Competition and the Use of Discretion in Financial Reporting: Evidence from Community Banks

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Abstract

This paper explores firms' use of discretion in financial reporting as a means to deter entry. The analysis uses the setting of deregulation in interstate branch banking, and a sample of community banks for whom geographic location is a critical aspect of competition. I provide empirical evidence that banks increase their loss provisioning and appear less profitable when faced with an increased threat of competition. Future losses do not justify the increase in provisions. The findings are consistent with managers' and regulators' use of discretion in financial reporting. Survey-based evidence collected as part of this study supports the premise that banks prefer to locate in markets where incumbents have high profitability and low credit losses, and that banks use competitors' financial statements in analyzing their competition.

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1 Introduction

Product market competition is widely seen as a positive force resulting in efficient allocation of resources, cost reduction, and increased innovation. As early as 1776, Adam Smith in The Wealth of Nations states that "Monopoly...is a great enemy to good management". The belief that competition has several benefits has influenced many deregulation initiatives around the world. However, policy initiatives that are designed to instill greater competition may be rendered less impactful if firms devise strategies to deter entry into their markets. This paper studies the use of discretion in accounting as a tool to deter entry. I seek to answer two key questions. First, do firms reduce profitability as an entry deterrence strategy? Second, what role does the regulator play?

There is a large and mainly theoretical literature in economics that deals with entry deterrence strategies employed by incumbents (Spence, 1977; Dixit, 1979, 1980; Milgrom and Roberts, 1982). However as Smiley (1988) suggests, economists have have neglected certain commonly used tactics such as hiding profits.[1] Although prior accounting literature has explored firms' incentives to appear less profitable during import relief investigations (Jones, 1991) and labor union contract negotiations (Liberty and Zimmerman, 1986), less is known about firms' incentives to reduce profitability as a strategy to deter entry. Voluntary disclosure literature finds that under the threat of competition, firms increase disclosure and the tone of disclosure becomes more negative (Darrough and Stoughton, 1990; Burks et al., 2015). However, the effect of an increase in the threat of competition on mandatory disclosure is less well understood.

Limited empirical work in entry deterrence is largely driven by the difficulty in identifying a threat of competition separately from an actual increase in competition (Goolsbee and Syverson, 2008). I achieve identification by exploiting the setting of interstate branch banking deregulation under the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 to obtain variation in the threat of competition. The Act allowed banks to engage in interstate branching, subject to certain state-level restrictions. Although federal law authorized banks to branch into any state, states

[1] In a survey of marketing executives 31% of all survey respondents cited hiding profits as a frequently used entry deterrence strategy. This compared to 7% who cited capacity expansion, and 6-7% who cited limit pricing, two strategies that have been extensively studied in the economics literature (Smiley, 1988).

were allowed to impose anticompetitive restrictions to prevent entry by outside banks. The magnitude and timing of such restrictions adopted, and subsequently abandoned, varied by state. To identify the banks most likely to be affected by entry of larger competitors into their local markets, I restrict the sample to community banks that tend to be small in size, compete on fewer dimensions, and whose reach is geographically limited.[2] Further, I focus on the period prior to adoption of state-level restrictions to interstate branching. Typically, regulation was passed by the state legislature or announced in the press one to two years before it became effective.

About 80% of all commercial banks in the United States are community banks. Further, over 80% of the revenue of a community bank consists of net interest income. This makes loss provisions a large accrual for the bank, one over which management has considerable discretion. Loan loss provisions indicate a bank's expectation of future loan losses. They include management's private information and may be influenced by the bank examination process. Since banks are required to provision based on loss-causing events,[3] this accrual becomes a leading indicator of local market credit quality and a barometer of future prospects for banks in that market. For instance, consider a situation where a bank is the primary lender for households in a county where a majority of the population works at a factory. If the factory shuts down, the bank is required to provision for expected losses, as the loss has been incurred, even though none of its customers may yet have defaulted on their payments.

Since loss provisions contain information about future market conditions, incumbent banks could increase provisions and appear less profitable in order to deter entry. Survey-based evidence supports this assertion. To understand incumbent behavior, I surveyed community bankers and asked the following question, "What factors do you think competitor banks assess before entering into your local market?"[4] 75% of all survey respondents cited profitability of incumbent banks and credit quality of incumbent banks' loan portfolio as relevant factors.[5] I then asked bankers how they would rate a market for attractiveness of entry based on these two factors. An overwhelming number (greater than 85 percent) of survey respondents replied that

[2]Community banks mainly compete for consumer and small business loans and deposits, as opposed to large banks that in addition, would compete for investment banking services, trading, brokerage and transaction services, as well as large corporate lending.

[3]Under the Incurred Loss Model, the loss-causing events may not yet have resulted in non-accruing loans. However, provisioning is subject to the condition that losses can be reasonably estimated.

[4]The survey had 59 respondents spread out over states with a community banking presence. Please see Appendix A for details regarding the survey.

[5]Please see Appendix A, survey question 9.

they would prefer to enter markets where incumbent banks had high profitability and low credit losses.[6]

However, there are alternate explanations for why provisions should increase under an increased threat of competition. The provisioning could be in response to future losses which may rise if anticipated competition led to a loosening of credit standards. Further, concerns that increased competition could encourage risky behavior by banks, thereby contributing to instability of the banking system, may cause regulators to induce greater provisioning.

I conduct two main analyses within a difference-in-difference framework to study the effect of an increase in the threat of competition on banks' loss provisioning behavior. In the first analysis, I use a sample of community banks from states that reduced restrictions to interstate branching. In the second analysis, I focus on banks from the state of Texas and, as a control group, use a matched sample of banks from states with a similar degree of openness to interstate branching.

I find that banks increase their loan loss provisions and appear less profitable one to two years before the deregulation event. The year of deregulation varies across states, reducing concerns that year- or state-specific factors may be driving the result. I also find that loss provisions increase with market concentration, measured using county-level Herfindahl index. This finding is consistent with managers' use of discretion as banks in concentrated markets have larger excess rents to protect and hence a greater incentive to deter entry. Further, in line with findings in prior literature (Beatty et al., 2002), public banks tend to have lower provisions compared to private banks in a neutral period. However, publicly-listed banks increase their provisions to a greater extent in the face of an increased threat of competition, consistent with increased regulator attention driving the results.

Focusing on Texas allows for better identification as it is less likely that local market conditions could have caused the deregulation event. Texas initially opted out of the provisions of the IBBEA. The state later eased restrictions to interstate branch banking in response to a court ruling that permitted out-of-state banks to circumvent Texas' ban on interstate branching.[7] As before, I find that banks increase their loss provisions in response to an increase in the threat of competition. The results hold when I use a matched control sample suggesting that time specific factors are not

[6] Please see Appendix A, survey questions 11 and 12.

[7] See *Texas to Let State Banks Branch Interstate*, American Banker, 15 May 1998.

driving the results. Results from a spatial analysis show that the strength of spatial correlation between loss provisions of banks in neighboring counties increases with the threat of competition, lending support to the argument that the results are reflective of managers' use of discretion.

As a further test of managers' use of discretion, I exploit variation between counties in Texas to identify banks that have greater incentive to increase provisions to deter entry. Survey-based evidence indicates that financial statements of competitors provide incremental information over economic indicators such as population growth and household income in aiding market expansion decisions.[8] This suggests that banks located in counties that are similar to neighboring counties based on economic indicators are more likely to increase their loss provisions to deter entry. I use this insight to identify banks that have a greater incentive to look less profitable. Using a measure of between-county variability based on population growth, I have not found evidence to suggest that these banks over-provision under an increased threat of competition.[9]

I conduct two tests to assess regulators' use of discretion in this setting. The first test uses the regulatory leniency index of Agarwal et al. (2014) who identify strict and lenient state regulators based on their rating of state-chartered banks relative to federal regulators. While I find that stricter regulators induce greater loss provisioning, I do not find significantly different results in anticipation of competition. In the second test, I use distance from the regulators' office as a measure of regulatory attention. I find that banks located closer to the regulators' offices increase provisions more in the face of an increased threat of competition. This finding is consistent with regulators driving increased provisioning.

To test whether future losses are driving the results I use the synthetic control methodology as described in Abadie and Gardeazabal (2003). I construct a synthetic state by optimizing over a set of states such that the pre-treatment characteristics of the synthetic state closely approximates that of the real state. I use banks in the state of Texas to conduct this analysis. I find that, relative to the synthetic control, non-

[8] Please see Appendix A, survey question 9.

[9] In un-tabulated analysis, I use a measure of between-county variability based on household income and find preliminary evidence in support of managers' use of discretion in this setting. Lack of significant results when using the measure based on population growth may be driven by the fact that immigration explains much of the population growth in Texas (Gibson and Jung, 2006), and banks may be less inclined to court this population.

performing assets in Texas increased after deregulation. However, this growth in non-performing assets does not explain increase in loss provisions in the period in which threat of competition intensifies.

This study contributes to several streams of literature. First, the paper contributes to literature on entry-deterrence by empirically exploring the use of profit-hiding as an entry-deterrence strategy. Prior literature in entry-deterrence has neglected the role of profit-hiding as a strategy to deter entry (Smiley, 1988). Further, given the difficulty in identifying the threat of competition separately from an actual increase in competition, there has been limited empirical work in this area (Goolsbee and Syverson, 2008; Ellison and Ellison, 2011).

This paper also contributes to the accounting literature on loan loss provisioning by studying managers' and regulators' use of discretion in loss provisioning under the threat of competition. Though the literature on bank loss provisioning is substantial (Beatty and Liao, 2014), there has been limited work on the effect of competition on loss provisioning.[10] Further, prior work has only considered managers' use of discretion in setting loan loss provisions and has largely overlooked the influence of regulators. The magnitude of discretion is likely to increase with the adoption of the proposed Current Expected Credit Loss model (CECL),[11] making it timely and relevant to explore conditions under which discretion can influence provisioning behavior.

Finally, by exploring the effect of regulators in bank loss provisioning, this study contributes to the limited empirical work on regulatory discretion, and its effect on accounting earnings (Agarwal et al., 2014; Costello et al., 2015).

[10] Dou et al. (2014) also explore the effect of competition on banks' loss provisioning. The paper uses the same setting of deregulation in interstate branching and makes the argument that incumbents would decrease provisions and appear more profitable in order to signal superior underwriting ability. The discrepancy in results could be because of sample selection and research design choices. The paper uses a sample of banks on borders of states in order to control for local market conditions. However, banks on state borders were exposed to interstate branching irrespective of change in restrictions brought about by the Act. National banks were able to circumvent state-level bans on interstate branching by using the 30-mile rule. This rule allowed a bank to move its headquarters across state lines without giving up existing branches. A limitation was that the new office could not be located more than 30 miles from the limits of the city, town, or village where the old main office was located. Though the rule was enacted in 1866, banks started using it more widely in the 1990s. Further, Dou et al. (2014) focus on the years after the change in restrictions to interstate branching. I focus on one to two years prior to the change, a period during which regulation was announced but not effective.

[11] See FASB Exposure Draft: Proposed Accounting Standards Update ASC 825-15, Financial Instruments – Credit Losses.

The paper is organized as follows. Section 2 presents the background. Section 3 develops hypotheses related to managers' and regulators' use of discretion. Section 4 discusses the data and sample. Section 5 presents the econometric framework and a discussion of the results. Section 6 presents additional analysis and robustness tests, and Section 7 concludes. Figures, tables, variable definitions, and survey results are provided in the appendices.

2 Background

The IBBEA was passed in September 1994, and dealt with both interstate banking (effective 1995) and interstate branching (effective June 1, 1997). However, by 1994 most states already allowed out-of-state bank holding companies to own in-state banks. Therefore, the landmark event of the regulation permitted interstate branching, which was not allowed in most states prior to the passage of this Act.[12]

Outside banks could branch into a state by acquiring a bank and converting it into a branch, acquiring existing branches of incumbent banks, or by establishing new branches (de novo entry). Even though federal law permitted interstate branching, states had considerable flexibility in preventing branching by outside banks. First, states could altogether opt-out of interstate branching provisions of the IBBEA before the date that the Act became effective. Second, states could employ more restrictive stipulations with respect to certain provisions that fell within the purview of state law. The main provisions that states could use to impose anticompetitive barriers were (1) the minimum age of the target institution, (2) de novo interstate branching, (3) the acquisition of individual branches, and (4) a statewide deposit cap. Rice and Strahan (2010) construct an index based on these four provisions. The index is set to zero for states that are most open to entry by out-of-state banks, and increases by one when any of the four barriers to entry are added by the state. Therefore, the index ranges from a minimum of zero (least restrictive) to four (most restrictive).

I use changes in this index as a measure of change in the threat of competition. Individual states varied in their timing for removing obstacles to interstate branching, providing temporal and geographic variation in the threat of competition.

[12] In 1994, there were only 62 out-of-state branches, whereas by 2005 the number had risen to 24,728, which was 37.28% of all domestic branches (Johnson and Rice, 2008).

3 Hypothesis Development

3.1 Managers' Use of Discretion

Deregulation of interstate branch banking led to an increased threat of entry by outside competitors into local banking markets. Congressional hearing records show that many community bankers were against deregulation and raised several objections.[13] These arguments related to perceived unfairness in the competition. Community banks argued that larger banks had access to lower cost funds, which would present them with an unfair advantage. Further, while too-big-to-fail banks would be bailed out by the FDIC, uninsured depositors of community banks would lose their deposits in the event of a bank failure. Larger banks, with greater financial resources, could initially charge lower fees and hike the fee once they had driven out competition.

