Testing for the underlying dynamics of bank capital buffer and performance nexus.

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Abstract

This paper reveals the underlying dynamics between capital buffer and performance for banks in EU-27. Dynamic panel analysis shows that capital buffer is significantly affected by bank performance, and also risk exposure. During the financial crisis of 2007 – 2008, we detect regime switches. We find positive relationship between capital buffer and bank performance for banks that fall in the low performance regime, while a negative relationship is reported for banks that belong to the high regime. Finally, threshold results show that capital buffer exerts a positive impact on bank stability for relatively better capitalized banks, while for relatively less capitalized banks increasing capital buffer reduces bank stability. These results provide evidence that although regulation reforms as regards capital requirements could improve bank performance and stability, these improvements are not homogeneous across banks.

Keywords: Dynamic threshold, Capital buffer; Regulation; Performance; Risk-taking

JEL classification: G21; G28+++ ?

1. Introduction

The financial crisis of 2007 – 2008 shows that sudden changes in asset quality and value can quickly diminish bank capital, leaving banks with inadequate capital to deal with unexpected losses. As a result, capital buffer requirements have become an instrument of providing cushion during adverse economic conditions and a macro-prudential tool preventing excessive risk-taking (Ayuso, Pérez, & Saurina, 2004; Jokipii & Milne, 2008). Under Basel III (BCBS, 2010b) banks are required to maintain a mandatory capital conservation buffer of 2.5 percent of common equity. In case of violation of the minimum requirement, restrictions on dividends and remunerations will be applied by Basel Committee. Furthermore, regulators may also require a discretionary countercyclical buffer up to another 2.5 percent of capital during periods of high credit growth. According to Basel Committee a rise in equity ratios lowers the probability of bank failures. From the perspective of banks, empirical evidence on the determinants of bank capital buffer suggests that banks may keep capital buffer in order to signal soundness to the markets and receive higher ratings from the rating agencies (Jackson et al., 1999). In addition, banks hold capital buffer to avoid costs related to penalties and restrictions that are imposed by the supervisors when the former violate minimum capital requirements (Buser, Chen, & Kane, 1981; Furfine, 2001; Jokipii & Milne, 2011).

Recent studies show that as raising capital through capital markets is costly especially during economic downturns, banks might rely on their own performance to build up capital buffers (Shim, 2013). The empirical results regarding the relationship between capital buffer and bank performance are inconclusive. There are studies that provide evidence for negative association between bank performance and capital buffer (Ayuso et al., 2004; Jokipii and Milne, 2008) suggesting that strong bank performance substitutes for capital as a cushion against unexpected losses. While, another strand of literature (Nier and Bauman, 2006; Shim, 2013) finds positive relationship between performance and capital buffer indicating that improvement in bank performance increases capital buffer. Apparently, the literature on the relationship between capital buffer and bank performance provides mixed results. To this end, in addition to the accounting ratios return on equity (ROE), return on assets (ROA) and net interest margin (NIM), we employ bank cost efficiency derived by Stochastic Frontier Analysis (SFA) as a measure of bank performance.

Concerning the capital buffer and risk nexus, several empirical studies (Ediz, Michal, & Perraudin, 1998 ; Francis & Osborne, 2012; Jokipii & Milne, 2008; Rime, 2001; Shim, 2013) have focused on the relationship between risk and bank capital buffer, testing whether increasing risks taken by banks force them to maintain higher capital buffer. The results show that there is a positive relationship between bank risk-taking and capital buffer, indicating that the riskier the bank the higher the capital buffer. Following previous literature (Ayuso et al., 2004; Jokipii & Milne, 2008), we employ non-performing loans, off-balance-sheet items and net loans to account for bank risk exposure while as an additional measure of bank default risk, we include Z-Score.

This paper contributes to the literature of the relationship between capital buffer, bank performance and risk in several ways. First of all, unlike previous studies this paper contributes to the existing literature by employing a dynamic panel threshold analysis in order to determine any switches in the relationships between capital buffer, bank performance and risk over the crisis years. This methodology allows data itself to define the crisis years indicating regime switches in the relationships between capital buffer and other bank-specific variables. Specifically, we investigate the presence of different regimes for the relationship between a) bank capital buffer and performance as measured by bank efficiency and b) bank capital buffer and risk of default as measured by Z-Score. Furthermore, we account for the inverse relationship between these variables. In particular, we examine the impact of capital buffer on bank performance and Z-Score by using capital buffer as a threshold variable. Second, we opt for different measures of bank performance and risk so as to reveal all potential determinants of bank capital buffer. Finally, this study covers a period (2004 – 2013) that includes the crisis years and therefore we take into account any differences due to the financial meltdown in 2007 – 2008 and the recovery thereafter.

Our results reveal significant relationships between bank capital buffer, performance and risk-taking. Specifically, results obtained by dynamic panel analysis show that bank performance and risk-taking have strong positive impact on capital buffer. In a further analysis, dynamic threshold results indicate different regimes for the underlying relationships. Estimated results report positive relationship between bank capital buffer and performance for banks that fall in the low performance regime, while negative relationship between capital buffer and performance is reported for banks that belong in the high regime. Furthermore, threshold results show that capital buffer exerts strong negative impact on bank stability for relatively less capitalized banks, while the impact of capital buffer on bank stability is positive for relatively better capitalized banks.

The paper is organised as follows. Section 2 sets the hypotheses to be tested in the empirical section. Section 3 presents our data, whilst section 4 discusses our methodology. Next, section 5 shows regression results and the subsequent threshold analysis and finally, section 6 concludes.

2. Hypotheses development

2.1.The adjustment cost hypothesis.

Following previous literature (Ayuso et al., 2004; Estrella, 2004; Guidara, Lai, Soumaré, & Tchana, 2013; Jokipii & Milne, 2008, 2011; Stolz & Wedow, 2011) we assume that banks need time to adjust their initial capital buffer towards their desired level. In the absence of adjustment costs in bank's capital ratio, banks would not have incentives to hold capital in excess of the minimum regulatory requirements. Therefore, banks prefer to maintain a capital buffer as it is costly to fall below the minimum requirement (Fonseca & González, 2010; Jackson et al., 1999; Rime, 2001; Stolz & Wedow, 2011). Considering adjustments costs, we assume that banks take time to adjust their capital buffer towards the internal targets and thereby the capital buffer of the previous period should have positive and statistically significant impact on the current capital buffer.

H1. Adjustment costs in bank capital would affect capital buffer.

2.2. Bank performance hypothesis.

Previous literature (Ayuso et al., 2004; Guidara et al., 2013; Jokipii & Milne, 2008; Nier & Baumann, 2006; Shim, 2013) uses ROE and ROA as bank performance measures and provides mixed results regarding the relationship between bank capital buffer and performance. In addition to the accounting ratios ROE, ROA and NIM, this study employs bank cost efficiency derived from the SFA as an alternative measure of bank performance and a source of capital buffer.

Although, there have been several studies about the link between total regulatory capital and efficiency, up till now the literature on the relationship between capital buffer and efficiency has been rather inconclusive. Specifically, Berger and Bonaccorsi di Patti (2006) find negative relationship between regulatory capital and efficiency for U.S. banks over the period 1990 – 1995. Their results show that banks hold lower regulatory capital as higher efficiency eliminates the potential risk of default. In line with these results, Altunbas et al. (2007) using a sample of European banks, covering the period 1992 – 2000, show that inefficient European banks tend to hold more capital and evolve in less risky activities.

Another strand of the literature (Barth, Caprio Jr, & Levine, 2004; Demirgüç-Kunt, Laeven, & Levine, 2004; Pasiouras, 2008; Pasiouras, Tanna, & Zopounidis, 2009) suggests positive relationship between bank performance, as measured by efficiency and capital. However, this relationship does not appear to be significant always. Furthermore, there is evidence that higher capital requirements mitigate the probability of bankruptcy, enhancing bank efficiency (Berger & Bonaccorsi di Patti, 2006; Demirgüç-Kunt & Huizinga, 1999). Thus, further analysis is warranted so as to determine the relationship between capital buffer and bank performance. The second set of hypotheses is developed as follows:

H2. Bank performance enhances bank capital buffer (and vis a versa) through regime switches.

2.3.Bank risk-taking hypothesis

During the last decades, regulators have emphasized the importance of capital requirements that financial institutions have to comply with in order to mitigate risk-taking and enhance financial stability in the banking industry (BCBS, 2010b). The implementation of higher capital requirements aims to create a direct link between banks' capital and risk. From the perspective of regulators, banks with higher risk should hold higher capital buffer. The reason is that banks that hold risky portfolios but do not maintain higher capital buffer are more likely to end up with capital below the minimum requirement. A wide range of literature has focused on understanding the relationship between capital buffer and risk (Jackson et al., 1999; Jokipii & Milne, 2011; Lindquist, 2004; Rime, 2001; Shrieves & Dahl, 1992). Most of these studies have found positive relationship between bank capital buffer and risk, indicating that banks with risky positions hold higher capital buffer. Therefore, we test the following hypotheses:

H4. Risk exerts positive impact on bank capital buffer (and vis a versa) through regime switches.

