamic EWS.

The dynamic index based on financial indicators considers that medium-sized and large private firms may lack the resources to develop complex predictive systems for financial crises, benefiting from a simpler dynamic system. Furthermore, an index based on regression coefficients allows for flexibility by considering interrelationships between indicators and enabling annual adjustments.

[4] The following formula was applied: Z' = $0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$, where X_1 is the ratio of working capital to total assets, X_2 is the ratio of retained earnings to total assets, X_3 is the ratio of operating income to total assets, X_4 is the ratio of total equity to total debt, X_5 is the ratio of total sales to total assets. To identify distressed companies, we used a cutoff value of 1.23.

Table 1 – Variable definitions

Variable Name	Definition
LEAD1	Dummy variable equal to 1 if the observed company entered into a crisis in the year following the observation and, 0 otherwise
LEAD2	Dummy variable equal to 1 if the observed company entered into a crisis after two years and before four years with reference to the last year of observation and, 0 otherwise
ALERT	Dummy variable equal to 1 if the observed company is on alert according to the CBDC system
ALTMAN	Dummy variable equal to 1 if the value of Z score adjusted for private companies is lower than 1.23
NEG_EQUITY	Dummy variable equal to 1 if the observed company reports a negative value of equity
DU_CBDC	Dummy variable equal to 1 if the observed company reports all five industry-specific indicators on alert and, 0 otherwise
TOT_ASSETS (k€)	Value of total assets
TOT_ASS	Natural logarithm of total assets
AGE	Age of the company (years)
CBDC_INDIC	Number of CBDC indicators on alert (min 0 max 5)
DUMMY_CENTRE	Dummy variable equal to 1 if the observed company is located in central Italy
DUMMY_SOUTH	Dummy variable equal to 1 if the observed company is located in southern Italy
MISSING_FS	Dummy variable equal to 1 if the observed company has at least one missing financial statement between the first and last statements available in the time frame of observation
SPOS_SNEG	Dummy variable equal to 1 if the ratio of net profit/net loss to total assets is between 0 and 2.5%.
INDUSTRY	Industries are identified according to the CBDC classification (10 industries)
FIN_EXP_RATIO	Ratio between total financial expenses and turnover
ED_RATIO	Ratio between the book value of equity and total debt
QUICK_RATIO	Ratio between total current assets (including cash and cash equivalents) and total current liabilities
CASH_RET_RATIO	Ratio between the operating cash flow and total assets
SOC_TAX_RATIO	Ratio between the value of debts for taxes and social security (both current and noncurrent) and total assets
INDEX	Dynamic index calculated as: 1.607+0.764*NEG_EQUITY+0.959*FIN_EXP_RATIO -0.61*CASH_RET_RATIO +0.447*SOC_TAX_RATIO

4. Results and discussion

4.1. Descriptive statistics (whole-sample and subsample analyses)

Table 2 presents some descriptive statistics for the whole sample and for the subsample. As expected, the dispersion of companies' size included in the whole sample is relevant. The companies' average age is equal to 28.5 years. The average number of industry-specific indicators on alert is 0.609 (the absolute number of indicators on alert is represented by the *CBDC_INDIC* variable).

Table 2 – Full sample and subsample – descriptive statistics

This table reports the descriptive statistics for the variables included in the main models. Panel A presents the descriptive statistics for the entire sample. Panel B reports the descriptive statistics for the subsample of companies that entered a crisis event. Detailed variable definitions are provided in Table 1.

