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Claudia Lambert
Goethe University Frankfurt

Dilek Bulbul
Goethe University Frankfurt

“Credit Portfolio Modelling and its Effect on Capital Requirements: Empirical Evidence from German Banks“

Credit Portfolio Modelling and its Effect on Capital Requirements

Empirical Evidence from German Banks*

Preliminary and incomplete

Claudia Lambert† Dilek Bülbül‡

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Abstract

The subprime crisis revealed that the adoption of credible credit risk instruments is of utmost concern. The Basel Committee on Banking Supervision (2009) advise banks to use credit portfolio models with caution when assessing the capital adequacy. This paper investigates whether decisions on total risk-based capital ratios (regulatory capital) are channeled through credit portfolio models. In other words, do credit portfolio models serve as a relevant determinant for banks to adjust their capital requirement? We test our hypothesis in estimating the average treatment effect. To empirically test the relationship we measure the average treatment effect by conducting a quasi-natural experiment in which we employ a propensity-matching approach to panel data. We find that the adoption of credit portfolio models postively and significantly affects regulatory capital decisions of banks both directly following the introduction as well as over a longer time horizon. This is in particular interesting as the banks in our sample performed well throughout the recent crisis. By now it is commonly accepted that overreliance on credit portfolio models composes a fundamental cause of the current financial crisis. Our results put the disussion on overreliance on quantitative models in a new perspective. This may prove valuable for regulators to conceive bank behaviour and thus advance regulation.

JEL-Classification: G21; L10

Keywords: risk management, regulation, capital requirement, credit portfolio model, propensity score

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†Goethe University of Frankfurt, Department of Applied Econometrics, Grüneburgplatz 1, 60323 Frankfurt am Main, Germany, E-mail: claudia.lambert@hof.uni-frankfurt.de (corresponding author).

‡Goethe-University Frankfurt, Department of Finance, Grüneburgplatz 1, 60323 Frankfurt am Main, Germany, E-mail: buelbuel@finance.uni-frankfurt.de.

1 Introduction

In view of the recent crisis, the adoption of credible risk management tools remains a continuous source of concern and debate. Credit portfolio models represent promising devices for enhanced supervisory oversight of banking organizations and allow for better internal risk management. To take advantage of the the risk-reducing benefits of diversifying loans in a large portfolio, a bank should manage its exposures on both the obligor and the portfolio level. More than one decade ago, the Basel Committee on Banking Supervision (1999) acknowledged that credit portfolio models can generate more accurate evaluations of capital adequacy and are fundamental components of most economic capital frameworks.

However, in view of the recent market turmoil the Basel Committee on Banking Supervision (2009) casted doubt on the validity of these models in a recent report. The committee stated that banks should exercise these instruments with caution when assessing "'the capital adequacy under stressed conditions against a variety of capital ratios such as regulatory ratios as well as ratios based on the internal definition of capital resources"'. Thus, recurring attempts to use credit portfolio models as a basis for calculating the regulatory requirement of banks (Jackson and Perraudin, 2000) did not receive approval, we regard this evaluation as an interesting development.

In this paper we investigate whether decisions with regard to total risk-based capital (or regulatory capital) ratios are channeled through credit portfolio models. In other words, do credit portfolio models serve as relevant determinants of a bank's decision to adjust its capital requirement? How does the adoption of credit portfolio models influence a bank's strategy for determining its capital requirement? That is, how does a bank's decision to actively analyze its risk of exposure on the portfolio level by adopting credit portfolio models affect its regulatory capital requirements?

The crises revealed that the banks that relied heavily on portfolio models overlooked the signs of trouble. Bankers had a false sense of security as a result of their overreliance on models (that may not have been well understood) (Rodgers, 2011), and as a result of fundamental failures in the risk control system (Lang and Jagtiani, 2010). Greenlaw et al. (2008) argue that the banks' active management of their capital requirements through economic and risk models is a fundamental cause of the current crisis. In contrast with regulatory constraints, these value-at-risk models dictated the manner in which banks adjust their balance sheets

(Greenlaw et al., 2008). These facts indicate that scholars do not fully understand the role of minimum capital ratios in reducing the moral hazard of banks with regard to their capital structure.

Although, the empirical literature on the determinants of capital requirements is extensive, this research has not examined the relationship between banks that opt for credit portfolio models and their respective capital requirements. The recent empirical literature has investigated the relationship between changes in the capital structures of banks and banking regulation (Gropp and Heider, 2010; Barrios and Blanco, 2003). Similar to the findings of Ashcraft (2001), Gropp and Heider (2010) find that regulation appears to have a second-order effect on the strategies that banks use to determine their capital requirements. A recent theoretical paper by Allen et al. (2009) suggests that, given the lack of interdependence between regulation and capital structures of banks, market discipline can be induced from the asset side of the balance sheet. Another strand of the literature has intensely assessed the effect of regulatory capital requirements on capital and risk (Shim, 2010; Repullo, 2004; Rime, 2001; Jacques and Nigro, 1997; Wall and Petersen, 1995; Shrieves and Dahl, 1992). The existing time-series-related literature analyzes the effects before and after regulatory changes, whereas cross-sectional studies compared the behaviour of banks in view of their distance from the minimum capital requirement (Jackson et al., 1999). Current bank practices show that financial intermediaries hold levels of capital that are above the regulatory minimum (Flannery and Rangan, 2004; Berger et al., 1995), which previous scholar have analyzed along the lines of capital buffers (Ayuso et al., 2004; Barrios and Blanco, 2003; Milne and Walley, 2001).

To empirically test the relationship we measure the average treatment effect by conducting a quasi-natural experiment in which we employ a propensity-matching approach to panel data. We provide further insight on the risk management practices of banks based on a survey that was conducted in 2009 among 438 banks of the German Savings Banks Finance Group. In total 279 completed questionnaires were returned which equals a response rate above 60 percent. We combined these data with unique and detailed data pertaining to balance-sheets, income-statements and regional economics. The resulting unique data set allows us to contribute to the literature in the following manner. We can directly link the use of credit portfolio models to the decisions of banks regarding their respective capital requirement. We can provide unbiased results because the banks in our sample face identical prices for implementing credit portfolio models and may access the same model to measure the correlation effects. Finally, our results provide useful information because the German banking industry is representative of other European and U.S. banks that are subject to the Basel Accord.

Our results provide empirical evidence that credit portfolio models channel the business decisions of banks such that the banks adjust their levels of total risk-based capital based on these models. Contrary to the expectations under Basel II, the banks in our sample adjusted their levels of total risk-based capital upward after the introduction of the model. This finding is particularly interesting given that the German Savings Bank Group demonstrated strong performance throughout the recent financial crisis. We find that the banks in our sample significantly adjusted their capital levels one year after implementing the credit portfolio models and throughout the period until 2006. Changes in the total risk-based capital significantly differed among the users of credit portfolio models one year after the introduction of the models. Interestingly, we find that these banks were primarily driven by precaution, as the banks held more capital after the introduction of the model.

Our results suggest that the discussion regarding the overreliance of banks on quantitative models can be viewed from another perspective. Rather than inappropriately utilizing the information that is generated by the model, the banks in our sample became more stable. The banks appeared to be primarily driven by risk aversion and precaution rather than incentives to potentially exploit their deposit insurance. The banks in our sample proved to be stable throughout the financial crisis and seemed to show more caution in interpreting the value-at-risk model to establish their capital requirements. Hence, the banks did not excessively rely on quantitative models to determine their risk strategies.

Our study expands upon prior work by empirically investigating whether the adoption of credit portfolio models amounts to a notable causation on total risk-based capital. Our findings may prove valuable for regulators who aim to understand bank behavior and thus advance regulation.

The remainder of the paper is structured as follows. Section 2 provides an overview on the recent discussion on regulation and banks' credit risk management and provides a brief overview of research concerning the usage of credit portfolio models. Section 3 provides background information on the sample used for the empirical analysis and in Section 4 we present the data and in Section 5 the univariate analysis. In Section 6 we show the results of the OLS regression. Section 7 presents the identification strategy and the final results. In Section 8 we relate our results to other banking systems, before we conclude in Section 9. All tables appear in the appendix.

2 Theoretical Background

2.1 Linking credit portfolio models and capital

It is essential for banks to manage the credit risk of exposures both on the obligor level and on the portfolio level. Idiosyncratic risk factors that are associated with individual borrowers differ from systemic risks that affect the creditworthiness of all obligors. Idiosyncratic risks are diversifiable, whereas systemic risks are not diversifiable (Pederzoli and Torricelli, 2005). Credit risk consists of an anticipated component that is conventionally referred to as the expected loss, which is a cost of conducting business rather than a risk, and an unexpected component that could be caused by, for example, a macroeconomic shock. Credit losses are uncertain with regard to the economic cycle and introduce considerable volatility (i.e., unexpected loss) with regard to the expected loss (Garside et al., 1999). To quantify this volatility, the banking industry has implemented credit portfolio models. The drivers of this volatility in portfolio losses consist of two factors: concentration (i.e., the lumpness of the portfolio) and correlation (i.e., the sensitivity of the portfolio to changes in various factors, such as underlying macroeconomic factors or ratings) (Pederzoli and Torricelli, 2005; Bangia et al., 2002).

Banks use credit portfolio models for different purposes. The most prominent purpose is to calculate a bank's economic capital. Economic capital is defined as the amount of capital that a bank must have to remain solvent (at a specified confidence level over a given time horizon). In other words, economic capital is the amount of capital that a bank needs to secure its survival in a worst-case scenario (Garside et al., 1999). In addition to calculating "economic capital from the tails of the credit risk distribution (by determining the probability that a reduction in portfolio value exceeds a critical value), credit portfolio models allow banks to break down the aggregate credit risk distribution of their portfolio" (Garside et al., 1999). Hence, by employing credit portfolio models, banks can obtain knowledge regarding the credit risk distribution of each element within their portfolios. This knowledge enables banks to identify the credit risk concentrations within their portfolios. Consequently, credit portfolio models allow banks to detect diversification possibilities.

2.2 Capital requirements and bank behavior

Currently, few scholars agree on the manner in which banks precisely determine their capital requirements (i.e., match their capital to their risk levels). Banks have certain risk appetites, which materialize in the form of risk-return profiles that are specific to each bank. Scholars have long suggested that banking regulations alleviate the problems that arise from the separation of ownership from management and reduce the moral hazards that banks encounter (Dewatripont and Tirole, 1994; Hellmann et al., 2000). The banking literature advocates regulation to mitigate the distortions that arise from inadequate risk shifting, which in turn, results from improperly priced deposit insurance.

Without proper regulation, a low charter value may have an incentive to assume excessive risks (Furlong and Keeley, 1989). Similarly, a bank's access to a safety net through deposit insurance may manipulate the bank's decision regarding the optimal capital structure (Kareken and Wallace, 1978; Merton, 1977). Banks risk bearing may turn out to be indadequate. Assuming greater risks (i.e., decreasing capital relative to assets or increasing asset risk) may result in greater expected subsidies for deposit insurance or capital confiscated from depositors than a loss in charter value (Gonzales, 2005). If the incentives of depositors to interfuse market discipline are reduced (Bhattacharya et al., 1998), then banks encounter a tradeoff between holding larger ratios of capital and generating greater profits with a greater exposure to risk.

Furlong and Keeley (1989) find that the establishment of higher capital requirements reduces the incentives of banks to increase their asset risks. Capital requirements reduce moral hazards and thus mitigate the distortions of deposit insurance. However, because capital requirements restrict risk-return profiles, the incentive of banks to invest in riskier projects might also increase (Kim and Santomero, 1988).

The empirical evidence on the relationship between capital and risk suggests that the decisions of banks with respect to their capital structures are driven by precautionary motives (e.g., bankruptcy cost avoidance, regulatory costs, the unintended effects of minimum capital standards, and the dominance of leverage and risk-related costs) rather than incentives to exploit the deposit insurance subsidy (Rime, 2001; Shrieves and Dahl, 1992; Aggarwal and Jacques, 1998; Jacques and Nigro, 1997). By employing a simultaneous equation framework, Shrieves and Dahl (1992) find a positive relationship between risk exposure and capital levels. Rime (2001) observes that Swiss banks whose capital is close to the minimum capital requirements adjust their capital levels upward. Shim (2010) estimates the risk and capital adjustments of insurers as a function of capital-based regulations. The researchers find that the externalities of capital regulation have a positive effect on the risk-bearing capacities of insurers (Shim, 2010). The capital adequacy of undercapitalized insurers can be improved through capital regulation.

