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Abstract

By examining the impact of capital regulation on bank risk-taking using a local estimation technique, we are able to quantify the heterogeneous response of banks towards this type of regulation in banking sectors of western-type economies. Subsequently, using this information on the bank-level responses to capital regulation, we examine the sources of heterogeneity. The findings suggest that the impact of capital regulation on bank risk is very heterogeneous across banks and the sources of this heterogeneity can be traced into both bank and industry characteristics, as well as into the macroeconomic conditions. Therefore, the present analysis has important implications on the way bank regulation is conducted, as it suggests that common capital regulatory umbrellas may not be sufficient to promote financial stability. On the basis of our findings, we contend that Basel guidelines may have to be reoriented towards more flexible, country-specific policy proposals that focus on the restraint of excess risk-taking by banks.

Keywords: Capital regulation, risk-taking of banks, local generalized method of moments
JEL classification: C14, C33, G21, G32; G38

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1. Introduction

While previous research has examined the relationship between regulations and bank risk-taking, it is much less clear whether and to what extent this relationship is homogeneous across banks and through time. In this study we attempt to explicitly quantify the degree of heterogeneity in the effect of a specific type of regulation, namely capital regulation, on bank risk-taking and analyze the sources of this heterogeneity. In doing this, we offer an understanding of why different banks take different risk positions owing to a particular type of regulation and we are able to describe how heterogeneity evolves during good and bad times for individual banks and on average.

There now exists a wide theoretical literature on the relationship between bank risk and regulations in the form of deposit insurance, capital requirements, solvency regulation, restrictions on bank activities etc. (see e.g. seminal contributions of Diamond and Dybvig, 1983; Kim and Santomero, 1988; and other studies reviewed in Freixas and Rochet, 2008). In fact, the theoretical arguments suggest quite diverse equilibrium solutions according to the initial conditions present at the bank- or industry-level, the health of bank portfolios, the degree of asymmetric information or expectations and even the existence of a moral hazard mechanism. The present analysis is restricted to examining the relationship between capital regulation and bank risk for two main reasons. First, this study presents an effort to (i) make a methodological contribution in the quantification of parameter heterogeneity in the regulations-bank risk nexus and (ii) explain the sources of this heterogeneity. This probably covers a lot of ground and, thus, examining auxiliary relationships between any other form of regulation and bank risk is left for future research. Second, the relationship between minimum capital requirements and bank risk has been central in the agenda of regulators (e.g. Basel I and II) and has attracted the attention of a rich line of research.[1] This allows us to use the theoretical underpinnings of this literature and build a robust empirical model that quantifies and explains heterogeneity.

A common belief, at least among regulators, is that higher capital requirements would probably result in higher stability of the banking sector. This has been the essence of Basel I and the first pillar of Basel II. Yet, early theoretical studies such as the ones of Kahane (1977), Kareken and Wallace (1978) and Sharpe (1978) that examine the influence of capital regulation on bank solvency in complete markets, show that with a flat insurance premium in place, banks

[1] For thorough reviews, see Santos (2001) and VanHoose (2007).

have incentives to increase risk-taking.[2] Koehn and Santomero (1980), and Kim and Santomero (1988) reach similar conclusions in an incomplete market setting, arguing that uniform capital regulations can increase rather than decrease banks' risk-taking incentives. Furlong and Keeley (1989) and Keeley and Furlong (1990) question the above conclusions. They show that once the possibility of bank failure and the effects of changes in the value of the deposit insurance put option are appropriately controlled for, the bank does not increase its portfolio risk with increased capital standards when it pays a flat-rate deposit insurance premium. This is attributed to the decrease in the marginal value of the deposit insurance option with respect to asset risk as leverage decreases. Consequently, an increase in capital standards has an adverse effect on risk-taking. Furthermore, in a model with information asymmetry and a principal-agent problem between the bank and the borrowing firm, Santos (1999) shows that an increase in capital standards results in lower incentives to take risk and therefore lower risk of insolvency.

Empirical studies also provide mixed results. The results of the global study of Barth et al. (2004) indicate that while more stringent capital requirements are associated with fewer non-performing loans, capital stringency is not robustly linked with banking crises when controlling for other supervisory-regulatory policies. Yet, in another international study, Pasiouras et al. (2006) find a negative relationship between capital regulation and overall banks' soundness as measured by Fitch ratings. Kendall (1992) suggests that higher capital requirements may cause riskier bank behavior at some point in time (especially in good times), but this does not necessarily imply a trend toward a riskier banking system. Kopecky and VanHoose (2007) argue that the introduction of binding regulatory capital requirements on a previously unregulated banking system may either improve or worsen loan quality. However, once regulations are in place, increased capital requirements will improve loan quality. Note that the two studies above introduce the notions of time and general macroeconomic conditions into the relationship in hand. Beatty and Gron (2001) examine a sample of U.S. banks between 1986 and 1995 and indicate that capital regulatory variables have significant effects for low-capital banks but not necessarily for other banks. Therefore, the level of capitalization of each bank can be considered as a source of heterogeneity in the relationship between capital regulation and risk. Finally,

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[2] Santos (2001) mentions that one shortcoming of these studies is that in complete markets with no information asymmetry either there is no need for deposit insurance or it can be appropriately priced, thus eliminating the incentives to take on extra risk.

Agoraki et al. (2009) show that capital regulation reduces risk in general, but for banks with high market power this effect significantly weakens or can even be reversed.

Subsequently, it becomes fundamentally an empirical question to identify whether and to what extent heterogeneity is important in analyzing the nexus of capital regulation and risk in banking. In the present paper we attempt to explicitly quantify this coefficient heterogeneity at the bank level by using a semiparametric smooth coefficient function approach and, in particular, the local generalized method of moments (henceforth LGMM). LGMM, first proposed by Lewbel (2007), was implemented in a dynamic panel data context by Tran and Tsionas (2009). It can be considered as an extension to the instrumental variables parametric model because it allows the regression coefficients of the parametric part to vary according to the smooth coefficient model. Unlike with parametric methods, the estimated coefficients of all explanatory variables (and thus of the capital regulation variable) are made observation-specific through localization and, therefore, one can gain full insight into the degree of heterogeneity of coefficients. The extent of heterogeneity can then be quantified by the standard deviation of the new vector of coefficients, which is generated by the estimated coefficients on the capital regulation variable in risk equations, and can be illustrated by plotting these coefficients in density figures. In addition, the sources of heterogeneity can be easily traced by explaining the vector of coefficients on the capital regulation variable on the basis of a number of bank-specific, industry-specific and macroeconomic variables.

Our findings suggest that capital regulation affects bank risk-taking in a very heterogeneous way. The level of this heterogeneity is attributed to a series of bank-level, regulatory and macroeconomic sources, which implies that different banks take widely different decisions regarding the level of risk in their portfolios. Notably, these results may be particularly important for the understanding of the impact on bank risk of the capital regulation framework set out by Basel II, as well as for the formation of general regulatory guidelines under the upcoming Basel III. Thus, in the results and conclusions sections we discuss in some detail the policy implications of our findings.

The rest of the paper proceeds as follows. The next section outlines the empirical methodology used to quantify and explain parameter heterogeneity. Section 3 presents the dataset and variables used for the empirical analysis. The empirical results are discussed and analyzed in Section 4. Finally, Section 5 concludes the paper with some policy implications.

2. Methodology

2.1. Empirical identification of the relationship between risk and regulations

Existing literature on the relationship between regulations and bank risk-taking (see e.g. Gonzalez, 2005; Laeven and Levine, 2009) proposes estimating a panel data model of the following general form:

$$r_{it} = a_1 R_t + a_2 B_{it} + a_3 M_t + e_{it} \tag{1}$$

where r is a measure of risk-taking of bank i at time t, R corresponds to indices of bank regulation common to all banks, B is a number of bank characteristics and M denotes macroeconomic and industry-specific control variables.

A significant concern of the empirical research on the risk-regulations nexus is the potential endogeneity of regulations. In the context of the present analysis, these concerns are well-justified if one considers that a history of high bank risk may force supervisors to improve the quality of the regulatory environment at some point in time by increasing capital requirements. The opposite may also be true: in the presence of a prolonged period of prudent risk-taking bank behavior and stable financial and economic environment, supervisory authorities may become more lax in regulating the banking system, thereby raising banks' incentives to increase their risk-taking activities. In these cases, endogenous effects prevail, and simple OLS estimation of (1) would produce inconsistent results.