3. Data and variables

We use an unbalanced bank-level panel data that includes saving and commercial banks from EU-27 countries over the period 2004 – 2013 on annual basis.[1] Our analysis uses 1017 banks and a total of 3788 observations. The primary source of our data is the Bankscope database by Bureau van Dijk. Furthermore, we obtain macroeconomic data from the World Bank.

3.1.Measuring bank capital buffer

In line with previous studies (Ayuso et al., 2004; Fonseca & González, 2010; Guidara et al., 2013; Jokipii & Milne, 2008, 2011)), we define as capital buffer the amount of capital banks hold in excess of the minimum requirement. Table 1 includes the variability of total regulatory capital (Tier 1 plus Tier 2 over Risk Weighted Assets) across country and over time. Following Jokipii and Milne (2008), the calculation of minimum capital requirement for each country is based on Table 2 that presents the national total regulatory capital requirements.

[Insert Table 1 and Table 2]

Table 3 reports descriptive statistics for bank capital buffer across countries and over time. Data for the years 2004 – 2013 shows that banks hold far more capital than required by the regulators. Banks with the highest mean capital buffer are located in the

[1] In our sample we include both saving and commercial banks following the study of Casu and Girardone (2010). The authors suggest that mainly commercial and saving banks in European Union form depositary institutions and they have a sufficient degree of cross-country homogeneity and comparability. Previous studies that include both saving and commercial banks in their analysis are Maudos et al. (2002), Delis and Kouretas (2011), Gropp et al. (2010), Kalyvas and Mamatzakis (2014). In order to account for any differences in the business model between saving and commercial banks, most of these studies employ a dummy variable. In line with these studies, we also include a dummy variable for commercial banks (COM).

north Europe such as Belgium and Austria (15.35 and 14.59 respectively), while banks with the lowest capital buffer are in Germany (10.89), Croatia (10.92) and Sweden (10.98). The average capital buffer across EU-27 is 11.75. As regards the evolution of bank capital buffer over time, we should note that for the period 2004 – 2006 there is a negative trend. However, bank capital buffer shows a positive development for the period over 2007 – 2009. For the years 2010-2012 the decreasing capital buffer suggests that European banks had difficulties in maintaining high capital buffer due to the financial crisis (Avramidis and Pasiouras, 2015) while after 2012 bank capital buffer shows a recovery trend.

[Insert Table 3]

3.2. *Measuring bank cost efficiency.*

Bank efficiency has been widely used in previous research to examine the impact of managerial structure such as ownership and compensation on bank efficiency (Dong et al., 2016; Matousek and Tzeremes, 2016; Tzeremes, 2015; Staub et al., 2010; Fries and Taci, 2005), to investigate the effects of regulation on bank efficiency (Kalyvas & Mamatzakis, 2014; Jaffry et al., 2013; Berger et al., 2005; Bhattacharyya et al., 1997) while another strand of literature has examined the impact of systematic differences across banks, such as size, on efficiency (Bos et al, 2009; Kwan, 2006; Isik and Hassan , 2002; Berger and Humphrey, 1997). In this paper, we derive bank performance from stochastic frontier analysis. This methodology combines the random error and efficiency in one composite error term (Berger & Humphrey, 1997). The cost efficiency model for SFA is the following:

$$TC_{i,t} = f\left(P_{i,t}, Y_{i,t}, N_{i,t}, Z_{k,t}\right) + v_{i,t} + u_{i,t} \tag{3a}$$

Where $TC_{i,t}$ stands for the total cost of bank *i* at year *t*, $P_{i,t}$ is a vector of inputs, $Y_{i,t}$ is a vector of outputs and $N_{i,t}$ is a vector of quasi-fixed netputs while country-specific variables are represented by the vector $Z_{k,t}$. As regards $v_{i,t}$, this term represents factors that affect the total cost function but are beyond the control of the managers. Finally $u_{i,t}$ stands for the bank inefficiency that is controlled by managers and follows a half-normal distribution. The cost efficiency scores lie between 0 and 1 and are calculated according to the below formula for each bank and each year:

$EFF_{i,t} = [\exp(-u_{i,t})] - 1$.

(3b)

To enhance flexibility, we resort to the translog cost specification:

$$lnTC_{i,t} = a_0 + \sum_i a_i lnP_{i,t} + \sum_i \beta_i lnY_{i,t} + \frac{1}{2}\sum_i \sum_j a_i lnP_{i,t} lnP_{j,t} + \frac{1}{2}\sum_i \sum_j \beta_i lnY_{i,t} lnY_{j,t} + \sum_i \sum_j \delta_{i,j} lnP_{i,t} lnY_{j,t} + \sum_i \zeta lnN_{i,t} + \frac{1}{2}\sum_i \sum_j \zeta_i lnN_{i,t} lnN_{j,t} + \frac{1}{2}\sum_i \sum_j \theta_{i,j} lnP_{i,t} lnN_{j,t} + \sum_i \sum_j \kappa_{i,j} lnY_{i,t} lnN_{j,t} + \mu_1 T^2 + \sum_i \nu_i T lnP_{i,t} + \sum_i \zeta_i T lnY_{i,t} + \sum_i \rho_i T lnN_{i,t} + \sum_i \varphi_i Z_{k,t} + v_{i,t} + u_{i,t} \quad (4)$$

Bank inputs and outputs are defined according to Sealey and Lindley (1977) based on the intermediation methodology. According to this methodology, the main purpose of banks is to use labour and capital to accumulate funds so as to transform them into loans and other income generating assets. We specify two inputs and two outputs. Specifically, inputs consist of labour as measured by the ratio of personnel expenses over total assets *(P1)* and financial capital measured as the ratio of total interest expenses over deposits and short term funding *(P2)*. In terms of output prices, we include gross loans *(Y1)* and other earning assets *(Y2)* such as T-bills, bonds, government securities and equity investments. Total cost *(TC)* is defined as the sum of total interest and non-interest expenses.

Finally, we include as quasi-fixed netput the fixed assets of each bank *(N1)* as a proxy for physical capital as it is used from Berger and Mester (1997). Furthermore, we include equity *(N2)* as a second qausi- fixed netput as equity represents alternative source of funding for banks and therefore, equity might affect the cost structure of banks (Berger & Mester, 1997; Fiordelisi, Marques-Ibanez, & Molyneux, 2011).

Furthermore, the translog function includes the time trend *(T)* to account for technological progresses and any potential time effects (Bonin, Hasan, & Wachtel, 2005; Gaganis & Pasiouras, 2013). Finally, we include country-specific dummy variable ($Z_{k,t}$), in order to capture country characteristics and cross country differences (Bonin et al., 2005; Gaganis & Pasiouras, 2013).

The variability in bank cost efficiency across country and over time is reported in Table 4. Table 4 shows that the average cost efficiency for the sample is around 78%. This indicates that banks need to improve their efficiency by 22% in order to converge to the cost efficiency frontier. At a country level, Hungary, Romania and Bulgaria have the lowest cost efficiency scores with scores of 0.63, 0.63 and 0.64 respectively whereas banks in Malta, Spain and Sweden are the best performers with efficiency scores around 0.85, 0.84 and 0.83 respectively. These efficiency scores are in line with previous literature (Barth, Lin, Ma, Seade, & Song, 2013; Casu & Girardone, 2010; Hasan, Koetter, & Wedow, 2009; Kalyvas & Mamatzakis, 2014; Pasiouras, Hasan, Wang, & Zhou, 2009).

Concerning the evolution of bank efficiency over time, one can notice that there is an apparent reduction in cost efficiency during the years 2006 – 2008 with the lowest score in 2008 (0.73). The next two years are characterized by a positive trend (0.79 in 2009 to 0.81 in 2010). After the year 2010, bank cost efficiency decreases possibly because most of the European banks are exposed to the sovereign debt crisis.

[Insert Table 4]

Regarding the accounting bank performance measures, we include ROE which is the return to shareholders on their equity. Our next measure of bank performance is the ROA which reflects the ability of managers to generate profits using banks assets indicating how efficient bank assets are managed. Finally, we employ NIM which focuses on the profits earned from interest activities.

3.3. Measuring bank risk exposure

Concerning bank risk exposure, we employ various measures of risk. We include the ratio of non-performing loans over total loans (NPL). We expect NPL to have positive impact on bank capital buffer. Banks with increasing NPL will increase their capital buffers, as they are obligated to hold higher levels of loan loss provisions (Jokipii & Milne, 2008).

We include the ratio of Off-Balance-Sheet items over total liabilities (OBS) as another measure for bank risk. OBS items are measured as the non-interest income and fee generating from various contingent liabilities such as derivatives, letters of credit, insurance and other types of non-traditional banking activities and securities underwriting. OBS items increase the risk that bank is exposed to and therefore, we expect that banks with higher amount of OBS items will hold higher capital buffer in order to deal with the higher risk exposure. Furthermore, banks with large loan portfolio are exposed to higher risk especially during economic recession. Therefore, we include the ratio of bank loans over total assets (NETLOANS) as an additional risk measure. As banks with increasing loan portfolio have higher exposure to risk, we expect a positive coefficient for NETLOANS (Jokipii & Milne, 2008). Moreover, we employ the Z-Score as proposed by Boyd and Graham (1986). Z-Score is measured according to the following formula: Z-Score = (1 + ROE) / Standard Deviation of ROE and indicates the risk of failure for a given bank. Higher the values of Z-Score, lower the probability of failure. This measure of default risk has been widely used in the literature (Barry, Lepetit, & Tarazi, 2011; Lepetit, Nys, Rous, & Tarazi, 2008; Radić, Fiordelisi, & Girardone, 2012).

