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Improving the Bank Recovery Process: Empirical Evidence for the Italian Banking System

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Abstract: We develop an empirical model with which we aim to reveal the conditions of a sample of listed banks over the period 2005-2016 in terms of their ability to survive potential extreme losses and the circumstances under which the regulator should intervene. In particular, we calculate the probability of distress of each bank by applying the Merton model; then we quantify the potential losses according to the Vasicek's approach. The probabilities of distress are then transformed into distances to default (DD), and the corresponding cumulative distribution of banks is used to identify the Type I error (not intervening to shut down operations of a bank that would subsequently fail) and Type II error (shutting down a bank that would survive on its own). Our results show that the banks analyzed have more concentrated levels of DD, with a Type II error of about 20%. This implies that for every one bank out of five, early intervention would have been triggered. The "optimal" recovery trigger should minimize the combination of the two types of error, identifying an "optimal" amount of DD as a criterion for early regulatory intervention.

Key words: bank recovery; bank resolution; contingent claim analysis; distance to default; loss absorption buffer; potential extreme losses

JEL codes: G21, G28, G33

1. Introduction

The Euro Area summit of June 2012 marked a turning point in the regulatory approach to tackle the financial crisis started in 2007 (Mourlon-Druol, 2016). The significant milestones in the process of building a more robust and resilient banking system in Europe were met through the creation of the Single Supervisory Mechanism (SSM), led by the European Central Bank (ECB), and the launch of the Single Resolution Mechanism (SRM), led by the Single Resolution Board (SRB), which is also responsible for the Single Resolution Fund (SRF). The Bank Recovery and Resolution Directive (BRRD), adopted by the European Union in May 2014, plays the most significant role; in fact, bail-in rules, together with the Single Resolution Fund, ensure the minimization of

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taxpayer funding for banks' failures. The BRRD has also increased the regulatory attention paid to the period preceding the resolution. In particular, rules on early intervention offer the possibility for a bank to be restored to normal conditions before it is forced to be solved. In this way, the early management of a bank likely to fail would be extremely important to help the financial system mitigate systemic risk (European Commission, 2014).

However, it might not always be clear when early intervention should take place. In fact, the Directive only generally outlines the conditions under which the recovery phase should be initiated and appoints the responsibility to issue guidelines to facilitate their consistent application to the European Banking Authority. In contrast to these guidelines, some studies have elaborated models that try to address the lack of appropriate quantitative indicators to trigger the early intervention (Goodhart & Segoviano, 2015). The quantitative approach can have several advantages, such as the opportunity for competent authorities to reduce the number of mistakes made during the decision to start the recovery, to sanction the institution or to not intervene at all. However, despite the significant discussion, among regulators, scholars and practitioners on the triggers for resolution, the models signaling the need to enter into the recovery stage are not as fully developed (Avgouleas et al., 2013; Calomiris, 2011; Schoenmaker, 2011).

In this sense, we would like to contribute to the existing literature (Summers, 2000; Ashcraft, 2005; Dewatripont, 2014; Schoenmaker, 2014) by developing a model for the banking system that allows to evaluate and compare both the past and the current conditions of banks with respect to their probability of default and their ability to absorb the potential extreme losses that may occur. The results could be used by competent authorities to better balance the quantitative intervention threshold.

The paper is organized as follows. In Section 2 we describe the literature that highlights the potential advantages in relation to having a scientific metric based on quantitative thresholds, which can help in the early intervention decision. In Section 3, we describe the model for the Italian banking system; in section 4 we discuss the main outcomes of the empirical analysis. The section 5 concludes the work with final remarks.

2. Quantitative Metrics for Optimal Bank Recovery: Literature Review

The BRRD has improved the regulatory attention to the period preceding the resolution of a bank. In particular, thanks to the early intervention phase, a bank has the possibility of being restored to normal conditions before it is forced to be resolved. Generally, a bank recovery is preferred to a bank resolution, since the early management of a likely failing bank would help the financial system to additionally mitigate the systemic risk (Boccuzzi, 2016).

At the same time, however, the legislation does not clearly specify the criteria that can trigger the start of the early intervention phase. To trigger the recovery, Article 27 of BRRD establishes that there must be the solid possibility of infringing the requirements of the relevant EU and national legislation, or a rapidly deteriorating financial condition with respect to the liquidity situation, the growth level of leverage and non-performing loans or the concentration of exposures. Such conditions are largely subjective and formulated in a general manner. Thus, during their assessment, it is reasonable to expect that Member States would apply diverse practices and, as a result, obtain different outcomes. These divergences can also have detrimental effects on the financial system, since they can lead to an uneven playing field for institutions. In order to avoid negative implications, the BRRD appointed the European Banking Authority to issue some guidelines to facilitate the consistent application of early intervention triggers (EBA 2015a, 2015b). Nevertheless, one of the most critical aspects of the EBA's guidelines is that they do not establish any quantitative factors and thresholds that should be applied by the competent authorities.

Several studies have highlighted the potential advantages of having a scientific metric through which the intervention decision can be taken, in order to find equilibrium between Type I errors, missing a required intervention, and Type II errors, initiating an unnecessary intervention.

The first part of the so-called "early-warning" literature focuses on discovering structural vulnerabilities and common patterns preceding financial crises. By using proxies for CAMELS[1] indicators, the majority of these studies exhibit a high degree of success in forecasting the US bank failures (Flannery, 1998; Lopez, 1999). Recently, Demyanyk and Hasan (2010) examined the financial and economic circumstances associated with the US subprime mortgage crisis and subsequent global financial distress that led to severe recessions in many countries.

Several studies dealt with the European banking sector (Hutchison, 2002; Fiordelisi *et al.*, 2011; Mody and Sandri, 2012), primarily for healthy banks; in contrast, a small amount of research papers take into consideration the distressed institutions, maybe due to data limitations arising from relatively few direct bank failures in the European core. Some of them focused on the optimal level of bank capital that an institution should hold to reduce the likelihood of distress. Haq and Heaney (2012) used information for 117 financial institutions across 15 European countries over the period 1996-2010 to develop a model that investigates the equity risk. The main result they obtain is that beside the expected negative relationship between bank capital and credit risk, there is also evidence of a non-linear relation. In particular, a U-shaped relation suggests that capital regulation may have unintended consequences. They suggested that there are limitations to the utility of capital regulation as a channel to decrease the possibility of bankruptcy. Similarly, but by using a different approach, Miles *et al.* (2012) estimated the costs and benefits for UK banks to have higher levels of loss-absorbing capital. They found that the inflection point that occurs when benefits exceed or are equal to costs might be much higher than the minimum regulatory requirements. Thus, they concluded that the desirable amount of equity capital is more than the amount that banks have held in recent years under the Basel III framework (BCBS, 2011).