To date, the empirical literature on the risk-taking incentives of banks has found that precautionary motives dominate the capital decisions of banks. This result may be counter-intuitive, especially in view of the current financial crisis. Would banks have been expected to appropriately cover their risk levels? In interpreting these results, one must consider that the risk measures that are typically employed in empirical studies disregard the risk that the banks hold off their balance sheets (Avery and Berger, 1991). According to Rime (2001), risk measures, such as risk-weighted assets, define portfolio risk by heavily relying on a portfolio's asset allocation among the different risk types. In other words, recent studies have neglected the risks that arise from, for example, the concentration of portfolios. The failure to account for such risks is only appropriate if the assigned Basel risk weights per category fully mirror the real underlying risks.

2.3 Challenges in establishing regulatory regimes

The BCBS's current initiative to enhance the Basel II framework and continually advance the regulatory framework highlights the challenges that are connected with the practical design of a sound framework. Given the aforementioned limitations of appropriate risk measures, this study attempts to assist banks' in fully assessing their credit risks (which cannot be captured solely by risk-weighted assets) through credit portfolio models and capital decisions. Although we are also limited because we do not know the particular risks that are carried by each bank, we can establish whether the adopters of credit portfolio models establish their capital requirements in a manner that systematically differs from the way in which we study the capital requirements of non-adopters.

To advance regulation, a regulator must learn about current banking practices. Although the theoretical literature has extensively addressed risk and capital as functions of regulation, as documented in section 2.2, scant empirical evidence exists with respect to the relationship between the adoption of credit risk instruments, especially credit portfolio models, and capital decisions.

The existing empirical literature has primarily addressed the decisions of banks to implement risk management instruments. Numerous studies have examined the determinants of credit derivative use (e.g., Sinkey and Carter 2000; Ashraf et al. 2007; Minton et al. 2009). However, to the best of our knowledge, no policy papers have analyzed the underlying decisions to adopt credit portfolio models, and no academic studies have investigated whether the capital decisions of adopters and non-adopters exhibit any systematic differences. The analysis of Cebenoyan and Strahan (2004) empirically investigates the ways in which the capital decisions of banks are influenced by their active risk management practices, which are proxied by their loan sales and purchases. Acharya et al. (2006) study the effects of diversification (as measured by sector concentration) on the risk-return profiles of banks. Their study focuses on the question of whether diversification or specialization yields higher returns but does not determine whether banks that adopt credit portfolio models to obtain a better picture of the concentration of sectors systematically adjust their capital decisions.

The regulatory regime implemented by the Basel Comittee on Banking Supervision intended to guide capital decisions (minimum capital requirement) of banks through the rules set in Pillar 1 of the framework. The guidelines summarized in Pillar 2 were to encourage banks' to continuously improve risk instruments and internal procedures that measure the institute specific risk situation and adequacy of the capital.

2.3.1 The Basel II framework - Pillar 2: economic capital

Pillar 2 of the Basel II framework was designed to evaluate the risk assessment procedures of banks by focusing on the extent to which industry best practices are embedded in the strategic decisions of banks. The abilities of banks to appropriately assess their economic capital are central to Pillar 2 of the framework. The guidelines that were formulated in Pillar 2 of the framework were designed to "enable the regulator to evaluate the adequacy of an internal's risk management and capital decision processes" (Saidenberg and Schuermann, 2003).

To match the credit risk of a loan portfolio to a bank's specific risk appetite (which must be covered by a bank's capital), a bank uses credit portfolio models. For example, if a credit portfolio model indicates that a bank does not possess the economic capital that is necessary to cover the risks to which it is exposed, then the bank can raise fresh capital, issue new credit lines only to less risky obligors from less concentrated sectors or become involved in loan sales activities. According to Bangia et al. (2002), it is not surprising that the financial industry has more heavily applied credit portfolio models, given the increased availability of credit risk transfer instruments, such as credit derivatives.

2.3.2 The Basel II framework - Pillar 1: regulatory capital

Pillar 1 of the Basel II framework regulates the minimum amount of capital that a bank must hold from a regulatory perspective. Similar to the Basel I framework, the Basel II framework requires each bank to hold a total amount of risk-based capital (i.e., regulatory capital/risk-weighted assets) that is equivalent to at least 8% of its risk-weighted assets. The Basel II accord allows banks to establish their minimum capital requirements in accordance with their implied risks (i.e., risk sensitivity). Under the Basel I regime, banks were required to hold capital amounts that were equivalent to at least 8% of their private-sector exposures[1]. However, the introduction of the Basel II framework changed this accord by utilizing a ratings-based approach. Under Basel II, the risk weights are assigned based on the external ratings of the exposures of banks. The change that was induced by the Basel Committee on Banking Supervision (1999) was justified on the grounds of regulatory arbitrage. Within the Basel I framework, banks had an incentive to shift their exposures for which their internal risk assessments were lower than the required 8% off their balance sheets (Jackson and Perraudin, 2000). Consequently, to mitigate the risk-shifting incentives of banks and thereby more closely align their regulatory capital requirements with their economic risks, the Basel Committee on Banking Supervision (1999) introduced the Basel II framework. Tieman and Bolt (2004) show in a theoretical model that from a pure regulatory perspective regulation based on risk weights is effective.

[1]In particular, under the Basel I accord, banks were obliged to hold at least 8% of the risk-weighted receivables.

2.3.3 Capital arbitrage and active credit portfolio management

The Basel Committee on Banking Supervision hoped to eliminate the incentives of banks to shift their exposures "for which their internal capital targets are much less than 8% out of their books through so called regulatory arbitrage transactions" (Jackson and Perraudin, 2000). Although the ratings-based approach that was introduced by the Basel II framework abolished frictions on individual exposure levels, the accord did not fully consider the diversification incentives of banks.

Since the implementation of the Basel I framework in 1988 and the Basel II framework in 2004, there have been recurring attempts to use credit portfolio models to calculate the regulatory capital of banks (Jackson and Perraudin, 2000). The unlimited acknowledgment of diversification would require a regulator's permission to "use the output from credit risk models to determine regulatory requirements" (Jackson and Perraudin, 2000). Currently, capital requirements are not directly based on the results that are derived from credit portfolio models. As a consequence, the incentives for risk-based capital arbitrage remain driven by incongruences between the underlying economic risks and the risks that are embodied in regulatory capital ratios. These incongruences are derived from the failure of the purely rating-based assessment of individual exposures to capture the overall risk to which an institution is exposed.

Therefore, banks are likely to utilize information regarding the economic risks that are derived from credit portfolio models to adjust their business decisions[2] and consequently to "fine-tune" their capital requirements. Figure 1 summarizes these relationships.

The previous derivation implies the following hypotheses:

Hypothesis 1: *Given that banks learn about their credit risk exposures on the portfolio level upon the implementation of credit portfolio models, these models channel the business decisions of banks with regard to their capital requirements. Accordingly, we expect that banks that have adopted credit portfolio models would hold significantly different levels of capital compared with their counterparts in the period following implementation.*

Hypothesis 2: *Given that banks learn about their credit risk exposures on the portfolio level upon the implementation of credit portfolio models, these models channel the business decisions of banks with regard to their capital requirements. Accordingly, we expect that banks*

[2] For an overview of the industry practices that facilitate capital arbitrage, refer to Jones (2000).

that have adopted credit portfolio models would significantly change their total risk-based capital levels compared with their counterparts in the period following implementation.

Hypothesis 3: *Given the initiative of Basel II to create a method by which banks can better align their capital and risk levels, we expect negative coefficients of both the level of total risk-based capital and the change in total risk-based capital.*

We suggest that, although the regulator has not directly stimulated banks to determine their regulatory capital requirements based on these models, banks have nevertheless adapted these models to conduct their business decisions as a consequence of either their concentration of credit risk or portfolio changes that are caused by underlying macroeconomic factors that do not directly translate into the respective rating of the exposure. Banks channel their capital requirements through credit portfolio models. This approach enables banks to indirectly "fine-tune" their capital requirements.

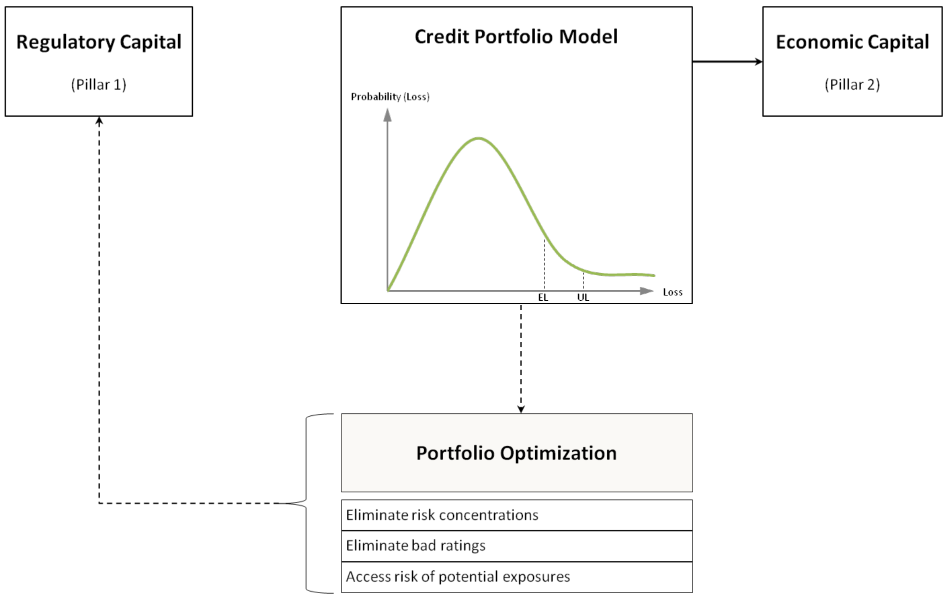

Figure 1: Linking credit portfolio models, economic capital and regulatory capital

3 Institutional background

This section provides background information pertaining to the banks in our sample. The banks in our sample are public banks and belong to the German Savings Banks Finance Group (i.e., the *Sparkassen-Finanzgruppe*), which forms one of the three pillars of the German banking system. These public banks are legally and economically independent institutions and provide financial services for their retail customers and for the small and medium-sized enterprises in their municipalities. We refer to this concept as the regional principle.[3] In contrast with the Landesbanks, the banks in our sample have proven to be stable throughout the financial crisis. The Landesbanks differ from other public banks because of their business model. As a result, we do not include these banks in our sample.

Credit portfolio models assist banks in managing the risk levels of their loan portfolios and assessing their economic capital. In principle, banks may use any credit portfolio model to manage their risks. Crouhy et al. (2000) compare various credit portfolio models, such as CreditMetrics, KMV, CreditRisk+ and CreditPortfolioView (CPV), and conclude that any of these models can be considered to be a reasonable internal model. These models are used to determine key risk figures. One commonly used risk measure is the value-at-risk (VaR) measure, which determines a bank's loan portfolio risk. The banks in our sample primarily use CreditPortfolioView, which the umbrella organization of the banking group, the German Savings Banks Association (DSGV), has adapted to their specific needs.[4]

The German Savings Bank Association (DSGV) is responsible for realizing the economies of scale in infrastructure. The organization has developed standardized finance products and provides business services to all of the banks within the group. The DSGV has implemented a standardized approach to determining credit risk by creating an internal rating system that was introduced in 2002. These ratings are used for internal risk management and regulatory capital calculations. In our sample, almost all of the banks calculate their credit risks with the standardized approach. Only one bank uses the IRB (internal ratings-based) approach.

Moody's (2010) confirms that back-office credit activities benefit from a standardized approach that is supported by uniform instruments and that is available to all banks. Therefore, all of the banks in our sample have access to the same portfolio model and have comparable costs. The cost structure of the adjusted portfolio model consists of two components. The banks are required to pay a one-time fee when obtaining the model and an additional monthly fee on a regular basis. Although the one-time fee is negligible because it is small, the monthly fee accounts for the size of the banks. Because smaller banks pay lower fees than

[3]This principle implies that these banks are allowed to generate business only within the defined region in which they operate and are not allowed to expand their businesses to other regions.

[4]For a detailed discussion of the banking group and its organizational structure, see Krahnen and Schmidt (2004), Ayadi et al. (2009) and Schmidt (2009).

larger banks, smaller banks can afford to adopt these credit portfolio models.

The CreditPortfolioView model considers the changes in market values and credit ratings. The model correlates default probabilities with macroeconomic factors (i.e., default frequencies increase during a recession) and links the default statistics that are produced by factor models to industrial and country-specific variables.