3.4. Other control variables

As a measure for market discipline, we include a dummy variable DISCLSR that takes the value 1 for listed banks and 0 for unlisted indicating information disclosures. We expect that the observability of bank’s risk choices, as captured by this dummy variable, will increase the incentive of banks to hold regulatory capital above the minimum requirement in order to reduce the risk of default and avoid being penalised by investors for choosing higher risk (Boot & Schmeits, 2000; Nier & Baumann, 2006).

We also include the explanatory variable SIZE to detect differences in the level of capital buffer according to bank size. Size may have an impact on capital buffer due to the extent of bank diversification, funding and investment opportunities. The natural log of total assets is used as a measure of bank size and the relationship could be positive or negative depending on how small and large banks adjust their capital buffers during the period under study. Size may have negative impact on capital buffer, as large and well diversified banks have much smaller probability of suffering from sharp decline in their capital ratios, while in line with previous studies(Ayuso et al., 2004; Berger, DeYoung, Flannery, Lee, & Oeztekin, 2008; Bikker & Metzemakers, 2004; Francis & Osborne, 2012; Jokipii & Milne, 2008; Rime, 2001; Shrieves & Dahl, 1992), we expect that smaller banks will increase their capital buffers in order to deal with their weaknesses in capital markets .

Moreover, we account for the concentration ratio (C5) in the banking industry by including the sum of the assets of the five largest banks as a share of all banks in each country and for each year. The impact of the concentration ratio on capital buffer could be positive or negative. The sign depends on whether low competition will increase or decrease the incentives for higher capital (Nicoló, Bartholomew, Zaman, & Zephirin, 2004; S. Mishkin, 1999).

Furthermore, in order to eliminate the potential biases associated with having omitted variables, we employ a dummy variable which takes the value 1 for European Monetary Union countries and 0 otherwise (EMU). In addition, we include time dummies to capture any potential time effects and a dummy variable for commercial banks (COM) in order to account for any differences between commercial and saving banks (Casu & Girardone, 2010). Table 5 identifies the variables and provides brief descriptions of the data sources, while Table 6 includes summary statistics for the key variables.

[Insert Table 5 and Table 6]

4. Methodology

4.1. Dynamic Panel Model

Following previous studies (Ayuso et al., 2004; Berger et al., 2008; Estrella, 2004; Flannery & Rangan, 2006; Jokipii & Milne, 2008; Rime, 2001), we employ partial adjustment process in order to examine the convergence of bank's initial capital buffer toward its target within each time period.

Therefore, the change in the capital buffer is specified as follows:

$$BUFF_{i,t} - BUFF_{i,t-1} = \lambda \, (BUFF^{*}{}_{i,t} - BUFF_{i,t-1}) + u_{i,t}$$

(1a)

Here, $BUFF_{i,t} - BUFF_{i,t-1}$ is the observed change in capital buffer as defined by bank *i* at year *t*. $\mathrm{BUFF}_{i,t}$ ($\mathrm{BUFF}^{*}{}_{i,t}$) is the actual (target) capital buffer of bank *i* in time *t*, λ is the speed of adjustment while $u_{i,t}$ is the error term.

Each year bank's actual buffer ($\text{BUFF}_{i,t}$) converges to its desired level ($\text{BUFF}^{*}_{i,t}$) by a proportion λ. Low estimated values of λ indicate that banks are passive managers of their capital buffer, while high values of λ indicate that banks actively manage their buffer toward their target level (Berger et al., 2008).

As suggested by the banking literature (Ayuso et al., 2004; Flannery & Rangan, 2006; Jokipii & Milne, 2008), the target capital buffer ($BUFF^{*}{}_{i,t}$) is not easily observable, but could be modelled using the bank-specific variables discussed in the data section. Therefore, target capital buffer is approximated as follows:

$$BUFF^{*}_{i,t} = \beta X_{i,t}$$

(1b)

Substituting Eq. (1b) into Eq. (1a) we end up with the following equation:

$$BUFF_{i,t} - BUFF_{i,t-1} = \lambda\beta X_{i,t} - \lambda BUFF_{i,t-1} + u_{i,t}$$

(2)

By adding $BUFF_{t-1}$ to both sides of Eq. (2), we specify our empirical model as follows:

$$BUFF_{i,t} = \lambda\beta X_{i,t} + (1-\lambda)BUFF_{i,t-1} + u_{i,t}$$

(3)

Where $X_{i,t}$ is a vector of bank-specific variables. The lagged value of the dependent variable ($BUFF_{i,t-1}$) captures the importance of adjustment costs and we expect a positive and significant coefficient for this variable as stated in our first hypothesis. The error term $u_{i,t}$ consists of a bank-specific component μ_i, which is assumed to be constant over time and a white noise $\varepsilon_{i,t}$. Hence, $u_{i,t} = \mu_i + \varepsilon_{i,t}$ where μ_i ~ *iid* $(o,\sigma_{\mu 2})$ and $\varepsilon_{i,t}$ ~ *iid* $(o,\sigma_{\varepsilon 2})$. [2]

We estimate of Eq. (3) by employing the two-step system generalized method of moments (GMM) estimator as developed by Arellano and Bover (1995).[3] Furthermore,

[2] Since $\text{BUFF}_{\text{i,t}}$ is a function of μ_i, $\text{BUFF}_{\text{i,t}-1}$ is also a function of μ_i and therefore the right hand regressor in Eq. (3) is correlated with the error term. As a result, the OLS estimator will be biased and inconsistent. Furthermore, although the fixed effect estimator eliminates μ_i, "Nickell bias" exists as T is relatively small compared to N meaning few time periods and many individuals (Nickell, 1981).

[3] This methodology is preferred for three main reasons. First, by taking first differences for all variables, we eliminate the presence of unobserved bank-specific effects. Second, we use the lagged dependent variable to capture the

we follow Roodman (2009) accounting for Windmeijer (2005) biased-corrected robust standard errors.

4.2. Dynamic panel threshold model

Given the financial crisis of 2007 - 2008, we opt for a novel methodology that enables us to identify any potential regime changes in the relationship between capital buffer, bank performance and risk-taking. We follow the estimation methodology developed by Hansen (1999) and Kremer et al. (2013). Threshold methodology uses the cross sectional model employed by Caner and Hansen (2004), where the authors allow for endogeneity by using GMM estimators. Kremer et al. (2013) extended this methodology to a dynamic unbalanced threshold methodology that identifies possible changes in the coefficient of the independent variables.

We employed the following threshold model:

$$BUFF_{i,t} = \mu_i + \lambda_1 m_{i,t}\, I\big(X_{i,t} \le \gamma\big) + \delta_1 I\big(X_{i,t} \le \gamma\big) + \lambda_2 m_{i,t} I\,\big(X_{i,t} > \gamma\big) + \varepsilon_{i,t}$$

(4)

The subscript i refers to the individual banks and the subscript t indexes the time. $BUFF_{i,t}$ is the dependent variable, μ_i is the bank-specific fixed effect and λ_1 and λ_2 the reverse regression slopes and based on these slopes we assume two regimes. $X_{i,t}$ is the threshold variable and γ is the threshold value, which distribute the observations above and below the threshold value composing the high and low regimes respectively. I is the indicator function that specifies the two regimes as defined by the threshold variable. Finally, $\varepsilon_{i,t}$ is the error term, which is assumed to be independent and identically distributed *(iid)* with mean zero and finite variance σ2. The model employed by Kremer et al. (2013) treats $m_{i,t}$ as a vector of explanatory variables that includes a subset $m1_{i,t}$ of exogenous variables uncorrelated with $\varepsilon_{i,t}$ and a subset $m2_{i,t}$ of endogenous variables correlated with $\varepsilon_{i,t}$. Furthermore, Kremer et al. (2013) extend Hansen's (1999)

dynamic nature of capital buffer and third, by using GMM methodology, we account for potential endogeneity of the explanatory variables. We consider as exogenous the country-specific variables and time dummies and as endogenous the bank-specific variables (Ayuso et al., 2004; Fonseca and González, 2010). The instruments chosen for the lagged endogenous variables are two-to-six period lags of the same variables. Finally, the results of the two-step system GMM estimator are tested by the Hansen's J diagnostic test for instrument validity and the test for the second-order autocorrelation of the error terms suggested by Arellano and Bond (1991).

work by accounting for the regime dependent variable δ_1 which represents the differences in the regime intercepts. According to Bick (2010), we include δ_1 as disregarding the regime intercepts would lead to biased estimates for both the regime coefficients and the threshold value.

In the first step, in order to estimate the predicted values, Kremer et al. (2013) following Caner and Hansen (2004) used the reduced form of regressions for the endogenous variable as a function of instruments. In step two, the threshold value γ is estimated by using the predicted values of the endogenous variables in Eq. (4). In the third step, in order to obtain the slope parameters λ_1 and λ_2, Eq. (4) is estimated via GMM for the threshold value γ, where the threshold variable is replaced by its predicted values calculated in the second step. According to Caner and Hansen (2004), the optimal threshold is estimated via a minimizer of the sum of squared errors by using 2SLS estimator. Following Caner and Hansen (2004) and Hansen (1999), the 95% confidence interval of the threshold value is given by the $\Gamma = [\gamma: LR(\gamma) \leq C(\alpha)]$. Here, $C(\alpha)$ indicates the asymptotic distribution of the likelihood ratio *(LR)* statistic at 95% significance level.

