BANCA D'ITALIA
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AN EARLY WARNING SYSTEM FOR LESS SIGNIFICANT ITALIAN BANKS

by F. Ferriani (coordinator)*, W. Cornacchia*, P. Farroni**, E. Ferrara**, F. Guarino**, and F. Pisanti**

Abstract

This paper presents a statistical early warning system for less significant institutions (LSIs) under the direct supervision of the Bank of Italy. The model is calibrated on the basis of a wider definition of possible distress events, using the universe of Italian LSIs active in the period 2008-2016 as a reference. We selected an extensive list of variables that might give early warnings of a crisis in relation both to the overall banking system and Italy's macro-financial situation, and to individual banks' performances. A logit model is used to calculate the probability of default (PD) for each bank, with time horizon estimates set at four and six quarters. The empirical specifications proposed are tested using several statistical indices; the ex-post analysis of the estimated PDs shows a percentage of correct bank classification in the range of 80-90 per cent, with better results the nearer the moment of prediction is to when a crisis situation actually occurs.

JEL Classification: G21, G28.
Keywords: early warning system, default, less significant institutions, CAMELS, banking supervision.

Contents

* Directorate General for Economics, Statistics and Research
** Directorate General for Financial Supervision and Regulation

Introduction[1]

In the context of banking supervision, it is crucial to identify financial institutions' problems at an early stage. This objective is typically pursued via a broad array of tools, which encompass the gathering of 'soft' information, e.g. via meetings with the management and the internal control functions of the institutions; off-site analysis, conducted on a routine basis, mainly using monthly supervisory data reporting from institutions, as well as ad hoc data collection exercises; on-site inspections; complaints made by the general public; and whistleblowing charges communicated to the supervisor by the institution's staff or management. Most of these analyses converge into the Supervisory Review and Evaluation Process (SREP), which provides a summary score of the overall state of health of the intermediary.

An Early Warning System (EWS) consists of a broad set of methods and tools whereby the supervisor pursues the early detection of difficulties and sets in motion a supervisory reaction aimed at addressing the problems. This set of methods and tools is often complemented by more formal statistical models aimed at selecting effective indicators for the early identification of banking crises. This study presents an econometric model to predict bank failures for less significant institutions (LSIs) under the direct supervision of the Bank of Italy. The exceptional double recession experienced by Italy has triggered several bank crises during the last decade, providing a wealth of observations to improve the identification process. In a nutshell, the model singles out a set of variables (measuring banks' capital adequacy, liquidity, asset quality, and so on) that can help predict a difficult situation for a bank based on their statistical significance. Finally, the model estimates – from a forward-looking perspective – the probability of default for each institution in the near future.

The rest of this study is organized as follows: Section 1 presents an overview of the Italian LSI sector; Section 2 reviews the most significant contributions in the literature on EWS applied to banks, both at the single institution level and the systemic level; Section 3 describes the corporate events and the administrative acts that are selected to identify a bank crisis; Section 4 presents the explanatory variables used in the empirical analysis; Section 5 offers an extensive analysis of the empirical findings, including some diagnostics and robustness tests; finally, Section 6 summarizes the main conclusions of this work.

[1] The views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Italy or the Eurosystem. The authors wish to thank Paolo Angelini, Filippo Calabresi, Antonio Di Cesare, and seminar participants at Bank of Italy for useful comments and suggestions. All remaining errors are our own.

1. Italian LSIs

This section describes the original dataset used in the empirical analysis, covering the 2008-16 period. It does not therefore consider important recent developments, such as the ongoing creation of the cooperative banking groups, the outcome of the reform of the *Popolari* banks, and the further reduction in the number of banks due to consolidation. For instance, the number of BCCs has declined from 355 in our dataset to 280 as of 2017 Q4. For these reasons, this section should be understood mainly as a description of the data underlying the estimates, and not as an up-to-date picture of Italy's LSI sector.

As of June 2016, the Italian LSI sector[2] was composed of 459 institutions (52 banking groups and 407 stand-alone banks; see Table 1) with a total asset value of almost €558 billion, accounting for 20 per cent of the total assets of the Italian banking system. The high number of Italian LSIs is also a key feature at the SSM level, where approximately 80 per cent of the LSIs are concentrated in three jurisdictions: Germany (50% of SSM LSIs), Austria (17%) and Italy (16%).

Table 1
Distribution of Italian LSIs by legal form and scope of consolidation
(data as of 30.06.2016)

Legal form	Banking groups	Stand-alone institutions	Tot.
BCC	11	344	**355**
Popolare	8	17	**25**
SpA	33	46	**79**
Tot.	**52**	**407**	**459**

Source: Supervisory data.

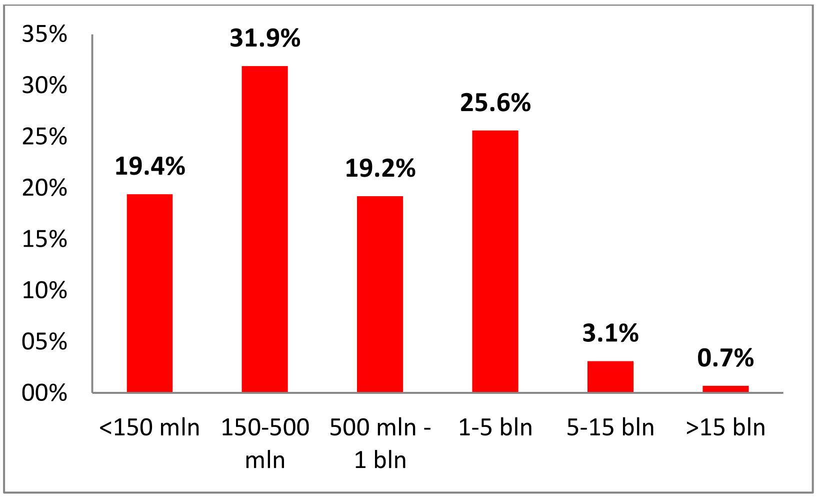
Other features of the Italian LSI sector are the following:

- **the sector comprises a majority of cooperative banks** (see Table 1): 83 per cent of Italian LSIs are either mutual banks (BCCs) or other cooperative banks (*Popolari* banks) with common specific features in terms of shareholding structure and operational schemes with respect to joint stock company banks (JSC, SpA in Italian). Although not specifically provided for by the regulations, small *popolari* banks also follow the principle of concentrating their operations locally.

- **the sector is predominantly composed of small banks** with a total asset value of below €500 million (see Figure 1). Only 4 per cent of Italian LSIs have total assets of above €5 billion. These features also stem from the prevailing cooperative legal form with consequences in terms of smaller banking size too (see previous point);

[2] For the purpose of this paper, foreign branches are not included in the LSI sample, given that supervisory reporting is limited for these institutions.

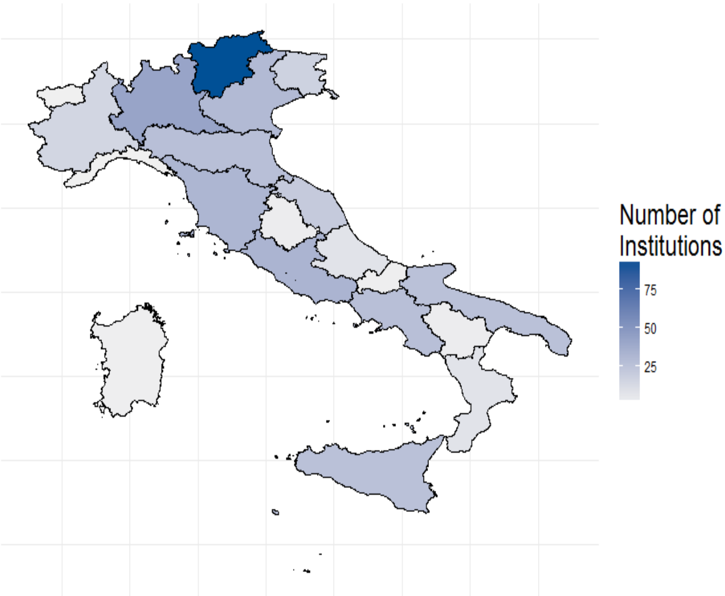
Figure 1
Distribution of Italian LSIs by size
(total assets in euros; data as of 30.06.2016)



Source: Supervisory data.

- **Italian LSIs mainly operate locally**, due to their cooperative legal form which restricts their activity to limited areas. In terms of geographical distribution, local banks are spread throughout the country (see Figure 2), with some notable concentrations in the North West (Trentino Alto Adige and Lombardy) and a less substantial presence in other regions (Liguria, Valle d'Aosta, Sardinia, Molise, Umbria, and Basilicata);

Figure 2
Regional distribution of Italian LSIs
(number of institutions; data as of 30.06.2016)



Source: Supervisory data.

- **most Italian LSIs are classified as 'traditional' banks**, i.e. banks predominantly engaged in deposit-taking and customer lending (see Table 2). These banks (commercial banks) represent almost all of the total LSI population and the total assets of the LSI sector. These banks are also characterized by a high share of interest income on total income and a high proportion of customer deposits on total funding. Trading activity is usually a marginal part of the business of these institutions, resulting in a limited exposure to market risk (for BCCs, additional limitations on speculative activities, e.g. derivatives, are also imposed by prudential regulation). The Italian LSI sector also includes investment and wealth management banks or some more specialized institutions such as payment system banks.

Table 2
Italian LSIs distribution by business model
(number of institutions; data as of 30.06.2016)

Business Model	#LSI
LSI with 'traditional' business model	430
Wealth management and portfolio advisory LSIs	20
Payment system/ICC	2
LSIs specialized in other activities	7

Source: Authors' classification based on supervisory reports.

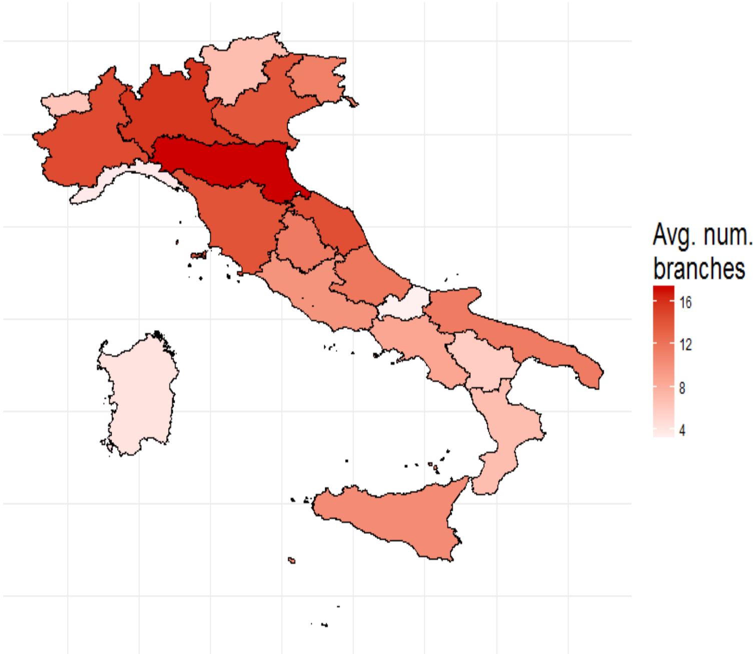
- **Italian LSIs' distribution channels rely on a dense branch network.** Indeed, cooperative banks (and all other local banks mainly engaged in granting loans to their customers) strategically base their business model on customer proximity and on large networks of branches. As of June 2016, Italian LSIs had approximately 8,700 branches (half of them run by BCCs) out of a total of 30,000 for the whole Italian banking system (see Table 3). Emilia Romagna is the region with the highest number of branches on the total LSIs operating in the region (average 17.1), followed by Lombardy (15.6) and Piedmont (14.5), see Figure 3.