Community banks argued that banks whose headquarters were farther from local markets would be less likely to meet local demands for credit and would be less interested in making small loans to borrowers, hurting the small business community. They were concerned that large banks could use the local market as a source of funding to obtain deposits that would then be used elsewhere, adversely affecting local investment and growth.

However, not all community bankers were against deregulation of interstate branching. Large and community banks tend to serve different customer bases and compete on different dimensions, due to which a community bank may not be threatened by the presence of larger banks. Therefore, it is not entirely clear that community banks would have employed strategies to keep larger players out of their local markets. In the following quote, sourced from the 1993 congressional hearings records, a community banker from the state of New York makes the following argument.

> "Due to the unique role of a community bank, I have not felt the negative impact of consolidation, and do not believe that further consolidations, which would increase the presence of larger banks in our area, will negatively affect our financed growth and success ...[I] am not concerned about their presence as much as I might be by another independently owned

[13] See "Interstate banking and branching - Hearing before the subcommittee on financial institutions supervision, regulation and deposit insurance of the committee on banking, finance and urban affairs." Sourced from https://babel.hathitrust.org .

community bank operating across the street."

- *Paul Settelmeyer, President, Bank of Great Neck, New York.*[14]

As discussed in Section 1, loss provisioning is a leading indicator of local market credit quality. Further, prior literature (Amel and Liang, 1997), empirical analysis of ex post entry presented in Section 4.3, as well as survey-based evidence suggest that entering banks prefer to locate in markets where incumbents have high profitability. Survey evidence also suggests that entering banks do not prefer to locate in markets where incumbents have high credit losses.[15] Analysis of competitor's financial statements is common practice in the banking industry. For instance, 94% of survey respondents use financial statements of competitors to analyze market competition. Banks assess information on competitors' profitability, loan growth and composition, capital ratios, funding costs, as well as credit losses.[16]

Entrant banks' preference to locate in markets with profitable incumbents, as well as banks' use of competitors' financial statements, suggests that incumbents have an incentive to bias their earnings downwards. Since there are several local banking markets within a state where the entrant could potentially locate, financially strong incumbent banks in the different local markets are trapped in a prisoner's dilemma type game with each other, as banks that do not bias earnings downward potentially invite competition. In such a case, the dominant strategy is to bias earnings to look less profitable. This suggests the following hypothesis.

H1: Incumbent banks will increase provisions to appear less profitable in the face of an increased threat of competition.

A critical aspect of bank competition is asymmetric information, both between the borrower and the lending (inside) bank, as well as between the inside bank and any competing (outside) banks. Given their monitoring role (Diamond, 1984; Rajan, 1992), inside banks are able to acquire superior quality information about the borrowers' credit-worthiness as compared to outside banks. Because of this informational advantage, inside banks are able to charge an information rent to captive borrowers (Von Thadden, 2004; Sharpe, 1990; Schenone, 2009).

Since entrants in this setting are larger banks, they have a cost advantage over the incumbents. Large banks have access to wholesale sources of funding and may also

[14]At the time, Bank of Great Neck had assets of $135 million, and 28 full-time employees.

[15]Please see Appendix A, survey questions 11 and 12.

[16]Please see Appendix A, survey question 14.

be able to direct deposits from branches in different locations. Therefore, the entrant in this setting has a cost advantage, whereas the incumbent has an informational advantage. Dell'Ariccia and Marquez (2004) show that the incumbent will lose market share so long as the cost advantage is sufficiently high and the informational advantage not as strong. However, anecdotal evidence suggests that a cost advantage can translate to an informational advantage.[17]

Incumbent banks with large informational advantages, as is the case in more concentrated markets, are likely to increase provisions more to protect their information rents. Further, in more dispersed markets, the financial statements of each incumbent bank conveys less information about the underlying market conditions, making it less worthwhile to bias earnings.

The above discussion suggests the following hypothesis.

H2: Banks in concentrated markets will increase provisions more in the face of an increased threat of competition.

Managers of publicly listed banks face additional capital markets-related incentives to inflate their stock price. Such an action may be aimed at preventing takeover, using overvalued stock to execute a takeover, or gaining a lower cost of capital. Further, competition can increase the precision of, and create pressure on, managerial incentive contracts, which may lead to manipulation of outcome measures associated with such contracts. This suggests that the cost of manipulating to look less profitable would be higher for managers of publicly listed firms, due to which such firms would decrease earnings less in the face of an increased threat of competition.

Prior work has explored incentives of private and public firms to manage earnings. However, the evidence has been mixed. Beatty et al. (2002) find that public banks manipulate earnings more, whereas Burgstahler et al. (2006) find that private firms manage earnings more, suggesting that capital markets either induce increased earnings informativeness, or firms with less informative earnings are screened out in the IPO process.

This leads to the following hypothesis.

H3: Publicly listed banks will increase provisions to a lesser extent as

[17] For instance, consider Wells Fargo's foray into Koreatown, Los Angeles. Wells Fargo was able to make inroads into this market by hiring the CEO of its competitor and Korean speaking bankers.

compared to private banks in the face of an increased threat of competition.

3.2 Regulators' Use of Discretion

I surveyed community bankers, asking them what motivated them to over-reserve for loan losses.[18] 88% of survey respondents cited regulator's expectations as a reason to over-reserve.

There is an ongoing debate about the effect of bank competition on financial system stability (Keeley, 1990; Hellman et al., 2000; Boyd and De Nicolo, 2005; Carletti and Vives, 2007). Bank competition has been argued to be a source of excessive risk-taking. The argument is that, as the franchise value of banks erodes due to greater competition, or because of withdrawal of market subsidies,[19] banks have less to lose in case of default and hence a greater incentive to take on more risk. Further, given a risk level, banks may charge lending rates that are too low and deposit rates that are too high simply to win more business. Such actions could also be taken in anticipation of increased competition, contributing to the instability of the banking system and erosion of deposit-insurance. In response to increased competition, and possible decline in the credit quality of loans, bank examiners may require that the bank increase provisions.

Recent empirical literature has examined the use of discretion by regulators. Agarwal et al. (2014) find that state banking regulators tend to be more lenient compared to federal regulators in applying identical rules to the same regulated entity. They also find that some state regulators tend to be more lenient than others. Costello et al. (2015) use this setting of differential leniency of state and federal regulators and explore the impact of regulatory discretion on financial transparency. They find that stricter regulators are more likely to enforce income-reducing accounting choices. These findings motivate the following hypothesis.

H4a: Banks located in states with stricter regulators will increase provisions more in response to regulator expectations, under an increased threat of competition.

[18] Please see Appendix A, survey question 19.

[19] Any regulation that prevents free entry into a market is akin to giving the incumbents a subsidy.

Prior literature indicates that regulatory leniency may also vary based on the geographical location of the regulator with respect to the regulated entity. Kedia and Rajgopal (2011) study SEC enforcements and find that, consistent with the theory of a resource-constrained regulator, the SEC is more likely to investigate firms that are geographically located close to its offices.

The onsite portion of a bank examination can extend to several weeks making distance to the regulator's offices a reasonable measure of regulatory attention. For instance, an audit of the FDIC's examination process from 2007 to 2011 for small community banks showed that the average length of time for onsite examinations ranged from 20 to 33 days for a bank rated 1 or 2 on the CAMELS score, and 42 to 66 days for a bank with a riskier rating of 3,4, or 5.[20]

The above discussion suggests the following hypothesis.[21]

H4b: Banks located closer to the regulator's offices will increase provisions more in response to regulator expectations, under an increased threat of competition.

4 Data and Sample

4.1 Bank and Branch data

This study uses branch level data from the FDIC's Summary of Deposits database and bank level data from the Reports of Condition and Income (Call data) from the Federal Reserve Bank of Chicago. FDIC's Community Banking Reference dataset is used to restrict the sample to community banks, and the SNL Financial database is used to identify banks that are publicly listed. Table 1 describes the sampling procedure.

Table 1a describes branch level data. There are a total of 1,104,016 bank branches in the years 1994 to 2005. In order to restrict variation in the cost of expansion, I

[20]See report titled "The FDIC's Examination Process for Small Community Banks" at https://www.fdicig.gov/reports12/12-011AUD.pdf.

[21]I do not consider the case where a regulator corrects over-provisioning by the manager. Given the mandate to ensure safety and soundness of the banking system, regulators are more likely to be concerned about under-provisioning. In un-tabulated analysis, I search the text of FDIC enforcement actions and find that in every case where loan loss provisions are mentioned, it is with respect to inadequate provisioning.

exclude Alaska and Hawaii from the sample. A few observations have zero or negative asset values, which is most likely due to faulty data. I exclude these observations from the analysis. The final sample consists of 1,008,339 branch years.

Table 1b describes the sample selection criteria for bank level data. I merge the FDIC's community banking reference dataset with bank Call data and remove observations that fall in a year of acquisition or failure. I further remove observations with missing, zero, or negative loans and restrict the sample to banks in contiguous United States. Since the paper relates to the effect of an increase in the threat of competition on financial reporting, I only include states that decreased restrictions to interstate branching. I further restrict the sample to states that have a significant community banking presence. The final sample consists of 130,939 bank-year observations from the years 1992 to 2008. Of these, 4,547 observations are publicly listed banks. Figure 1 presents the distribution of banks by state and demonstrates that Texas and Illinois have a large community banking presence. Table 2 presents descriptive statistics for private and public banks. On average, public banks comprise 3.6% of the sample. There are significant differences between the two groups. Public banks in the sample tend to be larger, less profitable, and have a lower tier-1 leverage ratio. The loan portfolio composition of these groups also differs significantly. Public banks tend to have a higher share of real estate, and commercial and industrial loans in their loan portfolio whereas private banks have a greater share of agricultural and consumer loans.

The sample is divided into public and private companies in order to test the differential impact of a threat of competition on the reporting behavior of the two groups. The list of public banks is sourced from the SNL Financial database. This database includes small public banks that are generally not available on CRSP. However, if a bank switches from public to private or vice-versa, the database overwrites the historic ownership status of the company to reflect only its most recent status. I address this issue by comparing the most recent SNL list of public banks to published hard copies of the SNL Executive Compensation Review, which are available from the Library of Congress in Washington D.C.

4.2 Measuring Changes in Regulation

As discussed in Section 2, I rely on an index created by Rice and Strahan (2010) to measure changes in state-level restrictions to interstate bank branching. Table 3a presents the number and percent of states that changed restrictions to interstate branching in a given year.

Table 3b presents the average number of branches and average deposits by state-year, by level of restrictiveness index. States that have greater barriers to interstate branching (index value of four) also tend to have a lower number of branches and lower deposits as compared to states that are open to interstate branching. Table 3c presents the change in the average number of branches and deposits by state-year, by year relative to the change in restrictiveness index. States that ease restrictions to interstate branching tend to show growth in branches and deposits.

4.3 Measuring Entry

I construct a measure of entry, $\Delta DIST$, to provide empirical support for the argument that banks prefer to locate in markets where incumbents have high profitability. The measure is based on distance to the entering bank and increases with competition. In order for $\Delta DIST$ to capture some dimension of competition, community banks must face more competitive pressure from banks that are geographically closer to them than from banks that are farther away. This argument has some support in existing literature. A key idea in the Organizational Ecology literature is that firms which have more similar resource requirements compete more intensely (Baum and Mezias, 1992). Banks in a locality compete for the same base of depositors and borrowers. The entry of new banks into that locality increases competition for incumbent banks.

$\Delta DIST$ is the change in $DIST$ and is calculated at the branch level before being aggregated to the bank level.

$DIST$ is specified as follows,

$$DIST_i = \sum_{\substack{i \neq j \\ d_{ij} < \mu}} \frac{1}{d_{ij}} \ , \tag{1}$$

where j refers to a neighboring branch within a radius of μ from the focal branch i, and d_{ij} is the geographic (great-circle) distance between branches i and j.

μ is based on the population of a region and is lower for areas that are more densely populated. μ is equal to 25 kilometers for branches located in regions with a population greater than 50,000, and 50 kilometers for branches in regions with a population of less than 50,000.

The change in $DIST$, denoted by $\Delta DIST$, measures entry into the vicinity of a given bank. Figure 2 presents the distribution of $log(\Delta DIST)$ for the lowest and highest quintile of lagged ROA for a bank. The mass of the distribution shifts to the right for the highest quintile of lagged ROA as compared to the lowest quintile, suggesting that entering banks prefer to locate in markets where incumbents have higher profitability.

5 Empirical Analysis and Discussion of Results

I conduct two main analyses in order to study the effect of a change in the threat of competition on the provisioning behavior of banks. In the first analysis, I use a sample of banks from states that reduced restrictions to interstate branch banking. In the second analysis, I focus on banks from the state of Texas. I create a matched sample from states that were similar to Texas in the pre-treatment period in their openness to interstate branching. I also exploit variation between banks in Texas. Additional analyses are related to ruling out alternate explanations, and distinguishing between the effect of the manager and regulator.

5.1 Multi-State Analysis

5.1.1 Econometric Framework

The main econometric specification is given by

$$Y_{ist} = \alpha + \sum_{\tau=-3}^{+3} \beta_k D_{s\tau t} + \omega X_{ist} + T_t + S_s + \epsilon_{ist} \ , \tag{2}$$

where Y is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses (LLP).[22] i, s and t are firm, state, and year indicators. k is a time period indicator and goes from 1 to 6.