Rather than predicting failures or distresses at the bank level, a second segment of the literature concentrates on the optimal "early-warning signals" for policy-makers (Davis & Karim, 2008). In particular, an important concept for these studies is the loss function of policy-makers that takes into account the costs for preventive action and the relative preferences between missing crises (Type I errors) and false alarms (Type II errors). An important empirical finding, achieved by Betz et al. (2014), is that their early-warning model, employing only publicly available data, produces useful out-of-sample predictions of bank distress in the period of the global financial crisis. Moreover, based on their results, they stated that a policy-maker should be significantly more worried about committing Type I errors rather than Type II errors. Many studies (Pettway & Sinkey Jr., 1980; Cole & Gunther, 1998) highlighted that in this trade-off, it is more important to minimize the former than the latter, because of the more punitive effects of bank failures. Instead, since recovery is more reversible, some Type II errors are allowed. However, since the expropriation of existing ownership rights, which may occur with bank recovery, is a drastic and legally complex measure, it is also important to avoid Type II errors. They argue that their model captures almost all banks that are dealing with severe probabilities of default and only few banks that would have survived on their own. In fact, an optimal recovery decision should in general regard all the banks that

[1] Acronym for Capital adequacy, Asset quality, Management quality, Earnings, Liquidity and Sensitivity to market risk.

would have failed without intervention, and at the same time should not affect too many banks that would have survived anyway.

Goodhart and Segoviano (2015) hypothesized an intervention metric built on the comparison between the loss absorbing buffers and the potential extreme losses that are driven by the institution's default probability. By analysing 19 large European and American banks between January 2007 and December 2012, they identified the periods in which potential losses were equal to or greater than the loss absorption buffers. Based on these results, they designed a ladder of sanctions[2] whose degree of intervention is increasingly punitive as the loss absorption buffer deteriorates and/or the potential extreme losses increase. Therefore, they fixed the recovery threshold at when the Distance to Default (DD) is equal to 1.50, or, equivalently, when the Probability of Default (PD) is 6.68%. In order to set such a trigger level, they calculated the cumulative frequency of those banks whose potential losses exceeded the respective loss absorption buffer. Then, they related those frequencies to the respective level of DD. By distinguishing the cumulative distributions of solvent and insolvent banks, they could understand how many banks in both categories would have been exposed to early intervention measures. Moreover, by setting the recovery threshold, they identified the lag that there would have been between the intervention and the insolvency announcement of their defaulting banks. Looking at the date when the threshold was reached, they concluded that recovery would have taken place 6 to 8 months before insolvency. In fact, the recovery phase should be triggered long before the bank is put under resolution. In this way, remedial actions, implemented by managers and supervisors, are more likely to take effect successfully and turn the bank around before resolution takes place.

3. Model Specification

We try to assess an optimal recovery framework for the banking system in order to obtain a quantitative framework to evaluate the intervention decisions. Our specifications start from the metric developed by Goodhart and Segoviano (2015), but we develop a model for the Italian banking system alone in order to focus the attention on a more homogeneous group. Moreover, we flesh out the analysis from 2005 to 2016 in order to generate a comprehensive framework that could be used to better balance the regulatory intervention threshold.

The model allowed us to evaluate and compare both the past and the current conditions of Italian banks with respect to their probability of default and their ability to absorb the potential extreme losses that may occur. In addition, after aggregating the results for the banks that remained solvent, it is possible to provide the estimates of Type II error.

This approach could be successfully implemented to different bank samples. For example, it is possible to make reference to a sample composed of European banks subject to the Asset Quality Review (ECB, 2014), identifying the "solvent" banks with the entities with a CET1 (Common Equity Tier 1) ratio equal to or greater than 8% under the base scenario, and the "potentially distressed" banks with the institutions with a CET1 ratio lower than 8%. Regulatory authorities, policy makers, or analysts could then determine the optimal recovery trigger threshold at a point that minimizes the combination of Type I errors and Type II errors, and fixing an "optimal" amount of DD as criterion for early intervention.

3.1 Criterion for Intervention

First, in order to choose a threshold, we need to define the criterion for intervention. This will be the critical

[2] From the least to the most severe: frequent visit sanction, pecuniary charge sanction, remuneration sanction, intervention.

ratio through which the institutions that should be subjected to intervention, whether through recovery or milder sanctions, can be identified. According to the Basel Accord's rules (BCBS, 2005), the early intervention measures should be triggered only when the potential extreme losses at time *t* are greater than the loss absorption buffer of the bank at time *t* (equation (1)):

$$Potential\ Extreme\ Losses_t > Loss\ absorption\ buffer_t \quad (1)$$

Hence, in order to develop this criterion, it is crucial to:

(1) define the components of the loss absorption buffer; and

(2) specify an approach to estimate the loss distribution, through which the potential extreme losses can be calculated.

3.2 Defining the Components of the Loss Absorption Buffer

The traditional techniques to assess absorption buffer levels use the accounting value of regulatory capital expressed in relation to a measure of its risk-weighted assets (RWA). According to Calomiris (2015), we believe there are essentially two motivations to avoid the use of accounting measures. First, when institutions experience losses on their tangible assets, such as loans, they typically postpone recognition of the problem. In addition, this delayed recognition is often permitted in order to continue normal operations since it is convenient to supervisors and to banks. Second, and perhaps more important, when a bank becomes financially distressed, it is extremely probable that the real value of its equity is already severely impaired before its recognition in the accounting and regulatory values. On the other hand, the value of the denominator also presents some problems. Specifically, the measure of the risk-weighted assets might have different regulatory definitions across countries and might be subject to the accounting manipulation problem.

Therefore, an adjustment of the parameters can help to get rid of these issues. In particular, since the book value of equity does not mirror market perceptions, the correct way to ensure the adequacy of equity capital might be to consider the economic value of capital itself. For listed banks, such a value is the Market Capitalization. It could represent the right measure to use not only because it is more accurate and reacts faster to changes, but also because it captures the opinions of the marketplace, which are important for the sustainability of the institution. However, since it can still be subject to both market over-shoots and temporary crashes, a quarterly moving average of Market Capitalization was implemented. Besides the value of capital, the provisions were also included as part of the numerator of the loss absorption buffer, since they are needed to protect against expected losses. Differently from Market Capitalization, these quantities are not subject to market over-shoots and they are usually kept in cash or in low-risk liquid fixed income assets. Moreover, given the simplicity of its calculation, Total Assets (TA) is used as denominator of the buffer. The idea of combining Capital Adequacy Ratios with Leverage Ratios should provide an efficient way to avoid the difficulties in assessing RWAs and allow for an easier comparison across institutions. As a result of these considerations, the risk sensitive loss absorption buffer ratio at time *t* can be defined as:

$$Loss\ absorption\ buffer_t = \frac{MA_4(Market\ Cap_t)+Provisions_t}{Total\ Assets_t} \quad (2)$$

where

$$MA_4(Market\ Cap_t) = \frac{Market\ Cap_t+Market\ Cap_{t-1}+Market\ Cap_{t-2}+Market\ Cap_{t-3}}{4} \quad (3)$$

This becomes the target ratio that will be compared to the potential extreme losses in order to understand which institutions should be subject to intervention.

