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Capital Regulation, Efficiency, and Risk Taking: A Spatial Panel Analysis of U.S. Banks

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Abstract

In this study, we empirically assess the impact of capital regulations on capital adequacy ratios, portfolio risk levels and cost efficiency for U.S. banks. Using a large panel data of U.S. banks between 2001-2016, we first estimate the model using two-step generalized method of moments (GMM) estimators. After obtaining residuals from the regressions, we propose a method to construct the network based on clustering of these residuals. The residuals capture the unobserved heterogeneity that goes beyond systematic factors and banks' business decisions that impact its level of capital, risk and cost efficiency and thus represent unobserved network heterogeneity across banks. We then re-estimate the model in a spatial error framework. The comparisons of Fixed Effects, GMM Fixed Effect models with spatial fixed effects models provide clear evidence of the existence of unobserved spatial effects in the interbank network. We find a stricter capital requirement causes banks to reduce investments in risk-weighted assets, but at the same time, increase holdings of non-performing loans, suggesting the unintended effects of higher capital requirements on credit risks. We also find the amount of capital buffers has an important impact on banks' management practices even when regulatory capital requirements are not binding.

Keywords: Spatial error model, spatial weight matrix, bank risk

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1 Introduction

Since the process of bank deregulation started in the 1970s, the supervision of banks has relied mainly on the minimum capital requirement. The Basel Accord has emerged as an attempt to create an international regulatory standard on how much capital banks should maintain to protect against different types of risks. The recent financial crisis revealed that, despite numerous refinements and revisions over the last two decades, the existing regulatory frameworks are still inadequate for preventing banks from taking excessive risks. The recent crisis also highlighted the importance of the interdependence and spillover effects within the financial networks.

Therefore, to prevent future crises, economists and policymakers must understand the dynamics of the intertwined banking systems and the underlying drivers of banks' risk-taking to better assess risks and adjust regulations. Theoretical predictions on whether more stringent capital regulation curtails or promotes banks' risk-taking behavior are ambiguous. It is ultimately an empirical question how banks behave in the light of capital regulation. This paper seeks to investigate the drivers of banks' risk-taking in the U.S. and to test how banks respond to an increase in capital requirements.

There is a large number of empirical studies testing whether increases in capital requirements force banks to increase or decrease risks (Shrieves and Dahl (1992); Jacques and Nigro (1997); Aggarwal and Jacques (2001); Rime (2001); Stolz, Heid, and Porath (2003); Lindquist (2004); Barth, Caprio, and Levine (2004); Demirguc-Kunt and Detragiache (2011); Camara, Lepetit, and Tarazi (2013) and etc). For example, Shrieves and Dahl (1992) and Jacques and Nigro (1997) suggest that capital regulations have been effective in increasing capital ratios and reducing asset risks for banks with relatively low capital levels. They also find that changes in risk and capital levels are positively related, indicating that banks that have increased their capital levels over time have also increased their risk appetite. However, other studies such as Stolz et al. (2003) and Van Roy (2005) report a negative effect of capital on the levels of risk taken by banks. Overall, both theoretical and empirical studies are not conclusive as to whether more stringent capital requirements reduce banks' risk-taking.

A different strand of literature provides evidence that efficiency is also a relevant determinant of bank risk. In particular, Hughes, Lang, Mester, Moon, et al. (1995) link risk-taking and banking operational efficiency together and argue that higher loan quality is associated with greater inefficiencies. S. Kwan and Eisenbeis (1997) link bank risk, capitalization and measured inefficiencies in a simultaneous equation framework. Their study confirms the belief that these three variables are jointly determined. Additional studies on capital, risk and efficiency are conducted by Williams (2004), Yener Altunbas, Carbo, Gardener, and Molyneux (2007), Fiordelisi, Marques-Ibanez, and Molyneux (2011), Deelchand and Padgett (2009) and Tan and Floros (2013) [1]. Taken together, these two strands of the empirical literature on banking business practices imply that bank capital, risk and efficiency are all related.

The third strand of literature that we are looking into deals with applying spatial econometrics to model banking linkages and the transmission of shocks in the financial system. Although spatial dependence has been studied extensively in a wide range of social fields, such as regional and urban economics, environmental sciences and geographical epidemiology, it is not yet very popular in financial applications. Recently, there are some applications in empirical finance. For instance, Fernandez (2011) tests for spatial dependency by formulating a spatial version of the capital asset pricing model (S-CAPM). B. Craig and Von Peter (2014) find significant spillover effects between German banks' probabilities of distress and the financial profiles of connected peers through a spatial probit model. Other studies such as Asgharian, Hess, and Liu (2013), Arnold, Stahlberg, and Wied (2013) and Weng and Gong (2016) analyze spatial dependencies in stock markets. However, the empirical literature appears to be silent on examining the effects of financial regulation on risks while taking spatial dependence into account. Banks' behaviors are likely to be inherently spatial. Ignoring these spatial correlations would lead to model misspecification, and consequently, biased parameter estimates.

In this paper, we combine these different strands of literature. Using a large sample of U.S. banking data between 2001-2016, we empirically assess the impact of capital regulation on capital adequacy ratios, portfolio risk levels and efficiency of banks in the United States under spatial frameworks. The sampling period includes banks that report their balance sheet data

[1] See Table A.2 for a concise summary of the recent empirical studies on capital, risk and efficiency.

according to both the original Basel I Accord and the Basel II revisions (effective from 2007 in the U.S.), and up to the most available date on 2016-Q3. More precisely, our paper addresses the following questions: to what extent are banks' risk-taking behaviors and cost efficiency sensitive to capital regulation? How do capital buffers affect a bank's capital ratios, the level of risk it is willing to take on, and its cost efficiency? How does the result change by taking into account spatial interactions among observed banks?

This paper makes several contributions to the discussion on bank capital, risk, and efficiency and has important policy implications. First, this analysis provides an empirical investigation linking capital regulation on bank risk-taking, capital buffer and bank efficiency in a spatial setting. The introduction of spatial dependence allows us to determine the importance of network externalities after controlling for bank specific effects as well as macroeconomic factors.

Second, this paper proposes a new approach for creating a spatial weights matrix. The key challenge in investigating spatial effects among banks is in defining the network, or in other words, constructing the spatial weights matrix. Spatial weights matrix is normally constructed in terms of the geographical distance between neighbors. In financial markets, however, it is not necessarily the case given that most transactions are performed electronically. we propose a method to construct a spatial weights matrix based on clustering of residuals from regressions. The residuals aim to capture the unobserved heterogeneity that goes beyond systematic factors and banks' own idiosyncratic characteristics and can be interpreted as a representation of unobserved network heterogeneity.

Third, this study employs a significantly larger and more recent data set than previous studies that used data only up to 2010. In addition, since Basel III maintains many of the defining features of the previous accords, this study will shed light on how a more risk-sensitive capital regulation (i.e. Basel III) could influence banks' behaviors in the U.S. after the financial crisis.

The rest of the paper is organized as follows. Section II lays out the regulatory background of this study. Section III explains the model. Section IV outlines the estimation methodology and addresses several econometric issues. Section V describes the data. Section VI presents and discusses the empirical findings and Section VII concludes.

2 Regulatory Background

The purpose of the Basel Committee on Banking Supervision is two-fold. Its aims are to provide greater supervision of the international banking sector, and to promote competition among banks internationally by having them comply with the same regulatory standards (Jablecki et al. (2009)). All three Basel Accords are informal treaties, and members of the Basel Committee may not adapt their rules as national laws. For example, the U.S. only adopted Basel II standards for its 20 largest banking organizations since 2007. Regardless, the accords have led to greater universality in global capital requirements, even in countries that are not represented on the formal Basel Committee.

Basel I, implemented in 1988, was designed to promote capital adequacy among banks internationally by promoting an acceptable ratio of capital to total risk-weighted assets. Specifically, Basel I required the ratio between regulatory capital and the sum of risk-weighted assets to be greater than 8%. This has become an international standard, with well over 100 countries adopting the Basel I framework. The first Basel Accord divided bank capital into two tiers to guarantee that banks hold enough capital to handle economic downturns. Tier 1 capital, the more important of the two, consists largely of shareholder's equity. Tier 2 consists of items like subordinated debt securities and reserves. The primary weakness of Basel I was that capital requirements were only associated with credit risk, and did not include operational or market risk. Additionally, risk weights assigned to assets are fixed within asset categories, creating incentives for banks to engage in regulatory capital arbitrage. For example, all commercial loans were assigned the same risk weight category (100% risk weight) regardless of the inherent creditworthiness of the borrowers. This tended to reduce the average quality of bank loan portfolios.

Basel II was initially published in June 2004 and was introduced to combat regulatory arbitrage and improve bank risk management systems. The Basel II Accord was much more complex and risk sensitive than Basel I and placed greater emphasis on banks' own assessment of risk. Basel II was structured in three pillars: pillar 1 defined the minimum capital requirements; pillar 2 was related to the supervisory review process; pillar 3 established the disclosure requirements on the financial condition and solvency of institutions. Basel II made several prominent changes to Basel I, primarily in regard to how risk-weighted assets were to be calculated. In addition to credit risk, Basel II extended the risk coverage to include a capital charge for market and operational risk. The total risk-weighted assets (RWA_T) was then calculated as follows:

$$RWA_T{=}RWA_C{+}12.5(OR_C{+}MR_C)$$

where RWA_C denotes the risk-weighted assets for credit risk. MR_C is the market risk capital charge and OR_C is the operational risk capital charge.

Also, Basel II allowed banks to use internal risk models to determine the appropriate risk weights of their own assets once approved by regulators. Additionally, Basel II calculated the risk of assets held in trading accounts using a "Value at Risk" approach, which takes into account estimates of potential losses based on historical data.

			Basel III						
	Basel I	Base II	2013	2014	2015	2016	2017	2018	2019
Common equity Tier 1 ratio			3.5%	4%	4.5%	4.5%	4.5%	4.5%	4.5%
Capital conservation buffer						0.625%	1.25%	1.875%	2.5%
Min Tier 1 Capital	4%	4%	4.5%	5.5%	6%	6%	6%	6%	6%
Min Total Capital	8%	8%	8%	8%	8%	8%	8%	8%	8%
Liquidity coverage ratio					60%	70%	80%	90%	100%

Source: Bank for International Settlements, http://www.bis.org/bcbs/basel3.htm

Table 2.1: Evolution of minimum capital requirements from Basel I to Basel III

In the aftermath of the financial crisis of 2007-2009, the Basel Committee revised its capital adequacy guidelines, and this became Basel III (BCBS (2011)). The primary additions to Basel II were higher capital ratios for both Tier 1 and Tier 2 capital, the introduction of liquidity requirement and the incorporation of a leverage ratio to shield banks from miscalculations in risk weightings and higher risk weightings of trading assets. As shown in Table 2.1, although the minimum regulatory capital ratio remained at 8%, the components constituting the total regulatory capital had to meet certain new criteria. A capital conservation buffer of 2.5% was introduced to encourage banks to build-up capital buffers during normal times. Liquidity risk also received much attention in Basel III. A Liquidity Coverage Ratio (LCR) and a Net Stable

Funding Ratio (*NSFR*) were introduced and was implemented since 2015 and will be completed by the end of 2018 (BCBS, 2013). Mid-way through the Basel III consultative process, the U.S. enacted the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) in 2010. The Dodd-Frank Act is generally consistent with Basel III but further addressed systemic risk by identifying a set of institutions as systemically important financial institutions (SIFIs). The Dodd-Frank Act placed more stringent capital requirements for these SIFIs and required them to undertake periodic stress tests (DFAST) to ensure these institutions are well capitalized in aggregate stress scenarios.

Despite these changes, critics remain skeptical that the same issues that plagued Basel II regarding incorrect risk-weights, as well as ease of circumvention are still prominent in Basel III. It is believed that regulatory capital requirements should be sufficiently attuned to the riskiness of bank assets. However, Vallascas and Hagendorff (2013) find a low risk sensitivity of capital requirements which enable banks to build up capital buffers by under-reporting their portfolio risk. Since the risk-weighting methodology remained essentially unchanged in Basel III, banks will still have the incentive to game the system by obtaining securities that may prove disastrous unexpectedly (Lall (2012)).

3 Hypotheses and Models

3.1 The Relationships among Capital, Risk, and Efficiency: Theoretical Hypotheses

The prevalence of a minimum capital requirement is primarily based on the assumption that banks are prone to engage in moral hazard behavior. The moral hazard hypothesis is the classical problem of excessive risk-taking when another party is bearing part of the risk and cannot easily charge for that risk. Due to asymmetric information and a fixed-rate deposit insurance scheme, the theory of moral hazard predicts that banks with low levels of capital have incentives to increase risk-taking in order to exploit the value of their deposit insurance (Kane (1995)). The moral hazard problem is particularly relevant when banks have high leverage and large assets. According to the *too-big-to-fail* argument, large banks, knowing that they are so systemically important and interconnected that their failure would be disastrous to the economy, might count on a public bailout in case of financial distress. Thus, they have incentives to take excessive risks and exploit the implicit government guarantee. In addition, the moral hazard hypothesis predicts that inefficiency is positively related to risks because inefficient banks are more likely to extract larger deposit insurance subsidies from the FDIC to offset part of their operating inefficiencies (S. H. Kwan and Eisenbeis (1996)). This suggests the following hypothesis.

Hypothesis 1. *There exists a negative relationship between capital/efficiency and risk, as banks with higher leverage and lower efficiency have incentives to take higher risk to exploit existing flat deposit insurance schemes.*

With regard to the relationship between cost efficiency and risks, Berger and DeYoung (1997) outline and test the "bad luck", "bad management", and "skimping" hypotheses using Granger causality test. Under the bad luck hypothesis, external exogenous events lead to increases in problem loans for the banks. The increases in risk incur additional costs and managerial efforts. Thus cost efficiency is expected to fall after the increase in problem loans. Under the bad management hypothesis, managers fail to control costs, which results in low cost efficiency, and they also perform poorly at loan underwriting and monitoring. These underwriting and monitoring problems eventually lead to high numbers of nonperforming loans as borrowers fall behind in their loan repayments. Therefore, the bad management hypothesis implies that lower cost efficiency leads to an increase in problem loans. On the other hand, the skimping hypothesis implies a positive Granger-causation from measured efficiency to problem loans. Under the skimping hypothesis, banks skimp on the resources devoted to underwriting and monitoring loans, reducing operating costs and increasing cost efficiency in the short run. But in the long run, nonperforming loans increase as poorly monitored borrowers fall behind in loan repayments.

Milne and Whalley (2001) develop a continuous-time dynamic option pricing model that explains the incentives of banks to hold their capital buffers above the regulatory required minimum. The capital buffer theory states that adjustments in capital and risk depend on banks' capital buffers. It predicts that, after an increase in the regulatory capital requirement (the same impact as a direct reduction in the capital buffer), capital and risk are initially negatively related as long as capital buffers are low, and after a period of adjustment when banks have rebuilt their capital buffers to some extent, capital and risk become positively related. This leads to the following hypothesis.