Table 3
Distribution of Italian LSIs branches by legal form
(data as of 30.06.2016)

Legal form	# Branches	%	# LSI	%	Avg. number of branches per LSI
BCC	4,385	*51.2*	355	*77.3*	12.4
Popolari	1,571	*18.3*	25	*5.4*	62.8
SpA	2,757	*3.2*	79	*17.2*	34.9

Source: Supervisory data.

Figure 3
Average number of LSI branches per region
(data as of 30.06.2016)



Source: Supervisory data.

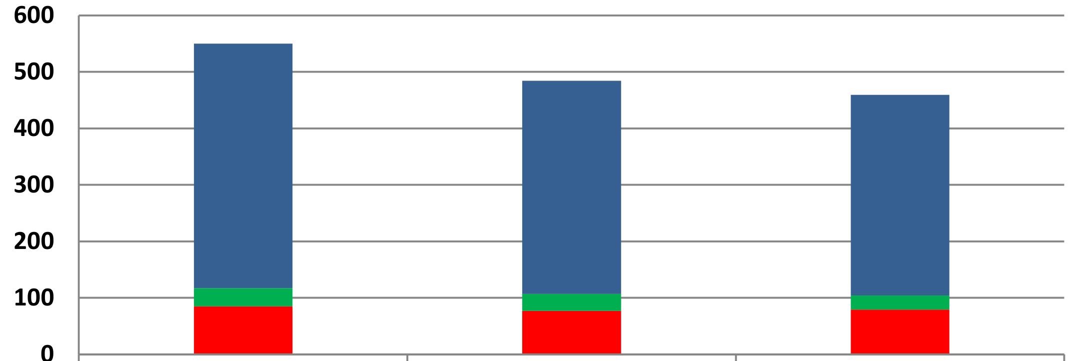
- **Governance systems characterized, for the smallest cooperative banks, by the presence of the bank's shareholders on the board of directors.**

In the last few years, several factors have been impacting the Italian LSI sector:

- The prolonged and severe economic downturn experienced by Italy in the last decade mostly hit 'traditional' banks, with a business model focused on lending to households and firms, and those with a limited ability to diversify income, characterized by a restricted geographical scope and relying on large branch networks;
- the regulatory harmonization and the launch of the Single Supervisory Mechanism have increased competitiveness at the European level also within the LSI sector;
- the reform of the cooperative banking system, establishing Cooperative banking groups led by a parent company and incorporated into a joint stock company.

The combined actions of these factors have accelerated the rationalization process within the Italian banking sector (see Figure 4): since 2008, the number of Italian LSIs has decreased significantly thanks to merger operations aimed at creating sounder institutions. More recently, in light of the future establishment of the Cooperative banking groups, the consolidation process among BCCs has further increased in order to create larger and more efficient institutions.

Figure 4
Time series evolution of the number of Italian LSIs by legal form
(number of institutions; data as of 30.06.2016)



	31/12/2008	31/12/2014	30/06/2016
BCC	433	377	355
Popolari	32	30	25
SpA	85	77	79

Source: Supervisory data.

Besides the operations arranged autonomously by the LSIs, the rationalization of the Italian LSI sector has also been encouraged by Bank of Italy in order to promote the efficiency and soundness of the Italian banking system. Especially in more recent years, an increasing number of merger operations have been arranged following Bank of Italy’s specific recommendations or requests made in the light of problematic situations. In other cases, mergers were organized following the closing of special administration or liquidation procedures, once the temporary managers or the Supervisory Authority had confirmed the irreversibility of an institution’s crisis. In some cases, episodes of mismanagement exacerbated the impact of the economic downturn and generated additional crisis situations.

2. Literature review

We classified the main contributions to the EWS literature according to two main criteria. A first criterion regards the scope of application of an EWS: on the one hand there are studies and models at the micro level designed to signal the potential distress of individual institutions early on, and on the other hand there are macro models attempting to identify threats to the soundness of the banking and financial system as a whole. A second classification criterion concerns the methodology used to implement an EWS and distinguishes between statistical-econometric models, such as the one proposed in this study, and non-parametric or machine learning techniques (see Fethi and Pasiouras 2009 or Demyanyk and Hasan 2010 for a detailed analysis of the various approaches proposed in the literature). The two classification criteria are closely linked and could generate a wide range of EWS models. In the following section we provide a description of the main studies available in the literature, without claiming to be exhaustive and without necessarily making a clear distinction with respect to either the scope of application or the methodology adopted.

As regards the EWS applied to individual institutions, an initial influential contribution is Martin (1977), who uses a logistic regression to predict the default of a panel of US banks between 1970 and 1976. His work introduces some important methodological features, such as the concept of 'extended' default which makes it possible to improve the model's forecasting power. More precisely, he widens the definition of distressed institutions to take into account bank mergers promoted by the Supervisory Authority to overcome a bank's crisis. The author only relies on regressors defined at micro level and representative of the balance sheet of each institution. The explanatory variables adopted in this paper can be traced back to the CAMELS paradigm developed for the rating models of the US Supervisory Authorities at the end of the 1970s, and subsequently revised during the 1990s. The CAMELS method has been widely employed in the literature as it serves to classify the most important determinants of a bank failure into homogeneous categories: 'Capital, Asset quality, Management, Earning, Liquidity and Sensitivity to Market risk'.

Since Martin's paper of (1977), the literature on EWS has evolved in several directions. One of the most successful strands has focused on the identification of the explanatory variables to be included in the model in order to improve the EWS predictive performance. Traditional indicators derived from the financial statements of the individual institutions have been complemented by sectoral explanatory variables and other regressors defined at the macro level (single country or geographical area), as in the case of González-Hermosillo (1999), Jagtiani et al. (2003), Kraft and Galac (2007), and Betz et al. (2014). In this vein, the predictive power of an EWS has also benefited from the inclusion of explicative variables that are usually more reactive in order to assess the health of an institution, such as market-based indicators (Flannery 1998, Krainer and Lopez 2003, Campbell et al., 2008).

Poghosyan and Čihák (2011) present the results of an EWS applied to a sample of European banks where the identification of defaulted institutions relies on a massive search within a financial news database of keywords such as 'rescue', 'state guarantee', and 'financial support'. Betz et al. (2014) also concentrate on the scope of the dependent variable; they do not limit it to cases of bankruptcy and liquidation, but extend the definition of default to include State interventions or institutions' crises classified on the basis of external agency ratings. The choice of external ratings for the identification of distress events is also proposed by Brossard et al. (2007) for a sample of European banks, while Thomson and Whalen (1988) and O'Keefe and Wilcox (2010) use the rating assigned by Supervisory Authorities as the dependent variable of their EWS model.

Besides parametric statistical models such as logit ones (Porath 2004, Kick and Prieto 2015), a very simple version of an EWS was developed by Kaminsky (1998) and Kaminsky and Reinhart (1999) based on the concept of signal extraction. In these models a crisis situation is detected whenever the value of one or more indicators exceeds predetermined threshold levels. Pettway and Sinkey (1980), Jordan et al. (2010), and Cox and Wang (2014) rely on standard multivariate analysis techniques, especially discriminant analysis, to identify banks in distress. On the other hand, several studies have suggested modelling the EWS in the context of the survival analysis, where the dependent variable is the time until the occurrence of a bank default (Lane et al. al. 1986, Whalen 1991 et al., Wheelock and Wilson 2000, Shumway 2001, Arena 2008, Cole and Wu 2009).

More recently, the literature on EWS has started to complement the traditional statistical approach with a wide range of non-parametric techniques that can be generically traced back to machine learning. Tam and Kiang (1992), Alam et al. (2000), Boyacioglu et al. (2009), among others, present an EWS based on neural networks, a nonlinear approach where the identification of distressed institutions relies on some interconnection measures among explanatory variables. Kolari et al. (2002), Lanine and Vander Vennet (2006) adopt a technique known as trait recognition where covariates are segmented on the basis of some threshold values. Building on the interdependencies among the segmented variables, the authors develop some matrices to classify companies' performance (traits) and distinguish between institutions in distress and viable ones. Olmeda and Fernandez (1997), Zhao et al. (2008) and Ioannidis et al. (2009) present a horse race among a set of classification methods and also include the results obtained by applying decision trees. This specific classification algorithm allows the authors to assess the viability of institutions according to multiple sequential nodes (variables) that make a binary split between healthy institutions and those in crisis.

Over the years, micro-level approaches to EWS have been integrated by a great deal of literature extending the scope of analysis to individual countries or to a group of countries with homogeneous characteristics. The methodologies adopted for a macro EWS recall many of the methodologies previously described, and we refer to Reinhart and Rogoff (2008) and Laeven and Valencia (2018) for comprehensive surveys of past banking crises, and to Kauko (2014) or Alessi et al. (2015) for a review of the most common approaches in the literature. In these studies, one of the greatest challenges is to construct a dependent variable which is indicative of a systemic banking crisis. The traditional strategy usually involves the combination of multiple indicators representative of systemic distress; see Demirgüç-Kunt and Detragiache (1998), Demirgüç-Kunt and Detragiache (2005) and Davis and Karim (2008) for commonly used crisis definitions. Among the various contributions to be cited, Borio and Drehman (2009) propose an EWS for banking crises identified via signal extraction from multiple alert indicators, Barrel et al. (2010) use a logit model to implement an EWS for OECD countries, Antunes et al. (2014) consider a dynamic setting to predict a banking crisis via probit models, while Jahn and Kick (2012) study the impact of a wide range of macroeconomic and sectoral variables on a stability indicator for the German banking system. Evrensel (2008) applies survival analysis to study banking crises in a sample of G-10 and non-G-10 countries, and Alessi and Detken (2014) build on decision trees to create an EWS for supporting Supervisory Authorities in the application of macro-prudential instruments. Ferrari et al. (2015) develop an early warning model based on a logit specification to examine the systemic banking crises stemming from the real estate market as reported by the European Systemic Risk Board. Sarlin and Peltonen (2013) propose an EWS based on a particular type of artificial neural network (self-organizing map) that visualizes potential sources of systemic risks and determines the position of each country within a financial stability cycle.

We end this section by mentioning some studies specifically focusing on EWS for Italian banks. Cannari and Signorini (1995) use discriminant analysis to predict micro-bank crises, while Vulpes (1999) presents an EWS based on a logit model where the explanatory variables derive from the indicators employed by the Interbank Deposit Protection Fund (‘Fondo Interbancario di Tutela dei Depositi’) for its internal monitoring system. A similar approach to Vulpes (1999), but improved in terms of both micro and macro indicators, was presented in an unpublished study by the BCCs’ Institutional Guarantee Fund (‘Fondo di Garanzia istituzionale del credito cooperativo’ - FGI 2011) to establish a risk assessment system for mutual banks. Finally, Fiordelisi and Mare (2013) apply survival analysis to study the defaults of Italian cooperative banks, while Ciocchetta et al. (2016) introduce a continuous vulnerability indicator for the Italian banking system stemming from the real estate sector and implement a Bayesian model averaging based on linear regression models.