3.3 Estimating the Loss Distribution: Probability of Default

The loss absorption buffer must be compared to the potential extreme losses, defined as the sum of the Expected and Unexpected Losses. In order to measure them, we need the loss distributions of the banks at each period of time. Thus, from the distribution it is possible to retrieve information about the amount of losses that a bank can potentially experience and their respective probability of occurrence.

The loss distribution function has been estimated following the Vasicek (2002) approach, which belongs to the so-called "analytical approximation" approach.

In order to determine the probabilities of default for each bank we implement the Merton's model (1974). It assumes that the total value of a firm's assets (A_t) follows a geometric Brownian motion, with a mean rate of return (μ_A) and volatility (σ_A). The debt instead is assumed to be a single outstanding bond with face value (F) and maturity (T). The firm defaults at the bond maturity when the value of its assets falls below the amount of debt it has to repay; otherwise, it pays its debt in full. Therefore, in Merton's view, the equity (E) is a call option on the firm's assets. As a result, the probability of default at time *T*, measured at time *t*, is given by (equation (4)):

$$P_t[A_T \leq F] = N[-d_2] \tag{4}$$

where

$$d_2 = \frac{\ln\left(\frac{A_t}{F}\right) + 0.5 * (\mu_A - \sigma_A{}^2)(T-t)}{\sigma_A\sqrt{T-t}} \tag{5}$$

We implement the specifications made by the KMV approach under the contingent claim analysis (Gapen, 2009); it overcomes the limits of Merton's model (Black & Cox, 1976; Geske, 1977; Vasicek, 1984; Longstaff & Schwartz, 1995; Moody's Investors Service, 2016). In order to implement the model, the first information required is the economic value of equity and the volatility of the equity returns (σ_E). Therefore, the market capitalisation is used as equity value, while to obtain the volatility, the historical values of stock prices are analyzed. Hence, we calculate the historical logarithmic returns of stock prices, and from them we retrieve the annualized standard deviation.[3] In particular, three different time windows of 180 days, 270 days and 360 days have been used to calculate the volatility. Moreover, as regards the values of the expected return on assets (μ_A), we follow the basic formulation of the Merton model. Thus, we replace the asset's expected return with the risk-free rate (r). In this way, the probability measure that governs the asset and default processes represents risk-neutral probabilities of default. They are valid only in a risk-neutral world in which $\mu_A = r$, but in the real world, investors demand $\mu_A > r$. As a result, this leads to an overestimation of the probabilities of default. We compare the results of using the yield of the 1-year BOT (*Buoni Ordinari del Tesoro*, short-term government bond), and the 10-year benchmark BTP (*Buoni del Tesoro Poliennali*, long-term government bond), since they incorporate the country risk. In any case, probabilities of default are not sensitive to the calibration of different expected returns, since the final results change very slightly.

For the next step, we set the forecasting horizon of one year ($T = 1$). According to this time window, the amount of debt that should be considered for the potential default is the portion of total liabilities that is due in one year. Therefore, the total debt is inadequate since not all of it is due in one year. However, the short-term debt maturing in one year is also unsuitable because, in case of default, the bank might be forced to serve senior liabilities with longer maturity first. Hence, the face value of the debt to be considered is the short-term liabilities plus half of the long-term liabilities. As in the equity volatility, the sensitivity of results with respect to different

[3] $\sigma_{Ea} = \sigma_{Ed}\sqrt{252}$

definitions of the default barrier has been checked.

At this point, the remaining input variables are the market value of assets (A_0) and the volatility of asset's returns (σ_A). Unfortunately, they are both usually directly unobservable. However, in accordance with the KMV specification, it is possible to use the prices of traded securities issued by the firm to identify these quantities implicitly. In fact, such values can be recovered by simultaneously solving the following system of equations (6):

$$\begin{cases} E_0 = A_0\, N(d_1) - Fe^{-rT}\, N(d_2) \\ \\ \sigma_E = \frac{A_0}{E_0}\, N(d_1)\, \sigma_A \end{cases} \tag{6}$$

The first function represents the present value of the firm equity, which can be defined through the Black–Scholes specification. In fact, the equity holders receive what remains after having paid the debtholders on date T. The second equation, which is obtained by applying Ito's lemma, determines the relation between the volatility of equity returns and the volatility of assets returns. Therefore, it is possible to simultaneously solve the system of equations (6).[4] However, since there are infinite pairs of values of A and σ_A, they are computed by minimizing the following function (7):

$$\varepsilon = \left(\frac{Obs\ E_t - Model\ E_t}{Obs\ E_t}\right)^2 + \left(\frac{Obs\ \sigma_E - Model\ \sigma_E}{Obs\ \sigma_E}\right)^2 \quad (7).$$

This function sums the squared errors between the observed values ($Obs\ E_t$ and $Obs\ \sigma_E$) and the new obtained values ($Model\ E_t$ and $Model\ \sigma_E$). To start the iterations, the two initial estimates of the unknowns are set as:

$$A_0 = E_0 + F_0 \quad (8),$$

and

$$\sigma_A = E_0 * \frac{\sigma_E}{A_0} \quad (9).$$

3.4 Quantification of Losses

We quantify the losses using the Vasicek's approach. Given the fact that in Merton's model the probability of default and the default threshold are linked through the normal distribution function, Vasicek (2002) showed that by applying the inverse normal distribution function to the unconditional probabilities of default ($N^{-1}(PD)$), it is possible to derive the appropriate default threshold for "average" conditions. Similarly, in Vasicek's formula the required conservative value of the systematic risk factor is also taken into consideration by using the inverse of the normal distribution function of the regulatory confidence level x ($N^{-1}(x)$). In particular, under the Basel II framework, losses are computed at the 99.9th percentile. The sum of the default threshold and the conservative value of the systematic factor yields to the "conditional default threshold". The new threshold is then used as an input into the original Merton model by applying the normal distribution function, which returns a conditional probability of default. All the steps performed are summarized in the following equation (10):

$$F(x; PD, \rho) = N\left(\sqrt{\frac{1-\rho}{\rho}}\, N^{-1}(x) - \sqrt{\frac{1}{\rho}}\, N^{-1}(PD)\right) \tag{10}$$

where

x = regulatory confidence level

PD = unconditional probability of default

[4] We develop a MatLab script.

ρ = asset correlation.

The last term ρ can be described as the dependence of the asset value of a borrower on the general state of the economy. Hence, the two elements of equation (10) must be weighted with respect to the asset correlation, since all borrowers are linked to each other by the single risk factor. The asset correlation was estimated following the instructions of the regulatory framework (BCBS, 2011).

The values of EL and UL, expressed as percentage of assets, were obtained by multiplying the conditional probability of default, calculated at the 99.9% percentile of loss distribution, with the Losses Given Default rate (LGD). According to Goodhart and Segoviano (2015), an LGD of 45% has been adopted by credit risk modellers as a reasonable assumption for loss estimation in the absence of data to otherwise estimate LGDs.