Hypothesis 2. *The coordination of capital and risk adjustments depends on the amount of capital buffer that a bank holds. Well capitalized banks adjust their buffer capital and risk positively while banks with a low capital buffer try to rebuild an appropriate capital buffer by raising capital and simultaneously lowering risk.*

3.2 Empirical Model

Taken all together, these studies and the models on which they are based imply that bank capital, risk and efficiency are simultaneously determined and can be expressed in general terms as follows:

$$\begin{aligned} RISK_{i,t} &= f(Cap_{i,t}, Eff_{i,t}, X_{it}) \\ Cap_{i,t} &= f(Risk_{i,t}, Eff_{i,t}, X_{it}) \\ Eff_{i,t} &= f(Cap_{i,t}, Risk_{i,t}, X_{it}) \end{aligned} \tag{1}$$

where X_{it} are bank-specific variables.

Following Shrieves and Dahl (1992) we use a partial adjustment model to examine the relationship between changes in capital and changes in risk. Shrieves and Dahl (1992) point out that capital and risk decisions are made simultaneously and are interrelated. In the model, observed changes in bank capital ratios and risk levels are decomposed into two parts: a discretionary adjustment and an exogenously determined random shock such that:

$$\begin{aligned} \Delta CAP_{i,t} &= \Delta^d CAP_{i,t} + \epsilon_{i,t} \\ \Delta RISK_{i,t} &= \Delta^d CAP_{i,t} + \mu_{i,t} \end{aligned} \tag{2}$$

where $\Delta CAP_{i,t}$ and $\Delta RISK_{i,t}$ are observed changes in capital and risk respectively, for bank i in period t. $\Delta^d CAP_{i,t}$ and $\Delta^d RISK_{i,t}$ represent the discretionary adjustments in capital and risk. $\epsilon_{i,t}$ and $\mu_{i,t}$ are the exogenous random shocks. Banks aim to achieve optimal capital and risk levels, but banks may not be able to achieve their desired levels instantaneously. Hence, banks can only adjust capital and risk levels partially towards the target levels. The discretionary adjustment in capital and risk is thus modeled in the partial adjustment framework:

$$\begin{aligned} \Delta^d CAP_{i,t} &= \alpha(CAP^*_{i,t} - CAP_{i,t-1}) \\ \Delta^d RISK_{i,t} &= \beta(RISK^*_{i,t} - RISK_{i,t-1}) \end{aligned} \tag{3}$$

where α and β are speed of adjustment; $CAP^*_{i,t}$ and $RISK^*_{i,t}$ are optimal level of capital and risk and $CAP_{i,t-1}$ and $RISK_{i,t-1}$ are the actual levels of capital and risk in the previous period.

Substituting Equations (3) into Equation (2) and accounting for the simultaneity of capital and risk decisions, the changes in capital and risk can be written as:

$$\begin{aligned} \Delta CAP_{i,t} &= \alpha(CAP^*_{i,t} - CAP_{i,t-1}) + \gamma \Delta RISK_{i,t} + \epsilon_{i,t} \\ \Delta RISK_{i,t} &= \beta(RISK^*_{i,t} - RISK_{i,t-1}) + \phi \Delta CAP_{i,t} + \mu_{i,t}. \end{aligned} \tag{4}$$

Equation (4) shows the observed changes in capital and risk are a function of the target capital and risk levels, the lagged capital and risk levels, and any random shocks. Examples of exogenous shocks to the bank that could influence capital or risk levels include changes in regulatory capital standards or macroeconomic conditions.

3.2.1 Network model

Shocks affect banks' decisions are likely to spillover to other banks, creating systemic effect. Following Denbee, Julliard, Li, and Yuan (2017), we model the network effect on banks' capital and risk holding decisions as a shock propagation mechanism where banks' decisions depend upon how the individual bank's shock propagates to its direct and indirect neighbors.

We decompose banks' decisions into a function of observables and an error term that captures the spatial spillover generated by the network:

$$Y_{it} = \underbrace{\alpha_i}_{\text{fixed effect}} + \underbrace{\sum_{m=1}^{M} \beta_m X_{it}}_{\substack{\text{effect of observable} \\ \text{bank characteristics}}} + \underbrace{\sum_{p=1}^{P} \gamma_p Macro_t}_{\substack{\text{impact of systematic} \\ \text{risk factors}}} + u_{it} \tag{5}$$

$$u_{it} = \underbrace{\lambda \sum_{j=1}^{N} w_{ij} u_{jt}}_{\text{shock propagation}} + \epsilon_{it} \tag{6}$$

where Y_{it} are banks' capital and risk holding decisions, λ is a spatial autoregressive parameter, and w_{ij} are the network weights. The network component u_{it} is thus modelled as a residual term.[2] The vector of shocks to all banks at time t can be rewritten in matrix form as:

$$u_t = (I_N - \lambda W)^{-1} \epsilon_t \equiv M(\lambda, W) \epsilon_t$$

[2]There may also be a more general spatial autoregressive structure that the network effect is modeled in the dependent or independent variables. But this study focuses on spillovers in how shocks of one bank propagate to other banks which is best represented by the spatial error model.

and expanding the inverse matrix as a power series yields:

$$M(\lambda, W) = I + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + ... \tag{7}$$

$$= \sum_{k=0}^{\infty} \lambda^k W^k \tag{8}$$

where λ can also be interpreted as network multiplier effect. We need $|\lambda| < 1$ for stability. The matrix $M(\lambda, W)$ measures all direct and indirect effect of a shock to bank i on bank j.

The network impulse-response function of banks' capital and risk holdings, to a one standard deviation shock σ_i to a given bank i is given by:

$$IRF_i(\lambda, \sigma_i) \equiv \frac{\partial Y_t}{\partial \epsilon_{i,t}} = 1' M(\lambda, W)_i \sigma_i.$$

The average network multiplier resulting from a unit shock equally spread across the n banks can be expressed as:

$$1' M(\lambda, W) 1 \frac{1}{n} = \frac{1}{1 - \lambda}.$$

A positive λ indicates an amplification effect that a shock to any bank would be amplified by the banking network system. On the other hand, a negative λ indicates a dampening effect on shock transmission.

3.2.2 Measures of capital and risk

Given the regulatory capital requirements associated with Basel I, II and III, capital ratios are measured in three ways: Tier 1 risk-based ratio, total risk-based ratio and Tier 1 leverage ratio. Tier 1 risk-based capital ratio is the proportion of core capital to risk-weighted assets where core capital basically consists of common stock and disclosed reserves or retained earnings. Tier 2 capital includes revaluation reserves, hybrid capital instruments and subordinated term debt, general loan-loss reserves, and undisclosed reserves. Total risk-based ratio is the percentage of Tier 1 and Tier 2 capital of risk-weighted assets. Tier 1 leverage ratio is the ratio of Tier 1 capital to total assets. The higher the ratio is, the higher the capital adequacy.

The literature suggests a number of alternatives for measuring bank risk. The most popular measures of bank risk are the ratio of risk-weighted assets to total assets (*RWA*) and the ratio of non-performing loans to total loans (*NPL*). The ratio of risk-weighted assets is the regulatory measure of bank portfolio risk, and was used by Shrieves and Dahl (1992), Jacques and Nigro (1997), Rime (2001), Aggarwal and Jacques (2001), Stolz et al. (2003) and many others. The standardized approach to calculating risk-weighted assets involves multiplying the amount of an asset or exposure by the standardized risk weight associated with that type of asset or exposure. Typically, a high proportion of RWA indicates a higher share of riskier assets. Since its inception, risk weighting methodology has been criticized because it can be manipulated (for example, via securitization), NPL is thus used as a complementary risk measure as it might contain information on risk differences between banks not caught by RWA. Non-performing loans is measured by loans past due 90 days or more and non-accrual loans and reflect the ex-post outcome of lending decisions. Higher values of the NPL ratio indicate that banks ex-ante took higher lending risk and, as a result, have accumulated ex-post higher bad loans.

3.2.3 Variables affecting changes in capital, risk and efficiency

The target capital ratio and risk level are not observable and typically depend on some set of observable bank-specific variables. We do so as well in our analysis. Loan loss provisions (LLP) as a percentage of assets are included as a proxy for asset quality. A higher level of loan loss provisions indicates an expectation of more trouble in the banks' portfolios and a resulting greater need for capital, and thus might capture ex-ante credit risk or expected losses. The loan-to-deposit ratio (LTD) is a commonly used measure for assessing a bank's liquidity. If the ratio is too high, it means that the bank may not have enough liquidity to cover any unforeseen fund requirements, and conversely, if the ratio is too low, the bank may not be earning as much as it otherwise earns. Size will likely impact a bank's capital ratios, efficiency and level of portfolio risk, because larger banks are inclined to have larger investment opportunity sets and are granted easier access to capital markets. For these reasons, they have been found to hold less capital ratios than their smaller counterparts (Aggarwal and Jacques (2001)). We include the natural log of total assets as the proxy for bank size. Bank profitability is expected to have a positive effect on bank capital if the bank prefers to increase capital through retained earnings. An indicator of profitability is measured by return on assets (ROA) and return on equity (ROE).

Macroeconomic shocks such as a recession and falling housing prices can also affect capital ratios and portfolios of banks. In order to capture the effect of common macroeconomic shocks that may have affected capital, efficiency and risk during the period of study, the annual growth rate of real U.S. GDP and Case-Shiller Home Price Index are included as controls. Crisis is a dummy variable that takes the value of 1 if the year is 2007, 2008 or 2009.

The regulatory pressure variable describes the behavior of banks close to or below the regulatory minimum capital requirements. Capital buffer theory predicts that an institution approaching the regulatory minimum capital ratio may have incentives to boost capital and reduce risk to avoid the regulatory cost triggered by a violation of the capital requirement. We compute the capital buffer as the difference between the total risk-weighted capital ratio and the regulatory minimum of 8%. Consistent with previous work, we use a dummy variable REG to signify the degree of regulatory pressure that a bank is under. Since most banks hold a positive capital buffer, we use the 10th percentile of the capital buffer over all observations as the cutoff point. The dummy REG is set equal to 1 if the bank's capital buffer is less than the cutoff value and zero otherwise. To test the predictions outlined above, we interact the dummy REG with variables of interest. For example, in order to capture differences in the speeds of adjustment of low and high buffer banks, we interact REG with the lagged dependent variables Cap_{t-1} and $Risk_{t-1}$. In addition, to assess differences in short term adjustments of capital and risk that depend on the degree of capitalization, we interact the dummy REG with $\Delta Risk$ and ΔCap in the capital and risk equations respectively. A summary of variable description is presented in Table C.2 in the Appendix.

Given the discussion above, Equation (1) can be written as:

$$
\begin{aligned}
\Delta RISK_{i,t} =& \alpha_0 + \alpha_1 \Delta Cap_{i,t} + \alpha_2 Eff_{i,t} + \alpha_3 RISK_{i,t-1} + \alpha_4 X_{i,t} + \alpha_5 \Delta Macro_t \\
& + \alpha_6 REG_{i,t} \times \Delta Cap_{i,t} + \alpha_7 REG_{i,t} \times Risk_{i,t-1} + v_{i,t} \\
\Delta Cap_{i,t} =& \gamma_0 + \gamma_1 \Delta Risk_{i,t} + \gamma_2 Eff_{i,t} + \gamma_3 Cap_{i,t-1} + \gamma_4 X_{i,t} + \gamma_5 \Delta Macro_t \\
& + \gamma_6 REG_{i,t} \times \Delta Risk_{i,t} + \gamma_7 REG_{i,t} \times Cap_{i,t-1} + u_{i,t} \\
Eff_{i,t} =& \sigma_0 + \sigma_1 \Delta Risk_{i,t} + \sigma_2 \Delta Cap_{i,t} + \sigma_3 X_{i,t} + \sigma_4 \Delta Macro_t + w_{i,t}
\end{aligned}
\tag{9}
$$

3.2.4 Measures of cost efficiency

Consistent with conventional bank efficiency studies, we use stochastic frontier analysis (SFA) to estimate efficiency for each bank. Stochastic frontier analysis, proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977), is often referred to as a composed error model where one part represents statistical noise with symmetric distribution and the other part, representing inefficiency. See Appendix A for a more detailed description of stochastic frontier models. The cost efficiency is the most widely used efficiency criterion in the literature, and measures the distance of a banks cost relative to the cost of the best practice bank when both banks produce the same output under the same conditions. A bank's production function uses labor and physical capital to attract deposits. The deposits are used to fund loans and other earning assets. Inputs and outputs are specified according to the intermediation model Sealey and Lindley (1977).

Following Yener Altunbas et al. (2007), we specify a cost frontier model with two-output three-input, and a translog specification of the cost function:

$$\begin{aligned}\ln TC = {} & \beta_0 + \gamma t + 0.5\gamma t^2 \\ & + \sum_{h=1}^{3}(\alpha_h + \theta_h t)\ln w_h + \sum_{j=1}^{2}(\beta_j + c_h t)\ln y_j \\ & + 0.5(\sum_{j=1}^{2}\sum_{k=1}^{2}\beta_{jk}\ln y_j \ln y_k + \sum_{h=1}^{3}\sum_{m=1}^{3}\lambda_{hm}\ln w_h \ln w_m) \\ & + \sum_{i=1}^{2}\sum_{m=1}^{3}\rho_{im}\ln y_i \ln w_m - u + v \end{aligned} \tag{10}$$

where TC represents the total cost, y are outputs, w are input prices, and t is a time trend to account for technological change, using both linear and quadratic terms. Inputs are borrowed funds, labor, and capital. Outputs are securities and loans. The inclusion of a quadratic time trend and a time interaction with outputs and input prices enables the measurement of time-dependent effects in costs, such as the pure technical change and non-neutral technological shifts of the cost frontier. The term v is a random error that incorporates both measurement error and luck. The term u is a firm effect representing the bank's technical inefficiency level. It measures the distance of an individual bank to the efficient cost frontier. A description of input and output variables are shown in Table C.1 in the Appendix.

4 Estimation

4.1 Endogenity

The system of Equation (9) suffers from endogeneity of variables. This endogeneity will make OLS estimators inconsistent. The Instrumental Variable (IV) - Generalized Method of Moments (GMM) estimator is suited to deal with endogeneity issues by means of appropriate instruments. Arellano and Bond (1991) suggest a GMM estimator that uses lagged levels of endogenous variables as instruments for equations in first differences. Later Blundell and Bond (1998) find that the lagged levels may become poor instruments for first differenced variables, especially if the variables are highly persistent. Their modification of the estimator includes lagged levels as well as lagged differences. Therefore, we use the 2-step efficient GMM procedure and the instruments (in lags and difference form) as suggested by Blundell and Bond (1998). These GMM types of instruments for endogenous capital and risk variables are also used in Stolz et al. (2003), Fiordelisi et al. (2011) and De-Ramon, Francis, and Harris (2016). To avoid the proliferation of the instrument set, we follow Roodman (2009)'s advice to collapse the instrument matrix so that there are not unique instruments for each time period as in Arellano and Bond (1991) and the number of lags is up to two.

To verify that the instruments are statistically valid, we use Hansen's J-test (for GMM estimator) and Sargan's test (for 2SLS estimator) of overidentifying restrictions. The null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. A failure to reject the null should be expected in the GMM regression. To evaluate the strength of instruments, we look at Cragg-Donald Wald F statistic and compare it to Stock and Yogo (2002) critical values for testing weakness of instruments. To reject the null of weak instruments, the Cragg-Donald F statistic must exceed the tabulated critical values.