3. Identification of distress events

The difference between sound and distressed banks is often not as clear as might be expected, especially in view of the long recession that has affected Italy in the most recent years.[3] Although an abrupt liquidity crisis (e.g., due to depositors' loss of confidence) may cause the sudden failure of an otherwise solvent institution, a self-evident state of crisis is usually preceded by a gradual and progressive deterioration of an institution's financial conditions. Every crisis, however, has its own story, and may differ in terms of both the preliminary phases and the subsequent interventions of the various subjects involved in the process of crisis management: shareholders, creditors, Supervisory Authorities, the Ministry of Economy and Finance, the deposit-guarantee fund, the European Commission, and so on. Furthermore, predicting a crisis is not sufficient to prevent it. Especially in recent times, various factors have contributed to substantially reducing the supervisor's ability to successfully manage difficult situations for banks.

In the most recent years, Supervisory Authorities and institutions have coped with an ever-changing regulatory and institutional framework: the new regulatory framework envisaged by CRR and CRD IV, the birth of the Single Supervisory Mechanism (November 2014) with the transfer to the ECB of the responsibility for the direct supervision of all significant euro-area institutions, the establishment of the Single Resolution Mechanism (January 2015), the introduction of a new banking crisis management paradigm (see BRRD Directive - 2014/59/EU) establishing, among other things, a more marked separation between supervisory duties and crisis management, and the change in state aid rules.

In this new context, the Supervisory Authority continues to play a central role. Generally speaking, the assessment of a bank's crisis situation occurs through one or more administrative measures taken by the Supervisory Authority; for the purposes of this work, we will use these measures as a primary source to identify the crisis of a bank.

A bank in distress is a rare event, partly thanks to the constant commitment of the Supervisory Authority to reduce the ex-ante probability of bankruptcy and to contain the ex-post risks of contagion and the occurrence of a systemic crisis.[4] In this study we adopted an 'extended' definition of distress that is as inclusive as possible of all manifestations of a bank's crisis. This choice builds on the necessarily conservative approach that must characterize the EWS of a Supervisory Authority. In line with Betz et al. (2014), we adopted a comprehensive definition of distress, which takes into account not only the procedure of compulsory administrative liquidation (*liquidazione coatta amministrativa*) similar to bankruptcy, but also other situations which arguably indicate a state of crisis.

Specifically, on the basis of the Italian regulatory framework, we identified the following distress events: compulsory administrative liquidation, extraordinary administration, temporary administration,

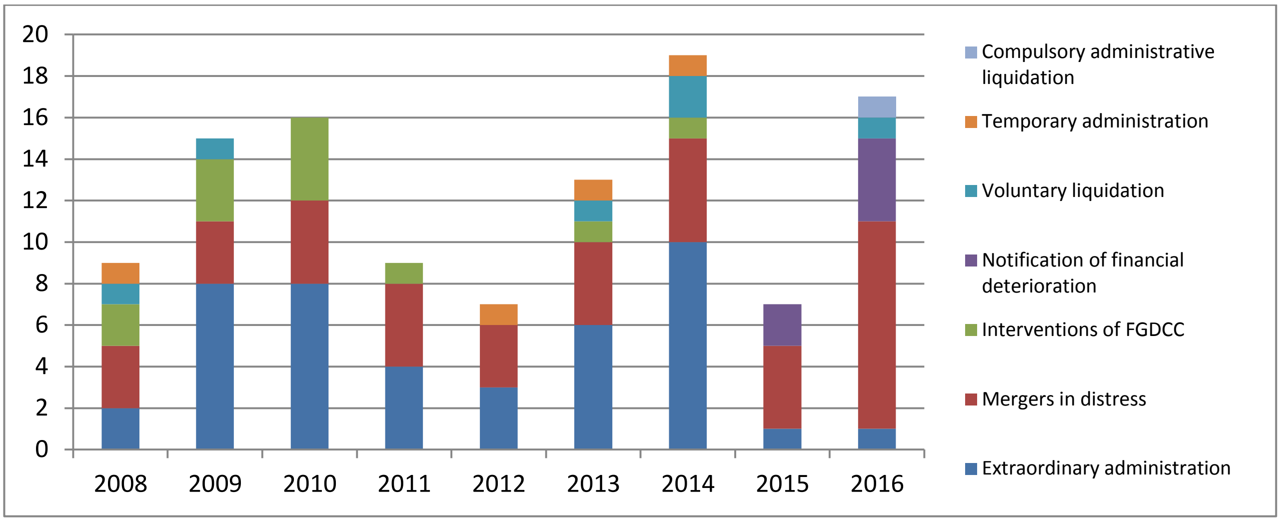
[3] See Ignazio Visco, European Parliament - Committee on Economic and Monetary Affairs - 11 April 2017, 'Exchange of views with the Governor of the Bank of Italy Ignazio Visco on the economic and financial situation of Italy and prospects for economic governance in the European Union': "From 2008 to 2013, as a result of a double – dip recession, GDP fell by almost 10 percentage points, industrial production by about a quarter, investment by 30 per cent and consumption by 8 per cent." […]; "Eventually, an economic crisis of these proportions could not leave Italian banks unaffected".

[4] In this perspective the recent comprehensive review of the prudential framework should be also interpreted, which aims to increase the quantity and quality of capital, introduce new liquidity requirements, contain leverage and strengthen banks' corporate governance and internal control systems.

voluntary liquidation, merger in distress,[5] disposal of assets (*cessione di rapporti giuridici)*, resolution, intervention of the depositors' guarantee funds (the Interbank Deposit Protection Fund – FITD – and the Guarantee Fund of Cooperative Credit Depositors – FGDCC – in the latter case also preventive), and notification of financial deterioration to the ECB.[6] State interventions are not considered as a distress event because none of the Italian LSIs were affected by these events over the period considered. Note that based on this broad definition, a distress event does not necessarily coincide with the 'disappearance' of a bank. Specifically, temporary and extraordinary administration procedures have often resulted in a bank returning to normal operations. However, we included these episodes in our definition of crisis because they have required an extraordinary intervention by the supervisor.

The starting point for constructing the sample used in the empirical analysis is the universe of Italian LSI banks operating in the period 2008-2016. The quarter in which the event occurred is selected as the reference date of crisis, represented by one of the events previously described. Given the importance of the time dimension in the construction of a model for predicting a crisis, we only considered the first distress situation for banks affected by more than one event. As an example, if a bank is first placed in temporary administration and, after one year, it merges with another bank because of a significant deterioration in its own financial conditions, then only the first crisis event is considered.

Figure 5
Time series distribution of first distress events classified by type
(data from 01-01-2008 to 30-06-2016)



Source: Supervisory data

Following the above criteria, 112 banks were identified as being in a state of distress over our sample period, against 195 total crisis events (see Figure 5). The two numbers differ, as we observed more than one distress event subsequent to the first one for almost half of the banks (49). Extraordinary administrations (43) and mergers in distress (40) represent 74 per cent of the first events, followed by: interventions of the Guarantee Fund of Cooperative Credit Depositors (12), notifications to the ECB of

[5] Mergers have been identified as crisis events if required by the Supervisory Authority within the scope of the measures imposed via the 'emergency procedure' and on condition that the latest available SREP score was extremely negative (e.g. 5-6 on a scale of 1-6 or 4 on a scale of 1-4).

[6] This event was considered following the formalization, by the ECB, of the 'Guidance on notification requirements' for the NCAs approved in April 2015. The guidance describes the triggers for notifying the ECB about deteriorating financial conditions of LSIs.

financial deterioration (6), voluntary liquidations (6), temporary administration (4) and compulsory administrative liquidation (1). The disposal of assets or legal relationships, the resolution and the interventions of the Interbank Deposit Protection Fund – although distress events in their own right – are not included in Figure 5 because they have always occurred after a different first event. For the same reason, even the most extreme crisis event – the compulsory administrative liquidation – only appears once in the sample; in 17 cases out of 18, the compulsory administrative liquidation was preceded by other distress events (see Table 4).

Table 4

Frequency distribution of distress events (first and subsequent events)

(data from 01-01-2008 to 30-06-2016)

	First distress event	**Events following the first distress event***											**Total distress events by type of event (first and following events)**
		Extraordinary administration	Mergers in distress	Intervention of FGDCC	Notification of financial deterioration	Voluntary liquidation	Temporary administ.	Compulsory administrative liquidation	Disposal of assets or legal relationships	Resolution	Intervention of FITD	**Total distress events following the first**	
Extraordinary administration	43		3	14	2	1		13	4	3	4	44	54
Mergers in distress	40	1	1		1				1			4	47
Interventions of FGDCC	12	6	2	6		2		2	2			20	34
Notification of financial deterioration	6	1	1									2	9
Voluntary liquidation	6								4			4	9
Temporary administration	4	3		2				2	1	1		9	4
Compulsory administrative liquidation	1												18
Disposal of assets or legal relationships	-												12
Resolution	-												4
Interventions of FITD	-												4
Total	112	11	7	22	3	3	0	17	12	4	4	83	195

Source: Supervisory data.

*For each row (first distress event), the table displays the subsequent distress events in the columns; for example, the 43 extraordinary administrations, identified as a first distress event, are followed by 3 mergers in distress, 14 interventions of the Guarantee Fund of Cooperative Credit Depositors, 2 notifications of financial deterioration, 1 voluntary liquidation, 13 administrative compulsory liquidations and so on, for a total of 44 events after 43 extraordinary administrations. For each column, the table shows the frequency distribution of a specific distress event following the first crisis event; for example, the extraordinary administration was not identified as the first distress event in 11 cases. Overall, the extraordinary administration was therefore found in 54 cases (in 43 as the first event and in 11 as a subsequent event).

4. Explanatory variables

In this study we built an indicator that provides timely signals about vulnerabilities at the individual bank level. Based on theoretical considerations and empirical evidence in the literature, a list of potential explanatory variables of banking crises has been identified. These indicators can be divided into two groups:

i. variables related to the overall banking system and Italian macro-financial variables (i.e. banking sector indicators and macro-financial variables);
ii. variables related to individual banks (i.e. micro variables).

For both groups, most of the variables used in the empirical analysis are available on a quarterly basis, and therefore with a frequency significantly higher than the one usually reported in the literature, where in most cases annual or semi-annual data are used, especially for micro variables.

a. Sectoral and macro-financial variables[7]

The environment where banks operate may affect their vulnerability; therefore, for our analysis we consider variables related to the overall banking system as well as the Italian macro-financial context. The banking system indicators are aimed at predicting the effect on the individual bank's vulnerability stemming from imbalances (mainly related to size, capital, credit and funding) within the overall banking sector. A banking sector experiencing excessively rapid growth compared with the country's real economy could suggest an excessive risk-taking attitude on the part of banks; this build-up of risk may exacerbate the effect of a financial crisis on weaker banks. Similarly, several features of a banking system (insufficient capitalization, high leverage, large exposure to the real estate and high reliance on wholesale funding) could make it vulnerable to contagion phenomena and to aggregate shocks due to the common exposure of banks to specific risk factors. The banking sector variables either come from institutional sources (e.g. Istat) or are constructed by aggregating supervisory reporting data from single institutions.

