Deposit Flows, Lending, and Securitization: Evidence from Bank Fraud*

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Abstract

This paper exploits plausibly exogenous shocks to deposit flows due to FDIC litigations on nearby competing banks to examine its impact on mortgage originations and private securitization activities. Following announcement of FDIC litigation due to fraudulent activities, depositors shift their accounts from the litigated bank's branches to those of nearby competitors, even when the bank is not closed. Using difference-in-difference estimators to exploit the resulting shock on competitor bank deposit flows, the analysis finds that deposits increases mortgage originations. The impact is strongest in banks with greater on-balance sheet liquidity, consistent with the existence of external financing frictions in commercial banks. However, deposit flows also increase private securitization volume. Securitization-deposit elasticities are unrelated to on-balance sheet liquidity, while deposit flows are unrelated to conditional securitization rates. The effect primarily exists in banks that are better integrated in the securitization chain, controlling for propensities to securitize. The results are consistent with the existence of implicit recourse in securitization, and that banks may achieve synergies by pooling together costs associated with managing risks associated with deposit withdrawals and recourse provision.

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1 Introduction

Deposit flows may impact bank lending capacity due to external financing frictions, and these dynamics are used to motivate the lending channel of monetary policy. However, the proliferation of securitization have arguably altered the effectiveness of monetary policy transmission. Loutskina (2011) provides evidence that securitization increases lending capacity, while Maddaloni and Peydro (2011) find that securitization magnifies the softening impact of monetary policy on lending standards, particularly in mortgages. While these studies examine the impact of external funding shocks directly related to monetary policy or indirectly through securitization costs, liquidity risk arising from demand deposit flows play an equally important role in the lending channel narrative. The impact of demandable deposit flows on lending capacity and securitization activities deepens understanding of how monetary policy transmission in a world with securitization.

This study focuses on examining a key mechanism related to the lending channel: how deposit flows directly impact lending and securitization activities. Exploiting plausibly exogenous shocks to deposit flows in bank branches, the analysis estimate elasticities of mortgage origination and private securitization to demand deposits. The analysis documents large positive shocks in deposit bases of bank branches located in close proximity to those that are accused of fraudulent activities by regulators. Even when the bank is not closed, depositors shift their accounts from litigated bank branches to those of nearby competing banks. Specifically, competing banks whose branches are located within a 5 mile radius of litigated banks experience an approximately 10% increase in deposit bases, and this effect attenuates in distance.

The impact of litigation events on nearby competing bank branches are captured in difference-in-difference estimators, alleviating econometric concerns prevalent in the financial constraints literature. In this manner, the impact of unobservable regional factors related to loan demand or profitable investment opportunities on the estimates are mitigated. Bank branch-level examination also poses advantages in addressing biases arising from tests using aggregated, institution-level inputs. Because the litigation event also affects the bank's investment opportunities due to the reduction in competition in the lending markets, appropriate control variables are included to minimize these effects. The results show that the mortgage-deposit elasticity estimates range from 0.32 to 0.42, and the elasticities are largest in banks with lower on-balance sheet liquidity. Jumbo mortgage-deposit elasticities are also positive, and are of similar magnitude to those related to non-jumbo mortgages. The results are consistent with the existing studies that examine the role of deposit financing in bank lending (Jayaratne and Morgan, 2000; Campello, 2002).

The analysis then decomposes mortgage originations into two components: retained mortgages and mortgages sold to governmental sponsored enterprises (GSEs), which have implicit taxpayer backing; and privately securitized mortgages. The motivation behind the decomposition is to exploit frictions related to segmentation in the secondary mortgage markets to distinguish between the various channels that are related to deposit flows and securitization.

Deposit flows may impact securitization activities through a number of channels. First, constrained banks that rely on securitization for financing new mortgages may rely less on securitization following greater availability of internal funds, leading to a negative association between deposit flows and securitization growth. However, banks may employ originate-to-distribute models to originate mortgages that they would not have normally, and may also in part require internal capital to operationalize these models. In this case, deposit flows will be positively associated with securitization growth. Second, deposit flows may be correlated with unobservable negative shifts in the applicant pool quality, and banks may selectively securitize new customers as these relationship may not be as valuable to the bank, leading to a positive association between deposit flows and securitization growth. Third, securitization activities may introduce liquidity risk if banks pledge to support their securitization trusts in bad states of the world. Banks may be able to achieve synergies by pooling together costs associated with managing risks related to deposit-taking and securitization activities, so as long as these withdrawals and recourse provision are negatively or imperfectly correlated. As a result, deposit flows and securitization growth will be positively related.

The analysis documents a positive relationship between private securitization and deposits. Securitization-deposit elasticities range between 0.07 to 0.13, and is robust to the addition of contemporaneous mortgages retained or sold to agencies as well as risky mortgages. The magnitudes are similar for jumbo mortgage securitization. Securitization-deposit elasticities do not vary in the bank's on-balance sheet liquidity, providing evidence suggesting that financial constraints may not be driving the results. Furthermore, deposit flows are unrelated to conditional securitization rates, suggesting adverse shifts in applicant pool quality do not explain the results.

In order to directly evaluate synergy channel, the analysis examines additional frictions related to securitization facilities. When banks choose to privately securitize a mortgage pool, they may choose to employ an institution that is either affiliated with unaffiliated with their bank holding companies to arrange the mortgage pool for securitization. Because recourse provision is thought be offered by arrangers rather than mortgage originators, the results should be strongest in banks that are better integrated in the securitization chain. Exploiting the organizational structure of bank holding companies within the sample, the analysis extend the tests by including interaction terms between integration and deposit flows. The results show that the inclusion of the interaction term considerably reduces the explanatory power of deposit flows, while the interaction term is positive and quite large. These results provide supportive evidence of the implicit recourse channel.

The analysis relates to the banking and capital constraints literature. Jayaratne and Morgan (2000) directly test whether deposits impact bank lending, and find supportive evidence. Kashyap and Stein (2000) finds that the impact of monetary policy on bank lending is negatively related to on-balance sheet liquidity, and find evidence of the lending channel primarily in small banks. Campello (2002) and Ashcraft (2006) exploit the organizational structure of multi-bank holding companies and finds that access to internal funds reduces the influence of monetary policy on bank lending. Loutskina (2011) and Maddaloni and Peydro (2011) exploit changes in the regulatory environment related to securitization to examine the impact of securitization on the effectiveness of monetary policy. Loutskina (2011) shows that securitization reduces the sensitivity of monetary policy on bank lending, while document that securitization accentuates the softening impact of monetary policy on lending standards. Those studies exploit exogenous variation in external financing costs, while this studies exploits exogenous shocks to internal capital.