4.2 Spatial Correlation

In order to estimate the network model described in Section 3.2.1, we need to map the observed adjustment in capital and risk as well as efficiency levels into two components - the common factors and the unobserved network ones. To do this, we employ a fixed effect spatial error model (SEM). The model takes the form:

$$\begin{aligned} y_{it} &= X_{it}'\beta + e_{it} \\ e_{it} &= e_i + \phi_t + u_{it} \end{aligned}$$

where e_i denotes the vector of individual effects, ϕ_t is a time period effect to capture common shocks and u_{it} is the remainder disturbances independent of e_i. The term u_{it} follows the first order autoregressive error dependence model:

$$\begin{aligned} u_{it} &= \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \epsilon_{it} \\ \epsilon &\sim N\left(0, \sigma^2 I_N\right) \end{aligned}$$

where W is the matrix of known spatial weights and λ is the spatial autoregressive coefficient. Or, in matrix notation

$$\begin{aligned} Y &= X\beta + \mathbf{u}, \\ \mathbf{u} &= \lambda W \mathbf{u} + \epsilon \end{aligned}$$

As with autocorrelation in time series, a failure to account for spatial error correlation when $\lambda \neq 0$ would cause a misspecification of the error co-variance structure and thus compromise interval estimates and tests of the importance of various regulatory interventions.

Therefore, we further decompose the error term in Equation (9) to capture the spatial dependence generated by the network:

$$\begin{aligned} \Delta RISK_{i,t} =& \alpha_0 + \alpha_1 \Delta Cap_{i,t} + \alpha_2 Eff_{i,t} + \alpha_3 RISK_{i,t-1} + \alpha_4 X_{i,t} + \alpha_5 \Delta Macro_t \\ & + \alpha_6 REG_{i,t} \times \Delta Cap_{i,t} + \alpha_7 REG_{i,t} \times Risk_{i,t-1} + v_{i,t} \\ \Delta Cap_{i,t} =& \gamma_0 + \gamma_1 \Delta Risk_{i,t} + \gamma_2 Eff_{i,t} + \gamma_3 Cap_{i,t-1} + \gamma_4 X_{i,t} + \gamma_5 \Delta Macro_t \\ & + \gamma_6 REG_{i,t} \times \Delta Risk_{i,t} + \gamma_7 REG_{i,t} \times Cap_{i,t-1} + u_{i,t} \\ Eff_{i,t} =& \sigma_0 + \sigma_1 \Delta Risk_{i,t} + \sigma_2 \Delta Cap_{i,t} + \sigma_3 X_{i,t} + \sigma_4 \Delta Macro_t + w_{i,t} \\ u_{it}(\text{or } v_{it} \text{ and } w_{it}) =& \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \epsilon_{it} \end{aligned} \tag{11}$$

This error term in the system of equations describes the process of bank i, which is the residual of individual bank i's risk-taking behavior/capital adjustment/level of efficiency in the network that is not due to bank-specific characteristics or systematic factors. The weights matrix, w_{ij}, is assumed to be constant over time. If there is no spatial correlation between the errors for connected banks i and j, the spatial error parameter λ will be 0, and the model reduces to the standard non-spatial model where the individual observations are independent of one another. If $\lambda \neq 0$, then we have a pattern of spatial dependence between the errors for connected banks. This could reflect other kinds of misspecifications in the systematic component of the model, in particular, omitted variables that are spatially clustered. Typically we expect to see a positive spatial correlation, implying the clustering of similar units, i.e., the errors for observation i tend to vary systematically in size with the errors for its nearby observations j. The above discussion suggests the following hypothesis.

Hypothesis 3. *There exists unobserved spatial dependence among banks such that any shocks on bank i will have an impact on bank j and the size of impact depends on the (economic) distance between them (i.e. $\lambda > 0$).*

As outlined in the Appendix B, we can estimate the parameters of the fixed effect spatial error model using a quasi-maximum likelihood (QML) approach.

Prior to fitting a spatial regression model to the data, we can test for the presence of spatial dependence using Moran's test to the residuals from an OLS regression. In general, Moran's statistic is given by:

$$M = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2}$$

where N is the number of spatial units indexed by i and j, X is the variable of interest, $\bar{X}$ is the mean of X, and w_{ij} is the (i, j)-element of the spatial weights matrix.

4.2.1 Spatial weights matrix and financial network

The choice of the spatial weights matrix is of crucial importance to estimate the spatial model. Commonly employed methods to assign weights include contiguity, k-nearest neighbor, distance decay, and non-spatial definitions. In the Euclidean distance case, distance is measured in terms of the inverse, or proximity, so that the weight attached to a distant bank is smaller than one that is near. In the common boundary and nearest neighbor cases, each element w_{ij} is a binary indicator of whether banks i and j share a common market boundary or are nearest neighbors, respectively. Different from commonly estimated spatial models, we do not consider physical distance in constructing the weighting matrix in this study because the interlinkages in the banking sector normally go beyond the geographical boundaries. In particular, geographical proximity may facilitate financial integration, but it is not a necessary condition for such an integration to hold, given that most transactions are performed electronically nowadays. Therefore, the challenge is how to construct a structure of the "economic distance" between banks and define the channel for cross-sectional spillovers.

In this section, we describe several approaches to identify banking networks. In the banking literature, several ways are considered to construct networks building on the economic concept of intermediation. For example, some authors use bilateral exposure positions based on balance sheet data (e.g. asset, liabilities, deposit and loans) to construct the interbank networks (see B. Craig and Von Peter (2014), B. R. Craig, Koetter, and Kruger (2014) and Upper and Worms (2004)). Furfine (2003) and Bech and Atalay (2010) use interbank payment flows to quantify the bilateral federal funds exposures in the U.S. federal funds market. Figure 1 below illustrates the evolution in the international financial networks, showing the trend of increasing scale and interconnectivity.

In addition to bilateral exposures, Fernandez (2011) use correlation between key financial indicators in the CAPM framework to construct weighting matrices. The metric distance between bank i and j is specified as:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}$$

where ρ is Spearman's correlation coefficient between a specific financial indicator (e.g. market-to-book ratio and market cap relative to bank size) associated with bank i and j.

We construct the network based on clustering of residuals. The key idea is to first estimate Equation (9) using two-step GMM regression and obtain the residuals $\hat{u}_{it}$ from the regressions. The residuals capture the unobserved heterogeneity that goes beyond systematic factors and banks' own idiosyncratic characteristics and thus might be a representation of unobserved network heterogeneity across banks. Based on the residuals $\hat{u}_{it}$, we construct data-driven

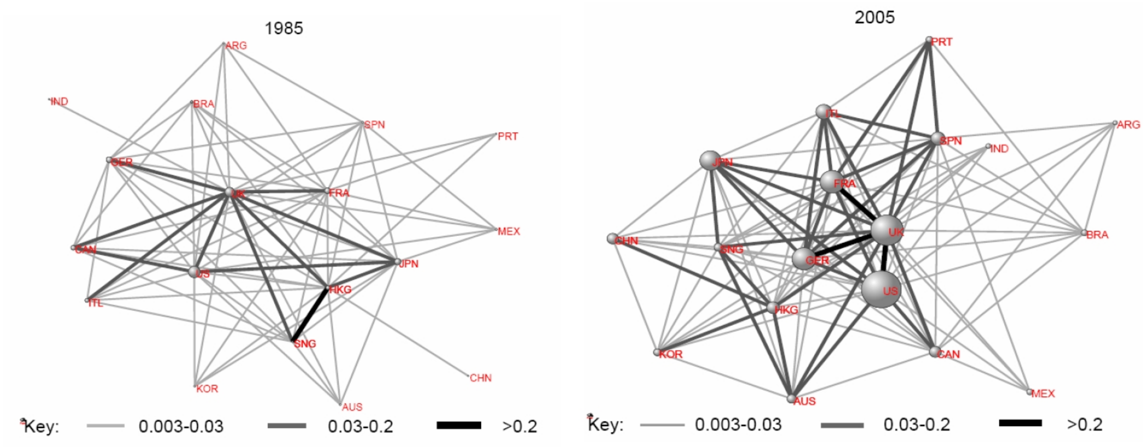

Figure 1: The Global Financial Network in 1985 and 2005

The nodes are scaled in proportion to total external financial stocks, and line thickness between nodes is proportional to bilateral external financial stocks relative to GDP.
Source: Figure taken from Haldane (2009).

correlation networks through different clustering methods. Here we consider k-nearest-neighbor and hierarchical clustering methods. These different clusters might be a way to represent the latent markets that the bank operates. For instance, Figure 2 below represents one of the outputs of the framework in terms of network visualization and it is a visualization of the estimated network based on assets, capital buffer and liabilities. Figure 3 is a network visualization of the top 10 banks in the U.S. by asset size in 2007 and 2015. Node size is proportional to total asset size of the bank.

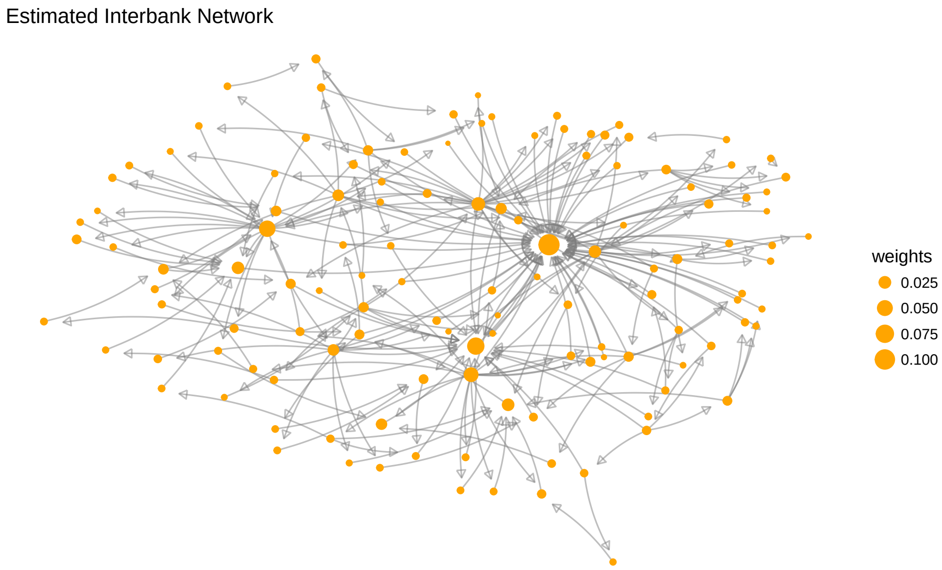

Figure 2: Estimated interbank network based on assets, capital buffer and liabilities

Note: Weight is a function of assets, capital buffer and liabilities.

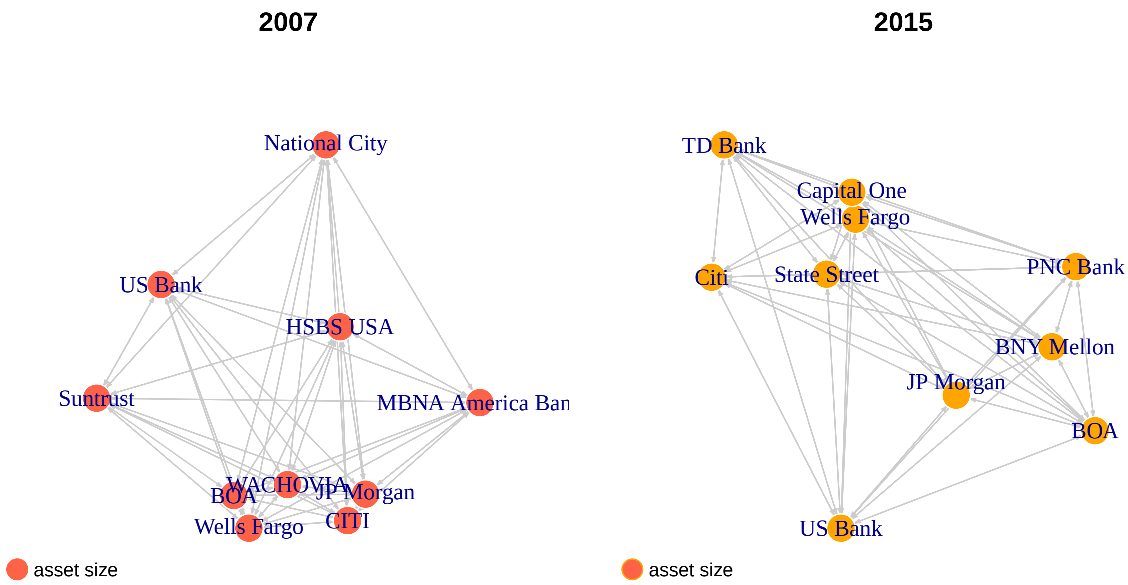

Figure 3: Network visualization of the top 10 banks in the U.S. by asset size in 2007 and 2015. Node size is proportional to total asset size of the bank.

Note: Wachovia was acquired by Wells Fargo in 2008. MBNA America Bank (renamed to FIA Card Services) was acquired by BOA in 2014. National City Bank was closed in 2009.

K-nearest-neighbor classifier is one of the most commonly used cluster methods that is normally based on the Euclidean distance between observations. Alternatively, we can implement a hierarchical clustering approach. we implement Ward's hierarchical clustering procedure and an example of the clustering output is displayed as a dendrogram below:

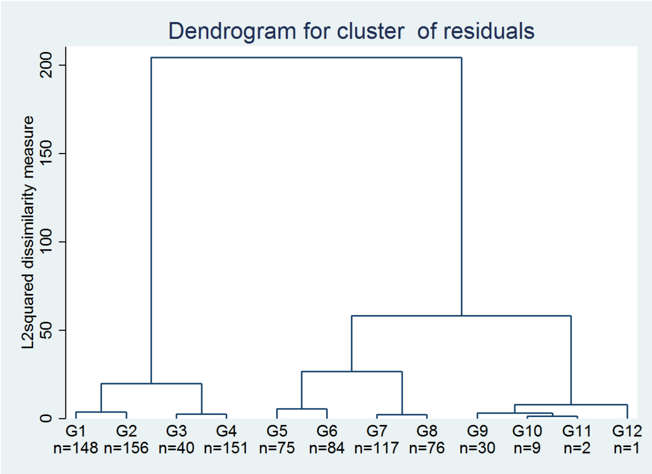

Figure 4: Dendrogram plots of the cluster of residuals

Now let's define the weights matrix. Let W be the k-dimensional square matrix representing a network composed of k banks. Each entry w_{ij} represents the possible connection between bank i and j. The spatial weights matrix is then defined as:

$$W_{ij} = \begin{cases} 1, & \text{if } j \in G_i \\ 0, & \text{otherwise} \end{cases}$$

where G_i denotes the group of i. An example of the binary weights matrix is as follows:

$$W = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix}$$

where the diagonal contains only null elements (each bank is not its own neighbor) and the network is symmetric. According to Elhorst (2003), W is row-normalized such that the elements of each row sum to unity. Therefore, the spatial weights matrix W is a row-normalized binary contiguity matrix, with elements $w_{ij} = 1$, if two spatial units are in the same group and zero otherwise.

The spatial weights matrix, W should satisfy certain regularity conditions:

Assumption A1: The diagonal elements of W are set to zero, since no spatial unit can be viewed as its own neighbor.