The Italian macro-financial variables are used to capture the effect that macroeconomic imbalances may have on individual banks. These variables also take into account the business cycle and the changes in the prices of financial and real assets (equity and real estate prices). For these variables we mainly rely on European sources (e.g. Eurostat, European Commission). As to the real economy variables, we select from among the indicators that have shown a greater informative contribution to forecasting systemic banking crises (see Demirgüç-Kunt and Detragiache 1998, 2000 or Davis and Karim 2008). Variables relating to the real estate sector play an important role based on past experience, as highlighted by Barrell et al. (2010), Crowe et al. (2013) and Hartmann (2015). Crises relating to the real estate sector are generally longer and costlier than the average downturn (Claessens et al., 2009). Financial variables are used instead because of their potential ability to anticipate banking crises and possible imbalances in the real economy. For example, among these, a rapid credit growth (measured by the credit-to-GDP gap) combined with a rise in asset prices may increase the likelihood of financial instability episodes (Borio and Lowe 2002, Borio and

[7] To save space we will not report the full list of all micro- as well as sectoral and macro-financial variables that have been considered as potentially informative about banking distress. The list is available from the authors upon request.

Drehmann 2009). An increase in the government yield curve, both in absolute and relative terms, is a signal of potential instability for national public accounts, which could have negative spillover effects on country banks (sovereign-bank feedback loop). A prolonged period of monetary expansion (M2 / GDP) could lead to excessive liquidity conditions in the financial markets, triggering a rapid growth of the credit sector (credit boom). In the event of a financial crisis, this imbalance may cause some instability in the banking sector, with negative effects on the money market (Von Hagen and Ho 2007).[8]

For both banking-sector and macro-financial variables, most of the indicators are available at the national level. When possible, some indicators have been computed at the provincial, regional or macro-area level (North-East, North-West, Centre, and South) in order to take into account the local nature of the Italian LSI sector. Given the very limited availability of these variables for our sample period, we only considered the prevalent area of operations calculated on the basis of the number of branches, the variables related to labour market conditions (unemployment rates and number of employees) and the variables related to the number and amount of non-payment claims (*protesti*).

b. Micro variables

In the literature on EWS there are many papers showing that the contribution of micro variables is generally the most significant in explaining the health of individual banks (see Arena, 2008, Cole and Wu, 2009). The list of micro variables to be included in the model has been drawn up taking into consideration the most common indicators used in the literature as well as expert judgments to comprehensively cover all the main risks commonly faced by banks. We identified approximately 80 variables that could be potentially useful in predicting a crisis. For all banks, the variables were constructed mainly from supervisory reports at the highest level of consolidation. The time series of the variables take into account changes in the regulatory, reporting and accounting framework. The literature has identified the accumulation of credit, market, liquidity and interest rate risks as the main cause of bank crises (Demirgüç-Kunt and Detragiache 1998, Ergungor and Thompson 2005).[9] The micro variables representing these risks and more generally the idiosyncratic indicators of the overall health of an institution can be classified, following a widespread approach in literature, on the basis of the 'CAMELS' paradigm (see Cole and Gunther (1998) among others). According to this classification, we use proxies for the following key bank profiles:[10]

[8] This could be due mainly to three factors: i) a reduction in the asset quality of banks generating a lack of liquidity in the banking sector; ii) a sudden reduction of deposits; and iii) a reduction in the volume of transactions on the interbank market.

[9] Credit risk measures the probability that a borrower will have difficulty repaying his debt and the bank's credit will then move from a performing status to a non-performing one. Credit risk can be particularly significant where credit is concentrated in a specific economic sector or in a specific geographical area. Furthermore, credit risk is positively correlated with the increase in the volume of credit granted to the economy and it is generally procyclical: in a situation of economic crisis, a credit reduction can exacerbate the recession, further increasing the default risk of debtors. Market risk measures how volatility and adverse movements in the prices of financial assets held in the trading book will negatively impact a bank's profitability. The liquidity risk reflects the likelihood that the bank will not be able to meet its payment obligations when they mature either because of its inability to raise funds on the market ('funding liquidity risk') or its difficulty in selling its assets ('market liquidity risk'); this risk is often associated with crisis situations that degenerate in a sudden and irreversible way. Interest rate risk is typical of banking activities since a bank operates a maturity transformation and generally holds assets with a longer duration than that of its liabilities. A movement in interest rates produces impacts on both the net interest income of the bank and the economic value of assets and liabilities held in the balance sheet.

[10] Some of the micro variables used in the empirical analysis (e.g. LCR) are not available for the whole observation period. For these variables, however, a proxy was available in the supervisory databases.

- **Capital**: this area identifies the capital strength of the bank and its ability to absorb losses without compromising its operational activity. The bank's capital acts as a buffer against losses, thereby preserving solvency and reducing the probability of a crisis. The adoption of early intervention measures by Supervisory Authorities, aimed at avoiding the further deterioration of institutions' crisis situations, is frequently based on banks' capital ratios. This category includes variables such as CET 1 ratio, tier 1 ratio, and leverage ratio.
- **Asset quality**: mainly provides information on the quality of the assets held by the banks, with particular reference to customer loans. It is closely linked to credit risk: a significant deterioration in the assets could generate high capital losses and increase the bank's probability of default, thus limiting its ability to provide new credit to the economy. This area includes variables related to the NPL ratio, loan value adjustments on total assets, number of large exposures, and the RWA density.
- **Management:** this is one of the most important areas of analysis because management abilities are fundamental for any firms, including banks. Unfortunately, the information relating to this area cannot be easily quantified and it is necessary to rely on some proxies in order to evaluate the quality of the management. In the literature, the most frequently used variables include the indicator of multiple directorships, which measures the number of boards in which a specific director sits simultaneously, the board turnover rate (average seniority measured in years), and the operational loss.
- **Earnings**: this area mainly includes information on the bank's income flows and on its ability to generate profits in relation to the risks taken. Repeated losses over time have a significant negative impact on the bank's capital strength and they also represent an indicator of business inefficiencies. On the other hand, an improvement in the bank's profitability profile generally leads to a reduction in the probability of default. This area of analysis includes variables such as ROE, ROA, cost to income ratio, net income on operating costs, and the WACC.
- **Liquidity**: Supervisory Authorities pay particular attention to this area, as liquidity-related pressures, in the absence of appropriate measures, could suddenly become crisis situations with potential effects at the systemic level too. For example, an adequate availability of readily liquid assets and the absence of a significant mismatch between assets and liabilities maturities are factors that contribute to ensuring the survival of a bank when liquidity stress occurs. In this respect, deposits are generally considered as a more stable source of funding than either the interbank market or other wholesale debt instruments. Therefore, an increase in the share of deposits over total loans is generally associated with a reduction in the probability of default. The liquidity profile includes indicators such as the LCR, the NSFR, the funding gap, the ratio between loans and total deposits, and the amount of high-quality liquid assets.
- **Sensitivity to market risk**: this is the risk that comes from the trading portfolio, generally composed of securities and derivatives. The relationship between this type of variable and the probability of a bank default is not univocal. On the one hand, a greater share of income from trading activity may be associated with a riskier business model, since trading activity is generally a volatile source of revenues. On the other hand, some financial assets are more liquid than the bank's traditional credit assets (such as mortgages) and this can reduce losses from fire sales if there is a negative shock to the macroeconomic and financial context. The variables belonging to this area are the ratio of capital requirements for market risk to total capital requirements and the ratio of trading income over gross operating income.

Among the micro variables, we intentionally chose to exclude the SREP score, which represents a synthetic assessment of the capital, financial and organizational strength that is periodically attributed to each bank by the Supervisory Authority. Although the SREP score has its own specific informative value, it has an annual frequency, while the EWS presented in this paper uses quarterly data, enabling, in principle, a more timely emergence of distress signals.

5. Empirical analysis

a. Model

Following a popular approach in the literature, we adopted a logit model to analyse the determinants of institutions' crises. The logit model represents a particular case of the generalized linear model where the link function is the logistic function. This model is generally used in the case of binary dependent variables $(\mathrm{y_i})$, i.e. only assuming the value 1 or 0 with probability equal to π e $1-\pi$, respectively. For instance, in the case of banking solvency, the dependent variable $(\mathrm{y_i})$ can be modelled as:

$$y_i = \begin{cases} 1 \ \text{ if the bank is in distress} \\ \quad 0 \ \text{ otherwise} \end{cases}$$

In general, y_i is distributed as a Bernoulli random variable with parameter π and probability function defined as follows:

$$Pr\{y_i\} = \pi^{y_i}(1-\pi)^{1-y_i} \qquad (1)$$

$$\text{if } y_i = 1 \text{ then } \Pr(y_i = 1) = \pi$$

$$\text{if } y_i = 0 \text{ then } \Pr(y_i = 0) = 1-\pi$$

For the purpose of this research, it would clearly be desirable to express the probability π as a function of a set of independent variables x_i representative of the financial and economic condition of each institution. The simplest way to proceed would be to define π_i as a linear function:

$$\pi_i = x_i'\beta \qquad (2)$$

where x_i is the vector of the explanatory variables and β is the vector of the regression coefficients, measuring the marginal effects of each explanatory variable on the probability of default. This model is commonly referred to as the linear probability model and can be estimated via ordinary least squares.

However, an initial problem stemming from the use of the linear probability model (2) is that the probability π_i must be between 0 and 1 while the linear predictor $x_i'\beta$ could potentially assume values out beyond this range unless additional restrictions are imposed on the coefficients. Moreover, the estimates obtained using the linear probability model yield heteroskedastic error terms and would not be normally distributed.

To overcome the limitations of the linear probability model, it is possible to transform the probability π_i, using a non-linear function which guarantees that the estimated probability is in the interval (0,1). In the case of a logit model, the logistic link function Λ is applied to probability π_i such that:

$$\Lambda\,(\pi_i) = \frac{\exp\{x_i'\beta\}}{1+\exp\{x_i'\beta\}} \qquad (3)$$

where the LHS variable is the probability measure assuming values in the usual interval (0,1), while the RHS variable is a non-linear function of the explanatory variables. In the logit model, the estimate of the parameter vector β is performed using maximum likelihood. The model coefficients, given that the specification is non-linear, cannot be directly interpreted as marginal effects. In other words, they do not quantitatively measure the impact of the marginal variation in the *i-th* regressor on the probability of default; on the contrary, they only provide information about the sign of the marginal effect.

Before analysing the model specification and the empirical results in detail, it is essential to recall that this model, like any other statistical model, is subject to error. For this reason, its signal must always be analysed in conjunction with other methodological tools in order to adopt the most appropriate and effective supervisory measures.

b. Empirical specification

Because of the large number of variables in our dataset (approximately 15 sectoral variables, 23 macro-financial, and 80 micro), the empirical specification required a preliminary analysis of the subset of variables that most likely explain the crisis of an institution. First of all we selected the best empirical specifications according to a number of statistical performance indices such as the Area Under the Receiver Operating Characteristic curve (AUROC), the confusion matrix and the pseudo R2[11] (see Section 5.d for further details). In selecting the relevant regressors we also tried to achieve an adequate representation of all the significant areas of risk for a bank, without compromising statistical robustness; for this reason, variables whose statistical significance was found to be weak or in any case strongly dependent on the model's specification were not included in the final preferred empirical specifications.