5. Empirical Results

5.1. Panel regression results

Dynamic Panel results are presented Table 7 and Table 8. In Table 7 we use the cost efficiency as the performance measure. We add control variables gradually in order to see the individual impact of the main variables. Model (3) includes NPL as the main measure of bank risk, while in Model (4) we use Z-Score as risk measure. Finally, Model (5) accounts for all bank and country-specific variables simultaneously. The cost of adjustment captured by the coefficient of the lagged dependent variable $BUFF_{i,t-1}$ is positive and highly significant in all specifications. These results confirm hypothesis H1 suggesting that banks take time to adjust current capital buffer towards their internal targets. The coefficients of $BUFF_{i,t-1}$ changes across different models when we include other control variables. Adding all bank and country-specific variables in Model (5), the speed of adjustment $(1 - \lambda)$, increases from 0.188 in Model (1) to 0.533 in Model (5). The speed of adjustment of 0.533 in Model (5) indicates that when we account for other determinants of bank capital buffer simultaneously, banks converge to their target capital buffers with a rate of 53.3% per annum.

In terms of regression estimates, the coefficient of cost efficiency (EFF) is positive and significant at 1% level (see Models (3) and (4)). In Model (5) which includes all control variables, EFF exerts positive impact on bank capital buffer at 5% level. These results are in line with our second hypothesis H2 indicating that efficient banks hold higher capital buffer possibly because efficient banks are more profitable and therefore accumulate more capital (Fiordelisi et al., 2011). Furthermore, this positive relationship between bank efficiency and capital buffer could be explained by the charter value theory according to which due to the income effect of high cost efficiency, banks keep higher capital to protect their reputation and charter value (Berger & Bonaccorsi di Patti, 2006).

As regards the impact of non-performing loans (NPL) on bank capital buffer, Model (5) indicates that NPL exerts positive impact on buffer at 1% level. This finding is in line with our expectations, as NPL reflects bank's asset quality and risk exposure. Therefore, higher level of NPL indicates lower asset quality and hence higher risk. As a consequence, banks with higher NPL increase their capital buffer in order to comply with minimum regulatory requirements and alleviate their solvency risk. These results confirm our hypothesis H4 and are in line with Ediz et al. (1998), Fonseca and González (2010) and Jokipii and Milne (2011).

While the positive sign of NPL suggests that riskier banks hold higher buffers, when we account for bank risk exposure by using the Z-Score as a measure of the distance from default, the findings reveal different relationship. The impact of Z-Score on bank capital buffer is positive and significant at 5% level in Model (5) suggesting that stable banks with low risk of default accumulate higher capital buffers. These findings reject hypothesis H4 and are in line with the charter value theory.[4] Stable banks with lower risk of default have higher charter value (Anderson & Fraser, 2000; Cordella & Yeyati,

[4] Charter value of a bank is defined as the value that would be foregone due to a bankruptcy. According to this theory there is ambiguous relationship between bank capital and risk taking. From the one hand, higher risk can increase the probability of default and therefore encourage banks to raise their capital. While from the other hand, higher risk can dump bank's charter value and hence reduce bank capital. This has been broadly discussed by (Boot & Schmeits, 2000; Hellmann, Murdock, & Stiglitz, 2000).

2003; Jokipii & Milne, 2011; Keeley, 1990) and therefore banks with high Z-Score will sustain their value by holding higher capital buffers.

The OBS items have positive impact on bank capital buffer at 10% level in Model (5), indicating that banks with large off-balance sheet activities prefer to hold higher capital buffer as a cushion against unexpected losses. Moreover, NETLOANS have positive impact on capital buffer at 5% level in Models (4) – (5). These results suggest that increasing loan portfolio exposes banks to higher risk and as a result riskier banks hold higher capital buffer (Jokipii & Milne, 2008). Furthermore, the 10% significant coefficient of the dummy variable DISCLSR in Model (5) indicates that due to the information disclosure listed banks might account for market discipline and hold higher capital buffer as a sign of solvency to markets.

Regarding the impact of bank size on capital buffer, our findings are contrary to previous literature. Most of the existing literature claim that bank size has negative impact on capital buffer as larger banks have more benefits from diversification and easier access to capital markets (Fonseca & González, 2010; Guidara et al., 2013; Jokipii & Milne, 2008; Lindquist, 2004; Rime, 2001; Stolz & Wedow, 2011). Given that larger institutions have easier access to capital markets, they will try to protect their reputation and ensure their capital adequacy by holding higher capital buffers.

All models pass the Hansen standard validity tests of the instruments used in the regressions. Moreover, AR(2) p-values show that there is no second-order correlation in the error terms, as should be if the residuals in levels are white noise.

[Insert Table 7]

In a further analysis, we use dynamic panel regressions to examine the relationship between bank capital buffer and alternative measures of bank performance as used in previous literature. Model (1) in Table 8 employs bank efficiency scores as performance measure, Model (2) uses the ROE as an indicator of bank performance, Model (3) examines the relationship between capital buffer and ROA while in Model (4) we include NIM, In Models (5) - (7) we analyse the simultaneous impact of the efficiency and one of the other performance measures on bank capital buffer.

In contrast with Ayuso et al (2004) and Jokipii and Milne (2008), results obtained from Model (2) indicate positive relationship between ROE and capital buffer at 1% level. These results are in line with Nier and Baumann (2006) who suggest that an increase in ROE increases capital buffer. As regards the impact of the other control variables on capital buffer, results show that when we use ROE as performance measure, NPL, Z-Score, OBS and NETLOANS maintain their positive impact on bank capital buffer. The significant coefficient of bank size indicates that even when we account for bank performance with ROE, increasing size leads to higher capital buffer. Finally, in Model (3) we use ROA as a determinant of bank performance while in Model (4) we employ NIM. Results suggest that both variables have positive but insignificant impact on capital buffer.

Next, Models (5) – (6) show the impact of bank efficiency on capital buffer when we include additional measures of bank performance. Specifically, in Model (5) we employ both EFF and ROE in our regression. Results suggest that even when we account for ROE, bank efficiency exerts positive impact on capital buffer at 5% level. Regarding the impact of the other variables, one can note that in Model (5) the sign and the significance of most control variables are identical with those obtained from our main regression in Model (1) indicating that the inclusion of ROE as performance measure does not affect our regression results.

In models (6) and (7), we include EFF with ROA and NIM respectively. Both regressions suggest that while ROA and NIM are insignificant, bank efficiency maintains its positive impact on capital buffer at 5% in models (6) and 1% in Model (7) respectively. Concerning the impact of the other variables in Model (6) and (7), NPL exerts positive impact on capital buffer at 1% and 10% respectively. The coefficients of Z-Score and NETLOANS are positive and significant when we include ROA, while SIZE maintains its positive impact on bank capital buffer in all specifications at 1% level.

[Insert Table 8]

5.2.Threshold estimations

5.2.1. The Capital Buffer – Efficiency nexus

Our sample for threshold estimation consists from 1735 observations for 314 banks for the period 2005-2013. The results for the empirical relationship between bank capital buffer and efficiency are presented in Table 9. We find a threshold variable of 0.818 for bank efficiency. This threshold value splits our sample into two regimes. The low regime includes 1033 banks with efficiency scores less than 0.818. The estimated coefficient λ_1 indicates that for banks that fall in the low efficiency regime, efficiency exerts positive impact on bank capital buffer at 1% level. This result suggests that for relatively less efficient banks, an increase in efficiency, increases bank capital buffer. The high regime consists from 702 banks with efficiency scores greater than the threshold value. The negative sign of the estimated coefficient λ_2 indicates that for banks in the high regime, efficiency has negative impact on bank capital buffer at 5% level.

A striking result of this analysis is that the relationship between capital buffer and bank efficiency is characterized by structural breakpoint indicating that the impact of efficiency on capital buffer depends on the level of bank's efficiency. The positive coefficient for banks that fall in the low regime suggests that relatively less efficient banks use their increasing efficiency to accumulate higher capital buffers. This finding confirms hypothesis H2 and is in line with the charter value theory according to which more efficient banks hold higher capital in order to protect their future income derived from high efficiency (Berger & Bonaccorsi di Patti, 2006; Keeley, 1990). Conversely, the negative coefficient for relatively more efficient banks is at odds with hypothesis H2 suggesting that higher efficiency might substitutes for capital as a buffer against unexpected losses. This finding could be compared with Jokipii and Milne (2008) and Ayuso et al. (2004) who find negative relationship between bank performance and capital buffer.

As regards the other bank specific variables, we find that in line with the results of the dynamic panel regressions in Table 8, the coefficient of the lagged value of capital buffer (Lag Buffer) is positive at 1% level, confirming hypothesis H1. Furthermore, Z-Score, Net Loans and Size have positive impact on bank capital buffer at 1% level. The positive coefficient of Z-Score shows that stable banks with low risk of default accumulate higher capital buffers. These findings are in line with the dynamic panel regressions in Table 8. The positive impact of net loans on capital buffer suggests that banks with large loan portfolios hold higher capital buffer as a cushion against unexpected risks. Finally, the positive impact of bank size on capital buffer might be due to the fact that as larger banks have easier access to capital markets, they prefer to hold higher capital buffers as a sign of solvency to markets.