An additional, yet different in nature, element of potential estimation bias in estimating risk equations is the fact that bank-level risk tends to persist. At least three theoretical reasons can be provided to backup these dynamics. First, relationship-banking with risky borrowers will have a lasting effect on the levels of bank risk-taking, despite the fact that dealing repeatedly with the same customer will improve efficiency. A similar mechanism would prevail if bank networks are in place or if the banking industry is opaque. Second, to the extent that bank risk is associated with the phase of the business cycle, banks may require time to smooth the effects of macroeconomic shocks. Third, risks may persist merely owing to regulation. In particular, deposit guarantees or capital regulation may exacerbate moral hazard issues leading to inefficient and risky investments over a considerable period of time.

Virtually all existing studies use parametric models to examine the relationship between capital regulation and bank risk-taking and find average equilibrium relationships or, at the very best, they examine heterogeneity by introducing in the estimated equations multiplicative terms of regulation indices with other variables of potential interest. We view these assumptions as particularly strong for two interrelated reasons. First, individual bank strategies may vary considerably owing to differential characteristics in (i) bank balance sheets, (ii) the general regulatory conditions and (iii) the institutional and macroeconomic environment. Second, parametric assumptions, such as normality of the distributions of the coefficients or the error term and the implicit imposition, when estimating risk equations, of a common production function for all banks and industries may be particularly strong, especially if bank strategic management and/or specialization indeed vary considerably. These issues are particularly important in estimating risk-capital regulation equations. Failing to account for them properly in an econometric model may be (at least partially) responsible for the many differences in the findings of the associated literature, as shown in the introduction of the paper. In what follows, we describe an empirical approach that completely solves the issue of parameter heterogeneity.

2.2. *Estimation using local GMM*

On the basis of the above theoretical considerations, we modify (1) as follows:

$$r_{it} = \delta(z_{it})r_{i,t-1} + a_1(z_{it})R_t + a_2(z_{it})B_{it} + a_3(z_{it})M_t + e_{it} \tag{2}$$

Equation (2) presents a dynamic panel, smooth coefficient model that solves completely the issue of parameter heterogeneity as it provides different estimates of a_1, a_2 and a_3 for each and every observation in the sample. In other words, LGMM allows for the estimation of vectors of coefficients of a_1, a_2 and a_3 of the same order with the vectors *R*, *B* and *M*. In forming (2) we assume that the coefficients on the dynamic adjustment, the regulation indices and all other independent variables may vary directly with a certain variable *z*, which thus becomes the so-called smoothing variable of the regression. Differently phrased, *z* represents the source of heterogeneity in the estimated coefficients a_1, a_2 and a_3. Moreover, the smooth coefficient model retains the appealing property of non-parametric methods that no assumptions are made globally on noise and on the functional form of the underlying production function of banks; thus potential estimation bias originating from such misspecifications is avoided. A notable implication of this merit of local methods is that they can accommodate samples from different banking sectors or different bank types because concerns regarding different technology structures of banks are dropped. Therefore, in the empirical analysis that follows we can use a large sample of banks of different types that are based in different countries.

Among the different local methods, we resort here to the LGMM, because it presents three additional virtues. First, by nature, GMM is preferable to ordinary least squares because it removes concerns regarding the presence of heteroskedasticity and serial correlation, which may be particularly important in bank panel datasets. Second, it avoids the bias arising from the correlation between any regressor and the error term by means of appropriate instruments (i.e. accounts for potential endogeneity of capital regulation). Finally, LGMM consistently models dynamic panel data models, such as the one described in (2). All the above, make LGMM a very general framework that is particularly suitable in the present analysis. The LGMM estimation procedure, in general, can be constructed as follows (Tran and Tsionas, 2009).

Let $y_i = \left(y_{i1},\ldots,y_{iT}\right)^{'}$ denote a $(T\times 1)$ vector of dependent variable, X_i is a $(T\times p)$ matrix of regressors having rows $x_{it}^{'}$, $\theta(Z_i) = \left(\theta(z_{i1}),\ldots,\theta(z_{iT})\right)^{'}$, Z_i is a $(T\times q)$ matrix having rows $z_{it}^{'}$, $t=1,\ldots,T$ and $e_i = \left(e_{i1},\ldots,e_{iT}\right)^{'}$ is a $(T\times 1)$ vector of random disturbances. Assume that there exists a $(T\times l)$ (where $l\geq p$) matrix of instruments W_i having rows $w_{it}^{'}$, $t=1,\ldots,T$ such that (X_i, Z_i, W_i, e_i) are *iid* over $i=1,\ldots,N$ and, for a given $z_{it}=z$

$$E(W_i^{'}e_i \mid Z_i = \tau_T z^{'}) = E\left[W_i^{'}(Y_i - X_i\theta(z)) \mid Z_i = \tau_T z^{'}\right] = 0 \qquad (3)$$

where $\tau_T = (1,\ldots 1)^{'}$ is a $(T\times 1)$ vector of ones. Equation (3) above provides the moment conditions that form the basis for the LGMM estimation. Thus, the LGMM estimates of $\theta(z)$ can be found by minimiing the following criterion function:

$$J_N(\delta) = \left[\frac{1}{N}(Y - X\theta(z))^{'}KW\right]R_N^{-1}\left[\frac{1}{N}W^{'}K(Y - X\theta(z))\right] \qquad (4)$$

where $Y=(Y_1^{'},\ldots,Y_N^{'})^{'}$ is a $(NT\times 1)$ vector, $W=(W_1^{'},\ldots,W_N^{'})^{'}$ is a $(NT\times l)$ matrix of instruments, $X=(X_1^{'},\ldots,X_N^{'})^{'}$ is a $(NT\times p)$ matrix of regressors, R_N is some $(l\times l)$ positive definite weighting matrix, and K is an $(NT\times NT)$ matrix of kernel weights with $K = diag\{K_1^T,...,K_N^T\}$. In the function K, $K_i^T = diag\left(K_H(z_{it}-z)\right)$, $t=1,\ldots,T$, is a $(T\times T)$ matrix and $K_H(\xi)=\prod_{j=1}^{q} h_j^{-1}k(\xi_j/h_j)$ in which $k(\varphi)\geq 0$, is a bounded univariate symmetric function with $\int k(\varphi)d\varphi = 1$, $\int \varphi^2 k(\varphi)d\varphi = \omega > 0$, $\int k^2(\varphi)d\varphi = \upsilon > 0$, so that

$K(\xi)=\prod_{j=1}^{q} k(\xi_j)$. Finally, $H = diag\{h_1,\ldots,h_q\}$ is a $(q\times q)$ matrix of bandwidths with $|H|=\prod_{j=1}^{q} h_j$, and $h_j > 0$.

For a given $z_{it} = z$, the LGMM estimate of $\theta(z)$ is then given by

$$\hat{\theta}(z)=\left[X^{'}KWR_N^{-1}W^{'}KX\right]^{-1}X^{'}KWR_N^{-1}W^{'}KY \tag{5}$$

Under certain regularity conditions, Tran and Tsionas (2009) show that the LGMM estimator given in (5) is consistent and asymptotically normal. In addition, they provide a detailed discussion on the choice of optimal weighting matrix, kernel function, optimal bandwidth and optimal instruments that can be implemented in practice. The choices made here on these practical issues are analyzed in Section 4 below.

3. Data

A large international panel dataset that includes banks from Australia, Austria, Belgium, France, Germany, Greece, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK and US is constructed for the empirical analysis. The dataset spans the 1998-2008 period. All data for the bank-level variables are collected from Bankscope. We limit the empirical analysis to the unconsolidated statements of banks in order to reduce the possibility of introducing aggregation bias in the results. Only supervised banks are included in the sample. A number of M&As and bank failures took place during the sample period, which are taken into account in our dataset so as to avoid selectivity bias. Also, the data were reviewed for reporting errors or other inconsistencies (extreme values for the variables used), and some observations are excluded accordingly. After applying these selection criteria, we are left with 3510 banks and 19253 observations. Table 1 presents the number of banks and observations on a country-specific basis and Table 2 the descriptive statistics for the variables used. We analyze the choice of these variables below.

