Is Bank Supervision Effective? Evidence from the Allowance for Loan and Lease Losses

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Abstract

I investigate whether bank supervision is effective in enforcing written rules on the estimations of the allowance for loan and lease losses (ALLL) consistently between public and private banks, which have different intensity of incentives to misreport the ALLL. Results suggest that bank supervision of the ALLL estimations was effective between 2002 and 2012, but has become lax recently. State-chartered public banks underestimated the ALLL by about 13% annually between 2013 and 2015. Bank regulators are willing to cater to banks' private interests when the economic environment is good and the regulatory emphasis is weak, but not during the crisis.

Keywords: bank regulation, bank supervision, bank accounting and disclosure, allowance for loan and lease losses (ALLL), loan loss provisioning, reporting incentives

JEL Classification: G21, G28, M41, M48

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1 Introduction

Is bank supervision effective to ensure that banks comply with written regulations?[2] Since the 2008 financial crisis, effective bank supervision is no longer taken for granted. Lax supervisory practices existed beforehand and are blamed for several high-profiled bank failures during the crisis. Recently, weaknesses in the institutional design of bank supervision also surface, casting doubt on the effectiveness of bank supervision. For example, Agarwal et al. (2014) find that state regulators are more lenient than federal regulators when assigning the CAMELS ratings to the same state-chartered banks. Rezende (2014) finds that both federal and state regulators assign more favorable CAMELS ratings to banks that switch charters to the regulators' jurisdictions.

Although these findings suggest that bank regulators do not consistently enforce written rules that govern the CAMELS ratings, they do not directly address the question of whether bank regulators effectively enforce written regulations that govern the banks' behaviors. As a result, three questions still remain. First, is supervisory laxity a widespread phenomenon? Second, do the institutional design weaknesse have an impact on supervisory effectiveness? And third, does supervisory laxity vary over time?

Because banking regulations are numerous and no single variable can summarize banks' compliance with all regulations, in this study, I address these questions by examining a common and important supervisory target: the allowance for loan and lease losses (ALLL). The reported ALLL is a direct and observable outcome of bank supervision. It covers estimated credit losses in a bank's loan and lease (hereafter "loan") portfolio. All

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[2] The definitions of bank regulation and supervision in this paper follow the Federal Reserve's. Bank regulation refers to "the written rules that define acceptable behavior and conduct for financial institutions." Bank supervision refers to "the enforcement of these rules." (https://www.stlouisfed.org/in-plain-english/introduction-to-supervision-and-regulation)

domestic banks with lending activities must follow written regulatory guidance to estimate the ALLL and document the estimation methodology for bank examiners' regular review. The bank examiners make the final determination on whether the level of the ALLL is appropriate.

The ALLL is also subject to misreporting, making it a suitable candidate for studying the effectiveness of bank supervision. Allocations to the ALLL via loan loss provisioning reduce banks' current-period earnings, and the impact of provisioning on earnings is pro-cyclical. During a credit expansion, when bank profits are high, banks have few problems collecting loan payments from borrowers. The level of the estimated ALLL is low and the allocation of net interest income to the ALLL is small. However, in an economic downturn, when bank profits are already under pressure, the level of the estimated ALLL also increases and the proportion of net interest income allocated to the ALLL is large. As a result, when bank profitability is high, banks have incentives to overestimate the ALLL to smooth out the cyclical impact of loan loss provisioning on earnings (Kanagaretnam et al. 2004; Liu and Ryan 2006). When bank profitability is low, banks have incentives to underestimate the ALLL to preserve earnings and minimize the negative impact of earnings declines on equity capital (Huizinga and Laeven 2012).

Because no benchmark exists for evaluating whether bank supervision of the ALLL estimations is effective, I compare the ALLL estimations between public and private banks to gain an inference to the open question. Because periodic performance measures, such as earnings and equity capital, are more important to public banks than to private banks, the incentives to misreport the ALLL are intensified among public banks (e.g., Balla and Rose 2015; Beatty et al. 2002). Effective bank supervision should restrict banks from misreporting the ALLL, no matter how incentivized the banks are. If bank supervision is effective, banks will report the same level of the ALLL regardless of whether they are publicly listed. Otherwise, if supervisory laxity is present, banks' private interests are catered to—when bank profitability is high, public banks are allowed to overestimate the ALLL relative to private banks; but when bank profitability is under pressure, public banks are allowed to underestimate the ALLL relative to private banks.

Because the directions banks take to misreport the ALLL vary with the banks' financial strength, I examine bank supervision of the ALLL estimations over three periods of different economic and regulatory environments. The first period runs from 2002 to 2007. During this pre-crisis period, bank profitability was high and the regulatory emphasis on compliant ALLL estimations was strong. Between 2001 and 2006, three policy statements on the ALLL estimations were issued, requiring banks to estimate the ALLL in accordance with generally accepted accounting principles (GAAP), essentially reinforcing the "incurred loss" model. The second period covers the recent financial crisis from 2008 to 2009, when bank profitability reached historical lows. During the last period from 2010 to 2015, the economy was in recovery. Since 2013, the proportions of problem loans held by banks have fallen to pre-crisis levels. But because of rising regulatory compliance costs and squeezed interest margins, bank profitability is still under pressure. Unlike the first period, the last two periods were not associated with a similarly strong regulatory emphasis on compliant ALLL estimations.

Based on the relation between bank profitability and their incentives to misreport the ALLL, I predict that if supervisory laxity was present, public banks would overestimate the ALLL relative to private banks between 2002 and 2007, despite the strong regulatory emphasis on compliant ALLL estimations during the period. But public banks would underestimate the ALLL relative to private banks between 2008 and 2015. If bank supervision of the ALLL estimations was effective, we should observe no ALLL differences between public and private banks over the entire sample period.

The observed ALLL differences between public and private banks cannot provide unbiased inference about whether bank supervision is effective, because they are confounded by institutional and loan portfolio characteristics that are associated with both the banks' listing decisions and their ALLL estimations. The ideal experimental setting for this study is to randomly assign banks to public and private status, so private banks can serve as the counterfactuals of public banks. To create such an experimental setting, I sample public and private banks at the end of each calendar year from 2002 to 2015 and use a weighting method proposed in Li and Greene (2013) to balance 55 covariates that capture institutional and loan portfolio differences between public and private banks. The 55 covariates are constructed around the key inputs in the ALLL estimation process as outlined in the regulatory guidance and are closely related to institutional factors affecting banks' listing decisions. The weighting method achieves better covariate balance than propensity score matching and creates a pseudo-population of public and private banks from which the unbiased effect can be estimated.

The results suggest that bank supervision of the ALLL estimations was effective between 2002 and 2012, but became lax between 2013 and 2015. Between 2002 and 2005, public banks only slightly overestimate the ALLL relative to private banks. The overestimations range from \$0.0004 to \$0.0006 per dollar of total loans. The overestimations disappear in 2006 and 2007. During the crisis period between 2008 and

2009, public banks do not underestimate the ALLL relative to private banks. The ALLL estimations between public and private banks do not differ in 2008, and public banks overestimate the ALLL by $0.0010 per dollar of total loans in 2009. During the post-crisis period from 2010 to 2012, the ALLL estimations do not differ between public and private banks. However, between 2013 and 2015, public banks underestimate the ALLL by $0.0016, $0.0015, and $0.0013 per dollar of total loans, respectively.

I conduct three additional tests to confirm that the variations of the ALLL differences between public and private banks over the sample period result from changes in supervisory effectiveness. First, I use the insight from Agarwal et al. (2014) that state regulators are more lenient than federal regulators to test whether the ALLL overestimations by public banks between 2002 and 2005 and the ALLL underestimations by public banks between 2013 and 2015 are due to supervisory laxity. If bank supervision was lax in these years, more supervisory laxity, in terms of larger ALLL differences between public and private banks, would occur between state-chartered public and private banks than between federally chartered public and private banks, and between state-chartered public and private banks located in more leniently supervised states than between state-chartered public and private banks located in less leniently supervised states. The results confirm such predictions. The ALLL underestimations by state-chartered public banks between 2013 and 2015 represent about 13% of their annually reported ALLL.

Second, I further rule out alternative explanations other than effective supervision for the undetected underestimations by public banks during the financial crisis and the insignificant ALLL differences between public and private banks during the rest of the sample periods, such as the “big bath” reporting behavior by public banks and the stock market discipline explanation.

My interpretation of the results implies that bank regulators are unwilling to cater to banks’ private interests during the financial crisis, or when the regulatory emphasis is strong, such as the period from 2002 to 2007. However, when the economic environment is good and the regulatory emphasis is weak, such as the period between 2013 and 2015, bank regulators are willing to cater to banks’ private interests.

The research design of this study invokes a crucial assumption that therer are no unobservable confounders to bias the results. Given that the set of covariates balanced in the study is comprehensive and closely tied to the ALLL estimation process in the regulatory guidance, any unobservable confounders very likely contain parallel information to the 55 covariates. Once the 55 covariates are balanced, the unobservable confounders are no longer a threat to the internal validity. As demonstrated in the sensitivity analysis, once current-year loan loss rates are balanced, including the loan loss information beyond the current year does not change the inference. Although the assumption cannot be tested directly, it is reasonable to doubt the existence of such unobservable confounders that can meaningfully alter the inference.

This paper makes three contributions to the literature. First, it provides direct evidence for whether bank supervision is effective—a question the literature does not adequately address. Agarwal et al. (2014) find that federal and state regulators are inconsistent in rating state-chartered banks under the CAMELS rating system. But inconsistency in assigning ratings cannot serve as conclusive evidence that bank supervision is ineffective, for two reasons. First, the rules governing the CAMELS ratings are not directed toward regulating banks' behaviors. Second, because state and federal regulators assign different ratings after observing the same information reported by banks, the reporting outcomes may not be compromised during the supervisory processes. This paper studies a supervisory target that directly governs the reporting behaviors of banks and is central to the safety and soundness of the banking system. The results provide direct inference on whether bank supervision is effective. In fact, despite the imperfections of the institutional design of bank supervision, during the majority of the sample period examined and especially during the recent financial crisis, bank supervision of the ALLL estimations does not appear to have been ineffective. But this study confirms the finding in Agarwal et al. (2014) that the federal-state alternate supervision scheme can lead to lax enforcement of written banking rules.

Second, existing literature on bank supervision often implicitly assumes that supervisory laxity is constant over time, with the exception of Costello et al. (2016), who explore the time-varying relation between supervisory strictness and accounting restatements. This paper documents the heterogeneity in supervisory laxity under various economic and regulatory environments. Bank regulators, especially local bank regulators, are willing to cater to banks' private interests when the economic environment is good and the regulatory emphasis is weak, but not during the financial crisis. This insight is consistent with a number of observations in which banks claim that the reason to switch from federal charters to state charters post crisis is that local regulators understand their business environments better. It also raises the doubt whether bank regulators exercised regulatory forbearance during the recent financial crisis.

Finally, this paper introduces a new method for modeling banks' provisioning decisions. When examining loan loss provisioning-related questions, the literature often fits an OLS model with a small number of covariates (see Beatty and Liao (2014) for a review of the literature). As demonstrated in Armstrong et al. (2010) via propensity score matching, controlling a small number of covariates in an OLS model is inadequate to remove bias in observational studies. Likely due to this shortcoming, the literature gives conflicting results regarding whether public or private banks are more timely to provision for loan losses (Nichols et al. 2009; Olszak et al. 2016). This study finds that public and private banks report almost the same level of the ALLL between 2002 and 2012 after balancing 55 covariates with a weighting method that is more effective than propensity score matching in removing bias. The finding suggests that public banks provision neither more nor less timely than private banks. Future research on banks' provisioning decisions can utilize and refine the method used in this paper for better inference.

2 Predictions

The current accounting standards require an "incurred loss" model to estimate the ALLL; the ALLL must reflect loan losses that have probably occurred as of the evaluation date. Under this model, the ALLL is high when banks have trouble collecting principal and interest payments from borrowers, usually during economic downturns, whereas the ALLL is low when banks have few problems collecting loan payments, usually during credit expansions.

The ALLL is funded by reducing banks' current-period earnings via the PLLL, an expense account that immediately follows the net interest income on banks' income statements. As a result, the impact of loan loss provisioning on banks' earnings is pro-cyclical and amplifies the cyclicality of bank profits. During credit expansions, bank profits are high and the allocation of net interest income to the ALLL is low. The average PLLL can be as low as 5% of a bank's net interest income. However, during economic downturns, when bank profits are already low, banks have to set aside more net interest income to fund increased ALLL. The ratio of the PLLL to net interest income can go over 30%, dragging banks' earnings into the negative territory.

Because the impact of loan loss provisioning on banks' earnings amplifies the cyclicality of bank profits, banks have incentives to overestimate the ALLL to book "cookie jar reserves" to smooth earnings when profits are high (Kanagaretnam et al. 2004; Liu and Ryan 2006). But when banks are financially weak, they are incentivized to underprovision to preserve earnings and mitigate the negative impact of reduced earnings on equity capital (Huizinga and Laeven 2012).

These incentives can be intensified among public banks. Public entities face more short-term profit pressure than private entities and focus more on periodic performance measures (Narayanan 1985; Stein 1989; Shleifer and Vishny 1990; Bushee 1998; Asker et al. 2015). As a result, when bank profits are high, public banks are more incentivized than private banks to overestimate the ALLL to smooth earnings (Balla and Rose 2015). But when facing profit declines, public banks are more incentivized to underprovision (Beatty et al. 2002). Because banks' incentives drive their incompliant reporting behaviors, the different intensity of incentives to misreport the ALLL between public and private banks forms a testing ground for effective bank supervision. If supervisory laxity is present, public banks will overestimate the ALLL relative to private banks when both are financially strong, whereas public banks will underestimate the ALLL relative to private banks when both are financially weak. If bank supervision is effective, no ALLL differences will exist between the two types of banks at any time.

I examine bank supervision of the ALLL estimations over a sample period from 2002 to 2015, during which economic environments differ. To show how bank profits vary during the period, I plot banks' ROA and ROE in Figure 1. Between 2002 and 2007, bank profits were high. During the crisis period between 2008 and 2009, bank profits, especially profits of public banks, experienced steep declines.

After the crisis, although the profits of both public and private banks recovered from historical lows, they are still under pressure. Banks' ROA and ROE have remained stable since 2013, but they have not reached the pre-crisis levels. Compared to the early 2000s, when banks came out of the "tech bubble" unscathed, banks today face rising regulatory compliance costs and a prolonged near-zero interest rate environment. Both factors slow banks' profit growth. For example, post crisis, the net interest margins of both public and private banks, shown in Figure 1, continued their downward trajectory, and in 2015, reached their lowest points in 14 years. The growth of total loans during this period, also shown in Figure 1, was tepid. Low margins and slow loan growth exacerbate banks' difficulties making a profit.

Unlike the period from 2008 to 2015, the period from 2002 to 2007 is associated with a strong regulatory emphasis on compliant ALLL estimations. Between 2001 and 2007, three policy statements on compliant ALLL estimations were issued. The strong regulatory emphasis on the ALLL estimations during this period is due to the SEC's concern that public banks overestimated the ALLL to book "cookie jar reserves" to smooth earnings. In

1998, as a warning signal to all banks, the SEC publicly ordered the IPO-pending SunTrust Bank to restate its past three years' ALLL by a total reduction of $100 million. In 2001, the securities regulator issued the Staff Accounting Bulletin No. 102 *Selected Loan Loss Allowance Methodology and Documentation Issues* (SAB 102), requiring all banks to estimate the ALLL in accordance with GAAP and properly document supporting methodologies. The SEC's stance was endorsed by all bank regulators, which in the same year issued the *Policy Statement on Allowance for Loan and Lease Losses Methodologies and Documentation for Banks and Savings Institutions* (2001 Policy Statement). In 2006, the bank regulators again issued the *Interagency Policy Statement on the Allowance for Loan and Lease Losses* (2006 Interagency Statement), reiterating the "key concepts and requirements included in GAAP and existing ALLL supervisory guidance."