With the credit portfolio model, a bank can assess the influence of new loans on its overall portfolio risk. On a portfolio basis, a bank also accounts for the default correlation within a credit risk model framework. A bank can analyze the effects of rating changes, macro-changes or micro-changes on its portfolio. Depending on the type of credit exposures in its portfolio, a bank can undertake stress testing on a daily basis or at a minimum of once a month. These exposures may range from simple unsecured exposures to more complex products, such as structured exposures or securitizations that are designed to derive appropriate strategies. A bank can frequently estimate the effect of future loans on its portfolio. Thus, credit portfolio models represent a tool for actively managing a bank's credit risk on the portfolio level.

Given the theoretical advantages of the determination of correlation effects in the portfolio through credit portfolio models, banks that employ these instruments can adjust their economic capital requirements accordingly. However, in our sample, we observe that only a limited number of banks adopt credit portfolio models. This finding is not unique to our sample. The Joint Forum (2008) of the Bank of International Settlements prepared a report based on a survey in 2008 to explore the progress that financial conglomerates have made in identifying, measuring and managing risk concentrations. This report states that most of the surveyed firms managed their credit risk concentration levels by employing traditional methods, such as the use of internal risk limits on exposures to particular obligor names, industry sectors, geographic regions, and product types. In this sense, banks have always been engaged in loan portfolio management. However, these techniques do not specifically measure each loan portfolio's correlation. Because the interdependency of credit risk is measured by correlation, banks can account for this risk by implementing credit portfolio models. Along these lines, Duellmann and Masschelein (2007) find that the economic capital requirements increase for concentrated portfolios and thus, that banks must employ credit portfolio models to adequately manage their credit risks.

In the following, we will empirically investigate whether the adopters of credit portfolio models differ from non-adopters with respect to regulatory capital after the introduction of the models. In other words, we will determine whether credit portfolio models serve as relevant determinants of the decisions of banks to adjust their capital requirements.

4 Data

For our analyses, we merged three data sets: the balance-sheets and income statements of banks, regional economic data and survey data. We examine a data sample of regional banks that operate in only one market area within Germany. In 2008, 438 regional banks operated in the rural and metropolitan areas of Germany. We have access to a unique panel data set that was provided by the German Savings Banks Association (Deutscher Sparkassen-und Giroverband, DSGV). These data include annual observations of detailed data that were obtained from balance sheets and income statements and cover an 11-year period from 1996 to 2006.

For our analyses, we also used regional economic data that were provided by the Statistical State Offices. Specifically, we used data on 439 administrative districts in Germany. In the data set, the business activities of regional banks are limited to a specific geographical area.[5] According to the *Nomenclature of Territorial Units for Statistics* (NUTS), Germany is divided into 439 administrative districts that are classified as level 3.[6] This definition allows us to investigate regional variables, such as regional GDP, the number of inhabitants and the sector concentration.

Additionally, we have conducted a paper questionnaire survey to elicit the information needed on credit risk management. We administered the survey in April 2009. Including the cover, the full questionnaire consisted of 10 pages. The questionnaire was accompanied by explanatory cover letters from the CEO of the German Savings Banks Association and the academic project team. These letters ensured the confidentiality of the responses. We printed the name and address of each bank on the questionnaires to ensure that we could identify and match the characteristics of the responding banks with other data sources. The front page

[5] This geographical area consists of an administrative unit in which an administrative authority has the power to make administrative or policy decisions.

[6] NUTS: The Nomenclature of Territorial Units for Statistics was established by *Eurostat* to break down territorial units in a uniform manner to produce regional statistics for the European Union.

included general instructions for completing the questionnaire and definitions of the terms that were used in the questionnaire. The questionnaire was primarily answered by the top managers of each firm.

Of the 438 questionnaires that were sent to all of the regional banks from the German Savings Bank Group, a total of 279 completed questionnaires were returned. This response rate is above 60 percent. For our analyses, we used 249 responses because some banks returned the questionnaire without the front page, which contained the name of the bank. To avoid potential bias, we also excluded banks that have been involved in mergers since 2006 because a merger of two or more banks has a considerable influence on the credit risk management of a merged bank. In total, 57 percent of the banks participated in the survey. This sample is highly representative of all regions and asset classes.

In Section D of the questionnaire, we asked the respondents to provide information regarding the instruments that are used in their daily corporate operations to manage their credit risks. We asked the banks to characterize the intensity of their use of different risk management tools (i.e., frequent use, occasional use or no use). A detailed description of the questionnaire can be found in the appendix.

We analyze data that cover the period from 2002 to 2006 for the following reason. In 2002, the banks in our sample adopted a group-wide strategy that included significant reorganizational activities and introduced standardized approaches to risk management and other business areas. Public banks have traditionally benefited from state guarantees, but by the letter of 11 April 2002, the German government had accepted an amendment to the European Commission's proposal for appropriate measures regarding the system of state guarantees for German public banks (Moser and Soukup, 2002). The discussion regarding the removal of state guarantees had begun much earlier, but with the abolishment of the state guarantees, the public banks had to restructure their organizations to guarantee their competitiveness. Therefore, we conduct our analyses beginning with 2002 to account for the structural changes that occurred after this date. To avoid measuring any effects of the financial crisis, we do not consider the years from 2007 to 2009. Furthermore, we have good reason to assume that risk management instruments well established in 2009 were most likely already in place in 2002. Risk management instruments, such as CreditPortfolioView or Loan Pooling and the Rating System, were first introduced in 2002 in part because of the group-wide strategy. Additionally, the successful acquisition of the knowledge that is necessary to operate risk management instruments is a long-term endeavor. Finally, to ensure the solidity of our approach, we spoke to the risk managers of selected banks and received feedback that encouraged us to proceed with our approach.

5 Univariate analysis

This section provides descriptive statistics pertaining to the banks in our sample. We present cross-sectional results for the full sample before we compare the characteristics of the banks that use credit portfolio models with those that do not use such models.

Table 2 summarizes the results of these comparisons. We obtain observations for a total of 249 banks. We calculate the mean values of the variables for the period from 2003 to 2006. We report the bank-, regional- and market characteristics of all of the banks in our sample in column 1. In column 2 of Table 2, we provide the means of the relevant variables for the credit portfolio users (CPM users). Similarly, column 3 of Table 2 presents the characteristics of the banks that do not use any credit portfolio models.

With respect to the total risk-based capital (i.e., our main variable of interest), we observe that there are no significant differences between the means of the two groups in Panel A of Table 2 for the levels or the changes in ratios. However, when we examine one component of regulatory capital (i.e., Tier 1 capital), we observe that the two groups differ significantly at the 5% level. With regard to the bank-, regional- and market characteristics, we observe that differences exist between the two groups for most of the variables.

[Table 2]

In Table 3, we present the same set of results that were observed for the first year following the adoption of the credit portfolio model. Interestingly, we find that the change in regulatory capital differs significantly between the two groups at the 5% level.

[Table 3]

Table 4 shows the distribution of the banks' employment of credit portfolio models and the results of their quantitative assessments of the credit risk instruments. We can distinguish between the banks that use CPV and the banks that use (other) credit portfolio models or those who use both types of models. Additionally, we report whether the banks frequently or occasionally exploit the information from the instruments to quantitatively access their capital requirements.

Panel A of Table 4 reports the answers of the banks with regard to the three fundamental questions of the questionnaire[7]. The first row reports the distribution of banks that use CPV frequently, occasionally or not at all. Approximately half of the banks (138) either frequently or occasionally employed the model that was specific to the Savings Banks Group, whereas 111 banks decided not to employ the instrument. In row 2 of Panel B, we find that 20 banks frequently used a credit risk model other than CPV. Additionally, 41 banks occasionally used another credit risk model. In contrast, 184 banks reported that they had not used any other credit risk model. With regard to the information that was generated by the models, 41 banks frequently used the information that was obtained from the quantitative assessment (through any credit portfolio model) to actively manage their credit portfolios, 88 banks occasionally took advantage of this information and 120 banks did not use this information at all.

To assess whether the banks that claimed not to employ this piece of information did not utilize the credit portfolio model at all or whether they simply did not actively manage their portfolios as a consequence of the quantitative assessment, we examine the intersection sets of the questions in Panel B of Table 4.

We report the number of banks that employed CPV and at least one other credit portfolio model to assess their portfolio credit risks in row 1 of Panel B. We detect seven intersections for the banks that frequently used CPV and at least one other credit portfolio model. Six banks reported that they occasionally used two or more instruments. In contrast, 75 of the banks in our sample did not use any credit portfolio model. In row 2 of Panel B of Table 4, we report the number of banks that used the results of the quantitative assessment to actively manage their portfolios through CPV. Similarly, row 3 of Panel B of Table 4 shows the number of banks that actively managed their portfolios with other credit portfolio models. We find that 66 banks either frequently or occasionally used CPV to actively manage their portfolio, whereas 28 banks managed their portfolios based on the quantitative assessment that was produced by at least one other credit portfolio model. Row 2 of Panel B of Table 4 shows that 91 banks did not use CPV to actively manage their portfolios, whereas row

[7]The questions are translated literally in section D of the appendix

3 of Panel B of Table 4 shows that 99 banks did not use any other model. In row 4 of Panel B of Table 4, we learn that 75 banks did not use either model to actively manage their portfolios. Interestingly, after comparing rows 1 and 4 of Panel B of Table 4 and double-checking by examining the data, we find that the banks that frequently employed both models also frequently used these models to actively manage their portfolios. The same finding applies to the banks that occasionally used more than one model.

[Table 4]

Next, we provide information regarding the intersection of all of the possible answers with regard to the first two questions in Table 5.

[Table 5]

Based on the information in Table 4 and Table 5, we observe that 173 banks employed at least one credit risk model, whereas 76 banks did not employ any models.

6 OLS estimation results

To initially analyse the effect of credit portfolio models on regulatory capital decisions of banks, we estimate a model of the following form:

$$\begin{aligned} CAP_{it} = \beta_0 + \beta_1 CPM_i + \beta_2 Risk_{it} + \beta_3 TA_{it} + \beta_4 MERG_i + \beta_5 East_{it} + \beta_6 HHI_{it} + \\ + \beta_7 Lerner_{it} + \beta_8 REG_{it} + \beta_9 GDP_{it} + \beta_{10} EQU_{it} + \beta_{11} NPL_{it} + \\ + \beta_{12} CORP_{it} + \beta_{13} DL_{it} + \beta_{14} ROA_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

CAP_{it} represents the total risk-based capital (i.e., the regulatory capital), which we calculate as the ratio of Tier 1 and Tier 2 capital divided by the total assets. In our model, we also measure the effect with regard to the change in this variable.

CPM is a binary variable that represents the selection decisions of banks (i.e., whether to approve of or refrain from employing the credit portfolio models). CPM is one if a bank utilized some type of credit portfolio model. In our sample, 173 banks either intensively or frequently used credit portfolio models, whereas 76 banks did not use any model. To refrain from offering any personal judgments, we attempt to ensure clarity in our construction of this variable. Therefore, we do not use the information that was generated by question 3 of the questionnaire. This item relies on a manager's personal judgment of the extent to which the bank used the quantitative assessment that was generated by the credit portfolio models for its business decisions[8] A detailed derivation of bank characteristics, regional and market characteristics we employ in our model can be found in the Appendix, section A[9].

- Bank characteristics: Bank characteristics either influencing the decision to participate in credit portfolio modelling, affecting the outcome or both are described in short below:
  - Portfolio Risk *(RISK)*: Measured as the ratio of risk weighted assets to total assets
  - Size *(TA)*: Measured as the log of banks' total asset
  - Merger *(MERG)*: Dummy equal to one if the bank was subject to a merger in the past and zero otherwise
  - Regulatory pressure *(REG)*: Bank dummy equal to one if a bank's capital ratio is within one standard deviation of the legal minimum and zero otherwise.
  - Capital Adequacy *(EQU)*: Measured as the ratio of balance sheet equity to total assets
  - Exposure to credit risk *(NPL)*: Measured by the ratio of nonperforming loans to total assets
  - Funding structure *(DL)*: Mesured by total deposits over total non-bank loans
  - Loan structure *(CORP)*: Measured as corporate loans over total non-bank loans
  - Return on assets *(ROA)*: Measured as the return over total assets
- Regional characteristics and market characteristics: Regional or market characteristics either influencing the decision to participate in credit portfolio modelling, affecting the outcome or both are described in short below:
  - Region *(EAST)*: Binary variable equal to 1 if the bank is located in the east of Germany

[8] A detailed description of the specific items can be found in the appendix, section B.
[9] A summary of the variables that influence CPM and/or total risk-based capital can be found in Table 1.