$D_{s\tau}$ is an indicator variable such that $D_{s-\tau}$ equals one for the τ^{th} year before the deregulation event, and zero otherwise. The deregulation event is defined as the easing of restrictions to interstate branch banking. Similarly, $D_{s\tau}$ equals one in the τ^{th} year after the deregulation event and zero otherwise. D_{s0} equals one for the year of the event and zero otherwise.

D_{s-3} is set equal to zero such that all coefficients are measured incremental to the third year before the event. The assumption is that $\tau-3$ is a neutral period and is not influenced by the event being studied. Even though the effect is studied relative to one period, there is less concern that this period reflects the idiosyncrasies of any one year. This is because the year of occurrence of the event, D_{s0}, varies by state making D_{s-3} an average of several years. The hypotheses indicate that coefficients associated with the time periods $\tau = -2$ and $\tau = -1$ should be positive and significant, suggesting that banks increased their provisions in anticipation of increased competition.

X is a vector of controls, and includes variables based on prior literature (Beatty and Liao, 2014) and interviews with community bankers. The control variables include the log of lagged assets ($SIZE$), the lagged, current, and leading changes in non-performing assets ($\Delta NPA_{-1}, \Delta NPA, \Delta NPA_{+1}$), the three year rolling average of past charge-offs (CO), growth in loans ($\Delta LOAN$), the state level change in per capita GDP (ΔGDP), as well as measures of loan portfolio diversity and change ($ShrRE$, $ShrCI$, $ShrCONS$, $\Delta ShrRE$, $\Delta ShrCI$, $\Delta ShrCONS$). The majority of community banks rely on fairly simple provisioning models, making Equation (2) a reasonable approximation for the provisioning behavior of banks in the sample. Appendix B presents definitions of variables. T and S represent year and state fixed effects, and ϵ denotes the error term.

For each bank in the sample, the data is limited to seven years around the change in regulation. Further, I require that banks have existed for all seven years to mitigate concerns that variation in sample size might be driving the results. I estimate Equation (2) for subsamples of firms that have a return on assets (returns measured before provisions) of greater than zero and one percent. To test hypotheses related

[22] In all specifications of the model, I multiply LLP with 10,000.

to the effect for public banks and in concentrated markets, I modify Equation (2) as follows,

$$Y_{ist} = \alpha + \sum_{\tau=-3}^{+3} \beta_k D_{s\tau t} + \sum_{\tau=-3}^{+3} \beta_m D_{s\tau t} * PH + \theta PH + \omega X_{ist} + T_t + S_s + \epsilon_{ist} \ , \quad (3)$$

where PH can take the value of $PUBLIC$ or $HERF$. $PUBLIC$ is an indicator variable that takes on a value of 1 if the firm is public, and 0 otherwise. $HERF$, a continuous variable, is the Herfindahl index measured at the county-year level and is a proxy for market concentration.

5.1.2 Discussion of Results

Table 4 presents OLS estimates of Equation (2). Model 1 presents the results without including state fixed effects, whereas Model 2 includes state fixed effects. In both cases, as predicted, the coefficients for D_{s-1} and D_{s-2} are positive and significant with t-statistics ranging from 1.86 to 3.19. Consistent with prior literature (Kim and Kross, 1998; Kanagaretnam et al., 2010; Bushman and Williams, 2012; Beck and Narayanamoorthy, 2013) $SIZE$, ΔNPA_{-1}, ΔNPA, and ΔNPA_{+1} are positively associated with loan loss provisions. $SIZE$ has a coefficient value of 2.171 and t-statistic of 6.55. Current and lagged change in non-performing assets are strongly associated with loss provisions with a coefficient value of 829 (t-statistic = 16.58) and 702 (t-statistic = 19.64). Leading change in non-performing assets is also significant, though weaker with a coefficient value of 238 (t-statistic = 6.19). This compares to coefficient values of 1310 for current, 933 for lagged, and 393 for leading change in non-performing assets in Bushman and Williams (2012).[23]

Prior literature that accounts for charge-offs in models of loss provisioning tend to include current period charge-offs. For instance, Kim and Kross (1998) and Beaver and Engel (1996) find current period charge-offs to be significant in predicting loss provisions. I use a three-year rolling average of scaled charge-offs. Interviews with community banks' CFOs reveal that given the volatile nature of this variable, most banks tend to use charge-offs averaged over 12 quarters in estimating provisions. I find

[23] Bushman and Williams (2012) also include twice lagged change in non-performing assets in their model of loan loss provisions. In un-tabulated analysis, I include this variable and do not find it to be significant in predicting loss provisions. However, this variable does load significantly when I exclude the three-year rolling average of charge-offs.

this variable to be strongly predictive of loss provisions, with a coefficient estimate of 6457 and t-statistic of 23.64.

Loan growth is positively and significantly associated with loan loss provisions. Further, change in state level per capital GDP is negatively associated with loss provisions. Consistent with prior literature (Wahlen, 1994; Kanagaretnam et al., 2010), measures of portfolio diversity have explanatory power in predicting LLP.

Table 5 presents the results for subsets of firms that had return on assets greater than zero (Model 1) and greater than one percent (Model 2), where returns are measured before provisions. Model 3 of Table 5 presents results of the analysis where the sample is restricted to banks with assets less than or equal to $500 million.[24] As before, the coefficients for D_{s-1} and D_{s-2} are positive and significant.

Model 4 includes a public-firm indicator. Consistent with prior research, public firms tend to under-provision in the neutral period (Beatty et al., 2002). However, the level of provisioning increases in the face of an increased threat of competition, which is consistent with increased regulatory attention on public banks.

In Model 5 of Table 5 the treatment period indicator is interacted with a measure of market concentration, $HERF$, the county level Herfindahl index. The results indicate that provisioning increases in market concentration. This provides support for the manager discretion hypothesis as firms located in concentrated markets have a greater incentive to deter entry and protect their excess rents.

5.2 Single-State Analysis

Since the banks and events are spread out spatially and temporally, there is less concern that time or region specific factors may be driving the effect demonstrated in Analysis 1. However, such a concern still exists as 62% of changes to the restrictiveness index occurred in only two years (1996 and 1997).[25]

In order to address this concern I focus on the state of Texas for which the restrictiveness index changed from a value of four in 1999 to a value of one in the year 2000. Texas has a large community banking presence and was one of only two states that

[24] Provisions are tax-deductible for banks with assets of less than $500 million, whereas this is not the case for banks with assets greater than $500 million, who can only deduct write-offs. This gives the smaller banks an incentive to over provision.

[25] This can be seen from the data presented in Table 3a.

initially opt-outed of the provisions of the IBBEA.[26] Opting out of the IBBEA was seen as a huge political victory for independent banks.[27] Texas later decided to allow interstate branching effective on the first of September, 1999 in response to a court ruling which permitted out of state banks to circumvent Texas's ban on interstate branching using the 30-mile rule.[28] The first press mention of this event was on the fifteenth of May, 1998.[29]

I create a matched sample of control firms from states that are similar to Texas in their approach to entry by outside banks, and also account for spatial correlations in the dependent variable.

5.2.1 Econometric Framework

The econometric specification for this analysis is given by

$$Y_{it} = \alpha + \beta D_{it} + \omega X_{it} + \epsilon_{it} \ , \tag{4}$$

where D_t is an indicator variable that takes on a value of 1 in the treatment period, and 0 otherwise. The treatment period is defined as the four years from the announcement of the regulation to one year after the regulation took effect. The control period is four years before the treatment period. The control period is extended to four years to address concerns that idiosyncratic effects of any one year may be driving the results. The sample extends from 1994 to 2001. As before, I require that the banks have existed for all eight years.

To include a control sample, Equation (4) is modified as follows,

$$Y_{ist} = \alpha + \beta D_t + \beta_2 TR_{is} + \beta_3 D_t * TR_{is} + \omega X_{ist} + T_t + S_s + \epsilon_{ist} \ , \tag{5}$$

where TR is an indicator variable that takes on a value of 1 for the treated banks, and 0 otherwise. Treated banks are headquartered in the state of Texas. The control

[26]Montana was the other state that opted out of the provisions of the IBBEA.

[27]See "Governor's Signature Makes Texas Lone State To Opt Out of Branching", American Banker, 12 May 1995.

[28]The 30-mile rule allowed a bank to move its headquarters across state lines without giving up existing branches. A limitation was that the new office could not be located more than 30 miles from the limits of the city, town, or village where the old main office was located.

[29]See *Texas to Let State Banks Branch Interstate*, American Banker, 15 May 1998.

sample is selected from states that did not witness a change in restrictions in the period of study. I also require that states in the control sample be similar to the treated state in terms of their openness to interstate branching laws. Banks from the following seven states are selected into the control sample: Colorado, Iowa, Missouri, New Mexico, Nebraska, Kansas, and Arkansas. Several of these states are located geographically close to Texas. These states also had a restrictiveness index of four for the entire period of study, which is the same as Texas in the pre-treatment period. Further, as with Texas, these states debated whether or not to opt-out of the federal law.

5.2.2 Spatial Correlations

Geographic location is a critical characteristic of community banks given the localized nature of their business operations. This suggests that financial reporting of banks which operate in the same geographic market is likely to be spatially correlated. Ignoring these spatial correlations could lead to model mis-specification, and consequently, biased parameter estimates. Further, hypothesis related to managers' use of discretion suggests explicit spatial dependence between the loss provisions of banks in neighboring markets, as banks in a given local market set their provisions relative to banks in a nearby market.[30] Regulatory pressures might also cause provisions of localized banks to be correlated, for instance, the bank with lowest provisions in the market may attract regulatory attention.

There are two main challenges in including spatial effects in the model. First, defining the local market or geographic area within and between which observations are likely to be correlated. Second, describing the nature of spatial dependence.

For the purpose of this study, I define local markets as counties within a state. Counties, being local level administrative units, are likely to have shared characteristics. County-level economic information is reported by the U.S. Census Bureau making this a practical choice for defining the local market, both for the purpose of this study, as well as for banks that make expansion decisions.[31]

[30] Even though the change in regulation affects all community banks in a state, the strength of correlation between provisions would depend on the relative location of the banks. Banks are not located equidistant from each other, but at varying distances.

[31] Interviews with community bankers suggest that a county is a reasonable way to define a local market.

Prior literature has suggested several methods to define the nature of spatial dependence between observations (LeSage and Pace, 2009). However, as recommended by Anselin (2013), the nature of spatial correlation should be defined in the light of the problem being studied.

Equation (4) is modified as follows in order to include spatial effects,

$$Y_{it} = \alpha + \beta D_{it} + \rho W_{ij} Y_{jt} + \omega X_{it} + \epsilon_{it} \ , \tag{6}$$

where W is the spatial weight matrix and captures the spatial autoregressive process in the dependent variable. W is assumed to be constant over time. The element W_{ij} of W specifies the correlation between observations i and j. The diagonal elements of W are set equal to zero signifying that an observation is not correlated with itself. Further, the matrix W is row normalized. In the presence of spatial correlations, ρ is expected to be positive and significant suggesting that the loss provisioning of a given bank is related to the loss provisioning of its geographic neighbors.

I construct three different specifications for the spatial weight matrix, which are listed below,

$$W^1_{ij} = \begin{cases} \frac{1}{d_{ij}} \ , & \text{if bank } j \text{ is located in the same county as bank } i \ , \\ 0 \ , & \text{otherwise.} \end{cases}$$

$$W^2_{ij} = \begin{cases} \frac{1}{d^2_{ij}} \ , & \text{if bank } j \text{ is located in the same county as bank } i \ , \\ 0 \ , & \text{otherwise.} \end{cases}$$

where d_{ij} is the great-circle distance between the geographic location of bank i and j, and,

$$W^3_{ij} = \begin{cases} 1 \ , & \text{if bank } j \text{ is located in the county adjacent to bank } i \ , \\ 0 \ , & \text{otherwise.} \end{cases}$$

The first two specifications use inverse distance and inverse distance-squared measures, and are based on the assumption that banks which are located geographically closer together are more strongly correlated than banks which are located farther apart. The third specification for W will allow me to directly test hypothesis related to the managers' use of discretion. If this hypothesis holds then ρ should be positive and significant in the treatment period.

In the presence of spatial correlations, Equation (6) cannot be estimated using ordinary least squares since the correlation between errors and regressors results in biased and inconsistent OLS estimates. Writing Equation (6) in matrix/vector notation and subsuming D in $\mathbf{x}$,

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \beta \mathbf{x} + \epsilon \; , \tag{7}$$

which can be written as

$$\begin{aligned} (I - \rho W)\mathbf{y} &= \beta \mathbf{x} + \epsilon \\ \implies \mathbf{y} &= (I - \rho W)^{-1} \beta \mathbf{x} + (I - \rho W)^{-1} \epsilon \end{aligned}$$

The error term $\epsilon^* = (I - \rho W)^{-1} \epsilon$ is not homoskedastic. Also, $\rho \neq 0$ implies that the model is no longer linear in parameters.[32]

Consistent with prior literature (Elhorst, 2014; Anselin, 2013; LeSage and Pace, 2009), I use the maximum likelihood principle to estimate spatial interaction effects.

5.2.3 Discussion of Results

The results of Analysis 2 are presented in Tables 6, 7, 8, and 9a.