Assumption A2: The matrices $(I_N - \lambda W)^{-1}$ are non-singular, where I_N represents the identity matrix of order N.

Assumption A3(a): The row and column sums of the matrices W, and $(I_N - \lambda W)^{-1}$ before W is row-normalized should be uniformly bounded in absolute value as N goes to infinity (Kelejian and Prucha (1998)), or

Assumption A3(b): The row and column sums of W before W is row-normalized should not diverge to infinity at a rate equal to or faster than the rate of the sample size N(L.-F. Lee (2004)).

4.2.2 Estimation and testing when the weights matrix is misspecified

Proper specification of the weighting matrix in the spatial error model is rather a daunting task for the econometricians. The specification of the spatial weights matrix W requires a prior knowledge of the spatial correlation between units and W needs to be exogenous to the model. Hence, the right choice of a spatial weights matrix is crucial to identify the correct model. To address this issue, in this section we include a discussion on the estimation and testing when the weights matrix is misspecified and propose a method to test for the misspecification of the weight matrix and ways of refinement.

Work by Qu and Lee (2015) and Liu and Prucha (2016) focuses on issues related to our objectives. Qu and Lee (2015) tackle the issue of an endogenous spatial weights matrix by exploring the model structure of spatial weights in a cross-sectional setting. They overcome the endogeneity problem using control function methods and propose three estimation methods: two-stage instrumental variable (2SIV) method, quasi-maximum likelihood estimation (QMLE) approach and generalized method of moments (GMM).

Liu and Prucha (2016) introduce a robust testing procedure by generalizing the widely used Moran (1950) I test for dependence in spatial networks. The problem in using the Moran I and available LM tests for spatial models are that one is often unsure about how to specify the weight matrix employed by the test and hence needs to adopt a sequential testing procedure based on different specifications of the weight matrix. Motivated by this problem Liu and Prucha (2016) propose a single test statistic by incorporating information from multiple weight matrices. In this sense, the test statistic combines a set of Moran I tests into a single test. By its construction the generalized Moran I test could be useful for detecting network generated dependence in a wide range of situations. This includes situations where the weights matrix representing the network is misspecified and/or endogenous.

We propose an alternative approach to test for misspecification of the weighting matrix by using a two step method based on the use of general factor-type structures introduced in Kneip, Sickles, and Song (2012) and Bai (2009).

Consider the following spatial error model:

$$
\begin{aligned}
Y_{it} &= X_{it}\beta + u_{it}, & (12)\\
u_{it} &= \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it}^{*}, & (13)\\
\varepsilon_{it}^{*} &= \eta_{it} + v_{it} & (14)
\end{aligned}
$$

where $\eta_{it} = \omega_i + \varpi_t$ and where ω_i is a $t \times t$ sparse matrix of terms that pick up any possible misspecified spatial correlations not addressed by the specification of the weighting matrix W. The assumption about the "measurement error" in W is crucial. Suppose the true W is a banded matrix. Then, by definition, any algorithm determining the cluster structure of the data will fail to a certain extent. It will determine, say K clusters – i.e., K diagonal blocks – where the true W that is not block-diagonal. In our model above we thus wish to first test for the presence of spatial effects left-over after the estimation of the system with $\omega_i = 0$ and then respecify the covariance structure to address any left over spatial correlations that may still exist due to the original misspecification using the standard approaches we have outlined above. The extent to which a simple clustering estimator fails – in case that the true W is not block-diagonal – depends on standard issues for clusters as well as to what extent the decay within blocks is misspecified by the assumed W in comparison with the true weighting matrix. A question is how to compare inadequate estimators in such a test that will depend on the "distance" (the measurement error) between the true and the identified W. There may be points which are outside of any cluster but correlated with others (undertreatment) and others that are inside the identified W which are truly independent (overtreatment). The outcome will depend on the variance-covariance of the over- and under-treated observations with the rest of the units. To do this, we again turn to the Kneip et al. (2012) estimator.

Kneip et al. (2012) (KSS) estimator can be utilized in the model setting we are considering by framing the misspecified weighting matrix in the error term above as:

$$Y_{it} = X_{it}\beta + \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \eta_{it} + v_{it}. \tag{15}$$

The effects η_{it} are assumed to be affected by a set of underlying factors and are formulated by linear combinations of some basis functions:

$$\eta_{it} = \sum_{r=1}^{L} \delta_{ir} g_r(t) \tag{16}$$

For identifiability, it is assumed that $\sum_i^n \eta_{it} = 0$, $t = 1, \ldots, T$. The intercept α_t can be eliminated by transforming the model to the centered form,

$$y_{it} - \bar{y}_t = (X_{it} - \bar{X}_t)'^{L}_{r=1} \delta_{ir} g_r(t) + v_{it} - \bar{v}_t \tag{17}$$

where $\bar{y}_t = \frac{1}{n}\sum_i y_{it}$, $\bar{X}_t = \frac{1}{n}\sum_i X_{it}$ and $\bar{v}_i = \frac{1}{n} v_{it}$. Denote $\tilde{y}_{it} = y_{it} - \bar{y}_t$ and $\tilde{X}_{it} = X_{it} - \bar{X}_t$, we return to the model setting

$$\tilde{y}_{it} = \tilde{X}'_{it}\beta + \sum_{r=1}^{L} \delta_{ir} g_r(t) + \tilde{v}_{it} \tag{18}$$

We can see that the individual effects η_{it} are assumed to be determined by a number of underlying factors, which are represented by a set of basis functions $(g_1(t), \ldots, g_L(t))$. Denote $\mathcal{L} \equiv span\{g_1, \ldots, g_L\}$ to be the space of the underlying factors. A problem is that the set of basis functions is not unique, and thus a normalization is needed for the estimation problem to be well defined. KSS used the following normalization.

(a) $\frac{1}{n}\sum_{i=1}^{n} \delta_{i1}^2 \geq \frac{1}{n}\sum_{i=1}^{n} \delta_{i2}^2 \geq \cdots \geq \frac{1}{n}\sum_{i=1}^{n} \delta_{iL}^2 \geq 0$

(b)$\frac{1}{n}\sum_{i=1}^{n} \delta_{ir} = 0$ and $\frac{1}{n}\sum_{i=1}^{n} \delta_{ir}\delta_{is} = 0$ for all r, $s \in 1, \ldots, L$, $r \neq s$.

(c) $\frac{1}{T}\sum_{t=1}^{T} g_r(t)^2 = 1$ and $\frac{1}{T}\sum_{t=1}^{T} g_r(t) g_s(t) = 0$ for all r, $s \in 1, \ldots, L$, $r \neq s$.

Provided that $n > L$, $T > L$, conditions (a) - (c) do not impose any restrictions, and they introduce a suitable normalization, which ensures identifiability of the components up to sign changes (instead of δ_{it}, g_r , one may use $-\delta_{ir}$, $-g_r$). Note that (a) - (c) lead to orthogonal vectors g_r as well as empirically uncorrelated coefficients δ_i. Bai (2003) uses expectations in (a) and (b), which leads to another standardization and different basis functions, which are determined from the eigenvectors of the (conditional) covariance matrix. Additionally, the KSS method utilizes cross-validation to determine the dimension of the underlying factor space, and then applies spline theory to obtain the estimates of basis functions.

The two-step version of the weighting matrix estimator proceeds as follows. First estimate the original model with the possibly misspecified weighting matrix, assuming that the misspecified portion of the weighing matrix is orthogonal to the spatial weights and the other regressors. Next, construct the residuals from this regression and utilize them in estimating the factor structure of the $\eta_{it}'s$. We can then decompose the estimated factors into cross-section and time effects ($\eta_{it} = \omega_i + \varpi_t$) and use the estimated $\omega_i's$ to test for the presence of misspecified spatial effects. If the testing results (possibly using the generalized new Moran test of Liu and Prucha, 2016) suggest that spatial errors are still present we can use the estimated $\omega_i's$ to further refine our models of the weighting matrix using the methods we have deployed above.

4.3 Correction for Selection Bias

An additional issue when estimating Equation (11) arises when observations are missing in the spatial model. This can occur for several different reasons but in the banking study, it occurs due to the fact that banks are either merged, or they are dissolved. Often the reasons for the banks no longer having autonomy or leaving the industry are not due to criteria that are easily modeled by the econometricians. As discussed in Almanidis, Qian, and Sickles (2014), one approach to deal with this issue is to express the data for a bank on a pro-forma basis that goes back in time to account for mergers, that is, all past balance sheet and income observations of non-surviving banks are added to the surviving banks. This approach is adopted by the Federal Reserve in estimating risk measurement models, such as the Charge-off at Risk Model (Frye and Pelz (2008)). This option is preferable when a large bank acquires a much smaller bank. An alternative is to use a balanced panel by deleting banks that attrite from the sample. This is the traditional approach that is applied by many existing studies in the banking literature.

However, there is a potential for substantial selection bias arising from the correlation of the error terms in the selection and capital/risk/efficiency equations. In order to utilize the available spatial econometrics toolbox that applies to balanced panel only and account for selection bias, we apply a Heckman (1979) type 2-step correction.

The first step of the Heckman type estimation is dealt with by using a probit regression of all banks in the full sample, with the stay/exit dummy as a function of a set of bank-specific and market characteristics variables:

$$\Pr(S = 1|Z) = \Phi(Z\gamma)$$

where $S = 1$ if the bank stays in the market and $S = 0$ otherwise, Z is a vector of explanatory variables, γ is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution. From these estimates, the non-selection hazard-what Heckman (1979) referred to as the inverse Mills ratio, m_i for each observation i is computed as

$$m_i = \frac{\phi(Z'\hat{\gamma})}{\Phi(Z'\hat{\gamma})}$$

where ϕ denotes the standard normal density function. The inverse-mills ratio (*invmills*) or m_{it}, is then added to the regression specified by (1) on a subsample of balanced panels excluding banks that exit the market. This is the second step of the procedure and a significant coefficient of *invmills* indicates the existence of sample selection bias.

5 Data

All bank-level data is constructed from the Consolidated Report of Condition and Income (referred to as the quarterly Call Reports) provided by the Federal Deposit Insurance Corporation (FDIC). The sample includes all banks in the Call Report covering the period from 2001:Q1 to 2016:Q3. Complete data of period 2001-2010 is available from the website of the Federal Reserve Bank of Chicago[3] and data after 2011 is available from the FFIEC Central Data Repository's Public Data Distribution site (PDD)[4]. we also collected data on U.S. Gross Domestic Product (GDP) and Case-Shiller Home Price Index from Federal Reserve Bank of St. Louis. we filter

[3]https://www.chicagofed.org/banking/financial-institution-reports/commercial-bank-data
[4]https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx

the sample as follows. First, we drop missing data for key variables in the model. The variables computed from the Call Reports frequently have a few extreme outliers, most likely due to reporting errors or small denominators, so we drop the lowest and highest 1% of the observations for key variables. we also dropped banks with negative and zero total assets, deposits and loans. Finally, we eliminate very small banks (total assets less than 25 million) and banks observed in only one year, which could introduce bias. we end up with an unbalanced panel data on 8055 distinct banks, yielding 330,970 bank-quarter observations over the whole sample period. To do spatial analysis using spatial econometrics toolbox that applies to the balanced panel only, we keep banks who existed for all periods, leading to a balanced panel data of 889 banks, yielding 55,118 bank-quarter observations over the whole sample period.

Table 5.1 presents a descriptive summary of key variables in the full sample (panel A) and compares the sample mean for 3 periods: pre-crisis, crisis and post-crisis (panel B). All variables are averaged by banks from 2001-2016. Figure 5 shows the time series plots of bank risks, capital ratios, assets, profits, liquidity, and average capital and interest costs for the average bank over 2001-2016.

In general, the majority of banks in the sample have been well capitalized throughout the sample period. The average bank has exceeded the minimum required capital ratio by a comfortable margin. In my sample, the mean capital buffer above capital requirements is 8.43 %. The average Tier 1 capital ratio is 15.26% and the average risk-based capital ratio is 16.43% during 2001-2016. The findings show that banks tend to hold considerable buffer capital.

Comparing average bank portfolios during the pre-crisis, crisis and post-crisis period, it is evident that an average bank was hit hard by the financial turmoil. The average *ROE/ROA* dropped from its highest level (7%/0.7%) in 2005 to its lowest (2%/0.2%) in 2009. The time trend of capital ratios show a steady movement until a drop in 2008 and then picked up after 2010. The time series plots of two measures of bank risks show a similar trend. Liquidity here is measured by cash ratio and *LTD*. The average *LTD* ratio increased steadily until the financial crisis hit and reached the peak of almost 100% in 2009, then fell precipitously until 2012 and have been rising again. The high *LTD* during crisis period suggests insufficient liquidity to cover any unforeseen risks. This sharp drop in *LTD* since 2010 could be attributed to the tightened credit management by banks after the financial crisis, the contraction in lending demand due to the sluggishness of the economy, and the measures undertaken by the government to curb excessive lending.

Panel A: Descriptive statistics of key variables for the full sample period				
	Mean	Std. Dev.	Min	Max
Stochastic frontier arguments				
Cost of physical capital	0.20	0.21	0.02	1.97
Cost of labor	35.05	18.46	8.33	102.43
Cost of borrowed funds	0.01	0.01	0.00	0.04
Total securities ($million)	51.19	74.95	0.41	770
Total loans($million)	160.17	212.36	7.61	1,726
Total Cost($million)	6.30	8.94	0.25	167
Regression arguments				
Assets($million)	239.4	301.6	9.6	3,540
Equity($million)	24.6	32.5	0.7	577
Deposit($million)	196.0	240.2	7.5	2,666
Net income ($million)	1.3	2.9	-261.6	109
Return on assets (%)	0.54	0.64	-27.48	9.16
Return on equity (%)	5.32	6.56	-304.34	83.21
Risk weighted assets (%)	68.05	11.80	36.43	95.78
NPL ratio (%)	2.73	2.73	0.00	51.27
Loan loss provision (%)	0.24	0.54	-20.92	44.54
Tier1 capital ratio (%)	15.30	5.38	7.23	43.09
Risk-based capital ratio (%)	16.43	5.37	9.91	43.48
Tier1 leverage ratio (%)	10.02	2.46	6.08	20.64
Capital buffer (%)	8.43	5.37	1.91	35.48

Panel B: Sample mean of key variables during pre-crisis, crisis and post-crisis period			
	Pre-crisis 2001q1-2007q2	Crisis 2007q3-2009q4	Post-crisis 2010q1-2016q3
Stochastic frontier arguments			
Cost of physical capital	0.201	0.192	0.192
Cost of labor	30.365	35.505	40.053
Cost of borrowed funds	0.014	0.016	0.004
Total securities ($million)	42.819	46.613	62.849
Total loans($million)	128.651	171.229	189.787
Total Cost($million)	5.747	7.702	6.205
Regression arguments			
Assets($million)	192.100	244.572	289.565
Equity($million)	18.815	24.544	31.085
Net income ($million)	1.342	0.899	1.451
Deposit($million)	155.824	196.543	240.498
Return on assets (%)	0.652	0.404	0.477
Return on equity (%)	6.720	3.989	4.440
Risk weighted assets (%)	68.244	71.086	66.302
NPL ratio (%)	2.216	3.328	2.994
Loan loss provision (%)	0.193	0.356	0.246
Loan-deposit ratio (%)	78.125	81.887	74.809
Tier1 capital ratio (%)	14.882	14.573	16.125
Risk-based capital ratio (%)	16.015	15.674	17.276
Tier1 leverage ratio (%)	9.752	9.955	10.354
Capital buffer (%)	8.015	7.674	9.276