[Please insert Table 1 about here]

[Please insert Table 2 about here]

3.1. Measures of bank risk

We proxy the risk-taking behavior of banks using the ratio of non-performing loans to total assets (NPL), the Z-index and the volatility in the return on assets (σ(ROA)) in alternative specifications. NPL, used in a large part of previous studies (e.g. Brissimis et al., 2008; Gonzalez, 2005) reflects the quality of bank assets, i.e., the potential adverse exposure to earnings and asset market values due to deteriorating asset quality. Since a portion of non-performing loans will result in losses for the bank, a high value for this ratio is unwanted. Note that NPL represents credit risk, which is closer to the notion of "bank risk-taking". The mean value in our sample equals 0.021. The lowest values are observed in the period 2003-2006, while this ratio increases substantially in 2007 and 2008 when the financial crisis erupted (the average value in 2008 is 0.048).

The Z-index, in turn, represents a more universal measure of bank risk (i.e. it encompasses risk attributed to banks' managerial practices and other forms of risk external to the banks' management decision). It is defined as $ln[Z\text{=(ROA+EA)}/\sigma\text{(ROA)}]$, where ROA is the rate of return on assets, EA is the ratio of equity to assets and σ(ROA) is an estimate of the standard deviation of the rate of return on assets. To calculate the standard deviation of ROA we use data from the three previous years and verified that using four or five years gives very similar results. The Z-index is monotonically associated with a measure of bank's probability of failure and has been widely used in the empirical banking and finance literature (e.g., Boyd et al., 2006; Laeven and Levine, 2009). A higher Z indicates that a bank is more distant from insolvency. Since Z is highly skewed, we use its natural logarithm, which is normally distributed. Z obtains a mean value equal to 3.84 in our sample. The correlation of the Z-score with NPL is negative and takes a value of -0.689. Finally, σ(ROA) is useful in separating the volatility of assets from the volatility of leverage in the Z-index. This helps identifying whether the results are primarily driven by the volatility in earnings or from the capitalization of banks.

3.2. Index of capital regulation

Information on capital regulation is obtained from the database developed by Barth et al. (2001) and updated in 2003 and 2008. The capital regulation index of this database shows the extent of both initial and overall capital stringency. Initial capital stringency refers to whether the sources of funds counted as regulatory capital can include assets other than cash or government securities and borrowed funds, as well as whether the regulatory or supervisory authorities verify these sources. Overall capital stringency indicates whether risk elements and value losses are considered while calculating the regulatory capital. Higher values on the capital regulation index indicate more stringent capital requirements. The components of this index are thoroughly discussed in the papers of Barth et al. and the index has been used in an extensive part of the relevant literature (see e.g. Laeven and Levine, 2009; Agoraki et al., 2009).

3.3. Potential sources of heterogeneity and control variables

The literature on the distributional effects of capital regulation on bank risk-taking is very limited and concerns mainly the effect of capitalization of banks (Beatty and Gron, 2001), market power (Agoraki et al., 2009) and deposit insurance (Keeley and Furlong, 1990). Besides the differential effect that deposit insurance may have on the capital regulation-bank risk nexus,[3] a number of other bank-specific, regulatory and macroeconomic variables may affect this relationship. These variables, their measures and the data sources are given in Table 3 and are briefly discussed below. Note that we can only speculate on how these variables are expected to affect the relationship between capital regulation and bank risk, since the literature on this issue is scant.

[Please insert Table 3 about here]

The bank-level variables are assumed to be capitalization, efficiency, size and market power. Bank capitalization (measured by the ratio of total equity to total assets) is expected to have a neutralizing effect on the bank risk-capital regulation nexus. In particular, banks with high levels of capitalization will probably not be affected by increased capital stringency and thus the impact of capital regulation on bank risk will be less potent. The same will probably hold for the efficient banks to the extend that efficiency implies better management of risk-taking activities. Bank efficiency is proxied by the ratio of total operating expenses to total bank revenue.[4] According to one view, and considering market power and size, if banks on average tend to take

[3] The role of deposit insurance is not examined here because all countries considered have an explicit deposit insurance scheme.

[4] An extensive literature on bank efficiency favors various frontier approaches to efficiency measurement. This is probably a side issue for the present analysis and thus we try to keep the measurement of bank efficiency as simple as possible (for a similar strategy, see e.g. Boyd et al., 2006). However, an analysis on the basis of stochastic frontier efficiency is available on request.

on higher credit risk in search for yield when capital regulation is in place, large banks and banks with high market power in lending will probably not engage in such activities because they already extract rents from the fact that they have market power (Keeley, 1990). In contrast, to the extend that networking effects between large banks prevail, an opposite mechanism attributed to moral hazard incentives may also be in place. If this holds banks with market power and of large size may further increase their risk-taking (Boyd et al., 2006; Agoraki et al., 2009).

While bank size can easily be measured by the natural logarithm of real total assets, estimation of market power is a challenging issue. Here we use the approach of Delis and Tsionas (2009), who provide a method for the estimation of the Lerner index of market power at the individual bank-level. We opt for estimating market power at the bank-level because there may be wide differences across banks of the same industry. The Lerner index is defined as $L_{it} = (p_{it}^{q} - mc_{it}) / p_{it}^{q}$ and shows the disparity between interest rate (p_{it}^{q}) on bank *i*'s output (*q*) at time *t* and marginal cost (*mc*) expressed as a percentage of p_{it}^{q}.[5] It takes values between -1 and 1, with values closer to 1 reflecting higher market power and values closer to 0 increased competitive behavior of banks. In the case of pure monopoly, L is statistically equal to 1; under perfectly competitive behavior, L is statistically equal to 0; and, finally, $L < 0$ implies pricing below marginal cost. Given the significant concerns of the industrial organization and banking literatures regarding the imposition of a constant marginal cost across banks when estimating the Lerner index, Delis and Tsionas (2009) relax this assumption. In particular, they offer a modeling framework that allows *mc* to differ across banks and time, thus deviating from the majority of previous literature on the estimation of the Lerner index (which assumes a constant marginal cost). We give the details on the estimation of market power in the Appendix.

Table 4 reports summary statistics of market power estimates by country and for the full sample. We test the hypotheses of perfectly competitive and monopolistic behavior (Lerner index=0 and Lerner index=1, respectively) using simple t-tests. We find that a Lerner index in the range (-0.107)-(0.103) shows perfectly competitive practices; an index in the range (0.897)-(1.092) shows monopoly power; values in between show intermediate structures, with higher values reflecting higher market power and vice versa. Countries like Greece and Spain obtain

[5] The main advantage of the Lerner index over other measures of market power (e.g. the H-statistic of Panzar and Rosse, 1987) is that it provides a continuous measure of the degree competition and therefore can have higher descriptive power (for a discussion on these issues, see Shaffer, 2003).

relatively high average market power scores (higher Lerner indices) and some banks in these countries are identified with considerable market power (i.e. values on the Lerner index statistically equal to 1). In contrast, in Germany, US and UK competition is intense, as reflected in the low values on the Lerner indices and the relatively small standard deviation of the market power estimates. However, in most countries and for over 90% of the banks in our sample, intermediate market structures prevail. More information on these results is available on request.

[Please insert Table 4 about here]

Besides the bank-level variables, an important source of heterogeneity may be the general regulatory environment of each banking system. In a recent line of literature, the different types of bank regulation are not viewed as separate mechanisms through which bank risk-taking is shaped; they are considered as complementary mechanisms. For example, Decamps et al. (2004) conclude that market discipline is a useful complement to supervision and capital regulation. Indirect market discipline (i.e. signals provided by market prices of banks' securities) can modulate the intensity of supervisory interventions, while direct market discipline (i.e., modifying the liability structure of banks) can be effective provided that banking supervisors are protected from political interference. Flannery and Thakor (2006) argue that there are linkages between informational transparency, regulatory supervision and capital regulation, with informational transparency facilitating supervision and impinging on the design of capital regulation. Van Hoose (2007) reaches the interesting conclusion that capital regulation does not necessarily produce a regulator's preferred outcome if not accompanied by supervisory or market discipline. Finally, Borio and Zhu (2008) notice that, despite its increasing importance, research on the interaction between capital regulation and supervision and their influence on the behavior of the financial system is still rather limited.

Following the paradigm of Barth et al. (2004), and more recent studies, other types of bank regulation mainly include the level and quality of supervisory power, restrictions on bank activities and private monitoring/market discipline. In the project of Barth et al., these three types of regulation correspond to three separate indices, which here are added to yield a single index of overall regulatory quality. By including this composite index of regulatory quality as k in Eq. (2) we essentially examine how the relationship between capital regulation and bank risk evolves with the quality of other types of bank regulation.