[32]For instance, consider a simple case where

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

The row normalized matrix is given by,

$$W = \begin{bmatrix} 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \end{bmatrix} \text{ and,}$$

$$(I - \rho W)^{-1} = \frac{1}{1 - \frac{7\rho^2}{9} - \frac{2\rho^3}{9}} \begin{bmatrix} (1 - \frac{\rho^2}{3}) & (\frac{\rho}{3} + \frac{\rho^2}{9}) & (\frac{\rho}{3} + \frac{\rho^2}{3}) & (\frac{\rho}{3} + \frac{\rho^2}{9}) \\ (\frac{\rho}{2} + \frac{\rho^2}{6}) & (1 - \frac{4\rho^2}{9} - \frac{\rho^3}{9}) & (\frac{\rho}{2} + \frac{\rho^2}{6}) & (\frac{\rho^2}{3} + \frac{\rho^3}{9}) \\ (\frac{\rho}{3} + \frac{\rho^2}{3}) & (\frac{\rho}{3} + \frac{\rho^2}{9}) & (1 - \frac{\rho^2}{3}) & (\frac{\rho}{3} + \frac{\rho^2}{9}) \\ (\frac{\rho}{2} + \frac{\rho^2}{6}) & (\frac{\rho^2}{3} + \frac{\rho^3}{9}) & (\frac{\rho}{2} + \frac{\rho^2}{6}) & (1 - \frac{4\rho^2}{9} - \frac{\rho^3}{9}) \end{bmatrix} .$$

Model 1 of Table 6 presents the analysis for all banks headquartered in Texas, whereas Models 2 and 3 subset the sample to banks with return on assets greater than zero and one percent, where returns are measured before provisions. As hypothesized, the coefficient on the treatment indicator D is positive and significant with coefficient values ranging from 7.74 to 9.088. However, the effect is not stronger for banks with a higher return on assets.[33]

Table 7 presents pre-treatment descriptive statistics for the treatment and control samples, both before and after the matching procedure. As can be seen from the t-statistics for difference in means and normalized differences, the matching procedure allows for greater covariate balance between treated and control samples. I use a greedy algorithm to match on several bank level characteristics in order to get a balanced sample in the pre-treatment period. Variables used in the matching procedure include size ($SIZE$), return on assets (ROA), the three year rolling average of scaled charge-offs (CO), tier-1 leverage ratio ($TIER1$), and lending portfolio composition ($ShrRE$, $ShrAGRI$, $ShrCI$, $ShrCONS$). Absolute differences in the treated and control values of these variables were used in the matching procedure, and all variables were equally weighted. There are 312 banks each in the treatment and control group after matching.

Table 8 presents results of the analysis using the matched sample of banks. Model 1 includes the entire sample whereas Model 2 subsets the sample to include banks with positive ROA, where returns are measured before provisions. The coefficient on the treatment indicator D remains positive and significant, however, the coefficient values decline to 5.461 and 5.886. Results from this analysis alleviates concerns that time specific factors may be driving the results.

Table 9a presents results of the maximum likelihood estimation including spatial effects. Models 1 and 2 use distance-based specifications of the weight matrix, as given by W^1 and W^2. Model 3 uses the specification based on adjacent counties as given by W^3. In all cases, the coefficient on WY is positive and significant suggesting the presence of spatial effects. However, the coefficient on D remains positive and significant, suggesting that spatial correlations do not completely explain the treatment effect. Models 4, 5, and 6 include the interaction of the treatment variable D with WY, and correspond to spatial weight matrices W^1, W^2 and W^3. While the spatial effect does

[33]In un-tabulated tests, I use return on equity as a measure of profitability. The results are qualitatively unchanged.

not become stronger in Models 4 and 5 in the treatment period, it becomes stronger in Model 6. This suggests that loan loss provisions in the treatment period is partly explained by loss provisions of neighboring local markets, providing support for the manager discretion hypothesis as managers in a given market set provisions relative to a neighboring market.

6 Additional Analysis and Robustness

The observed increase in provisions could be attributed to managers acting in their own agency, or to regulators requiring that banks increase provisions in the face of greater competition. The tests described in this section attempt to differentiate between the effect of the manager versus the regulator. I also provide analysis that suggests that future losses do not completely explain the increase in provisions.

6.1 Managers' Use of Discretion

Results presented in Table 9a, Model 6, show that spatial correlations with neighboring local markets becomes stronger in the treatment period. Further, results in Table 5, Model 5, show that banks in concentrated markets are more likely to increase their loss provisions. These findings are consistent with the hypothesis that managers' drive the increase in provisions in order to deter entry. In this section, I design a further test of this hypothesis.

Survey responses indicate that financial statement information of incumbents provide incremental information over other factors such as population and economic growth.[34] This suggests that banks located in counties which are similar to neighboring counties in terms of these factors have a greater incentive to increase provisions and look less profitable.

Figure 3a shows the average growth in county population from 1990 to 1999. The above discussion suggests that banks in the region marked as A would have a greater incentive to increase provisions to deter entry, as compared to banks in the region marked by B. I construct a measure of variability in order to capture the difference between a given county and its neighboring counties in terms of population

[34]Please see survey questions 9 and 10 in Appendix A.

growth.

The measure is defined as,

$$PopVar_i = \sqrt{\sum_{j=1}^{n} (g_i - g_j)^2}\ , \tag{8}$$

where i is the given county, j the neighboring county, and n the number of neighboring counties. $g_{i,j}$ represents population growth.

Figure 3b presents the spatial distribution of this measure. Banks in counties with low values of $PopVar$ are expected to increase provisions more as compared to banks in counties with high values of $PopVar$. I subset the sample to include only the top and bottom terciles of the distribution of $PopVar$. I create an indicator variable $PopVar^L$ that takes on a value of one if $PopVar$ falls in the bottom tercile of the distribution and zero otherwise, and create a matched sample from banks in the top tercile of the distribution of $PopVar$. As before, I use a greedy algorithm to create the matched sample of firms. The variables used for matching include measures of portfolio diversity ($ShrRE$, $ShrAGRI$, $ShrCI$, $ShrCONS$), and county population growth ($PopGr$). Matching on these variables achieves covariate balance for the larger set of variables included in the model.[35]

Table 9b presents results of the analysis including the measure of population variability. The coefficient on $PopVar^L * D$ is not very significant with t-statistics ranging from -0.86 to -1.55.[36]

6.2 Regulators' Use of Discretion

If the regulator was driving over-provisioning due to fears regarding the the stability of the banking system, then a measure of regulatory effectiveness should be positively associated with loss provisions in the treatment period. However, if the regulator was detecting and correcting the over-provisioning behavior of management, then the measure of regulatory effectiveness should be negatively associated with loss provisions in the treatment period. If the observed effect was purely attributable to the

[35]Tables showing the covariate balance before and after the matching procedure can be downloaded at https://sites.google.com/a/stanford.edu/rtomy/home/appendix.

[36]In un-tabulated analysis, I use another measure of variability specified as $Max_{i,j}|g_i - g_j|$, where i, j and $g_{i,j}$ are defined as before. The results are qualitatively unchanged.

management, then there should be no relation between the measure of regulatory effectiveness and loss provisioning in the treatment period, measured relative to the effect in a neutral period.

I use two measures of regulatory effectiveness. The first is constructed based on Agarwal et al. (2014) and is an index of regulatory leniency based on the average difference in CAMELS rating between state and federal regulators. The index uses data from 1996 to 2011, and is aggregated at the state level. I create an indicator variable $STRICT$ that takes on a value of 1 for states where regulators have a leniency index of < 0.05 and 0 if the leniency index is > 0.15. The sample is restricted to states where the state regulator has a leniency index of < 0.05 or > 0.15, and the data is subset to include only state-chartered banks. Table 10a presents the results using the index of regulatory leniency. The table shows that while stricter regulators tend to induce higher provisioning, the results are not significantly different in the treatment period.

The second measure is based on the argument presented in Kedia and Rajgopal (2011), that a resource-constrained regulator will be more attentive to firms that are located closer to its offices. Table 10b presents results using distance from the regulators' offices as a measure of regulatory effectiveness. As can be seen, banks located closer to the regulators' offices tend to increase provisions more in the face of an increase in the threat of competition.

6.3 Do future losses justify increased provisions?

In this section, I present analysis to understand whether the increase in provisions was in response to future expected losses.

I create a synthetic control (Abadie and Gardeazabal, 2003; Abadie et al., 2010) for the state of Texas in order to understand whether non-performing assets increased in Texas relative to the synthetic control. This method constructs a synthetic control based on a convex combination of control units that approximates the pre-treatment characteristics of the unit that was exposed to the treatment. As opposed to using the controls for a single year in the pre-treatment period, this method allows one to control for time-varying covariates.

The control states included in the sample are Arkansas, Colorado, Iowa, Kansas, Missouri, Nebraska, and New Mexico. Figure 4a presents change in the non-performing assets for the median firm in Texas and the control states. As can be seen from the figure, the two groups are very different on pre-treatment values of the variable. Figure 4b plots the same variable after applying the synthetic control method. Table 11a reports the pre-treatment means of predictor variables for Texas, synthetic Texas, and all seven control states. Table 11b reports the weights that were assigned to the various states in creating the synthetic control state.

In order to assess whether non-performing assets increased for the median bank in Texas relative to the synthetic control, I calculate the mean squared prediction error (MSPE) and construct synthetic states for all control states in the sample. MSPE is the average of the square of the difference between treated state and its synthetic control. A low value of pre-treatment MSPE indicates that the synthetic control closely matches the treated state on selected predictors, in the pre-treatment period. Synthetic states are constructed for each of the control states by using the remaining control states. For example, the synthetic control for Arkansas is constructed by using the remaining six control states of Colorado, Iowa, Kansas, Missouri, Nebraska, and New Mexico.

Column 2 of Table 11c reports pre-treatment MSPE for all states. As can be seen, Arkansas, Colorado, and New Mexico have high values of MSPE, indicating that there is no combination of states that will create a valid synthetic control for these states. Figures 5a and 5b present plots for the gaps between the treated and synthetic control for all states. Figure 5b presents the plot after removing states that had high values of pre-treatment MSPE. As can be seen from the figure, non-performing assets for Texas increased around 2002. This is confirmed by the ratio of post-treatment MSPE to pre-treatment MSPE presented in Table 11c.

To understand whether this increase in non-performing assets justified the increase in provisioning in the years 1998 and 1999, I regress loss provisions on future non-performing assets for upto five years. Table 12 presents the results of this analysis. As can be seen, the non-performing assets do not explain all the increase in provisions prior to the easing of restrictions to interstate branching.

6.4 Robustness

I randomly assign a pseudo year of treatment to the states in the sample and run the regression specified in Table 4, Model 2. I repeat the random assignment 1,000 times. The mean t-statistic for the coefficients on variables D_{-1} and D_{-2} is negative and insignificant.[37]

7 Conclusion and Future Work

Extant literature has largely overlooked firms' incentives to reduce profitability as a strategy to deter entry. Further, though the accounting literature has explored managers' use of discretion in financial reporting,[38] there is limited evidence on how regulators may be driving accounting choices. I contribute to limited work on the use of discretion in financial reporting as an entry deterrence strategy, as well as to literature on regulator's discretion in financial reporting. I find that community banks increase their loan loss provisions and appear less profitable when faced with an increase in the threat of competition. I also test and find that the results are consistent with managers' and regulators' use of discretion in financial reporting.

In future work, I aim to explore whether incumbents were successful in deterring entry through the use of this strategy. I also look forward to studying the effect of more recent regulation such as the Dodd-Frank Act on the community banking industry.

[37]Figures showing the distribution of t-statistics can be downloaded at https://sites.google.com/a/stanford.edu/rtomy/home/appendix.

[38]See, for example, Healy (1985), McNichols and Wilson (1988), Kasznik (1996), Healy and Wahlen (1999).

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A Competition in Community Banking Survey

I conduct a survey of community bankers in order to understand how these banks use financial statements of competitors, as well as to understand factors that play a role in market expansion decisions. The American Bankers Association (ABA)[39] assisted in administering the survey to community bank CEOs, CFOs, and CMOs (or similar positions). Staff at the ABA emailed the survey questionnaire to their networks of C-level executives at community banks. The networks included a group of about 100 CFOs who were participants of a conference held in Nashville, Tennessee in June 2015. The survey was also sent to 99 CEOs, the ABA Marketing Network of about 650 members, and was included in a periodic newsletter (ABA CFO Bullets) emailed to approximately 1000 CFOs. I pretested the survey questionnaire on three community bankers at the CEO/CFO level.

The survey asked community bankers about their industry. The questions primarily related to how banks perceived and responded to competition, and how they used accounting information in assessing their competitive landscape. The banks belonged to a range of asset sizes, with 64% of respondents belonging to banks with less than $500 million in assets. A majority of respondents were smaller players as borne out by the scope of their operations: the median bank operated 6 branches in 2 local markets and did not have any loan production offices.

Survey results suggest that banks use discretion in reporting loan loss provisions and have several incentives to over- and under- provision for loan losses. These results also indicate that financial statement information of competitors is used extensively to analyze the competitive landscape, and that financial statements of competitors provide incremental information in aiding decisions related to geographical expansion.

Aggregated survey results are presented below. A copy of the survey instrument can be downloaded at https://sites.google.com/a/stanford.edu/rtomy/home/appendix.

[39] http://www.aba.com/Pages/default.aspx

1. What is your role within the bank?

	No. of Responses	Percent Responses	Response Rate
CEO/President	7	12%	7%
CFO	32	54%	3%
CMO/Others	20	34%	3%
Total	**59**	**100%**	**3%**

2. What is your bank's approximate asset size?

	Percent answered
<$250 million	33%
$250 to $500 million	31%
$500 million to $1 billion	21%
>$1 billion	16%

3 & 4. How many branches and loan production offices does your bank currently operate?
5. How many separate markets does your bank operate in?