Based on my predictions of the relation between bank profitability and public banks' incentives to misreport the ALLL, under lax supervision, public banks would overestimate the ALLL relative to private banks between 2002 and 2007, despite the strong regulatory emphasis on compliant ALLL estimations during the period. But public banks would underestimate the ALLL relative to private banks between 2008 and 2015. If bank supervision of the ALLL estimations is effective, we should observe no ALLL differences between these two types of banks over the entire sample period.

Unlike private banks, the reporting of public banks is also subject to supervision from the SEC. But this supervisory difference between public and private banks does not change the validity of the inference from the aforementioned predictions with regard to whether bank supervision is effective. Bank regulators supervise the ALLL estimations of both public and private banks. Therefore, as long as the estimations differ between these two types of banks, bank regulators do not consistently enforce across the banks the regulation that governs the ALLL estimations. Whether bank supervision is effective is in question.

3 Method

3.1 Sample Selection

I use bank data reported as of December 31 of each calendar year from 2002 to 2015 to construct the sample. Bank data come from two sources: the Bank Regulatory database of Wharton Research Data Services (WRDS) for the years 2002 – 2013 and the FFIEC Central Data Repository's Public Data Distribution website for years 2014 and 2015.

A typical banking organization in the United States is structured as a bank holding company (BHC), a corporation that owns one or more commercial banks (hereafter "banks") and other non-banking subsidiaries. Amendments to the BHC Act in 1999 allow a BHC to declare itself a financial holding company (FHC) to engage in financial activities, such as securities underwriting and dealing, insurance underwriting and agency activities, and merchant banking.

Banks are supervised by one of the three regulatory agencies. The Office of the Comptroller of the Currency (the "OCC") supervises national banks that are federally chartered; the Federal Reserve Board (the "Fed") supervises state-chartered banks that are members of the Federal Reserve System; the Federal Deposit Insurance Corporation (the "FDIC") supervises state-chartered banks that are not members of the Federal Reserve System. The holding parent of a bank, either a BHC or an FHC, is supervised by the Fed.

To minimize observable and unobservable differences between public and private banks, I impose the following criteria on the sample selection: (1) every bank selected to the sample is a national bank, a state member bank, or a state nonmember bank and is held by a BHC or an FHC, (2) both the bank and its holding parent are headquartered in the continental United States, and (3) neither the bank nor its holding parent is owned by any foreign entity or person.

A bank is "public" if either the bank itself or its holding parent is listed on one of the three major exchanges, i.e., the NYSE, the AMEX, or the NASDAQ. I identify public banks in the sample using the CRSP-FRB link table (2014-3), which is available on the website of the Federal Reserve Bank of New York. The table lists the majority of the banks or their holding parents that were once listed on one of the three major exchanges between January 1, 1990 and March 31, 2014. I use the CRSP Daily Stock File of WRDS to obtain the start and end dates of the listings up to December 31, 2015, the last day of the sample period.

I delete the bank-year observations of a public bank before the start date and after the end date of its listing from the sample, for two reasons. First, many banks are traded on an OTC market before being listed on a major exchange, and almost all banks are moved to an OTC market after a delisting event. An OTC-listing is distinct from both "being public" and "being private" (Bushee and Leuz 2005). Such bank-year observations are not suitable to be considered either public or private. Second, Ball and Shivakumar (2008) show that prior to a public listing, private non-financial firms start to adjust their financial reporting to resemble that of public firms as early as three years before their IPOs. Banks that consider an IPO may do the same. Given that the exact dates when banks contemplate going public are unknown, considering such pre-IPO bank-year observations either public or private is not appropriate.

For banks that do not have a match in the CRSP-FRB link table, I search SNL Financials to identify omitted public listings and code the remaining banks "private" if I cannot find a trading history on any OTC market. A few banks have holding parents that are themselves subsidiaries of a BHC or an FHC. If the higher holders are publicly listed, the banks held underneath are coded "public".

3.2 The Regulatory Guidance on the ALLL Estimations

Estimating the ALLL is essentially estimating loan losses (impairments) that have probably occurred as of the evaluation date. The ALLL has two major components: loan losses estimated under ASC 310-10-35 (FAS 114) and loan losses estimated under ASC 450-20 (FAS 5).[3] Figure 2 illustrates the steps a bank must follow to estimate loan losses. The first step is to classify each loan into the FAS 114 pool and the FAS 5 pool, based on whether the loan is considered impaired. Loans in the FAS 114 pool are evaluated individually for impairments, using one of the three valuation methods: fair value of the collateral if the loan is collateral-dependent, present value of expected future cash flows, or the loan's observable market price. Which method to use is at the banks' discretion.

Loans that are not considered impaired are evaluated under FAS 5. Loan losses estimated under FAS 5 often constitute the largest component of the ALLL. The evaluation follows three steps: (1) segmenting the loan pool into different loan categories based on common risk characteristics, (2) estimating the adjusted historical loan loss rate (net charge-off rate) for each loan category, and (3) applying the estimated loan loss rate to estimate loan losses. The regulatory guidance does not prescribe how to segment the loan

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[3] A small component of the ALLL is estimated under ASC 310-30 (SOP 03-3), *Accounting for Certain Loans or Debt Securities Acquired in a Transfer.*

pool and how to estimate the adjusted historical loan loss rate. Banks determine how to do so, based on the complexity of the banks' lending activities and the capability of the banks' information systems.

The historical loan loss rate is estimated from historical net charge-offs. To determine the historical net charge-offs relevant to the loan loss rate estimation, banks either take a simple average of the net charge-offs over a period of time in the past or use a more complex migration analysis assigning more weights to more recent net charge-offs. Because the loan portfolio condition when historical loan losses occurred may differ from the loan portfolio condition at the date of the evaluation, the historical loan loss rate must adjust for environmental factors that are relevant to the current condition of the loan portfolio before being applied to estimate loan losses. The environmental factors can include the following: volume and changes in volume of past due and nonaccrual loans; changes in volume and types of loans; changes in lending policies and procedures; changes in experience, ability, and depth of lending staff and management; and changes in local and national economic and business conditions (2001 Policy Statement; 2006 Interagency Statement).

The ALLL covers estimated losses within all loans held for investment, but does not cover estimated losses within loans carried at fair value, loans held for sale, off-balance sheet credit exposures, or general business risks.

3.3 Covariate Construction

The raw ALLL differences between public and private banks cannot provide unbiased effects of reporting incentives due to public listing on the ALLL estimations, because they are confounded by loan portfolio and institutional characteristics, which are associated with both the ALLL estimations and the banks' listing status. First, based on the regulatory guidance, the ALLL estimations are determined by the characteristics of the banks' loan portfolios and institutional factors, such as the complexity of the banks' lending activities and the capability of the banks' management, lending staff, and information systems. Second, the same loan portfolio and institutional characteristics are also associated with the banks' public listing status. A major factor that influences a bank's decision to go public is access to the equity market to fund expansions of their lending businesses. Banks that opt for an IPO also have the capability to carry out such endeavors. Over time, with an objective to pursue faster growth, public banks not only build loan portfolios vastly different from the loan portfolios of private banks, but they also become more sophisticated institutions.

To adequately control for confounding, these loan portfolio and institutional characteristic differences must be balanced between public and private banks. Moreover, the covariates to capture these characteristic differences must closely tie to the ALLL estimations. To an academic researcher who does not have access to individual loan impairment data, estimating the ALLL is no different from estimating probable loan losses by banks for the FAS 5 loan pool, of which banks also cannot observe the loan losses. I follow the FAS 5 estimation steps to identify and construct 55 covariates that capture these loan portfolio and institutional differences between public and private banks. This approach does not consider the factors that influence the loss estimations of the FAS 114 loans. But because the FAS 114 factors are specific to individual loans, they are likely idiosyncratic in nature and do not contribute to systematic ALLL differences between public and private banks. Therefore, ignoring these factors is not likely to introduce bias in the effect estimation.

3.3.1 Covariates that Reflect Loan Portfolio Characteristics

According to FAS 5, the first step in estimating loan losses is to segment the loan pool into different loan categories based on common risk characteristics. Following this approach, I segment the loan portfolios of the banks in the sample into the following six categories: residential real estate loans, commercial real estate loans, commercial & industrial loans, consumer loans, loans secured by farmland, and agricultural loans.

These loan categories expose banks to significant credit risks, and the risk exposures are statistically different between public and private banks. To illustrate this point, I list all loan categories reported by banks in the Call Report filings in Figure 1 and compare the average concentration of credit of each loan category between public and private banks over the sample period. I calculate a concentration of credit by dividing the amount of loans in each category by the sum of Tier 1 risk-based capital and the ALLL. This formula for calculating the concentration of credit is taken from the Comptrollers Handbook (December 2011) of the OCC.

The OCC considers a concentration of credit exceeding 0.25 a material exposure to credit risks. For both public and private banks, the concentrations of credit of residential real estate loans (real estate loans secured by 1-4 family residential properties), commercial real estate loans (real estate loans secured by commercial properties), commercial & industrial loans, and consumer loans all exceed 0.25. The p-values from the Kruskal-Wallis

Rank Sum Test[4] and the SMDs both suggest that the differences in the concentrations of credit of these loans are statistically significant between public and private banks. Unlike private banks, public banks engage in less agriculture-related lending. For public banks, the concentrations of credit of real estate loans secured by farmland and agricultural loans are below 0.25, but for private banks, these concentrations of credit are often above 0.5.

For the rest of the loan categories held by both public and private banks, such as municipal loans, loans to depository institutions, loans to foreign government, other loans, and lease financing receivables, the concentrations of credit are small. Many of these loan categories do not exhibit statistically significant differences between public and private banks. Therefore, I do not consider these loan categories when constructing the covariates.

Based on the regulatory guidance, the second step in the ALLL estimation under FAS 5 is to estimate the adjusted historical loan loss rate for each loan category. Loan loss rates are estimated from historical net charge-offs and are adjusted for environmental factors. First, I construct the covariate "current-year loan loss rate" for each loan category using current-year net charge-offs of each loan category divided by total loans. Using average 12-month net charge-offs over the past 12 to 36 months is common among banks in estimating loan loss rates. In the sensitivity analysis, I show that including information from the prior-year net charge-offs does not change the inference.

Next, I construct covariates to capture the environmental factors related to loan portfolio characteristics when adjusting the historical loan loss rates. These environmental factors include the volume of loans, the change in the volume of loans, and the volume and the change in the volume of problem loans. I measure the volume of loans and the change

[4] The null hypothesis of the test is that the two comparison groups originate from the same distribution. Unlike the t-test, the Kruskal-Wallis test is non-parametric and does not assume normal distributions.

in the volume of loans of each loan category by its concentration of credit and its year-over-year growth, respectively. I follow the Call Report filings to categorize problem loans into three likelihoods of default: past due 30-89 days and still accruing principal and interest payments, past due 90 or more days and still accruing principal and interest payments, and in nonaccrual status. I measure the volume of problem loans by dividing the amount of problem loans in each loan category by the amount of total loans. The reason to use total loans as the scaler is that the ALLL is reported at the total loan level. The impact of problem loans in each loan category on the ALLL estimations should consider their proportional relevance to the entire loan portfolio. Because zero values appear often when individual banks report problem loans in each loan category, I calculate the change in the volume of problem loans as the year-over-year growth of problem loans at the total loan level to preserve the sample size. A total of 39 covariates are constructed to reflect the banks' loan portfolio characteristics. They are listed in Appendix A-I.

3.3.2 Covariates that Reflect Institutional Characteristics

In this section, I discuss covariate construction to capture the environmental factors associated with institutional characteristics of the banks, such as the capability of the banks' management, lending staff, and information systems. A common covariate that reflects banks' institutional characteristics is the size of the bank. Bank size is measured as the log of total assets. Banks can be held by either an FHC or a BHC. Because an FHC engages in more complex financial activities and must meet more stringent performance criteria, I use an indicator variable TYPE to differentiate banks held by FHCs from banks held by BHCs.

I construct the rest of the covariates to be closely related to the CAMELS rating system, following the variable definitions in Bassett et al. (2015), Falato and Scharfstein

(2016), and the Uniform Bank Performance Report. The CAMELS rating system is the only uniform rating system to evaluate a bank's managerial, operational, financial, and compliance performance. The CAMELS ratings consist of six components: capital adequacy (C), asset quality (A), management capability (M), earnings quantity and quality (E), the adequacy of liquidity (L), and sensitivity to market risk (S). Appendix A-II lists and defines the covariates constructed under each of the six components. The covariates that reflect loan portfolio characteristics also reflect the "asset quality" of the banks, so only one covariate is included under "asset quality". A total of 16 covariates are constructed to reflect the banks' institutional characteristics.

3.4 Weighting to Estimate the Unbiased Effect

This study uses the ALLL rather than the PLLL as the dependent variable. The reason for this selection is twofold. First, the ALLL is the named supervisory target in all supervision manuals published by the three regulatory agencies. Second, the ALLL is closely related to two component ratings in the CAMELS rating system: asset quality and earnings. Under "asset quality", a bank is assessed for "the adequacy of the allowance for loan and lease losses and other asset valuation reserves." Under "earnings", a bank is assessed for "the adequacy of provisions to maintain the allowances for loan and lease losses and other valuation allowance accounts." (FDIC Statements of Policy, Uniform Financial Institutions Rating System). These two observations suggest that compared to the PLLL, the ALLL is of first-order importance to bank regulators.

Prior literature often uses an OLS approach to model banks' provisioning decisions. The success of an OLS model in removing bias depends on the validity of two assumptions: first, that the comparison groups share the same distributions in the covariates, and second, that not only is the relationship between the dependent variable and the covariates linear, but also that the linear relationship is the same between the comparison groups. These assumptions are often too stringent to be satisfied using observational data, causing effects estimated under an OLS model to be model-dependent.

Instead of imposing model assumptions on the data, I use a matching method for this study. The advantage of a matching method over the OLS approach is that the former mimics a randomized experiment to separate the stages of design and outcome analysis. In the design stage, comparison groups are balanced over covariates that likely contribute bias to the effect estimation. Under the conditional independence assumption, once the covariates are balanced, the outcomes of comparison groups no longer depend on the treatment assignment, just like the outcomes of comparison groups do not depend on the treatment assignment in a randomized experiment. In the outcome analysis stage, the effect can be estimated by simply calculating the difference in group means.

A common matching method is matching on the propensity score—the probability of receiving the treatment conditional on the covariates. A disadvantage of propensity score matching is that it often does not use all the data in the sample. In a typical one-to-one matching without replacement, observations in one of the comparison groups without a match in the other are dropped from the sample, reducing the estimation precision and the external validity. K-to-one matching or matching with replacement can keep more data in the matched sample. But the former can introduce bias in the effect estimation, whereas the latter makes inference more complicated, because units selected from one of the comparison groups are likely sampled multiple times and are no longer independent of each other in the matched sample (Stuart 2010).

Because private banks outnumber public banks in my sample, I use a weighting method developed by Li and Greene (2013) to circumvent the disadvantage of propensity score matching. The weighting method is analogous to one-to-one without-replacement propensity score matching, but uses all the data in the sample. In their simulation study, Li and Greene (2013) demonstrate that the weighting method achieves better balance and more efficient estimation than propensity score matching.

The first step of the weighting method, as in propensity score matching, is to estimate the propensity scores. I run the following logistic regression for each sample year to estimate the propensity scores:

$$\mathrm{Log}\left(\frac{\mathrm{Pr}(Z_i=1)}{1-\mathrm{Pr}(Z_i=1)}\right) = \alpha_i + \boldsymbol{\beta X_i}.$$

Z_i is the "Public" dummy. Z_i = 1 if bank i is public; Z_i = 0 if bank i is private. α_i indexes the state where bank i is physically headquartered. Because the environmental factors for adjusting the historical loan loss rates take into account regional economic conditions, adding the state indicator controls for all observable and unobservable economic and business environmental differences across states. $\boldsymbol{X_i}$ is a vector containing the 55 covariates of bank i.