		PANEL A (Full Sample)				
Variable	Obs.	Mean	Std. Dev.	p25	p50.	p75
LEAD1	140,469	0.006	0.076	0.000	0.000	0.000
LEAD2	140,469	0.012	0.109	0.000	0.000	0.000
ALERT	140,469	0.019	0.136	0.000	0.000	0.000
ALTMAN	140,469	0.242	0.428	0.000	0.000	0.000
NEG_EQUITY	140,469	0.018	0.134	0.000	0.000	0.000
TOT_ASSETS (k€)	140,469	108,729	793,120	15,168	28,270	63,743
AGE	140,469	28.501	18.159	15.000	26.000	38.000
DUMMY_CENTRE	140,469	0.164	0.370	0.000	0.000	0.000
DUMMY_SOUTH	140,469	0.111	0.314	0.000	0.000	0.000
MISSING_FS	140,469	0.106	0.308	0.000	0.000	0.000
SPOSSNEG	140,469	0.470	0.499	0.000	0.000	1.000
FIN_EXP_RATIO	140,469	0.012	0.051	0.002	0.005	0.014
ED_RATIO	140,469	0.995	2.620	0.211	0.477	1.053
QUICK_RATIO	140,469	1.661	7.301	1.023	1.298	1.808
CASH_RET_RATIO	140,469	0.074	0.112	0.036	0.067	0.110
CBDC_INDIC	140,469	0.609	0.902	0.000	0.000	1.000
		PANEL B (Subsample)				
Variable	Obs.	Mean	SD	p25	p50	p75
LEAD1	7,555	0.107	0.309	0.000	0.000	0.000
LEAD2	7,555	0.207	0.405	0.000	0.000	0.000
ALERT	7,555	0.185	0.389	0.000	0.000	0.000
ALTMAN	7,555	0.656	0.475	0.000	1.000	1.000
NEG_EQUITY	7,555	0.178	0.382	0.000	0.000	0.000
TOT_ASSETS (k€)	7,555	73,888	170,473	17,573	30,239	61,762
AGE	7,555	26.810	18.640	13.000	24.000	36.000
DUMMY_CENTRE	7,555	0.228	0.420	0.000	0.000	0.000
DUMMY_SOUTH	7,555	0.154	0.361	0.000	0.000	0.000
MISSING_FS	7,555	0.089	0.285	0.000	0.000	0.000
SPOSSNEG	7,555	0.523	0.500	0.000	1.000	1.000
FIN_EXP_RATIO	7,555	0.030	0.061	0.010	0.020	0.034
ED_RATIO	7,555	0.188	0.799	0.030	0.132	0.296
QUICK_RATIO	7,555	1.754	30.722	0.799	1.030	1.260
CASH_RET_RATIO	7,555	-0.021	0.330	-0.021	0.021	0.046
CBDC_INDIC	7,555	1.851	1.469	1.000	2.000	3.000

The distribution of companies among different industries shows the predominance of the manufacturing (2), trade (6) and business services (9) industries (74%). Finally, as expected, the geographical distribution confirms the predominance of companies headquartered in northern Italy (72%).

In contrast, the subsample is composed only of companies entering into a crisis during the observation period, and the statistics present lower dispersed values for size and a slightly lower average age (26.81 years). Finally, an increase in the average number of industry-specific indicators on alert is observed.

4.2. Main results

To test the predictive ability and timeliness (H1a) of the new alert system on the basis of alert indicators, companies' past economic and financial information is used.

Table 3 summarizes the results of the retrospective analysis.

Table 3 – Retrospective analysis of the full sample and subsample

This table provides the results of the retrospective simulation analysis of the CBDC alert system indicating the number of companies on alert for each year. Panel A presents the results for the entire sample. Panel B reports the results for the subsample of companies that entered a crisis event. Detailed variable definitions are provided in Table 1.

			PANEL A (Full Sample)				
YEAR	COMPANIES	NEG_EQUITY (1)	DU_CBDC=1 (2)	ALERT (3)	OVERLAP (4=1+2-3)	LEAD1	LEAD2
2010	11,288	100	6	104	2	1	23
2011	13,371	160	18	164	14	30	200
2012	13,898	411	124	430	105	203	310
2013	13,920	379	109	402	86	145	245
2014	14,043	338	84	356	66	109	185
2015	14,471	255	52	271	36	68	157
2016	14,952	259	44	265	38	69	145
2017	15,396	235	40	240	35	65	159
2018	15,031	244	32	246	30	72	104
2019	14,099	173	14	176	11	47	-
Total	**140,469 (100%)**	**2,554 (1.82%)**	**523 (0.37%)**	**2,654 (1.89%)**	**423 (0.30%)**	**809 (0.58%)**	**1,528 (1.09%)**
			PANEL B (Subsample)				
YEAR	COMPANIES	NEG_EQUITY (1)	DU_CBDC=1 (2)	ALERT (3)	OVERLAP (4=1+2-3)	LEAD1	LEAD2
2010	1,021	20	5	23	2	1	23
2011	1,233	64	13	68	9	30	200
2012	1,283	265	113	279	99	203	310
2013	1,032	239	88	252	75	145	245
2014	838	198	72	209	61	109	185
2015	667	133	39	139	33	68	157
2016	556	131	36	134	33	69	145
2017	434	127	31	130	28	65	159
2018	306	116	21	116	21	72	104
2019	185	50	7	50	7	47	-
Total	**7,555**	**1,343 (17.78%)**	**425 (5.63%)**	**1,400 (18.53%)**	**368 (4.87%)**	**809 (10.71%)**	**1,528 (20.23%)**