	Qs 3. Branches	Qs 4. LPOs	Qs 5. Markets
Mean	15.5	0.6	6.9
Median	6.0	0.0	3.0
Std	39.0	1.0	17.0
Min	1	0	1
Max	276	5	120

6. Which of the following describes your bank? Please select all options that apply.

	Percent answered
Private company	44%
C Corp	26%
Public company	25%
Mutual	19%
S Corp	18%
Exchange traded	4%

7. Which of the following best describes the geographic area that your bank serves?

	Percent answered
Rural (population < 50,000)	34%
Small Metropolitan Area (population between 50,000 and 500,000)	47%
Large Metropolitan Area (population > 500,000)	19%

8. Which of the following types of organizations does your bank directly compete with?

	Number answered	
	Loan Products and Services	**Deposits**
Large National Banks	51	55
Interstate Regional Banks	46	48
Intrastate Regional Banks	43	43
Other Community Banks	53	55
Credit Unions	50	51
On-line Banks	26	32
Shadow Banking Institutions	11	8
Others	6	3

9. What factors do you think competitor banks assess before entering into your local market?
10. What factors do you assess before expanding into a new geographic market?

	Percent "Very Relevant" and "Relevant"	
	Qs 9. Factors assessed by competitors	**Qs 10. Factors assessed by given bank**
Economic growth	100%	94%
Identified opportunity in new market	98%	96%
Population growth	91%	83%
Household income	84%	79%
Profitability of incumbent banks	75%	56%
Credit quality of incumbent banks' loan portfolio	75%	52%
Existing branch density in new market	73%	87%
Proximity	69%	79%
Talent	50%	55%

11. How would you rate the following markets in terms of attractiveness of de novo entry?
12. How would you rate the following markets in terms of attractiveness of entry through mergers and acquisitions?

	Percent "Very Attractive" and "Attractive"	
	Qs 11. De Novo	**Qs 12. M&A**
Markets where incumbent banks have high profitability	85%	88%
Markets where incumbent banks have high credit losses	2%	6%

13. What information do you use to analyze current and expected competition in your market?

	Percent answered
Financial statements of competitors	94%
Market surveys	75%
Other [40]	27%

[40] Other sources cited were variants of financial statements such as call reports, Uniform Bank Performance Reports, FDIC and Federal Reserve reports, SNL Financial, State Banking associations, and County Recorders Office Mortgage filings. Survey respondents also suggested word-of-mouth and professional networks as sources of competitor information.

14. What types of information do you assess from competitors' financial statements?

	Percent answered
Net Interest Margin	90%
Loan Portfolio Composition and Growth	88%
Profitability	86%
Capital Ratios	84%
Cost of Deposits	82%
Charge-offs	76%
Loan Loss Provisions	53%
Others	16%

15. To what extent are the following actions taken in response to increased competition from larger banks?
16. To what extent are the following actions taken in response to an anticipated increase in competition from larger banks?

	Percent "Always" and "Usually"	
	Qs 15. Actual competition	Qs 16. Anticipated competition
Increase loan growth	48%	40%
Increase deposit growth	48%	37%
Expand products offered	29%	20%
Increase lobbying activity	16%	22%
Re-balance loan portfolio composition	16%	5%
Expand loans to borrowers with lower credit quality	9%	2%
Reduce products offered	0%	0%

17. What are some reasons to change the methodology used to estimate loan loss reserves?

	Percent answered
At the bank examiner's or auditor's request	91%
Change in composition of loan portfolio	84%
Change in lending policy	78%
Change in current macroeconomic conditions	69%
Expected change in macroeconomic conditions	47%
Loss of high quality clients due to increased competition	22%
Expected loss of high quality clients due to increased competition	20%
Current or expected loss of talent due to increased competition	18%
Others	7%

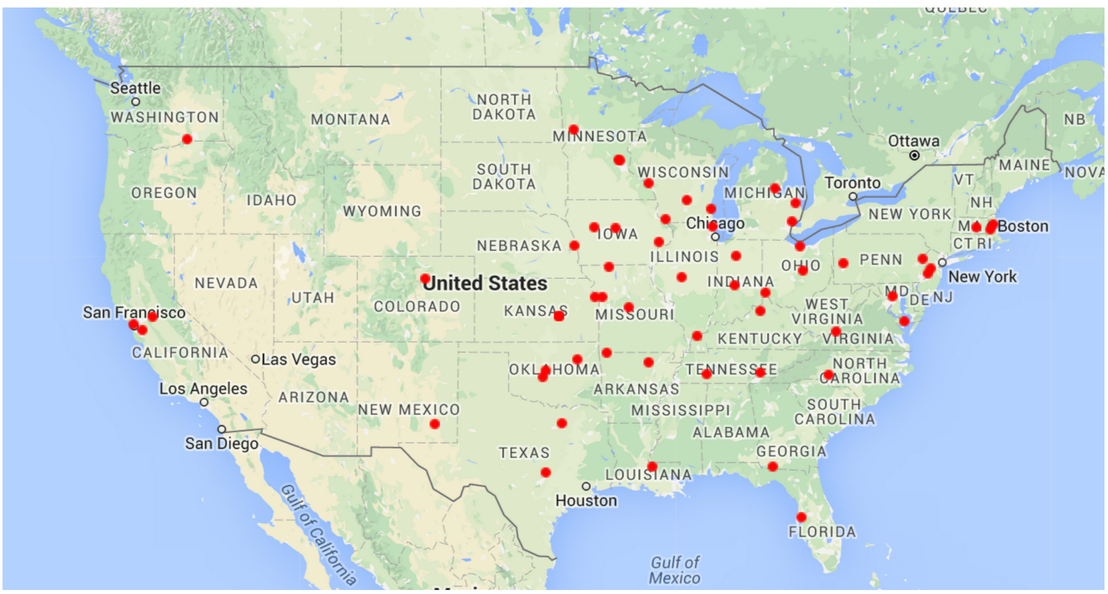
18. Based on your judgment, what percent of competing community banks knowingly over-reserve or under-reserve for loan losses?

	Percent answered
0%	5%
1 - 10%	30%
11 - 30%	34%
31 - 50%	16%
Greater than 50%	16%

19. What are some factors that motivate community banks to over-reserve for loan losses?

20. What are some factors that motivate community banks to under-reserve for loan losses?

	Percent answered [41]	
	Qs 19. Reasons to over-reserve	**Qs 20. Reasons to under-reserve**
Regulator's expectation	88%	24%
Threat of increased competition	12%	21%
Actual increase in competition	15%	21%
Others	27%	55%



Location of Survey Respondents

[41]Responses to Qs. 19 and 20 for the option "Regulator's expectation" are significantly different ($pvalue < 0.0001$). Responses to Qs. 19 and 20 for the options "Threat of increased competition" and "Actual increase in competition" are not significantly different ($pvalues = 0.3144$ & 0.4741). Other motivating factors to over-reserve, mentioned under the option "Others", include potential weaknesses identified with specific borrowers, decline in the quality of loan portfolio, anticipated growth in portfolio, anticipated economic downturn, anticipated loss expectations relating to specific credits, being overly conservative, or an inability to re-capture excess provisions due to regulator objection. Other reasons to under-provision include earnings pressure, and the desire to inflate earnings.

B Variable Definitions

Variable	Definition	Data Source
LLP	Provision for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses (multiplied by 10,000 when used as a dependent variable in regressions)	Call data items 4230, 1400, 3123, 2123
$SIZE$	Natural log of lagged Assets	Call data item 2170
ΔNPA	Change in Non-performing assets scaled by lagged total loans and leases, net of unearned income and allowance for losses	Call data items 1403, 1407, 1400, 3123, 2123
CO	Three year rolling average of net charge-offs (charge-offs less recoveries) scaled by lagged total loans and leases, net of unearned income and allowance for losses	Call data items 4635, 4605, 3123, 1400, 2123
$\Delta LOAN$	Change in Gross Total Loans scaled by lagged Gross Total Loans	Call data item 1400
ΔGDP	Change in per capita GDP for State	Bureau of Economic Analysis
$ShrRE$	Loans secured by real estate scaled by Gross Total Loans	Call data items 1410, 1400
$ShrAGRI$	Agricultural loans scaled by Gross Total Loans	Call data items 1590, 1400
$ShrCI$	Commercial and Industrial loans scaled by Gross Total Loans	Call data items 1766, 1400
$ShrCONS$	Consumer loans scaled by Gross Total Loans	Call data items 1975, 1400
$\Delta ShrRE$	Change in $ShrRE$	Call data items 1410, 1400
$\Delta ShrAGRI$	Change in $ShrAGRI$	Call data items 1590, 1400
$\Delta ShrCI$	Change in $ShrCI$	Call data items 1766, 1400
$\Delta ShrCONS$	Change in $ShrCONS$	Call data items 1975, 1400
ROA	Return on Assets: Net Income scaled by Average Total Assets	Call data items 4340, 2170
$TIER1$	Tier 1 leverage ratio, calculated as Tier 1 Capital scaled by Average Assets	Call data items 8274, 2170

C Figures

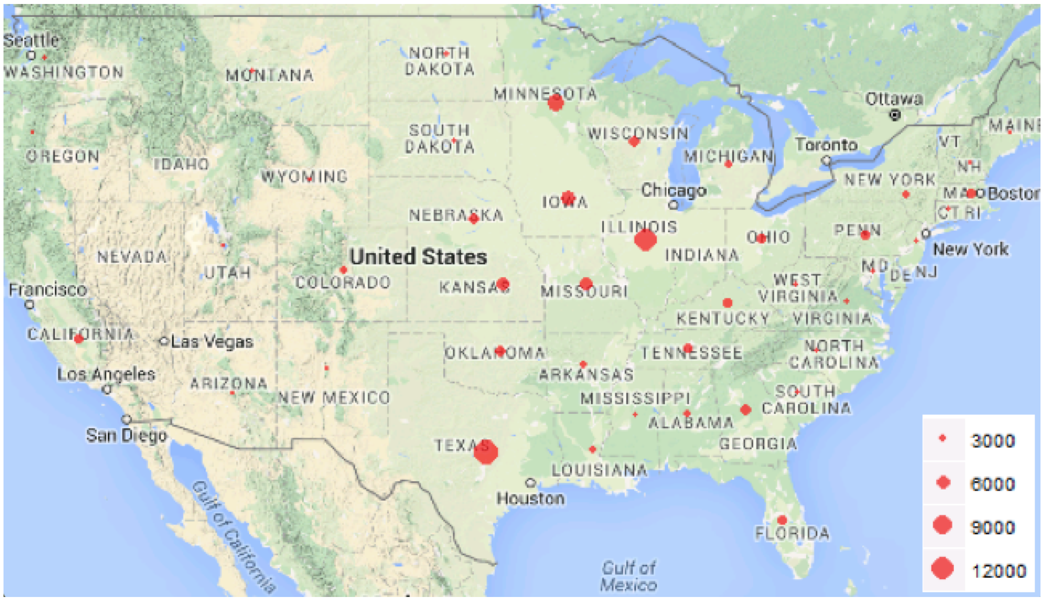


Figure 1: Distribution of sample community banks

This figure shows the distribution of community banks-years in the sample, by state. The size of the bubble represents number of bank-years in a given state.

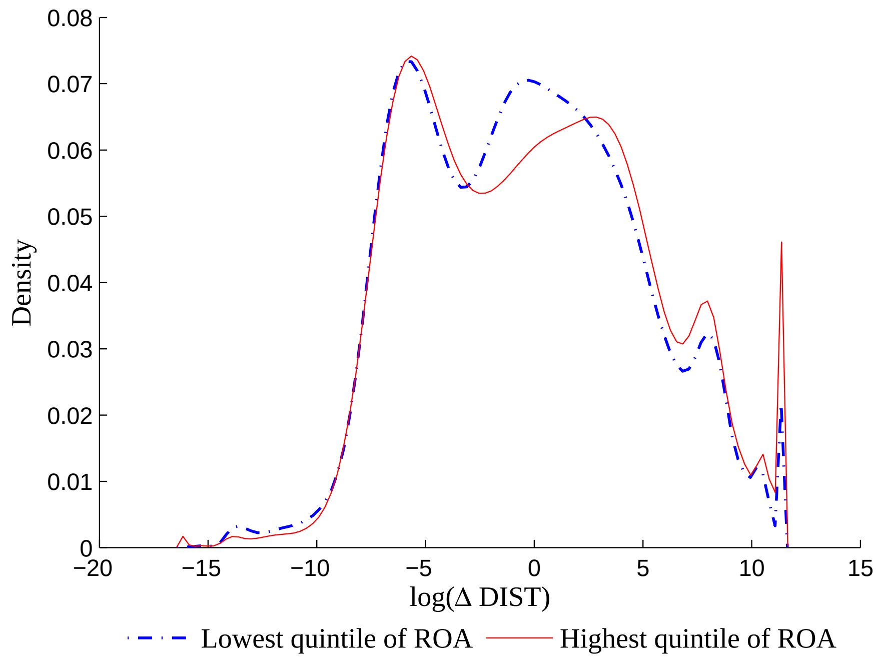


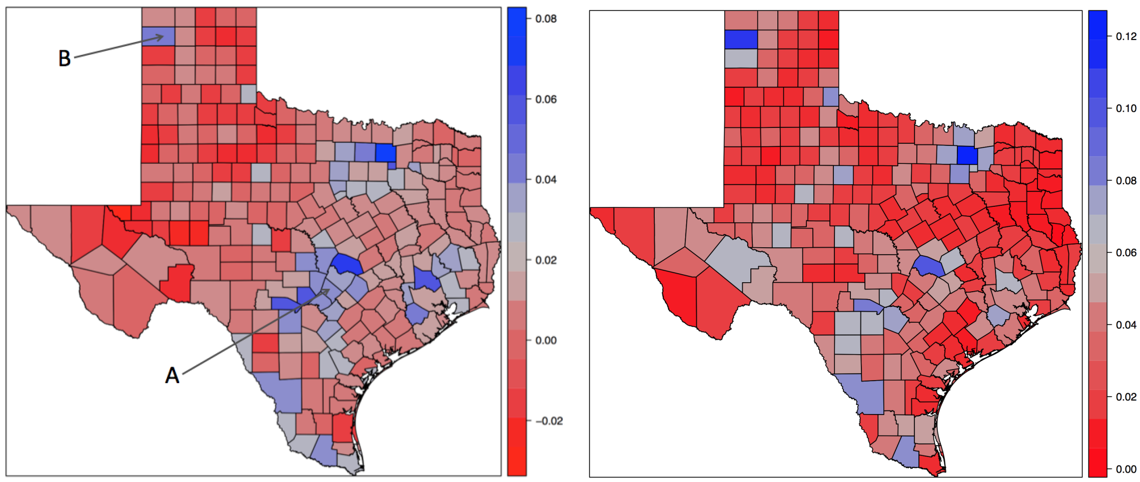
Figure 2: Density of $log(\Delta DIST)$ conditional on positive $\Delta DIST$

This figure shows the distribution of $log(\Delta DIST)$ for the highest and lowest quintile of lagged ROA for a bank. $\Delta DIST$ is the change in $DIST$, measured at the branch level and aggregated to the bank level. $\Delta DIST$ is a measure of entry, and increases when a new firm enters within a radius μ of the incumbent firm. $DIST$ is calculated as follows,

$$DIST_i = \sum_{\substack{i \neq j \\ |d_{ij}| < \mu}} \frac{1}{|d_{ij}|} \ ,$$

where j refers to a neighboring branch within a radius of μ from the focal branch i, and d_{ij} is the geographic distance between branches i and j.