Two general concerns exist regarding the propensity score estimation. First, the estimation model may be misspecified. This concern, however, is not an issue if the 55 covariates are balanced between public and private banks. Once such balance is achieved, the estimated propensity scores are consistent estimators of the true propensity scores (Ho et al. 2007).

The second concern is that some unobservable confounders continue to contribute bias in the estimation. However, the unobservable confounders can only contribute bias to the effect estimation when they are both related to the ALLL estimations and orthogonal to the 55 covariates. Otherwise, if the unobservable confounders are correlated with one or more covariates, once the 55 covariates are balanced, the unobservable confounders are also balanced. Given that this study uses a large set of covariates to estimate the propensity scores and the covariates are constructed around the key inputs of the ALLL estimation process, the unobservable confounders likely contain parallel information to the 55 covariates and therefore, are not threats to the internal validity. I demonstrate in the sensitivity analysis that the 55 covariates can indeed balance omitted variables that contain parallel information to the 55 covariates.

The second step of the weighting method is to calculate the "matching weight" (Li and Greene 2013) assigned to each observation based on the estimated propensity score. The following is the formula for calculating the matching weight for bank i:

$$\frac{\min(\theta_i, 1-\theta_i)}{Z_i\theta_i + (1-Z_i)(1-\theta_i)},$$

where θ_i denotes the estimated propensity score of bank i. The matching weight closely resembles the weight used in the inverse probability of treatment weighting (IPTW). They share the same denominator, but the matching weight replaces the numerator "1" in the IPTW weight with $\min(\theta_i, 1-\theta_i)$. As a result, unlike IPTW, which often suffers from extreme propensity score values, this weighting method assigns smaller weights to observations with extremely large and small propensity scores (when θ_i equals 0 or 1, the observation receives zero weight).

The final step is to run a matching weight-weighted regression:

$$\frac{ALLL_i}{Total\ Loans_i} = \alpha_1 + \mu_1 Z_i + e_{1i}.$$

μ_1 is the estimated effect of reporting incentives due to public listing on the ALLL estimations. If the 55 covariates are balanced between public and private banks, the above regression will give the unbiased effect estimate under the conditional independence assumption.

I also run a longer version of the above regression, controlling for all 55 covariates used in the propensity score estimation model and with the state fixed effects:

$$\frac{ALLL_i}{Total\ Loans_i} = \alpha_i + \mu_2 Z_i + \boldsymbol{\beta_2 X_i} + e_{2i}.$$

If the covariates are balanced between public and private banks, adding covariates and fixed effects to the regression will not alter the size of the estimated effect from the shorter regression, i.e., $\mu_1 = \mu_2$, but may yield a smaller standard error on μ_2. If $\mu_1 = \mu_2$, the estimated effect is indeed unbiased under the conditional independence assumption.

4 Results[5]

4.1 Check Balance

Before moving to the outcome analysis stage to estimate the effect, we need to make sure that the estimated propensity scores can balance the 55 covariates between public and private banks. To test whether the state fixed effects in the propensity score estimation model can balance the differences of economic conditions between states where the public and private banks are located, I also check the balances of three economic indicators: the state unemployment rate (UNST), the state GDP growth (GDPST), and the state year-over-

[5] Data analysis is conducted in R (R Core Team 2016) and uses the following R packages: "data.table" (Dowle et al. 2015), "dplyr" (Wickham and Francois 2016), "ggplot2" (Wickham 2009), "glm2" (Marschner 2014), "lmtest" (Zeileis and Hothorn 2012), "Matching" (Sekhon 2011), "multcomp" (Hothorn et al. 2008), "multiwayvcov" (Graham et al. 2016), "reshape2" (Wickham 2007), "survey" (Lumley 2016, 2004), and "tableone" (Yoshida and Bohn 2015).

year change in the value of housing permits (PMST). I obtain these economic indicators from the websites of the Bureau of Labor Statistics, the Bureau of Economic Analysis, and the Census Bureau, respectively.

I use the SMDs to check balances of the 58 covariates between public and private banks. The SMDs are preferred to the p-values from a statistical test of hypothesis to infer whether covariates between comparison groups are balanced, because the SMDs are calculated independent of the sample size (Austin and Stuart 2015). If the sample size is reduced during the design stage, the p-values from a hypothesis test can be inflated simply because of a loss of statistical power.

I graph the SMDs of the 58 covariates of the unmatched and the weighted samples by sample year in Figure 2. To compare the balancing capability of the weighting method with that of propensity score matching, I also graph the SMDs from a matched sample after applying one-to-one without-replacement matching on the logit of the propensity score, with a caliper of width equal to 0.2 of the standard deviation of the logit of the propensity score. In simulation studies, this particular propensity score matching method estimates the treatment effect with smaller bias and mean squared error than optimal and nearest neighbor matching (Austin 2014). The propensity scores used in the matching method are the same as the ones used in the weighting method.

Covariates are listed in each graph in the descending order of the magnitude of the SMDs of the unmatched sample. In each graph, the red line plots the SMDs of the unmatched sample, the green line plots the SMDs of the matched sample, and the blue line plots the SMDs of the weighted sample. SMD = 0.1 is noted in all graphs as a solid straight line to the right of 0.0. An SMD < 0.1 usually suggests that the covariate is balanced between the comparison groups, whereas an SMD > 0.1 often suggests that the covariate is not balanced and may contribute bias to the effect estimation.

The rank order of the magnitude of the SMDs among covariates in the unmatched samples varies from year to year, but bank size (SIZE) remains the covariate with the largest imbalance between public and private banks across all years. Imbalances of entity type (TYPE) and concentrations of credit of agricultural loans (AG.CON), real estate loans secured by farmland (FARM.CON), and commercial real estate loans (CRE.CON) are also frequently among the top five largest.

The graphs clearly show that the weighting method achieves better balances among covariates than propensity score matching in all years. All SMDs under the weighting method, including the SMDs of the three economic indicators, are smaller than 0.1. In fact, across all years and all covariates, the maximum SMD under the weighting method is 0.067, whereas the maximum SMD under the propensity score matching is 0.267. In addition, the propensity score matching often causes the SMDs of several covariates that are balanced in the unmatched samples to exceed 0.1 after matching.

4.2 Baseline Results

Table 2 presents the estimated effects of reporting incentives due to public listing on the ALLL estimations. The effects are reported under "Public" and are estimated under three methods: (1) an OLS model with the 55 covariates as control variables and the state fixed effects, (2) a matching-weight weighted regression without any control variables or the state fixed effects, and (3) a matching-weight weighted regression with the 55 covariates as control variables and the state fixed effects. All standard errors are in parentheses and are clustered at the state level. The effects estimated under the third method are the baseline results.

A side-by-side comparison of the effects estimated under the two weighting methods shows that either the coefficients on "Public" under both methods are identical or the discrepancy is no larger than 0.0003 across all years. It suggests that the weighting method is successful in removing the bias captured by the 55 covariates and the state indicator variable in the propensity score estimation model. A side-by-side comparison of the effects estimated under the weighting method with a weighted regression with controls and the state fixed effects and the OLS model shows that although the signs of the coefficients are almost identical in all years under both the weighting method and the OLS model, the effect estimates from the OLS model are often larger. The OLS approach likely continues to give biased effect estimates.

Based on the predictions discussed in section 2, if bank supervision of the ALLL estimations was effective, public and private banks in the weighted sample would report the same level of the ALLL throughout the entire sample period. If bank supervision of the ALLL estimations was lax, public banks would overestimate the ALLL relative to private banks between 2002 and 2007, when bank profitability was high. But public banks would underestimate the ALLL between 2008 and 2015, when bank profitability was under pressure.

The baseline results suggest that bank supervision of the ALLL estimations was effective between 2002 and 2007. During this period, public banks only overestimate the ALLL between 2002 and 2005. The overestimations range from \$0.0004 to \$0.0006 per dollar of total loans. Based on the average total loans held by public banks during the period, these ALLL overestimations are small in economic magnitude; they represent 2.1%-4.1% of reported ALLL. In 2006 and 2007, the ALLL estimations do not differ between public and private banks. These results can be explained by the strong regulatory emphasis on compliant ALLL estimations during this period. After the issuance of the SAB 102 and the 2001 Policy Statement, public banks constrained their behaviors to smooth earnings (Balla and Rose 2015). The disappearance of the ALLL differences between public and private banks in 2006 and 2007 also coincides with the issuance of the 2006 Interagency Statement.

The results between 2008 and 2015 suggest that bank supervision was effective during the crisis and the short period afterward, but became lax in the last three years of the sample period. In 2008, the ALLL difference between public and private banks is zero, and in 2009, public banks overestimate the ALLL by $0.0010 per dollar of total loans. From 2010 to 2012, public and private banks report the same level of the ALLL. However, between 2013 and 2015, public banks underestimate the ALLL by $0.0016, $0.0015, and $0.0013 per dollar of total loans, respectively. These ALLL underestimations are both statistically and economically significant. The average total loans of public banks in 2013, 2014, and 2015 are $13.42 billion, $14.24 billion, and $18.22 billion, respectively, which convert the per-dollar-of-total-loan ALLL underestimations in these three years to respective dollar amounts of $21.47 million, $21.37 million, and $23.68 million. They account for about 9% of reported ALLL of public banks.

4.3 Additional Tests for Supervisory Laxity

I conduct two additional tests to confirm that the observed ALLL differences between public and private banks, especially the differences in recent years, are due to lax supervision. The tests are based on the finding in Agarwal et al. (2014) that state regulators are more lenient than federal regulators when assigning the CAMELS ratings to the same state-chartered banks, which are subject to the federal-state alternate supervision scheme. If the ALLL differences between public and private banks are due to supervisory laxity, we should observe more supervisory laxity, in terms of larger ALLL differences between public and private banks, between state-chartered public and private banks than between federally chartered public and private banks, which are subject to supervision from federal regulators only. We should also observe larger ALLL differences between state-chartered public and private banks located in more leniently supervised states than between state-chartered public and private banks located in less leniently supervised states.

To test the first prediction that the ALLL differences are larger between state-chartered public and private banks, I interact the “Public” dummy with an indicator variable “State charter”, which equals “1” if the bank has a state charter and “0” if the bank has a federal charter. The results are reported in Table 3. The ALLL differences between federally chartered public and private banks are the coefficients on “Public”. The ALLL differences between state-chartered public and private banks are the combined coefficients of “Public” and “Public × State charter”. All standard errors are in parentheses and are clustered at the state level.

The ALLL differences between state-chartered public and private banks can almost entirely explain the ALLL differences estimated from the all-bank sample. The ALLL overestimations of state-chartered public banks between 2002 and 2004 are not statistically different from those of federally chartered public banks in 2002 and 2004[6]. Between 2013

[6] I conduct the statistical test for the equality of two coefficients throughout the study by constructing 95% confidence intervals of the two coefficients. If the confidence interval of either coefficient does not contain the other coefficient, the two coefficients are considered statistically different, and vice versa. The confidence

and 2015, the ALLL underestimations of state-chartered public banks are larger than the underestimations of public banks from the all-bank sample, the former averaging \$0.0022, \$0.0016, and \$0.0015 per dollar of total loans in the respective three years. Federally chartered public banks do not underestimate the ALLL in 2013. In 2014 and 2015, federally chartered public banks only underestimate the ALLL by \$0.0009 and \$0.0007 per dollar of total loans, respectively. The differences are statistically different between federally chartered and state-chartered public and private banks in 2013 and 2015, but not in 2014. These results are consistent with the conclusion that bank supervision of the ALLL estimations has become lax in recent years.

To test the second prediction that the ALLL differences are larger between state-chartered public and private banks located in more leniently supervised states than between state-chartered public and private banks located in less leniently supervised states, I split the sample of state-chartered banks into two subsamples. One subsample consists of state-chartered banks located in states with an above-average state leniency index as computed in Agarwal et al. (2014), and the other consists of state-chartered banks located in states with an average or below-average state leniency index. The state leniency index, which is generously made available by Amit Seru, is the average spread between the CAMELS ratings assigned by the federal regulator and the ratings assigned by the state regulator to the same state-chartered banks in a given state. The higher the index value, the more differently state and federal regulators rate the same state-chartered banks in a given state. Because state regulators are found to assign more favorable ratings to the same state-

intervals are not reported. This test, unlike the Z-score test, does not assume the covariance of the two coefficients is zero.

chartered banks than federal regulators, the higher the index value, the more lenient the state regulator in a given state.[7] Table 4 reports the results of this test.

As predicted, larger ALLL differences appear between state-chartered public and private banks located in more leniently supervised states than between state-chartered public and private banks located in less leniently supervised states. Between 2002 and 2005, state-chartered public banks located in more leniently supervised states overestimate the ALLL in 2003 and 2005 by $0.0010 and $0.0008 per dollar of total loans, respectively. During the same period, state-chartered public banks located in less leniently supervised states only overestimate the ALLL by $0.0004 per dollar of total loans in 2005. The differences are statistically different between the two subsamples. Between 2013 and 2015, the ALLL underestimations are larger among state-chartered public banks located in more leniently supervised states than among state-chartered public banks located in less leniently supervised states. The differences are statistically different between the two subsamples in 2013 and 2015, but not in 2014. These findings are again consistent with the conclusion that bank supervision has become lax recently.

The above two tests also suggest that between 2006 and 2011, bank supervision of the ALLL estimations was effective. First, during this period, state-chartered public and private banks report the same level of the ALLL, and except for 2006, the ALLL estimation differences between state-chartered public and private banks are not statistically different between more and less leniently supervised states. These results suggest little supervisory laxity, consistent with the conclusion from the all-bank sample.

[7] The index is computed up to the fourth quarter of 2010. But because the rating spreads are persistent over time, the state leniency index is still a good proxy for the post-2010 period of this study.

Second, the ALLL overestimation by public banks in 2009 is not associated with state supervisory leniency. In the federal-state split, neither state-chartered public banks nor federally chartered public banks overestimate the ALLL relative to their private counterparts in 2009. In the split by the state leniency index, the differences under the two subsamples are not statistically different. These results are inconsistent with evidence of a “big bath” reporting behavior, which also suggests ineffective bank supervision. In the next section, I further rule out the possibility of the existence of stock market discipline as an alternative explanation for the results.

4.4 Tests for the Existence of Stock Market Discipline

Either voluntarily or as required by securities regulations, public entities communicate and disclose more to their shareholders and the investment community than private entities. Therefore, compared to private entities, public entities are subject to added scrutiny from stock market participants, and the scrutiny may help discipline their reporting behaviors (e.g., see studies by Ball and Shivakumar (2005) and Burgstahler et al. (2006) on non-financial firms).

Because we do not have empirical evidence on whether the stock market can discipline banks’ reporting behaviors, I conduct three tests to find out whether stock market discipline exists and helps suppress public banks’ incentives to misreport the ALLL. Because institutional investors are generally believed to actively monitor the management of public entities, I use the following three proxies to capture the intensity of stock market discipline: the percentage of institutional ownership, the institutional ownership HHI, and the number of institutional block owners. Data for the three proxies come from the database of Thomson Reuters Institutional (13f) Holdings of WRDS.

The tests use the all-bank sample. I split the sample of public banks into two subsamples based on whether the banks have an above-average, or an average or below-average proxy, and retain all private banks as the comparison group for both subsamples. If stock market discipline exists, during those misreporting years, we should observe smaller ALLL underestimations or overestimations among public banks with an above-average proxy than we should among public banks with an average or below-average proxy. Table 5 reports the results.