[Insert Table 9]

Moreover, in Table 10 we consider the evolution of banks in low and high regimes for the period 2005 –2013. One can notice a negative trend in the percentage of banks with relatively high efficiency scores for the years 2006 - 2008 (68% in 2006 decreases to 27% in 2007 and in 15% in 2008). Although, for the years 2009 – 2010 there is a significant recovery in the number of banks that fall in the high efficiency regime (from 15% in 2008 to 54% in 2009 and 57% in 2010), the trend in the following years is negative. These results are supported by the impact of the financial crisis of 2007 – 2008 on the banking sector. The reduction in the number of banks with efficiency above the threshold value, mirrors the deteriorating performance of banks during the crisis.

[Insert Table 10]

In a further analysis we account for the impact of capital buffer on bank efficiency. Therefore, we employ the threshold methodology using the capital buffer as a threshold variable and the bank efficiency as dependent variable. The impact of capital buffer on efficiency is presented in Table 11. The estimated capital buffer threshold is 13.594. The low regime consists of 1273 banks with relatively low capital buffer while the high regime consists of 462 banks. The coefficient λ_1 for banks in the low regime is significant at 10% level. This result is consistent with hypothesis H3, according to which an increase in the amount of capital buffer enhances bank performance. Our findings could be compared with those of Fiordelisi et al. (2011) and Pasiouras et al. (2009) who find that increasing bank capital leads to efficiency improvements.

As regards the impact of bank specific variables on bank efficiency, our results show that the lagged value of efficiency (Lag Efficiency) exerts positive impact on efficiency at 1% level, suggesting persistence in bank performance. The negative coefficient for non-performing loans at 1% level indicates that higher risk exposure harms banks' efficiency. These results are in line with previous findings about the negative relationship between bank risk exposure and efficiency (Fiordelisi et al., 2011; Fries & Taci, 2005; Goddard, Molyneux, & Wilson, 2004; Mamatzakis & Bermpei, 2014). In addition, the negative impact of net loans on efficiency shows that larger loan portfolios decrease bank efficiency. This negative relationship might be due to the less credit monitoring from banks that expand their loan portfolios (Kwan et al., 1997).

The impact of bank size on efficiency is negative implying that bank efficiency decreases as bank size increases. This results are in line with Kwan (2006) and Isik and Hassan (2002) who suggest negative relationship between bank size and efficiency. Furthermore, Leightner and Lovell (1998), Stiroh and Rumble (2006) and Pasiouras and Kosmidou (2007) find that size is negatively correlated with efficiency for both domestic and foreign banks due to agency costs, bureaucratic processes and other costs relating to managing extremely large institutions.

[Insert Table 11]

The evolution of banks in the low and high regimes over the sample period is presented in Table 12. It is obvious that the percentage of banks classified in low regime is consistently above the percentage of banks in the high regime. Table 12 shows negative trend in the percentage of banks with high capital buffer for the years 2006 – 2008 (27% in 2006 to 21% in 2007 and 23% in 2008), while after 2009 there is a recovery in the percentage of banks in the high regime. These results could be explained by the high cost of raising capital during distress (Campbell, 1979). Thus, our findings show that banks' ability to accumulate regulatory capital over the minimum requirement has deteriorated due to the financial crisis of 2007 – 2008.

[Insert Table 12]

5.2.2. Capital Buffer - Z-Score nexus

We further examine the relationship between bank capital buffer and risk of default as measured by the Z-Score. High values of Z-Score indicate more stable banks with lower risk of default. Table 13 presents threshold estimation results using capital buffer as dependent variable and Z-Score as threshold regime variable. The threshold value for the Z-Score is 0.881. This value splits our sample into the low regime which consists of banks with relatively high risk of default and the high regime consisting from more stable banks. The coefficient λ_1 is positive and significant at 1% level for banks that fall in the low regime while the impact of Z-Score on capital buffer is insignificant for banks in the high regime. These results contradict with our hypothesis H4 and are in line with those obtained by the dynamic panel regressions in Table 8 indicating that for banks with relatively low Z-Score and therefore high risk of default an increase in Z-Score increases capital buffer.

As Regards the impact of the other bank specific variables on capital buffer, the estimated results in Table 13 are in line with those of Table 9 where the threshold variable was the efficiency. The lagged value of bank capital buffer, efficiency, net loans and bank size exert positive impact on capital buffer at 1% significance level.

[Insert Table 13]

Concerning the evolution of the banks in low and high regime over time, Table 14 shows that the percentage of banks in high regime is above the percentage of banks in the low regime for the years between 2005 – 2008 and 2011. Apparently, there is a decreasing trend in the number of banks in the high regime with relatively low risk of default after 2007 with the lowest value of 46% in 2012 and 2013.

[Insert Table 14]

In order to examine the impact of capital buffer on bank stability, we employ the threshold methodology using Z-Score as the dependent variable and capital buffer as the threshold regime variable. Table 15 presents the estimated results. The threshold value of capital buffer is 11.274 and splits our sample in low regime that consists of banks with relatively low capital buffers and the high regime with banks holding relatively higher capital buffers. Both regime-dependent coefficients of capital buffer are significant at 1% level but of different sign. The low regime has negative coefficient λ_1, indicating that for banks with relatively low capital buffer an increase in capital buffer, decreases the Z-Score and therefore increases the risk of default providing evidence in favour of H5. These findings are in line with previous literature (Delis, Hasan, & Tsionas, 2014; Shrieves & Dahl, 1992) who state that banks increase their capital level by increasing their risk exposure.

Conversely, the positive coefficient λ_2 for banks that belong in the high regime with relatively high capital buffers shows that an increase in capital buffer increases Z-Score and therefore decreases the risk of default. These results are at odds with hypothesis H5 and in line with previous studies (Duran & Lozano-Vivas, 2014, 2015; Guidara et al., 2013; Jacques & Nigro, 1997), who support that the implementation of minimum capital requirements by Basel Committee, has succeed in its main aim of reducing the risk taking by banks. According to these studies, the larger the capital buffer, the weaker the incentives of banks to engage in risky activities as banks increase their capital buffers due to the introduction of risk-based capital standards.

[Insert Table 15]

Furthermore, as regards the impact of other control variables on Z-Score, we find that non-performing loans decrease bank stability and hence increase the risk of default. In addition, efficiency exerts positive impact on Z-Score at 1% level, indicating that an increase in the efficiency enhances bank stability. Moreover, the positive coefficient of GDP growth indicates that during periods of increasing GDP growth, banks operate in a more favourable environment by making higher profits and as a result they are more stable with low risk of default (Albertazzi & Gambacorta, 2009; Bolt, de Haan, Hoeberichts, van Oordt, & Swank, 2012; Dietrich & Wanzenried, 2011; Williams, 2003).

Finally, Table 16 shows that the percentage of banks with relatively high capital buffer decreases for the years 2006 – 2007 with the highest reduction in 2007 (55% in 2005 to 47% in 2007). This might be due to the costly capital during the crisis of 2007 - 2008 that renders difficult for banks to increase their regulatory capital, while in 2013 there is a recovery in the number of banks that hold capital buffer above the threshold value (61% in 2013).

[Insert Table 16]

6. Conclusion

This study empirically addresses the association between bank capital buffer, performance and risk-taking. Using a sample of EU-27 banks over the period 2004 – 2013, the findings of this study could be of interest to both supervisory authorities and bank managers. Given that our sample covers the financial crisis of 2007 – 2008, we employ the dynamic panel threshold methodology as developed by Kremer et al. (2013). Results show different regimes over the sample period. Strong positive impact of bank performance on capital buffer is reported for banks in the low performance regime, while for relatively better performing banks improvement in performance decreases capital buffer. Moreover, threshold estimation results indicate positive impact of capital buffer on bank performance in the low capital buffer regime. These findings provide evidence that the regulatory framework as regards the capital adequacy requirements can enhance bank performance.

Furthermore, empirical evidence suggests regime changes for the relationship between capital buffer and bank stability as measured by Z-Score. Threshold results show that capital buffer exerts strong negative impact on bank stability for banks that fall in the low capital buffer regime. Conversely, the impact of capital buffer on bank stability is positive for banks in the high capital buffer regime. The positive relationship between capital buffer and Z-Score for the high regime banks suggests that the implementation of minimum capital requirements by Basel Committee might have succeed in its main aim of creating a more stable banking system by reducing bank default risk for relatively better capitalized banks. However, the negative impact of capital buffer on Z-Score for banks that fall in the low regime indicates that the minimum capital requirements might have undermined bank stability by increasing the risk-taking incentives for relatively less capitalized banks.

Notably, we find changes in the percentage of banks in each threshold regime during and after the financial crisis of 2007 – 2008. More specifically, there is an increasing trend in the percentage of banks in the low performance regime over time, especially after the years 2007 – 2008. This indicates that banks in the EU-27 region experienced a period of substantial performance deterioration, while the number of banks in the low capital buffer regime increases during the financial crisis. Given that the cost of raising capital is high during economic downturn, our findings indicate that banks accumulate lower capital during the recession period. These results are of some value for managers and policy makers in particular as they clearly indicate that the impact of capital requirements is different for banks with different performance and risk-taking characteristics.