Supporting tables for this analysis can be downloaded at https://sites.google.com/a/stanford.edu/rtomy/home/appendix.

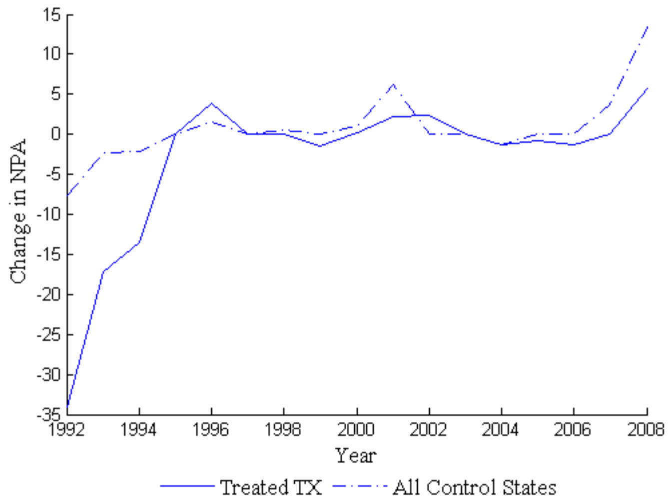


(a) Population growth

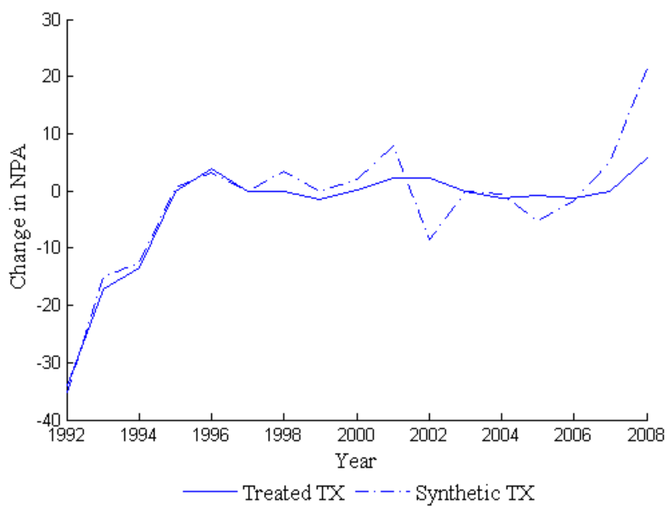
(b) Variation measure $PopVar$

Figure 3: Spatial distribution of county population growth and variation measure

Figure (a) shows the average population growth for counties in Texas from 1990 to 1999. Figure (b) shows the distribution of $PopVar$, a measure which captures the difference between a given county and its neighboring counties in terms of population growth. This measure of variability are defined as follows, $PopVar_i = \sqrt{\sum_{j=1}^{n}(g_i - g_j)^2}$ where i is the given county, j the neighboring county, and n the number of neighboring counties. $g_{i,j}$ represents population growth.



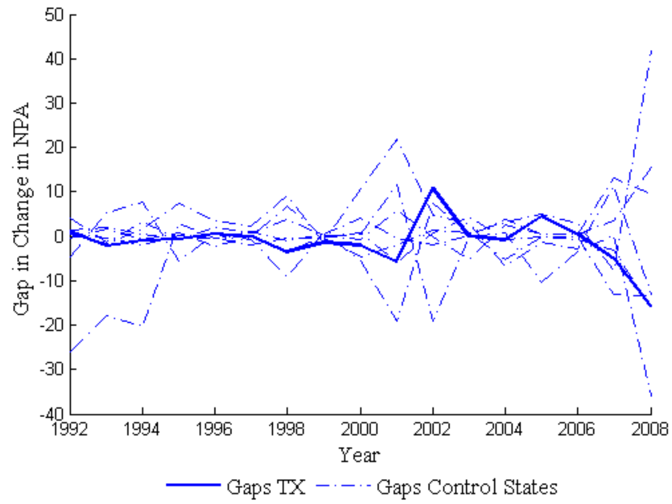
(a) Texas vs all control States



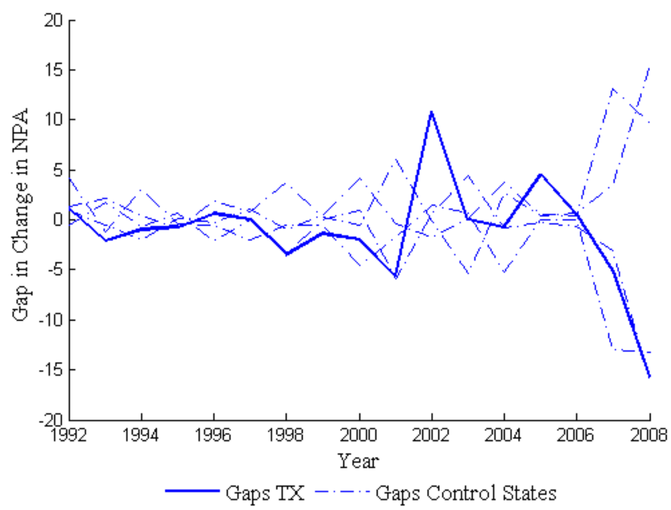
(b) Texas vs Synthetic Texas

Figure 4: Change in non-performing assets for the median firm

Figure (a) presents the change in non-performing assets for Texas and all control States. Figure (b) shows the change in non-performing assets for Texas vs Synthetic Texas. Synthetic Texas is constructed using the procedure described in Abadie and Gardeazabal (2003), and is a convex combination of control states that approximates the pre-treatment characteristics of Texas. The control states used in this analysis include Arkansas, Colorado, Iowa, Kansas, Missouri, Nebraska, and New Mexico.



(a) Gaps in change in non-performing assets between states and their synthetic control



(b) Gaps in change in non-performing assets between states and their synthetic control, excluding states with high pre-treatment MSPE

Figure 5: Gaps between states and their synthetic control

Synthetic controls were constructed for Texas as well as the control states of Arkansas, Colorado, Iowa, Kansas, Missouri, Nebraska, and New Mexico, using the synthetic control method described in Abadie and Gardeazabal (2003). The synthetic controls for the control states were created using the other control states and excluding Texas. Figures (a) and (b) plot the gap in the change in non-performing assets for state and its synthetic control.

D Tables

Table 1: Sample selection

(a) Sampling criteria for branch-year observations

	Branch-years	**Obs. lost**
Total branch dataset	1,014,016	
Restrict to contiguous United States	1,008,403	5,613
Exclude observations with assets <= 0	1,008,339	64

(b) Sampling criteria for bank-year observations

Sampling Criteria	**Bank-years**	**Obs. lost**
FDIC community banking reference dataset merged with bank Call data (1988 - 2013)	214,571	
Remove year of acquisition or failure	209,201	5,370
Remove observations with missing, zero or negative loans	209,172	29
Restrict to years from 1992 to 2008	134,698	74,474
Restrict to contiguous United States, and to states that decreased restrictions to interstate branching	132,097	2,601
Remove states that have an average of less than 20 community banks a year	130,939	1,158
Number of publicly listed banks (sourced from SNL Financial database)	4,547	-

Panel (a) reports the sample selection procedure for bank branches. The data are for the years from 1994 to 2005, and are sourced from the FDIC's Summary of Deposits database. It includes all branches of all banks located in the United States. Panel (b) presents the sample selection criteria for banks. The data is sourced from the Federal Reserve Bank's Reports of Condition and Income for commercial banks. Public banks were identified using the SNL Financial database.

Table 2: Sample description

(a) Number of banks and percent of public banks, by year

Year	No. of Banks	% Public
1992	9699	2.23
1993	9418	2.37
1994	8929	2.41
1995	8577	3.46
1996	8375	3.40
1997	8107	3.60
1998	7738	4.23
1999	7613	4.91
2000	7463	4.88
2001	7320	4.99
2002	7184	4.57
2003	7096	3.91
2004	6930	3.59
2005	6839	4.17
2006	6686	3.48
2007	6577	3.02
2008	6388	2.98
TOTAL	**130939**	**3.60**

(b) Descriptive statistics for private and public bank years

	Private (N = 126,392)		**Public (N =4,547)**		**Difference in Means**		
Variables	**Mean**	**s.d.**	**Mean**	**s.d.**	**t-stat**	**pvalue**	**Nor-diff**
$SIZE$	11.190	1.057	12.049	0.761	73.621	0.000	0.933
ROA	0.010	0.010	0.008	0.009	-11.994	0.000	-0.179
$\Delta LOAN$	0.437	29.192	0.558	19.534	0.390	0.696	0.005
$TIER1$	0.107	0.041	0.100	0.033	-13.463	0.000	-0.207
LLP	0.008	0.372	0.007	0.094	-0.473	0.636	-0.003
CO	0.003	0.008	0.003	0.005	-1.254	0.210	-0.014
ΔNPA	0.001	0.027	0.005	0.277	1.044	0.296	0.022
$ShrRE$	0.601	0.206	0.715	0.153	48.889	0.000	0.631
$ShrAGRI$	0.103	0.155	0.011	0.032	-143.921	0.000	-0.823
$ShrCI$	0.155	0.111	0.169	0.122	7.413	0.000	0.117
$ShrCONS$	0.125	0.108	0.091	0.093	-24.363	0.000	-0.341

Panel (a) presents the number of banks and percent of public banks in the sample, by year. The data is sourced from the Federal Reserve Bank's Report of Condition and Income data for commercial banks. Public banks were identified using the SNL Financial database. Panel (b) presents descriptive statistics for private and public banks, pooled across years. The data are for the years from 1992 to 2008. The variables listed are natural log of total assets ($SIZE$), return on assets (ROA), growth in total loans ($\Delta LOAN$), Tier-1 Capital Ratio ($TIER1$), scaled loan loss provisions (LLP), three year rolling average of scaled net charge-offs (CO), growth in non-performing assets (ΔNPA), and share of real estate ($ShrRE$), agricultural ($ShrAGRI$), commercial and industrial ($ShrCI$) , and consumer loans ($ShrCONS$) in the lending portfolio. The table also reports normalized differences (Nor-diff) which is measured as the difference in means scaled by average within group standard deviations.

Table 3: Descriptive tables related to Restrictiveness Index

(a) Number and percent of changes to restrictiveness index

YEAR	**1995**	**1996**	**1997**	**1998**	**2000**	**2001**	**2002**	**2004**	**2005**
No. of Events	2	11	15	3	3	2	3	1	2
Percent of Events	5%	26%	36%	7%	7%	5%	7%	2%	5%

(b) Average branches and deposits by level of restrictiveness index

Level of Restrictiveness Index	**No. of branches**	**Deposits ($ mn)**
0	1,831	82.3
1	2,020	107.6
2	2,080	187.7
3	1,740	94.9
4	1,470	55.8

(c) Average change in branches and deposits by year relative to event

Year relative to Event	**Change in No. of branches**	**Change in deposits ($ mn)**
-2	6.76	2.19
-1	(5.25)	2.25
0	13.08	3.50
1	13.31	3.93
2	14.21	3.44

Panel (a) presents the number and percent of events by year. An event is defined as a change in restrictions to interstate branching, measured using the restrictiveness index of Rice and Strahan (2010). The index, measured at the state level, counts the number of restrictions to interstate branching. The index varies from zero for the least restrictive states, to four for states with the greatest number of restrictions. Please see Section 4.2 for a description of the index. Panel (b) presents the average number of branches and average deposits by state-year, by restrictiveness index. Panel (c) presents the average change in the number of branches and deposits by state-year, by year relative to the event, where 0 is the period of the event. Data on number of branches and volumes of deposits are sourced from the FDIC's Summary of Deposits database.