Finally, it is rather clear that the macroeconomic conditions may affect the potency of the impact of capital regulation on bank risk-taking, since regulators may loosen or tighten capital regulation according to the special conditions prevailing in each country. The macroeconomic variables included as *k*s are the annual GDP growth rate as a proxy for the economic conditions and inflation as a measure of monetary conditions.

Note that many other variables have been used as potential sources of parameter heterogeneity, including bank liquidity, revenue growth, banking sector concentration etc. The findings of the empirical analysis suggest that heterogeneity in the capital regulation-bank risk nexus due to these variables is not significant. Therefore, we only use these variables as controls in the estimations below. Bank liquidity is measured by the ratio of liquid assets to total assets. Revenue growth is used as a control variable only when risk is measured by NPL, as profits are included in the calculation of both the Z-index and σ(ROA), and is measured by the annual growth in real total revenue. Concentration is measured by the 3-bank concentration ratio constructed in terms of total assets. Also, the variables described above as sources of heterogeneity (i.e. the ones reported in Table 3) in the capital regulation-bank risk nexus are included as *k* in Eq. (2) in alternative specifications. When they are not included as the source of heterogeneity they enter the estimated equations as control variables. Having discussed the dataset, we now turn to the empirical analysis.

[Please insert Table 5 about here]

4. Estimation results

4.1. Practical issues in the Local GMM estimation

A number of practical issues emerge in the estimation of Eq. (2) using LGMM.[6] First, we specify an Epanechnikov kernel of the form $K(u) = 0.75(1-u^2)$ for $-1 < u < 1$ and zero for u outside that range. In this kernel function $u = (x - x_i)/h$ where h is the window width (bandwidth), x_i are the values of the independent variable in the data and x is the value of the scalar independent variable for which one seeks an estimate. Second, we determine the optimal bandwidth based on a variable bandwidth selection procedure proposed by Zhang and Lee (2000); we report this bandwidth along with the estimates in the relevant tables/figures. Zhang

[6] All LGMM estimations were carried out using GAUSS.

and Lee show that the optimal variable bandwidth is superior to the theoretical optimal constant bandwidth and the bandwidth obtained by the cross-validation method.

Third, and probably more important for our purposes, the precision of the LGMM estimator depends on the choice of instrumental variables. As discussed above, capital regulation is probably endogenous and thus an appropriate set of instruments is required to account for both this endogeneity and the dynamic nature of bank risk. Admittedly, choosing a correct set of instruments is a difficult problem. Here we combine the approaches of Blundell and Bond (1998) and Tran and Tsionas (2009), which both refer to dynamic panel data models. In particular, we use r_{it-2}, R_{it-2}, B_{it-2} as instruments, which means that we treat the dependent variable symmetrically with the independent (for the reasoning of this approach in treating endogeneity, see Bond, 2002). In addition, we exploit as additional instruments the second-order lags in the change in the general regulatory environment of each country by employing the composite index of Freedom House and the legal origin of each country in our sample (data obtained from La Porta et al., 2008). Both these variables are used by related literature on the regulations-risk nexus (see e.g. Demirguc-Kunt et al., 2008; Laeven and Levine, 2009), as they are potentially related with the regulatory environment but not with changes in bank risk.[7]

4.2. Quantifying parameter heterogeneity

Table 6 reports the estimation results. The first three columns present the results of the NPL regressions, the next three the Z-index regressions and the last three the σ(ROA) regressions. To save space, we only report the results with capitalization, other regulations and GDP growth being the smoothing variable z; using the rest of the variables described in Section 3 produces very similar results, which are available on request. Overall, the averages of coefficients presented, and their statistical significance, are quite similar with previous literature on determinants of bank risk (see e.g. Laeven and Levine, 2009; Demirguc-Kunt et al., 2008). However, all equations show that bank risk persists to a significant extent and, therefore, exclusion of a dynamic adjustment in a static modeling framework may produce biased results.

[7] We have experimented with many other sets of instruments, including country dummy variables, the ratio of stock market capitalization to GDp as a proxy for financial development etc. The reasoning behid the choice of these instruments is that they would probably affect decisions of regulatory authorities regarding the level of capital stringency, while they would not be correlated with risk. However, we found that in some cases these variables were correlated with average risk-taking of banks, while the results were more sensitive across the different specifications.

Moreover, Figure 1a shows the frequency distribution of the coefficients on the lagged dependent variable, as obtained from the NPL equation.[8] Notably, coefficients vary significantly across banks. Banks obtaining coefficients on the left end of the distribution show moderate persistence in bank risk, a situation usually linked to transparent and competitive banking markets. In contrast, banks obtaining coefficients that reflect very high persistence are usually linked to banking markets characterized by informational asymmetries, impediments to competition and opaqueness.

The average coefficient on the capital regulation variable is statistically insignificant at the 5% level, irrespective of the measure used to proxy bank risk-taking. As discussed in the introduction, a series of previous studies on the capital regulation-bank risk nexus present controversial results on this issue. However, what is not uncovered in previous studies is the wide heterogeneity in the bank-level coefficients. Given that we have generated a new vector including the bank-level coefficients on the capital regulation variable, we can measure heterogeneity in these coefficients by their standard deviation and we can graph them in frequency distributions. The standard deviation of capital regulation coefficients is reported in Table 6 and presents a first indicator that heterogeneity is important and cannot be ignored. In other words, capital regulation does not have a uniform effect on bank risk-taking, with different banks following clearly different strategies.

[Please insert Table 6 about here]

[Please insert Figure 1 about here]

This result becomes more perceptible by plotting the distribution of the estimated coefficients of the capital regulation variable. Figures 1b-1d show the frequency distribution of coefficients on capital regulation, as obtained from the NPL, Z-index and σ(ROA) equations, respectively. The horizontal axes give the values of coefficients and vertical axes measure percentage points. Obviously, the distributions presented are very different from the normal distributions that would be assumed under a parametric model. In all three cases the distributions have more than one mode and apparently parameter heterogeneity is important. In Figure 1b banks obtaining coefficients around the highest mode (i.e. the one on the left end of the

[8] The smoothing variable used in this equation is bank capitalization. Quantitatively similar results are obtained with any other of the smoothing variables used in this study.

distribution) tend to have a lower share of non-performing loans when capital stringency is higher (i.e. coefficients on this mode are negative). For these banks, the results are in line with e.g. Barth et al. (2004) and Keeley and Furlong (1990). Yet, there also exists a large share of banks that seems to take on higher risks when capital stringency increases (i.e. banks around the second highest mode on the right end of the distribution). This is explained by the other part of the same literature, which suggests that as capital regulation reduces future profits, banks have diminished incentives to avoid default since they have less to lose in the case of bankruptcy. Moreover, considering that capital rules elevate the value of equity capital of banks, the latter are incited to increase risk today in order to acquire a higher amount of equity tomorrow in case of success (Blum, 1999; Pasiouras et al., 2006).

The same picture is reflected in the σ(ROA) regressions, where coefficients again overlap with 0. Finally, Figure 1c shows that the Z-index increases with capital stringency for most banks in our sample; however, this effect is much more pronounced for a small number of banks (i.e. those obtaining higher coefficients on the right end of the distribution). On the one hand these findings suggest that the average impact of capital regulation on bank risk is close to zero, but on the other that the effect is very heterogeneous across banks so that inference for the average bank is misleading. Thus, the findings are in line with Demirguc-Kunt et al. (2008), who suggest that bank soundness is positively related with regulations, but this is not the case for all banks.

What do all these have to say about the general regulatory guidelines of Basel II concerning capital requirements? Most countries have adopted minimum capital requirements, which are associated with higher values on our capital regulation index, in an effort to contain bank risk-taking. An inherent assumption in these policies is that the risk management of all banks will respond in a uniform way to capital regulation. The evidence presented here clearly point out to a different outcome. An immediate question that arises concerns the sources of this wide heterogeneity. If we answer this question we should probably be able to provide more specific policy implications regarding the future of banking regulation. Yet, before turning to this issue let us briefly comment on the findings for the control variables.