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Table 1: Total regulatory capital across country and over time for EU-27 (2004 - 2013).

Total regulatory capital across country for EU-27, (2004 - 2013).

Country	Mean	Max	Min	Country	Mean	Max	Min
AUSTRIA	25.97	190	9.19	LATVIA	16.11	80.29	8.02
BELGIUM	16.5	43.81	8.87	LITHUANIA	14.1	29.6	8.95
BULGARIA	16.23	40.15	10.2	LUXEMBOURG	21.65	111.7	8.68
CROATIA	17.59	38.67	9.17	MALTA	16.24	44.86	8.06
CYPRUS	14.27	47.34	8.2	NETHERLANDS	16.48	45.9	9.3
CZECH REPUBLIC	18.08	108.15	9.11	POLAND	13.84	33.64	8.63
DENMARK	17.77	132.3	8.3	PORTUGAL	14.97	79.8	8.4
ESTONIA	19.58	32.5	10.54	ROMANIA	18.41	122.63	9.77
FINLAND	16.79	26.75	10.6	SLOVAKIA	15.31	30.38	9.05
FRANCE	12.79	57	8.87	SLOVENIA	13.49	51.3	8.06
GERMANY	18	95.7	8.1	SPAIN	15.88	71.9	8.17
GREECE	13.74	36.6	8.51	SWEDEN	18.16	44.96	1.04
HUNGARY	13.05	22.13	8.89	UNITED KINGDOM	18.07	102.9	9.7
IRELAND	12.83	25	8.3	Mean	17.17	190	1.04
ITALY	15.95	187	7.8				

Year	Mean	Max	Min	Year	Mean	Max	Min
2004	16.9	51.3	8.63	2010	18.1	187	8.1
2005	15.2	78	8.12	2011	18.3	170	8.4
2006	15.1	127	8.07	2012	18.3	188	8.1
2007	15	129	7.81	2013	18.3	190	8
2008	15	88.9	1.04	Mean	17.2	190	1
2009	16.4	131.6	8.1				

Note: The table reports the mean total regulatory capital by country and by time over the period 2004 – 2013 for EU-27 countries. The total regulatory capital is calculated as the sum of Tier 1 and Tier 2 capital over Risk Weighted Assets.

Table 2: National total regulatory capital requirements

	Minimum capital requirement	Year of Implementation
UK	9%	1979
Cyprus	8%	1997
	10%	2001
Estonia	10%	1997
Latvia	10%	1997
	8%	2004
Lithuania	10%	1997
	8%	2005

Note: The table shows the minimum capital requirements for countries that had set different minimum ratio over time. The minimum capital requirements for all other EU-27 countries is calculated with 8% of Risk Weighted Assets.

Table 3: Bank capital buffer across country and over time for EU-27 (2004 - 2013).

Bank capital buffer across country for EU-27, (2004 - 2013).

Country	Mean	Max	Min	Country	Mean	Max	Min
AUSTRIA	14.59	15.7	13.12	LATVIA	11.53	16.54	4.79
BELGIUM	15.35	17.25	13.01	LITHUANIA	11.91	16.54	7.35
BULGARIA	11.28	17.02	8.44	LUXEMBOURG	13.82	15.22	11.5
CROATIA	10.92	14.11	6.09	MALTA	11.3	12.91	10.4
CYPRUS	11.03	14.43	6.23	NETHERLANDS	13.05	17.02	10.9
CZECH REPUBLIC	12.34	14.94	9.03	POLAND	12.48	15.35	9.66
DENMARK	11.41	16.54	7.72	PORTUGAL	14.54	17.72	9.22
ESTONIA	12.28	14.06	8.8	ROMANIA	11.68	13.95	8.73
FINLAND	13.4	15.88	10.53	SLOVAKIA	11.57	13.62	9.63
FRANCE	14.45	17.53	11.18	SLOVENIA	11.07	13.24	8.81
GERMANY	10.89	17.25	6.34	SPAIN	13.67	16.44	9.46
GREECE	12.42	15.17	9.01	SWEDEN	10.98	15.35	6.29
HUNGARY	12.56	14.92	8.36	UNITED KINGDOM	13.92	17.72	9.06
IRELAND	14.01	17.53	9.82	Mean	11.75	17.72	4.61
ITALY	11.12	17.13	4.61				

Year	Mean	Max	Min	Year	Mean	Max	Min
2004	11.8	16.23	8.77	2010	12.07	17.54	6.73
2005	11.48	16.36	6.78	2011	11.66	17.46	7.14
2006	11.43	16.58	6.1	2012	11.47	17.56	6.09
2007	11.85	17.23	6.55	2013	11.8	17.72	4.79
2008	12.01	17.26	4.61	Mean	11.75	17.72	4.61
2009	12.08	17.46	6.23				

Note: The table reports the mean bank capital buffer by country and by time over the period 2004 – 2013 for EU-27 countries. The bank capital buffer is calculated the natural logarithm of total regulatory capital minus minimum capital requirement, where total regulatory capital is the sum of Tier 1 plus Tier 2 over Risk Weighted Assets.

Table 4: Bank cost efficiency estimates across country and over time for EU-27 (2004 - 2013).

Bank cost efficiency estimates across country for EU-27, (2004 - 2013).

Country	Mean	Max	Min	Country	Mean	Max	Min
AUSTRIA	0.78	0.88	0.7	LATVIA	0.77	0.94	0.59
BELGIUM	0.7	0.86	0.4	LITHUANIA	0.76	0.87	0.55
BULGARIA	0.64	0.82	0.42	LUXEMBOURG	0.72	0.84	0.52
CROATIA	0.66	0.79	0.48	MALTA	0.85	0.92	0.78
CYPRUS	0.76	0.93	0.44	NETHERLANDS	0.73	0.86	0.5
CZECH REPUBLIC	0.8	0.95	0.57	POLAND	0.73	0.9	0.52
DENMARK	0.8	0.9	0.61	PORTUGAL	0.72	0.89	0.43
ESTONIA	0.78	0.94	0.55	ROMANIA	0.63	0.78	0.46
FINLAND	0.79	0.95	0.48	SLOVAKIA	0.78	0.86	0.57
FRANCE	0.76	0.92	0.42	SLOVENIA	0.78	0.88	0.57
GERMANY	0.8	0.89	0.29	SPAIN	0.84	0.97	0.43
GREECE	0.75	0.91	0.52	SWEDEN	0.83	0.98	0.46
HUNGARY	0.63	0.75	0.45	UNITED KINGDOM	0.79	0.96	0.47
IRELAND	0.79	0.91	0.62	Mean	0.78	0.98	0.29
ITALY	0.82	0.95	0.48				

Year	Mean	Max	Min	Year	Mean	Max	Min
2004	0.82	0.9	0.57	2010	0.81	0.95	0.47
2005	0.84	0.98	0.44	2011	0.78	0.95	0.43
2006	0.81	0.95	0.52	2012	0.77	0.97	0.29
2007	0.77	0.89	0.52	2013	0.77	0.94	0.42
2008	0.73	0.9	0.43	Mean	0.78	0.98	0.29
2009	0.79	0.96	0.46				

Note: The table reports the mean cost efficiency by country and by time over the period 2004 – 2013 for EU-27 countries. The bank cost efficiencies are estimated employing Stochastic Frontier Analysis (SFA). We assume a common cross-country frontier for the EU-27 countries.

Table 5: Variable definitions and data sources.

Variables	Definition	Source

Bank-specific variables		
Buffer (BUFF)	The amount of capital banks hold in excess of the minimum requirement and is calculated as regulatory capital (Tier 1 plus Tier 2 over Risk Weighted Assets) minus minimum capital requirement.	BankScope
Cost Efficiency (EFF)	A measure of bank performance. This variable indicates how close a firm's profits are to the benchmark of the best practice firm. The measure of EFF is given by the ratio of minimum cost to actual cost and is bounded between zero and unity. We employ Stochastic Frontier Analysis in order to estimate cost efficiency for each bank.	SFA
ROE	Return on equity. This variable is defined as the ratio of net profits over equity (%).	BankScope
ROA	Return on assets. This variable is defined as the ratio of net profits over total assets (%).	BankScope
NIM	Net interest margin. This variable is defined as the ratio of net interest income over total assets.	BankScope
Non-performing loans (NPL)	The ratio of non-performing loans over total loans.	BankScope
Net Loans (NETLOANS)	The ratio of bank loans over total assets.	BankScope
Off-Balance-Sheet items (OBS)	Measured as the non-interest income and fee generating services from various contingent liabilities such as letters of credit, derivatives, securities underwriting, insurance and other types of non-traditional banking activities.	BankScope
Z-Score (Z-SCORE)	Z-Score indicates the risk of failure for a bank and is measured according to the following formula: z-score = (1 + ROE) / Standard Deviation of ROE and indicates the probability of failure for a given bank.	BankScope
Bank size (SIZE)	The natural log of total assets is used as a measure of bank size.	BankScope
Disclosure (DISCLSR)	A dummy variable that takes the value 1 for listed banks and 0 unlisted indicating information disclosure.	BankScope
Commercial banks (COM)	A Dummy taking the value 1 for commercial banks and 0 for saving banks.	BankScope
Country-specific variables		
GDP growth (GDPGR)	GDP growth of each country.	World Development Indicators (WDI)
Concentration ratio (C5)	The concentration ratio (C5) in the banking industry measured by the sum of the assets of the five largest banks as a share of all banks in each country and for each year.	BankScope
European Monetary Union countries (EMU)	Dummy variable which takes the value 1 for European Monetary Union countries and 0 otherwise.	