Table 4: Estimated parameters for regression of scaled loan loss provisions on explanatory variables and time period indicators (Test of H1)

		Model 1			Model 2		
Variables	**Prediction**	**Estimate**	**t-stat**	**pvalue**	**Estimate**	**t-stat**	**pvalue**
Intercept	?	-5.776	-1.360	0.172	2.531	0.270	0.790
$\boldsymbol{D}_{s-2}$	+	**2.289**	**2.690**	**0.007**	**1.605**	**1.860**	**0.063**
$\boldsymbol{D}_{s-1}$	+	**3.410**	**3.190**	**0.001**	**2.389**	**2.150**	**0.032**
D_{s0}	?	1.966	1.740	0.082	0.434	0.360	0.722
D_{s1}	?	1.841	1.680	0.093	-0.341	-0.280	0.781
D_{s2}	?	0.922	0.830	0.409	-1.303	-0.990	0.323
D_{s3}	?	1.346	1.110	0.268	-1.542	-1.040	0.297
$SIZE$	?	2.319	7.490	<.0001	2.171	6.550	<.0001
ΔNPA_{-1}	+	732.535	18.260	<.0001	702.307	19.640	<.0001
ΔNPA	+	849.127	17.690	<.0001	828.511	16.580	<.0001
ΔNPA_{+1}	+	251.115	7.080	<.0001	237.550	6.190	<.0001
CO	+	6685.404	33.430	<.0001	6457.024	23.640	<.0001
$\Delta LOAN$	+	34.033	7.980	<.0001	33.206	7.860	<.0001
ΔGDP	-	-54.179	-3.490	0.001	-57.251	-3.480	0.001
$ShrRE$	?	-5.019	-2.560	0.011	-7.548	-3.050	0.002
$ShrCI$	?	28.356	7.370	<.0001	25.728	6.190	<.0001
$ShrCONS$	?	24.398	6.690	<.0001	27.036	5.260	<.0001
$\Delta ShrRE$	?	4.870	0.360	0.722	11.710	0.840	0.401
$\Delta ShrCI$	?	-40.197	-3.090	0.002	-30.185	-2.260	0.024
$\Delta ShrCONS$	?	-7.024	-0.450	0.652	-7.511	-0.490	0.623
Year Fixed Effects		Yes			Yes		
State Fixed Effects		No			Yes		
Firm-clustered s.e.		Yes			Yes		
N		36,897			36,897		
Adj-R^2		44.18			43.87		

This table presents results of a regression based on 7 years of data for each bank in the sample. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. $D_{s\tau}$ are time period indicators where $\tau = 0$ is the year in which restrictions to interstate branching were eased for state s. Explanatory variables include the natural log of lagged total assets ($SIZE$), lagged, current and leading change in non-performing assets ($\Delta NPA_{-1}, \Delta NPA, \Delta NPA_{+1}$), three year rolling average of scaled net charge-offs (CO), growth in total loans ($\Delta LOAN$), change in state per capita GDP (ΔGDP), share of real estate ($ShrRE$), commercial and industrial ($ShrCI$), and consumer ($ShrCONS$) loans in the lending portfolio, and change in the share of real estate ($\Delta ShrRE$), commercial and industrial ($\Delta ShrCI$), and consumer ($\Delta ShrCONS$) loans.

Table 5: Estimated parameters for regression of scaled loan loss provisions on explanatory variables and time period indicators, by sample subset and including treatment indicators (Test of H2 and H3)

		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Prediction	***ROA*** **>0**	***ROA*** **>1%**	***ASSET*** **<= $500 mn**	***TREAT*** **=** ***PUBLIC***	***TREAT*** **=** ***HERF***
$\boldsymbol{D_{s-2}}$	+	**1.904**	**1.617**	**1.792**	1.743	-1.774
		(2.29)	**(1.73)**	**(2.03)**	(1.96)	(-1.17)
$\boldsymbol{D_{s-1}}$	+	**2.598**	**2.227**	**2.930**	2.882	0.275
		(2.39)	**(1.83)**	**(2.56)**	(2.50)	(0.15)
D_{s0}	?	0.753	0.871	0.793	0.781	-2.325
		(0.64)	(0.66)	(0.63)	(0.61)	(-1.23)
D_{s1}	?	0.401	0.536	-0.099	-0.082	-2.349
		(0.33)	(0.40)	(-0.08)	(-0.06)	(-1.23)
D_{s2}	?	-0.597	-0.302	-0.829	-0.923	-6.854
		(-0.47)	(-0.21)	(-0.60)	(-0.67)	(-3.39)
D_{s3}	?	-0.665	-0.177	-1.056	-1.206	-3.544
		(-0.46)	(-0.11)	(-0.68)	(-0.78)	(-1.61)
TREAT	-/?				**-10.049**	**-6.793**
					(-1.58)	**(-2.33)**
$\boldsymbol{TREAT*D_{s-2}}$	-/+				**9.692**	**8.652**
					(1.41)	**(2.73)**
$\boldsymbol{TREAT*D_{s-1}}$	-/+				**10.602**	**5.252**
					(1.45)	**(1.41)**
$TREAT * D_{s0}$	?				9.463	6.650
					(1.34)	(1.81)
$TREAT * D_{s1}$	?				9.570	4.996
					(1.44)	(1.39)
$TREAT * D_{s2}$	?				11.961	13.250
					(1.81)	(3.43)
$TREAT * D_{s3}$	?				12.724	4.830
					(1.85)	(1.32)
N		36,192	27,162	35,385	35,385	36,897
Adj-R^2		45.09	47.95	43.61	43.61	43.48

This table presents results of a regression based on 7 years of data for each bank in the sample. T-statistics are reported in parentheses. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. $D_{s\tau}$ are time period indicators where $\tau = 0$ is the year in which restrictions to interstate branching were eased for state s. Explanatory variables (unreported) include the natural log of lagged total assets, lagged, current and leading change in non-performing assets, three year rolling average of scaled net charge-offs, growth in total loans, change in state per capita GDP, share of real estate, commercial and industrial, and consumer loans in the lending portfolio, and change in the share of real estate, commercial and industrial, and consumer loans. Models 1 and 2 present the results for firms with ROA greater than 0 and 1, where returns are measured before provisions. Model 3 subsets the sample to firms with assets <= $500 million. Models 4 and 5 include variables $PUBLIC$ and $HERF$. $PUBLIC$ is an indicator variable that takes on a value of 1 for public banks, and a value of 0 otherwise. $HERF$ is the Herfindahl index measured at the county level. The regressions include state and year fixed effects. Standard errors are clustered by firm.

Table 6: Estimated parameters for regression of scaled loan loss provisions on explanatory variables and time period indicators, for the state of Texas (Test of H1)

		Model 1			Model 2			Model 3		
Variables	**Prediction**	**Estimate**	**t-stat**	**pvalue**	**Estimate**	**t-stat**	**pvalue**	**Estimate**	**t-stat**	**pvalue**
Intercept	?	-20.956	-1.380	0.168	-18.686	-1.170	0.244	-7.938	-0.420	0.676
$\boldsymbol{D}$	+	**9.088**	**3.470**	**0.001**	**8.231**	**3.160**	**0.002**	**7.740**	**2.810**	**0.005**
$SIZE$	?	1.579	1.070	0.284	1.251	0.770	0.442	0.712	0.420	0.676
ΔNPA_{-1}	+	1056.838	7.540	<.0001	1074.781	7.230	<.0001	992.805	5.380	<.0001
ΔNPA	+	1083.180	7.340	<.0001	1188.057	7.290	<.0001	1069.145	6.330	<.0001
ΔNPA_{+1}	+	326.122	3.150	0.002	350.069	2.990	0.003	287.487	2.350	0.019
CO	+	8793.410	19.560	<.0001	8765.252	17.670	<.0001	8401.871	14.280	<.0001
$\Delta LOAN$	+	53.512	2.710	0.007	32.726	3.310	0.001	33.493	2.630	0.009
ΔGDP	-	85.236	0.880	0.380	91.300	1.030	0.303	69.648	0.780	0.438
$ShrRE$	?	-14.201	-1.750	0.080	-10.271	-1.330	0.185	-11.676	-1.360	0.173
$ShrCI$	?	21.075	1.470	0.141	30.886	2.300	0.022	30.662	2.030	0.043
$ShrCONS$	?	14.783	1.410	0.158	15.924	1.510	0.131	21.245	1.770	0.077
$\Delta ShrRE$	?	112.922	2.140	0.033	121.618	2.330	0.020	58.648	1.310	0.192
$\Delta ShrCI$	?	-16.631	-0.310	0.754	2.780	0.050	0.958	-55.424	-1.170	0.243
$\Delta ShrCONS$	?	141.153	2.020	0.044	152.004	2.180	0.030	74.141	1.360	0.175
N		4,280			4,229			3,318		
Adj-R^2		44.76			45.38			47.92		

This table presents results of a regression based on 8 years of data, from1994 to 2001, for each bank in the sample. The sample is restricted to community banks headquartered in the state of Texas. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. D is an indicator variable that takes on a value of 1 in the treatment period, and 0 otherwise. Model 1 includes a constant sample of all community banks. Models 2 and 3 subset the sample to banks with ROA > 0 and 1%, where returns are measured before provisions. Explanatory variables include the natural log of lagged total assets ($SIZE$), lagged, current and leading change in non-performing assets ($\Delta NPA_{-1}, \Delta NPA, \Delta NPA_{+1}$), three year rolling average of scaled net charge-offs (CO), growth in total loans ($\Delta LOAN$), change in state per capita GDP (ΔGDP), share of real estate ($ShrRE$), commercial and industrial ($ShrCI$), and consumer ($ShrCONS$) loans in the lending portfolio, and change in the share of real estate ($\Delta ShrRE$), commercial and industrial ($\Delta ShrCI$), and consumer ($\Delta ShrCONS$) loans. Standard errors are clustered by firm.

Table 7: Pre-treatment descriptive statistics for treated and control groups

(a) Before matching

	Control (N = 1343)		Treated (N = 535)		Difference in Means		
Variables	**Mean**	**s.d.**	**Mean**	**s.d.**	**t-stat**	**pvalue**	**Nor-diff**
$SIZE$	10.498	0.836	10.700	0.789	4.941	0.000	0.249
ROA	0.011	0.005	0.012	0.005	2.318	0.021	0.120
$\Delta LOAN$	0.108	0.097	0.155	0.840	1.278	0.202	0.078
$TIER1$	0.109	0.036	0.103	0.031	-3.697	0.000	-0.183
LLP	0.002	0.004	0.004	0.021	2.178	0.030	0.131
CO	0.002	0.004	0.003	0.006	6.144	0.000	0.341
$ShrRE$	0.474	0.176	0.427	0.172	-5.310	0.000	-0.270
$ShrAGRI$	0.241	0.198	0.137	0.161	-11.790	0.000	-0.576
$ShrCI$	0.142	0.082	0.176	0.093	7.498	0.000	0.394
$ShrCONS$	0.130	0.081	0.247	0.131	19.095	0.000	1.067

(b) After matching

	Control (N = 312)		Treated (N = 312)		Difference in Means		
Variables	**Mean**	**s.d.**	**Mean**	**s.d.**	**t-stat**	**pvalue**	**Nor-diff**
$SIZE$	10.687	0.723	10.766	0.729	1.361	0.174	0.109
ROA	0.012	0.003	0.012	0.004	1.162	0.246	0.093
$\Delta LOAN$	0.103	0.072	0.114	0.114	1.502	0.134	0.120
$TIER1$	0.105	0.028	0.102	0.028	-1.343	0.180	-0.107
LLP	0.002	0.003	0.002	0.003	-1.314	0.189	-0.105
CO	0.002	0.003	0.002	0.003	0.589	0.556	0.047
$ShrRE$	0.471	0.139	0.469	0.175	-0.146	0.884	-0.012
$ShrAGRI$	0.173	0.156	0.157	0.175	-1.185	0.236	-0.095
$ShrCI$	0.161	0.078	0.167	0.078	0.927	0.354	0.074
$ShrCONS$	0.183	0.092	0.193	0.090	1.383	0.167	0.111

This table reports descriptive statistics for banks in the treated and control samples for the pre-treatment period, before and after the matching procedure. Treated banks include community banks from the state of Texas. Banks in the control sample include community banks from states of Colorado, Iowa, Missouri, New Mexico, Nebraska, Kansas, and Arkansas. Covariate balance was obtained by matching on firm characteristics by using a greedy algorithm. The variables used in the matching procedure include natural log of total assets ($SIZE$), return on assets (ROA), Tier-1 leverage ratio ($TIER1$), three year rolling average of scaled net charge-offs (CO), share of real estate ($ShrRE$), agricultural ($ShrAGRI$), commercial and industrial ($ShrCI$) , and consumer loans ($ShrCONS$) in the lending portfolio. Variables reported in this table also include growth in total loans ($\Delta LOAN$), and scaled loan loss provisions (LLP). The table also reports normalized differences (Nor-diff) which is measured as the difference in means scaled by average within group standard deviations.