The average coefficients on the control variables (reported in Table 6) have the sign and significance found in the majority of existing literature. We find that a higher volume of liquid assets in bank portfolios increases problem loans and earnings' volatility. This result is probably explained by two mechanisms. First, banks that hold a high volume of liquid, low yield assets are less profitable. Second, a moral hazard mechanism may prevail if liquidity requirements are in place, causing banks to increase their risk-taking appetite in search for yield. Similarly, the results on the bank equity capital-credit risk relationship suggest that the majority of banks mitigate the effects of increases in capital by increasing asset risk posture. In contrast banks with high market power do not seem to take on higher risks on average (i.e. market power is an insignificant determinant of NPL), while these banks are associated with a higher Z-index probably owing to their higher profitability and capitalization. Bank efficiency is a negative and significant determinant of risk, irrespective of the measure used to proxy banks' risk-taking appetite. This shows that efficient banks are probably better able to manage credit risk and are associated with higher profitability ratios and lower volatility in earnings. Bank size is positively related to the Z-index, yet its impact on problem loans and σ(ROA) is insignificant. This shows that larger banks are more profitable, presumably due to economies of scale, while the role of size in managing credit risk is negligible. Finally, the impact of revenue growth is found to be insignificant.

As far as the macroeconomic variables are concerned, banks in countries with a high level of growth are assigned a higher Z-index and their credit risk exposure is lower. In addition, high inflation is associated with lower Z-scores and a high volume of non-performing loans. These results are intuitive considering that in countries with high growth rates and stable monetary conditions bank insolvency problems are less frequent, fewer resources are employed by banks to forecast the future levels of inflation and loan demand is strong. Finally, once market power is controlled for, concentration is usually an insignificant determinant of bank risk and only when risk is proxied by σ(ROA) concentration gains in significance. In the words of Boyd et al. (2006), taken together these results indicate that the positive association between concentration and risk of failure is driven primarily by a positive association between concentration and volatility of the return on assets.

4.2. Explaining parameter heterogeneity

The variables used as potential sources of bank heterogeneity are the ones included as k in alternative specifications of (2) and discussed in Section 3.3. An immediate candidate method to identify the sources of heterogeneity would be to regressing the vector of a_1s on the variables representing the source of heterogeneity. However, this would probably yield inconsistent estimates because the error term of this second stage regression would be correlated with the error term of (2). To this end, we follow the methodology proposed by Balaguer-Coll et al. (2007), who suggest using nonparametric kernel regression in a second stage to avoid the concerns raised above. In particular, we regress the a_1s on each and every potential determinant of this variable and we obtain graphical bivariate relationships that show exactly how the relationship evolves across observations.[9] We use the Nadaraya-Watson estimator, an Epanechnikov kernel and a large bandwidth to capture the relationship for the full range of observations. Thus, the main advantage of our approach over potential alternatives (including both parametric two-stage methods and also nonparametric methods such as those using resampling techniques) is that, in our case, the term nonparametric refers to the flexible functional form of the regression curve, and neither the error distribution nor the functional form of the mean function are pre-specified.

We present the results for the a_1s obtained from the NPL and Z-index estimations in Figures 2 and 3, respectively.[10] The vertical axes on the graphs measure the coefficients on the capital regulation variable (a_1) and the horizontal axes the determinants of a_1. We place more emphasis on the results based on the NPL regressions, since this measure is closer to the notion of "risk-taking behavior of banks", whereas Z-index represent the risk of insolvency. We find that for banks with negative capitalization (left end of Figure 2a) a_1 takes extreme negative or positive values, indicating that for banks in near-insolvency situations capital regulation can have a stressing, "very positive or very negative" effect on banks' risk management. In contrast, for the majority of banks with positive values of equity capital, the impact of capital regulation on bank risk is marginally positive. This finding validates the results of Beatty and Gron (1999) who suggest that capital regulation has significant effects only for low-capital banks.

[Please insert Figure 2 about here]

[Please insert Figure 3 about here]

Another interesting finding is the U-shaped relationship between market power and a_1 (Figure 2b), which implies that banks with very low or very high market power seem to take on

[9] Bivariate kernel regression can be carried out using any commercially available statistical package such as STATA and EVIEWS.

[10] Due to space considerations we do not report the results for the a_1s obtained from the σ(ROA) estimations.

excess credit risk when capital stringency increases. Thus, market power is important in shaping bank risk-taking through a combined effect with capital regulation, even though it does not seem to have an independent effect on bank risk as we showed in the previous section. As regards solvency risk, Figure 3b shows that as market power increases capital regulation lowers the Z-index. In connection with the finding on the basis of the NPL estimation, this result suggests that excess market power and exposure to credit risk may increase the risk of insolvency if capital stringency is high. In general, these findings are in line with the recent empirical work of Agoraki et al. (2009).

For the effect of the rest of the sources of variation in a_1 we do not have any priors in the literature. Bank efficiency and size are more clear determinants of heterogeneity in the capital regulation-bank risk relationship. Efficient banks (i.e. those on the left end of the distributions of Figures 2c and 3c) are associated with a negative relationship between capital regulation and NPL and a positive one between capital regulation and Z. This implies that bank efficiency is a prerequisite for capital regulation to have a negative impact on bank risk. Also, bigger banks tend to take on higher credit risk when stricter capital regulations are in place, a result in line with the moral hazard mechanism highlighting a further increase in the risk-taking activities of banks that consider themselves as leaders in the market. Note two things: first this situation may be rewarding in good times but very problematic during episodes of financial distress and second capital regulation in its current format is clearly insufficient to contain the risk-taking activities of large banks.

Concerning the impact of other regulations on a_1, we find that higher regulatory quality in (i) official supervisory power, (ii) restrictions in bank activities and (iii) private monitoring and market discipline is a prerequisite for a negative relationship between capital regulation and bank risk (see Figures 2e and 3e). Empirical and theoretical research has been progressively shifting its attention to examining the interplay between different forms of banking regulation on bank risk. From this perspective, our research validates the criticism that Caprio et al. (2008) leveled against Basel II for devoting just "16 pages to issues of market discipline and 225 pages to spelling out formulas and strategies impeded in pillar one (that concerns capital regulation alone)".

In line with the impact of other types of regulation, the impact of the macroeconomic and monetary environments also seems crucial in explaining variations in a_1. In particular, it seems that a_1 becomes negative for GDP growth rates between 3 and 4%, but increases substantially for very high growth rates, implying that banks give out very risky loans when the economy is booming. All in all, this represents a potential failure of capital regulation to contain credit risk during very good times, a situation that may lead to a bubble in the loan market. However, during episodes of high growth capital regulation also has a positive effect on the Z-index, indicating that the increase in bad loans is neutralized by increases in profitability from bonds and most importantly non-interest income. In contrast, the impact of inflation on a_1 is as expected. When stable monetary conditions prevail, capital regulation reduces problem loans and is associated with a lower risk of insolvency, as reflected in Figures 2g and 3g.

Note that many other variables have been used as potential sources of heterogeneity, including the loan to asset ratio (proxy for bank specialization), the liquidity ratio (proxy for bank liquidity, revenue growth (proxy for bank growth), industry concentration and general economic freedom; the coefficients on the capital regulation variable a_1 showed no significant variation due to these variables. For the loan to assets ratio this is particularly interesting as it shows that banks of different specialization do not respond, in terms of their risk-taking appetite, substantially different to capital regulation. However, the extensive heterogeneity in the relationship between capital regulation and bank risk-taking and the significant effect of certain variables in creating this heterogeneity point out to important policy implications towards a new regulatory agenda. That is our findings suggest that banks (i) with very low or very high market power, (ii) with low operating efficiency, (iii) of big size (iv) operating within a booming, monetary unstable and/or within a low-quality regulatory environment, take on higher risks regardless of the level of capital stringency. We discuss the policy implications of these findings below.

5. Conclusions and policy implications

In this paper we showed the importance of heterogeneity in characterizing the relationship between capital regulation and bank risk-taking. Strong evidence is presented that capital regulation can have a positive or negative effect on bank risk owing to (i) certain bank characteristics, (ii) other regulations and (iii) the state of the macroeconomic environment. Striking results are that large banks and banks with market power take on higher credit risk when capital requirements are more stringent, while other types of bank regulation are clearly complementary to capital regulation in reducing bank risk. Finally, during economic booms and unstable monetary conditions banks tend to take more risky positions. These findings suggest that placing all banks under a common regulatory umbrella is highly problematic, as banks with certain characteristics may find themselves exposed in very high risks. Even though these risks may be rewarding during periods of high growth, sudden episodes of financial distress will have a catastrophic impact on the quality of bank portfolios and this may be more pronounced for important players in the banking sector. Without attempting to provoke any generalization, the recent financial turmoil presents an example of how large financial institutions may quickly face insolvency if they are exposed to very high risks, despite the existence of capital regulation.