We estimated the model between 31 March 2011 and 30 June 2016 to ensure a sufficiently long time-series for all the explanatory variables, leaving the last two quarters of 2016 for an out-of-sample validation. An important point concerns the choice of the forecast horizon. For practical purposes, it should be as long as possible, to allow the Supervisory Authority to implement measures to address the situation of difficulty at an early stage and avoid a crisis. However, a longer-term forecast horizon poses serious challenges to the correct identification of banks' crises because of the decreasing explanatory power of the variables used in the analysis. Following previous papers in this field, we considered two prediction horizons: 4 and 6 quarters before the occurrence of the distress event; see Lang et al. (2018) for the pros and cons of different time horizons in EWS. We shall see that, in line with expectations, the 6 quarters horizon comes at the cost of a reduction in the model's ability to correctly anticipate crisis situations.[12] On the other hand, a very short-term forecast horizon would not allow the Supervisory Authority to promptly implement measures to address the crisis at hand.

c. Results

Tables 5 and 6 display the results for the main empirical specifications at 4- and 6-quarter forecast horizons, respectively. Before examining in detail our findings, there are some more general results that we would like to highlight. First, there is a substantial overlap between the two specifications, as we found that there is quite a stable subset of variables that contributes significantly to forecasting a distress event. Regressors in the asset quality area are mostly related to credit quality, while indicators of risk concentration are instead excluded from the final models. It was harder to find explanatory variables in the managerial subgroup, probably because of its nature which is hard to represent through quantitative proxies. In the liquidity area, most predictors are related to the funding structure of banks rather than to 'true' liquidity indicators such as the LCR. This finding is not surprising, considering the long-term horizon of

[11] These indexes are commonly used to assess model performance and compare the various empirical specifications with respect to their predictive ability.

[12] Considering the time lag with which data become available (typically, up to one quarter), the lead time allowed even by the 6-quarter horizon is relatively modest. This represents an objective challenge that will need to be addressed in future work.

the analysis and that a liquidity crisis typically develops in the (very) short-term. Hence, liquidity crises are quite hard to predict in advance, especially with an EWS with a larger forecast horizon of 4-6 quarters.

Another interesting general feature is the absence of significant macroeconomic or sectoral variables among the empirical specifications estimated in Tables 5 and 6. Previous studies on EWS for individual banks had already shown that the contribution of this type of variable is frequently marginal, or even absent (Arena 2008, Cole and Wu 2009, Poghosyan and Čihák 2011). Even when we restricted the comparison to studies carried out with samples that are more closely comparable with ours (FGI 2011, Fiordelisi and Mare 2013), we noticed that the contribution of macro variables is significantly lower than that of the variables representative of banks' idiosyncratic risk. This result could have two possible interpretations, which are not necessarily mutually exclusive. On the one hand, it is plausible that the micro variables are able to explain most of the individual heterogeneity in the sample and therefore adding macro or sector explanatory variables does not increase the model's predictive ability. On the other hand, it is possible that the macro variables, being mainly defined at national level, are not particularly suited to modelling the localism of most of the Italian LSIs with business models restricted to a limited geographical area.

Since the ultimate goal of this work is not to estimate the impact of each regressor but rather to build an appropriate forecasting model, in the following we only comment on the signs of the coefficients, and thus the direction of the effect of the various explanatory variables. We recall that, the model being nonlinear and also using several explanatory variables expressed as ratios, the value of each coefficient should not be taken as a measure of the magnitude of the impact. In general, a negative coefficient identifies the variables that are negatively correlated with the probability of default (PD); conversely, a positive estimate indicates the variables for which a higher value of the regressor is associated with an increase in the probability of observing a crisis event. To guide the reader through our discussion of the results, we will use the grouping of variables based on the CAMELS paradigm:[13]

- **Capital:** capital adequacy, measured with the CET1 ratio, is negatively correlated with the PD. This finding, recurrent in the literature (see for example Porath 2004, Jahn and Kick 2012, Haq and Haney 2012), is not surprising if we think of capital as a measure of bank soundness and as a loss-absorbing factor reducing the institutions' moral hazard. Similar estimates, not reported in the table, are also obtained using the other variables related to the capital area, such as T1 ratio and TC ratio.[14]
- **Asset quality**: although we have considered several variables to represent the quality of assets, it is not surprising that the ones linked to credit quality are particularly relevant for the specific sample considered. Among these, the NPL ratio is also the one most frequently adopted in the literature, even though there are sometimes differences with regard to the scope used in the definition of impaired loans (Martin 1977, Vulpes 1999, Betz et al. 2014). Higher values for the NPL ratio increase the bank's PD, as they reduce a bank's profitability and soak up resources to improve the coverage of loans. The degree of credit quality is also taken into account through the ratio of loan value adjustments to total

[13] To save space and not complicate the discussion, we will focus on the main empirical findings and display the estimates for the 4 best specifications in terms of predictive ability (AUROC) and representativeness of the banks' risk profiles. The entire set of results can be requested from the authors.

[14] This result is consistent with the high degree of correlation among the different measurements of capital quality. For LSI banks, and in particular for BCCs, there is frequently a limited difference between CET1 ratio, T1 ratio and TC ratio. For this reason, the inclusion of multiple variables related to capital adequacy was rejected because of multicollinearity issues and we only retain the variable with the highest predictive power among capital adequacy indicators.

assets which shows a positive impact on the PD as in FGI (2011) or Jagtiani et al. (2003). As part of the sub-category of asset quality, we also consider a measure of interconnectedness quantifying the scale of banking intermediation towards the whole financial system. Banks with a high degree of interconnectedness, on both sides of the balance sheet, are perceived as more solid and this is reflected in a reduction of the PD.[15] The size factor, measured by the quarterly growth of the assets, produces a negative effect on the PD; all other factors being equal, asset expansion is considered a positive feature which could be interpreted as an element of greater solidity (Cole and Wu 2009, Fiordelisi and Mare 2013). Finally, the estimates show a positive link between exposures to the real estate sector and PD; this result signals that the occurrence of a distress event is more likely for institutions with a sizeable asset concentration in one of the sectors that was most affected by the latest and exceptionally severe economic recession (see Ferrari et al. 2015).

- **Management**: both variables in this category exhibit a negative effect on the probability of observing a bank crisis. For the first variable, when measuring the number of positions held by a member of the board, the result could seem counter-intuitive if we consider that a greater number of tasks reduces the time that a director can dedicate to the management of a bank. However, we emphasize that the literature has not established the link between multiple directorships and probability of default very clearly, with some important contributions (e.g. Ferris et al. 2003) finding a positive correlation between performance of firms and number of appointments. In a more recent study focusing on the banking sector, Elyasiani and Zhang (2015) also documented a positive effect of the number of multiple directorships on banks' performance. This result is traditionally explained by the fact that multiple directorships could represent a valuable indicator of manager quality. A manager who is simultaneously member of a number of boards is seen as a more competent director, as well as having the opportunity to interact with other directors and create a tighter network of relationships. An analogous interpretation could also be suggested for the regressor measuring the level of turnover within the board. While the presence of long-term directorships within the board could lead to conflicts of interest, on the other hand, a more contained rate of turnover may signal high quality directors who are reappointed by virtue of the results achieved. On average both variables produce, at least for the sample considered, a negative effect on the PD.
- **Earning**: this sub-category allows us to assess the bank's business model and measure its ability to generate income streams that could both remunerate the use of resources in the short term (viability) and sustain bank operations and growth over time (sustainability). The variables included in the various specifications always display a sign in line with expectations, i.e. the greater the profitability and the operational efficiency of the bank, the lower the PD. Two of the variables adopted in FGI (2011) are also significant in our analysis, albeit for a different observation period and a larger sample of banks. The first one is a measure of total profitability in relation to costs (net income/operating costs) while the latter is an indicator of the efficiency of the funding process (customer deposits/administrative expenses). A similar result is also expressed by the ratio between gross operating profits and managed resources[16] which measures a bank's profitability with respect to its main liability items. Finally, a negative effect on the PD is also observed for one of the most widespread indicators used to assess the

[15] A possible explanation is the monitoring action reciprocally carried out by banks which will be more willing to be exposed to financial counterparts that are perceived as more sound.

[16] The aggregate 'managed resources' mainly include deposit from banks and customers, debt securities in issue, capital and other liabilities.

profitability of banks, namely the return on assets (ROA) with a similar impact found, among others, by Martin (1977) and Logan (2001).

- **Liquidity**: as previously mentioned, the variables included in the different specifications are mainly representative of the funding structure and of the degree of asset liquidity, while short-term indicators such as the LCR are less effective in predicting crisis situations over the medium-term. The presence of high quality liquid assets is an indicator of banks' resilience and measures its ability to find resources promptly to cover bank run episodes. Similar to Poghosyan and Čihák (2011), we find that a greater amount of readily available assets in proportion to deposits reduces the PD of the bank. The short-term maturity mismatch measured by the current ratio exhibits a negative coefficient, signalling that the PD increases when an institution's balance sheet is excessively tilted towards short-term liabilities (Logan 2001). Concerning the sources of funding, we observe that both the funding gap and the short-term deposits from banks as a proportion of total funding display a positive and significant coefficient. An increasing funding gap is a clear sign of structural weakness and identifies a situation in which there is an imbalance between the total amount of loans and the sources of financing (see FGI 2011). The dependence on demand funding from banks over total financing can also be thought of as an indicator of the fragility of banks. This result is in line with the standard observation that retail financing is traditionally perceived as less volatile than interbank financing. A creditor institution is generally able to perform a more accurate monitoring activity than a retail investor, so it will be more active in recouping its funds at the first signs of crisis for the financed bank (Bologna 2011, Vazquez and Federico 2015). Finally, the ratio of loans to customers over total funds negatively impacts the PD, a result that may appear to be in contrast with the estimates obtained for the funding gap. As a possible explanation, however, we observe that only the funding gap is measured net of loan loss provisions, which makes this indicator more symptomatic of a bank's actual level of risk; conversely, a gross value in relation to total funding is closer to a measure of allocation efficiency and bank performance with respect to its available resources.
- **Sensitivity to market risk:** this area is clearly less important in explaining the PD compared with the other sub-categories of the CAMELS paradigm. No explanatory variable is found to be statistically significant when accounted for as part of broader model specifications that also include the other areas of analysis. The result corroborates previous empirical studies, where the predictive contribution of this sub-category is generally limited. This finding is even less surprising considering the type of banks on which the estimate is made, in which the exposure to market risk is extremely low, if not nil.

The yearly dummy variables included to take into account the presence of possible time effects are generally not significant, a result similar to that found in FGI (2011). On the contrary, the dummy variable identifying the cooperative banks is significant and displays a positive sign which implies that banks in this sector are more frequently involved in distress events. The result is in line with the fact that cooperative banks are most represented in the subset of distressed banks and supports the repeated calls from the Bank of Italy to overcome the critical issues affecting the cooperative credit sector.[17] Finally, bearing in mind the degree of fragmentation and the geographical heterogeneity of Italian LSIs discussed in Section 1, we extended the baseline empirical specifications and controls for

[17] See Barbagallo (2016) "*La riforma del Credito Cooperativo nel quadro delle nuove regole europee e dell'Unione bancaria*" for a review of the main issues concerning cooperative banks.

the geographical area in which banks mainly operate; these regressors, however, are not statistically significant.