Table 5.1: Summary statistics of the portfolios of U.S. banks

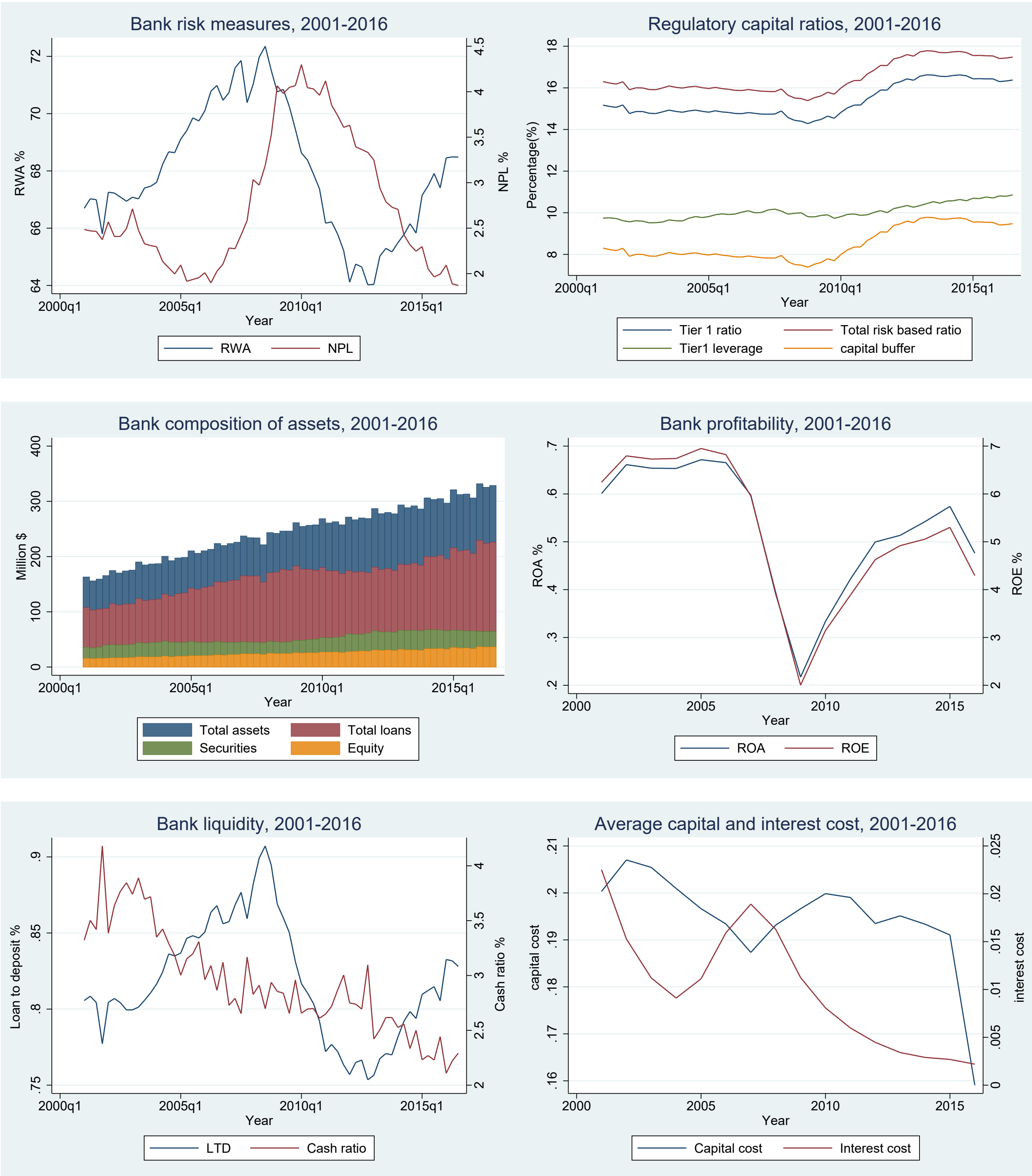

Figure 5: Time series plots of key variables for the pooled sample over 2001-2016

6 Results

We conduct two main analyses to study the effect of capital regulation on bank capital, risk, and efficiency. In the first analysis, we use a full sample of the unbalanced panel by employing two-step GMM fixed effects estimation and the results are analyzed in Section 6.2. In the second analysis, we exacted the residuals from the GMM FE regressions in the first analysis and use those to construct the weighting matrices using a balanced panel. we re-estimate the simultaneous equations using spatial FE, FE, and GMM FE respectively. The results are analyzed in Section 6.3. Capital ratios here are measured by Tier 1 risk-based ratio. we also did additional tests that used two other measures of capital ratios, and none of these cause material changes to the results reported in the tables.

6.1 Estimation of Cost Efficiency

We estimate cost efficiency specifications in Equation (10) using Battese and Coelli (1992)'s method. Parameter estimates are reported in Table D.1 in the Appendix. Estimates of the firm-specific inefficiencies, $E[u_i|\epsilon_i]$, were computed using the Jondrow et al. method. Table D.1 shows average cost inefficiency at U.S. banks to be around 0.508 and mean cost efficiency to be 0.619. That is, given its particular output level and mix, on average, the minimum cost is about 61.9% of the actual cost. Alternatively, if a bank were to use its inputs as efficiently as possible, it could reduce its production cost by roughly 50.8%.

Table 6.1 presents the level of cost efficiency for the entire sample and for different ownership and size classes during 2001-2016. Cooperative banks have higher costs efficiency than commercial and savings banks. The results are in line with Altunbas, Carbo Valverde, and Molyneux (2003)'s findings, who showed that cooperative banks have higher cost efficiency as compared to the commercial banks. Also, smaller banks are more cost efficient than are the larger banks during all periods.

	Commercial Banks	Cooperative Banks	Savings Banks	Large Banks	Small Banks	Full Sample
2001	0.667	0.740	0.642	0.581	0.668	0.667
2002	0.661	0.734	0.636	0.575	0.662	0.661
2003	0.653	0.729	0.625	0.558	0.655	0.653
2004	0.646	0.718	0.616	0.549	0.648	0.645
2005	0.638	0.712	0.607	0.539	0.640	0.638
2006	0.630	0.703	0.598	0.527	0.633	0.630
2007	0.624	0.684	0.588	0.513	0.626	0.623
2008	0.620	0.680	0.584	0.504	0.623	0.619
2009	0.615	0.671	0.576	0.492	0.619	0.614
2010	0.608	0.665	0.567	0.479	0.612	0.606
2011	0.600	0.651	0.556	0.465	0.604	0.599
2012	0.597	0.650	0.547	0.469	0.601	0.595
2013	0.588	0.648	0.542	0.469	0.592	0.587
2014	0.578	0.646	0.529	0.459	0.583	0.576
2015	0.569	0.642	0.515	0.451	0.574	0.567
2016	0.564	0.639	0.508	0.455	0.569	0.561

Notes: Large banks are banks with assets greater than 1 billion and small banks are banks with assets less than 1 billion.

Table 6.1: Cost efficiency scores by size and type of banks over years

6.2 GMM Results for the Full Sample

6.2.1 Relationships between changes in capital, risk and efficiency

Table D.2 shows the GMM fixed effect estimates of risk, capital, and efficiency equation for the full sample using two different measures of risk. Fixed effects are used to account for the possible bank-specific effects and provide consistent estimates. The Hansen statistics are also presented. The non- significance of the Hansen J-statistics indicates that the null hypothesis of valid instruments cannot be rejected for each model, confirming the validity of the instruments used.

The empirical results show that there is a strong positive two-way relationship between changes in *NPL* and changes in capital. This means banks' *NPL* holdings increase when capital increases and vice versa. This finding is consistent with Shrieves and Dahl (1992), suggesting the unintended effects of higher capital requirements on credit risk. However, when risk is measured by risk-weighted assets, the relationships become negative, contrary to the findings by Shrieves and Dahl (1992) but consistent with Jacques and Nigro (1997). This together suggests that when capital ratio increases, banks reduce ex-ante investments in risk-weighted assets but, at the same time, can have ex-post higher non-performing loans. The different signs on *NPL* and *RWA* raise concern whether risk-weighted assets are a credible measure of risk. It might be the case that banks "optimize" their capital by under-reporting *RWA* in an attempt to minimize regulatory burdens. Banks have two ways to boost their capital adequacy ratios: (i) by increasing the amount of regulatory capital held or (ii) by decreasing risk-weighted assets. Therefore, if banks capital adequacy ratios fall, banks can immediately reduce risk-weighted assets to increase the capital ratio to meet the regulatory requirement. However, non-performing loans will still stay on the balance sheets and increase over time due to compounded unpaid interests. The high non-performing loans can erode bank's financial health despite having lower rates of risk-weighted assets.

With regard to efficiency, the results show a positive relationship between efficiency and change in *NPL* as well as change in capital, suggesting more efficient banks increase capital holdings and take on greater credit risk (*NPL*), supporting the "skimping hypothesis". This finding is contrary to the results by S. H. Kwan and Eisenbeis (1996) but consistent with Yener Altunbas et al. (2007). While when risk is measured by *RWA*, efficiency and change in *RWA* is negatively related, implying that less efficient banks take on greater overall risk, supporting *Hypothesis 1* which is the moral hazard hypothesis.

Further, the results show the parameter estimates of lagged capital and risk are negative and highly significant. The coefficients show the expected negative sign and lie in the required interval [0,-1]. The can be interpreted as the speed of capital and risk adjustment towards banks' target level (Stolz et al. (2003)). The speed of risk adjustment is significantly slower than the capital adjustment, which is in line with findings by Stolz et al. (2003).

Regarding buffers, capital buffers are negatively related to adjustment in *RWA*. This finding is consistent with Vallascas and Hagendorff (2013) and according to them it might be a sign that banks underreport their portfolio risk.

6.2.2 Impact of regulatory pressures on changes in capital and risk

One important goal of this study is to assess what impact the risk-based capital standards had on changes in bank capital ratios, portfolio risk, and efficiency levels. To answer this question, an examination of the dummy REG and its interaction term provides some interesting insights. The negative coefficients of REG on both capital equations suggest that banks with low capital buffers increase capital by less than banks with large capital buffers. This result reflects the desire of very-well capitalized banks to maintain a large buffer stock of capital, and the regulatory capital requirement was effective in raising capital ratios among banks which were already in compliance with the minimum risk-based standards. The parameter estimates of REG are negative and significant on ΔNPL but positive and significant on ΔRWA, suggesting that banks with low capital buffers reduce their level of nonperforming loans by more but decrease overall risk-weighted assets by less than banks with high capital buffer. The dummy REG has a positive sign on both efficiency equations, implying banks with lower capital buffer has higher cost efficiency than banks with high capital buffer.

The interaction terms $REG \times Risk_{t-1}$ and $REG \times Cap_{t-1}$ shed further light on how the speed of adjustment towards the target level depends on the size of the capital buffer. The coefficients on $REG \times Cap_{t-1}$ are significant and positive, indicating that banks with low capital buffer adjust capital toward their targets faster than better capitalized banks. This is in line with the study by Berger, DeYoung, Flannery, Lee, and Oztekin (2008) in which they find that poorly capitalized and merely adequately capitalized banks adjust toward their capital targets at a faster speed than do already well capitalized banks. With respect to risk, we find that the coefficient of $REG \times Risk_{t-1}$ has the negative sign when risk is measured by *RWA* but becomes positive when risk is measured by *NPL*. The results suggest that banks with low capital buffer adjust *NPL* faster but adjust *RWA* slower than banks with high capital buffers.

The interaction terms of $REG_{i,t} \times \Delta Cap_{i,t}$ and $REG_{i,t} \times \Delta Risk_{i,t}$ represent the impact of capital buffer on the management of short term risk and capital adjustments. We find that the coefficients on $REG_{i,t} \times \Delta Cap_{i,t}$ is insignificant when risk is measured by *NPL* but is significant and negative when risk is measured *RWA*. This finding indicates that banks with low capital buffer reduce overall risk-taking when capital is increased. We also find the coefficients on $REG_{i,t} \times \Delta Risk_{i,t}$ is significant and negative when risk is measured by *NPL* but is significant and positive when risk is measured *RWA*, suggesting that banks with low capital buffer reduce capital holding when *NPL* is increased but increase capital holding when *RWA* is increased. In sum, the findings are in line with the capital buffer theory hypothesis.

6.2.3 Variables affecting target capital and risk, and efficiency levels

With regards to the bank specific variables, We find that larger banks (in terms of total assets) tend to be less cost efficient, implying dis-economies of scale for banks. This results are contrary to previous studies where they find large institutions tend to exhibit greater efficiency associated with higher scale economies (Wheelock and Wilson (2012); Hughes and Mester (2013)). Bank size (*SIZE*) has a significant and negative effect on changes in capital and *RWA* but positive effect on changes in *NPL*. The finding is consistent with literature that larger banks generally have lower degrees of capitalization (Shrieves and Dahl (1992), Aggarwal and Jacques (2001), Rime (2001), Stolz et al. (2003) and etc.). Larger banks have larger investment opportunity sets and are granted easier access to capital markets (Ahmad, Ariff, and Skully (2008)), which renders their target capital level smaller than the target capital levels of smaller banks. The negative relationship between size and change in *RWA* can be explained as larger banks are believed to be more diversified and could contribute to a reduction of their overall risk exposure (Lindquist (2004)). The results also show that size has a positive impact on change in *NPL*, suggesting larger banks tend to increase credit risk (*NPL*) more than smaller banks. This can be attributed to their *Too-Big-To-Fail* position, whereby larger banks believe any distress will be bailed out by government assistance.

In addition, the results support the findings of Stolz et al. (2003) and Yener Altunbas et al. (2007) that profitability (measured by ROA) and capital are strongly positively related. Hence, banks seem to rely strongly on retained earnings in order to increase capital. The coefficients of loan loss provision ratio on ΔNPL ratio is positive but negative on ΔRWA ratio. The results are contrary to the finding of Aggarwal and Jacques (2001) where they find U.S. banks with higher loan loss provision have higher risk-weighted assets. Liquidity (measured by loan-deposit ratio) appears to be negatively related to change in capital and positively related to efficiency. There is a strong significant positive relationship between liquidity and change in *RWA*. Banks with more liquid assets need less insurance against a possible breach of the minimum capital requirements. Therefore banks with higher liquidity generally have smaller target capital levels and may also be willing to take on more risk.

6.3 The Spatial Effects

As a benchmark, we estimate Equation (9) by non-spatial FE, and test for the presence of spatial correlation in the regression residuals by utilizing the aforementioned weights matrices. Estimation results using the weights matrices constructed by k-nearest neighbors where k=10 are reported in Table D.3 - Table D.8. Column 1-3 report estimates from Spatial FE, FE, and GMM FE respectively. To minimize the impact of selection bias, the regressions reported are re-estimated using a Heckman type two-step procedure (Heckman (1979)) to control for the likelihood of surviving long enough to remain in the sample. The results using Heckman correction are reported in column 5-7 in the table.