The balance of the paper is summarized as follows. Section 2 provides the hypothesis development along with a discussion of the related literature. Section 3 describes the data sources, including the FDIC orders, as well as the impact of the orders on deposit bases of the litigated and competing banks. Detailed descriptions of the empirical methodology are also provided. Section 4 presents the main results, while section 5 provide additional robustness checks. Section 6 concludes.

2 Deposit Flows and Securitization

2.1 Financial Constraints in the Banking Industry

Financing frictions related to agency problems may create differential costs in internal and external financing, so that firms may be unable to undertake profitable investment opportunities when internal funds are limited. In the context of the commercial banking industry, internal resources may include demand deposits, though is an imperfect substitute for cash due to the risk of withdrawals.

Studies in the intersection of the financial constraints and banking literature have primarily examined the impact of financial constraints through the lending channel of monetary policy. Monetary policy may be used to reduce the costs of large certificates of deposits or federal funds to offset the impact of withdrawals on lending capacity. Jayaratne and Morgan (2000) document a positive relationship between lending and insured deposits, while Kashyap and Stein (2000) show that the impact of monetary policy on lending is negatively related to on-balance sheet liquidity.

A key econometric issue in the financial constraints literature is in dealing with the impact of omitted variables related to the profitability of investment opportunities in regression models of capital expenditure on proxies for the availability of internal financial resources. Some studies use exogenous variation in internal resources to estimate its impact of investment (Blanchard et al., 1994; Lamont, 1996; Rauh, 2006; and so on). Similar attempts to address these econometric issues have been made in the context of the banking industry. Campello (2002) exploits differences of banks in multi-bank holding companies and stand-alone entities to show that investment-cash flow sensitivities vary across access to internal funds, and that the availability of internal funding diminishes the impact of monetary policy on lending. Ashcraft (2006) also exploits the multi-bank holding company affiliation, but shows that the impact of monetary policy on real output is economically marginal.

The proliferation of securitization activities over the past three decades has introduced a new set of dynamics in how banks finance loans and the effectiveness of monetary policy in stimulating credit. Recent studies have exploited changes in regulatory environment related to securitization for identification. Loutskina (2011) examines the impact of regulatory changes related to securitization costs, and finds that banks with loan portfolios that are more easily securitizable also lend more. She also shows that securitizability diminishes lending sensitivity to monetary policy. Maddaloni and Peydro (2011) use cross-country country variation in securitization regulation to show that securitization magnifies the ability of monetary policy to soften lending standards, particularly in mortgages.

2.2 Securitization

Traditionally, loans are considered nonmarketable due to information asymmetry problems (Gorton and Pennacchi, 1995), and securitization provides banks with a means to transfer these illiquid assets from their balance sheets to legally distinct, bankruptcy-remote entities. Particularly, the complexity of mortgage securities inherently reflect attempts to minimize adverse selection problems, and other features, such as credit enhancements, allow banks to minimize the impact of private information.

The securitization decision involves whether to sell their loans to government sponsored enterprises or on the private market. Government sponsored enterprises (GSEs) have guidelines on which loans qualify for agency loan sales, generally determined by algorithms programmed in software used by loan officers in the screening process. These guidelines include quantitative metrics, such as loan size and credit worthiness of the borrower. Alternatively, banks may be able to privately securitize mortgages, where no restrictions are in place. Because GSEs have implicit taxpayer backing, banks may prefer to sell qualifying mortgages to agencies rather than privately securitizing them.

Deposit flows can impact securitization activities through a number of channels. Securitization may be used as a financing tool to enhance lending capacity, and so banks may become less reliant on it when cheaper sources of financing becomes available. However, banks may employ originate-to-distribute models to originate mortgages that would not normally. Because these model may in part require internal capital to operationalize them, constrained banks may increase securitization activities in response to financial slack. Deposit flows may also be correlated with unobservable negative shifts in applicant quality. Finally, securitization activities may introduce liquidity risk due to implicit guarantees provided to investors of the securitization trusts, and so banks may attempt to achieve synergies by pooling the costs related to managing risks associated with withdrawals and recourse provision.

2.2.1 Financial Constraints

Securitization is a multifaceted tool that provides banks with an additional source of financing as well as a vehicle for risk management (Loutskina and Strahan, 2009; Loutskina, 2011). Frictions related to time-to-origination, screening costs, and availability of high quality applicants limit banks from originating and distributing mortgages in infinite quantities. If these costs limit slack obtained through securitization in constrained banks, then access to greater internal funds may increase mortgage originations. If internal resources are sufficient to exhaust every profitable investment opportunity, and if costs associated with internal financing are sufficiently lower than those of securitization due to adverse selection problems, then banks may rely less on securitization for financing and respond to positive shocks to internal funds with lower securitization volume. That is to say, deposit flows may decrease securitization growth.

However, banks may employ originate-to-distribute models in order to maintain financial flexibility as well as managing credit risk by shifting these loans off their balance sheet. Not all mortgages originated by a bank are immediately securitized by banks with originate-to-distribute models, though the fraction securitized may reflect the bank's desire to manage risk, among other considerations. Furthermore, originate-to-distribute models may specialize in mortgages that the bank would not normally originate. Securitization costs may prevent constrained banks from investing in mortgages intended for securitization. Access to greater internals funds may allow banks to increase capacity in their originate-to-distribute lending. In other words, internal funds grease the gears of originate-to-distribute models. As such, positive shocks to internal funds may increase securitization growth.

2.2.2 Dilution in Applicant Pool Quality

Securitization activities may be positively associated with deposit flows if the latter is correlated with distributional shifts in the quality of applicant pools. Deposit flows may reflect marketing or advertising campaigns which in turn may also be related to attracting new mortgage customers or customers of poorer quality. A spurious relationship between deposit flows and securitization may result if incentives to securitize these types of mortgages are high.

Banks may be unable to scale up their lending without diluting the average quality of their loan portfolio, as the pool of high quality borrowers may be limited. While lending to low quality borrowers may also be profitable through higher associated with fees and points charged, credit risk from subprime mortgages will be substantially riskier. Information production is costlier with poor quality borrowers, as approval may depend on other factors that are not easily quantified. Perverse incentives related to ease in securitizing subprime mortgages may lead to lax screening or lower standards, and a greater likelihood of originating these risky loans with the intention of securitizing them.[1] Such is a smaller concern with agency loan sales, due to the threat of GSEs choosing to discontinue business with the bank in the future.