Hence, employing the following equation (11) it is possible to calculate the sum of expected and unexpected losses:

$$EL + UL = N\left(\sqrt{\frac{1-\rho}{\rho}}\,N^{-1}(x) - \sqrt{\frac{1}{\rho}}N^{-1}(PD)\right) * LGD * MA \tag{11}$$

where MA is the Maturity Adjustment coefficient, defined as:

$$MA = \frac{1+(M-2.5)*b(PD)}{1-1.5*b(PD)} \tag{12}$$

where,

$$b(PD) = [(0.11852 - 0.05478 * LN(PD))]^2 \tag{13}$$

and M is the maturity of the instrument. In fact, since credit portfolios consist of instruments that have different maturities, the regulatory framework proposes that the longer the maturity, the higher the capital requirements. Nevertheless, in our work, M is equal to 1 year and consequently equation (12) results in a maturity adjustment coefficient of 100%.

4. Data Sources and Descriptions

We take into account the Italian banks listed on the Milan Stock Exchange, excluding the institutions that conduct mainly investment banking activities.[5]

The sample of banks consists of the following listed “solvent banks”: UniCredit (UCG), Intesa Sanpaolo (ISP), Unione di Banche Italiane (UBI), Banco Popolare (BP), Banca Popolare dell’Emilia Romagna (BPER), Banca Popolare di Milano (BPM), Banca Monte dei Paschi di Siena (BMPS), Credito Emiliano (CE), Banca Popolare di Sondrio (BPSO), Credito Valtellinese (CVAL), Banca Carige (CRG), Banco Desio e Brianza (BDB) and Banco di Sardegna (BSRP). The “insolvent banks” considered are Banca Popolare dell’Etruria e del Lazio (PEL) and Banca Popolare di Spoleto (SPO). As input variables, we use the stock prices (daily frequency); the 1-year BOT rates, and the benchmark 10-year BTP rates with a monthly frequency. Then, total assets, total liabilities and number of total common shares outstanding are recorded with quarterly frequency. As estimated variables, we calculate the stock returns and the returns volatilities (daily frequency); the market capitalization, the short-term liabilities, the long-term liabilities, the provisions, the asset value and the asset volatilities (quarterly frequency).

We obtain or estimate the variables from 31 December 2005 to 30 June 2016, for a total of 2664 daily

[5] Mediobanca, Banca Finnat, FinecoBank and Banca Profilo are excluded from the sample.

observations for each of the 15 banks analyzed.[6]

5. Empirical Analysis

Figure 1 shows the evolution over time of the volatility; we can observe that a small window has more extreme values: the peaks of volatilities are reached during the crisis periods. For many banks the stock return volatilities recently assumed high values, specifically in the last period. In fact, the last observations, which for solvent banks correspond to 30 June 2016, are influenced by the extremely negative returns reached on 24 June after the publication of the results of the British referendum on remaining in the European Union. That day, the announcement of the so-called “Brexit” caused a loss of 12.48 percentage points on the FTSE MIB index. In particular, the banking sector’s shares dropped by more than 20%. As a result, we expect that the probabilities of default of the last period will be dramatically influenced by both the high volatility values and low stock prices. For these reasons, the results that we present are based on the equity volatility computed with the 360-day window.

With the described dataset and the estimated parameters, we quantify the loss absorption buffers and the potential extreme losses for each bank in each period of time as components of the intervention criterion. The first step involved the calculation of the daily probabilities of default. Table 1 illustrates the evolution of the 1-year probabilities of default, obtained at the end of each quarter through the application of Merton’s model to all the banks under analysis.

According to our expectations, the last period of observation is characterized by rising probabilities of default for all the banks in the sample. In particular, the highest probability of default of 15.78% belongs to BMPS, whose difficulties recently became more evident. Together with BMPS, CRG is the other Italian bank that has to raise capital after failing the ECB stress tests in 2014 (ECB, 2014). From December 2015, the probability of default increased by over 8%. Similarly to BMPS, CRG’s stock price experienced a huge price drop and hit an historical low of 0.2854 on 7 July 2016.

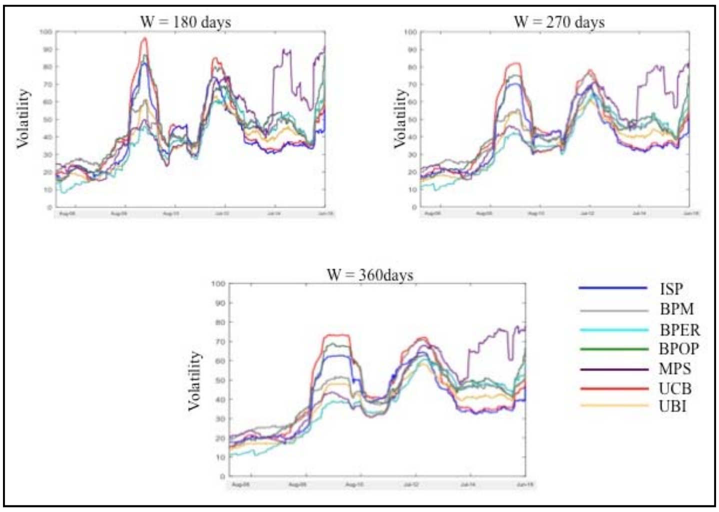

Figure 1 Stock Return Volatility Evolution in Different Time Windows (W)

Source: Authors’ elaboration

[6] As regards the input variables, all the balance sheets’ information and stock prices were retrieved from the Thomson Reuters Eikon Database. The risk-free rates were instead acquired from the statistical database (Infostat) provided by the Bank of Italy.

Table 1 Estimated One-Year Probabilities of Default (% Values; Quarterly Frequency)