Table 5
Empirical estimates for selected specifications at the 4-quarter time horizon

Explanatory variable	Model 1	Model 2	Model 3	Model 4
CET1 ratio	**-0.070*** **	**-0.083*** **	**-0.088*** **	**-0.097*** **
	[0.019]	[0.022]	[0.024]	[0.018]
NPL ratio	**0.061*** **	**0.088*** **	**0.093*** **	**0.097*** **
	[0.018]	[0.014]	[0.011]	[0.010]
Bank interconnectedness	**-0.051*** **	**-0.054*** **	**-0.026* **	
	[0.015]	[0.015]	[0.015]	
Loan value adjustments / total assets	**0.090* **	**0.070** **		
	[0.049]	[0.031]		
Total assets	**-4.079** **	**-1.075**		
	[2.057]	[1.537]		
Exposure to real estate sector / total assets				**0.001* **
				[0.000]
ROA	**-0.256*** **	**-0.343*** **	**-0.251* **	
	[0.087]	[0.093]	[0.135]	
Net income / operating costs	**-1.098*** **	**-0.911*** **	**-1.282*** **	**-1.564*** **
	[0.268]	[0.337]	[0.348]	[0.208]
Customer deposits / administrative expenses	**-0.121*** **	**-0.135*** **	**-0.134*** **	**-0.124*** **
	[0.032]	[0.031]	[0.026]	[0.022]
Gross operating profit / managed resources				**-0.262** **
				[0.121]
Demand assets / demand liabilities	**-0.265** **	**-0.283** **	**-0.295*** **	**-0.272** **
	[0.115]	[0.119]	[0.113]	[0.111]
Demand funding from banks / total financing	**0.055*** **	**0.055*** **		
	[0.021]	[0.021]		
Loans to customer / total financing	**-3.001*** **	**-3.975*** **	**-3.278*** **	**-2.695*** **
	[0.419]	[0.809]	[0.510]	[0.291]
Highly liquid assets / total deposits	**-0.027*** **	**-0.033*** **	**-0.025*** **	**-0.018** **
	[0.009]	[0.009]	[0.008]	[0.007]
Funding gap	**0.002*** **	**0.002*** **	**0.001*** **	**0.001*** **
	[0.000]	[0.000]	[0.000]	[0.000]
Board turnover rate	**-0.002*** **			
	[0.000]			
Number of directorships	**-0.533*** **			
	[0.136]			
BCC dummy	**2.033*** **	**0.986*** **	**0.648** **	**0.544** **
	[0.425]	[0.329]	[0.296]	[0.275]
Constant	**5.665*** **	**3.006** **	**2.404*** **	**1.453** **
	[1.189]	[1.239]	[0.871]	[0.572]
Time dummies	YES	YES	YES	YES
Pseudo R-squared	0.309	0.248	0.239	0.226
N	9047	9101	9571	9523

Logit model estimates. For each explanatory variable, the first line displays in bold the value of the coefficient, while the corresponding standard errors are reported in brackets in the second line. *, **, and *** denote significance at, respectively, the 10%, 5% and 1% confidence level. The standard errors are robust to the presence of heteroskedasticity and autocorrelation.

Table 6
Empirical estimates for selected specifications at the 6-quarter time horizon

Explanatory variable	Model 1	Model 2	Model 3	Model 4
CET1 ratio	**-0.059*** **	**-0.068*** **	**-0.050** **	**-0.062*** **
	[0.019]	[0.021]	[0.020]	[0.019]
NPL ratio	**0.059*** **	**0.055*** **	**0.062*** **	**0.068*** **
	[0.020]	[0.021]	[0.020]	[0.021]
Bank interconnectedness	**-0.066*** **	**-0.058*** **	**-0.043*** **	**-0.049*** **
	[0.012]	[0.012]	[0.010]	[0.009]
Loan value adjustments / total assets	**0.108* **	**0.198*** **	**0.123** **	**0.178*** **
	[0.059]	[0.062]	[0.057]	[0.061]
Exposure to real estate sector / total assets				**0.045*** **
				[0.010]
ROA			**-0.199*** **	**-0.419*** **
			[0.067]	[0.114]
Net income / operating costs	**-1.339*** **	**-1.376*** **	**-0.963*** **	
	[0.255]	[0.243]	[0.298]	
Customer deposits / administrative expenses	**-0.150*** **	**-0.166*** **	**-0.128*** **	**-0.170*** **
	[0.032]	[0.031]	[0.030]	[0.035]
Gross operating profit / managed resources	**-0.198** **	**-0.288*** **		**-0.286** **
	[0.087]	[0.062]		[0.137]
Demand assets / demand liabilities	**-0.407*** **	**-0.473*** **	**-0.220** **	**-0.441*** **
	[0.148]	[0.156]	[0.095]	[0.156]
Loans to customer / total financing	**-2.659*** **	**-3.604*** **	**-2.605*** **	**-3.884*** **
	[0.476]	[0.618]	[0.437]	[0.657]
Highly liquid assets / total deposits	**-0.024*** **	**-0.029*** **	**-0.023*** **	**-0.024*** **
	[0.009]	[0.008]	[0.008]	[0.008]
Funding gap	**0.002** **	**0.001** **	**0.001*** **	**0.001** **
	[0.001]	[0.001]	[0.001]	[0.001]
Board turnover rate	**-0.002*** **		**-0.002*** **	
	[0.000]		[0.000]	
Number of directorships	**-0.506*** **		**-0.239** **	
	[0.141]		[0.108]	
BCC	**1.684*** **	**0.816*** **	**1.401*** **	**0.752** **
	[0.383]	[0.306]	[0.379]	[0.301]
Constant	**6.736*** **	**4.445*** **	**3.759*** **	**3.616*** **
	[1.071]	[1.043]	[0.747]	[1.119]
Time dummies	YES	YES	NO	YES
Pseudo R-squared	0.266	0.217	0.245	0.215
N	8480	8527	8480	8484

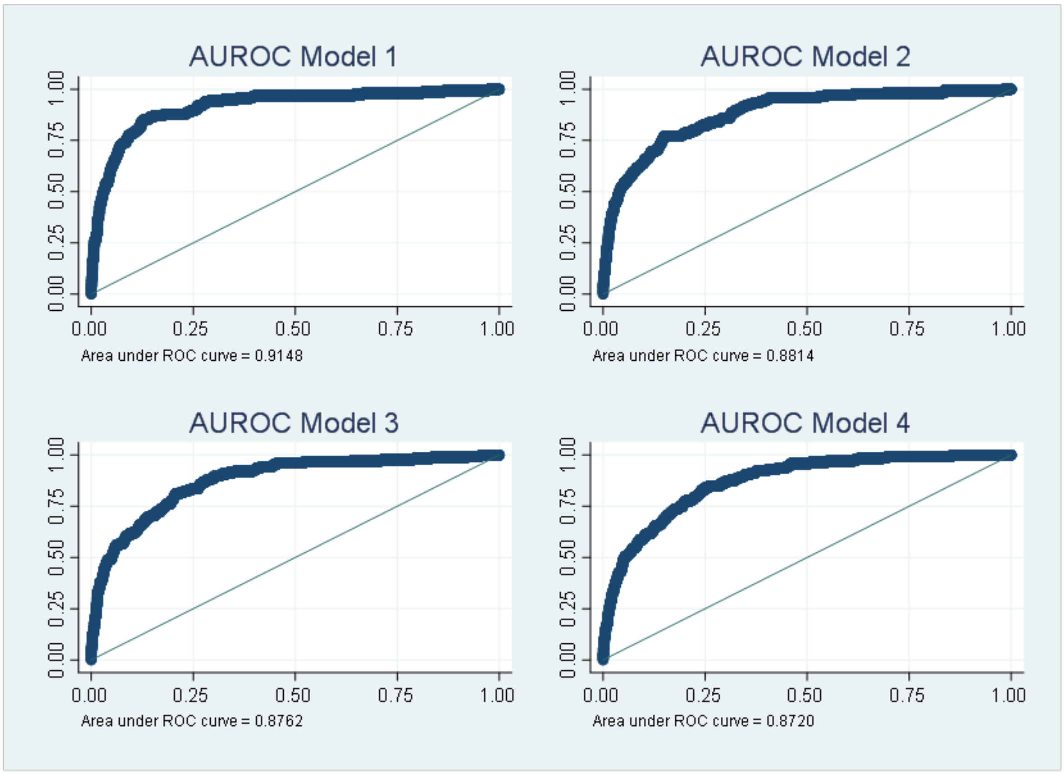
Logit model estimates. For each explanatory variable, the first line displays in bold the value of the coefficient, while the corresponding standard errors are reported in brackets in the second line. *, **, and *** denote significance at, respectively, the 10%, 5% and 1% confidence level. The standard errors are robust to the presence of heteroskedasticity and autocorrelation.

d. Diagnostics and robustness tests

In this Section we examine some model diagnostics and we further analyse our findings, with the aim of testing the ability of the EWS to predict bank distress in advance. To this end, the first performance indicator to be used is the AUROC curve, reported in Figures 6 and 7 for 4-quarter and 6-quarter forecast horizons respectively. The AUROC is a normalized indicator with values contained in the interval [0,1], where the upper bound indicates a model that manages to distinguish perfectly between banks in distress and healthy banks. In each graph the bisector, corresponding to a value of 0.5, represents the performance of a model in which bank classification is completely random.