Table 6: Descriptive statistics for variables.

Variable	Mean	Std. Dev.	Min	Max
BUFF	11.75	2.14	4.61	17.72

EFF	0.78	0.09	0.29	0.98
ROE	4.27	21.36	-135	146
ROA	0.39	1.70	-29.86	77.81
NIM	2.57	1.79	-36.27	34.689
NPL	0.06	0.8	-0.04	0.92
NETLOANS	0.58	0.22	0.002	1.83
OBS	0.15	0.49	-0.04	19.72
Z-SCORE	2.49	4.44	-4.56	55.07
SIZE	15.13	2.36	9.40	21.51
GDPGR	0.65	3.21	-17.95	12.23
C5	0.82	0.10	0.49	1

Note: **BUFF** is the capital buffer calculated as the regulatory capital (Tier 1 plus Tier 2 over Risk Weighted Assets) minus minimum capital requirement. **EFF** stands for performance measure and is derived from SFA. **ROE, ROA** and **NIM** stand for additional bank performance measures and are the ratios of return on equity, return on assets and net interest margin respectively. **NPL** stands for the ratio of non-performing loans over total loans, **NETLOANS** is calculated as the ratio of bank loans over total assets, **OBS** stands for the Off-Balance-Sheet items measured as the ratio of Off-Balance-Sheet items over total liabilities, **Z-SCORE** measures bank's risk of default and **SIZE** is the log of total assets and measures the bank size. **GDPGR** stands for the GDP growth, while **C5** stands for the five-firm concentration ratio of each country's banking industry.

Table 7: Dynamic Panel results for bank capital buffer using efficiency as performance measure (2004 – 2013).

VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
L.BUFF	0.812***	0.849***	0.496***	0.611***	0.467***

	(0.0483)	(0.0389)	(0.0525)	(0.0512)	(0.0530)
EFF		0.633	1.023***	0.760***	0.831**
		(0.388)	(0.341)	(0.290)	(0.365)
NPL			0.00221		0.0111***
			(0.00309)		(0.00410)
Z-Score				0.0258*	0.0484**
				(0.0135)	(0.0195)
OBS			0.0397*	0.0512**	0.0431*
			(0.0203)	(0.0218)	(0.0232)
NETLOANS			0.322	0.366**	0.521**
			(0.204)	(0.147)	(0.228)
DISCLSR			0.337**	0.120	0.256*
			(0.165)	(0.150)	(0.149)
SIZE			0.469***	0.333***	0.527***
			(0.0513)	(0.0508)	(0.0548)
COM			-0.114	0.0827	-0.225*
			(0.0753)	(0.0561)	(0.136)
C5			-0.105	0.0680	-0.00117
			(0.184)	(0.160)	(0.250)
GDPGR			0.0103*	0.00430	-0.000340
			(0.00613)	(0.00751)	(0.00752)
EMU			-0.154***	-0.173***	-0.279***
			(0.0510)	(0.0508)	(0.0670)
CONSTANT	2.172***	1.223**	-2.047***	-1.479***	-2.463***
	(0.522)	(0.480)	(0.470)	(0.435)	(0.559)
Time Dummies	YES	YES	YES	YES	YES
AR(2)	0.066	0.071	0.267	0.155	0.241
Hansen test	0.052	0.065	0.304	0.281	0.191

Note: The table reports the dynamic panel regression results. The two step GMM (Arellano and Bover, 1995) is used with Windmeijer corrected (robust) errors. We consider as exogenous the country-specific and time dummy variables and as endogenous the bank-specific variables. The instruments chosen for the lagged endogenous variables are two-to-six period lags. AR(2) stands for the p-value of the second order residual autocorrelation tests. Hansen test stands for the p-value of Hansen's J diagnostic test for instrument validity. The dependent variable is the capital buffer (**BUFF**) calculated as the regulatory capital (Tier 1 plus Tier 2 over Risk Weighted Assets) minus minimum capital requirement. **L.BUFF** is the lagged value of the dependent variable BUFF representing the dynamic nature of the model. **EFF** stands or the cost efficiency scores calculated using SFA methodology. **NPL** stands for the ratio of non-performing loan over total loans, **Z-SCORE** stands for the risk of default and is calculated as Z-Score = (1 + ROE) / Standard Deviation of ROE and indicates the risk of failure for a given bank, **OBS** stands for the Off-Balance-Sheet items measured as the ratio of Off-Balance-Sheet items over total liabilities. **NETLOANS** stands for the bank exposure to loans and is calculated as the ratio of total loans over total assets, **DISCLSR** is a dummy taking the value 1 for listed banks and 0 unlisted and stands as a second measure of market discipline indicating information disclosure. **SIZE** is the log of total assets and measures the bank size while **C5** stands for the five-firm concentration ratio of each country's banking industry. **GDPGR** stands for the GDP growth, **EMU** is a dummy taking the value 1 for banks in Eurozone and 0 otherwise and **COM** is a dummy taking the value 1 for commercial banks and 0 for saving banks.

***, ** and * indicate 1%, 5% and 10% significance levels respectively

Table 8: Dynamic Panel results for bank capital buffer using different performance measures (2004 – 2013).

VARIABLES	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
L.BUFF	0.467***	0.470***	0.519***	0.480***	0.472***	0.510***	0.492***
	(0.0530)	(0.0607)	(0.0577)	(0.0583)	(0.0547)	(0.0570)	(0.0524)
EFF	0.831**				0.850**	0.929**	0.898***
	(0.365)				(0.355)	(0.392)	(0.347)
ROE		0.00232***			0.00217***		
		(0.000673)			(0.000635)		
ROA			0.0262			0.0304	
			(0.0263)			(0.0272)	
NIM				0.00806			0.0358
				(0.0431)			(0.0287)
NPL	0.0111***	0.00824**	0.00768*	0.00883*	0.0115***	0.0108***	0.00749*
	(0.00410)	(0.00395)	(0.00410)	(0.00461)	(0.00370)	(0.00404)	(0.00384)
Z-Score	0.0484**	0.0367*	0.0321*	0.0532**	0.0380**	0.0336**	0.0266
	(0.0195)	(0.0194)	(0.0185)	(0.0235)	(0.0178)	(0.0170)	(0.0165)
OBS	0.0431*	0.0231	0.0275	0.0260	0.0433*	0.0446*	0.0455*
	(0.0232)	(0.0190)	(0.0201)	(0.0219)	(0.0242)	(0.0242)	(0.0237)
NETLOANS	0.521**	0.484**	0.444**	0.521*	0.443**	0.465**	0.312
	(0.228)	(0.240)	(0.222)	(0.301)	(0.210)	(0.198)	(0.241)
DISCLSR	0.256*	0.143	0.266	0.146	0.250*	0.314	0.214
	(0.149)	(0.176)	(0.228)	(0.194)	(0.147)	(0.206)	(0.143)
SIZE	0.527***	0.524***	0.455***	0.521***	0.513***	0.464***	0.496***
	(0.0548)	(0.0625)	(0.0593)	(0.0661)	(0.0540)	(0.0571)	(0.0538)
COM	-0.225*	-0.189	-0.133	-0.191	-0.227*	-0.151	-0.225*
	(0.136)	(0.141)	(0.136)	(0.176)	(0.120)	(0.129)	(0.130)
C5	-0.00117	-0.0467	-0.0379	0.0774	0.00818	-0.0550	0.0924
	(0.250)	(0.220)	(0.222)	(0.282)	(0.220)	(0.228)	(0.201)
GDPGR	-0.000340	0.00210	0.00541	0.00356	-0.00114	0.00223	0.00485
	(0.00752)	(0.00663)	(0.00649)	(0.00757)	(0.00679)	(0.00654)	(0.00675)
EMU	-0.279***	-0.219***	-0.155**	-0.233***	-0.251***	-0.203***	-0.214***
	(0.0670)	(0.0660)	(0.0634)	(0.0727)	(0.0609)	(0.0660)	(0.0627)
Constant	-2.463***	-1.691***	-1.252**	-2.148***	-2.265***	-2.060***	-2.537***
	(0.559)	(0.481)	(0.488)	(0.669)	(0.509)	(0.513)	(0.572)
Time Dummies	YES	YES	YES	YES	YES	YES	YES
AR(2)	0.241	0.223	0.203	0.219	0.234	0.220	0.237
Hansen test	0.191	0.290	0.218	0.250	0.283	0.132	0.170