Bank / M.Y	UCG	ISP	UBI	BP	BPER	BPM	BMPS	CE	BPSO	CVAL	CRG	BDB	BSRP	PEL	SPO
06.16	3.28	1.56	3.92	9.27	5.17	4.26	15.78	0.27	0.41	2.36	8.59	0.38	0.01		
03.16	1.07	0.43	1.72	3.41	2.45	1.69	15.37	0.09	0.27	1.71	8.05	0.13	0.00		
12.15	0.21	0.11	0.47	0.70	1.09	0.66	6.06	0.02	0.11	0.81	1.75	0.01	0.00		
09.15	0.26	0.17	0.77	1.05	1.61	1.05	14.27	0.03	0.20	1.13	2.45	0.01	0.00		
06.15	0.19	0.10	0.79	1.88	1.80	1.33	13.94	0.04	0.19	1.47	3.46	0.03	0.00		
03.15	0.16	0.08	0.62	2.20	1.65	1.48	12.54	0.04	0.14	1.33	2.82	0.03	0.00	6.23	
12.14	0.16	0.10	0.71	2.19	1.79	1.32	10.77	0.06	0.07	0.99	2.74	0.02	0.00	2.65	
09.14	0.08	0.07	0.59	1.94	1.58	1.40	7.76	0.03	0.05	0.56	1.38	0.03	0.00	2.80	
06.14	0.19	0.11	0.62	2.11	1.56	1.61	8.33	0.05	0.12	0.36	1.76	0.02	0.00	4.26	
03.14	0.20	0.10	0.48	1.92	1.25	1.35	2.32	0.04	0.05	0.23	0.76	0.01	0.00	0.82	
12.13	0.43	0.38	0.84	1.29	1.92	1.54	3.60	0.06	0.16	0.13	0.70	0.01	0.00	1.75	
09.13	1.34	0.94	1.60	2.27	3.47	2.47	4.61	0.29	0.37	0.67	1.04	0.14	0.00	1.23	4.40
06.13	2.18	1.37	2.02	3.68	4.00	4.58	6.71	0.77	0.49	1.51	1.31	0.18	0.00	1.02	3.82
03.13	6.81	3.09	3.24	5.36	5.54	7.86	9.48	1.50	0.51	1.57	1.64	0.21	0.64	0.37	5.41
12.12	10.61	6.38	4.36	6.48	5.88	9.91	9.02	2.61	0.75	1.69	2.17	0.25	0.80	0.74	0.54
09.12	12.05	7.88	5.24	7.14	5.97	11.44	9.70	3.29	0.97	1.85	2.62	0.19	0.95	1.15	0.56
06.12	10.77	6.69	3.98	6.21	3.90	10.47	7.01	2.83	0.48	1.51	1.74	0.07	0.99	2.71	0.23
03.12	8.53	5.30	2.87	4.12	1.99	7.84	4.94	1.93	0.23	0.34	0.89	0.00	0.87	2.46	1.07
12.11	4.51	4.65	2.05	2.13	1.29	4.59	1.65	1.14	0.12	0.11	0.41	0.00	0.65	1.87	0.88
09.11	2.67	3.20	1.09	1.37	0.67	2.79	0.71	1.03	0.15	0.08	0.28	0.00	0.01	0.19	0.48
06.11	0.70	0.81	0.18	0.39	0.14	0.70	0.12	0.17	0.02	0.01	0.03	0.00	0.00	0.00	0.00
03.11	0.66	0.57	0.12	0.40	0.11	0.34	0.04	0.23	0.01	0.01	0.01	0.00	0.00	0.00	0.00
12.10	0.64	0.43	0.04	0.41	0.09	0.45	0.03	0.35	0.01	0.00	0.01	0.00	0.00	0.02	0.02
09.10	1.06	0.58	0.13	0.97	0.12	0.70	0.05	0.51	0.01	0.00	0.01	0.00	0.00	0.02	0.02
06.10	4.74	2.32	0.89	4.83	0.42	1.13	0.18	1.67	0.01	0.03	0.04	0.00	0.01	0.03	0.00
03.10	7.64	3.88	0.95	6.80	0.19	0.75	0.14	1.64	0.00	0.08	0.19	0.00	0.03	0.00	0.00
12.09	12.54	6.51	1.79	9.54	0.40	2.60	0.36	2.27	0.03	0.22	1.14	0.03	0.12	0.21	0.00
09.09	12.50	6.71	1.77	9.46	0.40	2.57	0.49	1.90	0.01	0.18	1.26	0.04	0.17	1.13	0.10
06.09	12.67	6.61	1.75	9.77	0.37	2.44	0.63	1.79	0.01	0.22	1.52	0.09	0.16	1.67	0.71
03.09	11.59	5.71	0.94	7.70	0.20	1.90	0.53	1.36	0.03	0.19	1.46	0.14	0.11	0.94	0.82
12.08	5.78	2.42	0.16	2.80	0.03	1.23	0.15	0.23	0.01	0.03	1.22	0.05	0.02	0.32	0.60
09.08	0.32	0.01	0.00	0.29	0.00	0.17	0.02	0.04	0.00	0.00	0.11	0.02	0.00	0.05	0.10
06.08	0.05	0.00	0.00	0.11	0.00	0.04	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.05	0.13
03.08	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02
12.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
09.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
06.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
03.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
09.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
06.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
03.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11
12.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03

Source: Authors' elaboration

By contrast BPSO, BDB, and BSRP never experience probabilities of default over 1%. UBI, BPER, CE, and CVAL even show low probabilities of default for all the periods under analysis. Instead, by looking at the values of UCG and ISP, the two leading Italian banks, it is possible to notice how the probabilities of default increased in the period following the global financial crisis and the European sovereign debt crisis. The same pattern can be observed in the values of BP, and BPM, two banks that on 24 March 2016 announced their merger. Finally, as regards the two insolvent banks, we can see a dramatic jump in the probabilities of default. On the one hand, SPO, as of 31 December 2012, had a Tier 1 capital ratio of 6.45%, and from February 2013 it was put under extraordinary administration by the Ministry of Economy and Finance; a period that ended on 31 July 2014, after which the institution joined BDB. On the other hand, PEL was one of the first banks whose rescue was treated in accordance with the Bank Recovery and Resolution Directive. On 30 June 2014, the Tier 1 capital ratio fell to just 6.1%, and in early 2015 the bank was administrated by the Ministry of Economy and Finance.

Similar conclusions can be drawn if we look at the transformation of probabilities of default in distances to default[7] (DD, Table 2). In particular, by focusing on this variable, we can evaluate which institutions fell under the "recovery trigger" threshold of 1.5 established by Goodhart and Segoviano (2015). Again, BMPS crosses the threshold level many times, together with the last two quarters of CRG. UCG, ISP, BP, and BPM show low levels of DD during the crisis periods. In addition, only BP fell under the threshold level in the last quarter as well. The other banks would have never triggered intervention at the specified threshold level. Again, for insolvent banks the results appear to be unconvincing. However, better conclusions can be achieved if we look at the differences between extreme losses and the loss absorption capital (Table 3).

Table 3 highlights the periods in which the potential extreme losses, calculated using the probabilities of default, are higher than the loss absorption buffer.[8] As expected, there are significant differences for BMPS, CRG and BP, as regards the last quarter. For many banks, such a difference was spread out during the financial crisis. Besides that, it is possible to see that for the insolvent banks, such a difference extends drastically 3 or 4 periods before the last available observation. These scores can indeed offer a better insight into their distress. Moreover, from Figure 2, which analyses the evolution of both the loss absorption buffer and the potential extreme losses expressed as percentages of assets, we can deduct that, for the two insolvent banks, the latter is much greater than the former. For the remaining banks in the sample, it is important to draw attention to first the descending path of the loss absorption buffer, and second, to the peaks of potential losses. The buffer is severely affected by the deterioration of market capitalization, while the highest potential losses match the period of crisis.