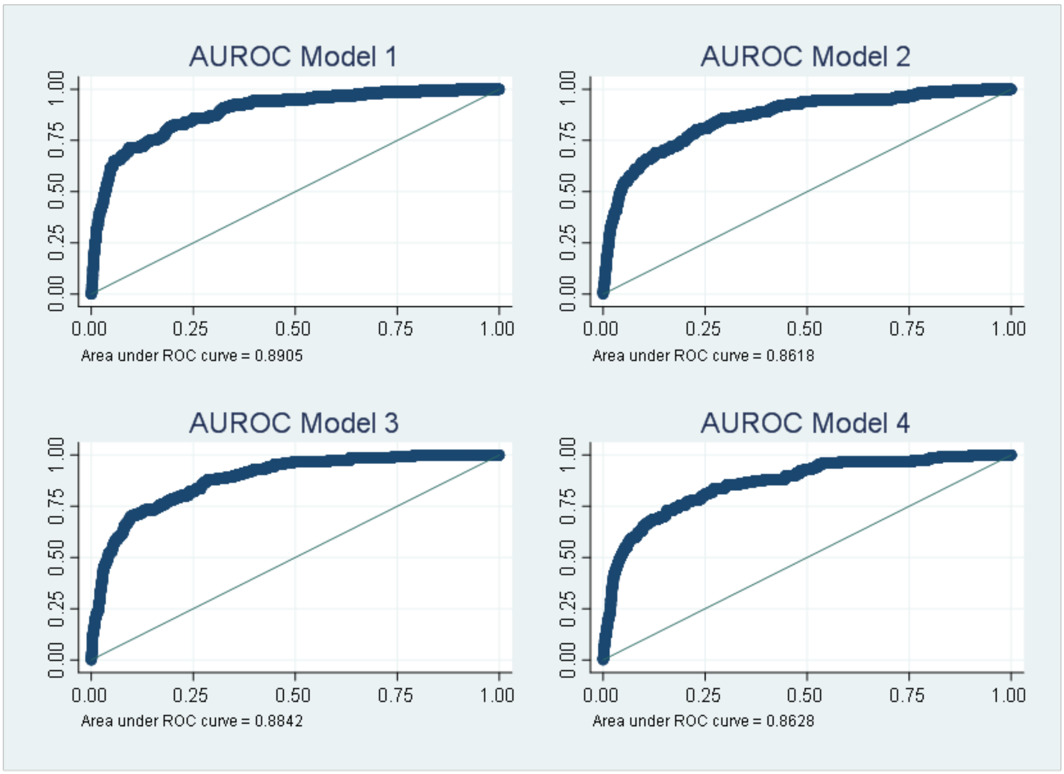
Figure 6

AUROC for empirical specifications estimated at a 4-quarter forecast horizon



Values lower than 0.5 for the AUROC denote an empirical specification with lower predictive ability than the random model; on the contrary, values higher than 0.5 are representative of models with a forecasting performance that becomes greater as the AUROC approaches 1. The analysis of the AUROC for both forecast horizons shows, first of all, a more than satisfactory performance of the EWS; this is apparent when looking at the AUROC index, which always displays values higher than 0.85, which is equal to or even higher than that found in most of the empirical studies available in the literature. Second, we observe that the discriminating ability of the 4-quarter forecast horizon model is generally superior to that of the 6-quarter specification; this result is not surprising as it is reasonable to expect an increase in the model performance when the forecast horizon decreases. As a general remark, we anticipate that this result will also be confirmed by the additional diagnostics discussed in this Section. The AUROC provides an absolute indicator of the model's fitting performance, but in order to assess the adequacy of the EWS we also rely on the confusion or classification matrices. A confusion matrix allows us to compare the final prediction of the model (bank in distress/not in distress) with the actual state in which the bank is found, according to the classification scheme illustrated in Table 7.

Figure 7
AUROC for empirical specifications estimated at a 6-quarter forecast horizon



The confusion matrix is a common diagnostic for binary dependent variable models and it allows us not only to evaluate the performance of the model but also to determine the magnitude of type I and II errors.[18] The analysis based on the classification matrix firstly requires the definition of a threshold (cut-off point) that is used to discriminate between distressed banks and healthy institutions. In a classical logit model, a threshold of 0.5 is usually adopted when the units are more or less equally distributed between the two categories (0/1); therefore, only banks with an estimated PD of more than 0.5 are assigned to the class of banks in distress. However, this approach has two major flaws. First, and as previously mentioned, the studies on banks' defaults show a significant imbalance in terms of sample composition. In addition, choosing a threshold value equal to 0.5 would not lead to a very conservative classification because the distress condition would only be achieved for high PD values, thus substantially reducing the number of banks to be brought to the attention of the Supervisory Authority. Therefore, in line with the approach suggested by similar contributions (see for example FGI 2011), we adopt a cut-off point equal to the empirical default rate observed in the sample, namely 2.4 per cent.[19] The confusion matrices are reported in Table 8 for the 4-quarter forecast horizon and in

[18] The type I error represents the probability of not receiving a warning signal from the model in the event that a distress event actually occurs, while the type II error represents the probability of receiving an alarm signal in the absence of distress. Using the confusion matrix provided in Table 7, the type I error is equal to C / (C + D), while the type II error corresponds to B / (A + B); on the other hand, the correctly predicted distress events are equivalent to D / (C + D) while healthy institutions correctly classified by the model are equal to A / (A + B).
[19] Alessi and Detken (2011) and Sarlin (2013) suggest a cut-off point based on the policy maker's preferences between type I and type II errors. The Supervisory Authority is asked to pay particular attention to the definition and the calibration of an EWS, bearing

Table 9 for the 6-quarter forecast horizon. The correct classification values are in line with and sometimes higher than what had been reported in other empirical studies; in this case too, the 4-quarter specification exhibits a better performance in terms of type I and II errors and with respect to the percentage of correct classifications.

Table 7

Sample confusion matrix for distress classification

		Actual	
		Not in distress	**In distress**
Predicted	**Not in distress**	*Viable banks correctly classified* ***(A)***	*Missed distress* ***(C)***
	In distress	*False alarms* ***(B)***	*Distress correctly classified* ***(D)***

The confusion matrix compares the predicted with the actual classification of banks; correctly classified institutions are found along the main diagonal of the table (cells 'Viable banks correctly classified' and 'Distress correctly classified').

Table 8

Confusion matrix at 4-quarter forecast horizon

		Actual			
		Not in distress		**In distress**	
Predicted	**Not in distress**	**M1**	88%	**M1**	15%
		M2	87%	**M2**	25%
		M3	86%	**M3**	28%
		M4	87%	**M4**	29%
	In distress	**M1**	12%	**M1**	85%
		M2	13%	**M2**	75%
		M3	14%	**M3**	72%
		M4	13%	**M4**	71%

% Correct classification	**M1**	90%
	M2	89%
	M3	88%
	M4	88%

The confusion matrix displays the percentage of correctly classified banks for the four specifications displayed in Table 5. Percentages are computed with respect to column totals; in the lower table we also report the percentage of correctly classified banks defined as (A+D)/(A+B+C+D).

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in mind the possible trade-off between the diffusion of false alarms and the risk of missing defaults; however, the application of their approach is beyond the scope of this study. We emphasize that the empirical default rate in FGI (2011), which represents the research contribution closest to ours, is about 1 per cent. Although our sample has a broader scope and does not exclusively represent mutual cooperative banks, it is interesting to note how the recent financial crisis has led to a significant increase in the empirical rate of default.

Table 9
Confusion matrix at 6 quarters forecast horizon

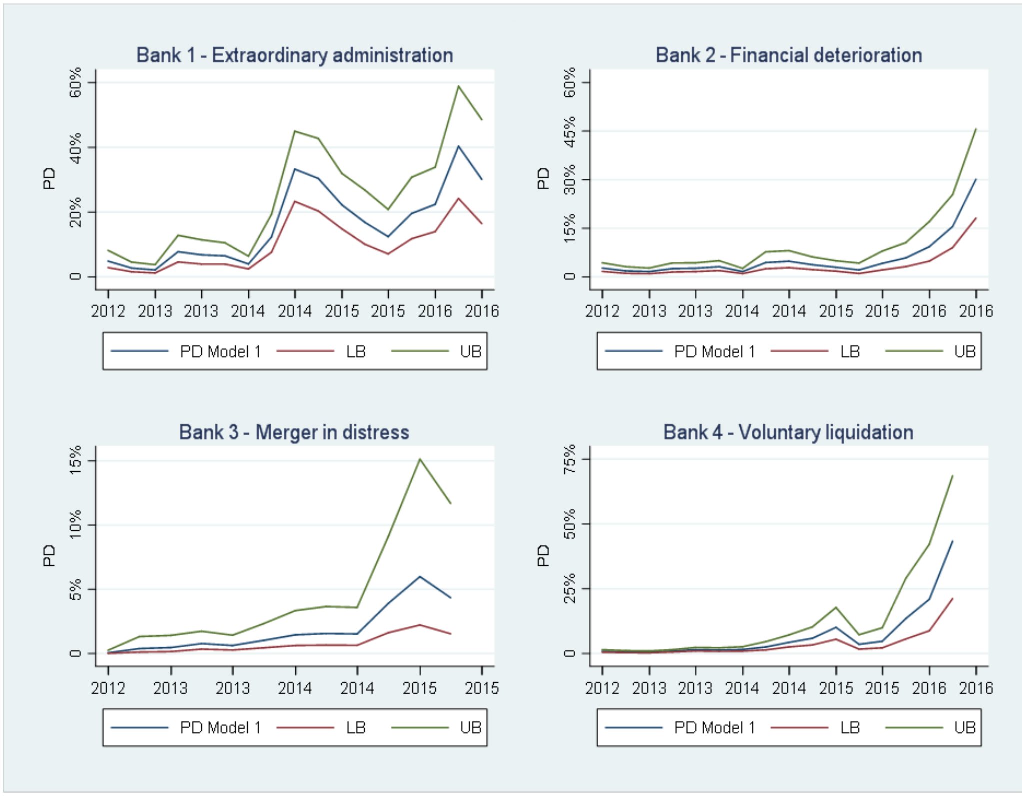
		Actual			
		Not in distress		In distress	
Predicted	Not in distress	M1	86%	M1	25%
		M2	84%	M2	27%
		M3	86%	M3	25%
		M4	84%	M4	25%
	In distress	M1	14%	M1	75%
		M2	16%	M2	73%
		M3	14%	M3	75%
		M4	16%	M4	75%

% Correct classification	M1	87%
	M2	85%
	M3	88%
	M4	86%

The confusion matrix displays the percentage of correctly classified banks for the four specifications displayed in Table 6. Percentages are computed with respect to column totals; in the lower table we also report the percentage of correctly classified banks defined as (A+D)/(A+B+C+D).

Besides the assessment of the model with respect to the different forecast horizons, it is also worth looking at model type I and II errors. In the first place, the fact that the bank classification achieved is not perfect must necessarily be attributed to the difficulty in identifying an optimal specification that can fully account for the individual heterogeneity within the sample. Nonetheless, it is also worth mentioning some other elements that may affect the values of type I and II errors and produce an incorrect classification. First of all, we recall that the Supervisory Authority frequently encourages banks to overcome a crisis situation through 'alternative measures' (e.g. capital increase and ad-hoc capital requirements, reforms of the internal governance structure, restrictions on the exercise of certain activities and so on) before adopting one of the administrative acts discussed in Section 3. This attitude can lead to cases in which the model predicts a distress situation for which there is not (yet) a corresponding administrative act attesting the crisis of the institution (type II error). On the other hand, as far as type I error is concerned (banks in distress not foreseen by the model) it should be noted that in some cases the administrative acts identifying the crisis of an institution are determined by mismanagement practices and not by the economic and financial performance of the bank. For this type of crisis event, the prediction of distress by means of a statistical model is clearly more complex and its modelling is extremely challenging. Once again, the values of the two errors for the 6-quarter specifications confirm the greater difficulty in predicting crisis events over a longer period. To further examine our results, we selected four representative institutions that reported a distress event in our sample and, to save space, we only show the analysis of PD estimated on the basis of 'Model 1' with forecast horizons at 4 and 6 quarters. The four institutions are differentiated in terms of the first crisis event: extraordinary administration ('Bank 1'), financial deterioration notification ('Bank 2'), merger in distress ('Bank 3'), and voluntary liquidation ('Bank 4').[20] Figures 8 and 9 plot the time series of the banks' PD. From the graphs, two key facts are clear: first, PD dynamics are quite similar for both forecast horizons; second, the PD is already above the cutoff of 2.4 per cent (the empirical default rate) some quarters before the distress event. This trend confirms the predictive power of our EWS and is in line with the arguments of Section 3 on distress identification: crises are usually preceded by a period of progressive financial deterioration. On this point, it is crucial to recall once more that the successful management of a bank crisis may be sometimes hard to achieve because of several factors affecting the process of crisis management; these factors include, but are not limited to, the plurality of subjects involved, the continuous evolution of the regulatory framework for crisis management, and the nature of the corrective measures that must be put in place in order to avoid an irreversible crisis and preserve financial stability.[21] Most importantly, bank failures cannot be avoided whenever internal (e.g. weaknesses in the governance scheme) or external conditions (e.g. limited access to capital markets, lack of interested buyers) constrain the action of the Supervisory Authority. Hence, it follows that the estimated PD may be above the cut-off for some quarters before the date identifying the distress event.