Panel A of Table 5 presents the results from the split by the percentage of institutional ownership. Between 2002 and 2005, public banks with an above-average percentage of institutional ownership overestimate the ALLL in 2002 and 2004 by $0.0007 and $0.0015 per dollar of total loans, respectively. Public banks with an average or below-average percentage of institutional ownership only overestimate the ALLL in 2002 by $0.0003 per dollar of total loans. Public banks with an above-average percentage of institutional ownership starts to underestimate the ALLL in 2012, one year earlier than public banks with an average or below-average percentage of institutional ownership. In two out of the three years between 2013 and 2015, the ALLL underestimations by public banks with an above-average percentage of institutional ownership are larger than the underestimations by public banks with an average or below-average percentage of institutional ownership. For the rest of the sample period, public and private banks do not differ in the ALLL estimations in either subsample. The differences are all statistically different between the two subsamples. Even if the results cannot conclude that higher institutional ownership drives public banks to misreport the ALLL, they suggest that stock market discipline is absent in the context of ALLL estimations.

Panels B and C of Table 5 present the results from the splits by the institutional ownership HHI and the number of institutional block owners, respectively. The results show that throughout the entire sample period and especially for the period between 2013 and 2015, when bank supervision became lax, public banks subject to a higher intensity of institutional monitoring do not misreport the ALLL less than public banks subject to a lower intensity of institutional monitoring. The results again suggest that stock market discipline is absent regarding the ALLL estimations. The insignificant ALLL differences between public and private banks, especially during the financial crisis, are due to effective bank supervision.

The stock market discipline hypothesis is a counter-argument to the underpinnning of the predictions raised by this study—the stock market creates pressure for banks to engage in misreporting. Therefore, the conclusion that stock market discipline is absent proves that the predictions of this study are well reasoned.

4.5 Sensitivity Analysis

The validity of my results rests on a crucial assumption that no unobservable confounders exist to meaningfully bias the effect estimations. This assumption cannot be tested directly. But I argue that such confounders very likely do not exist, because the 55 covariates balanced between public and private banks are comprehensive and capture the key inputs of the ALLL estimation process as outlined in the regulatory guidance. Unobservable confounders, which must also relate to the ALLL estimations, very likely contain parallel information to the 55 covariates. Therefore, once the 55 covariates are balanced, the unobservable confounders can no longer contribute bias to the effect estimations.

I offer a demonstration of this argument. So far in this study, I have only used the current-year net charge-offs to calculate the historical loan loss rates. However, banks often use average net charge-offs of both the current year and the past few years to calculate the historical loan loss rates. Such loan loss rate calculation contains information about past loan losses that are not balanced in this study. But because the average net charge-offs correlate with the current-year net charge-offs, the historical loan loss rate calculated using only the current-year net charge-offs can balance the historical loan loss rate containing information about past loan losses.

I calculate an alternative historical loan loss rate by averaging both the current-year and the prior-year net charge-offs, and use this alternative loan loss rate to re-estimate the ALLL differences between public and private banks, between federally chartered public and private banks, and between state-chartered public and private banks. The results are reported in columns (2), (4), and (6) of Table 6. The original estimates as reported in Table 3 are presented in columns (1), (3), and (5) of Table 6. The sizes of the estimated effects are fairly similar under the two different loan loss rate calculations. The inference from the original results still holds.

4.6 Implications of the Overall Results

Table 7 presents the impact of the ALLL underestimations of state-chartered public banks between 2013 and 2015 on their reported earnings, equity capital, and Tier 1 risk-based capital ratio. Columns (1) to (3) convert the per-dollar-of-total-loan ALLL underestimations to dollar amounts. In these three years, state-chartered public banks underestimate the ALLL by \$10.40 million, \$8.35 million, and \$8.84 million, respectively. The ALLL underestimations account for about 11.9%-14.4% of reported ALLL (reported in column (8)), 5.8%-8.5% of reported income before taxes and extraordinary items (reported in column (9)), and 0.8%-1.2% of reported equity capital (reported in column (10)). However, the ALLL underestimations account for only 0.1%-0.2% of total risk-weighted assets (reported in column (11)), the maximum impact on Tier 1 risk-based capital ratio absent income taxes. These calculations suggest that bank regulators allow state-chartered public banks to underestimate the ALLL to report higher earnings, and to a lesser degree, equity capital. Because the impact on Tier 1 risk-based capital ratio is marginal, the allowed reporting discretion is not to inflate the banks' regulatory capital adequacy.

Overall, the results imply that bank regulators are unwilling to cater to banks' private interests when the regulatory emphasis is strong—the ALLL overestimations at the beginning of the sample period are small. Bank regulators are also unwilling to cater to banks' private interests during the financial crisis, because public banks do not underestimate the ALLL between 2008 and 2009. However, bank regulators are willing to cater to banks' private interests when the economic environment is good and the regulatory emphasis is weak, such as the period between 2013 and 2015. During these three years, the proportions of problem loans held by banks almost reached the pre-crisis low levels (see Figure 4), but as discussed before, bank profits were still under pressure. Supervisory laxity is not a constant; it varies with changing economic and regulatory environments.

5 Conclusion

I study whether bank supervision is effective in enforcing the written regulation governing the estimations of the allowance for loan and lease losses (ALLL) consistently between public and private banks between 2002 and 2015. Based on prior literature, public banks are more incentivized than private banks to overestimate the ALLL when bank profitability is high, but public banks are more incentivized than private banks to underestimate the ALLL when bank profitability is low. I predict that if bank supervision was lax, public banks would overestimate the ALLL relative to private banks between 2002 and 2007 and underestimate the ALLL relative to private banks between 2008 and 2015.

By balancing 55 covariates that confound the effect of reporting incentives due to public listing on the ALLL estimations, I create a pseudo-population of public and private banks from which the unbiased effect can be estimated. I find that public banks, especially state-chartered public banks, slightly overestimated the ALLL between 2002 and 2005 and significantly underestimated the ALLL between 2013 and 2015. Public and private banks did not differ in their ALLL estimations during the financial crisis and the rest of the sample period. Bank supervision of the ALLL estimations was effective between 2002 and 2012, but has become lax recently. The results imply that bank regulators are only willing to cater to banks' private interests when the economic environment is good and the regulatory emphasis is weak, but not during the financial crisis.

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Appendix A Covariate Definitions

I. Covariates that reflect loan portfolio characteristics

- Volume of loans past due 30-89 days and still accruing principal and interest payments (scaled by total loans) by loan category.
    1) Residential real estate loans (RRE.PD30)
    2) Commercial real estate loans (CRE.PD30)
    3) Commercial and industrial loans (CI.PD30)
    4) Consumer loans (CS.PD30)
    5) Loans secured by farmland (FARM.PD30)
    6) Agricultural loans (AG.PD30)

- Volume of loans past due 90 days or more and still accruing principal and interest payments (scaled by total loans) by loan category.
    7) Residential real estate loans (RRE.PD90)
    8) Commercial real estate loans (CRE.PD90)
    9) Commercial and industrial loans (CI.PD90)
    10) Consumer loans (CS.PD90)
    11) Loans secured by farmland (FARM.PD90)
    12) Agricultural loans (AG.PD90)

- Volume of nonaccrual loans (scaled by total loans) by loan category.
    13) Residential real estate loans (RRE.NAC)
    14) Commercial real estate loans (CRE.NAC)
    15) Commercial and industrial loans (CI.NAC)
    16) Consumer loans (CS.NAC)
    17) Loans secured by farmland (FARM.NAC)
    18) Agricultural loans (AG.NAC)

- Growth of total past due and nonaccrual loans: year-over-year change of total volume of problem loans.
    19) Total loans past due 30-89 days and still accruing principal and interest payments (PD30.G)
    20) Total loans past due 90 days or more and still accruing principal and interest payments (PD90.G)
    21) Total nonaccrual loans (NAC.G)

- *Current-year loan loss rate* by loan category: current-year net charge-offs (charge-offs minus recoveries) of each loan category divided by total loans.
    22) Residential real estate loans (RRE.NCH)
    23) Commercial real estate loans (CRE.NCH)
    24) Commercial and industrial loans (CI.NCH)
    25) Consumer loans (CS.NCH)
    26) Loans secured by farmland (FARM.NCH)
    27) Agricultural loans (AG.NCH)

- *Loan growth*: year-over-year change of loan volume of each loan category.
    28) Residential real estate loans (RRE.G)
    29) Commercial real estate loans (CRE.G)
    30) Commercial and industrial loans (CI.G)
    31) Consumer loans (CS.G)
    32) Loans secured by farmland (FARM.G)
    33) Agricultural loans (AG.G)

- *Credits of concentration*: loan volume of each loan category divided by the sum of Tier 1 risk-based capital and the ALLL.
    34) Residential real estate loans (RRE.CON)
    35) Commercial real estate loans (CRE.CON)
    36) Commercial and industrial loans (CI.CON)
    37) Consumer loans (CS.CON)
    38) Loans secured by farmland (FARM.CON)
    39) Agricultural loans (AG.CON)

II. Covariates that reflect institutional characteristics

40) *Type* (TYPE): an indicator variable. "1" if a bank's holding parent is a financial holding company (FHC), "0" if a bank's holding parent is a bank holding company (BHC).
41) *Bank size* (SIZE): the natural logarithm of total assets.

- Capital adequacy
    42) *Tier 1 leverage ratio* (T1LR): the ratio of Tier 1 capital divided by total assets for the leverage ratio purpose.
    43) *Tier 1 risk-based capital ratio* (T1CR): the ratio of Tier 1 capital divided by total risk-weighted assets.
    44) *Total risk-based capital ratio* (TTCR): the ratio of total capital divided by total risk-weighted assets.
    45) *Total delinquent loans to the ALLL* (DELAL): total delinquent loans are the sum of total loans past due 30-89 days and still accruing principal and interest payments, total loans past due 90 days or more and still accruing principal and interest payments, and total nonaccrual loans.

- Asset quality
    46) *Private securities to total assets* (PSEC): private securities are available-for-sale and held-to-maturity securities, excluding U.S. Treasury securities, U.S. Government agency obligations, and mortgage-backed securities issued or guaranteed by the U.S. Government or U.S. Government-sponsored agencies.

- Management quality

47) *Efficiency ratio* (EFF): the ratio of noninterest expense to sum of net interest income and noninterest income.

- Earnings
  48) *Return on assets* (ROA): the ratio of income (loss) before extraordinary items and other adjustments to total assets.
  49) *Return on equity* (ROE): the ratio of income (loss) before extraordinary items and other adjustments to total equity capital.
  50) *Net interest margin* (NIM): the ratio of net interest income to total assets.

- Liquidity
  51) *Core deposits to total assets* (CD): prior to March 31, 2010, core deposits equal the sum of all transaction accounts, nontransaction money market deposit accounts, other nontransaction savings deposits, total time deposits of less than \$100,000, and total deposits in foreign offices (if applicable) minus total brokered retail deposits issued in denominations of less than \$100,000. Beginning March 31, 2010, core deposits equal the sum of all transaction accounts, nontransaction money market deposit accounts, other nontransaction savings deposits, total time deposits of \$250,000 or less, and total deposits in foreign offices (if applicable) minus total brokered retail deposits issued in denominations of \$250,000 or less.
  52) *Volatile liability dependence ratio* (VLDR): prior to March 31, 2010, the ratio equals the sum of total interest-bearing deposits in foreign and domestic offices, total time deposits of \$100,000 or more, federal funds purchased, securities sold under agreements to repurchase, other borrowed money, and total trading liabilities minus federal funds sold, securities purchased under agreements to resell, and total trading assets. Beginning March 31, 2010, the ratio equals the sum of total interest-bearing deposits in foreign and domestic offices, total time deposits of more than \$250,000, federal funds purchased, securities sold under agreements to repurchase, other borrowed money, and total trading liabilities minus federal funds sold, securities purchased under agreements to resell, and total trading assets. The ratio measures the extent to which a bank funds long-term investments with short-term liabilities.
  53) *Liquid assets to total assets* (LQ): liquid assets are the sum of interest-bearing assets, federal funds sold, securities purchased under agreement to resell, debt securities with a remaining maturity of one year or less, and loans and leases with a remaining maturity of one year or less.

- Sensitivity to market risk
  54) *Return to risky assets* (RORA): the ratio of total noninterest income minus income from fiduciary activities and service charges on deposit accounts to total assets.
  55) *Large time deposits with maturity less than one year to total assets* (LTD): large time deposits are time deposits of \$100,000 or more.

III. Covariates that reflect regional economic conditions

The following covariates are not used in the propensity score estimation model, but are checked for balances between public and private banks.

56) *State unemployment rate* (UNST)
57) *State GDP growth* (GDPST)
58) *State year-over-year change of housing permit (value)* (PMST)

Figure 1 Plots of ROA, ROE, Net Interest Margin, and Total Loan Growth of Public and Private Banks