The whole sample analysis shows a significant number of companies with an alert status, as they have negative equity (1), whereas the number of companies presenting an alert status based on the industry-specific indicators (identified by the dummy variable *DU_CBDC*) is much lower (2). As the two conditions are not mutually exclusive, a consistent overlap (4) between 1 and 2 emerges (423 out of 523 companies that are on alert on the basis of the industry-specific indicators show a negative equity value). It follows that only 4% of those companies with an alert status are signaled by industry-specific indicators.

Furthermore, the number of companies with an alert status exceeds the number of crisis events observed in the short term (*LEAD1*) and in the medium term (*LEAD2*), demonstrating that negative equity represents a necessary but not sufficient condition for a crisis.

The results of the analysis on the subsample confirm the pattern shown by the whole sample (only 4% of companies with an alert status are signaled by industry-specific indicators only). However, as expected, the number of false positives (where an alert status is not followed by a crisis event) substantially decreases.

In Table 4, the correlation matrix of *NEG_EQUITY*, *DU_CBDC*, *ALERT*, *LEAD1* and *LEAD2* is illustrated.

Table 4 – Correlation matrix for the subsample

This table provides the correlation matrix for the subsample of companies that entered a crisis event. Detailed variable definitions are provided in Table 1.

Variables	(1)	(2)	(3)	(4)	(5)
(1) ALERT	1.000				
(2) NEG_EQUITY	0.975*	1.000			
(3) DU_CBDC	0.512*	0.439*	1.000		
(4) LEAD1	0.507*	0.514*	0.307*	1.000	
(5) LEAD2	0.193*	0.181*	0.154*	-0.078*	1.000

* Shows significance at the 0.05 level.

The results confirm that an alert status is strongly related to a negative value of equity (r=0.975), whereas its correlation with industry-specific indicators is still relevant but weaker (r=0.512). Additionally, there is a high correlation between *NEG_EQUITY* and *DU_CBDC* (r=0.439). Moreover, the results suggest that alert status is significantly correlated with crises in the short term (r=0.507), whereas this relationship is weaker in the medium term (r=0.193).

To test H1a, a panel LR on the subsample of companies entering into a crisis during the observation period was conducted. Model 1 (with *LEAD1* as the dependent variable) shows that alert status (*ALERT*) has a positive and significant ($p < 0.001$) relationship with the probability of a crisis event in the short term[5]. *TOT_ASS* is positively and significantly ($p < 0.01$) correlated with the dependent variable, indicating that company size affects default likelihood. Smaller companies are more likely to face voluntary procedures, which are less expensive and exclude public authority, whereas larger firms tend to experience public authority interventions during distress. Model 1 also reveals a significant negative ($p < 0.01$) relationship between *SPOS_SNEG* and the dependent variable, showing that companies in short-term crises do not have small earnings/losses, which aligns with prior findings on earnings management (Charitou et al., 2011) and is consistent with previous evidence on earnings management practices (Charitou et al., 2011), which, in the case of persistent financial distress, may not be feasible.

Finally, Model 1 shows a negative and significant ($p < 0.05$) impact of *DUMMY_CENTRE* and *DUMMY_SOUTH*. These results are further investigated in the Additional Analyses section. The remaining control variables are not significant.