- Portfolio concentration *(HHI)*: Measured by the Herfindahl-Hirschmann index for sector concentration; calculation is based on the number of firms conducting business by sectors as of 2005 in each region (KREIS)
- Competition *(LERNER)*: Measured by the Lerner index, calculated in how far banks can set prices above marginal cost
- Earnings in the region *(GDP)*: Measured as GDP per capita on regional level

Table 6 represents the panel results for the regression above. The rows on the left estimate the effect of the credit portfolio models on the level of total risk-based capital for the initial year following the adoption of the models (2003) and for the entire period (2003-2006). The two regressions on the right assess the effect on the change in total-risk based capital for both the initial year and the entire period.

We detect a positive significant effect at the 5% level for the two level equations. Observing the change in capital ratios, we find a positive significant effect for the sample over the entire period, but not for the initial year. For the panel regression, we clustered the standard errors at the bank level (Petersen, 2009).

[Table 6]

In Table 7, we re-estimate the equation above for the cross-section by averaging all of the variables for the period from 2003 to 2006. With regard to the level of capital, similar to the results above, we find a positive effect at the 5% significance level. The equation to the right of Table 7 measures the effect of the adoption of a credit portfolio model on the change in capital and does not appear to be significant.

[Table 7]

7 Identification strategy and estimation

7.1 Theoretical background of the propensity-matching approach

To determine whether the employment of credit portfolio models affects the regulatory capital decisions of banks, we must recognize that simply testing whether the adoption of credit portfolio models affects the total risk-based capital for the observed outcomes would be misleading. Thus, we cannot simply rely on the results above. To evaluate whether banks channel their regulatory capital decisions through credit portfolio models, we must recognize any potential selection biases because a bank's decision to employ credit portfolio models is unlikely to be exogenous. Firm characteristics such as size or concentration of sectors are likely to select banks into using credit portfolio models. Simply estimating the effect of using credit portfolio models on banks' capital ratios may be misleading, as credit portfolio choice may be endogenous.

To estimate the causal effect of credit portfolio models on total risk-based capital, we must determine what would have occurred if the users had not involved in using credit portfolio models. To do so, let *CPM* be a binary variable that indicates whether bank i adopted credit portfolio models ($CPM = 1$) or did not adopt credit portfolio models ($CPM = 0$) at time t. In the following let $\Delta y^1_{i,t+1}$[10] represent the change in capital ratios of bank i at $t+1$ after the implementation of credit portfolio models in time t. $\Delta y^0_{i,t+1}$ represents bank i's hypothetical adjustment of regulatory capital at time $t+1$ if the bank had not implemented the credit portfolio model.

The evaluation literature (see for example Angrist and Pischke, 2009) classifies this effect as the average treatment effect on the treated, formally stated as:

$$ATT = E(\Delta y^1_{i,t+1}|CPM = 1) - E(\Delta y^0_{i,t+1}|CPM = 1) \tag{2}$$

The term $E(\Delta y^1_{i,t+1}|CPM = 1)$ represents the expected value of the change in total risk-based capital of bank i at time $t+1$ and can be identified by the observed average effect of the banks that use credit portfolio models. $E(\Delta y^0_{i,t+1}|CPM = 1)$ represents the hypothetical effect of these banks on the total risk-based capital at time $t+1$ if they had not initially employed these models. This effect being unobservable represents the central problem of causal inference (Holland, 1986). Therefore, $E(\Delta y^0_{i,t+1}|CPM = 1)$ needs to be approximated. By relying on the mean outcome of the non-users, we would obtain biased results by capturing both the selection effect and the credit portfolio effect.

[10]Note that we also estimate the effect of the decision to adopt credit portfolio models on the level of total risk-based capital in the empirical section.

Although experimental studies rely on random assignments for both groups, according to Dehejia and Wahba (2002), there is no "direct estimate of the counterfactual mean" in non-experimental studies such that researchers must construct quasi-experiments to identify the causal effect. We employ the propensity score-matching technique in our study to ensure that the causal effect of using a credit portfolio model can be represented as follows:

$$ATT = E(\Delta y^1_{i,t+1}|CPM = 1, X_{i,t-1}) - E(\Delta y^0_{i,t+1}|CPM = 0, X_{i,t-1}) \tag{3}$$

where $E(\Delta y^1_{i,t+1}|CPM = 1, X_{i,t-1})$ is the mean change in the total risk-based capital ratios of the banks in time $t+1$ after employing credit portfolio models at time t and $E(\Delta y^0_{i,t+1}|CPM = 0, X_{i,t-1})$ for the control group. $X_{i,t-1}$ is a vector that contains the observable covariates that select banks into using credit portfolio models or that may influence the capital decisions of the banks.

To reduce selection bias, we rely on a propensity score-matching approach in accordance with the recommendation of Rosenbaum and Rubin (1983). As a result, we match the users of credit portfolio models (i.e., the treatment group, which is denoted as $CPM_i = 1$ for bank i) with the banks that do not employ credit portfolio models (i.e., the control group, which is denoted as $CPM_i = 0$ for bank i) on the basis of their propensity scores. The equation for the average effect of credit portfolio model adoption on total risk-based capital becomes the following:

$$ATT = E(\Delta y^1_{i,t+1}|CPM = 1,\ p(X_{i,t-1})) - E(\Delta y^0_{i,t+1}|CPM = 0,\ p(X_{i,t-1})) \tag{4}$$

To consistently estimate this effect, we must satisfy the conditional independence assumption and the overlap assumption. According to Smith and Todd (2005), conditional independence holds if the mean outcome is independent after conditioning on $X_{i,t-1}$, as shown by the following:

$$(\Delta y^0_{i,t+1} \perp CPM|X_{i,t+1})\ or\ (\Delta y^0_{i,t+1} \perp CPM|p(X_{i,t+1})) \tag{5}$$

where $\Delta y^1_{i,t+1}$ represents the change in the total risk-based capital ratios of the banks after they adopt credit portfolio models and $\Delta y^0_{i,t+1}$ is the hypothetical change in the capital ratios of bank i at $t+1$ that would have occurred if this bank had not used the credit portfolio models at time t. Equation 5 requires that there exist no unobservable disparities between the users and non-users of credit portfolio models after conditioning on $X_{i,t-1}$. If Equation 5 holds, systematic differences can be assigned to the credit portfolio model effect.

Furthermore, the common support or overlap condition must hold:

$$0 < Pr(CPM = 1|X_{i,t-1}) < 1 \tag{6}$$

Furthermore, the common support or overlap condition must hold:

$X_{i,t-1}$ represents a set of variables that determine either the outcome (i.e., regulatory capital) or a bank's adoption decision (i.e., the decision to adopt credit portfolio models). This assumption requires an overlap in the distribution of the covariates between the two groups (Smith and Todd, 2005) to ensure that the treated and non-treated groups can be matched.

Smith and Todd indicate that if Equations 5 and 6 hold, then "the mean outcome observed for the matched non-participant group can be substituted for the missing counterfactual mean for the participants"'(Smith and Todd, 2005). In other words, if both assumptions hold, then we can use the matched non-users of credit portfolios to approximate the change in regulatory capital ratios that would have occurred if the users of credit portfolios had not employed these models.

7.2 Propensity matching analysis

To disentangle the selection effect from the credit portfolio effect, we estimate a logit model that includes variables that determine the outcome (i.e., total risk-based capital) and the decisions of banks with regard to the use of credit portfolio models. We require the bank-, regional- and market characteristics to be similar before the credit portfolio models are introduced. Rubin and Thomas (1996) suggest that all of the variables that influence the outcomes should be included in the model.

We estimate a logit model of the following form:

$$\begin{aligned}CPM_{it} = \beta_0 + \beta_1 Risk_{it-1} + \beta_2 TA_{it-1} + \beta_3 MERG_{it-1} + \beta_4 East_{it} + \beta_5 HHI_{it-1} + \\ + \beta_6 Lerner_{it-1} + \beta_7 REG_{it-1} + \beta_8 GDP_{it-1} + \beta_9 EQU_{it-1} + \beta_{10} NPL_{it-1} + \\ + \beta_{11} CORP_{it-1} + \beta_{12} DL_{it-1} + \beta_{13} ROA_{it-1} + \epsilon_{it-1} \qquad (7)\end{aligned}$$

The results of this regression are reported in Table 8[11]. Acknowledging that the total risk-based capital ratios may differ between the two groups before the credit portfolio model is introduced, we control for these differences. To match the banks with similar risk characteristics, we include *Portfolio Risk (RISK)* in our model. To obtain a precise picture of each bank's capacity to absorb losses, we include balance sheet equity in the propensity regression *(Equity to assets (EQU))*. Balance sheet equity is a direct proxy for total risk-based capital and represents one component of regulatory capital. Furthermore, a loss in balance sheet equity will also affect Tier 2 capital (i.e., the other component of regulatory capital) because the amount of Tier 2 capital is bounded by the amount of balance sheet equity that is held by each bank. By controlling for these effects prior to the introduction of the model, we can match banks with similar risk capacities.

To alleviate concerns of multicollinearity in the model, we repeated our analysis with different model specifications. For instance, in one specification we excluded regulatory pressure from our model as this variable is likely to represent similar developments as the variabel capturing balance sheet equity. Examination of the variance inflation factors exhibited values below 10, which is considered the rule-of-thumb cut-off (Neter et al., 1985). Results remained robust.

[Table 8]

For the sake of comparison, we report the distribution of the propensity scores for both the banks that have adopted credit portfolio models and those that have not adopted these models in Figure 2. The graph shows the concentration of the scores to the right of the distribution for the treated group and in the middle for the control group. However, the model shows a sufficient overlap between the two groups.

[Figure 2]

[11] The balancing property is satisfied.

For the sake of completeness, we also compare the mean statistics after matching the two groups in Table 9. We find a reduction in bias for all of the variables. The differences in the means remain for only a few variables. However, these variables also exhibited reduced bias.

[Table 9]

7.3 Credit portfolio effect on total risk-based capital: results

This section presents the results of our estimation. In this setting, credit portfolio models serve as the *treatment* that is imposed on the treated group (i.e., the group that adopted credit portfolio models in 2002). The control group consists of the banks that did not use credit portfolio models in 2002 and that were matched based on their propensity scores. We are interested in determining whether the introduction of credit portfolio models affects the regulatory capital of the treated group compared with the control group.

In the following, we examine two effects:

- Effect on the level of total risk-based capital (both for the subsequent year of CPM introduction (2003) and for the whole period (2003-2006)
- Effect on the change in total risk-based capital (both for the subsequent year of CPM introduction (2003) and for the whole period (2003-2006)

7.3.1 Nearest Neighbor Matching and caliper matching

First, to conduct our analysis, we use the most straightforward nearest-neighbor matching approach. For each bank that uses credit portfolio models, the nearest-neighbor matching method selects a bank that is closest in terms of its propensity score. We need to conduct the analysis using a replacement technique because of the availability of the observations. By allowing for replacement, we can use each neighbor more than once. However, this approach introduces a trade-off between bias and variance (Caliendo and Kopeinig, 2005). Under an estimation with a replacement, the average quality of the matching increases, and this increase subsequently reduces bias (Smith and Todd, 2005). This effect is of particular concern if the distribution of the propensity scores for the two groups varies considerably. The use of matching without replacement introduces potential pitfalls if the matching process is performed in a non-random fashion. The use of an oversampling method creates matches beyond the nearest neighbor for every treated bank. Previous scholars have suggested the use of oversampling because this method reduces variance (which is a consequence of the information that is used), but this method also increases the potential bias by generating a greater number of inappropriate matches (Smith, 1997). We require common support for our estimation.

To avoid poor matches, we can impose a tolerance level on the maximum distance of the propensity score, which is called the caliper. We set the tolerance level at 1%. Through caliper matching, we match the treated bank that is closest in terms of the propensity score to a bank from the control group within a predefined caliper (Caliendo and Kopeinig, 2005). In Panels A and B of Table 10 and 13, we present the results of the matching process. We match the banks to their nearest neighbors and impose common support and a caliper of 1 %.

In Panel A of Table 10, we present the results of the single nearest-neighbor matching with replacement and common support on the change in total risk-based capital. We present the results with bootstrapped standard errors with 50, 100 and 300 replications. For the sake of completeness, we also report the results without bootstrapping. In Panel B of Table 11, we allow for oversampling while holding everything else constant.

In Panels A and B of Table 10, we find that a statistically significant effect occurs directly after the banks adopted credit portfolio models in 2003 (left column). Gaining knowledge from the model, the banks seem to have instantaneously altered their total risk-based capital ratios (change). The relationship between the adoption of credit portfolio models and the relative change in regulatory capital ratios becomes insignificant one year after the models are adopted (right column). When we examine all of the years in the right column of Table 10, the initial effect in 2003 seems to be overcompensated by the effect that was observed for the period from 2004 to 2006.