As suggested by Elhorst (2010), two measures of goodness-of-fit are reported for each model, R^2 and $Corr^2$. The R^2 reported for SFE differs from the R^2 for an OLS regression with a disturbance variance-covariance matrix $\sigma^2 I$. According to Elhorst (2010), there is no precise counterpart of the R^2 for an OLS regression for a generalized regression with a disturbance variance-covariance matrix $\sigma^2\Omega$, where $we \neq \Omega$. We also report the squared correlation coefficient between actual and fitted values $corr^2(Y, \hat{Y})$. This measure ignores the variation explained by the spatial fixed effects (Verbeek 2000,p320). Thus the difference between R^2 and $corr^2$ indicates how much variation is explained by the spatial fixed effects.

The presence of spatial correlation is tested by applying Moran's statistic to the residuals after regression in Section 6.2. Here we report two Moran's I statistics. The first Moran's I is obtained by applying Morans statistic to the residuals after GMM FE regression obtained in Section 6.2. The second Moran's I is obtained by applying Moran's statistic to the residuals after spatial fixed effect regression using weight matrices constructed. The null hypothesis of absence of spatial correlation in the errors is rejected for all weights matrices I used, suggesting the validity of applying the spatial error model in the first place. The second Moran's I's statistics are non-significant in all models, suggesting there is zero spatial autocorrelation present in the residuals after FE spatial error regression.

	Model where risk= NPL		
	Y = NPL	Y = Tier 1 ratio	Y = Efficiency
Network Effect λ	0.0974***	0.152***	0.797***
Average Network Multiplier	1.108	1.179	4.926
$Corr^2$	0.115	0.924	0.622
Number of banks	889	889	889
	Model where risk= RWA		
	Y = RWA	Y= Tier 1 ratio	Y= Efficiency
Network Effect λ	0.189***	0.135***	0.797***
Average Network Multiplier	1.233	1.156	4.926
$Corr^2$	0.235	0.924	0.621
Number of banks	889	889	889

Table 6.2: Spatial Error Model Estimation

Table 6.2 reports results from the spatial error fixed effect model with estimates of the spatial dependency parameter λ, the implied average network multiplier $\frac{1}{1-\lambda}$, and the $Corr^2$ of the regression. Full coefficient estimates are reported in Table D.3 - Table D.8 in the Appendix. The autocorrelation term λ captures unobserved dependencies arising from links in the interbank network. The importance of the spatial dependence phenomenon is confirmed by the positive significant value of λ (significant at 1%) in all models, indicating the presence of a substantial network multiplier effect. For example, the estimated λ on Tier 1 ratio is about 0.152, suggesting that a \$1 idiosyncratic capital shock to one bank would result in a \$1.179 shock to aggregate change in capital in the banking network.

Parameter estimates resemble a large extent those obtained in the previous section. For the risk equation (measured by *NPL*), the coefficients on $\Delta Capital$ and *efficiency* have the expected positive sign for all columns. This is also consistent with the results in Section 6.2. When risk is measured by *RWA*, the coefficients on $\Delta Capital$ and *efficiency* become negative for all columns. Banks increase *NPL* (decreases *RWA*) when capital increases and vice versa.

The high significance of the inverse mills ratio suggests that controlling for survival bias is important. For the risk equation, the coefficient on the inverse Mills ratio is positive, suggesting positive selection has occurred, that is being said, without the correction, the estimate would have been upward-biased.

The coefficients on REG measure the impact of the risk-based capital standards had on changes in bank risk-taking. In Section 6.2, the parameter estimates of REG are negative and significant on ΔNPL but positive and significant on ΔRWA, suggesting that banks with low capital buffers reduce their level of nonperforming loans by more but decrease overall risk-weighted assets by less than banks with high capital buffer. While the coefficients on REG are not significant when risk is measured by NPL as seen in Table D.3 column 1-3 and become significant and negative after Heckman correction.

The interaction terms $REG \times Risk_{t-1}$ shed further light on how the speed of adjustment towards the target level depends on the size of the capital buffer. In Section 6.2, the coefficient is positive and significant, however in this case all coefficients are non-significant, suggesting size of capital buffer does not affect the speed of Risk (NPL) change. The positive effect of size on the change of NPL is in line with the too-big-to-fail notion that larger banks are more likely to take more risks.

For the capital equation (risk measured by NPL), the coefficients on $\Delta Risk$ are negative without correction but become positive and highly significant with Heckman correction. Results in column 4-6 are consistent with the results obtained in Section 6.2. When risk is measured by RWA, the coefficients on $\Delta Risk$ are negative in all specifications and comparable with results in Section 6.2.

Size initially has a non-significant impact on changes in capital without correction term but has a negative impact on changes in capital when the correction term is included. The negative sign of size is in line with findings in Section 6.2, suggesting that larger banks generally have lower degrees of capitalization. The coefficients on REG are negative in all specifications and on both capital equations, suggesting that banks with low capital buffers increase capital by less than banks with large capital buffers. The magnitude of the REG coefficients is smaller after correction for selection bias and smaller in the case of spatial fixed effect error model.

In sum, the fixed effect spatial error model fits the data well, as the spatial interaction terms are both statistically and economically significant and both pseudo R^2 and $corr^2$ give reasonable goodness-of-fit. The comparison of FE, GMM models with spatial fixed effects models provides clear evidence on the existence of unobserved spatial effects in the interbank network on individual bank risk, capital and efficiency levels and that such effects can be captured by the error term in the form of the non-systematic risk of neighboring banks.

6.4 Robustness Checks

One skepticism about spatial econometric methods is that the results are said to depend on the choice of the weighting matrix. As mentioned above, there is no clear guidance in the literature as to what the best weighting matrix might be. In order to check the robustness of the results, we also estimated spatial models for alternative weight matrices using hierarchical clustering methods. These results are consistent with estimations using KNN clustering.

7 Concluding Remarks

In this paper, we investigate the drivers of banks' risk-taking in the U.S., and test how they respond to an increase in capital requirements. We use the most recent dataset of U.S. banks between 2001-2016 and model risk, capital and banks' best business practices (proxied by cost efficiency) in a robust framework. Controlling for endogeneity between risk, capital and cost efficiency, we propose a method to construct the network based on clustering of residuals from GMM estimates. We then re-estimate the model in a spatial error framework to further address the issue of spatial correlation among banking networks.

Our findings suggest that a stricter capital requirement causes banks to reduce investments in risk-weighted assets, but at the same time, increase ex-post non-performing loans, suggesting the unintended effects of higher capital requirements on credit risk. We also find capital buffer has important impact on capital, risk adjustments and cost efficiency. Banks with low capital buffer adjust capital toward their targets faster than better capitalized banks. In addition, my results show that there exist unobserved spatial effects in the interbank network and such effects can be captured by the error term in the form of the non-systematic risk of neighboring banks.

This study has important policy implications and will shed light on how a more risk-sensitive capital regulation (i.e. Basel III) could influence banks' behavior. The different signs on non-performing loans (NPL) and risk-weighted assets (RWA) raise concern whether risk-weighted assets are a credible measure of risk. It might be the case that banks under-report RWA to minimize regulatory burdens. Since the risk-weighting methodology remains essentially unchanged in Basel III, banks will still have the incentive to game the system by reallocating portfolios away from assets with high risk weights to assets with low risk weights.

The results also imply that current capital requirements are still not sufficient to ensure effective loss absorption during stress scenarios such as those experienced during the financial crisis. Basel III introduces a conservation buffer of 2.5 %. My study finds that the majority of banks actually maintained capital buffer levels that significantly exceeded Basel III requirements. Hence, the introduction of an additional capital buffer may not be effective in affecting bank's risk-taking as much as expected.

Taken as a whole, these results suggest that the effectiveness of the Basel III to increase capital and reduce risk-taking might be limited as it does not properly address the shortcomings of Basel II. Therefore, policymakers will have to carefully revise the risk-weighting approach and conduct tight and efficient supervision to minimize banks' ability to game the system.

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A Stochastic Frontier Model

In the same spirit as Schmidt and Sickles (1984) and Cornwell, Schmidt, and Sickles (1990), we specify a panel data application of stochastic frontier model. Let y_{it} and x_{it} represent, respectively, the scalar output level and the input vector of k inputs for firm i at time t. The model has the general form:

$$\begin{aligned} y_{it} &= \alpha_t + f(x_{it};\beta) + v_{it} - u_{it},\ \ i = 1,2,\dots N, t = 1,2,\dots T_i \\ &= \alpha_{it} + f(x_{it};\beta) + v_{it} \\ v_{it} &\sim_{iid} N(0,\sigma_v^2) \end{aligned}$$

where α_t is the frontier intercept, i.e. the maximum possible value for α_{it}. v_{it} is a two-sided symmetric, idiosyncratic component. Normal distribution is usually assumed for v_{it}. $u_{it} \geq 0$ is a firm effect representing technical inefficiency of firm i at time t. $f(x_{it};\beta)$ is a log-linear production function (e.g. Cobb-Douglas, translog or fourier flexible form). The fundamental idea of stochastic frontier technical efficiency can be formalized as the ratio of realized output, given a specific set of inputs, to maximum attainable output:

$$TE_{it} = \frac{y_{it}}{y_{it}^*} = \frac{f(x_{it};\beta)e^{-u_{it}}e^{v_{it}}}{f(x_{it};\beta)e^{v_{it}}} = e^{-u_{it}} \in (0,1]$$

with y_{it}^* is the maximum attainable output for unit i given x_{it}.

Cornwell et al. (1990) proposed a model that the technical inefficiency term u_{it} is a quadratic function over time. They assumed that the intercepts depend on a vector of observables W_t in the following way:

$$\alpha_{it} = \delta_i W_t = \delta_{i1} + \delta_{i2}t + \delta_{i3}t^2$$

where the parameters $\delta_{i1}, \delta_{i2}, \delta_{i3}$ are firm specific and t is the time trend variable. Following a slightly different strategy, Y. H. Lee and Schmidt (1993) specifies u_{it} as the form of $g(t)u_i$ in which

$$g(t)u_i = (\sum_{t=1}^{T} \beta_t d_t)u_i$$

where d_t is a time dummy variable and one of the coefficients is set equal to one.

Numerous similarly motivated specifications have been proposed for u_{it}. Two that have proved useful in applications are Kumbhakar (1990)'s model,

$$g(t) = (1 + exp(\eta_1 t + \eta_2 t^2)^{-1}.$$

and Battese and Coelli (1992)'s "time decay model" (which is the model of choice in many recent applications),

$$g(t) = exp[-\eta(t - T_i)].$$

where T_i is the last period in the i_{th} panel, η is the decay parameter. The decay parameter gives information on the evolution of the inefficiency. When $\eta > 0$, the degree of inefficiency decreases over time; when $\eta < 0$, the degree of inefficiency increases over time. If η tends to 0, then the time-varying decay model reduces to a time-invariant model.

The specifications of u_{it} are summarized below.

Model	**Specification of u_{it}**
CSS(1990)	$\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2$, $\hat{u}_{it} = \max \hat{\alpha}_{it} - \hat{\alpha}_{it}$
Kumbhakar (1990)	$u_{it} = (1 + exp(\eta_1 t + \eta_2 t^2)^{-1} u_i$
Battese & Coelli(1992)	$u_{it} = exp[-\eta(t - T_i)]u_i$
Lee & Schmidt(1993)	$u_{it} = (\sum_{t=1}^{T} \beta_t d_t)u_i$

Table A.1: Different specifications of u_{it}

The main purpose of the stochastic frontier analysis is to estimate inefficiency u_{it} or efficiency $TE_{it} = exp(-u_{it})$. Since only the composed error term $\epsilon_{it} = v_{it} - u_{it}$ is observed, the firms inefficiency is predicted by the conditional mean $\hat{u}_{it} = E[u_{it}|\epsilon_{it}]$. Jondrow, Lovell, Materov, and Schmidt (1982) (JLMS) present the explicit result of $E[u_{it}|\epsilon_{it}]$ for the half-normal model

$$E[u_{it}|\varepsilon_{it}] = \left[\frac{\sigma\lambda}{1+\lambda^2}\right]\left[\tilde{\mu}_{it} + \frac{\phi(\tilde{\mu}_{it})}{\Phi(\tilde{\mu}_{it})}\right], \ \tilde{\mu}_{it} = \frac{-\lambda\varepsilon_{it}}{\sigma}$$

where $\sigma^2 = (\sigma_u^2 + \sigma_v^2)$, $\lambda = \sigma_u^2/\sigma_v^2$ and $\phi(.)$ and $\Phi(.)$ are the density and CDF of the standard normal distribution. With these in hand, estimates of technical efficiency $E[TE_{it}|\epsilon_{it}] = E[exp(-u_{it})|\epsilon_{it}]$ is also obtained.

Authors	Period of study	Countries	Methodology	Main empirical results
Kwan and Eisenbeis (1996)	1986-1991	254 large U.S. BHCs	2SLS	Less efficient banks took on more risk to offset the inefficiency; less efficient banks tend to be less well capitalized
Berger and DeYoung (1997)	1985-1994	U.S. commercial banks	Granger-causality OLS	Increases in NPL is followed by reductions in cost efficiency; decreases in cost efficiency are followed by increases in NPL; for the most efficient banks, increases in cost efficiency is followed by increases in NPL; thinly capitalized banks have incentive (moral hazard) to take increased risks.
Williams(2004)	1990 - 1998	European savings banks	Granger causality OLS	Poorly managed banks (lower cost efficiency) tend to make more risky loans supporting the "bad management" hypothesis; results are sensitive to the number of lags included
Altunbas et al., (2007)	1992-2000	Large sample of Banks from 15 European countries	SUR	Positive relationship between capital and risk; inefficient banks appear to hold more capital and take on less risk; relationships vary depending on types of banks.
Deelchand (2009)	2003-2006	263 Japanese cooperative banks	2SLS	Negative relationship between risk and capital; inefficient banks appear to operate with larger capital and take on more risk; larger banks holding less capital take on more risk and are less efficient.
Fiordelisi et al., (2011)	1995-2007	Commercial banks from EU-26 countries	Granger-Causality GMM	Subdued bank efficiency (cost or revenue) granger causes higher risk supporting the "bad management" hypothesis; more efficient banks seem to eventually become more capitalized; higher capital also tends to have a positive effect on efficiency levels
Tan & Floros(2013)	2003-2009	101 Chinese banks	3SLS	Positive and significant relationship between risk and efficiency; relationship between risk (Z-score) and capital is negative and significant.

Table A.2: Recent empirical studies on risk, capital and efficiency of banks

B Derivation

Quasi-Maximum Likelihood Formulation

The Equation (11) can be re-written as

$$Y = X\beta + (I_n - \lambda W)^{-1}\epsilon$$

Since $\epsilon \sim N\left(0, \sigma^2 I_N\right)$, then $u \sim N\left(0, \Omega\right)$ where $\Omega = \sigma^2 \left(I_n - \lambda W\right)^{'} \left(I_n - \lambda W\right)^{-1}$. Note that $(I_n - \lambda W)^{-1}$ should be non-singular, this imposes restrictions on the value of λ. If W is row standardized, so that the influence of neighbours can be represented in terms of averages, then $1/r_{min} < \lambda < 1$, where r_{min} is the smallest negative eigenvalue of W (Ord, 1975; Anselin, 1982).