Apart from CRG and BMPS, if we exclude the period characterized by the crisis and the last period, almost all the solvent banks satisfy the intervention criterion, or at least they are very close to it. Again, the high volatility and the overall decline of the stock prices of Italian banks can explain the rapid increase of potential extreme losses in the last quarter.

[7] $DD = d_2 = -N^{-1}(PD)$ and $PD = N(-DD)$.

[8] Values of differences lower than 1% are excluded.

Table 2 Distances to Default (Quarterly Frequency)

Bank / M.Y	UCG	ISP	UBI	BP	BPER	BPM	BMPS	CE	BPSO	CVAL	CRG	BDB	BSRP	PEL	SPO
06.16	1.84	2.15	1.76	1.32	1.63	1.72	1.00	2.78	2.64	1.98	1.37	2.67	3.62		
03.16	2.30	2.63	2.11	1.82	1.97	2.12	1.02	3.11	2.78	2.12	1.40	3.00	4.53		
12.15	2.86	3.07	2.60	2.46	2.29	2.48	1.55	3.50	3.07	2.41	2.11	3.82	5.34		
09.15	2.80	2.92	2.42	2.31	2.14	2.31	1.07	3.39	2.87	2.28	1.97	3.77	6.01		
06.15	2.89	3.10	2.41	2.08	2.10	2.22	1.08	3.34	2.89	2.18	1.82	3.40	5.56		
03.15	2.95	3.15	2.50	2.01	2.13	2.18	1.15	3.35	2.98	2.22	1.91	3.40	5.32	1.54	
12.14	2.95	3.09	2.45	2.02	2.10	2.22	1.24	3.26	3.20	2.33	1.92	3.48	5.02	1.93	
09.14	3.14	3.21	2.52	2.07	2.15	2.20	1.42	3.41	3.31	2.54	2.20	3.47	5.17	1.91	
06.14	2.89	3.05	2.50	2.03	2.16	2.14	1.38	3.29	3.03	2.69	2.11	3.49	4.95	1.72	
03.14	2.88	3.11	2.59	2.07	2.24	2.21	1.99	3.35	3.28	2.83	2.43	3.65	5.29	2.40	
12.13	2.63	2.67	2.39	2.23	2.07	2.16	1.80	3.24	2.94	3.01	2.46	3.83	5.18	2.11	
09.13	2.22	2.35	2.15	2.00	1.82	1.97	1.68	2.76	2.67	2.47	2.31	2.99	5.23	2.25	1.71
06.13	2.02	2.21	2.05	1.79	1.75	1.69	1.50	2.42	2.58	2.17	2.22	2.91	4.90	2.32	1.77
03.13	1.49	1.87	1.85	1.61	1.59	1.41	1.31	2.17	2.57	2.15	2.13	2.87	2.49	2.68	1.61
12.12	1.25	1.52	1.71	1.52	1.56	1.29	1.34	1.94	2.43	2.12	2.02	2.80	2.41	2.44	2.55
09.12	1.17	1.41	1.62	1.47	1.56	1.20	1.30	1.84	2.34	2.09	1.94	2.90	2.34	2.27	2.54
06.12	1.24	1.50	1.75	1.54	1.76	1.26	1.48	1.91	2.59	2.17	2.11	3.18	2.33	1.92	2.83
03.12	1.37	1.62	1.90	1.74	2.06	1.42	1.65	2.07	2.84	2.71	2.37	3.93	2.38	1.97	2.30
12.11	1.69	1.68	2.04	2.03	2.23	1.69	2.13	2.28	3.03	3.07	2.64	4.14	2.49	2.08	2.37
09.11	1.93	1.85	2.30	2.21	2.47	1.91	2.45	2.32	2.98	3.17	2.77	4.30	3.83	2.89	2.59
06.11	2.46	2.41	2.91	2.66	3.00	2.46	3.04	2.92	3.61	3.72	3.42	4.90	4.51	4.45	4.50
03.11	2.48	2.53	3.03	2.65	3.07	2.70	3.33	2.83	3.66	3.65	3.74	4.76	4.58	4.85	4.93
12.10	2.49	2.63	3.33	2.64	3.13	2.61	3.46	2.70	3.63	3.95	3.85	5.00	4.53	3.59	3.60
09.10	2.31	2.53	3.02	2.34	3.02	2.46	3.32	2.57	3.74	4.06	3.76	4.86	4.09	3.54	3.52
06.10	1.67	1.99	2.37	1.66	2.64	2.28	2.92	2.13	3.63	3.43	3.34	4.04	3.64	3.45	3.90
03.10	1.43	1.77	2.35	1.49	2.89	2.43	3.00	2.13	4.19	3.16	2.89	4.06	3.44	4.21	4.82
12.09	1.15	1.51	2.10	1.31	2.65	1.94	2.69	2.00	3.42	2.85	2.28	3.46	3.03	2.86	4.36
09.09	1.15	1.50	2.10	1.31	2.65	1.95	2.58	2.07	3.65	2.91	2.24	3.35	2.93	2.28	3.10
06.09	1.14	1.51	2.11	1.29	2.68	1.97	2.50	2.10	3.67	2.85	2.16	3.12	2.94	2.13	2.45
03.09	1.20	1.58	2.35	1.43	2.88	2.08	2.55	2.21	3.39	2.89	2.18	2.99	3.07	2.35	2.40
12.08	1.57	1.97	2.95	1.91	3.48	2.25	2.96	2.84	3.66	3.41	2.25	3.30	3.53	2.73	2.51
09.08	2.73	3.63	4.22	2.76	4.26	2.93	3.57	3.36	5.09	4.55	3.07	3.49	4.84	3.31	3.09
06.08	3.27	4.49	4.87	3.07	5.04	3.36	4.19	3.80	5.31	5.13	3.78	3.70	5.20	3.28	3.02
03.08	3.62	4.92	5.17	3.46	5.34	3.76	5.09	4.27	5.49	4.85	3.99	3.82	5.76	3.67	3.52
12.07	4.63	5.56	6.17	4.11	5.97	3.97	6.20	4.79	6.08	5.42	5.12	4.18	6.63	4.10	4.29
09.07	4.79	5.32	6.05	4.29	6.09	4.09	6.66	4.28	9.32	5.46	5.03	4.19	7.33	5.28	5.66
06.07	5.25	5.12	6.18	5.22	6.72	4.04	6.50	4.34	9.47	5.47	5.31	4.22	7.94	6.51	6.58
03.07	5.21	5.23	6.23	5.20	7.54	4.19	6.14	4.40	11.18	5.75	5.68	4.49	8.66	6.43	5.77
12.06	5.36	5.44	6.22	5.49	8.90	4.24	6.12	4.38	11.58	5.73	5.93	4.51	9.04	4.86	4.54
09.06	4.94	5.37	6.28	5.71	8.59	4.32	5.41	4.34	11.26	5.58	6.17	4.70	8.59	4.38	3.63
06.06	5.00	5.39	6.29	5.67	8.59	4.51	5.36	4.36	8.52	5.53	6.50	4.36	8.78	4.29	3.40
03.06	5.84	5.90	6.86	6.44	9.36	4.80	5.76	5.06	8.85	5.84	8.48	4.35	7.89	4.41	3.06
12.05	6.53	6.03	7.24	6.91	9.19	5.35	5.69	5.60	9.16	6.25	9.37	4.40	7.90	4.43	3.45