Alternatively, by securitizing a loan, banks may lose valuable information derived from the lending relationship. Value from information produced from the lending relationship is lost when a mortgage is securitized, and so the decision to securitize may depends on factors such as whether the customer has a previous working relationship with the bank. If deposit flows are correlated with mortgage business from new customers, banks may choose to selectively securitize loans of borrowers without existing relationships with the bank. If large shocks to deposit flows are linked with large influxes in new mortgage customers, securitization volume may be positively related to deposit flow.

As a result, distributional shifts in applicant quality imply changes in conditional securitization rates. Banks may be reluctant to retain mortgages of borrowers of lower quality or without existing relationships due to the additional risk those mortgages pose. If these mortgages are originated with the intent to securitize, then distributional shifts should be captured by changes in securitization rates.

2.2.3 Implicit Recourse

Due to strategic adverse selection problems, banks may need to offer implicit guarantees in order to participate in private securitization markets (Gorton and Pennacchi, 1995; Gorton and Souleles, 2006). Implicit recourse in private securitizations has been discouraged by regulators due to possible distortions in reported, risk-weighted asset values, which may lead to regulatory capital arbitrage.[2]

[1]Note that if investors suspected heightened adverse selection problems, they may demand a steeper discounts, leading to lower securitization volume. This would result in a negative association between deposit flows and securitization.

[2]Boemio and Edwards (1989) provides early analysis on implicit recourse in securitizations.

For example, a sponsor may provide support by purchasing failing receivables held by a trust in order to avoid early amortization triggers. Anecdotal evidence of recourse provision range from blatant violations of rules regarding the treatment of the trust's asset as a true sale (FASB 140) to cases where recourse was disguised by exploiting loopholes in when voluntary recourse can be legally provided.

A number of studies provide evidence suggesting its existence by employing tests on the trust-level (Gorton and Pennacchi, 1995; Gorton and Souleles, 2006), while others construct tests focused on the bank-level (Vermilyea et al., 2008; Higgins and Mason, 2004). However, Tufano (2006) argues that these tests are confounded by omitted variables related to a common risk factor shared by the trust and their sponsor. For example, when a customer holds multiple accounts within the same bank, the bank may choose to securitize only some of the accounts. This may possibly cause credit risk to be correlated between the securitized and retained assets.

Most studies of implicit recourse have focused on revolving forms of loans, particularly credit card receivables (Calomiris and Mason, 2004; Higgins and Mason, 2004; Gorton and Souleles, 2006; Vermilyea et al., 2008). Revolving loans have a greater risk of entering into early amortization. Furthermore, because the structure of the credit card ABS are less complex than private MBS (e.g. waterfalls), the premium demanded by investors on credit card receivables are also likely to be higher (Higgins and Mason, 2004). However, given the size of the private MBS market compared to that of ABS, the cost of supporting these trusts will be nontrivial; while information asymmetry concerns are in part reduced due to more elaborate structuring of the trust or information asymmetry is generally lower in mortgages, they are not completely eliminated. Examples of recourse provision in term ABS markets can be found during the recent financial crisis period. In cases where trusts were not supported, the sponsor would not have been able to without dramatically increasing insolvency risk.

As banks commit to recourse provision in certain states of the world, these commitments may introduce liquidity risk on the bank's balance sheet. A number of studies suggest that liquidity risk arises from deposit-taking activities, as well as loan commitments. Kashyap et al. (2002) present a simple model of how banks can achieve synergies across their deposit-taking and loan commitment operations by pooling together the costs of managing these risks, and empirically show a positive relationship between deposit bases and loan commitments. Gatev et al. (2009) provides additional empirical evidence by showing that deposits and loan commitments are each positively related to equity risk, while the interaction effect between the two is negative. Kashyap et al. (2002) argues that such synergies are possible if these risks are negatively or uncorrelated with each other, and so should not be attainable through deposit-taking and term lending.

As with deposit-taking, banks may hold buffer stock to mitigate the impact of states of recourse provision. If recourse provision and deposit withdrawals are imperfectly or negatively correlated, banks may also be able to achieve synergies by pooling the costs of hedging these risks. As a result, banks may respond to positive shocks to deposit flows by increasing private securitization volume.

The parties involved in the securitization chain are numerous (Ashcraft and Schuermann, 2008), and when the securitization process is better integrated, these parties may collaborate closely when determining which loans to package. Because implicit guarantees are generally though to relate to the arranger, and not the originator, sensitivity of securitization volume to deposit flows due to implicit recourse is likely to be strongest in banks that are better integrated in the securitization chain, or that the originator, arranger and broker all belong to the same holding company.

3 Empirical Design

3.1 Data

The analysis employs data from a variety of sources. Branch-level deposit data, as well as the branch's address, are collected from the FDIC's Summary of Deposits (SOD) file. Depository institutions are required to report branch-level data on an annual basis. The SOD data relevant to the analysis covers the 1994 to 2007 sample period. Mortgage-level data is collected from the Home Mortgage Disclosure Act (HMDA) file from the FFEIC. The HMDA dataset includes detailed mortgage application data, including origination status, property type, mortgage amount, and so on. For a large part of the sample, the dataset contains all mortgage applications for most lending institutions in major Metropolitan Statistical Areas (MSAs).

The HMDA data relevant to the analysis covers the 2000 to 2007 sample period. For the 2004 to 2007 period, additional characteristics, including lien status and a high-priced mortgage field, are also observable. The analysis examines conventional mortgage applications, focusing primarily on the non-jumbo mortgage sample. One drawback of the HMDA dataset is that it does not include fields related to FICO scores and documentation. However, an advantage of the HMDA dataset is that rejected applications are also observable.

The Call Report data includes characteristics on the institution-level, such as total assets and on-balance sheet liquidity measures. The analysis incorporates the Call Report data for some of the tests using fourth quarter data for the 2000 to 2007 sample period. The National Information Center website is used to hand-collect information regarding whether the bank's holding company also owns a securities dealer as a subsidiary.

FDIC enforcement decisions and orders are collected from the FDIC website for the 1994 to 2007 sample period. Each order includes the date of issuance, the name of the institution, the institution's address, enforcement action type, as well as detailed information outlining consequent prescriptive restrictions imposed on the institution. Further description of these orders are described in the next section.