The loglikelihood of the spatial error model if the spatial specific effects are assumed to be fixed can be obtained as:

$$\ln L = -\frac{NT}{2}\ln\left(2\pi\sigma^2\right) + T\ln|I_n - \lambda W| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\nu_{it}^{'}\nu_{it} \tag{B.1}$$

where $\nu = (I_n - \lambda W)(y - X\beta)$.

β, σ^2 and λ can be estimated jointly using (quasi) maximum likelihood methods:

$$\widehat{\beta} = \left(\widetilde{X}'\widetilde{X}\right)^{-1}\widetilde{X}'\widetilde{Y},\ \widehat{\sigma^2} = \frac{\widehat{\nu}'\widehat{\nu}}{NT}$$

where $\widetilde{X} = X^* - \lambda(I_T \otimes W)X^*$ and $\widetilde{Y} = Y^* - \lambda(I_T \otimes W)Y^*$.

Y^* and X^* are demeaned form of X and Y. The maximization of (B.1) can be done by searching over a grid values for λ. The asymptotic variance matrix of the parameters is:

$$\text{Asy. Var}(\beta, \lambda, \sigma^2) = \begin{bmatrix} \frac{1}{\sigma^2}X^{*'}X^* & 0 & 0 \\ 0 & T^* tr(\widetilde{W}\widetilde{W} + \widetilde{W}'\widetilde{W}) & 0 \\ 0 & \frac{T}{\sigma^2}tr(\widetilde{W}) & \frac{NT}{2\sigma^4} \end{bmatrix}$$

where $\widetilde{W} = W(I_N - \lambda W)^{-1}$.

C Variable Definitions

Variable	Symbol	Description
Total cost	TC	Interest + non-interest expenses
Outputs		
Total securities	Y1	Securities held to maturity + securities held for sale
Total loans	Y2	Net loans (Gross loans - reserve for loan loss provisions)
Inputs prices		
Price of physical capital	W1	Expenditures on premises and fixed assets/premises and fixed assets
Price of labor	W2	Salaries/full-time equivalent employees
Price of borrowed funds	W3	Interest expenses paid on deposits/total deposits

Table C.1: Input and output description

Variables	**Descriptions**
Capital :	
Tier 1 risk-based ratio	Core Capital (Tier 1)/ Risk-weighted Assets
Total risk-based ratio	Core Capital (Tier 1)+Tier 2 capital/ Risk-weighted Assets
Tier 1 leverage ratio	Core Capital (Tier 1)/Total assets
Risk:	
NPL ratio	Non-performing Loans/Total assets
RWA ratio	Risk-weighted Assets /Total assets
Bank-specific variables:	
Size	The natural logarithm of banks total assets
ROA	Annual net income/total assets
ROE	Annual net income/total equity
LLP ratio	Loan loss provisions/total assets
Cash ratio	Noninterest-bearing balances, currency, and coin/total assets
Loan-deposit ratio	Total loans/ Total deposits
Buffer	Total risk weighted capital ratio -8%
REG (Regulatory Pressure)	1 if a bank has a capital buffer $\leq$ 10th percentile capital buffer over all observations, and zero otherwise
Macro indicators:	
GDPG	Growth rate of real GDP for the United States
Crisis	1 if year is between 2007 and 2009 and 0 otherwise
Case-Shiller Home Price Index	Growth rate of 20-city composite constant-quality house price indices

Table C.2: Description of variables used in the study

D Tables

Dependent	Total Cost	
	Parameter	**SE**
lny_1	0.066***	0.005
lny_2	-0.009	0.009
lnw_1	-0.063***	0.007
lnw_2	0.454***	0.010
lnw_3	0.593***	0.006
$lny_1 lny_2$	-0.049***	0.000
$lnw_1 lnw_2$	0.036***	0.001
$lnw_1 lnw_3$	-0.011***	0.001
$lnw_2 lnw_3$	-0.102***	0.001
$1/2 lny_1^2$	0.068***	0.000
$1/2 lny_2^2$	0.099***	0.001
$1/2 lnw_1^2$	-0.031***	0.001
$1/2 lnw_2^2$	0.041***	0.002
$1/2 lnw_3^2$	0.119***	0.001
$lny_1 lnw_1$	0.000	0.000
$lny_1 lnw_2$	-0.005***	0.001
$lny_1 lnw_3$	0.006***	0.000
$lny_2 lnw_1$	0.007***	0.001
$lny_2 lnw_2$	-0.007***	0.001
$lny_2 lnw_3$	0.005***	0.001
t	0.016***	0.000
t^2	0.000***	0.000
$lny_1 t$	-0.001***	0.000
$lny_2 t$	-0.001***	0.000
$lnw_1 t$	-0.001***	0.000
$lnw_2 t$	0.001***	0.000
$lnw_3 t$	0.001***	0.000
constant	1.302***	0.056
μ	0.555***	0.006
η	-0.008***	0.000
γ	0.888	
σ_{u_2}	0.099	
σ_{v_2}	0.013	
Estimated inefficiencies $\hat{u}_{it}$		
Mean	0.508	
SD	0.243	
Min	0.006	
Max	1.290	
Estimated cost efficiency $\hat{C}E_{it}$		
Mean	0.619	
SD	0.149	
Min	0.275	
Max	0.994	
Observations	330,790	

Note: The top and bottom 5% of inefficiencies scores are trimmed to remove the effects of outliers.

Table D.1: Parameter estimates of the translog cost functions on the full sample

Variables	Model where risk= NPL			Model where risk= RWA		
	Y = ΔNPL	Y = ΔTier1 ratio	Y = Efficiency	Y = ΔRWA	Y= ΔTier1 ratio	Y= Efficiency
ΔCapital	0.0243***		0.0517***	-0.987***		0.0378***
	(0.00313)		(0.00612)	(0.00615)		(0.00694)
ΔRisk		0.00686***	-0.00509		-0.00866***	-0.00967***
		(0.00246)	(0.00456)		(0.000192)	(0.00236)
Efficiency	0.00439***	0.00117***		-0.114***	0.000474***	
	(0.00103)	(0.000214)		(0.00192)	(0.000174)	
$RISK_{t-1}$	-0.263***			-0.320***		
	(0.00139)			(0.00122)		
Cap_{t-1}		-0.947***			-0.934***	
		(0.00129)			(0.000497)	
Buffer	0.00139	0.937***	-0.266***	-0.223***	0.925***	-0.265***
	(0.00126)	(0.00136)	(0.00243)	(0.00263)	(0.000494)	(0.00244)
Size	0.124***	-0.00482	-8.505***	-1.099***	-0.0156***	-8.507***
	(0.0124)	(0.00318)	(0.0175)	(0.0232)	(0.00210)	(0.0175)
ROA	-0.175***	0.0184***	0.761***	0.0972***	0.0175***	0.760***
	(0.00545)	(0.00111)	(0.0106)	(0.0100)	(0.000910)	(0.0106)
LLP ratio	0.323***	-0.0451***	0.275***	-0.400***	-0.0477***	0.270***
	(0.00583)	(0.00122)	(0.0111)	(0.0105)	(0.000955)	(0.0112)
LTD	-0.000540*	-0.00145***	0.0150***	0.163***	-0.000988***	0.0155***
	(0.000305)	(5.88e-05)	(0.000605)	(0.000683)	(5.29e-05)	(0.000620)
REG	-0.111***	-0.298***	0.773***	2.000***	-0.234***	0.773***
	(0.0143)	(0.0413)	(0.0217)	(0.214)	(0.0229)	(0.0217)
Crisis	0.0300***	0.0313***	1.474***	0.293***	0.0322***	1.473***
	(0.00886)	(0.00144)	(0.0173)	(0.0166)	(0.00150)	(0.0173)
REG*$RISK_{t-1}$	0.0344***			-0.0223***		
	(0.00387)			(0.00268)		
REG*Δ CAP	0.00301			-0.151***		
	(0.0154)			(0.0290)		
REG*Cap_{t-1}		0.0357***			0.0286***	
		(0.00418)			(0.00232)	
REG*Δ Risk		-0.0122***			0.00731***	
		(0.00273)			(0.000520)	
GDP growth	-11.81***	-0.316***	11.99***	25.04***	0.0444	12.32***
	(0.476)	(0.0838)	(0.946)	(0.888)	(0.0808)	(0.947)
Spcs growth	-2.418***	-0.108***	23.31***	3.186***	-0.0779***	23.34***
	(0.142)	(0.0229)	(0.277)	(0.264)	(0.0240)	(0.277)
Hansen J statistic	0.063	0.097	0.217	1.403	0.92	0.233
	(0.8019)	(0.7553)	(0.6414)	(0.1084)	(0.3374)	(0.6295)
No. of Observations	265,905	265,905	265,985	265,905	265,905	265,985
Number of banks	7,644	7,644	7725	7,644	7,644	7725

Notes: Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table D.2: Two-step GMM estimations (FE) for the relationships between bank capital, cost efficiency and risk-taking

	Without correction			Heckman correction		
VARIABLES	Spatial FE	FE	GMM FE	Spatial FE	FE	GMM FE
ΔCapital	0.0342***	0.0601***	0.0349***	0.0313***	0.0631***	0.0350***
	(0.00649)	(0.00553)	(0.00671)	(0.00632)	(0.00552)	(0.00648)
Efficiency	0.0231***	0.00633***	0.0224***	0.0295***	0.0101***	0.0164***
	(0.00291)	(0.000981)	(0.00279)	(0.00286)	(0.000997)	(0.00113)
$RISK_{t-1}$	-0.319***	-0.314***	-0.315***	-0.352***	-0.348***	-0.356***
	(0.00322)	(0.00315)	(0.00331)	(0.00320)	(0.00318)	(0.00327)
Buffer	0.00448*	0.00206	0.00349	0.00867***	0.00479**	0.00738***
	(0.00237)	(0.00228)	(0.00250)	(0.00231)	(0.00230)	(0.00241)
Size	0.0787***	0.0162	0.0961***	0.638***	0.540***	0.659***
	(0.0229)	(0.0175)	(0.0254)	(0.0247)	(0.0209)	(0.0231)
ROA	-0.131***	-0.139***	-0.138***	0.291***	0.282***	0.361***
	(0.0122)	(0.0116)	(0.0121)	(0.0143)	(0.0138)	(0.0145)
LLP ratio	0.338***	0.351***	0.341***	0.0991***	0.118***	0.0661***
	(0.0144)	(0.0139)	(0.0146)	(0.0147)	(0.0145)	(0.0148)
LTD	4.06e-05	-0.000261	-0.000333	-0.0192***	-0.0199***	-0.0240***
	(0.000607)	(0.000591)	(0.000629)	(0.000691)	(0.000692)	(0.000728)
REG	-0.0313	-0.0237	-0.0322	-1.554***	-1.560***	-1.890***
	(0.0416)	(0.0412)	(0.0430)	(0.0494)	(0.0498)	(0.0523)
Crisis	0.0343*	0.0157	0.0489***	0.0167	-0.0150	-0.0105
	(0.0190)	(0.0168)	(0.0181)	(0.0186)	(0.0166)	(0.0167)
REG*$RISK_{t-1}$	-0.00668	-0.00885	-0.00966	-0.00197	-0.00683	-0.00798
	(0.0151)	(0.0150)	(0.0155)	(0.0147)	(0.0148)	(0.0150)
REG*Δ CAP	-0.0244	-0.0447	-0.0229	0.0111	-0.0209	0.0106
	(0.0444)	(0.0439)	(0.0461)	(0.0433)	(0.0436)	(0.0445)
GDP growth	-12.67***	-11.78***	-12.33***	-34.51***	-34.26***	-38.92***
	(1.003)	(0.895)	(0.929)	(1.064)	(0.984)	(1.006)
Home index growth	-1.903***	-2.150***	-1.812***	-4.460***	-4.804***	-5.327***
	(0.297)	(0.270)	(0.276)	(0.295)	(0.268)	(0.269)
Invmills				4.001***	4.025***	4.869***
				(0.0741)	(0.0749)	(0.0831)
Constant		0.453*	-1.124***		-10.23***	-12.80***
		(0.233)	(0.393)		(0.318)	(0.353)
λ	0.0912***			0.0974***		
	(0.00944)			(0.00942)		
$\frac{1}{1-\lambda}$	1.100**			1.108***		
Moran's I (1)	0.9481***			0.9481***		
Moran's I (2)	0.02			0.03		
Observations	55,118	55,118	52,451	55,118	55,118	52,451
R-squared(within)	0.164	0.164	0.163	0.203	0.203	0.210
$Corr^2$	0.0907	0.0908	0.0886	0.115	0.117	0.123
Number of banks	889	889	889	889	889	889

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table D.3: Estimation results using KNN: Risk equation (risk=NPL)

	Without correction			Heckman correction		
VARIABLES	Spatial FE	FE	GMM FE	Spatial FE	FE	GMM FE
ΔCapital	-1.191***	-1.213***	-1.200***	-1.164***	-1.182***	-1.160***
	(0.0136)	(0.0116)	(0.0140)	(0.0134)	(0.0115)	(0.0137)
Efficiency	-0.0477***	-0.0149***	-0.0588***	-0.0406***	-0.00937***	-0.0475***
	(0.00647)	(0.00200)	(0.00548)	(0.00633)	(0.00198)	(0.00543)
$RISK_{t-1}$	-0.290***	-0.281***	-0.288***	-0.313***	-0.304***	-0.314***
	(0.00259)	(0.00255)	(0.00268)	(0.00261)	(0.00257)	(0.00271)
Buffer	-0.198***	-0.180***	-0.192***	-0.214***	-0.197***	-0.212***
	(0.00536)	(0.00520)	(0.00556)	(0.00529)	(0.00514)	(0.00548)
Size	-0.222***	0.137***	-0.197***	0.675***	0.949***	0.714***
	(0.0510)	(0.0371)	(0.0499)	(0.0543)	(0.0420)	(0.0559)
ROA	-0.0454*	-0.114***	-0.0955***	0.652***	0.543***	0.648***
	(0.0263)	(0.0227)	(0.0235)	(0.0309)	(0.0279)	(0.0298)
LLP ratio	-0.423***	-0.533***	-0.493***	-0.851***	-0.937***	-0.958***
	(0.0289)	(0.0265)	(0.0275)	(0.0303)	(0.0281)	(0.0296)
LTD	0.142***	0.142***	0.144***	0.120***	0.121***	0.120***
	(0.00147)	(0.00143)	(0.00149)	(0.00154)	(0.00151)	(0.00158)
REG	1.095	1.198*	1.036	-1.127*	-0.940	-1.459**
	(0.668)	(0.659)	(0.690)	(0.660)	(0.652)	(0.680)
Crisis	-0.0251	0.0750**	-0.0713**	-0.0342	0.0577*	-0.0919***
	(0.0428)	(0.0334)	(0.0356)	(0.0418)	(0.0329)	(0.0349)
REG*$RISK_{t-1}$	-0.0135	-0.0144*	-0.0124	-0.0150*	-0.0153*	-0.0131
	(0.00848)	(0.00836)	(0.00873)	(0.00835)	(0.00824)	(0.00857)
REG*Δ CAP	-0.197**	-0.175*	-0.170*	-0.144	-0.132	-0.134
	(0.0909)	(0.0896)	(0.0922)	(0.0895)	(0.0883)	(0.0906)
GDP growth	25.50***	26.38***	23.84***	-9.029***	-6.238***	-13.64***
	(2.272)	(1.806)	(1.824)	(2.373)	(1.963)	(2.024)
Home index growth	-0.299	1.151**	0.231	-4.063***	-2.518***	-4.017***
	(0.671)	(0.529)	(0.541)	(0.661)	(0.530)	(0.539)
Invmills				6.258***	5.901***	6.761***
				(0.152)	(0.150)	(0.169)
Constant		8.544***	14.68***		-6.721***	-2.754***
		(0.504)	(0.781)		(0.630)	(0.923)
λ	0.194***			0.189***		
	(0.00907)			(0.00907)		
$\frac{1}{1-\lambda}$	1.241***			1.233***		
Moran's I (1)	0.975***			0.975***		
Moran's I (2)	0.01			0.01		
Observations	55,118	55,118	52,451	55,118	55,118	52,451
R-squared(within)	0.411	0.412	0.412	0.427	0.428	0.430
$Corr^2$	0.223	0.216	0.209	0.235	0.226	0.220
Number of banks	889	889	889	889	889	889