Source: authors' elaboration

Table 3 Differences between Potential Extreme Losses and Loss Absorption Buffers (% Values; Quarterly Frequency)

Bank / M.Y	UCG	ISP	UBI	BP	BPER	BPM	BMPS	CE	BPSO	CVAL	CRG	BDB	BSRP	PEL	SPO
06.16	6.76	0.43	7.08	13.47	8.11	4.87	21.33			5.26	13.77	0.58			
03.16	2.13		3.10	5.56	3.40	0.00	20.57			3.21	12.17				
12.15							10.90			0.23	3.87				
09.15				0.75	1.41		19.51			1.57	5.33				
06.15			0.00	2.87	2.12		19.19			2.70	6.81				
03.15				3.70	2.34	0.32	17.79			2.85	6.32			11.99	
12.14			0.02	3.99	3.01	0.70	16.04			2.42	5.88			7.17	
09.14				3.99	2.75	1.39	13.08			1.17	3.13			7.34	
06.14			0.43	4.89	3.25	2.60	14.21			0.45	4.45			9.28	
03.14			0.39	5.29	2.92	3.01	7.22			0.26	1.90			3.12	
12.13			2.65	4.48	4.92	3.80	9.15				1.76			5.93	
09.13	3.62	1.39	4.91	6.55	7.57	5.46	10.44			3.32	2.67			4.99	10.31
06.13	5.57	2.81	5.93	8.61	8.13	8.42	13.06	0.76		5.69	3.29			3.39	9.39
03.13	11.89	5.87	7.88	10.68	10.09	12.38	16.21	2.90		5.38	3.93		0.97	0.61	11.26
12.12	16.06	10.03	9.35	11.84	10.52	14.67	15.44	4.94		5.94	4.35		1.65	1.89	2.49
09.12	17.86	11.77	10.53	12.83	10.40	16.82	15.90	6.32		6.06	4.62		2.09	3.75	2.37
06.12	16.67	10.49	8.94	11.63	7.59	16.12	11.98	5.93		5.53	2.70		2.43	7.79	0.33
03.12	13.96	8.40	7.16	8.79	4.54	13.55	7.96	4.19		0.60	0.05		2.03	6.88	3.92
12.11	8.79	7.34	5.64	5.61	2.97	9.65	0.97	2.20					1.17	5.45	3.04
09.11	5.88	5.44	3.41	4.19	0.83	7.32		1.35							0.90
06.11	0.87	0.02		0.72		2.62									
03.11	0.58			0.91		0.49									
12.10	0.45			1.20		0.64									
09.10	1.90			3.31		1.06									
06.10	7.58	2.45	0.89	9.49		1.99		1.85							
03.10	11.13	4.52	0.47	11.83		0.08		1.98							
12.09	16.61	7.68	2.64	15.08		4.20		3.25							
09.09	17.09	8.60	2.37	14.95		4.46		3.71						0.79	
06.09	17.42	8.19	1.63	14.07		4.21		3.25						1.62	0.37
03.09	16.03	6.44		11.01		2.89		1.72							0.29
12.08	8.70	0.53		3.82		0.69									