The FDIC orders are hand-matched to the SOD database using the National Information Center database. Banks are matched using the name and location of the institution. The SOD database is linked to the Call Report database using the institution's RSSD ID. The dataset can be then merged to HMDA database using additional fields in the Call Report database. Branch-level information is not available the HMDA dataset, though each mortgage application is identifiable up to the census tract-level. Consequently, the analysis aggregates the SOD and HMDA databases on the county-level.[3] Within a given county, the distance between each bank's branches and the branches of the litigated bank are calculated using the Haversine formula using coordinates based on the bank branch's address. The minimum of all the pairwise distances for each bank within a county is used in the analysis.

Table 1 presents the summary statistics of the variables used in the analysis. The columns denote the cross-sectional mean, standard deviation, 25th percentile, median and 75th percentile for each variables over the 2000 to 2007 period in banks located in counties that include a litigated bank. The book value of total assets has a mean of $70 billion and a median of $0.95 billion. Liquidity ratios are defined as cash plus liquid securities scaled by total assets (LiqRat), and has a mean value of 8.1%. Total originated dollar mortgage volume ($MortgageVol) has a mean of

[3]Because both county-level SOD and HMDA data is not always available for a given bank, the analysis restricts the sample to those banks that exist in both dataset in at least the prior year.

\$5.7 million. Deposits (Dep) has a mean of \$54.0 million. The average total number of mortgage applications is 66.6, and the average number of branches in a given county is 5.8. The average number of branches for all banks in a given county in the sample (#CtyBranch) is 181.9. The Herfindhal indices constructed using mortgage volume and deposits in a given county across banks is 34.7% and 30.1%, respectively.

3.2 Effect of Litigation on Competitor Deposit Bases

The FDIC can issue an order, or litigate a bank, based on information collected from on- and off-site examinations, or supplied by other stakeholders in the bank. Unlike litigation brought about by stakeholders in non-regulated industries, the FDIC has power to immediately impose restrictions on the institution. The litigation may in some cases result in the closure of the bank. When the bank is allowed to continue to operate, restrictions are imposed on the bank, which may be lifted in the future if the bank demonstrates to regulators that the causes for the order has been rectified.

The reasons for suing a depository institution can vary. In particular, an order may be issued if the bank has or is about to engage in a banking practice that is deemed to unsound; these types of actions generally fall in the category of cease and desist order. For example, the FDIC litigated First National Bank of Keystone in West Virginia in September 1999 for a variety of reasons. Over the 1994 to 1999 period, Keystone Bank achieved a 28% growth in deposit bases due to extremely favorable rates offered on their deposit accounts. Instead of using these deposits to originate more mortgages, the bank fabricated their asset base by forging mortgage applications from another bank. The consequence of the litigation cases generally result in closure of the bank, penalty that may include tighter regulatory requirements (e.g. capital requirements), or a settlement payment. Keystone Bank was closed the day after the order was issued, and many of their customers received their deposits back within a year of the closure.

Figure 1 displays the number of FDIC litigations that are used in the sample by year from 1994 to 2007. The figure under-represents the total number of cases, as the analysis requires that the bank to have a positive levels of deposits at the time of the litigation announcement. The time series spikes in 1995, and steadily increases from 2001. Extending the series past 2007 reveals that the number of orders dramatically increased during the financial crisis period, and many of these cases are related to bank closures.

Figure 2 plots a density chart of the number of cases by county from 1994 to 2007, as well as the number of bank branches in a county. The color used to shade each county becomes darker when the frequency increases, with white denoting a zero count. Panel A shows that litigated banks are not necessarily clustered in a particular area, and is to some degree similar to the number of banks located in the county as displayed in Panel B. The incidence of cases becomes sparse in lower populated regions. Because the mortgage level data generally focuses on well-populated regions, the analysis is able to obtain a sufficiently large number observations to be used in the analysis.

While banks that are closed due to FDIC orders should predictably lead to displaced depositors, as was the case of Keystone Bank, it may be interesting to also estimate the impact of these orders in banks that are allowed to continue their operations. Depositors may discipline the banks, despite the presence of deposit insurance, as local newspapers generally report when local banks are litigated. Banks generally rely on fostering trust between the bank and the depositors in order to attract accounts. For example, IndyBank used the slogan "You can count on us" in their marketing campaigns.

In order to answer this question, the analysis estimates the following lagged dependent variable regression model.

$$\begin{aligned}\ln(Deposits)_{i,c,t} &= a + b * \text{Fraud}_{i,Prior} + c * \text{Fraud}_{i,Present} + d * \text{Fraud}_{i,Post} \\ &\quad + e * \ln(TotAssets)_{i,t} + f * \ln(\#Branches)_{i,c,t} + g * \ln(Deposits)_{i,c,t-1} + \varepsilon_{i,c,t}\end{aligned}$$

For bank i located in county c at year t, $Deposits_{i,c,t}$ denotes the total dollar value of deposit bases, $Fraud_{i,prior}$ is an indicator function that takes value 1 if an order is issued to the bank in year *t-1*, $Fraud_{i,present}$ is an indicator function that takes value 1 if an order is issued to the bank in year t, $Fraud_{i,post}$ is an indicator function that takes value 1 if an order is issued to the bank in year *t+1*, $TotAssets_{i,c,t}$ denotes the book value of total assets, and $\#Branches_{c,t}$ denotes the number of bank branches. Only banks that are allowed to continue are included in the sample. In addition, year and county fixed effects are included in some of the models. Standard errors are calculated using a double-clustering procedure on the bank and year levels. These calculations are adjusted for the fact that the observations are on the branch-year level. This procedure is used in all the subsequent tests.

Table 2 displays the estimates. Models 2, 4 and 5 include county fixed effects. Models 3 and 4 restricts the sample to the 2001 to 2007 sample period, and model 5 restricts the sample to the 2005 to 2007 sample period. All models include year fixed effects. Across the model specifications, the coefficients on $Fraud_{prior}$ are close to zero and is statistically insignificant at the 10% level. As anticipated, the $Fraud_{i,present}$ coefficient is negative and statistically significant at the 1% across all the specifications. On average, the deposit bases in the litigated banks contract by approximately 5%. The $Fraud_{i,post}$ coefficients are smaller in absolute magnitude than those of $Fraud_{i,present}$, but all remain negative. Model 5 shows qualitatively similar results. The results of Table 1 indicate that the orders are not anticipated by at least the depositors. They confirm that depositors withdraw their accounts from the litigated bank in the year of the announcement even when the bank is allowed to remain open, and the withdrawals continue to some extent in the following year.