[Table 10]

In Table 13, we re-estimate the model for the absolute levels of total risk-based capital. The results are reported in Panels A and B in Table 13. We find a positive and significant effect, which is reported in the left column of Panels A and B in Table 13. The results are significant at the 1% level. Banks seem to not only alter their capital ratios after adopting credit portfolio models, as reported in the left column of Table 10, but they also seem to differ in their total risk-based capital levels.

In the right column of Table 13, we measure the effect of credit portfolio models during the time period from 2003 to 2006. We observe that the banks that adopted the model in 2003 continued to hold higher levels of capital throughout this time period. The results are statistically significant at the 1% level for the nearest-neighbor matching both with and without oversampling. The economic significance amounts to approximately 0.65 %.

[Table 13]

7.3.2 Kernel estimation

Kernel matching uses the weighted averages of the control group to generate the counterfactual outcome of a treated bank (Caliendo and Kopeinig, 2005). Contrary to the nearest-neighbor matching approach, which uses only a few observations of the control group for each matched pair, kernel estimation uses all of the information that is available to construct the counterfactual.

Kernel matching can decrease variance because this method utilizes a greater amount of information (Caliendo and Kopeinig, 2005). However, poor observations may also be used. Therefore, the imposition of common support is crucial.

Dinardo and Tobias (2001) show that the choice of kernels is of minor importance, whereas the choice of an appropriate kernel bandwidth is important (Pagan and Ullah, 1999). Because of a smoothed density function, bandwidths at the higher end of the distribution yield a better fit and a smaller variance between the true and the predicted density functions. Conversely, because of the smoothing, the estimates may be biased.

Panels C through E in Table 11 report the results for the Gaussian normal kernel specification. We set the bandwidths at 0.06, 0.4 and 0.7. We present the results with bootstrapped standard errors with 50, 100 and 300 replications. These findings support the results of the nearest-neighbor matching method. We find a statistically significant positive effect for the initial year after the adoption of the credit portfolio model (left column of Table 11). The changes in total risk-based capital ratios become insignificant when we include the period from 2003 to 2006 (right column of Table 11).

[Table 11]

Table 12 presents the results for the uniform kernel estimation. We set the bandwidths at 0.06, 0.4 and 0.7. We present the results with bootstrapped standard errors with 50, 100 and 300 replications. The results support our findings in Table 11.

[Table 12]

In Table 14, we re-estimate the model for the absolute levels of total risk-based capital by employing a Gaussian normal kernel specification. We set the bandwidths at 0.06, 0.4 and 0.7. We present the results with bootstrapped standard errors with 50, 100 and 300 replications. The results are reported in Panels C through E in Table 14. Both the results for the total risk-based capital level after the introduction of the credit risk model in 2003 and the levels that were observed for the longer horizon are significant at the 1% level.

The banks that adopted credit portfolio models in 2002 held higher levels of total risk-based capital in 2003 (left column of Table 14). The coefficients are approximately 0.5%. The economic significance of these coefficients is noteworthy when compared with the average levels of capital, which are approximately 11%.

In the right column of Table 14, we measure the effect of credit portfolio models during the time period from 2003 to 2006. We observe that the banks that adopted the model in 2003 continued to hold higher levels of capital throughout this time period. The results are statistically significant at the 1% level for all of the chosen bandwidths. The economic significance amounts to 0.7 %.

[Table 14]

In Table 15, we report the results for the uniform kernel specification. We chose the same bandwidths and standard errors as we had chosen previously, and our results remain robust.

[Table 15]

8 Discussion: external validity

We must discuss the question regarding the extent to which the results can be generalized. Are the results representative of other banking systems and financial markets? When interpreting these results, one must recall that we conducted this study within a unique environment (i.e., the banks of the German Savings Bank Group) such that we are almost confronted with a laboratory setting in this study.

However, during the last 20 years, banks throughout the world have extensively used credit risk instruments, whereas others have not used such instruments (Cebenoyan and Strahan, 2004)[12]. Therefore, our study is relevant and can provide some unique suggestions regarding the manner in which credit portfolio models channel the capital decisions of banks.

The banks in our sample adjust their capital requirements upward. Given the initiative of Basel II to better align capital and risk and thus create a path toward lower capital ratios for banks that carry less risk, our results may initially seem surprising. One could argue that the banks discovered that they were actually exposed to greater risks by utilizing the credit portfolio models and consequently, they increased their capital requirements upward. However, from a purely regulatory perspective, the banks in our sample would not have been required to adjust their total risk-based capital ratios. Their economic risks were sufficiently covered by their economic capital. The banks in our sample seemed to act on the basis of their economic judgments rather than on the basis of regulatory pressure. Given the German Savings Bank Association's 2002 initiative requesting that banks adjust their capital ratios upward, the sign of the coefficient in our study is satisfactory.

Therefore, we suggest that the channel effect of credit portfolio models on total risk-based capital can be generalized (with some caution) to other banking systems. However, the sign of the coefficient may be unique with regard to the particular business model of a specific bank or banking group.

9 Conclusion

We have documented that only 176 of the 249 banks in our sample adopted credit portfolio models to better align their capital and risk levels. There is only a limited amount of knowledge regarding the causality of the usage of credit portfolio models and their effects on the capital requirements of banks. We analyzed whether the banks that use credit portfolio models differ from the non-users in terms of their total risk-based capital ratios. Using a propensity-matching technique, we aligned the adopters and non-adopters of credit portfolio

[12] One of our recent papers addresses this question in greater detail (Bülbül et al., 2011).

models. Thereafter, we estimate the average treatment effect.

We find that the banks that use credit portfolio models hold significantly higher levels of regulatory capital. The direct implementation of the model affected the total risk-based capital ratios both one year after the adoption (2003) and throughout 2006. As a result, the users differed from the non-users. Model adoption also affected the changes in total risk-based capital ratios one year after the models were directly implemented in 2003 but did not influence these values during the period from 2003 to 2006.

The adoption of credit portfolio models affects the capital structures of banks. The banks in our sample that acquired information regarding their risk exposure both on the obligor and portfolio levels from their credit portfolio models used this information to adjust their capital ratios upward. As a result, internal risk models seem to be a dominant determinant of the decisions of banks to adjust their capital requirements.

Given that the banks in our sample demonstrated good performance throughout the financial crisis and did not rely on capital injections from the state, our results contribute to the discussion of the overreliance on quantitative models that began before the crisis occurred. The results are indicative of an interesting direction; the banks seem to have used their credit portfolios to fine-tune their capital requirements in addition to relying on their bank-specific knowledge of the market and their clients to assess their potential risks.

In this paper, we focused on the question of whether banks channel their capital decisions through credit risk instruments, particularly credit portfolio models. This more integrated view of capital requirements and capital targets provides a sound understanding of risk management practices. This knowledge may prove valuable for regulators who aim to understand bank behavior and thus to advance regulation.

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Appendix

A Detailed derivation of variables

A.1 Bank characteristics

Portfolio risk: To measure portfolio risk we include the ratio of risk weighted assets to total assets in our model. According to the buffer capital theory banks have an incentive to ameliorate the implicit cost of regulation in requiring higher capital ratios (Buser et al., 1981; Milne and Walley, 2001; Barrios and Blanco, 2003). To prevent from a decline in charter value it is in the interest of the bank to hold an amount of capital exceeding the regulatory minimum. Along these lines the theory predicts a positive relationship between portfolio risk and capital. On the other hand banks with a lower charter value or banks that are close to the minimum capital requirement have an incentive to exploit the deposit insurance subsidy. Thus, this might result in a negative relationship between capital and portfolio risk.

Along these lines it is equally likely that banks measuring high exposures in risk weighted assets, want to learn about the exact risk structure of their portfolio. Incentives to employ credit portfolio models may increase.

Size: Banks' size may influence both the outcome variable as well as a banks' decision to employ credit portfolio models.

We proxy the size effect by the log of banks' total asset. The bank size is an important factor since larger banks due to diversification may require less capital. According to Titman and Wessels (1988) fixed costs of banktruptcy comprise a smaller share of company's good will for larger banks. Larger banks may thus have an incentive to hold a smaller cushion against insolvency. Larger banks may have easier access to the capital market and face smaller transaction costs. As the banks in our sample have limited access to the capital market, this effect may be of smaller importance. The banks conduct refinancing through retained earnings rather than other alternatives.

Merger: The banks in our sample that consolidated in the recent past might have been subject to changes in managment post the merger. Incentives to adopt credit portfolio models may be affected consequentially. Therefore we include a dummy variable in our model being one if the bank was subject to a merger and zero otherwise.

Regulatory Pressure: The buffer capital theory suggests that banks hold amounts of capital exceeding the regulatory minimum foremost to circumvent the implicit cost of regulation and thus to prevent the regulator from interfering (Barrios and Blanco, 2003; Milne and Walley, 2001; Buser et al., 1981). Calem and Rob (1999) complement this hypothesis showing that poorly capitalized banks (or low charter value banks) may take on excessive risks to generate higher expected returns that will increase their capital ("'gambling for resurrection"').

We expect regulatory pressure to influence capital decisions of banks foremost. Additionally, one can imagine that banks that under increased supervisory authority may be inclined to learn more about the specific structure of their loan portfolio to ensure going concern around the regulatory mininum.

In measuring regulatory pressure we follow Ediz et al. (1998). Ediz et al. (1998) suggest to exploit information on the volatility of capital ratios to forecast the probability of falling below the regulatory requirement. As such we measure regulatory pressure to be unity if the bank's capital ratio is within one standard deviation of the legal minimum and zero otherwise.

Capital Adequacy: To obtain a precise picture of banks'capacity of absorbing losses, we include balance sheet equity over total assets in the regression. Balance sheet equity is a direct proxy of total risk-based capital and comprises one component of regulatory capital. Furthermore, a loss in balance sheet equity will also effect Tier 2 capital (the other component of regulatory capital), as the amount of Tier 2 capital is bounded by the amount of balance sheet equity a bank holds (Hortmann and Seide, 2006).

Exposure to credit risk/Loan losses: is measured by the ratio of nonperforming loans to total assets and may induce banks to require larger levels of capital. The sign of the effect could point in either direction. A bank that is exposed to financial distress faces difficulties to increase its capital ratio and may thus hold lower levels of capital. Similarly, to compensate potential risk banks may increase the capital they require.

Loan structure: The structure of lending is proxied by the ratio of corporate loans over total non-bank loans. A pure rating based assessment of individual exposures within the Basel II framework directly relates the type of the loan to the required capital.

Funding structure: The funding structure is measured by total deposits over total non-bank loans.

Profits: are measured by the return on assets. Profits may influence banks' equity requirement, either in the sense that banks may hold more equity given higher availability of capital or in the sense of remunerating excess capital, following Ayuso et al. (2004). The latter argument would typically hold for buffer requirements. Following Myers and Majluf (1984) banks prefer refinancing through retained earnings to other alternatives given comparatively smaller costs.

A.2 Regional and Market characteristics

Regional characteristics: To capture effects which may be driven by the German reunification, we control for the regional area by including a dummy variable *east* being one when the bank is located in the east of Germany.

Portfolio concentration: We calculate Herfindahl-Hirschmann index for sector concentration based on the number of firms conducting business by sectors as of 2005 in each region. Twelve sectors are specified [13]: (i) Mining and Quarrying, (ii) Manufacturing, (iii) Electricity, Gas, Steam and Air Conditioning Supply, (iv) Construction, (v) Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles Transportation and Storage, (vi) Accomodation and Food Service Activites, (vii) Transportation and Storage, (viii) Financial and Insurance Activities, (ix) Real Estate Activities, (x) Education, (xi) Human Health and Social Work Activities and (xii) Other Service Activities. Given that the banks in our sample conduct business in a defined regional area, the sector concentration in the respective region should be reflected in the lending portfolio of the bank. Thus, sector concentration in the region should lead to risk concentration in the loan portfolio of the bank. A bank with a highly concentrated loan portfolio is generally considered to be more risky. Credit risk concentration has played a critical role in past bank failures in mature economies. The Basel Committee on Banking Supervision (2004) studied the patterns of bank failures in highly developed economies with long functioning banking systems that were exposed to significant bank failures or banking crises during the past 30 years. They found that credit concentration risk was cited in nine out of 13 bank failures. Using credit portfolio models banks may learn about credit risk concentration of their portfolio.[14] Duellmann and Masschelein (2007) claim that it is necessary to

[13] Statistical Classification of Economic Activities in the European Community

[14] The Deutsche Bundesbank (2006) defines credit risk concentration as "‘concentration of loans to individual borrowers [...] and an uneven distribution across sectors of industry or geographical regions (sectoral concentration). A further risk category consists of risks arising from a concentration of exposures to enterprizes connected with one another through bilateral business relations."’

take inter-sector dependency into account for the measurement of credit risk. Credit portfolio models account for this. Banks may upon the implementation of credit portfolio models learn about the credit risk structure and consequently alter their business decisions. We expect banks with high sector concentration to be more likely to use credit portfolio models to learn about the exact concentration structure.