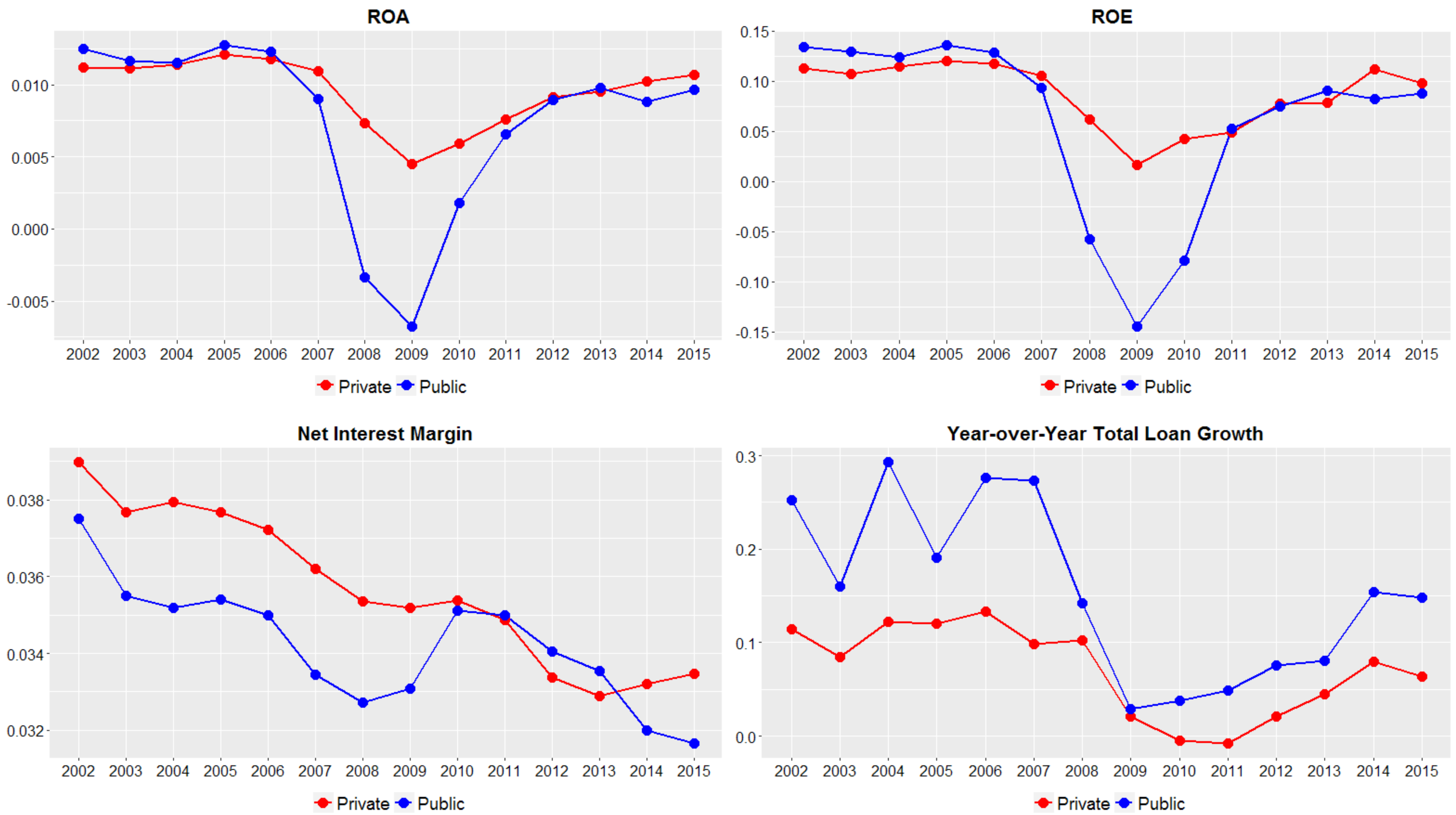


Figure 2 Illustration of Steps to Estimate Loan Losses under FAS 5 and FAS 114

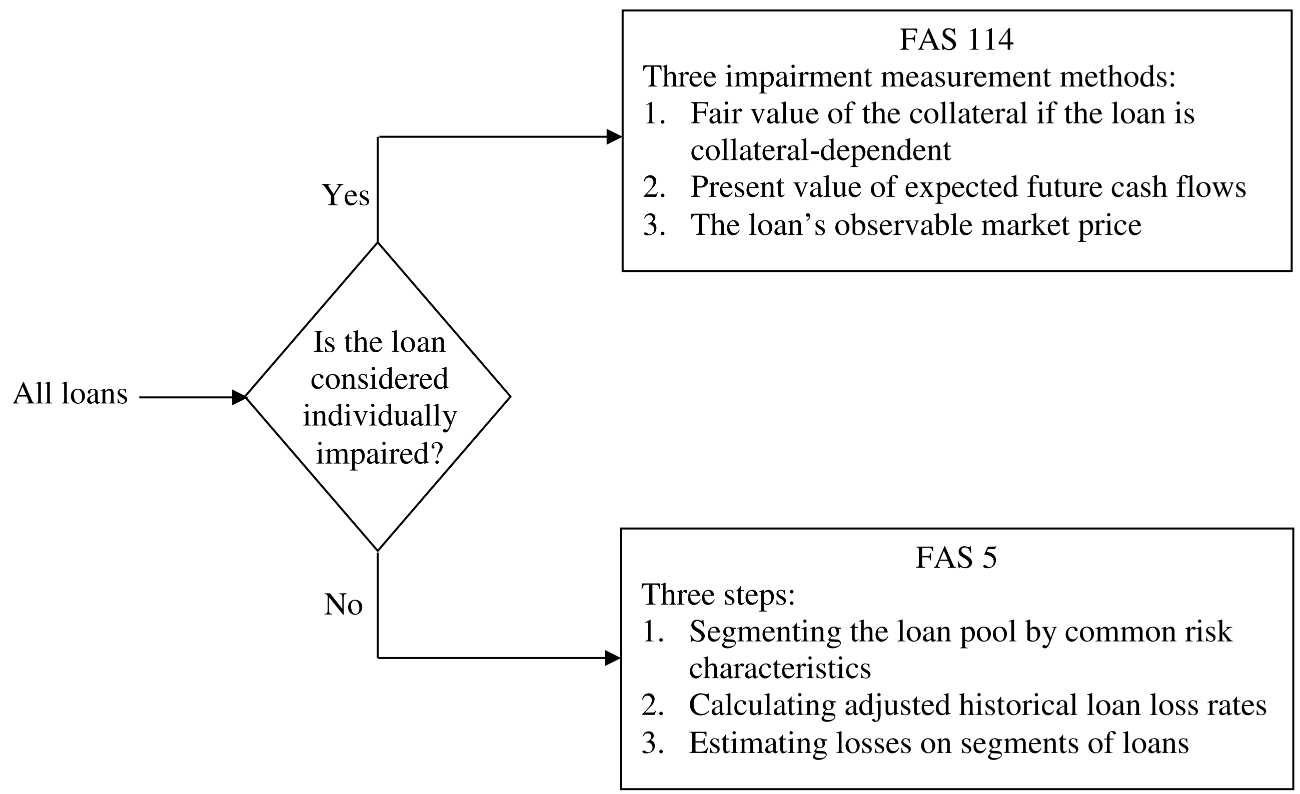
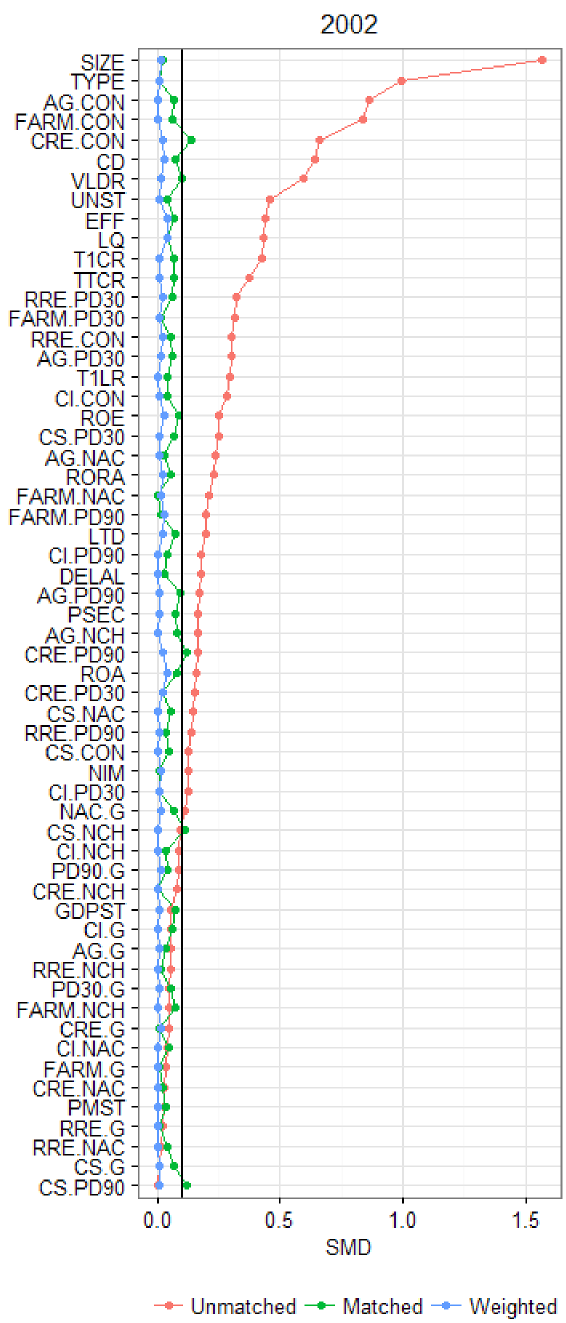


Figure 3 Standardized Mean Differences (SMDs) of the 58 Covariates in Unmatched, Matched, and Weighted Samples

The following 14 graphs plot the SMDs of the 58 covariates as defined in Appendix A in the unmatched, the matched, and the weighted samples by sample year from 2002 to 2015. A matched sample is created from one-to-one without-replacement matching on the logit of the propensity score θ_i, with a caliper of width equal to 0.2 of the standard deviation of the logit of the propensity score. θ_i is estimated from a logistic regression with the first 55 covariates as defined in Appendix A and the state fixed effects. A weighted sample is created from weighting each bank observation i in the unmatched sample by the matching weight $\frac{\min(\theta_i,1-\theta_i)}{Z_i\theta_i+(1-Z_i)(1-\theta_i)}$ (Li and Greene 2013), where $Z_i = 1$ if bank i is public and $Z_i = 0$ if bank i is private. The vertical straight line to the right of 0.0 represents SMD = 0.1. In general, an SMD < 0.1 suggests that the covariate is balanced between the comparison groups, whereas an SMD > 0.1 suggests that the covariate is unbalanced between the comparison groups and may contribute bias to the effect estimation. Please refer to Appendix A for definitions of the 58 covariates.



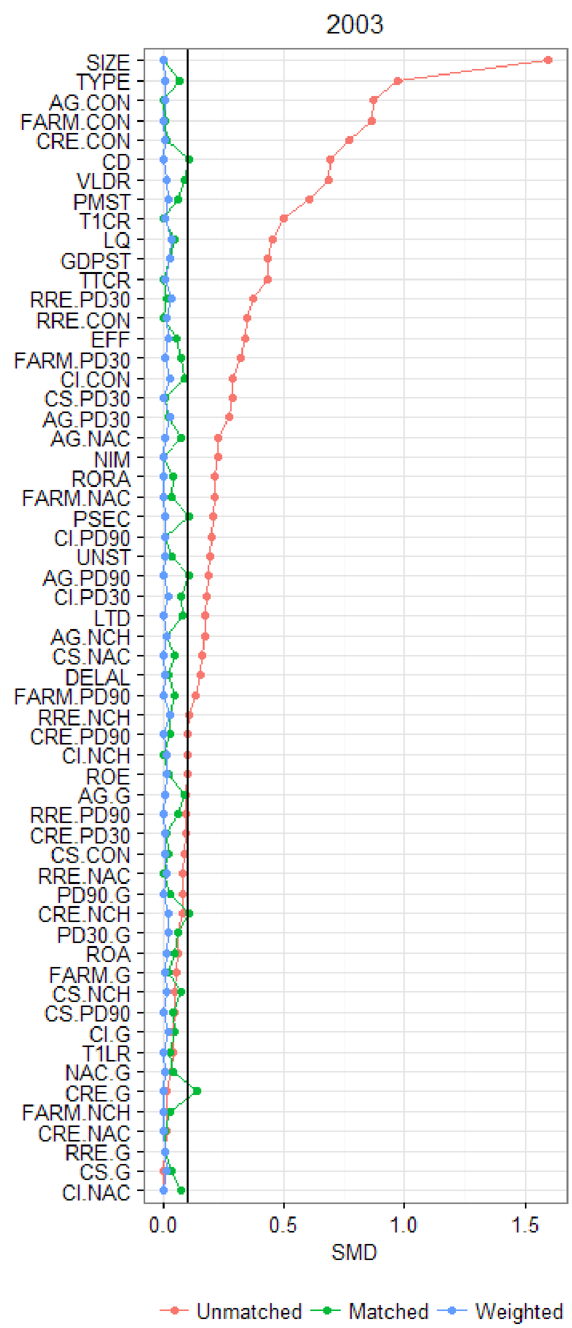


Figure 2 (continued)

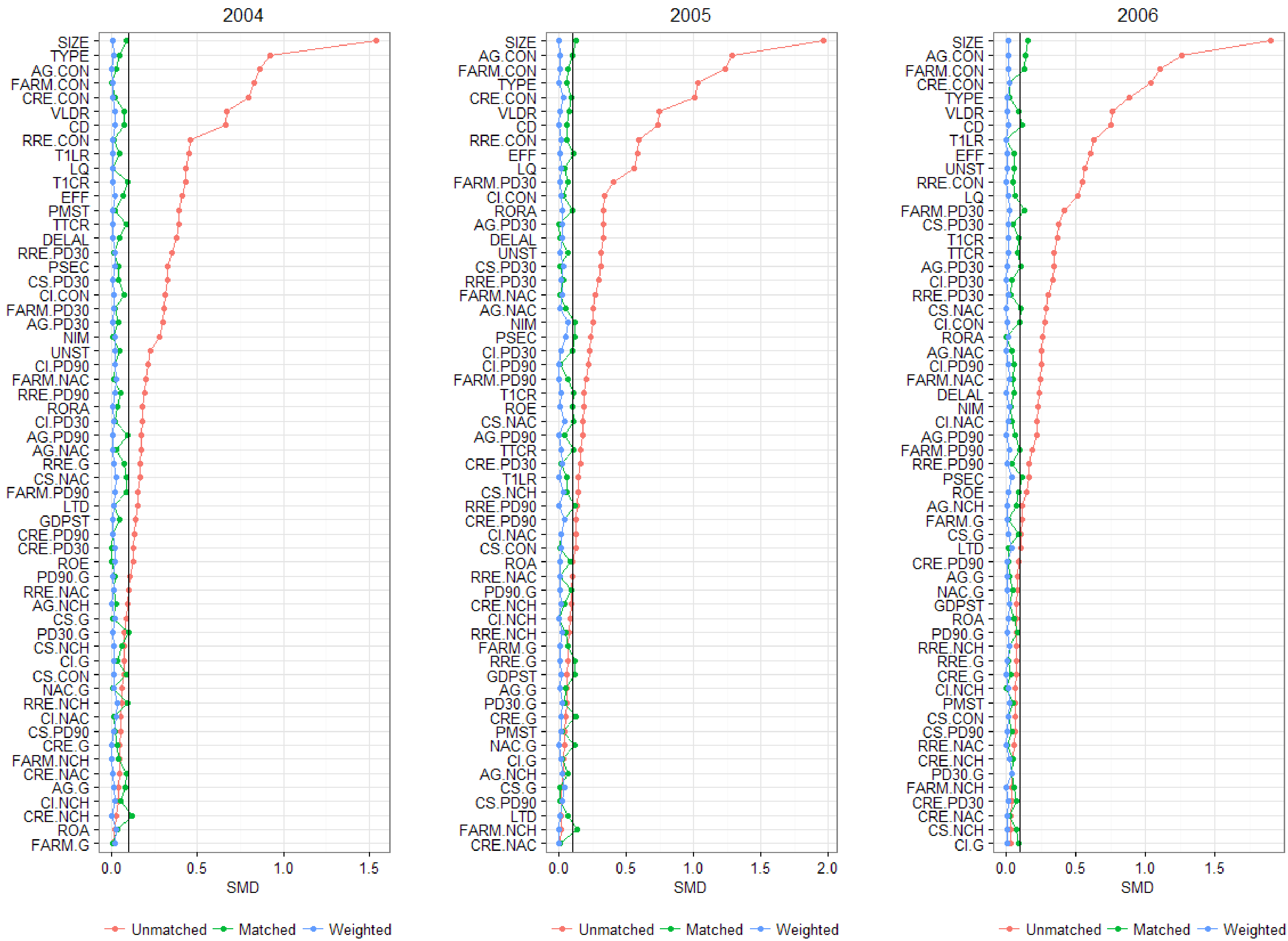


Figure 2 (continued)