In order to estimates the flow of deposits from the affected bank to its nearby competitors, the analysis next estimates the following model.

$$\begin{aligned}
\ln(Deposits)_{i,c,t} \quad = \quad & a + b * \mathrm{D}_{i,[0mi,5mi),t} + c * \mathrm{D}_{i,[5mi,10mi),t} + d * \mathrm{D}_{i,[10mi,15mi),t} \\
& + e * \mathrm{D}_{i,[15mi,20mi),t} + \mathrm{f} * \mathrm{D}_{i,[20mi,30mi),t} + g * \ln(TotAssets)_{i,t} \\
& + h * \ln(\#Branches)_{i,c,t} + i * \ln(Deposits)_{i,c,t-1} + \varepsilon_{i,c,t}
\end{aligned}$$

For bank i located in county c at year t, $\mathrm{D}_{i,[x,y),t}$ is an indicator function that takes value 1 if the minimum distance between any of the bank's branches is located between x and y miles of any of the affected bank's branches. The control variables are identical to those used in Table 2. The sample excludes effected bank branches in this specification.

Table 3 displays the estimates. Models 2 through 7 restrict the sample to include only counties that contains at least one effected bank branch in year t. Models 2, 4 and 6 include county fixed effects. Models 5 and 6 restrict the sample to the 2001 to 2007 subperiod, while model 7 restricts the sample to the 2005 to 2007 subperiod. All models include year fixed effects. The coefficients on the indicator functions non-linearly decrease in the distance from the affected bank. Banks within a five mile radius of an effected bank experience the strongest deposit inflows, while the effect is non-positive for banks located outside a 15 mile radius. Specifically, deposit bases increase by approximately 10% in competing banks located within a five mile radius. Models 1 and 2 show that the flows become negative for banks located between 20 and 30 miles from the affected bank, but the coefficients become statistically indistinguishable from zero in models 3 through 6, where the sample is subsetted to only included effected counties. In model 7, the coefficient on the dummy variable for banks located between a 5 to 10 mile radius becomes statistically insignificant at the 10% level, and the coefficient on the dummy variable for banks located between a 20 to 30 mile radius is negative and statistically significant again.

Figure 3 graphically displays some of the coefficients from Table 3. The error bars in the figures represent a 95% confidence interval. Panel A displays the coefficients on the indicator functions from model 5, Panel B displays the coefficients from model 6, and Panel C displays the coefficients from model 7. The results show that the effect on banks located within a five mile radius is quite large and stable across the specifications. The coefficients contract two to three fold when the distance is between five to 10 miles, and becomes statistically indistinguishable past 15 miles for most specifications.

3.3 Difference-in-difference Regressions

Following a litigation event, the treatment group is accordingly set to banks who have branches located within a five mile radius to those of the litigated bank. Because the bank may lose business due to reputational effects or closure, the litigation event is also likely to impact neighboring banks in their lending opportunities. That is to say, it will impact both competitor deposit bases as well as competitor mortgage applications. To control for the impact to possible shocks to opportunity sets, a number of additional regressors are added to the model. The regression model can be specified as follows.

$$\begin{aligned}\Delta\ln(\$Loan)_{i,c,t} \quad &= \quad a_x + b_x * \Delta\ln(Deposits)_{i,c,t} + c_x * \Delta\ln(\#Applications)_{i,c,t} \\ &\quad +d_x * \Delta\ln(\$Loan)_{fraud,c,t} + e_x * \Delta ln(HERF)_{c,t} + \varepsilon_{i,c,t}\end{aligned}$$

For bank i located in county c at year t, $\$Loan_{i,j,t}$ denotes the total dollar volume of mortgage mortgage originations, $Deposits_{i,c,t}$ denotes the total dollar value of deposit bases, $\$Loan_{fraud,c,t}$ denotes the total dollar volume of mortgage mortgage originations in fraudulent banks, $\#Applications_{i,c,t}$ denotes the total number of mortgage applications received, and $\Delta HERF_{c,t}$ denotes the Herfindahl index over the total number mortgage applications. $\Delta(.)$ denotes the first difference operator from *t* to *t-1* around the litigation event.

The additional regressors are designed to capture a number of factors that can potentially bias the deposits coefficient. The change in the number of applications directly measures the bank's investment opportunity sets. Changes in the mortgage origination volume of the litigated bank as well as the Herfindahl index capture the direct impact of the business lost by the litigated bank.

However, estimating the parameters of the model above may still be contaminated by unobservable characteristics related to product market competition in the mortgage markets, as well as information about the bank's opportunity sets that may be related to regional dynamics. In particular, some banks be better able to attract the accounts of displaced depositors, and this ability may be correlated with the desire for high mortgage origination growth. The following matching procedure is designed to account for these unobservable characteristics.

The control group is restricted to banks who only have branches located outside a 15 mile radius of the allegedly fraudulent bank's branches, but located in the same county. For bank j in the control group, the matching criteria is based on year *t-1* characteristics related to the bank's technology to attract deposit bases: $DepShare_{i,c,t}$ is the proportion of deposits held by the bank's branches, $AppShare_{i,c,t}$ is the proportion of mortgage application held by the bank's branches, and $\#Branch_{i,c,t}$ is the number of bank's branches. For the main tests, the analysis assume equal importance to each factor, though this assumption is relaxed in the robustness checks. Each matching variable is initially standardized across banks in county c and year *t-1*. Bank j is paired with bank i by minimizing distance function, $d_{i,j,c,t-1}$, as specified below.

$$\begin{aligned} d^2_{i,j,c,t-1} \quad = \quad & (\ln(DepShare)_{i,c,t-1} - \ln(DepShare)_{j,c,t-1})^2 \\ & + (\ln(AppShare)_{i,c,t-1} - \ln(AppShare)_{j,c,t-1})^2 \\ & + (\ln(\#Branch)_{i,c,t-1} - \ln(\#Branch)_{j,c,t-1})^2 \end{aligned}$$

The difference-in-difference estimator employed by the analysis takes the following form.

$$\begin{aligned}\Delta\ln(\$Loan)_{i,c,t} - \Delta\ln(\$Loan)_{j,c,t} &= a + b * [\Delta\ln(Deposits)_{i,c,t} - \Delta\ln(Deposits)_{j,c,t}] \\ &+c * [\Delta\ln(\#Applications)_{i,c,t} - \Delta\ln(\#Applications)_{j,c,t}] \\ &+d * \Delta\ln(\$Loan)_{fraud,c,t} + e * \Delta\ln(HERF)_{c,t} + \varepsilon_{i,j,c,t}\end{aligned}$$

Parameter b represents the mortgage elasticity of deposits, and will be the focus of the analysis. Subsequent specifications replaces the dependent variable with one that include only privately securitized loans; retained or agency mortgages; extremely risky mortgages; and so on. Finally, the analysis will primarily focus on non-jumbo mortgages, and will ultimately focus on first lien mortgages to help control for heterogeneity in loan types.