Competition: There is a broad literature documenting the relationship between competition and risk taking of banks (Boyd and De Nicolo, 2005; Bergstresser, 2004; Keeley, 1990). Allen et al. (2009) in a theoretical model show that banks are inclined to hold higher levels of capital given that they are exposed to higher competition. Hellmann et al. (2000); Morrison and White (2005); Repullo (2004) emphasize the role of capital resulting in decreased risk incentives of banks. Similarly, Diamond and Rajan (2000) shows how capital functions as a buffer against unexpected events.

Naturally, learning more on the portfolio structure through credit portfolio models allows banks (in altering their business decisions) to fine tune their capital ratios. We expect banks that are exposed to higher competition to be more likely to use credit portfolio models to channel the capital they require.

We use the Lerner index as a proxy for market power. We construct the Lerner index following Berger et al. (2009). The Lerner index *(LERNER)* measures by how far banks can set prices above their marginal costs and is calcualted as:

$$Lerner_{it} = \frac{(P_{it} - MC_{it})}{P_{it}}. \tag{8}$$

where P_{it} is the price proxied by the ratio of total revenues (interest and non-interest income) to total assets and MC_{it} is the marginal cost which is derived from the following translog cost function:

$$\begin{aligned} lnCost_{it} =& \beta_0 + \beta_1 lnTA_{it} + \frac{\beta_2}{2} lnTA_{it}{}^2 + \sum_{k=1}^{3} \gamma_{kt} lnW_{k,it} + \sum_{k=1}^{3} \phi_k lnTA_{it} lnW_{k,it} \\ &+ \sum_{k=1}^{3} \sum_{j=1}^{3} lnW_{k,it} lnW_{j,it} + \epsilon_{it}, \end{aligned} \tag{9}$$

where banking output is proxied by total assets TA_{it} ((Fernandez de Guevara et al., 2005; Carbo et al., 2009) and three input prices $W_{k,it}$ are defined as ratio of personnel expenses to total asset (price of labor), the ratio of interest expenses to total deposits (price of funding) and the ratio of operating and administrative expenses to total assets (price of capital). We estimate the equation by introducing year fixed and bank specific effects with robust standard errors using panel data covering all banks over 1996-2006. Marginal cost is computed as:

$$MC_{it} = \frac{Cost_{it}}{TA_{it}} \left[\beta_1 + \beta_2 lnTA_{it} + \sum_{k=1}^{3} \phi_k lnW_{k,it} \right] \tag{10}$$

We average the Lerner index for the observation period as we are interested in the competitive stance of the bank.

Earnings in the region Moreover we can account for regional characteristics on bank level since since the "'Regional Principle"' bars banks from conducting business in other regions. Therefore we include to our model regional indicators, such as regional earnings, calculated by GDP per capita.

Table 1: Overview: Influences of variables on CPM and Total risk-based capital (outcome)

Variable	**CPM**	**Total risk-based capital**
Panel A: Bank characteristics		
Risk	X	X
Total assets	X	X
Merger		X
Regulatory Pressure	X	X
Equity to Assets	X	X
NPL	X	X
Corporate Loans to Loans		X
Savings to Loans		X
ROA		X
Panel B: Regional and market characteristics		
East	X	X
Sector concentration	X	X
Lerner	X	X
GDP per Capita		X

B Survey Structure

The survey is structured as follows. The first section, *section A* contains questions about the institute and the person who takes the questionnaire. The information on the institute is beyond that which is available in balance sheet data or income statements. In particular we ask that information on the amount of market share the bank holds in the corporate loans market and deposit market be provided in percent. Moreover we ask that the proportion of their corporate business in which they have a close customer-bank-relationship as a Hausbank also be provided in percent. We also ask for information on the person answering the questionnaire. In particular we are eager to know about his/her position in the bank and how long he/she has been with the institute and in his/her current position.

In *section B* we ask questions on the market situation and how they evaluate it. We investigate if and to what extent banks have experienced or observed certain developments over time, such as the pressure on interest margin and increase in competitiveness in their markets. We further examine how they have reacted to the increasing pressure of the interest margins and what strategies they have pursued. Finally, we ask questions on their business model.

In the next section, the *section C* we want to know whether the banks have to deal with considerable risk concentration in their credit portfolio. In particular we asked the respondents what the sources of concentration risk in their bank are and if and how they avoid concentration risk. Moreover, we find it of particular interest to investigate how they deal with high volume engagements in the loan business and also what actions are taken to avoid concentration risk, if any.

In *section D* the respondents were asked to provide information on the instruments used in their daily corporate business to manage credit risk. We differentiate beween credit risk instruments used to measure credit risk and those instruments to manage credit risk actively. In this section the respondents have given open questions to list other instruments which were not covered by the question items.

The next *section E* builts on the previous section and addresses questions on the management of credit risk beyond the use of credit risk instruments. For example we investigate whether they have an efficient reporting system in place.

The last *section F* deals with the topic credit risk transfer within the banking group and their assessments of credit risk transfer in general. Moreover, we ask for a particular risk transfer instrument called "‘Kreditpoooling"’ (loan pooling) which is a product provided within the banking group. The respondents have the chance of providing comments or suggestions as they are offered two open questions.

The variable on the use of credit portfolio models is constructed from Question 13 of *section D*. The participants can indicate the usage of instruments as frequently, occasionally or no use.

Question 13: Credit portfolio modelling.

1– How intensively does your bank use the credit portfolio model "CreditPortfolioView (CPV)" to analyse credit portfolio risk?

2– How intensively does your bank use other credit portfolio models to analyse credit portfolio risk?

3– How intensively does your bank use the results from quantitative credit portfolio analyses (CPV, other) for an active management of the credit portfolio?

C Tables

Table 2: Summary Statistics for the period 2003 to 2006

This table shows the mean values of banks' characteristics, market measures and regional characteristics calculated for four years from 2003 to 2006 for all banks in column 1. In column 2 characteristics are reported for CPM-Users. Mean values for banks that do not employ credit portfolio models are presented in column 3. In column 4 we test for comparison of means between the two groups. The sample compromises 249 participating banks. Regulatory capital to risk is measured by the sum of Tier 1 and Tier 2 capital over risk weighted assets. Core Capital to risk is Tier 1 capital over risk weighted assets. Risk to total assets is calculated as risk weighted assets over total assets. Nonperformińg loans is represented by loan provisions (past due assets) over total assets. Total assests are in billion EUR. Regulatory pressure is a binary variable indicated to be one when the bank's regulatory capital is within one standard deviation of the minimum capital requirement. The banks funding structure is represented by savings to loans. ROA measures the return on assets. LERNER indices measure how far banks can set prices above their marginal costs. S_HHI is the Herfindahl-Hirschmann index for sector concentration in each region. Regional earnings are calculated by GDP per capita. East is a binary variable amounting to one when the bank is located in the east of Germany.

	(1) All banks		**(2) CPM Users**		**(3) CPM Non-Users**			
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**Difference**	**p-values**
Panel A: Regulatory Ratios								
Regulatory Capital to Risk (Level)	0.1279	0.0008	0.1286	0.0009	0.1263	0.0010	-0.0023	0.1835
Core Capital to Risk (Level)	0.0828	0.0006	0.0821	0.0007	0.0846	0.0010	0.0025	0.0477
Regulatory Capital to Risk (Change)	0.0056	0.0002	0.0056	0.0002	0.0055	0.0004	-0.0020	0.7052
Core Capital to Risk (Change)	0.0035	0.0002	0.0035	0.0002	0.0036	0.0003	0.0002	0.6007
Panel B: Bank Characteristics								
Risk to Total Assets	0.5846	0.0030	0.5830	0.0038	0.5883	0.0051	0.0053	0.4287
Total Assets	2452.2	100.7	2981.6	138.7	1247.3	48.5	-1734	0.0000
Merger	0.3293	.0149	0.3699	0.0184	0.2368	0.0244	-0.1331	0.0000
Regulatory Pressure	0.0120	0.0035	0.01300	0.0043	0.0099	0.0056	-0.0031	0.6764
Equity over Assets	0.0477	0.0003	0.0471	0.0004	0.0488	0.0005	0.0017	0.0103
Nonperforming Loans	0.0211	0.0003	0.0218	0.0004	0.0195	0.0007	-0.0023	0.0012
Corporate Loans to Loans	0.3099	0.0022	0.3196	0.0026	0.2877	0.0036	-0.0320	0.0000
Savings to Loans	0.5575	0.0076	0.5494	0.0091	0.5761	0.0136	0.0267	0.1034
ROA	0.0044	0.00007	0.0042	0.00009	0.0050	0.0001	0.0008	0.0000
Panel C: Market and Regional characteristics								
East	0.1165	0.0102	0.1329	0.0129	0.07894	0.0155	-0.0540	0.0144
Lerner	0.3118	0.0023	0.2993	0.0028	0.3404	0.0035	0.0410	0.0000
S_HHI	0.1583	0.0004	0.1589	0.0005	0.1568	0.0005	-0.0021	0.0197
GDP per Capita	24.4537	0.2501	24.9292	0.3378	23.3712	0.2741	-1.5581	0.0041

Table 3: Summary Statistics for the year 2003

This table shows the mean values of banks' characteristics, market measures and regional characteristics calculated for the year 2003 for all banks in column 1. In column 2 characteristics are reported for CPM-Users. Mean values for banks that do not employ credit portfolio models are presented in column 3. In column 4 we test for comparison of means between the two groups. The sample compromises 249 participating banks. Regulatory capital to risk is measured by the sum of Tier 1 and Tier 2 capital over risk weighted assets. Core Capital to risk is Tier 1 capital over risk weighted assets. Risk to total assets is calculated as risk weighted assets over total assets. Nonperformíng loans is represented by loan provisions (past due assets) over total assets. Total assests are in billion EUR. Regulatory pressure is a binary variable indicated to be one when the bank's regulatory capital is within one standard deviation of the minimum capital requirement. The banks funding structure is represented by savings to loans. ROA measures the return on assets. LERNER indices measure how far banks can set prices above their marginal costs. S_HHI is the Herfindahl-Hirschmann index for sector concentration in each region. Regional earnings are calculated by GDP per capita. East is a binary variable amounting to one when the bank is located in the east of Germany.