Model 2 (with *LEAD2* as the dependent variable) demonstrates that the *ALERT* variable is still positive and significant ($p < 0.01$); however, the coefficient is lower than that presented in Model 1. Moreover, the percentage of companies that are correctly classified by the model is lower with reference to Model 1. This finding highlights that the CBDC alert system based on static indicators is related to crisis probabilities in the medium term, but the magnitude of the relationship is weaker. With respect to the control variables, the *TOT_ASS* variable is not significant, whereas the *SPOS_SNEG* variable remains negative and significant ($p < 0.01$). No other control variables are significant.

To enhance our results and test the predictive ability of a well-known alert system, two additional models aimed at testing Altman's Z score (proxied by the variable *ALTMAN*) were built. The results confirm the decrease in the *ALTMAN* variable coefficient when shifting from the short term (Model 3) to the medium term (Model 4) and a decrease in the percentage of companies correctly classified by the model[6].

Table 5 presents the results of the four models.

[5] To consider the distribution of the dependent variable, skewed LR (Nadarajah, 2009) is performed. Untabulated evidence confirms all the results of the logit model.

[6] Once again, skewed LR is performed as additional (untabulated) analyses. All the results are confirmed.

Table 5 – Output panel logistic regression (Models 1, 2, 3 and 4). Random effects logistic regression

This table provides the results of four panel logit models regressing the probability of a crisis event, proxied by LEAD1 (Models 1 and 3) and LEAD2 (Models 2 and 4), on a set of independent and control variables for the subsample of companies that entered a crisis event. The first (last) two columns use ALERT (ALTMAN) as the main predictor of a crisis event. All the models include industry and year fixed effects. Detailed variable definitions are provided in Table 1.

	Model 1 LEAD1	Model 2 LEAD2		Model 3 LEAD1	Model 4 LEAD2
	Coef. (p value)	Coef. (p value)		Coef. (p value)	Coef. (p value)
ALERT	**2.466***** **(0.000)**	**0.434***** **(0.000)**	**ALTMAN**	**1.663***** **(0.000)**	**0.768***** **(0.000)**
TOT_ASS	0.139*** (0.003)	-0.044 (0.155)	TOT_ASS	-0.132*** (0.002)	-0.129*** (0.000)
AGE	0.002 (0.373)	0 (0.867)	AGE	-0.001 (0.604)	-0.002 (0.295)
DUMMY_CENTRE	-0.231** (0.043)	-0.006 (0.941)	DUMMY_CENTRE	-0.146 (0.169)	0.016 (0.836)
DUMMY_SOUTH	-0.284** (0.04)	0.069 (0.439)	DUMMY_SOUTH	-0.155 (0.227)	0.061 (0.496)
MISSING_FS	-0.146 (0.414)	-0.144 (0.196)	MISSING_FS	-0.374** (0.023)	-0.184 (0.100)
SPOS_SNEG	-1.174*** (0.000)	-0.698*** (0.000)	SPOS_SNEG	-2.117*** (0.000)	-0.716*** (0.000)
Control for Industry	YES	YES	Control for Industry	YES	YES
Control for Year	YES	YES	Control for Year	YES	YES
Constant	-8.239*** (0.000)	-2.777*** (0.000)	Constant	-5.581*** (0.000)	-2.333*** (0.000)
Number of obs.	7,555	7,370	Number of obs.	7,555	7,370
Chi^2	1,066.333	483.143	Chi^2	613.513	528.086
Prob > Chi^2	0.000	0.000	Prob > Chi^2	0.000	0.0000
% of firms correctly classified	90.18%	77.06%	% of firms correctly classified	89.28%	77.10%
Model's specificity	97.41%	99.08%	Model's specificity	99.94%	99.25%
Model's sensitivity	29.91%	2.22%	Model's sensitivity	0.37%	1.77%
AUROC	0.8893	0.7081	AUROC	0.8476	0.7183

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

The results suggest that the predictive ability of an EWS based on static indicators is confirmed only in the short term, whereas its accuracy decreases in the medium term. In addition, a system based on static indicators generates a relevant number of false positives, undermining the efficiency of the entire system. Thus, H1a is supported.