4 Results

The analysis begins by examining the impact of deposit bases on mortgage origination volume around the litigation announcements. The results show that the mortgage-deposit elasticities range from 0.32 to 0.42, depending on the sample period and set of controls. On the other hand, restricting the dependent variable to private securitization volume, securitization-deposit elasticities range from 0.09 to to 0.14. The results appear similar in jumbo mortgage sample as well.

4.1 Total Mortgage Originations

Table 4 displays model estimates using total dollar mortgage origination growth as the dependent variable. Models 1 through 3 displays the results using the 2001-2007 sample period, while models 4 through 6 display the results restricting the sample to the 2005 to 2007 period. Models 5 and 6 further restricts the sample to first lien mortgages. Models 2 through 6 include county and year fixed effects, which help absorb any time- and regional-invariant omitted factors. In the univariate regression, the deposit coefficient in model 1 is quite large (0.42, t-value 6.47). Model 2 includes additional controls variables to capture variables related to the changes in the bank's investment opportunity sets and product market dynamics. The deposit coefficient in model 2 decreases by 15% (0.35, t-value 12.79). The deposit coefficient further contracts by approximately 10% (0.32, t-value 12.06) after the inclusion of year and bank fixed effects. Model 4 reproduces the results restricting the sample period to the 2005 through 2007 period, and the deposit coefficient remains similar (0.32, t-value 13.08).

The dependent variable is reconstructed using only first-lien mortgages for models 5 through 6, and so the sample is restricted to the 2005 through 2007 subperiod. The deposit coefficient in model 5 remains relatively similar (0.32, t-value 9.69). Further restricting the dependent variable to exclude high-priced mortgages, the deposit coefficient in model 6 slightly increases (0.35, t-value 10.14).

The results suggest that positive shocks to deposit bases generate financial slack on average, leading to greater mortgage origination volume. Inclusion of various control variables contracts mortgage-deposit elasticities from 0.42 in model 1 to a range between 0.32 and 0.35 in models 2 through 6, alleviating concerns that the estimates are driven by confounding factors related to the litigation event. The estimated elasticities are all less than unity, which is not surprising given reserve requirements on insured deposits.

4.2 Private Securitizations

The analysis next reconstructs the dependent variable using only growth in private securitization dollar volume. As in Table 4, the tests are performed on various restrictions on the sample period as well as the dependent variable. Models 1 through 6 includes county and year fixed effects as explanatory variables. Models 2 through 6 restrict the sample to the 2005 to 2007 period, and models 4 through 6 restricts the dependent variable to first-lien mortgages.

Model 1 shows that the deposits coefficient is positive (0.09, t-value 1.81), though approximately 70% smaller than the coefficients displayed in Table 4. Restricting the subsample to the 2005 to 2007 subperiod increases the securitization-deposit elasticities by approximately 33% (0.12, t-value 2.22) in model 2. Retained or agency mortgages represents actual contemporaneous investment that partially capture the response of constrained banks, and so are included as an additional control in models 3 through 6. The deposit coefficient contracts two-fold (0.08, t-value 1.75), though remains statistically significant at the 10% level.

Restricting the dependent variable to first-lien mortgages, the securitization-deposit elasticity doubles (0.13, t-value 4.24) in model 4. In models 5 and 6, the dependent variables are reconstructed based on whether the mortgage is high-priced, conditional on private securitization. The dependent variables or model 5 and 6 are constructed excluding or only using high-priced mortgages, respectively. To help address concerns of applicant pool dilution, privately securitized high-priced mortgages are included in model 5 to help capture these dynamics. The deposit coefficient augments (0.14, t-value 5.44) in model 5, and is close to zero (-0.00, t-value 0.04) in model 6.

Securitization-deposit elasticities are positive across all but the high-priced specification. Because the privately securitized, high-priced mortgage control variable only partially changes in applicant quality, concerns with regard to lax screening as a response to the litigation event lingers. The analysis further evaluates these concern in later sections.

4.3 Jumbo Mortgages

The preceding analysis has exclusively examined non-jumbo mortgages. One drawback with examining non-jumbo mortgages is in the unobservability of whether the mortgage is of "conforming" status. On the other hand, because jumbo mortgages cannot be sold to GSEs, the bank's options are limited to retaining or privately securitizing the mortgage. Changes in jumbo mortgage originations may be able to better reflect the existence of financial constraints, as jumbo mortgages are inherently more difficult to sell. Furthermore, banks may be more likely to expend resources to collect "soft" information than non-jumbo mortgages. As such, information asymmetry problems related to lax screening are also partially alleviated. As before, the regression models are estimated over various subperiods, and include all control variables present in Table 4.

Table 6 presents the results restricting the dependent variables to only jumbo mortgages. Models 1 through 3 are estimated using total jumbo mortgage dollar volume as the dependent variable. The results are similar to those in Table 4. The jumbo mortgage-deposit elasticities range from 0.33 to 0.39, and the deposit coefficient slightly contract with the inclusion of additional control variables. The deposit coefficients are slightly smaller in the 2005 through 2007 subperiod (0.33, t-value 10.85) than the whole sample period (0.37, t-value 12.44), though the coefficients are statistically indistinguishable.

Models 4 through 6 restricts the dependent variable to only private securitizations. These results are similar to those of Table 5. Securitization-deposit elasticities range from 0.13 to 0.16. Inclusion of year and county fixed effects contracts the deposit coefficients from 0.16 (t-value 4.65) to 0.13 (t-value 4.40) over the 2001 through 2007 subperiod, and restriction to the 2005 through 2007 subperiod leaves the deposit coefficient unaffected (0.14, t-value 6.83).

In untabulated results, inclusion of non-jumbo mortgage growth contracts the deposit coefficients, though they remain positive and statistically significant at the 1% level. Controlling for non-jumbo mortgage growth may be useful in controlling for demand side loan market dynamics, as in Loutskina and Strahan (2009). However, non-jumbo mortgage growth also capture other dynamics related to supply side factors that may sap explanatory power from deposit flows.