The regulatory authorities should probably then be looking at very different tactics in order to discipline bank risk-taking. General guidelines, such as those of Basel I are probably not efficient in promoting a stable banking environment because uniform capital regulation causes a differential response of bank risk-taking behavior. Basel II grants national regulators substantial discretion, which may or may not help lowering the risk-taking of banks. On the one hand, more powerful national regulators would be better able to tackle insolvency situations of financial institutions, because they have deeper knowledge of their own banking system. However, on the other hand, with distinct policies among regulators, countries could end up with divergent levels of capital requirements, which can generate regulatory arbitrage and further undermine banking stability.

In our view, the result that regulatory authorities can contain bank risk-taking only if capital regulation is combined with other forms of regulation included in the other two pillars of Basel II is key to an effective regulatory and supervisory framework. In particular, an effective regulation may have to state more clearly (i) that the three pillars should be viewed as complementary mechanisms in the path to banking stability and (ii) that effective supervision is the only element for which discretion is granted to national authorities. This may bring the best from both worlds: first, it will maintain and enhance the common regulatory umbrella and second it will give national authorities the power to take all necessary actions for the implementation of the common framework. It should be kept in mind that effective supervision should include a separate examination of the strategies of each supervised bank, external auditing, stretched disciplinary action or subordinated debt requirements and that these policies should be focused on all banks, irrespective of their size, market power or efficiency levels.

Finally, as Caprio et al. (2008) point out, to be effective, prudential regulation must be adaptive and it must combine supervisory stress tests with market oversight. Our finding that in times when economies boom banks tend to increase their risk-taking appetite suggests that supervisors may have to take action in a timely fashion. After all, this is probably the clearest aftermath of the recent financial turmoil.

APPENDIX: Estimation of market power

To estimate marginal cost at the bank-level and use it to calculate the Lerner index we use the following Cobb-Douglas cost function

$$\ln c_{it} = b_0 + b_1 \ln q_{it} + b_2 \ln d_{it} + b_3 \ln w_{it} + e_{it} \qquad \text{(A.1)}$$

where c is the total cost of bank i at time t (measured by real total expenses), q is bank output (proxied by real total assets), d is the value of real bank deposits, w are the prices of three inputs (namely the price of funds as measured by the ratio of interest expenses to total deposits, the price of physical capital measured by the ratio of overhead expenses to total fixed costs and the price of labor measured by the ratio of personnel expenses to total assets) and e is a stochastic disturbance. All bank data are collected from Bankscope.

This cost function assumes that banks use inputs and deposits to produce output q (for a similar implementation, see e.g. Brissimis et al., 2008). From (A.1), the marginal cost of bank output is simply b_1. Hence, in order to obtain observation-specific estimates of the marginal cost, we need to obtain observation-specific estimates of b_1. This is accomplished by drawing on a non-parametric estimation technique to estimate (A.1), in particular the local regression (LR) technique as put forth by Cleveland and Devlin (1988). Bank-level estimates of all of the bs (and thus of b_1) are obtained through localization of the parameters.

The underlying model for local regression is $y_{it} = \mu(x_{it}) + \varepsilon_{it}$, where x are the predictor variables q, d and w in (A.1) above and y is the response variable (corresponding to c in (A.1)). The unknown function $\mu(x)$ is assumed to be smooth and is estimated by fitting a polynomial model (a quadratic in our case, as in most of the literature) within a local sliding window. Therefore, no strong assumptions are made about μ globally, but locally around x we assume that μ can be well approximated. Note that this not a strong assumption when using large and rich datasets like the one of the present analysis. For a fitting point x, define a bandwidth h that controls the smoothness of the fit and a smoothing window (*x-h(x)*, *x+h(x)*). To estimate μ, only observations within this sliding window are used.

Unlike the LGMM case, here for each fitting point a locally weighted least squares criterion of the following form is considered:

$$\sum_{i=1}^{n} W\left(\frac{x_i - x}{h}\right)\left(Y_i - (b_0 + b_1(x_i - x))\right)^2 \tag{A.2}$$

where W is the weight function that assigns largest weights to observations close to x, and takes the form

$$W(u) = \begin{cases} (1-|u|^3)^3 & \text{if } |u| < 1 \\ 0 & \text{otherwise} \end{cases} \tag{A.3}$$

The local least squares criterion of (A.2) is minimized to produce estimates $\widehat{b}_0$ and $\widehat{b}_1$ for each observation.

Estimations were carried out using the program LOCFIT, which is a software system for fitting curves and surfaces to data, using the local regression and likelihood methods (for a thorough discussion, see Loader, 1999). An important issue in the implementation of LR is the choice of an optimal bandwidth. Much like in the case of LGMM, we used the method of Zhang and Lee (2000), which in our case yields a bandwidth equal to 0.542. For other applications of local methods to bank data, see e.g. Kumbhakar et al. (2007) and Delis and Tsionas (2009).

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Table 1
Data coverage

Country	Number of banks	Number of observations
Australia	24	167
Austria	133	789
Belgium	68	416
France	302	2101
Germany	980	3855
Greece	30	210
Netherlands	38	261
Norway	45	260
Portugal	33	228
Spain	132	915
Sweden	162	969
Switzerland	207	1112
UK	94	620
USA	1262	7350
Total	3510	19253

The table reports the number of banks and the number of observations for each country included in our panel.

Table 2
Descriptive statistics

	Mean	Std. dev.	Min.	Max.
Z-index	3.841	1.292	-1.301	9.048
NPL	0.021	0.046	0.004	0.466
σ(ROA)	0.750	1.420	0.032	11.491
capitalization	0.088	0.107	-0.202	0.240
liquidity	0.045	0.060	0.002	0.503
market power	0.306	0.228	-0.194	1.042
capital regulation	6.000	1.443	3.000	8.000
other regulations	17.090	3.548	12.000	23.000
efficiency	0.408	0.445	0.092	1.241
bank size	13.003	4.821	9.957	19.845
revenue growth	0.021	0.218	-0.501	2.140
concentration	0.403	0.407	0.096	0.645
GDP growth	2.240	1.872	-0.691	5.621
inflation	2.217	0.828	0.500	3.591

The table reports basic descriptive statistics for the variables used in the empirical analysis. The variables are defined as follows: Z-index is calculated as ln[Z=(ROA+EA)/σ(ROA)], where ROA is the ratio of profits before tax to total assets and EA is the ratio of equity to total assets; NPL is the ratio of non-performing loans to total loans; σ(ROA) is the variance of ROA; capitalization is the ratio of equity capital to total assets; liquidity is the ratio of liquid assets to total assets; market power is the bank-level Lerner index; capital regulation is the Barth et al. (2001 and updates) index of capital regulation; other regulations is a composite index pertaining to all other regulations except capital regulation, as constructed on the basis of the database of Barth et al. (2001 and updates); efficiency is the ratio of total operating expenses to total bank revenue; bank size is the natural logarithm of total bank assets; revenue growth is the annual growth in real total revenue; concentration is the 3-bank concentration ratio in terms of total assets; GDP growth is the annual GDP growth rate of each country; inflation is the inflation rate (consumer price index) of each country.

Table 3
Variables used as sources of heterogeneity (*k*)

	Measure	Source
capitalization	Ratio of equity capital to total assets	Bankscope
market power	Lerner index of market power	Own estimations on the basis of Bankscope data
efficiency	Ratio of total operating expenses to total revenue	Bankscope
bank size	Natural logarithm of real total assets	Bankscope
other regulations	Barth et al. (2001) composite index pertaining to official supervisory power, activity restrictions and private monitoring	Barth et al. (2001) and updates
GDP growth	Annual GDP growth rate	World Development Indicators
inflation	CPI inflation rate	World Development Indicators

The table reports the variables used as sources of heterogeneity in the relationship between capital regulation and bank risk-taking, the way these variables are measured and the data sources.