To test H1b, a panel LR model used to analyze the subsample of companies that entered into a crisis was applied with the aim of identifying the financial indicators that are significantly related to a crisis in the medium term (*LEAD*2 is the dependent variable).

The results of Model 5 (Table 6) suggest that the *NEG_EQUITY* dummy variable and 3 out of 5 financial indicators (*FIN_EXP_RATIO*, *CASH_RET_RATIO* and *SOC_TAX_RATIO*) are significantly related to a crisis in the medium term, whereas the other two financial indicators (*ED_RATIO* and *QUICK_RATIO*) are not significant.

Table 6 – Output panel logistic regression (Models 5 and 6). Random effects logistic regression

This table provides the results of two panel logit models regressing the probability of a crisis event in the medium term, proxied by LEAD2, on the raw values of the alert indicators provided by the CBDC alert system. Detailed variable definitions are provided in Table 1.

LEAD2	**Model 5 LEAD2**	**Model 6 LEAD2**
	Coef. (p value)	**Coef. (p value)**
NEG_EQUITY	0.739*** (0.000)	0.764*** (0.000)
FIN_EXP_RATIO	0.973** (0.021)	0.959** (0.022)
ED_RATIO	-0.045 (0.452)	-
QUICK_RATIO	-0.001 (0.654)	-
CASH_RET_RATIO	-0.601*** (0.000)	-0.61*** (0.000)
SOC_TAX_RATIO	0.443*** (0.004)	0.447*** (0.004)
Constant	-1.594*** (0.000)	-1.607*** (0.000)
Number of obs.	7,370	7,370
Chi^2	259.234	257.739
Prob > Chi^2	0.000	0.000
% of firms correctly classified	77.26%	77.26%
Model's specificity	99.33%	99.33%
Model's sensitivity	2.22%	2.22%
AUROC	0.6850	0.6827

*** p < 0.01, ** p < 0.05, and * p < 0.1.

The result for *ED_RATIO* is consistent with our expectations since the indicator is strongly related to the *NEG_EQUITY* dummy variable (ρ=–0.3065). In contrast, the result for *QUICK_RATIO* aligns with the literature (Lin et al., 2011), confirming the limited predictive ability of this indicator.

As *ED_RATIO* and *QUICK_RATIO* are not significantly related to the dependent variable, they are excluded from Model 6, which confirms that *NEG_EQUITY, FIN_EXP_RATIO, CASH_RET_RATIO* and *SOC_TAX_RATIO* are significantly related to crises in the medium term.

Using the coefficients reported in Table 6 (Model 6), the dynamic index[7] was built, and its value was estimated for the whole sample (126,370 observations). To test the goodness of fit of the three alternative models (the CBDC alert system proxied by the variable *ALERT*, the Z' score model proxied by the variable *ALTMAN* and the dynamic model proxied by the variable *INDEX*), ROC regression (Alonzo, 2002) was conducted. The ROC curve was subsequently estimated.

ROC regression allows for the development of a quantitative measure of the accuracy of a predictor that clarifies the performance of a classifier between two states (Hernandez-Orallo 2013). In this research, it tests the ability of each alternative model (CBDC, Altman and our INDEX) to correctly classify those observations during a crisis event (*LEAD2*=1). To enhance robustness, we applied parametric ROC regression (probit) with bootstrapping, which requires weak assumptions on the distribution of classifiers (Alonzo, 2002).

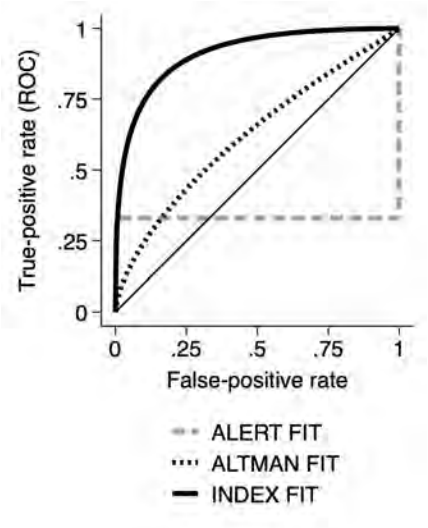
The results confirm that, compared with mere chance, the models better classify companies in terms of the occurrence/absence of a crisis event. The graphical representation of the curve (Figure 1) shows the true positive rate of each classifier. The area under the curve (AUC) was 0.33 for the CBDC alert system, 0.62 for the Altman model and 0.91 for the dynamic model (Figure 1), and the difference between the three AUCs was significant (p=0.000). Because the AUC is significantly larger for the dynamic system, it is considered a better classifier for companies than the CBDC and Altman systems are (Figure 1). The results show that the false positive rate is limited, despite the index having been applied to many observations.