The results in Table 6 are quantitatively similar to those in Tables 4 and 5. Assuming that jumbo mortgages uniformly require greater screening costs on the part of the bank, these results are less likely to be impacted by differential "soft" information collection created by credit score cut-off rules in agency market, as described in Keys et al. (2011). The results also reinforce the interpretation that deposit flows due to litigation events create financial slack in nearby, competing banks.

5 Discussion

The preceding sections provide some preliminary evidence that positive deposit flows creates financial slack on average, leading to greater mortgage originations. Additionally, securitization-deposit elasticities remain positive even after inclusion of various control variables capturing constrained banks and dilution in applicant pool quality, and appear to be similar across the jumbo and non-jumbo mortgage samples. This section provides sharper tests to distinguish the various channels that may lead to associations between deposit bases and securitization volume.

5.1 On-balance Sheet Liquidity

The positive association between securitization volume and deposit flows may reflect the inability of constrained banks with originate-to-distribute models that may partly require internal capital to make them operational. This section directly assesses these concerns, and verifies whether the mortgage regression results are related to financial constraints. If positive deposit flows create financial slack to banks that are capital constrained, then mortgage-deposit elasticities should vary along direct measures of financial constraints. Likewise, if securitization-deposit elasticities are driven as a response to financial constraints, then they should also vary along direct measures of financial constraints.

This section extends tests in previous section by including on-balance sheet liquidity, or *LiqRat*, as well as its interaction term with deposits, as additional explanatory regressors. *LiqRat* is defined as the sum of cash and other liquid assets, scaled by total assets. If the positive association between mortgage volume and deposits is due to greater capital available in the bank's internal capital markets, the coefficient on the interaction term between deposit flows and on-balance sheet liquidity should be negative in the total mortgage origination volume regressions. If financial constraints are also driving the positive securitization-deposit association, then the coefficient on the interaction term in that model should also be negative.

Table 6 displays the results. Models 1 displays the results using retained or agency mortgages excluding high-priced mortgages to construct the dependent variables. Models 2 and 3 show the results using only private securitizations excluding high-priced mortgages to construct the dependent variable. Model 4 shows the results using only privately securitized, high-priced mortgages to construct the dependent variable. As in the earlier sections, jumbo mortgages are excluded from the analysis. The tests restrict the sample to the 2005 through 2007 subperiod due to data restrictions.

Model 1 confirms that the documented positive mortgage-deposit elasticities reflects financial slack. While the sign on the *LiqRat* coefficient is statistically indistinguishable from zero, the coefficient on the interaction term is negative and large (-0.77, t-value 8.34). However, models 2 and 3 show that securitization-deposit elasticities do not vary across financial constraints, and the coefficients on the interaction term do not qualitatively change without (0.02, t-value 0.08) and with (-0.01, t-value 0.03) the non-conforming mortgage control variable. When restricting the dependent variable to non-conforming mortgages in model 4, the interaction coefficient remains statistically indistinguishable from zero (0.10, t-value 0.43). The deposit coefficients in models 2 and 3 remain qualitatively similar to those of model 5 in Table 5. Together, the results suggest that the financial constraints channel does not explain the positive securitization-deposit elasticities.

5.2 Conditional Securitization Rates

Deposit flows may be correlated with dilution in applicant pool quality due to revelation of fraud in a competitor bank, leading to a positive relationship with securitization activities. This may be a symptom of perverse incentives that result in relaxed screening policies, or may result from relatively lower costs associated with severing lending relationships with new customers.

Similarly, banks may attempt to aggressively increase market share by claiming these customers through relaxation of their lending standards. The omitted variable problem arises when banks that attract the greater deposit flows following the fraud revelation were the banks that invested the heavily in increasing market share in both markets. Effectively, the omitted variable would be correlated with deposit flows and mortgage volume, biasing the deposit coefficient upwards in the mortgage origination models. Banks may wish to offset the increased risk taken on their balance sheets by privately securitizing these mortgages, biasing the deposit coefficients upwards in the securitization models.

Table 8 examines these possibilities. Because mortgage-level performance is not available in the HMDA dataset, the analysis conducts tests on securitization rates. A consequence of dilution in applicant pool quality is that conditional securitization rates should increase, as banks may not wish to retain these types of mortgages on their balance sheet. Securitization rates are defined as the proportion of mortgages privately securitized, conditional on the mortgage being accepted.[4] Accordingly, the regression models test whether deposit flows are related to changes in securitization rates.

Table 8 displays the results from the securitization rate tests. Model 1 shows the estimates over the 2001 through 2007 period, models 2 through 4 show the estimates over the 2005 through 2007 subperiod, and models 3 and 4 restrict the sample to first lien mortgages only. The results show that deposit flows have no relationship with conditional securitization rates. Across all specifications, the deposit coefficients are statistically indistinguishable from zero at the 10% level, and that the coefficient is negative in three of the four specifications. Not surprisingly, retained and agency mortgages and privately securitized, high-priced mortgages load negatively (-0.02, t-value 3.21) and positively (0.01, t-value 24.9), respectively.

[4] Keys et al. (2011) interprets conditional securitization rates as ease of securitization, and examines discontinuities in securitization rates around credit score cut-offs.

The results of model 4 suggests that securitization-deposit elasticities are not due to distribution shifts in applicant quality. Additionally, the discovery of fraudulent activities in neighboring banks may increase regulatory scrutiny, casting further doubt whether litigation events are also contributing to lax screening or lending standards.

5.3 Integration in Securitization Process

The next section constructs direct tests for the synergy channel. Securitization activities may introduce liquidity risk on the bank's balance sheet if the bank offers implicit guarantees on the performance of their off-balance-sheet trusts. Some banks are may be more integrated in the securitization chain than others, as these banks may belong to holding companies with subsidiaries dedicated to arranging and issuing MBS securities. As a result, integrated banks may be able to achieve synergies between their deposit-taking and securitization activities by pooling together the costs of managing risks associated with each operation, particularly associated with withdrawals and recourse provision. However, those that are not integrated will not be able to. As such, securitization-deposit elasticities should increase in securitization chain integration.

Identifying banks that arrange and issue their own mortgage securities is difficult, and such information cannot be readily found if the bank is not publicly-traded. However, regulators require banks to disclose their organizational structure, so that banks belonging to holding companies that have broker or dealer subsidiaries are observable. The dummy variable denoting the existence of broker / dealer subsidiaries in their parent bank's holding company is used to proxy for relatively greater integration in the securitization process. The prediction is that the private securitization results should generally only hold for better integrated banks.