	(1) All banks		**(2) CPM Users**		**(3) CPM Non-Users**			
	mean	**sd**	**mean**	**sd**	**mean**	**sd**	**Difference**	**p-values**
Panel A: Regulatory Ratios								
Regulatory Capital to Risk (Level)	0.1182	0.0013	0.1191	0.0016	0.1163	0.0020	-0.0027	0.3209
Core Capital to Risk (Level)	0.0770	0.0010	0.0764	0.0012	0.0782	0.0017	0.0017	0.4279
Regulatory Capital to Risk (Change)	0.0030	0.0004	0.0036	0.0004	0.0019	0.0008	-0.0017	0.0469
Core Capital to Risk (Change)	0.0020	0.0003	0.0020	0.0003	0.0014	0.0005	-0.0010	0.0868
Panel B: Bank Characteristics								
Risk to Total Assets	0.5956	0.0058	0.5930	0.0073	0.6014	0.0094	0.0085	0.5055
Total Assets	2426.7	200.1	2955.5	275.7	1222.9	97.1	-1732.7	0.0001
Merger	0.3293	0.0298	0.3699	0.0368	0.2368	0.049	-0.1331	0.0397
Regulatory Pressure	0.0361	0.0118	0.0405	0.0150	0.0263	0.0185	-0.0141	0.5836
Equity to Assets	0.0453	0.0005	0.0449	0.0007	0.0462	0.0009	0.0013	0.2555
Nonperforming Loans	0.0207	0.0006	0.0210	0.0007	0.0198	0.0015	-0.0012	0.3983
Corporate Loans to Loans	0.3136	0.0043	0.3225	0.0050	0.2933	0.0076	-0.0292	0.0014
Savings to Loans	0.5576	0.0144	0.5463	0.0173	0.5835	0.0260	0.0372	0.2341
ROA	0.0050	0.0002	0.0047	0.0002	0.0056	0.0003	0.0009	0.0055
Panel C: Market and Regional characteristics								
Lerner	0.2937	0.0047	0.2801	0.0057	0.3250	0.0073	0.0448	0.0000
S_HHI	0.1583	0.0008	0.1589	0.0011	0.1568	0.0012	-.0021	0.2454
GDP per Capita	23.6261	0.4844	24.1011	0.6564	22.5119	0.5192	-1.5892	0.1311
East	0.1165	0.0203	0.1329	0.0259	0.07895	0.03114	-0.0540	0.2229

Table 4: Distribution of banks that use credit portfolio models

Instruments	Frequent use	Occasional Use	No Use
Panel A: Questionnaire Results			
Credit Portfolio View (CPV)	87	51	111
Credit Portfolio Model (other than CPV)	20	41	188
Credit Portfolio Model (Quantitative Assessment)	41	88	120
Panel B: Intersection sets of Questionnaire Results			
Employment of two Models	7	6	75
Quantitative Assessment (CPV)	35	31	91
Quantitative Assessment (other than CPV)	9	19	99
Quantitative Assessment (both models)	7	6	75

Table 5: Intersection detail of two model employment

	Frequent use CPV	Occasional Use CPV	No Use CPV
Frequent use (other than CPV)	7	3	10
Occasional use (other than CPV)	10	6	25
No use (other than CPV)	70	42	75

Table 6: OLS estimation results

This table shows the result of the OLS regression investigating the relationship the use of credit portfolio models and regulatory capital. CPM is a dummy variable, measuring credit portfolio model implementation. Risk represents the ratio of risk weighted assets to total assets. Total assets is the log of total assets. Merger is a dummy variable indicating whether the bank was involved in a merger in the consolidation period. EAST represents the region. Sector Concentration is measured by the Herfindahl-Index for sector concentration in each region. Lerner indices measure how far banks can set prices above their marginal costs. Regulatory Pressure is a dummy variable amounting to one if the bank's total risk-based capital ratio is within one standard deviation of the regulatory minimum. GDP per capita is included on regional level. Equity to assets represents bank's core capital. NPL stands for bank's non performing loans to total assets. Corporate loans are standardized over total loans. ROA represents return on assets. N represents the number of observations. Standard errors presented in parentheses.

Variable	**(1) Tier 1 & 2 (Level) 2003**	**(2) Tier 1 & 2 (Level) 2003-2006**	**(3) Tier 1 & 2 (Change) 2003**	**(4) Tier 1 & 2 (Change) 2003-2006**
CPM	0.0045**	0.0040**	0.0009	0.0019**
	(0.0021)	(0.0020)	(0.0006)	(0.0010)
Risk	-0.1585***	-0.1298***	-0.0251***	-0.0194***
	(0.0127)	(0.0128)	(0.0044)	(0.0060)
Total Assets	0.0054***	0.0034*	0.0013*	0.0009
	(0.0019)	(0.0019)	(0.0007)	(0.0010)
Merger	-0.0020	-0.0005	-0.0005	-0.0007
	(0.0021)	(0.0021)	(0.0005)	(0.0008)
East	0.0039	0.0050	-0.0031***	-0.0017
	(0.0047)	(0.0045)	(0.0011)	(0.0016)
Sector Concentration	0.0029	-0.0088	0.0045	-0.0048
	(0.0805)	(0.0750)	(0.0239)	(0.0344)
Lerner Index	0.0940***	0.0597***	0.0221***	0.0040
	(0.0229)	(0.0227)	(0.0083)	(0.0099)
Regulatory Pressure	-0.0115***	-0.0133***	-0.0027*	-0.0009
	(0.0027)	(0.0026)	(0.0016)	(0.0015)
GDP per Capita	-0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Equity to Assets	1.2568***	0.9344***	0.1744***	0.2157***
	(0.1104)	(0.1231)	(0.0378)	(0.0421)
NPL	-0.2376***	-0.1750*	0.0237	-0.0187
	(0.0825)	(0.0973)	(0.0283)	(0.0647)
Corporate Loans to Loans	0.0218	0.0276*	-0.0012	0.0021
	(0.0147)	(0.0150)	(0.0043)	(0.0060)
Saving to Loans	0.0022	0.0085	-0.0004	0.0015
	(0.0056)	(0.0053)	(0.0020)	(0.0027)
ROA	0.3326	0.7632	0.1983**	0.1011
	(0.4502)	(0.4979)	(0.0992)	(0.2071)
Constant	0.0445	0.0718**	-0.0150	-0.0107
TE	NO	YES	NO	YES
SE	Robust	Cluster	Robust	Cluster
N	988	245	981	240
adj. R2	0.6309	0.5617	0.1421	0.1127

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Propensity score distribution of treated and control group

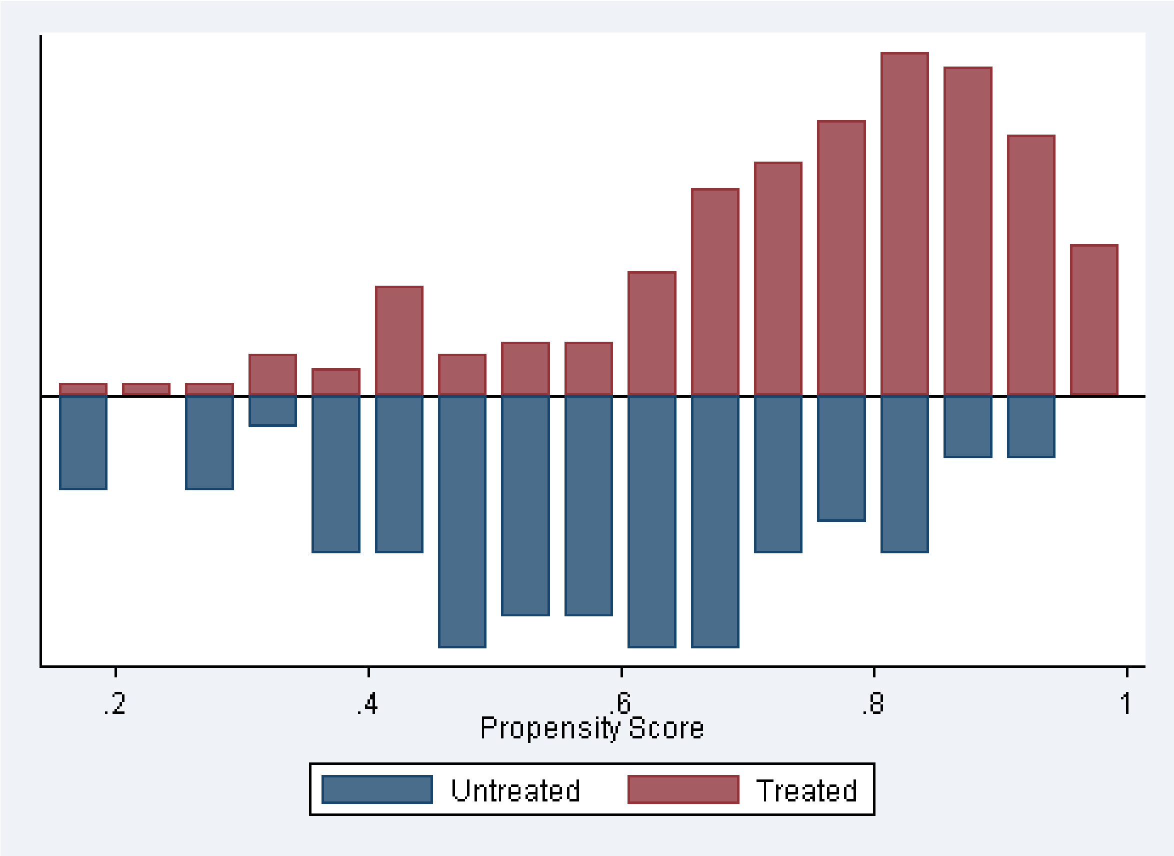

Table 7: OLS estimation results: cross section

This table shows the result of the OLS regression investigating the relationship the use of credit portfolio models and regulatory capital for the cross section. Variables are averaged over the period 2003 to 2006. CPM is a dummy variable, measuring credit portfolio model implementation. Risk represents the ratio of risk weighted assets to total assets. Total assets is the log of total assets. Merger is a dummy variable indicating whether the bank was involved in a merger in the consolidation period. EAST represents the region. Sector Concentration is measured by the Herfindahl-Index for sector concentration in each region. Lerner indices measure how far banks can set prices above their marginal costs. Regulatory Pressure is a dummy variable amounting to one if the bank's total risk-based capital ratio is within one standard deviation of the regulatory minimum. GDP per capita is included on regional level. Equity to assets represents bank's core capital. NPL stands for bank's non performing loans to total assets. Corporate loans are standardized over total loans. ROA represents return on assets. N represents the number of observations. Standard errors presented in parentheses.

Variable	**(1) Tier 1 & 2 (Level)**	**(2) Tier 1 & 2 (Change)**
CPM	0.0043**	0.0007
	(0.0020)	(0.0006)
Risk	-0.1524***	-0.0143***
	(0.0154)	(0.0043)
Total Assets	0.0069***	0.0024***
	(0.0022)	(0.0006)
Merger	-0.0007	-0.0005
	(0.0021)	(0.0006)
East	0.0006	-0.0032**
	(0.0048)	(0.0013)
Sector Concentration	-0.0193	-0.0141
	(0.0821)	(0.0227)
Lerner Index	0.1266***	0.0359***
	(0.0312)	(0.0086)
Regulatory Pressure	-0.0300***	0.0106***
	(0.0103)	(0.0028)
GDP per Capita	0.0000	-0.0000
	(0.0001)	(0.0002)
Equity to Assets	1.0524***	0.1359***
	(0.1170)	(0.0324)
NPL	-0.2366**	0.0050
	(0.1096)	(0.0304)
Corporate Loans to Loans	0.0238	-0.0031
	(0.0148)	(0.0041)
Saving to Loans	0.0018	0.0021
	(0.0057)	(0.0016)
ROA	0.7575	0.1324
	(0.6427)	(0.1780)
Constant	0.0217	-0.0364***
	(0.0390)	(0.0108)
N	249	249
adj. R2	0.6126	0.2541

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Logit Model of CPM-Use

This table reports coefficient estimates of a logit model to identify the determinants of banks' choosing to use credit portfolio models. The dependent variable is CPM, a dummy variable measuring the credit portfolio model implementation. Variables included are lagged one year prior to the CPM implementation decision of a bank. Risk represents the ratio of risk weighted assets to total assets. Total assets is the log of total assets. Merger is a dummy variable indicating whether the bank was involved in a merger in the consolidation period. EAST represents the region. Sector Concentration is measured by the Herfindahl-Index for sector concentration in each region. Lerner indices measure how far banks can set prices above their marginal costs. Regulatory Pressure is a dummy variable amounting to one if the bank's total risk-based capital ratio is within one standard deviation of the regulatory minimum. GDP per capita is included on regional level. Equity to assets represents bank's core capital. NPL stands for bank's non performing loans to total assets. Corporate loans are standardized over total loans. ROA represents return on assets. N represents the number of observations. Standard errors presented in parentheses.

Variable	**CPM-Use**
Risk	-1.7832
	(2.6424)
Total Assets	0.8761**
	(0.3794)
Merger	-0.1049
	(0.4059)
East	2.0440**
	(0.8832)
Sector Concentration	14.3075
	(15.6351)
Lerner Index	-0.6210
	(4.7596)
Regulatory Pressure	1.2127
	(0.9880)
GDP per Capita	0.0041
	(0.0335)
Equity to Assets	6.0536
	(21.3471)
NPL	-39.3723**
	(18.6203)
Corporate Loans to Loans	5.9064**
	(2.7317)
Savings to Loans	-2.3871**
	(1.0711)
ROA	-138.0188*
	(79.0752)
Constant	-12.0765*
	(6.3844)
N	246
Log Likelihood	-126.40

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: T-test for comparison of means after matching

This table reports the means of various bank-, regional- and market characteristics for the treatment and control group after matching. Percent bias and bias reduction are presented in %. Difference in means and statistical significance is reported. Risk represents the ratio of risk weighted assets to total assets. Total assets is the log of total assets. Merger is a dummy variable indicating whether the bank was involved in a merger in the consolidation period. EAST represents the region. Sector Concentration is measured by the Herfindahl-Index for sector concentration in each region. Lerner indices measure how far banks can set prices above their marginal costs. Regulatory Pressure is a dummy variable amounting to one if the bank's total risk-based capital ratio is within one standard deviation of the regulatory minimum. GDP per capita is included on regional level. Equity to assets represents bank's core capital. NPL stands for bank's non performing loans to total assets. Corporate loans are standardized over total loans. ROA represents return on assets.