To further confirm our results, we calculated the AUC of the standard Altman model (0.622), the AUC of the Altman model supplemented with the *ALERT* variable (0.641) and the AUC of the Altman model supplemented with the *INDEX* variable (0.739). This test also confirms the greater predictive power of the Altman model when it is combined with our dynamic index.

Accordingly, we can conclude that, *ceteris paribus*, the dynamic system is significantly more accurate in predicting crises in the medium term. Thus, H1b is supported.

[7] INDEX=-1.607+0.764*NEG_EQUITY+0.959*FIN_EXP_RATIO-0.61*CASH_RET_RATIO +0.447*SOC_TAX_RATIO.

Figure 1 – ROC curve



ROC						
Classifier	**Obs.**	**Area**	**Std. Err.**	**% of firms correctly classified**	**Model's specificity**	**Model's sensitivity**
ALERT	126,370	0.329	0.0122	88.87%	100%	0%
ALTMAN	126,370	0.622	0.0072	88.87%	100%	0%
INDEX	126,370	0.912	0.0036	88.86%	99.95%	2.75%
H0: All classifiers have equal AUC values						
Prob = 0.0000						

This figure provides the results of three ROC models regressing the probability of a crisis in the medium term (LEAD2) using ALERT, ALTMAN and INDEX as classifiers on the full sample of companies. Detailed variable definitions are provided in Table 1.

4.3. Out-of-sample performance

4.3.1. K-fold cross-validation

To assess model performance on out-of-sample data, we used K-fold cross-validation with Schonlau's (2020) STATA package, a method commonly used to reduce overfitting (Hastie et al., 2001). This approach divides the dataset into subsets, rotating each as a validation set. We tested our models via the random forest algorithm, with *LEAD2* as the dependent variable. The results show that both the *ALERT* and Altman Z score consistently predict 0 values with a 100% error rate for real crises, whereas *INDEX*, despite a 90% error rate, performed better, supporting our main findings.

4.3.2. Monte Carlo simulation

To mitigate potential bias from the methodology and sample selection, a Monte Carlo simulation was conducted. For each of the ten industries, we generated raw values of the "static" alert indicators, assuming a skewed normal distribution for continuous variables (*FIN_EXP_RATIO*, *ED_RATIO*, *QUICK_RATIO*, *CASH_RET_RATIO*, and *SOC_TAX_RATIO*) and a binomial distribution for dichotomous variables (*LEAD1*, *LEAD2*, and *NEG_EQUITY*). The parameters used in the simulation were derived from a similar distribution based on the full sample (140,469 firm-year observations). Since Italy is a large economy with a predominance of private companies, our simulation assumes that the overall distribution of financial indicators and crisis events is representative of other economic systems. To reduce generalizability issues further and prevent a small number of outliers from biasing our results, the simulation generated one million observations per industry.

We subsequently estimated the *ALERT* and the value of the dynamic *INDEX* (as determined through Model 6[8]). In the simulated sample, 1.9% of the observations are on alert status, whereas 2.3% of the observations are expected to enter crisis status.

To assess the predictive ability of the index on the simulated sample for all observations with a positive equity value (*NEG_EQUITY* = 0), we replicated the ROC regression analysis with bootstrap replications. The untabulated results confirm that the AUC of the *ALERT* variable is 0.0036 (meaning that this variable fails to predict a crisis event in 99% of cases), whereas the AUC of the *INDEX* variable is 0.5094 (meaning that *INDEX* correctly classifies 51% of crisis events), and the difference between the two areas is significant (p value=0.000). Owing to the relevant number of observations included in the simulated sample (10 million), it is possible to conclude that the dynamic index is a better classifier of companies than the CBDC alert system is.