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table D.4: Estimation results using KNN: Risk equation (risk=RWA)

	Without correction			Heckman correction		
VARIABLES	Spatial FE	FE	GMM FE	Spatial FE	FE	GMM FE
ΔRisk	-0.000277	-0.00131**	-9.97e-05	0.00204***	0.00288***	0.00258***
	(0.000692)	(0.000635)	(0.000712)	(0.000675)	(0.000623)	(0.000695)
Efficiency	-0.000634***	-0.000673***	-0.00139***	-0.000988***	-0.00127***	-0.00195***
	(0.000226)	(0.000159)	(0.000224)	(0.000222)	(0.000155)	(0.000218)
Cap_{t-1}	-0.954***	-0.953***	-0.955***	-0.955***	-0.955***	-0.957***
	(0.000851)	(0.000858)	(0.000873)	(0.000829)	(0.000836)	(0.000846)
Buffer	0.941***	0.941***	0.942***	0.942***	0.942***	0.943***
	(0.000852)	(0.000860)	(0.000874)	(0.000830)	(0.000838)	(0.000847)
Size	-0.00443	-0.00545*	-0.0154***	-0.0886***	-0.0890***	-0.108***
	(0.00327)	(0.00294)	(0.00335)	(0.00355)	(0.00326)	(0.00365)
ROA	0.00510***	0.00665***	0.00668***	-0.0622***	-0.0613***	-0.0715***
	(0.00194)	(0.00180)	(0.00184)	(0.00227)	(0.00216)	(0.00225)
LLP ratio	-0.0506***	-0.0522***	-0.0527***	-0.00799***	-0.00862***	-0.00244
	(0.00217)	(0.00210)	(0.00213)	(0.00225)	(0.00220)	(0.00225)
LTD	-0.00211***	-0.00196***	-0.00195***	0.000804***	0.000964***	0.00146***
	(9.47e-05)	(9.44e-05)	(9.68e-05)	(0.000107)	(0.000107)	(0.000111)
REG	-0.407***	-0.447***	-0.491***	-0.187***	-0.223***	-0.228***
	(0.0574)	(0.0580)	(0.0586)	(0.0560)	(0.0566)	(0.0569)
Crisis	0.0456***	0.0448***	0.0408***	0.0482***	0.0475***	0.0455***
	(0.00306)	(0.00265)	(0.00268)	(0.00300)	(0.00258)	(0.00260)
REG*Cap_{t-1}	0.0487***	0.0526***	0.0570***	0.0499***	0.0536***	0.0582***
	(0.00579)	(0.00586)	(0.00592)	(0.00564)	(0.00570)	(0.00573)
REG*Δ Risk	-0.00172	-0.000728	-0.00303	0.000791	-2.43e-05	-0.00107
	(0.00368)	(0.00371)	(0.00378)	(0.00358)	(0.00362)	(0.00366)
GDP growth	0.0740	0.0551	0.0285	3.441***	3.488***	4.025***
	(0.166)	(0.144)	(0.143)	(0.174)	(0.154)	(0.156)
Home index growth	-0.220***	-0.222***	-0.248***	0.146***	0.151***	0.205***
	(0.0485)	(0.0420)	(0.0418)	(0.0480)	(0.0415)	(0.0412)
Invmills				-0.614***	-0.620***	-0.725***
				(0.0114)	(0.0116)	(0.0127)
Constant		6.909***	7.072***		8.623***	9.007***
		(0.0398)	(0.0470)		(0.0502)	(0.0576)
λ	0.146***			0.152***		
	(0.00930)			(0.00928)		
$\frac{1}{1-\lambda}$	1.171**			1.179***		
Moran's I (1)	0.9371***			0.9371***		
Moran's I (2)	0.06			0.06		
Observations	55,118	55,118	52,451	55,118	55,118	52,451
R-squared(within)	0.961	0.961	0.962	0.963	0.963	0.964
$Corr^2$	0.917	0.917	0.916	0.924	0.923	0.923
Number of banks	889	889	889	889	889	889

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table D.5: Estimation results using KNN: Capital equation (risk=NPL)

	Without correction			Heckman correction		
VARIABLES	Spatial FE	FE	GMM FE	Spatial FE	FE	GMM FE
ΔRisk	-0.00798***	-0.00549***	-0.00796***	-0.00726***	-0.00428***	-0.00694***
	(0.000361)	(0.000317)	(0.000373)	(0.000352)	(0.000310)	(0.000363)
Efficiency	-0.000617***	-0.000757***	-0.00140***	-0.000981***	-0.00130***	-0.00194***
	(0.000223)	(0.000159)	(0.000224)	(0.000218)	(0.000155)	(0.000218)
Cap_{t-1}	-0.942***	-0.945***	-0.943***	-0.944***	-0.948***	-0.946***
	(0.00101)	(0.000980)	(0.00104)	(0.000984)	(0.000958)	(0.00101)
Buffer	0.930***	0.933***	0.930***	0.932***	0.936***	0.934***
	(0.000991)	(0.000968)	(0.00102)	(0.000967)	(0.000945)	(0.000992)
Size	-0.00378	-0.00589**	-0.0158***	-0.0859***	-0.0868***	-0.104***
	(0.00323)	(0.00293)	(0.00334)	(0.00350)	(0.00325)	(0.00364)
ROA	0.00473**	0.00520***	0.00504***	-0.0607***	-0.0602***	-0.0694***
	(0.00192)	(0.00180)	(0.00184)	(0.00224)	(0.00215)	(0.00224)
LLP ratio	-0.0547***	-0.0551***	-0.0569***	-0.0129***	-0.0124***	-0.00839***
	(0.00216)	(0.00210)	(0.00214)	(0.00224)	(0.00221)	(0.00226)
LTD	-0.00162***	-0.00166***	-0.00151***	0.00118***	0.00112***	0.00171***
	(9.61e-05)	(9.57e-05)	(9.87e-05)	(0.000108)	(0.000107)	(0.000112)
REG	-0.413***	-0.438***	-0.463***	-0.192***	-0.221***	-0.209***
	(0.0590)	(0.0599)	(0.0605)	(0.0577)	(0.0585)	(0.0588)
Crisis	0.0449***	0.0442***	0.0399***	0.0475***	0.0472***	0.0446***
	(0.00301)	(0.00264)	(0.00268)	(0.00293)	(0.00258)	(0.00260)
REG*Cap_{t-1}	0.0491***	0.0515***	0.0538***	0.0496***	0.0526***	0.0548***
	(0.00598)	(0.00607)	(0.00613)	(0.00583)	(0.00591)	(0.00594)
REG*Δ Risk	0.00164	0.00119	0.00301**	0.00235*	0.00125	0.00331**
	(0.00141)	(0.00144)	(0.00150)	(0.00138)	(0.00141)	(0.00145)
GDP growth	0.316*	0.245*	0.261*	3.547***	3.483***	4.022***
	(0.163)	(0.143)	(0.143)	(0.170)	(0.153)	(0.155)
Home index growth	-0.189***	-0.205***	-0.220***	0.162***	0.154***	0.210***
	(0.0476)	(0.0419)	(0.0418)	(0.0469)	(0.0414)	(0.0412)
Invmills				-0.599***	-0.601***	-0.693***
				(0.0113)	(0.0115)	(0.0126)
Constant		6.833***	6.956***		8.512***	8.824***
		(0.0399)	(0.0471)		(0.0504)	(0.0579)
λ	0.135***			0.135***		
	(0.00849)			(0.00848)		
$\frac{1}{1-\lambda}$	1.156**			1.156***		
Moran's I (1)	0.949***			0.949***		
Moran's I (2)	0.03			0 .03		
Observations	55,118	55,118	52,451	55,118	55,118	52,451
R-squared(within)	0.961	0.961	0.962	0.963	0.963	0.964
$Corr^2$	0.918	0.918	0.917	0.924	0.924	0.924
Number of banks	889	889	889	889	889	889

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table D.6: Estimation results using KNN: Capital equation (risk=RWA)

	Without correction			Heckman correction		
VARIABLES	Spatial FE	FE	GMM FE	Spatial FE	FE	GMM FE
ΔRisk	-0.0193	0.0703***	-0.334***	-0.0234	0.0887***	-0.461***
	(0.0758)	(0.0173)	(0.118)	(0.0758)	(0.0173)	(0.121)
ΔCap	-0.00383	0.125***	0.0461	-0.00301	0.108***	0.0602**
	(0.0184)	(0.0240)	(0.0284)	(0.0184)	(0.0240)	(0.0283)
Buffer	0.0325***	0.0156	-0.00219	0.0299***	-0.00897	-0.0580***
	(0.00682)	(0.00999)	(0.0102)	(0.00682)	(0.0101)	(0.0104)
Size	-6.583***	-3.437***	-4.249***	-6.835***	-4.921***	-6.114***
	(0.0854)	(0.0754)	(0.0790)	(0.0924)	(0.0890)	(0.102)
ROA	1.009***	-0.431***	-0.460***	0.847***	-1.036***	-0.817***
	(0.0503)	(0.0500)	(0.0498)	(0.0552)	(0.0607)	(0.0744)
LLP ratio	0.351***	0.619***	0.624***	0.451***	1.012***	1.101***
	(0.0469)	(0.0582)	(0.0583)	(0.0489)	(0.0618)	(0.0696)
LTD	0.0405***	-0.00145	-8.38e-05	0.0476***	0.0234***	0.00946***
	(0.00176)	(0.00258)	(0.00262)	(0.00202)	(0.00300)	(0.00336)
REG	0.330***	-0.0541	-0.0771	0.893***	1.889***	1.567***
	(0.0775)	(0.119)	(0.120)	(0.111)	(0.171)	(0.219)
Crisis	-2.442***	-1.224***	-1.585***	-2.445***	-1.572***	-2.060***
	(0.228)	(0.0732)	(0.0731)	(0.228)	(0.0723)	(0.0717)
GDP growth	3.030	49.62***	17.34***	10.95	50.78***	21.13***
	(12.82)	(3.916)	(4.202)	(12.86)	(4.315)	(5.465)
Home index growth	-28.41***	-18.56***	-17.57***	-27.72***	-14.25***	-15.67***
	(3.648)	(1.174)	(1.155)	(3.647)	(1.164)	(1.168)
Invmills				-1.488***	-5.216***	-4.495***
				(0.208)	(0.324)	(0.487)
Constant		79.02***	89.21***		103.1***	118.2***
		(0.961)	(1.005)		(1.317)	(1.640)
λ	0.797***			0.797***		
	(0.00274)			(0.00274)		
$\frac{1}{1-\lambda}$	4.926**			4.926***		
Moran's I (1)	0.995***			0.995***		
Moran's I (2)	0.003			0.004		
Observations	55,118	55,118	52,451	55,118	55,118	52,451
R-squared	0.0467	0.046	0.0523	0.0468	0.066	0.0822
$Corr^2$	0.618	0.609	0.630	0.622	0.623	0.641
Number of banks	889	889	889	889	889	889

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table D.7: Estimation results using KNN: Efficiency equation (risk=NPL)

	Without correction			Heckman correction		
VARIABLES	Spatial FE	FE	GMM FE	Spatial FE	FE	GMM FE
ΔRisk	0.267**	-0.0608***	0.435***	0.265**	-0.0534***	0.416**
	(0.107)	(0.00857)	(0.164)	(0.107)	(0.00854)	(0.162)
ΔCap	0.433**	0.0314	0.753***	0.431**	0.0283	0.719***
	(0.176)	(0.0276)	(0.270)	(0.176)	(0.0275)	(0.266)
Buffer	0.0108	0.0197**	-0.0887***	0.00838	-0.00524	-0.0912***
	(0.0111)	(0.0100)	(0.0175)	(0.0111)	(0.0101)	(0.0175)
Size	-6.579***	-3.441***	-5.527***	-6.830***	-4.883***	-6.363***
	(0.0854)	(0.0754)	(0.0871)	(0.0923)	(0.0889)	(0.104)
ROA	1.072***	-0.444***	-0.260***	0.910***	-1.012***	-0.996***
	(0.0565)	(0.0500)	(0.0609)	(0.0609)	(0.0604)	(0.0644)
LLP ratio	0.522***	0.577***	1.094***	0.621***	0.951***	1.548***
	(0.0826)	(0.0584)	(0.119)	(0.0837)	(0.0620)	(0.143)
LTD	0.0264***	0.00184	-0.0365***	0.0336***	0.0249***	-0.00313
	(0.00590)	(0.00262)	(0.00919)	(0.00599)	(0.00302)	(0.00751)
REG	0.334***	-0.0536	-0.139	0.897***	1.770***	2.441***
	(0.0775)	(0.119)	(0.124)	(0.111)	(0.170)	(0.239)
Crisis	-2.439***	-1.221***	-2.103***	-2.442***	-1.570***	-2.050***
	(0.228)	(0.0731)	(0.0739)	(0.228)	(0.0722)	(0.0739)
GDP growth	-5.232	50.76***	-10.57*	2.779	49.68***	27.10***
	(13.23)	(3.919)	(6.257)	(13.27)	(4.297)	(5.133)
Home index growth	-29.23***	-18.37***	-19.92***	-28.53***	-14.28***	-15.53***
	(3.663)	(1.174)	(1.263)	(3.662)	(1.164)	(1.200)
Invmills				-0.296***	-1.598***	-1.310***
				(0.0742)	(0.170)	(0.181)
Constant		78.79***	97.13***		90.95***	110.4***
		(0.961)	(1.011)		(1.275)	(1.326)
λ	0.797***			0.797***		
	(0.00274)			(0.00274)		
$\frac{1}{1-\lambda}$	4.926**			4.926***		
Moran's I (1)	0.970***			0.970***		
Moran's I (2)	0.0023			0.003		
Observations	55,118	55,118	52,451	55,118	55,118	52,451
R-squared	0.0332	0.046	0.0776	0.172	0.050	0.0818
$Corr^2$	0.618	0.610	0.630	0.621	0.623	0.641
Number of banks	889	889	889	889	889	889

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table D.8: Estimation results using KNN: Efficiency equation (risk=RWA)