Variable	**Treated**	**Control**	**% percent bias**	**% reduction in bias**	**t**	$p > t$
Panel A: Bank Characteristics						
Risk	0.59245	0.60501	-14.0	-50.4	-1.31	0.191
Total Assets	14.384	14.290	11.5	84.3	1.07	0.285
Merger	0.37126	0.35329	3.9	85.6	0.34	0.734
Regulatory Pressure	0.04192	0.08982	-26.1	-229.9	-1.77	0.078
Equity to Assets	0.04475	0.04661	-22.1	-37.7	-2.01	0.045
NPL	0.02101	0.01767	29.5	-243.1	2.97	0.003
Corporate Loans	0.32254	0.32654	-6.1	86.6	-0.54	0.589
Savings to Loans	0.55135	0.5441	3.2	81.1	0.35	0.724
ROA	0.00468	0.0049	-8.9	76.3	-0.81	0.421
Panel B: Market and Regional Characteristics						
East	0.13772	0.04192	30.6	-72.5	3.10	0.002
Sector Concentration	0.15814	0.15966	-12.7	-34.2	-1.18	0.239
Lerner	0.28337	0.27374	14.0	76.9	1.27	0.207
GDP per Capita	23.489	23.776	-4.7	73.3	-0.42	0.674

Table 10: Average treatment effects on the change in total risk-based capital

This table presents the results of the average treatment effect of credit portfolio models on total risk-based capital ratio (change) in the left column for the year 2003 and the change in total-risk based capital in the right column for the period 2003 to 2006. Groups are matched on basis of the propensity score. Panel A reports the results of the nearest neighbor matching without oversampling. Panel B presents the results of the nearest neighbor matching with oversampling. Coefficients are presented on the left, standard errors below in parantheses and t-values on the right. Standard errors are bootstrapped with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications.

	Tier capital to risk weighted assets			
	Tier 1 & 2 Change 2003		**Tier 1 & 2 Change 2003-2006**	
	Panel A: Nearest Neighbor Matching ($NN = 1$, caliper 1, replacement)			
No	0.00272	1.36	0.00189	1.82
	(0.00200)		(0.00104)	
BS 50	0.00272	1.56	0.00189	0.90
	(0.00174)		(0.00211)	
BS 100	0.00272	2.19	0.00189	0.97
	(0.00124)		(0.00195)	
BS 300	0.00272	2.03	0.00189	0.97
	(0.00134)		(0.00210)	
	Panel B: Nearest Neighbor Matching ($NN = 3$, caliper 1, replacement)			
NN	0.00260	1.71	0.00292	2.78
	(0.00152)		(0.00105)	
BS 50	0.00260	2.06	0.00292	1.20
	(0.00126)		(0.00244)	
BS 100	0.00260	1.96	0.00292	1.35
	(0.00132)		(0.00216)	
BS 300	0.00260	2.23	0.00296	1.07
	(0.00117)		(0.00276)	

Table 11: Average treatment effects on the change in total risk-based capital c'tnd

This table presents the results of the average treatment effect of credit portfolio models on total risk-based capital ratio (change) in the left column for the year 2003 and the change in total-risk based capital in the right column for the period 2003 to 2006. Groups are matched on basis of the propensity score. Panel C to E report the results of the Gaussian normal kernel estimation for various bandwidths. Coefficients are presented on the left, standard errors below in parantheses and t-values on the right. Standard errors are bootstrapped with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications.

	Tier capital to risk weighted assets			
	Tier 1 & 2 Change 2003		**Tier 1 & 2 Change 2003-2006**	
	Panel C: Kernel Matching (Gaussian normal) *bandwith* $= 0.06$			
NN	0.00264	1.33	0.00252	1.89
	(0.00198)		(0.00133)	
BS 50	0.00264	2.45	0.00252	
	(0.00108)		(0.00188)	1.34
BS 100	0.00264	1.63	0.00252	
	(0.00162)		(0.00193)	1.31
BS 300	0.00264	2.09	0.00252	
	(0.00126)		(0.00197)	1.28
	Panel D: Kernel Matching (Gaussian normal) *bandwith* $= 0.4$			
NN	0.00264	1.33	0.00253	1.89
	(0.00198)		(0.00133)	
BS 50	0.00264	1.89	0.00252	1.45
	(0.00140)		(0.00173)	
BS 100	0.00264	2.15	0.00252	1.30
	(0.00123)		(0.00193)	
BS 300	0.00264	2.08	0.00252	1.25
	(0.00127)		(0.00201)	
	Panel E: Kernel Matching (Gaussian normal) *bandwith* $= 0.7$			
NN	0.00264	1.33	0.00252	1.90
	(0.00198)		(0.00133)	
BS 50	0.00264	1.56	0.00252	1.37
	(0.00169)		(0.00184)	
BS 100	0.00264	2.17	0.00252	1.49
	(0.00122)		(0.00169)	
BS 300	0.00264	1.68	0.00252	1.22
	(0.00157)		(0.00205)	

Table 12: Average treatment effects on the change in total risk-based capital c'tnd

This table presents the results of the average treatment effect of credit portfolio models on total risk-based capital ratio (change) in the left column for the year 2003 and the change in total-risk based capital in the right column for the period 2003 to 2006. Groups are matched on basis of the propensity score. Panel F to H report the results of the uniform kernel estimation for various bandwidths. Coefficients are presented on the left, standard errors below in parantheses and t-values on the right. Standard errors are bootstrapped with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications.

	Tier capital to risk weighted assets			
	Tier 1 & 2 Change 2003		**Tier 1 & 2 Change 2003-2006**	
	Panel F: Kernel Matching (Uniform) *bandwith* $= 0.06$			
NN	0.00264	1.33	0.00252	1.89
	(0.00198)		(0.00133)	
BS 50	0.00264	2.47	0.00252	1.10
	(0.00107)		(0.00229)	
BS 100	0.00264	2.09	0.00252	1.31
	(0.00126)		(0.00193)	
BS 300	0.00264	1.57	0.00252	1.19
	(0.00168)		(0.00212)	
	Panel G: Kernel Matching (Uniform) *bandwith* $= 0.4$			
NN	0.00264	1.33	0.00252	1.89
	(0.00198)		(0.00133)	
BS 50	0.00264	1.63	0.00252	1.16
	(0.00162)		(0.00217)	
BS 100	0.00264	1.93	0.00252	1.23
	(0.00137)		(0.00204)	
BS 300	0.00264	2.13	0.00252	1.09
	(0.00124)		(0.00231)	
	Panel H: Kernel Matching (Uniform) *bandwith* $= 0.7$			
NN	0.00264	1.33	0.00252	1.89
	(0.00198)		(0.00133)	
BS 50	0.00264	2.32	0.00252	1.13
	(0.00114)		(0.00223)	
BS 100	0.00264	2.12	0.00252	1.22
	(0.00125)		(0.00206)	
BS 300	0.00264	1.90	0.00252	1.15
	(0.00139)		(0.00218)	

Table 13: Average treatment effects on level total risk-based capital

This table presents the results of the average treatment effect of credit portfolio models on total risk-based capital ratio (level) in the left column for the year 2003 and the level in total-risk based capital in the right column for the period 2003 to 2006. Groups are matched on basis of the propensity score. Panel A reports the results of the nearest neighbor matching without oversampling. Panel B presents the results of the nearest neighbor matching with oversampling. Coefficients are presented on the left, standard errors below in parantheses and t-values on the right. Standard errors are bootstrapped with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications.

	Tier capital to risk weighted assets			
	Tier 1 & 2 Level 2003		**Tier 1 & 2 Level 2003-2006**	
	Panel A: Nearest Neighbor Matching ($NN = 1$, caliper 1, replacement)			
NN	0.00593	2.08	0.00687	2.29
	(0.00285)		(0.00300)	
BS 50	0.00593	2.44	0.00687	2.45
	(0.00243)		(0.00280)	
BS 100	0.00593	2.12	0.00687	2.74
	(0.00281)		(0.00250)	
BS 300	0.00593	1.95	0.00687	2.76
	(0.00304)		(0.00249)	
	Panel B: Nearest Neighbor Matching ($NN = 3$, caliper 1, replacement)			
NN	0.00479	1.99	0.00596	2.30
	(0.00241)		(0.00259)	
BS 50	0.00479	2.25	0.00596	2.82
	(0.00213)		(0.00211)	
BS 100	0.00479	2.21	0.00596	2.94
	(0.00217)		(0.00203)	
BS 300	0.00479	2.09	0.00596	2.51
	(0.00229)		(0.00237)	

Table 14: Average treatment effects on level total risk-based capital c'ntd

his table presents the results of the average treatment effect of credit portfolio models on total risk-based capital ratio (level) in the left column for the year 2003 and the level in total-risk based capital in the right column for the period 2003 to 2006. Groups are matched on basis of the propensity score. Panel C to E report the results of the Gaussian normal kernel estimation for various bandwidths. Coefficients are presented on the left, standard errors below in parantheses and t-values on the right. Standard errors are bootstrapped with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications.

	Tier capital to risk weighted assets			
	Tier 1 & 2 Change 2003		**Tier 1 & 2 Change 2003-2006**	
	Panel C: Kernel Matching (Gaussian normal) *bandwith* = 0.06			
NN	0.00593	2.08	0.00740	3.00
	(0.00285)		(0.00247)	
BS 50	0.00593	2.64	0.00740	3.59
	(0.00225)		(0.00206)	
BS 100	0.00593	1.99	0.00740	3.00
	(0.00298)		(0.00247)	
BS 300	0.00593	2.25	0.00740	3.54
	(0.00264)		(0.00209)	
	Panel D: Kernel Matching (Gaussian normal) *bandwith* = 0.4			
NN	0.00593	2.09	0.00740	3.00
	(0.00283)		(0.00247)	
BS 50	0.00593	2.44	0.00740	2.91
	(0.00243)		(0.00254)	
BS 100	0.00593	2.22	0.00740	3.03
	(0.00267)		(0.00244)	
BS 300	0.00593	2.08	0.00740	2.95
	(0.00285)		(0.00251)	
	Panel E: Kernel Matching (Gaussian normal) *bandwith* = 0.7			
NN	0.00593	2.08	0.00740	3.00
	(0.00285)		(0.00247)	
BS 50	0.00593	2.19	0.00740	3.36
	(0.00271)		(0.00220)	
BS 100	0.00593	2.21	0.00740	3.27
	(0.00268)		(0.00226)	
BS 300	0.00593	2.25	0.00740	3.08
	(0.00264)		(0.00240)	

Table 15: Average treatment effects on level total risk-based capital c'ntd

his table presents the results of the average treatment effect of credit portfolio models on total risk-based capital ratio (level) in the left column for the year 2003 and the level in total-risk based capital in the right column for the period 2003 to 2006. Groups are matched on basis of the propensity score. Panel C to E report the results of the Gaussian normal kernel estimation for various bandwidths. Coefficients are presented on the left, standard errors below in parantheses and t-values on the right. Standard errors are bootstrapped with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications.

	Tier capital to risk weighted assets			
	Tier 1 & 2 Change 2003		**Tier 1 & 2 Change 2003-2006**	
	Panel F: Kernel Matching (Uniform) $bandwith = 0.06$			
NN	0.00593	2.08	0.00740	3.00
	(0.00285)		(0.00247)	
BS 50	0.00593	2.08	0.00740	3.19
	(0.00285)		(0.00232)	
BS 100	0.00593	2.36	0.00740	3.10
	(0.00251)		(0.00239)	
BS 300	0.00593	2.06	0.00740	3.10
	(0.00288)		(0.00239)	
	Panel G: Kernel Matching (Uniform) $bandwith = 0.4$			
NN	0.00593	2.08	0.00740	3.00
	(0.00285)		(0.00247)	
BS 50	0.00593	2.13	0.00740	3.15
	(0.00279)		(0.00235)	
BS 100	0.00593	2.35	0.00740	2.92
	(0.00252)		(0.00253)	
BS 300	0.00593	2.29	0.00740	3.08
	(0.00259)		(0.00240)	
	Panel H: Kernel Matching (Uniform) $bandwith = 0.7$			
NN	0.00593	2.08	0.00740	3.00
	(0.00285)		(0.00247)	
BS 50	0.00593	2.06	0.00740	3.19
	(0.00288)		(0.00232)	
BS 100	0.00593	2.04	0.00740	3.44
	(0.00291)		(0.00215)	
BS 300	0.00593	2.17	0.00740	3.14
	(0.00273)		(0.00236)	