[8] To strengthen the conclusions stemming from this additional analysis, the dynamic index was not re-estimated on the simulated sample; rather, we used Model 6's index, without any adaptation. The relative lower value of the AUC (0.5094) compared to the value derived from our main analysis (0.91) could be explained by the need to adapt, periodically, the value of the index. However, given the relevant number of observations included in our simulated sample and the value of the AUC for the CBDC model, our conclusions can be confirmed.

5. Robustness checks and additional analyses

First, we acknowledge that some control variables may be related to a crisis event (*TOT_ASS, AGE,* and *SPOS_SNEG*), and consequently, there could be a reverse causality issue that influences the error term of our empirical models. To mitigate this issue, analyses excluding the observations that are manifested in crisis in the year of observation were conducted, as they report a negative equity value. Untabulated evidence confirms all the above results.

Moreover, some omitted variables (e.g., management quality, corporate governance) may impact our estimates. To assess coefficient stability, we conducted an Oster test (Oster, 2017) using three reduced models where the dependent variable is *LEAD2* and the variables of interest are *ALERT*, *ALTMAN,* and *INDEX*. These models included only year fixed effects. The complete models included all the controls used in our main analyses. As shown in Table 7, the model with *ALTMAN* is unaffected by omitted variable bias (Oster delta >1), whereas the models with *ALERT* and *INDEX* may be influenced. However, the low difference in betas and the *INDEX* model's delta being close to 1 (Delta=0.566) suggest that the bias is not severe enough to undermine our conclusions.

Table 7 – Oster test for omitted variable bias

This table provides the results of the Oster test for our main model regressing the probability of a crisis event in the medium term (LEAD2) on ALERT, ALTMAN and INDEX. The reduced model includes only year fixed effects, whereas the controlled model includes all the control variables used in our main analysis. Detailed variable definitions are provided in Table 1.

Variable of Interest	**ALERT**	**ALTMAN**	**INDEX**
Beta reduced	0.194	0.036	0.177
Beta controlled	0.192	0.041	0.176
Oster Delta	0.185	4.992	0.567

Third, as mentioned above, crisis events are not normally distributed, and consequently, the logit model could be biased. To strengthen our results, all the analyses were replicated via skewed logit distribution regression. Untabulated evidence confirms the results for Models 1, 2, 3 and 4. Accordingly, we estimated a "skewed" version of our dynamic index (*SK_INDEX*), and we ran the ROC regression again.[9] Moreover, the true positive rate of *SK_INDEX* is 91.58%, confirming that it is the best classifier compared with the CBDC alert system (32.92%) and Altman's Z score (62.25%).

[9] SK_INDEX=2.301+2.203*NEG_EQUITY+12.59*FIN_EXP_RATIO-6.431*CASH_RET_RATIO+3.161*SOC_TAX_RATIO.

Finally, to check the influence of the geographical contextual factors, our main empirical models were estimated separately for each region (North, Centre and South).

The results for Models 1, 2, 3 and 4 are synthetized in Table 8, which reports the signs and p values for the relevant covariates. While the main results are confirmed, several interesting conclusions emerge. Indeed, when we estimate the crisis in the short term (Models 1 and 3), we notice that for South-based companies, there is a positive relationship between size (proxied by *TOT_ASS*) and the occurrence of crisis events (as observed in Model 1). This relation disappears when the probability of a crisis in the medium term is investigated. (Model 2 and Model 4). The unexpected association for southern companies suggests that larger firms face short-term crises due to limited cooperation and hierarchical social structures (Putnam 1993). Lacking support from local economic actors, these firms in southern Italy often rely on public procedures for creditor negotiations. In contrast, larger companies in northern and central Italy typically handle financial distress through private transactions, avoiding public procedures.