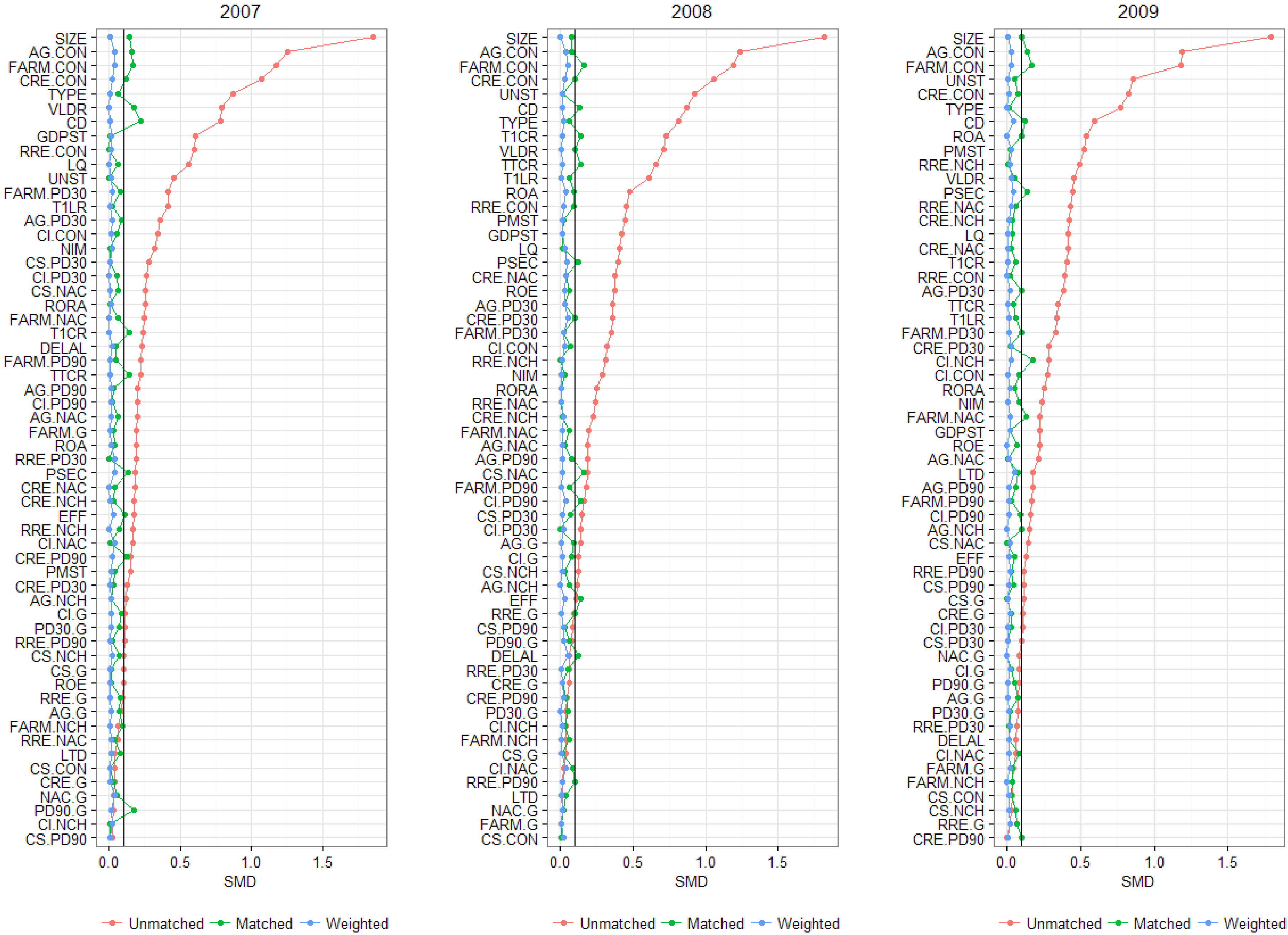


Figure 2 (continued)

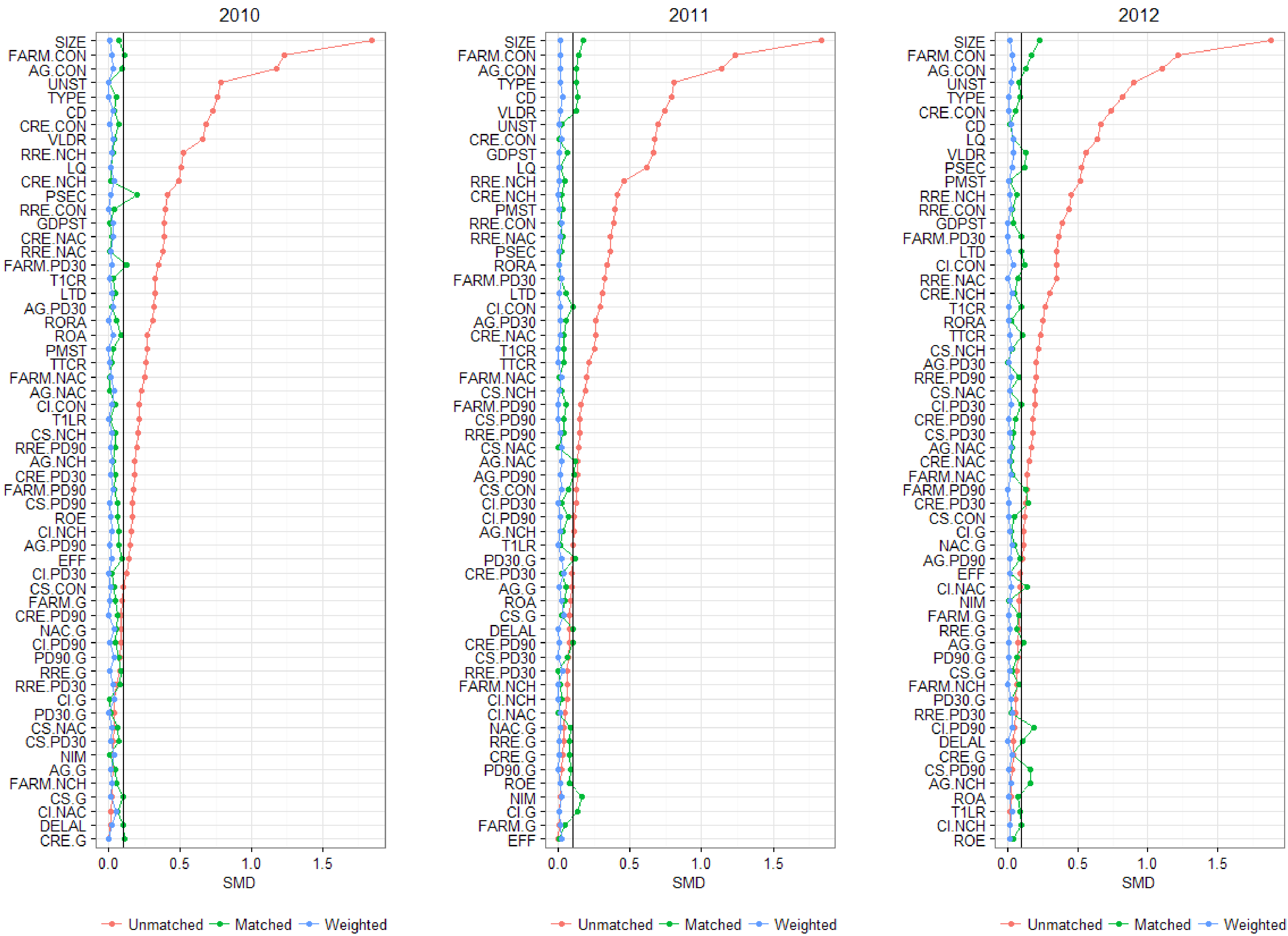


Figure 2 (continued)

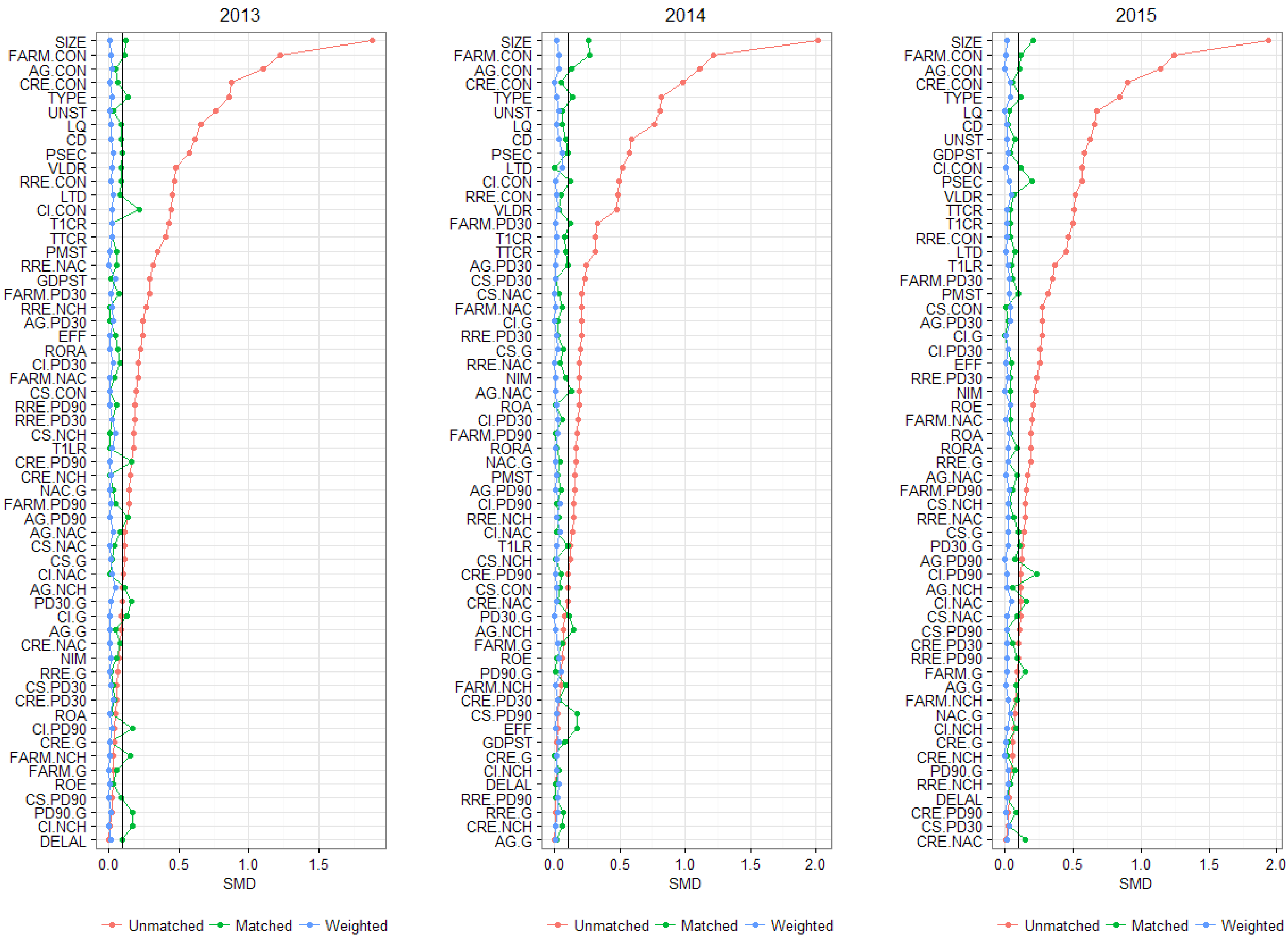


Figure 4 Plots of Ratios of Total Non-Current Loans and Total Net Charge-Offs to Total Loans of Public and Private Banks

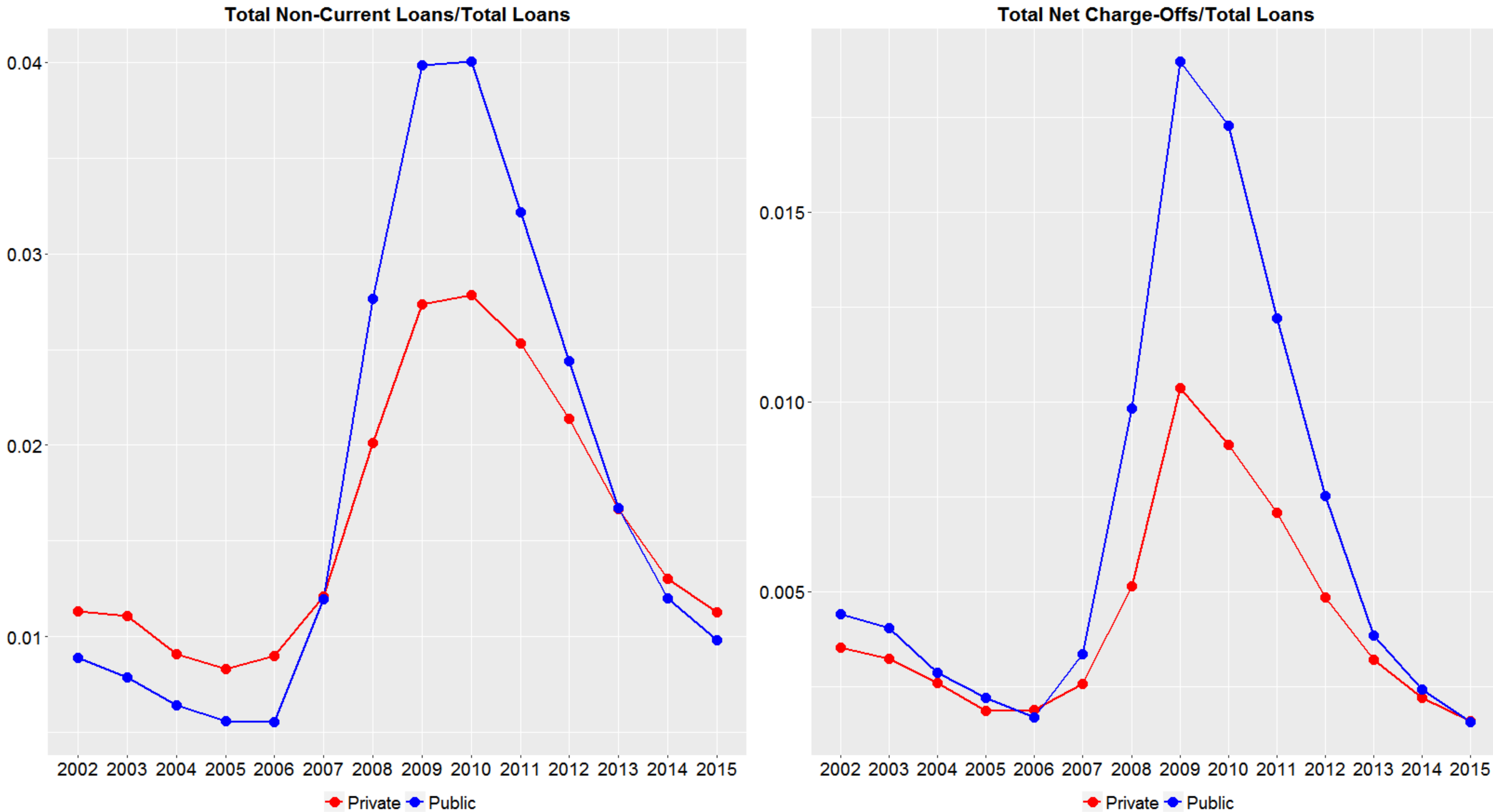


Table 1 Comparison of Concentrations of Credit between Public and Private Banks

This table presents the average concentrations of credit of loan categories held by public and private banks on the last day of each sample year from 2002 to 2015. The concentration of credit of each loan category is calculated as the amount of loans in each category divided by the sum of Tier 1 risk-based capital and the ALLL. P-values are calculated under the Kruskal-Wallis Rank Sum Test. The null hypothesis of the test is that the two comparison groups originate from the same distribution. SMD stands for standardized mean difference. In general, an SMD < 0.1 suggests that the variable is balanced between the two comparison groups, whereas an SMD > 0.1 suggests that the variable is unbalanced between the two comparison groups and may contribute bias to the effect estimation.