Table 4
Descriptive statistics of the bank-level estimates of market power (Lerner index) by country

Country	Mean	Std. dev.	Min	Max
Australia	0.27	0.41	-0.01	0.81
Austria	0.35	0.45	-0.12	0.76
Belgium	0.25	0.38	-0.07	0.71
France	0.32	0.51	-0.19	0.87
Germany	0.18	0.39	-0.07	0.59
Greece	0.68	0.59	-0.12	1.03
Netherlands	0.41	0.40	0.07	0.78
Norway	0.55	0.51	-0.06	0.88
Portugal	0.52	0.55	-0.09	0.90
Spain	0.61	0.59	-0.03	1.07
Sweden	0.58	0.48	0.12	0.86
Switzerland	0.36	0.38	0.06	0.69
UK	0.28	0.37	0.06	0.68
USA	0.24	0.47	-0.04	0.79
Average	0.33	0.42	-0.19	1.07

The table presents descriptive statistics of the vector that contains the bank-level estimates of market power. Mean is the average value of the series, Std. dev. is the standard deviation of the market power estimates, and min and max are the minimum and maximum values of these estimates. A Lerner index in the range (-0.107)-(0.103) shows perfectly competitive practices; an index in the range (0.897)-(1.092) shows monopoly power; values in between show intermediate structures, with higher values reflecting higher market power and vice versa.

Table 5
Correlation matrix

	capitaliz.	liquidity	market power	capital requir.	other regulat.	efficiency	bank size	revenue growth	concent.	GDP growth	inflat.
capitalization	1.000										
liquidity	0.162	1.000									
market power	0.063	0.114	1.000								
capital regulation	0.082	0.142	0.065	1.000							
other regulations	-0.025	-0.078	-0.026	0.227	1.000						
efficiency	-0.003	0.004	-0.082	-0.036	-0.118	1.000					
bank size	-0.455	-0.179	0.137	-0.059	0.245	-0.017	1.000				
revenue growth	0.150	0.101	0.181	-0.027	-0.079	0.125	0.023	1.000			
concentration	0.038	0.006	0.059	-0.027	-0.062	-0.005	0.110	0.033	1.000		
GDP growth	-0.115	-0.027	-0.027	-0.302	0.450	-0.021	0.391	0.080	-0.003	1.000	
inflation	-0.082	-0.002	0.055	0.325	0.321	-0.042	0.042	-0.028	0.002	-0.217	1.000

The table reports correlations between the explanatory variables of the empirical analysis. The variables are defined as follows: capitalization is the ratio of equity capital to total assets; liquidity is the ratio of liquid assets to total assets; market power is the bank-level Lerner index; capital regulation is the Barth et al. (2001 and updates) index of capital regulation; other regulations is a composite index pertaining to all other regulations except capital regulation, as constructed on the basis of the database of Barth et al. (2001 and updates); efficiency is the ratio of total operating expenses to total bank revenue; bank size is the natural logarithm of total bank assets; revenue growth is the annual growth in real total revenue; concentration is the 3-bank concentration ratio in terms of total assets; GDP growth is the annual GDP growth rate of each country; inflation is the inflation rate (consumer price index) of each country.

Table 6
Risk and capital regulation

	NPL			Z-index			σ(ROA)		
	(1) k: capitalization	(2) k: other regulations	(3) k: GDP growth	(4) k: capitalization	(5) k: other regulations	(6) k: GDP growth	(7) k: capitalization	(8) k: other regulations	(9) k: GDP growth
lagged dependent	0.406*	0.423*	0.397*	0.307*	0.295*	0.323*	0.220*	0.219*	0.232*
	(0.074)	(0.068)	(0.073)	(0.055)	(0.061)	(0.060)	(0.051)	(0.054)	(0.050)
capital regulation	**0.120**	**0.149**	**0.132**	**0.058**	**0.061**	**0.060**	**-0.004**	**-0.004**	**-0.003**
	(0.077)	**(0.081)**	**(0.078)**	**(0.045)**	**(0.046)**	**(0.043)**	**(0.006)**	**(0.007)**	**(0.005)**
standard deviation of coefficients	**0.203**	**0.194**	**0.247**	**0.166**	**0.160**	**0.153**	**0.011**	**0.012**	**0.011**
other regulations	-0.113*		-0.125*	0.246*		0.267*	-0.503*		-0.614*
	(0.046)		(0.043)	(0.081)		(0.079)	(0.181)		(0.203)
capitalization		0.041*	0.043*				0.021	0.019	0.023
		(0.017)	(0.016)				(0.015)	(0.015)	(0.017)
liquidity	0.063*	0.064*	0.061*	0.016	0.021	0.015	0.036	0.042*	0.040*
	(0.024)	(0.022)	(0.021)	(0.023)	(0.024)	(0.025)	(0.023)	(0.021)	(0.018)
market power	-0.071	-0.077	-0.069	0.313*	0.348*	0.295*	0.147	0.172	0.203
	(0.062)	(0.059)	(0.059)	(0.100)	(0.107)	(0.091)	(0.097)	(0.118)	(0.141)
efficiency	-1.071*	-1.042*	-1.033*	0.729*	0.814*	0.800*	-0.316*	-0.401*	-0.307*
	(0.303)	(0.349)	(0.327)	(0.181)	(0.202)	(0.209)	(0.096)	(0.117)	(0.093)
bank size	-0.125	-0.144	-0.141	0.086*	0.083*	0.081*	-0.021	-0.010	0.017
	(0.104)	(0.117)	(0.113)	(0.027)	(0.031)	(0.031)	(0.082)	(0.061)	(0.030)
revenue growth	-0.327	-0.342	-0.333						
	(0.248)	(0.245)	(0.237)						
concentration	0.405	0.432	0.401	-0.067	-0.023	-0.021	0.107	0.181*	0.203*
	(0.340)	(0.363)	(0.367)	(0.104)	(0.087)	(0.061)	(0.066)	(0.078)	(0.089)
gdp growth	-0.047*	-0.0439*		0.060*	0.052*	0.072*	-0.021*	-0.019*	
	(0.008)	(0.009)		(0.019)	(0.016)	(0.022)	(0.009)	(0.009)	
inflation	0.046*	0.036*	0.038*	-0.052*	-0.061*	-0.055*	0.093*	0.088*	0.090*
	(0.010)	(0.009)	(0.011)	(0.018)	(0.025)	(0.021)	(0.028)	(0.032)	(0.030)

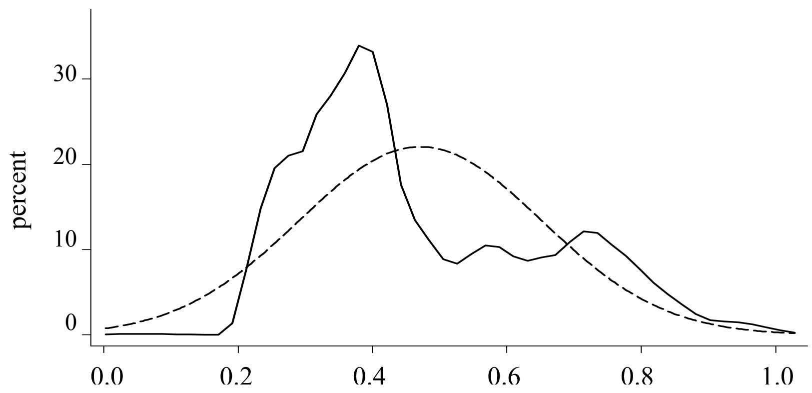
Table 6 (continued)

	NPL			Z-index			σ(ROA)		
σê	0.081	0.084	0.077	0.103	0.095	0.095	0.081	0.077	0.086
bandwidth	0.653	0.598	0.614	1.721	1.815	1.797	0.918	0.901	0.960