Table 8 – Synthesis of the geographical analysis for Models 1, 2, 3 and 4. Random effects logistic regression

This table provides a synthesis of the results of four panel logit models regressing the probability of a crisis event, proxied by LEAD1 (Models 1 and 3) and LEAD2 (Models 2 and 4), on a set of independent and control variables for the subsample of companies that entered a crisis event considering separately north-based, center-based and south-based observations. All the models include industry and year fixed effects. Detailed variable definitions are provided in Table 1.

	LEAD1 (Model 1)						LEAD2 (Model 2)					
	North		Centre		South		North		Centre		South	
	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.
ALERT	+	***	+	***	+	***	+	***	+	***	+	*
TOT_ASS	+		+		+	***	-		-		+	*
AGE	+		+	**	-	**	+		-		-	
MISSING_FS	-		-		-		-		-		-	
SPOS_SNEG	-	***	-	***	-		-	***	-	***	-	***
	LEAD1 (Model 3)						LEAD2 (Model 4)					
	North		Centre		South		North		Centre		South	
	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.	Sign	Coeff.
ALTMAN	+	***	+	***	+	***	+	***	+	***	+	***
TOT_ASS	-	***	-	**	+	**	-	***	-	***	+	***
AGE	-		+		-		-		-		-	*
MISSING_FS	-		-	**	-		-		-		-	
SPOS_SNEG	-	***	-	***	-	***	-	***	-	***	-	***

*** p<.01, ** p<.05, and * p<.1.

6. Conclusions

This research contributes to the financial crisis prediction literature by proposing a new methodological approach to implementing EWSs based on alert indicators tailored for private companies. Specifically, the identification of accurate predictors of corporate failure is relevant from both ethical and economic perspectives. Additionally, regulators and policy makers worldwide are demanding innovative approaches to preemptively detect companies' crisis signs. The European Directive on Preventive Restructuring and Insolvency represents a remarkable achievement toward the modernization of insolvency and restructuring regimes in the EU. However, its harmonization effect is likely to be limited, given the many options for its implementation: 143 different options. In this context, the evidence arising from the Italian system can be relevant for other European countries, which are going to implement the European Directive, and for practitioners who will be involved in applying the new predictive models.

Using an econometric EWS approach, this study contributes to identifying the methodological approaches that are more accurate in the implementation of EWSs. Using the Italian context as a suitable basis for research, the findings for H1a highlight several structural issues with static EWSs (CBDC alert system). The overlap among explanatory variables indicates a limited predictive ability of static industry-specific indicators, leading to a high number of false positives that can generate unnecessary stakeholder panic and misallocate resources.

Further analysis shows that the introduction of lead variables significantly reduces the predictive ability of the static EWS in the medium term, emphasizing that models based solely on static indicators are inadequate for timely corrective actions. In contrast, dynamic EWSs demonstrate superior accuracy in detecting crisis signs, enabling practitioners to implement effective interventions without being overly burdensome for small enterprises. The findings demonstrate a better ability of the dynamic EWS without any prejudice against the alert indicator selection process, meaning that in any other context – even though the EWS is based on a different set of alert indicators – the implementation of dynamic models is beneficial for avoiding false positives.

To address endogeneity concerns, the dynamic index was developed via a subsample of companies with crisis statuses and subsequently tested on a full sample. The limited number of false positives supports the absence of systematic Type II errors. Additionally, the dynamic index was validated on a simulated sample of 10 million observations generated through Monte Carlo simulation.

While this study offers valuable insights, it has limitations that future research could address. First, a cross-country analysis could help test the impact of different capital structures across European countries. Second, this study focuses on financial crises involving public procedures and authorities, excluding voluntary liquidations due to data limitations. This exclusion may overlook company distress resolved privately, but public procedures often indicate management's failure to address crises. An EWS that detects such events is essential to reduce their occurrence and mitigate risks to the economic system. Third, this study employs financial data collected from publicly available financial statements. We acknowledge that this type of disclosure can be manipulated and that our results reflect all the limitations inherent to these data. Additional evidence collected through qualitative methods could complement our conclusions.

Finally, the empirical analysis was conducted over the period 2010–2019 to avoid any impact due to the COVID-19 pandemic, the effect of which is currently still not measurable. Further research addressing this issue might be useful.

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