		2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Total Loans and Leases	Public	7.165	7.179	7.435	7.429	7.516	7.620	7.515	7.025	6.450	6.008	6.074	6.215	6.567	6.677
	Private	6.341	6.186	6.272	6.280	6.311	6.360	6.544	6.391	6.082	5.728	5.604	5.538	5.682	5.678
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	0.005	<0.001	<0.001	<0.001	<0.001
	SMD	0.318	0.461	0.547	0.532	0.409	0.588	0.456	0.271	0.162	0.151	0.243	0.376	0.326	0.544
1. Loans Secured by Real Estate	Public	4.871	5.058	5.417	5.520	5.651	5.742	5.666	5.330	4.857	4.402	4.373	4.424	4.670	4.671
	Private	3.884	3.894	4.060	4.134	4.199	4.264	4.474	4.424	4.231	3.982	3.897	3.816	3.920	3.926
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.467	0.584	0.666	0.665	0.617	0.705	0.566	0.400	0.278	0.231	0.258	0.355	0.294	0.423
1.1 Secured by 1-4 Family Residential Properties	Public	2.030	1.974	2.065	1.934	1.851	1.825	1.836	1.800	1.755	1.683	1.705	1.655	1.678	1.678
	Private	1.706	1.603	1.609	1.570	1.537	1.524	1.613	1.632	1.580	1.511	1.486	1.433	1.469	1.474
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	0.001	0.002	<0.001	<0.001	<0.001	<0.001
	SMD	0.243	0.298	0.352	0.279	0.234	0.223	0.175	0.137	0.143	0.153	0.193	0.215	0.204	0.197
1.2 Secured by Commercial Properties	Public	2.727	2.958	3.226	3.455	3.670	3.792	3.702	3.407	2.996	2.615	2.574	2.670	2.891	2.884
	Private	1.693	1.806	1.958	2.075	2.172	2.238	2.340	2.253	2.102	1.932	1.860	1.821	1.875	1.851
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.644	0.708	0.749	0.776	0.792	0.864	0.758	0.615	0.497	0.491	0.517	0.643	0.469	0.746
1.2.1 Construction and Land Development	Public	0.628	0.721	0.902	1.123	1.331	1.407	1.199	0.841	0.571	0.408	0.356	0.357	0.403	0.446
	Private	0.384	0.425	0.508	0.603	0.690	0.734	0.692	0.548	0.427	0.337	0.309	0.308	0.329	0.337
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.012	0.005	0.001	<0.001
	SMD	0.395	0.438	0.498	0.556	0.619	0.646	0.564	0.394	0.260	0.197	0.145	0.161	0.207	0.303
1.2.2 Secured by Multi-Family Residential Properties	Public	0.168	0.187	0.197	0.201	0.192	0.202	0.212	0.225	0.216	0.219	0.237	0.292	0.345	0.349
	Private	0.092	0.100	0.106	0.106	0.107	0.112	0.130	0.142	0.140	0.139	0.139	0.139	0.151	0.149
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.282	0.293	0.326	0.313	0.310	0.305	0.298	0.289	0.312	0.327	0.397	0.467	0.417	0.472
1.2.3 Secured by Nonfarm Nonresidential Properties	Public	1.932	2.051	2.128	2.131	2.147	2.183	2.291	2.340	2.209	1.988	1.981	2.021	2.142	2.090
	Private	1.217	1.280	1.344	1.365	1.376	1.393	1.519	1.563	1.534	1.455	1.412	1.374	1.394	1.364
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

	SMD	0.623	0.680	0.693	0.674	0.638	0.710	0.663	0.606	0.498	0.493	0.519	0.622	0.436	0.691
1.3 Secured by Farmland	Public	0.111	0.121	0.122	0.126	0.125	0.118	0.119	0.117	0.105	0.104	0.092	0.094	0.100	0.109
	Private	0.485	0.486	0.494	0.489	0.490	0.502	0.521	0.539	0.550	0.538	0.551	0.562	0.576	0.600
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.825	0.791	0.799	0.775	0.771	0.818	0.847	0.872	0.927	0.929	0.961	0.964	0.965	0.966
2. Commercial & Industrial Loans	Public	1.235	1.188	1.192	1.157	1.161	1.194	1.223	1.075	0.982	0.960	1.033	1.078	1.197	1.197
	Private	1.035	1.001	0.990	0.976	0.975	0.977	0.974	0.907	0.844	0.796	0.781	0.782	0.789	0.779
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.230	0.236	0.256	0.234	0.210	0.283	0.316	0.239	0.206	0.242	0.345	0.398	0.519	0.552
3. Consumer Loans	Public	0.737	0.643	0.563	0.501	0.446	0.427	0.387	0.383	0.375	0.381	0.380	0.394	0.365	0.425
	Private	0.686	0.615	0.557	0.516	0.487	0.464	0.438	0.411	0.375	0.339	0.320	0.305	0.302	0.295
	p	0.043	0.225	0.766	0.474	0.033	0.066	0.009	0.152	0.981	0.044	0.006	<0.001	0.005	<0.001
	SMD	0.060	0.038	0.010	0.023	0.070	0.061	0.094	0.052	0.001	0.071	0.101	0.148	0.119	0.204
4. Agricultural Loans	Public	0.092	0.079	0.080	0.082	0.073	0.069	0.072	0.071	0.063	0.064	0.057	0.061	0.059	0.068
	Private	0.633	0.579	0.571	0.561	0.557	0.557	0.556	0.550	0.534	0.520	0.516	0.539	0.576	0.581
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.838	0.829	0.811	0.796	0.801	0.808	0.800	0.792	0.808	0.781	0.790	0.792	0.812	0.817
5. Municipal Loans	Public	0.045	0.046	0.048	0.046	0.046	0.043	0.047	0.056	0.059	0.066	0.069	0.090	0.107	0.121
	Private	0.037	0.039	0.039	0.039	0.039	0.039	0.041	0.043	0.043	0.041	0.040	0.040	0.041	0.043
	p	0.006	0.017	0.012	0.045	0.037	0.250	0.145	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.096	0.086	0.091	0.075	0.076	0.044	0.057	0.126	0.150	0.227	0.245	0.358	0.428	0.430
6. Loans to Depository Institutions	Public	0.055	0.036	0.013	0.012	0.011	0.019	0.010	0.011	0.009	0.010	0.008	0.010	0.005	0.008
	Private	0.004	0.004	0.003	0.002	0.002	0.002	0.003	0.003	0.004	0.004	0.003	0.004	0.002	0.001
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	<0.001	0.044	0.030	0.029	0.232	0.007	<0.001
	SMD	0.157	0.194	0.158	0.151	0.133	0.140	0.124	0.133	0.091	0.102	0.096	0.069	0.094	0.137
7. Loans to Foreign Governments	Public	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Private	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	p	0.001	0.001	<0.001	0.964	0.747	0.600	0.570	<0.001	0.213	<0.001	<0.001	<0.001	0.002	<0.001
	SMD	0.080	0.080	0.094	0.002	0.016	0.020	0.025	0.124	0.062	0.098	0.101	0.160	0.074	0.132
8. Other Loans	Public	0.064	0.061	0.056	0.054	0.059	0.069	0.062	0.051	0.055	0.072	0.093	0.095	0.096	0.125
	Private	0.029	0.028	0.027	0.026	0.027	0.030	0.033	0.032	0.031	0.028	0.028	0.030	0.032	0.031
	p	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	SMD	0.245	0.228	0.224	0.240	0.223	0.239	0.202	0.137	0.183	0.228	0.278	0.286	0.277	0.350
9. Lease Financing Receivables	Public	0.066	0.067	0.065	0.054	0.069	0.056	0.047	0.049	0.051	0.052	0.061	0.063	0.068	0.059
	Private	0.033	0.026	0.024	0.025	0.025	0.026	0.024	0.023	0.019	0.018	0.019	0.021	0.021	0.021

p	0.038	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
SMD	0.093	0.221	0.215	0.162	0.141	0.153	0.131	0.115	0.150	0.157	0.166	0.159	0.197	0.181

Table 2 Estimated ALLL Differences between Public and Private Banks

This table presents the estimated effects (coefficinets on "Public") of reporting incentives due to public listing on the ALLL estimations under an OLS model and the weighting method. The dependent variable in all methods is $\frac{ALLL}{Total\ Loans}$. The control variables are the first 55 covariates as defined in Appendix A, but the coefficients on the 55 covariates are not reported. The numbers of public and private banks in the parentheses reported under the weighting method are effective numbers of banks in the sample after applying the matching weights to the sample. Standard errors are clustered at the state level and are reported in the parentheses under "Public". *p<0.1; **p<0.05; ***p<0.01.

	OLS, with controls and state FE				Weighted, without controls and state FE				Weighted, with controls and state FE			
	Public	R-squared	# Public	# Private	Public	R-squared	# Public	# Private	Public	R-squared	# Public	# Private
2002	0.0010*** (0.0003)	0.599	661	3493	0.0004 (0.0003)	0.001	661 (263.6)	3493 (261.0)	0.0004*** (0.0002)	0.794	661 (263.6)	3493 (261.0)
2003	0.0016*** (0.0003)	0.609	652	3508	0.0004 (0.0006)	0.001	652 (260.3)	3508 (252.7)	0.0005* (0.0003)	0.813	652 (260.3)	3508 (252.7)
2004	0.0013*** (0.0003)	0.692	607	3546	0.0008 (0.0006)	0.003	607 (273.8)	3546 (269.0)	0.0006* (0.0003)	0.733	607 (273.8)	3546 (269.0)
2005	0.0006* (0.0003)	0.618	467	2060	0.0006 (0.0006)	0.004	467 (146.3)	2060 (141.4)	0.0005* (0.0003)	0.816	467 (146.3)	2060 (141.4)
2006	0.0008** (0.0003)	0.492	460	2032	0.0004 (0.0006)	0.002	460 (147.0)	2032 (147.2)	0.0004 (0.0003)	0.736	460 (147.0)	2032 (147.2)
2007	0.0007** (0.0003)	0.648	426	1949	0.0002 (0.0005)	0.000	426 (149.9)	1949 (147.0)	0.0003 (0.0002)	0.830	426 (149.9)	1949 (147.0)
2008	-0.0000 (0.0004)	0.700	415	2031	0.0003 (0.0009)	0.000	415 (171.7)	2031 (165.6)	0.0000 (0.0003)	0.877	415 (171.7)	2031 (165.6)
2009	0.0009 (0.0006)	0.705	404	2075	0.0011 (0.0010)	0.003	404 (140.9)	404 (140.9)	0.0010* (0.0005)	0.819	404 (140.9)	2075 (142.6)
2010	0.0015** (0.0006)	0.712	366	2070	0.0008 (0.0014)	0.001	366 (146.5)	2070 (145.5)	0.0006 (0.0006)	0.824	366 (146.5)	2070 (145.5)
2011	0.0004 (0.0008)	0.579	342	2080	0.0004 (0.0011)	0.000	342 (133.8)	2080 (134.3)	0.0005 (0.0007)	0.653	342 (133.8)	2080 (134.3)
2012	-0.0004 (0.0007)	0.523	316	2016	-0.0000 (0.0016)	0.000	316 (116.1)	2016 (114.7)	0.0001 (0.0005)	0.748	316 (116.1)	2016 (114.7)
2013	-0.0012* (0.0006)	0.545	331	2008	-0.0017* (0.0010)	0.013	331 (121.0)	2008 (120.9)	-0.0016*** (0.0006)	0.703	331 (121.0)	2008 (120.9)
2014	-0.0014*** (0.0005)	0.622	283	1972	-0.0016** (0.0007)	0.017	283 (103.4)	1972 (101.7)	-0.0015*** (0.0003)	0.768	283 (103.4)	1972 (101.7)
2015	-0.0012*** (0.0004)	0.524	320	1840	-0.0013** (0.0005)	0.017	320 (98.2)	1840 (99.4)	-0.0013*** (0.0003)	0.694	320 (98.2)	1840 (99.4)

Table 3 Estimated ALLL Differences between Federally Chartered Public and Private Banks and between State-Chartered Public and Private Banks

This table presents the estimated effects of reporting incentives due to public listing on the ALLL estimations between federally chartered public and private banks and between state-chartered public and private banks. The estimation method is a matching-weight weighted regression with the dependent variable $\frac{ALLL}{Total\ Loans}$, the first 55 covariates as defined in Appendix A as control variables, and the state fixed effects. The "Public" dummy is interacted with an indicator variable "State charter", which equals "1" for banks with a state charter and "0" for banks with a federal charter. The ALLL differences between federally chartered public and private banks are the coefficients on the "Public" dummy. The ALLL differences between state-chartered public and private banks are the combined coefficients on "Public" and "Public × State charter". Standard errors are clustered at the state level and are reported in parentheses under the coefficients. The numbers in parentheses under columns "# Public" and "# Private" are effective numbers of public and private banks in the sample after applying the matching weights to the sample. The coefficients on the 55 covariates are not reported. *p<0.1; **p<0.05; ***p<0.01.

	ALLL Differences between Federally Chartered Public and Private Banks	ALLL Differences between State-Chartered Public and Private Banks	R-squared	# Public	# Private
2002	0.0003 (0.0004)	0.0005** (0.0002)	0.796	661 (263.6)	3493 (261.0)
2003	-0.0002 (0.0005)	0.0007** (0.0004)	0.816	652 (260.3)	3508 (252.7)
2004	0.0006 (0.0005)	0.0006* (0.0004)	0.733	607 (273.8)	3546 (269.0)
2005	0.0004 (0.0005)	0.0005 (0.0003)	0.817	467 (146.3)	2060 (141.4)
2006	0.0003 (0.0006)	0.0004 (0.0003)	0.737	460 (147.0)	2032 (147.2)
2007	0.0005 (0.0003)	0.0002 (0.0002)	0.831	426 (149.9)	1949 (147.0)
2008	0.0002 (0.0005)	-0.0000 (0.0004)	0.877	415 (171.7)	2031 (165.6)
2009	0.0011 (0.0009)	0.0009 (0.0006)	0.822	404 (140.9)	2075 (142.6)
2010	0.0004 (0.0007)	0.0006 (0.0007)	0.826	366 (146.5)	2070 (145.5)
2011	0.0008 (0.0011)	0.0006 (0.0008)	0.660	342 (133.8)	2080 (134.3)
2012	0.0010 (0.0011)	-0.0003 (0.0006)	0.751	316 (116.1)	2016 (114.7)
2013	0.0001 (0.0010)	-0.0022*** (0.0005)	0.708	331 (121.0)	2008 (120.9)
2014	-0.0009** (0.0004)	-0.0016*** (0.0004)	0.769	283 (103.4)	1972 (101.7)
2015	-0.0007* (0.0004)	-0.0015*** (0.0003)	0.696	320 (98.2)	1840 (99.4)

Table 4 Estimated ALLL Differences between State-Chartered Public and Private Banks in More and Less Leniently Supervised States

This table presents the estimated effects of reporting incentives due to public listing on the ALLL estimations from two subsamples consisting of only state-chartered banks: state-chartered banks located in more leniently supervised states and state-chartered banks located in less leniently supervised states. More leniently supervised states are states with an above-average state leniency index as computed in Agarwal et al. (2014), and less leniently supervised states are states with an average or below-average state leniency index. The estimation method for both subsamples is a matching-weight weighted regression with the dependent variable $\frac{ALLL}{Total\ Loans}$, the first 55 covariates as defined in Appendix A as control variables, and the state fixed effects. The matching weight for each bank observation i is calculated from $\frac{\min(\theta_i, 1-\theta_i)}{Z_i\theta_i+(1-Z_i)(1-\theta_i)}$ (Li and Greene 2013), where $Z_i = 1$ if bank i is public, $Z_i = 0$ if bank i is private, and θ_i is the estimated propensity score for bank i. θ_i is estimated from a logistic regression using the 55 covariates and the state fixed effects. Column "Public" lists the coefficients and standard errors (in parentheses and clustered at the state level) on the "Public" dummy. The numbers in parentheses under columns "# Public" and "# Private" are effective numbers of public and private banks in the sample after applying the matching weights to the sample. The coefficients on the 55 covariates are not reported. *p<0.1; **p<0.05; ***p<0.01.