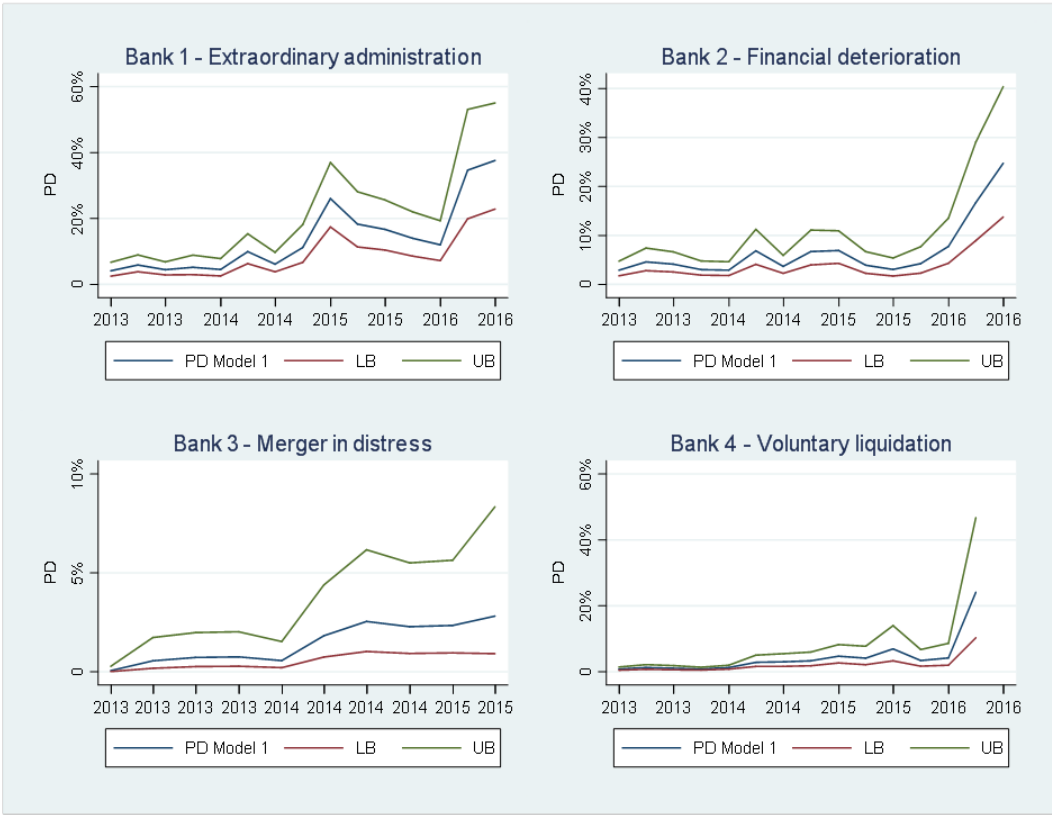
Figure 8
Historical PD for selected banks at 4-quarter forecast horizon



The graph displays the estimated PD for selected banks under the Model 1 specification and 4-quarter forecast horizon together with the corresponding lower and upper bound of the confidence interval at 95 per cent ('LB' and 'UB' respectively).

[20] For confidentiality reasons we do not report the quarter of distress and the name of each single institution. However, to display a longer time series for the estimated PD, we selected four banks where the distress event has generally occurred close to the end of the estimation time span (2016 Q2).
[21] See for example Visco (2018a) 'Banks and finance after the crisis: lessons and challenges' or Visco's speech (2018b) at the Annual Meeting of the Italian Banking Association.

Figure 9
Historical PD for selected banks at 6-quarter forecast horizon



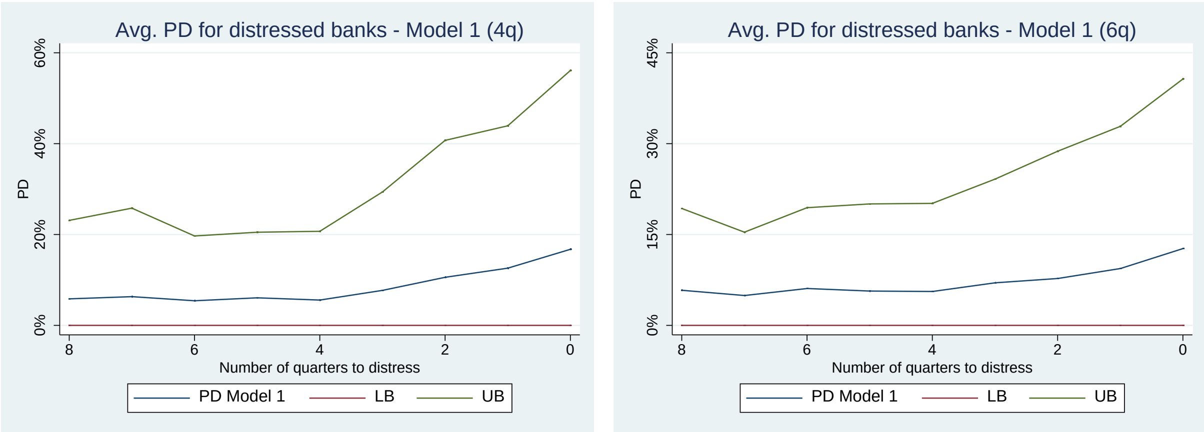
The graph displays the estimated PD for selected banks under the Model 1 specification and 6-quarter forecast horizon together with the corresponding lower and upper bound of the confidence interval at 95 per cent ('LB' and 'UB' respectively).

The trend of progressive financial deterioration before a well-identified crisis is also explained by Figure 10 which shows the average PD of distressed banks up to 8 quarters before the distress event; from the figure it is also clear how the average estimated PD increases when approaching the quarter in which the crisis occurs. Instead, Figure 11 plots the average PD for 'healthy' banks, i.e. those banks that did not report any distress in our sample. For these institutions, the graph shows an almost flat dynamic for the PD, whose estimated average value is always *below* the empirical default rate used as a cut-off point.

Out-of-sample forecasting is one of the more useful measurements to assess the predictive power of a model; in this study, the out-of-sample period was 2016 Q3-Q4 during which we identified three crisis events. Using a forecast horizon of 4 quarters,[22] each specification of the model correctly identifies two distress cases out of three. However, the PD of the financial institution incorrectly classified is just below the cut-off of 2.4 per cent with the upper bound of the confidence interval above the distress threshold. Similar results also occur for the model with a forecast horizon at 6 quarters, although in this case the confidence interval of the misclassified bank lies entirely below the distress cut-off.

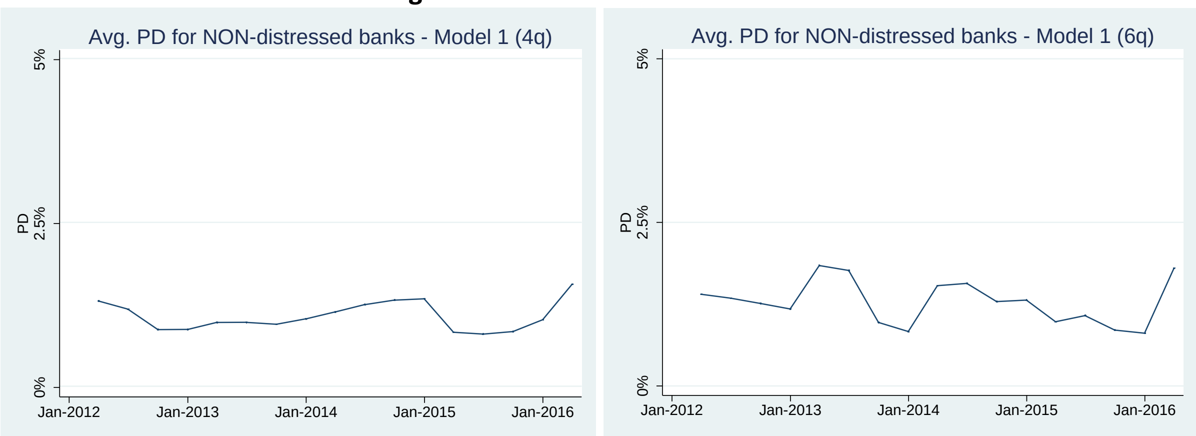
[22] The models with a forecast horizon at 4 quarters have the best predictive power at the individual level.

Figure 10
Average PD for distressed banks in the 8 quarters before the distress event



The left-hand graph displays the sample's average PD for distressed banks computed under the Model 1 specification and 4-quarter forecast horizon; the right- plot shows the same statistics for the 6-quarter forecast horizon. "LB" and "UB" indicate respectively lower and upper bound of the confidence interval at 95 per cent.

Figure 11
Average PD for non-distressed banks



The left-hand graph shows the average PD for non-distressed banks computed under the Model 1 specification and 4-quarter forecast horizon; the right-hand graph displays the same statistics for the 6-quarter forecast horizon. For reasons of readability we only report the average estimated PD. For both graphs the lower bound of the confidence interval at 95 per cent is always equal to zero, while the upper bound of the confidence interval fluctuates and attains a maximum value of about 10 per cent over the whole period.

Finally, to conclude the analysis of the results and of the various diagnostic checks, we re-estimated the original models using a bootstrap approach. This technique is particularly well-suited for our study because of the unbalanced nature of our sample with relatively few distress events. Using bootstrapping techniques, we can 'fictitiously' check the stability of our estimates on samples different from the original one. For the sake of exposition, the bootstrapped standard errors are not reported but are available from the authors upon request; in general, we obtain results that are qualitatively similar to the estimates reported in Tables 5 and 6.

6. Conclusions

This study presents a new tool to add to the existing set of early warning systems for less significant institutions under the direct supervision of the Bank of Italy. Building on previous empirical contributions in this field, we proposed a statistical model by making use of the indicators with the greatest predictive power for the early signalling of individual banking crises. For the calibration of the model we first identified an exhaustive list of distress events involving Italian LSI during the period 2008-2016. Then we adopted a logit specification where the distress of an institution is explained by using an extensive set of explanatory variables representative of the economic and financial conditions of institutions as well as of the macro context in which they operate. We adopted a forward-looking perspective and proposed two forecast horizons, 4 and 6- quarters ahead. We found that micro variables representative of banks' idiosyncratic risk (capital, asset quality, liquidity…) are the most important predictors of a bank's probability of default. On the contrary, macro variables, being mainly defined at national level, are probably not particularly suited to modelling the localism of most Italian LSIs. For each institution our model delivers a point-in-time PD, with an overall forecasting performance that is in line, if not higher, with other similar studies on early warning systems for the banking sector. The predictive ability of the model is confirmed both in sample and out of sample, with better results the shorter the forecast horizon considered. Despite its common application in empirical studies in this field, we acknowledge that a time horizon limited to 4-6 quarters may be too short to have truly effective early intervention measures implemented by Supervisory Authorities. On the one hand, we showed that our model is quite successful in identifying distress events some quarters before the actual date of crisis. On the other hand we find that the predictive power of the model diminishes significantly with a prediction horizon longer than 6 quarters. This represents a challenge which will need to be addressed in future work. The benefit of our model is that it can produce predictions in a framework that is more amenable to statistical analysis.

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