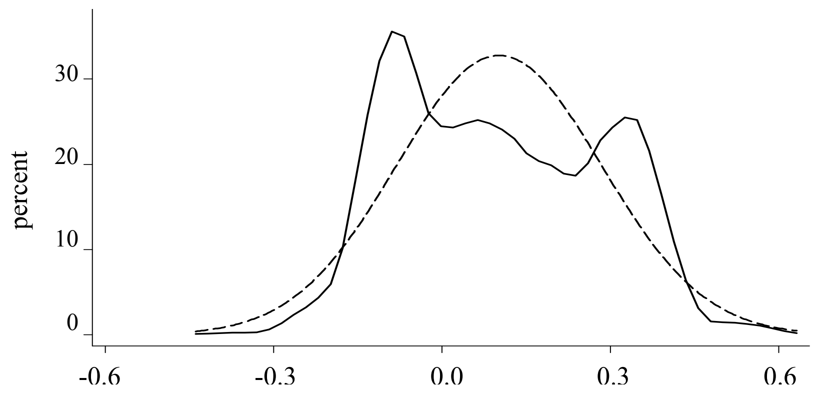
The table reports average coefficients and standard errors (in parentheses). For the capital regulation variable the standard deviation of the bank-level coefficients (measure of parameter heterogeneity) is also reported. In regressions (1)-(3) dependent variable is the ratio of non-performing loans to total loans (NPL), in regressions (4)-(6) the Z-index and in regressions (7)-(9) σ(ROA), as measured by the variance of the ratio of profits before tax to total assets. k is the smoothing variable used in each regression of the empirical model presented in Eq. (2). For each dependent variable we report the estimates from the equations that employ capitalization, other regulations and GDP growth as k. The variables included in the table are defined as follows: lagged dependent is the first lag of the risk variable; capital regulation is the Barth et al. (2001 and updates) index of capital regulation; other regulations is a composite index pertaining to all other regulations except capital regulation, as constructed on the basis of the database of Barth et al. (2001 and updates); capitalization is the ratio of equity capital to total assets; liquidity is the ratio of liquid assets to total assets; market power is the bank-level Lerner index; efficiency is the ratio of total operating expenses to total bank revenue; bank size is the natural logarithm of real total bank assets; revenue growth is the annual growth in real total revenue; concentration is the 3-bank concentration ratio in terms of total assets; GDP growth is the annual GDP growth rate of each country; inflation is the inflation rate (consumer price index) of each country. σê is the variance of the estimated error term and bandwidth is the optimal bandwidth used in each regression as estimated by the method of Zhang and Lee (2000). * denotes statistical significance at the 5% level.

Figure 1
Distributions of estimated coefficients

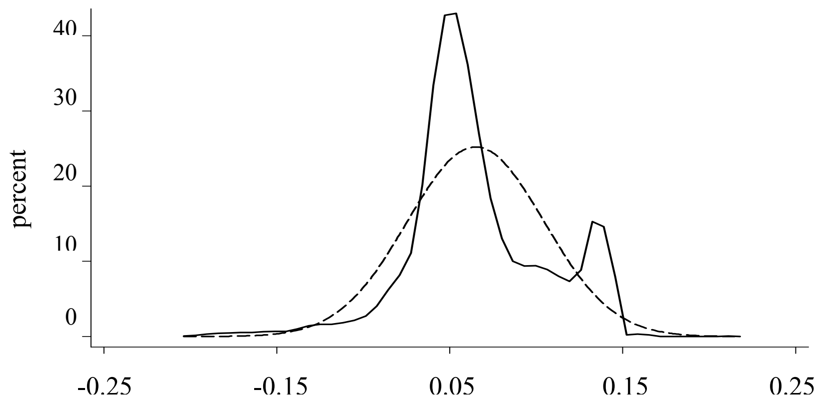
1a. Coefficients on lagged dependent variable



1b. Coefficients of capital regulation in the NPL equation



1c. Coefficients of capital regulation in the Z-index equation



1d. Coefficients of capital regulation in the σ(ROA) equation

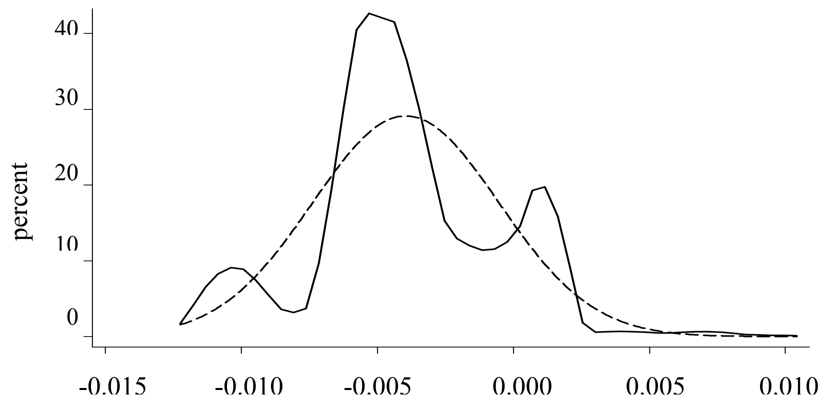


Figure 1a presents the distribution of coefficients on the lagged dependent variable obtained from the NPL equation when the smoothing variable is bank capitalization. Figures 1b-1d present distributions of coefficients on the capital regulation variable obtained from the NPL, Z-index and σ(ROA) equations, again using bank capitalization as the smoothing variable.

Figure 2
Sources of parameter heterogeneity in the relationship between capital regulation and bank risk (a_1s obtained from NPL equations)

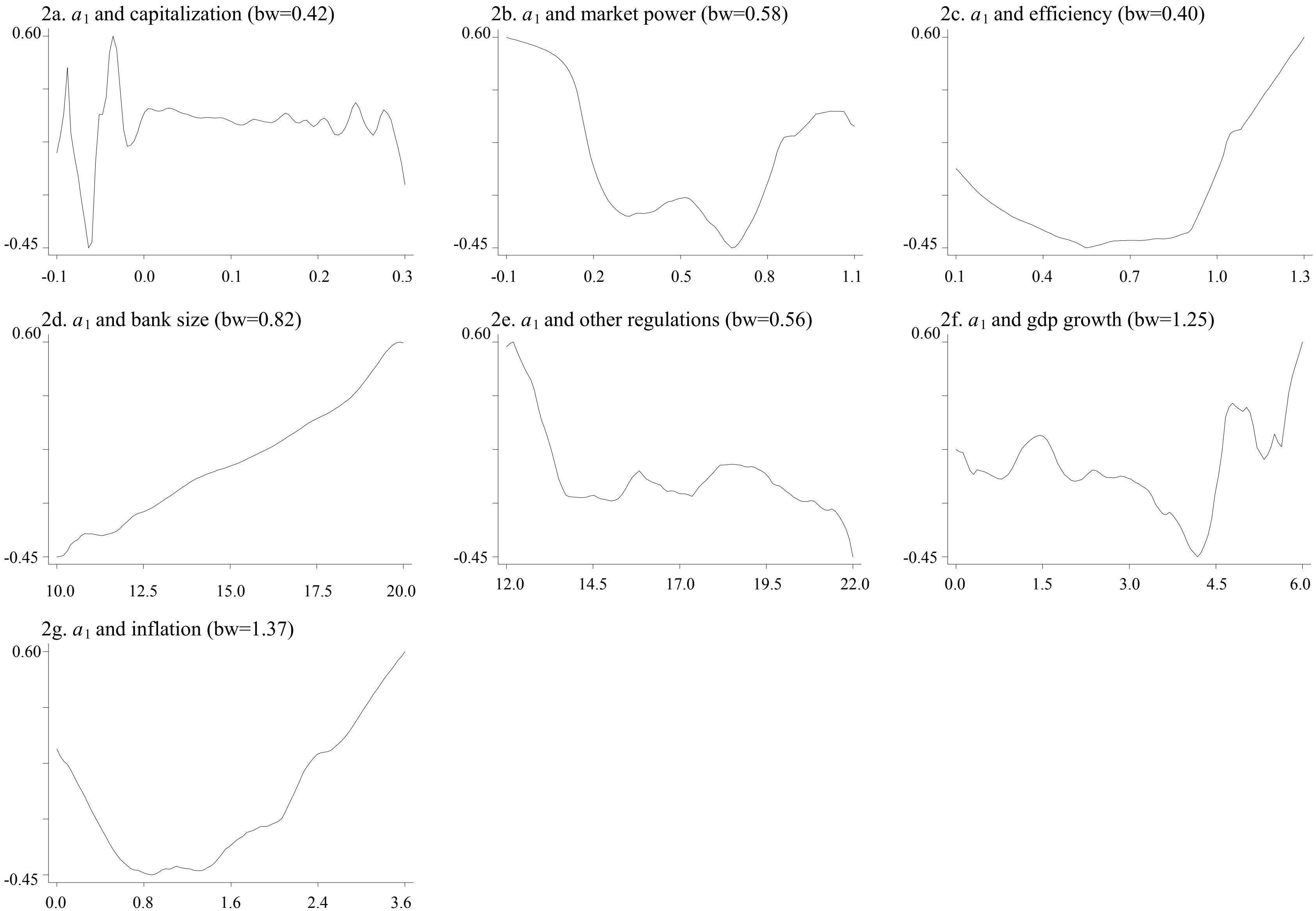


Figure 3
Sources of parameter heterogeneity in the relationship between capital regulation and bank risk (a_1s obtained from Z-index equations)