Note: The table reports the dynamic panel regression results. The two step GMM (Arellano and Bover, 1995) is used with Windmeijer corrected (robust) errors. We consider as exogenous the country-specific and time dummy variables and as endogenous the bank-specific variables. The instruments chosen for the lagged endogenous variables are two-to-six period lags. AR(2) stands for the p-value of the second order residual autocorrelation tests. Hansen test stands for the p-value of Hansen's J diagnostic test for instrument validity. The dependent variable is the capital buffer (**BUFF**) calculated as the regulatory capital (Tier 1 plus Tier 2 over Risk Weighted Assets) minus minimum capital requirement. **L.BUFF** is the lagged value of the dependent variable BUFF representing the dynamic nature of the model. **EFF** stands or the cost efficiency scores calculated using SFA methodology. **ROE** is the return on equity ratio, **ROA** the return on assets while **NIM** is the net interest margin. **NPL** stands for the ratio of non-performing loans over total loans, **Z-SCORE** stands for the risk of default and is calculated as Z-Score = (1 + ROE) / Standard Deviation of ROE and indicates the risk of failure for a given bank, **OBS** stands for the Off-Balance-Sheet items measured as the ratio of Off-Balance-Sheet items over total liabilities. **NETLOANS** stands for the bank exposure to loans and is calculated as the ratio of bank loans over total assets, **DISCLSR** is a dummy taking the value 1 for listed banks and 0 unlisted and stands as a second measure of market discipline indicating information disclosure. **SIZE** is the log of total assets and measures the bank size while **C5** stands for the five-firm concentration ratio of each country's banking industry. **GDPGR** stands for the GDP growth, **EMU** is a dummy taking the value 1 for banks in Eurozone and 0 otherwise and **COM** is a dummy taking the value 1 for commercial banks and 0 for saving banks.

***, ** and * indicate 1%, 5% and 10% significance levels respectively.

Table 9: Results for dynamic panel threshold estimation with efficiency as threshold variable and buffer as dependent variable (2005 – 2013).

EFF	0.818		
95% confidence interval	(0.763 - 0.835)		
	Coefficient		S.E.
Impact of Eff on Buffer			
λ1	0.963	***	0.382
λ2	-1.616	**	0.797
Impact of covariates			
Lag Buffer	0.761	***	0.082
Non-performing loans	0.004		0.004
Z-Score	0.049	***	0.021
Off-Balance-Sheet items	0.012		0.015
Net Loans	0.654	***	0.262
Size	0.208	***	0.072
C5	-0.234		0.780
GDP growth	-0.012	***	0.005
Time Dummies	Yes		
δ	-0.842		0.836
Observations	1735		
Low Regime	1033		
High Regime	702		

Notes: The table reports the estimation for dynamic panel threshold model. The threshold value of efficiency variable for banks ranges between 0.763 - 0.835. We denote bank capital buffer (BUFF) as the dependent variable while as the threshold and the regime dependent variable we impose bank cost efficiency (EFF). Following Bick (2007), the model accounts for regime dependent intercepts (δ). In this model, $m_{it,}$ includes bank-specific and country explanatory variables. As regards the bank-specific variables, we use: lagged capital buffer (Lag Buffer), non-performing loans, Z-Score, off-balance-items, net loans and size. As country variables we employ: GDP growth rate and concentration ratio (C5). Finally we include time dummies.

***, ** and * indicate 1%, 5% and 10% significance levels respectively.

Table 10: Dynamic Threshold Analysis: classification of banks into low and high regimes based on threshold value of cost efficiency.

Threshold: Efficiency									
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Low Regime	31%	32%	73%	85%	46%	43%	52%	67%	73%
High Regime	69%	68%	27%	15%	54%	57%	48%	33%	27%

Note: The table shows the classification of banks based on the bank efficiency threshold value that we obtained following Kremer, Bick and Nautz (2013).

Table 11: Results for dynamic panel threshold estimation with buffer as threshold variable and efficiency as dependent variable (2005 – 2013).

BUFF	13.594		
95% confidence interval	(9.332 - 13.855)		
	Coefficient		S.E.
Impact of Buffer on Eff			
λ1	0.005	*	0.003
λ2	-0.071		0.079
Impact of covariates			
Lag Efficiency	0.317	***	0.042
Non-performing loans	-0.003	***	0.001
Z-Score	-0.001		0.003
Off-Balance-Sheet items	-0.002		0.002
Net Loans	-0.055	**	0.027
Size	-0.027	***	0.009
C5	0.150	*	0.077
GDP growth	0.000		0.001
Time Dummies	Yes		
δ	0.044	*	0.025
Observations	1735		
Low Regime	1273		
High Regime	462		

Notes: The table reports the estimation for dynamic panel threshold model. The threshold value of buffer variable for banks ranges between 9.822 - 13.754. We denote bank efficiency (EFF) as the dependent variable while as the threshold and the regime dependent variable we impose the bank capital buffer (BUFF). Following Bick (2007), the model accounts for regime dependent intercepts (δ). In this model, m_{it}, includes bank-specific and country explanatory variables. As regards the bank-specific variables, we use: Lagged efficiency (Lag Efficiency), non-performing loans, Z-Score, off-balance-items, net loans and size. As country variables we employ: GDP growth rate and concentration ratio (C5). Finally we include time dummies.

***, ** and * indicate 1%, 5% and 10% significance levels respectively.

Table 12: Dynamic Threshold Analysis: classification of banks into low and high regimes based on threshold value of buffer.

Threshold: Buffer									
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Low Regime	69%	73%	79%	77%	72%	71%	74%	72%	72%
High Regime	31%	27%	21%	23%	28%	29%	26%	28%	28%

Note: The table shows the classification of banks based on the buffer threshold value that we obtained following Kremer, Bick and Nautz (2013).

Table 13: Results for dynamic panel threshold estimation with Z-Score as threshold variable and Buffer as dependent variable (2005 – 2013).

Z-Score	0.881		
95% confidence interval	(-0.679 - 0.973)		
	Coefficient		S.E.
Impact of Z-Score on Buffer			
λ1	0.143	***	0.031
λ2	0.068		0.050
Impact of covariates			
Lag Buffer	0.645	***	0.079
Non-performing loans	0.002		0.004
Efficiency	0.900	***	0.281
Off-Balance-Sheet items	0.017		0.014
Net Loans	0.752	***	0.260
Size	0.279	***	0.071
C5	-0.290		0.752
GDP growth	-0.011	***	0.005
Time Dummies			
Δ	-0.047	*	0.024
Observations	1735		
Low Regime	794		
High Regime	941		

Notes: The table reports the estimation for dynamic panel threshold model. The threshold value of Z-Score variable for banks ranges between -0.679 - 0.973. We denote bank capital buffer (BUFF) as the dependent variable while as the threshold and the regime dependent variable we impose Z-Score. Following Bick (2007), the model accounts for regime dependent intercepts (δ). In this model, $m_{it,}$ includes bank-specific and country explanatory variables. As regards the bank-specific variables, we use: lagged capital buffer (Lag Buffer), non-performing loans, Efficiency, off-balance-items, net loans and size. As country variables we employ: GDP growth rate and concentration ratio (C5). Finally we include time dummies.

***, ** and * indicate 1%, 5% and 10% significance levels respectively.

Table 14: Dynamic Threshold Analysis: classification of banks into low and high regimes based on threshold value of Z-Score.

Threshold: Z-Score									
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Low Regime	17%	16%	21%	40%	50%	51%	48%	54%	54%
High Regime	83%	84%	79%	60%	50%	49%	52%	46%	46%

Note: The table shows the classification of banks based on the Z-Score threshold value that we obtained following Kremer, Bick and Nautz (2013).

Table 15: Results for dynamic panel threshold estimation with Buffer as threshold variable and Z-Score as dependent variable (2005 – 2013).

BUFF	11.274		
95% confidence interval	(9.183 - 13.519)		
	Coefficient		S.E.
Impact of Buffer on Z-Score			
λ1	-0.319	***	0.100
λ2	2.246	***	1.049
Impact of covariates			
Lag Z-Score	0.442	***	0.078
Non-performing loans	-0.027	***	0.006
Efficiency	1.735	***	0.459
Off-Balance-Sheet items	0.000		0.011
Net Loans	-0.162		0.349
Size	0.058		0.120
C5	0.027		1.238
GDP growth	0.033	***	0.008
Time Dummies	Yes		
δ	-0.020		0.059
Observations	1735		
Low Regime	599		
High Regime	1136		

Notes: The table reports the estimation for dynamic panel threshold model. The threshold value of BUFF variable for banks ranges between 9.183 - 13.519. We denote Z-Score as the dependent variable while as the threshold and the regime dependent variable we impose capital buffer (BUFF). Following Bick (2007), the model accounts for regime dependent intercepts (δ). In this model, $m_{it,}$ includes bank-specific and country explanatory variables. As regards the bank-specific variables, we use: lagged Z-Score (Lag Z-Score), non-performing loans, Efficiency, off-balance-items, net loans and size. As country variables we employ: GDP growth rate and concentration ratio (C5). Finally we include time dummies.

***, ** and * indicate 1%, 5% and 10% significance levels respectively

Table 16: Dynamic Threshold Analysis: classification of banks into low and high regimes based on threshold value of buffer.

Threshold: Buffer									
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Low Regime	45%	52%	53%	46%	43%	42%	46%	46%	39%
High Regime	55%	48%	47%	54%	57%	58%	54%	54%	61%

Note: The table shows the classification of banks based on the buffer threshold value that we obtained following Kremer, Bick and Nautz (2013).