Source: Authors' elaboration

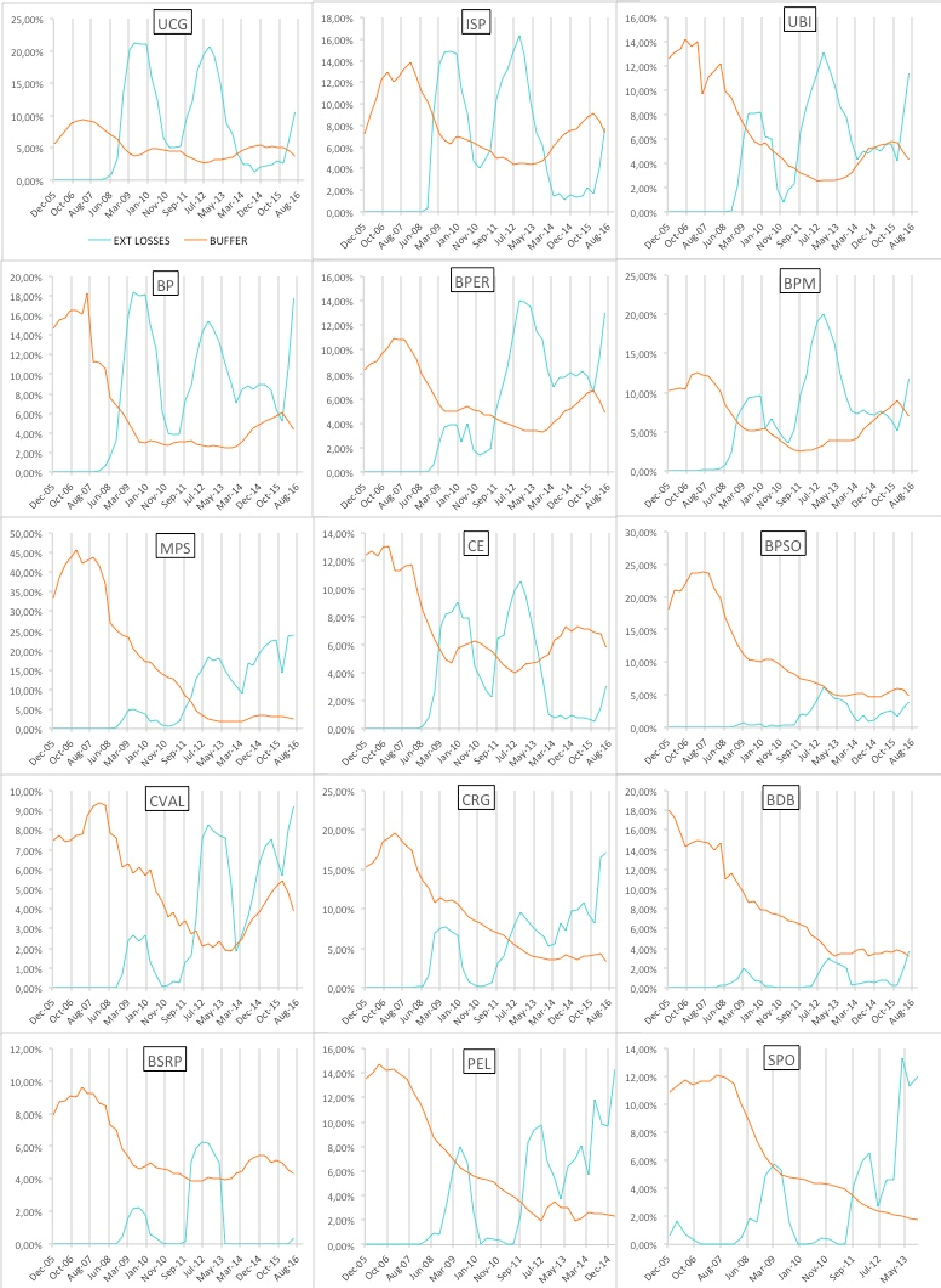

Figure 2 Evolution of Potential Extreme Losses and Loss Absorption Buffers

Source: Authors' elaboration

Some conclusions can be drawn about the optimal choice of an intervention threshold. In order to set an optimal trigger, it is necessary to evaluate the Type I and Type II errors. In other words, we have to identify how many wrong decisions the supervisory authority would have taken if a certain threshold had been implemented. According to Gropp et al. (2004), and to Bharat and Shumway (2008), we collect all the values of DD that occurred when the potential extreme losses were equal to or greater than the buffers. Rearranging the values from the lowest to the highest, it is possible to construct the cumulative distribution function (Figure 3). Since we employ different combinations of equity volatilities and default barriers obtaining very similar results, we can state that the shape of the distribution is not due to the specification of the model. Therefore, for a specific DD, the distribution gives the number of solvent banks, expressed in a percentage, whose potential extreme losses were above the loss absorption buffer. For example, we can infer that 50% of all the banks that satisfied the criterion would have been subject to early intervention if the DD level was set at approximately 2. Consequently, it is possible to state that this intervention threshold would have caused an unnecessary recovery of solvent banks half of the time. In other words, this amounts to a Type II error of 50%.

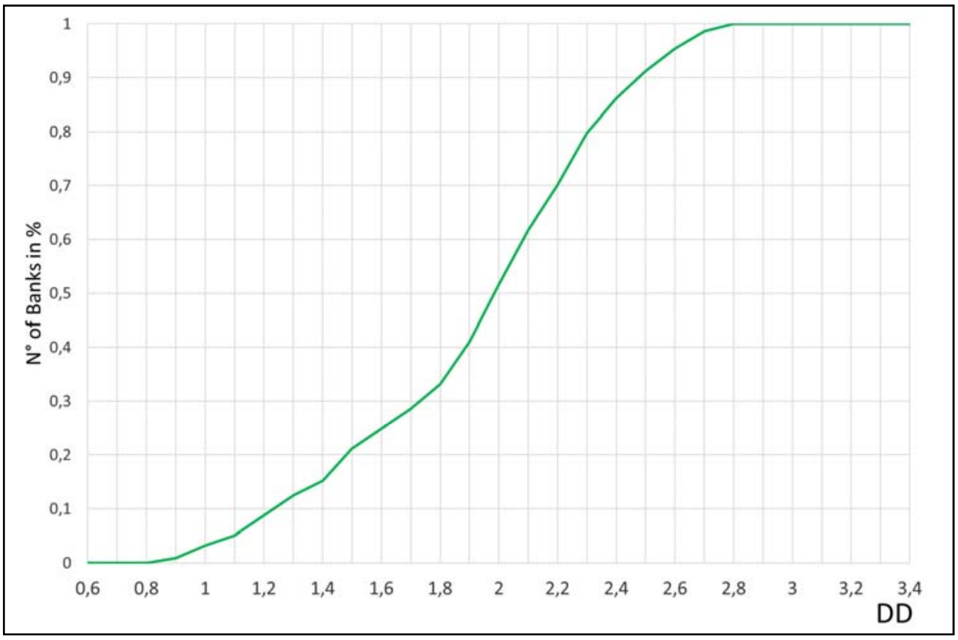

Figure 3 Cumulative Distribution of Banks Fulfilling the Criterion of Intervention

Source: Authors' elaboration

Compared to the findings obtained by Goodhart and Segoviano (2015), the cumulative distribution for the Italian solvent banks (Figure 3) appears to have more concentrated levels of DD. In fact, using the Italian dataset, the optimal threshold of $DD = 1.5$ proposed by Goodhart and Segoviano would have led to a Type II error of about 20%. This means that for every one bank out of five, early intervention would have been triggered. Equally, when the DD is equal to or lower than 2.8 ($DD \leq 2.8$), all the banks that satisfied the criterion for intervention are taken into account.

By contrast, as regards the insolvent banks and thus the Type I error, the results were not as reliable as they were for the solvent ones. Due to the small amount of observations of insolvent banks and the relatively low importance of those in the sample, the final results cannot be considered satisfactory.

6. Conclusions

We analyzed the banking system with respect to the early intervention stage. This phase, which is set out by the BRRD, is an important characteristic of the new Banking Union project. However, the models signaling the need to enter into the recovery stage are not as highly developed as those studying the triggers for resolution (Koutsomanoli-Filippaki and Mamatzakis, 2009; Fiordelisi et al., 2011). Since the legislation does not provide a clear definition of the conditions that can trigger the early intervention phase, a quantitative metric would increase the convergence of supervisory activities and, being built on observable, verifiable and objective data, it would be less vulnerable to manipulation and more clear and transparent to institutions. In addition, these models would be more effective in reducing and balancing Type I and Type II errors.

We assume that the criterion for intervention consists of the evaluation of the institutions' ability to absorb both expected and unexpected losses (BCBS, 2011). Specific definitions are applied for the identification of the components of the loss absorption buffer, in particular by implement some adjustments to the regulatory values of capital and risk-weighted assets. In order to quantify the potential extreme losses, we employ Merton's model and Vasicek's approach to recover the probabilities of default and the loss distribution functions, respectively.

The empirical analysis involves the Italian listed commercial banks; we evaluate and compare both the past and the current (up to 30 June 2016) conditions of each bank, with respect to their probability of default and their ability to absorb the potential extreme losses that may occur. For supervisory authorities, policy makers, and analysts the tested model could represent a useful tool to define the intervention threshold and to understand the probabilities of committing Type I and Type II errors. Moreover, we try to contribute to improve the current literature about optimal recovery plans by implementing an approach that could be successfully adapted to different bank samples.

The main outcomes evidence the difficulties of BMPS under all the analyses made. Then, we also show that the peaks of potential extreme losses and the highest probabilities of default for bigger banks match the periods following the global financial crisis and the European debt crisis. By contrast, the smaller and solvent banks did not exhibit particular outcomes, while the insolvent ones showed evidence of distress prior to insolvency, but not at a noticeable level that one might expect. Moreover, we illustrate the descending path, since the end of 2005, of the loss absorption buffer, that is more or less pronounced depending on the bank under examination. Then, after aggregating the results for the banks that remained solvent, it is possible to provide the estimates of Type II error. The optimal threshold of $DD = 1.5$, identified by Goodhart and Segoviano (2015), would have led to a Type II error of about 20%. This means that for every one bank in five, the early intervention would have been triggered unnecessarily.

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