Table 8: Estimated parameters for regression of scaled loan loss provisions on explanatory variables and time period indicators, using a matched sample of firms (Test of H1)

		Model 1			Model 2		
Variables	**Prediction**	**Estimate**	**t-stat**	**pvalue**	**Estimate**	**t-stat**	**pvalue**
Intercept	?	-6.697	-0.860	0.389	-7.387	-1.000	0.318
D	?	5.310	4.110	<.0001	4.401	3.560	0.000
$TREAT$	?	-1.190	-0.410	0.682	-1.785	-0.610	0.544
TREAT*D	+	**5.461**	**3.060**	**0.002**	**5.886**	**3.430**	**0.001**
$SIZE$	?	0.701	1.050	0.292	0.906	1.460	0.144
ΔNPA_{-1}	+	595.885	10.010	<.0001	565.956	9.870	<.0001
ΔNPA	+	611.112	8.770	<.0001	567.872	8.170	<.0001
ΔNPA_{+1}	+	133.730	2.810	0.005	139.195	3.120	0.002
CO	+	7577.943	29.430	<.0001	7606.194	31.850	<.0001
$\Delta LOAN$	+	28.143	6.700	<.0001	27.374	6.870	<.0001
ΔGDP	-	-25.234	-0.940	0.350	-24.836	-0.940	0.348
$ShrRE$	?	-3.725	-1.090	0.277	-4.326	-1.330	0.183
$ShrCI$	?	23.603	3.660	0.000	20.818	3.470	0.001
$ShrCONS$	?	9.105	1.740	0.083	6.984	1.390	0.165
$\Delta ShrRE$	?	36.796	2.160	0.031	38.885	2.320	0.021
$\Delta ShrCI$	?	8.945	0.530	0.598	7.045	0.410	0.682
$\Delta ShrCONS$	?	1.763	0.100	0.919	5.482	0.330	0.745
N		4,992			4,918		
Adj-R^2		47.19			49.44		

This table presents results of a regression based on 8 years of data, from1994 to 2001, for each bank in the sample. Model 1 includes the entire sample, whereas Model 2 subsets the sample to firms with $ROA > 0$ in the pre-treatment period, where returns are measured before provisions. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. D is an indicator variable that takes on a value of 1 in the treatment period, and 0 otherwise. $TREAT$ is an indicator variable for treated units, which are community banks headquartered in the state of Texas. A matched control sample of banks is drawn from the following states: Colorado, Iowa, Missouri, New Mexico, Nebraska, Kansas, and Arkansas. Explanatory variables include the natural log of lagged total assets ($SIZE$), lagged, current and leading change in non-performing assets ($\Delta NPA_{-1}, \Delta NPA, \Delta NPA_{+1}$), three year rolling average of scaled net charge-offs (CO), growth in total loans ($\Delta LOAN$), change in state GDP (ΔGDP), share of real estate ($ShrRE$), commercial and industrial ($ShrCI$), and consumer ($ShrCONS$) loans in the lending portfolio, and change in the share of real estate ($\Delta ShrRE$), commercial and industrial ($\Delta ShrCI$), and consumer ($\Delta ShrCONS$) loans. The regressions include state fixed effects. Standard errors are clustered by firm.

Table 9: Tables related to testing for effect of manager(Test of H1)

(a) Estimated parameters for regression of scaled loan loss provisions on explanatory variables, including spatial effects

	Prediction	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
D	+	10.003	10.019	8.715	10.863	11.081	5.309
		(3.670)	(3.677)	(3.134)	(3.795)	(3.890)	(1.457)
WY	+	0.022	0.021	0.078	0.034	0.036	0.049
		(1.616)	(1.627)	(2.711)	(2.408)	(2.692)	(1.617)
$D * WY$	?				-0.026	-0.033	0.076
					(-1.103)	(-1.436)	(1.575)
R^2		45.16	45.16	45.25	45.19	45.20	45.26
Log-likelihood		-22647	-22647	-22645	-22647	-22647	-22644

(b) Estimated treatment parameter for regression of scaled loan loss provisions on explanatory variables, including measure of population variability

	Prediction	**Model 1**	**Model 2**	**Model 3**	**Model 4**
D	+	8.403	11.269	12.795	11.533
		(2.13)	(2.06)	(2.27)	(1.92)
$PopVar^L$	?	-5.417	-2.585	-61.652	26.827
		(-1.69)	(-0.54)	(-1.64)	(1.39)
$PopVar^L * D$	?		-5.700	-6.057	-9.973
			(-0.86)	(-0.89)	(-1.55)
County Fixed Effects		No	No	Yes	No
Firm Fixed Effects		No	No	No	Yes
Adj-R^2		45.30	45.29	45.85	52.83

This table presents results of a regression based on 8 years of data for each bank in the sample. The sample is restricted to community banks headquartered in the state of Texas. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. D is an indicator variable that takes on a value of 1 in the treatment period, and 0 otherwise. T-statistics are shown in parentheses below the parameter estimates. Panel (a) presents maximum likelihood estimates and includes spatial effects, as characterized by the spatial weight matrix W. Models 1 and 4 use an inverse distance measure to define W, Models 2 and 5 use the inverse distance squared, whereas Models 3 and 6 use adjacent counties. Section 5.2.2 describes the weight matrices. Panel (b) presents OLS estimates of a regression that uses a matched sample of banks and includes a measure of population variability $PopVar^L$. Please see Section 6.1 for details related to the construction of $PopVar^L$ and the matching procedure. Explanatory variables (unreported) in both panels include the natural log of lagged total assets, lagged, current and leading change in non-performing assets, three year rolling average of scaled net charge-offs, growth in total loans, change in state GDP, share of real estate, commercial and industrial, and consumer loans in the lending portfolio, and change in the share of real estate, commercial and industrial, and consumer loans.

Table 10: Tables related to testing for effect of regulator (Test of H4)

(a) Estimated parameters for regression of scaled loan loss provisions on explanatory variables, including indicator for strict regulators

Variables	**Prediction**	**Estimate**	**t-stat**	**pvalue**
$STRICT$	+	23.124	3.000	0.003
$STRICT * D_{s-2}$	?	-8.810	-1.160	0.247
$STRICT * D_{s-1}$	?	-10.614	-1.320	0.186
$STRICT * D_{s0}$	?	-17.498	-2.420	0.016
$STRICT * D_{s1}$	?	-10.788	-1.360	0.173
$STRICT * D_{s2}$	?	-9.127	-1.310	0.192
$STRICT * D_{s3}$	?	-12.194	-1.840	0.066
N		5,698		
Adj-R^2		37.22		

(b) Estimated treatment parameter for regression of scaled loan loss provisions on explanatory variables, by quintile of distance to regulator's office

Distance to Regulator		**Treatment effect (D)**				
Quintile	**Mean**	**Coeff**	**t-stat**	**pvalue**	**Adj-R^2**	**N**
1	25.7	15.789	4.630	$<.0001$	67.76	448
2	68.1	9.021	1.870	0.068	66.38	440
3	113.7	5.827	1.890	0.064	47.90	440
4	168.1	-4.095	-1.040	0.303	56.76	440
5	273.1	5.563	1.330	0.190	54.21	440

Panel (a) presents results of a regression based on 7 years of data for each bank in the sample. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. $D_{s\tau}$ are time period indicators where $\tau = 0$ is the year in which restrictions to interstate branching were eased for state s. $STRICT$ is an indicator variable that takes on a value of 1 for states where regulators have a leniency index of < 0.05 and 0 if the leniency index is > 0.15. The sample only includes states where the state regulator has a leniency index of < 0.05 or > 0.15. Panel (b) presents results of regressions based on 8 years of data for each bank in the sample, for the state of Texas, by quintile of distance to the regulator's office. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. D is an indicator variable that takes on a value of 1 in the treatment period, and 0 otherwise. Explanatory variables (unreported) in both panels include the natural log of lagged total assets, lagged, current and leading change in non-performing assets, three year rolling average of scaled net charge-offs, growth in total loans, change in state GDP, share of real estate, commercial and industrial, and consumer loans in the lending portfolio, and change in the share of real estate, commercial and industrial, and consumer loans.

Table 11: Tables related to synthetic control analysis

(a) Pre-treatment means for predictor variables

	Texas		
Variables	**Real**	**Synthetic**	**Average of 7 control states**
$log(GDP)$	10.234	10.147	10.163
$\Delta UNEMP$	-0.272	-0.111	-0.163
ΔNPA (1992)	-34.374	-35.507	-19.927
ΔNPA (1993)	-17.203	-15.080	-6.538
ΔNPA (1994)	-13.508	-12.541	-4.629
ΔNPA (1995)	0.000	0.680	0.722
ΔNPA (1996)	3.810	3.179	3.060
ΔNPA (1997)	0.000	-0.014	0.224

(b) State weights in synthetic Texas

State	Weight
Arkansas	0.0000
Colorado	0.0003
Iowa	0.0002
Kansas	0.0001
Missouri	0.3553
Nebraska	0.1368
New Mexico	0.5073

(c) Pre and post treatment mean squared prediction error (MSPE) for Texas and control states

		Post-treatment MSPE			Ratio of Post-MSPE to Pre-MSPE		
State	**Pre-treatment MSPE**	**1998 - 2003**	**1998 - 2005**	**1998 - 2008**	**POST 98-03 /PRE**	**POST 98-05 /PRE**	**POST 98-08 /PRE**
Texas	1.26	27.95	23.59	42.01	22.11	18.66	33.24
Arkansas	13.15	116.48	93.43	96.17	8.86	7.11	7.32
Colorado	23.62	89.43	71.49	216.57	3.79	3.03	9.17
Iowa	1.86	13.19	10.85	30.91	7.11	5.84	16.64
Kansas	1.50	11.19	8.47	30.80	7.48	5.66	20.58
Missouri	1.03	3.55	4.50	27.23	3.46	4.38	26.49
Nebraska	5.65	4.54	6.89	36.16	0.80	1.22	6.40
New Mexico	236.08	90.75	81.63	178.21	0.38	0.35	0.75

This table presents descriptive statistics and results for the synthetic control analysis. Panel (a) reports pre-treatment means of predictor variables for Texas, synthetic Texas, and all control states. Panel (b) presents the output of an optimization procedure to create a convex combination of states that closely resembles Texas on pre-treatment predictor variables reported in Panel (a). Panel (c) presents the mean squared prediction error (MSPE) for Texas and all control states. MSPE is the average squared difference between a state and its synthetic control. Synthetic controls were created for all 7 control states by using the remaining 6 control states (excluding Texas).

Table 12: Estimated parameters for regression of scaled loan loss provisions on explanatory variables and time period indicators, including additional variables

		Model 1			**Model 2**		
Variables	**Prediction**	**Estimate**	**t-stat**	**pvalue**	**Estimate**	**t-stat**	**pvalue**
Intercept	?	-28.627	-2.140	0.033	-14.495	-1.030	0.304
$\boldsymbol{D}$	?	**10.234**	**4.850**	**<.0001**	**8.459**	**3.630**	**0.000**
$SIZE$	?	2.403	1.960	0.050	1.176	0.910	0.364
ΔNPA_{-1}	+	904.171	9.920	<.0001	915.355	6.330	<.0001
ΔNPA	+	819.795	7.820	<.0001	720.002	5.720	<.0001
ΔNPA_{+1}	+	199.502	2.180	0.030	167.116	1.270	0.205
CO	+	8308.313	21.670	<.0001	7652.317	16.760	<.0001
$\Delta LOAN$	+	56.620	6.670	<.0001	54.056	4.430	<.0001
ΔGDP	-	86.927	1.470	0.143	79.442	0.920	0.356
$ShrRE$	?	-16.815	-2.960	0.003	-15.649	-2.280	0.023
$ShrCI$	?	21.850	2.260	0.024	10.127	0.870	0.383
$ShrCONS$	?	14.134	1.720	0.085	-0.452	-0.050	0.958
$\Delta ShrRE$	?	27.353	0.790	0.430	35.178	0.820	0.411
$\Delta ShrCI$	?	-68.347	-2.090	0.037	-76.594	-1.720	0.086
$\Delta ShrCONS$	?	43.946	1.270	0.203	59.232	1.320	0.188
ΔNPA_{+2}	?	-147.459	-1.82	0.069	-109.196	-0.74	0.459
ΔNPA_{+3}	?				-17.481	-0.17	0.868
ΔNPA_{+4}	?				19.684	0.25	0.802
ΔNPA_{+5}	?				67.505	0.82	0.411
LLP_{+1}	?				0.159	7.47	<.0001
LLP_{+2}	?				-0.007	-0.34	0.734
LLP_{+3}	?				0.028	1.54	0.123
N		4,280			4,280		
Adj-R^2		53.17			50.14		

This table presents results of a regression based on 8 years of data, from 1994 to 2001, for each bank in the sample. The sample is restricted to community banks headquartered in the state of Texas. The dependent variable is provisions for loan losses scaled by lagged total loans and leases, net of unearned income and allowance for losses. D is an indicator variable that takes on a value of 1 in the treatment period, and 0 otherwise. Explanatory variables include the natural log of lagged total assets ($SIZE$), lagged, current and leading change in non-performing assets ($\Delta NPA_{-1}, \Delta NPA, \Delta NPA_{+1}$), three year rolling average of scaled net charge-offs (CO), growth in total loans ($\Delta LOAN$), change in state per capita GDP (ΔGDP), share of real estate ($ShrRE$), commercial and industrial ($ShrCI$), and consumer ($ShrCONS$) loans in the lending portfolio, and change in the share of real estate ($\Delta ShrRE$), commercial and industrial ($\Delta ShrCI$), and consumer ($\Delta ShrCONS$) loans. Additional variables in this table include two to five year ahead change in non-performing assets (NPA_{+2}, NPA_{+3}, NPA_{+4}, NPA_{+5}), and one to three year ahead scaled loan loss provisions (LLP_{+1}, LLP_{+2}, LLP_{+3}).