	State Leniency Index > Mean				State Leniency Index ≤ Mean			
	Public	R-squared	# Public	# Private	Public	R-squared	# Public	# Private
2002	0.0003 (0.0002)	0.816	187 (76.8)	1282 (72.3)	0.0002 (0.0002)	0.896	217 (71.5)	1277 (71.5)
2003	0.0010*** (0.0003)	0.781	209 (78.7)	1301 (74.8)	0.0002 (0.0007)	0.826	213 (71.4)	1302 (70.2)
2004	0.0003 (0.0003)	0.786	199 (86.8)	1333 (89.0)	0.0006 (0.0005)	0.861	190 (74.9)	1318 (72.5)
2005	0.0008** (0.0004)	0.824	175 (49.7)	854 (47.4)	0.0004* (0.0002)	0.916	129 (22.1)	690 (23.9)
2006	-0.0005** (0.0002)	0.775	190 (47.3)	842 (47.5)	0.0010*** (0.0003)	0.862	122 (33.9)	698 (33.1)
2007	-0.0001 (0.0003)	0.879	160 (48.1)	817 (45.1)	0.0002 (0.0002)	0.917	122 (37.0)	664 (36.9)
2008	0.0002 (0.0005)	0.874	163 (62.0)	885 (58.8)	-0.0004 (0.0003)	0.911	123 (35.4)	690 (34.8)
2009	0.0008 (0.0008)	0.919	153 (45.9)	903 (43.8)	0.0009*** (0.0003)	0.937	125 (29.4)	706 (27.0)
2010	0.0002 (0.0009)	0.922	140 (48.9)	908 (45.4)	0.0001 (0.0005)	0.936	103 (39.3)	704 (39.4)
2011	0.0010** (0.0005)	0.862	124 (36.3)	922 (36.1)	0.0002 (0.0006)	0.907	104 (38.2)	714 (38.5)
2012	-0.0012*** (0.0004)	0.825	124 (34.2)	893 (32.9)	-0.0006 (0.0009)	0.784	96 (33.5)	696 (33.9)
2013	-0.0023*** (0.0006)	0.726	132 (43.6)	908 (43.9)	-0.0015*** (0.0004)	0.853	96 (29.3)	704 (30.9)
2014	-0.0013*** (0.0004)	0.826	112 (29.8)	895 (28.4)	-0.0010*** (0.0003)	0.823	94 (27.0)	709 (26.6)
2015	-0.0018*** (0.0004)	0.816	130 (35.7)	818 (35.5)	-0.0007*** (0.0002)	0.873	99 (32.0)	683 (31.3)

Table 5 Tests for the Existence of Stock Market Discipline

This table presents the estimated effects of reporting incentives due to public listing on the ALLL estimations under three sample splits. Panel A splits the sample of public banks by the average percentage of institutional ownership. Panel B splits the sample of public banks by the average institutional ownership Herfindahl–Hirschman Index (HHI). Panel C splits the sample of public banks by the average number of institutional block owners. All private banks are retained as the comparison group for each split sample. The estimation method for all split samples is a matching-weight weighted regression with the dependent variable $\frac{ALLL}{Total\ Loans}$, the first 55 covariates as defined in Appendix A as control variables, and the state fixed effects. The matching weight for each bank observation i is calculated from $\frac{\min(\theta_i, 1-\theta_i)}{Z_i\theta_i+(1-Z_i)(1-\theta_i)}$ (Li and Greene 2013), where $Z_i = 1$ if bank i is public, $Z_i = 0$ if bank i is private, and θ_i is the estimated propensity score for bank i. θ_i is estimated from a logistic regression including the 55 covariates and the state fixed effects. Column "Public" lists the coefficients and standard errors (in parentheses and clustered at the state level) on the "Public" dummy. The numbers in parentheses under columns "# Public" and "# Private" are effective numbers of public and private banks in the sample after applying the matching weights to the sample. The coefficients on the 55 covariates are not reported. *p<0.1; **p<0.05; ***p<0.01.

Panel A Split of Public Banks by Percentage of Institutional Ownership

	Percentage of Institutional Ownership > Mean				Percentage of Institutional Ownership ≤ Mean			
	Public	R-squared	# Public	# Private	Public	R-squared	# Public	# Private
2002	0.0007** (0.0003)	0.923	225 (42.0)	3493 (43.0)	0.0003* (0.0002)	0.759	320 (184.8)	3493 (186.2)
2003	0.0007 (0.0006)	0.879	224 (54.2)	3508 (53.5)	0.0001 (0.0002)	0.775	314 (181.1)	3508 (179.5)
2004	0.0015*** (0.0004)	0.874	204 (64.9)	3546 (67.7)	-0.0001 (0.0002)	0.804	302 (192.3)	3546 (191.0)
2005	0.0002 (0.0003)	0.892	169 (35.0)	2060 (36.5)	0.0002 (0.0002)	0.776	225 (100.2)	2060 (97.4)
2006	0.0000 (0.0004)	0.782	174 (41.0)	2032 (41.4)	0.0003 (0.0002)	0.821	211 (99.6)	2032 (100.6)
2007	0.0007 (0.0005)	0.864	155 (34.0)	1949 (35.5)	0.0001 (0.0002)	0.851	207 (102.7)	1949 (101.1)
2008	-0.0005 (0.0004)	0.937	141 (27.7)	2031 (27.7)	-0.0001 (0.0003)	0.812	212 (125.7)	2031 (124.1)
2009	0.0015 (0.0009)	0.922	145 (30.0)	2075 (28.8)	-0.0000 (0.0003)	0.830	194 (93.4)	2075 (93.6)
2010	0.0004 (0.0006)	0.933	156 (27.4)	2070 (27.1)	-0.0002 (0.0006)	0.858	180 (97.5)	2070 (97.8)
2011	-0.0003 (0.0009)	0.793	160 (31.3)	2080 (32.1)	0.0000 (0.0007)	0.819	162 (90.4)	2080 (90.4)
2012	-0.0020*** (0.0007)	0.836	146 (22.0)	2016 (20.7)	-0.0007 (0.0006)	0.800	151 (74.8)	2016 (73.0)
2013	-0.0024*** (0.0008)	0.901	153 (14.6)	2008 (15.8)	-0.0015*** (0.0003)	0.708	163 (85.3)	2008 (86.8)
2014	-0.0007*** (0.0004)	0.920	143 (17.0)	1972 (15.2)	-0.0015*** (0.0003)	0.786	134 (64.6)	1972 (62.8)
2015	-0.0014*** (0.0005)	0.784	156 (17.9)	1840 (17.4)	-0.0008*** (0.0003)	0.754	161 (72.4)	1840 (74.9)

Panel B Split of Public Banks by Institutional Ownership HHI

	Institutional Ownership HHI > Mean				Institutional Ownership HHI ≤ Mean			
	Public	R-squared	# Public	# Private	Public	R-squared	# Public	# Private
2002	0.0001 (0.0002)	0.790	168 (118.8)	3493 (119.6)	0.0002 (0.0002)	0.804	377 (129.3)	3493 (124.7)

2003	0.0004 (0.0003)	0.824	158 (105.6)	3508 (105.6)	0.0004 (0.0003)	0.754	380 (145.6)	3508 (140.8)
2004	0.0001 (0.0003)	0.836	157 (110.9)	3546 (113.2)	0.0007 (0.0004)	0.738	349 (153.9)	3546 (150.1)
2005	0.0002 (0.0002)	0.786	128 (66.1)	2060 (65.8)	0.0007* (0.0003)	0.843	266 (78.0)	2060 (79.9)
2006	0.0006*** (0.0002)	0.854	122 (65.6)	2032 (64.3)	-0.0001 (0.0003)	0.685	263 (74.8)	2032 (75.8)
2007	-0.0000 (0.0003)	0.893	119 (67.3)	1949 (68.2)	0.0005 (0.0003)	0.830	243 (71.9)	1949 (71.4)
2008	0.0002 (0.0003)	0.882	120 (75.6)	2031 (73.4)	-0.0000 (0.0004)	0.830	233 (88.2)	2031 (89.1)
2009	0.0007** (0.0003)	0.942	114 (57.2)	2075 (57.9)	0.0012** (0.0006)	0.843	225 (70.2)	2075 (69.7)
2010	0.0003 (0.0007)	0.884	114 (71.0)	2070 (72.0)	0.0005 (0.0007)	0.864	223 (69.8)	2070 (71.9)
2011	-0.0001 (0.0006)	0.843	113 (70.6)	2080 (67.8)	-0.0005 (0.0007)	0.777	209 (56.6)	2080 (58.8)
2012	-0.0007 (0.0006)	0.837	92 (55.9)	2016 (54.5)	0.0006 (0.0007)	0.780	205 (50.3)	2016 (49.3)
2013	-0.0013*** (0.0003)	0.744	102 (59.2)	2008 (60.8)	-0.0019*** (0.0006)	0.780	214 (49.9)	2008 (50.3)
2014	-0.0015*** (0.0003)	0.808	88 (58.5)	1972 (55.2)	-0.0012*** (0.0003)	0.894	189 (34.0)	1972 (34.4)
2015	-0.0009*** (0.0003)	0.796	92 (47.4)	1840 (49.4)	-0.0013*** (0.0003)	0.755	225 (50.7)	1840 (50.6)

Panel C Split of Public Banks by Number of Institutional Block Owners

	Number of Institutional Block Owners > Mean				Number of Institutional Block Owners ≤ Mean			
	Public	R-squared	# Public	# Private	Public	R-squared	# Public	# Private
2002	-0.0000 (0.0003)	0.839	180 (79.4)	3493 (80.8)	0.0005** (0.0002)	0.829	365 (165.8)	3493 (167.5)
2003	0.0004 (0.0004)	0.743	240 (99.5)	3508 (101.5)	0.0002 (0.0003)	0.794	298 (160.2)	3508 (154.0)
2004	0.0009* (0.0005)	0.847	235 (113.2)	3546 (116.5)	0.0000 (0.0002)	0.727	271 (157.6)	3546 (155.1)
2005	-0.0001 (0.0002)	0.897	199 (66.6)	2060 (65.9)	0.0007** (0.0003)	0.795	195 (84.0)	2060 (81.7)
2006	0.0003 (0.0003)	0.802	195 (63.4)	2032 (62.4)	0.0000 (0.0001)	0.700	190 (83.9)	2032 (84.0)
2007	0.0005 (0.0003)	0.903	98 (39.4)	1949 (38.1)	0.0002 (0.0002)	0.865	264 (107.9)	1949 (107.4)
2008	0.0000 (0.0004)	0.915	105 (34.2)	2031 (34.5)	-0.0001 (0.0003)	0.825	248 (128.4)	2031 (126.7)
2009	0.0004 (0.0008)	0.930	118 (26.7)	2075 (24.2)	0.0010** (0.0004)	0.881	221 (98.8)	2075 (100.3)
2010	-0.0012 (0.0007)	0.907	136 (40.4)	2070 (40.5)	0.0005 (0.0006)	0.865	201 (98.6)	2070 (96.5)
2011	-0.0000 (0.0007)	0.772	147 (55.7)	2080 (55.9)	0.0002 (0.0007)	0.811	175 (77.6)	2080 (76.3)
2012	-0.0007 (0.0006)	0.766	166 (49.6)	2016 (47.8)	-0.0005 (0.0006)	0.818	131 (63.4)	2016 (62.3)
2013	-0.0014** (0.0006)	0.817	152 (43.8)	2008 (42.6)	-0.0015*** (0.0004)	0.756	164 (78.7)	2008 (78.8)
2014	-0.0012***	0.822	145 (33.9)	1972 (32.3)	-0.0011***	0.844	132 (65.9)	1972 (65.4)

	(0.0004)				(0.0003)			
2015	-0.0015*** (0.0005)	0.624	161 (35.6)	1840 (36.0)	-0.0010*** (0.0003)	0.787	156 (62.0)	1840 (63.4)

Table 6 Sensitivity Analysis

This table compares the estimated effects of reporting incentives due to public listing on the ALLL estimations using two different loan loss rate calculations. Columns (1), (3), and (5) of this table respectively list the ALLL differences between public and private banks as reported in Table 2, and between federally chartered public and private banks and between state-chartered public and private banks as reported in Table 3. Columns (2), (4), and (6) of this table list the effects estimated with an alternative loan loss rate. The alternative loan loss rate is calculated by dividing the average of current-year and prior-year net charge-offs by current-year total loans. This loan loss rate calculation replaces the calculations for covariates (22) to (27) in Appendix A. Except for the change in the loan loss rate calculation, the estimation methods for columns (2), (4), and (6) follows the estimation methods for columns (1), (3), and (5), respectively. Standard errors are in parentheses and are clustered at the state level. *p<0.1; **p<0.05; ***p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	All banks		Federally chartered banks		State-chartered banks	
	As reported in Table 2	With alternative loan loss rate	As reported in Table 3	With alternative loan loss rate	As reported in Table 3	With alternative loan loss rate
2002	0.0004***	0.0004***	0.0003	0.0003	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0002)
2003	0.0005*	0.0003	-0.0002	-0.0002	0.0007**	0.0006*
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0003)
2004	0.0006*	0.0005*	0.0006	0.0004	0.0006*	0.0005
	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
2005	0.0005*	0.0004	0.0004	0.0004	0.0005	0.0004
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0003)	(0.0004)
2006	0.0004	0.0006**	0.0003	0.0007*	0.0004	0.0005**
	(0.0003)	(0.0002)	(0.0006)	(0.0004)	(0.0003)	(0.0002)
2007	0.0003	0.0002	0.0005	0.0003	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0002)
2008	0.0000	-0.0000	0.0002	0.0002	-0.0000	-0.0001
	(0.0003)	(0.0003)	(0.0005)	(0.0006)	(0.0004)	(0.0003)
2009	0.0010*	0.0010*	0.0011	0.0004	0.0009	0.0011
	(0.0005)	(0.0005)	(0.0009)	(0.0009)	(0.0006)	(0.0007)
2010	0.0006	0.0007	0.0004	0.0004	0.0006	0.0008
	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0007)	(0.0006)
2011	0.0005	0.0002	0.0008	0.0002	0.0006	0.0003
	(0.0007)	(0.0006)	(0.0011)	(0.0010)	(0.0008)	(0.0008)
2012	0.0001	0.0003	0.0010	0.0006	-0.0003	0.0002
	(0.0005)	(0.0006)	(0.0011)	(0.0012)	(0.0006)	(0.0006)
2013	-0.0016***	-0.0019***	0.0001	-0.0007	-0.0022***	-0.0022***
	(0.0006)	(0.0005)	(0.0010)	(0.0009)	(0.0005)	(0.0005)
2014	-0.0015***	-0.0014***	-0.0009**	-0.0006	-0.0016***	-0.0016***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
2015	-0.0013***	-0.0014***	-0.0007*	-0.0010**	-0.0015***	-0.0015***
	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0004)

Table 7 Impact of ALLL Underestimations in 2013, 2014, and 2015 on Performance Measures of State-Chartered Public Banks

This table presents the dollar amounts of the ALLL underestimations by state-chartered public banks between 2013 and 2015 and the impact of the underestimations on the banks' performance measures. Column (1) lists the per-dollar-of-total-loan ALLL underestimations by state-chartered public banks as reported in Table 3. Column (2) lists the average dollar amount of total loans reported by state-chartered public banks as of December 31 of each sample year. Column (3) converts the per-dollar-of-total-loan ALLL underestimations to dollar amounts. Columns (4) to (7) list the average ALLL, income before taxes and extraordinary items, equity capital, and total risk-weighted assets reported by state-chartered public banks as of December 31 of each sample year, respectively. Columns (8) to (11) calculate the percentage of dollar-amount ALLL underestimations to the reported ALLL, income before taxes and extraordinary items, equity capital, and total risk-weighted assets, respectively. All dollar amounts are in thousands.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				As reported				ALLL underestimation as a % of reported			
	ALLL underestimation (scaled by total loans)	Total loans	ALLL underestimation (dollar amount)	ALLL	Income before taxes and extraordinary items	Equity capital	Total risk-weighted assets	ALLL	Income before taxes and extraordinary items	Equity capital	Total risk-weighted assets
2013	-0.0022	4,725,987.10	10,397.17	72,400.82	122,482.07	881,567.19	5,824,877.20	14.4%	8.5%	1.2%	0.2%
2014	-0.0016	5,220,139.60	8,352.22	70,289.27	122,074.84	919,869.67	6,059,285.30	11.9%	6.8%	0.9%	0.1%
2015	-0.0015	5,893,455.60	8,840.18	68,001.22	153,240.54	1,162,645.04	7,683,280.20	13.0%	5.8%	0.8%	0.1%