The analysis also imposes an additional criterion that matched banks must be similar in terms of integration in the matching procedure. Propensities to securitize are also included in all the specifications, captured by a past securitization dummy takes on value one if the bank had previously securitized a mortgage at that point in time and zero otherwise. Table 9 presents the results using the enhanced matching procedure. A broker dummy as well as an interaction term with deposit flow are displayed when included in the model. Models 1 and 2 provide placebo tests, using retained and agency mortgage volume as the dependent variables. The results show that the mortgage-deposit elasticities are similar to those in Table 4, and do not differ even after inclusion of the broker interaction terms.

Models 3 through 6 use privately securitized mortgages excluding high-priced mortgages as the dependent variables. Models 3 and 4 shows that the securitization-deposit elasticities remain positive even with the addition of the broker matching criterion. Models 5 and 6 explicitly include the broker variable terms. The interaction term between broker and deposit flows loads positively and is statistically significant at the 10% level (0.17, t-value 1.92) in model 5, and is quantitatively similar in model 6 (0.16, t-value 1.97). The deposit coefficient, however, decreases to 0.02 (t-value 0.56) in model 6.

In untabulated results, inclusion of past securitization rates or changes in securitization rates, such as those used in Keys et al. (2011), do not qualitatively change the results. Furthermore, refining the matching procedure to include propensity to securitize contracts the sample size by more than a third, but do not dramatically alter the results: the deposit coefficients in the securitization model remain statistically insignificant, while the interaction term loading remains positive and statistically significant at the 1% level.

In summary, the results confirm that the securitization results are strongest in integrated banks. The deposit coefficients in the retained and agency mortgage tests are similar, indicating that operational differences related to integration in the securitization process are not driving the results. Furthermore, the results suggest that securitization-deposit elasticities may be determined by risk management motives related to implicit recourse provision.

5.4 Alternative Matching Procedures

One concern is that the results described above may be biased if the control banks do not properly account for differences in mortgage origination models or other product market dynamics not captured in the control variables. In order to evaluate these concerns, the results are reproduced using a stricter matching criteria. Specifically, independent sorts are performed in each county and year on each of the three matching variables producing tercile groupings on each dimension. In addition to minimizing the distance function, d, matched banks are required to reside in the same ranking on a particular matching variable. In this manner, improper matches will be excluded from the analysis.

Table 10 displays the estimates. Panel B uses retained mortgage volume and mortgages sold to GSEs as the dependent variable over the 2005 to 2007 sample period. Panel B uses private securitization volume as the dependent variable. The dependent variables in both panels excludes subordinate lien mortgages.

Models 1 through 4 of Panel A show that the deposit coefficients range from 0.18 to 0.35, and they are all statistically significant at the 1% level. Model 1 restricts the sample to matches based on #Branches. As can be seen from the number of observations, close to a third of the banks in the treatment group are able to be matched with a control bank with this additional restriction. However, the deposit coefficient remains large (0.259, t-value 7.87). Using DepShare as the matching variable, the number of banks contracts three-fold as well, though the deposit coefficient remains large (0.176, t-value 4.59). Similar results obtain when using AppShare as the matching variable in model 3. Finally, model 4 requires matching on all three variables. Consequently, the sample size contracts to 163, though the coefficient augments to 0.345 (t-value 11.35).

The securitization-deposit elasticities are all positive across the specifications, and are relatively similar to those report in Table 5. The deposit coefficient in models 1 (0.09, t-value 5.01), 2 (0.09, t-value 5.01), and 3 (0.10, t-value 5.44) remain stable. However, the coefficient in model 4 contracts to 0.05 (t-value 1.15), and could be attributed to the reduction in sample size. These results suggest that the findings in the previous sections are robust to alternative matching criteria.

6 Conclusion

How do deposit flows impact mortgage lending and securitization behavior? Exploiting plausibly exogenous shocks to deposit flows arising from discovery of fraudulent activities in neighboring banks, the analysis finds evidence consistent with external capital market frictions. The impact of deposit flows on mortgage growth is strongest in banks with low on-balance sheet liquidity, and the magnitude of mortgage-deposit elasticities are similar in jumbo mortgages. The evidence is broadly consistent with the capital constraints literature, and provides evidence for necessary arguments related to monetary policy transmission.

Deposit flows are also positively related to private securitization growth. Additional tests suggest that this relationship is not driven through a financial constraints or adverse selection channels, and securitization-deposit elasticities do not vary across direct measures of financial constraints nor are changes securitization rates related to deposit flows. The impact of deposit flows on securitization growth appears to be strongest in banks better integrated in the securitization chain, suggestive of the synergies channel.

Existing studies have documented a positive relationship between securitization and lending using changes associated with securitization regulation, and argue that it is related to lower lending standards (Maddaloni and Peydro, 2011) or financing and risk management concerns (Loutskina, 2011). This paper argues an alternative mechanism that may not necessarily be mutually exclusive. Funding shocks stemming from deposit bases results in both greater internal funds as well as increased liquidity risk resulting from additional demandable deposits. While greater internal resources may propagate greater lending for constrained banks, banks may also wish to achieve synergies in risk management by pooling together costs of managing risks associated with withdrawals and recourse provision, if the two are imperfectly or negatively correlated. Implicit recourse provision may be necessary for the bank securitize their loans due to adverse selection issues (Gorton and Souleles, 2006), and liquidity risk is introduced through these guarantees has banks agree to support their trusts in bad states of the world.

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Table 1: Summary Statistics

Summary statistics for the variables used in the analysis are displayed. The cross-sectional mean, standard deviation, 25th percentile, median and 75th percentile are calculated for banks located in the same county that contains a bank litigated by the FDIC for the 2001 through 2007 sample period. The variables include total assets (TotAssets), cash and liquid assets scaled by total assets (LiqRat), total mortgage volume for all the bank's branches in the affected county ($MortVol), total number of mortgage applications for all the bank's branches in the affected county (#Applications), the total number of branches for a given bank in the affected county (#Branch), the total number of bank braches for all banks in the affected county (#CtyBranch), and Herfindahl indices calculated using total mortgage volume (MortHERF) and deposit bases (DepHERF) for all banks in the affected county.

	Mean	StDev	P(25)	Median	P(75)
TotAssets ($Mil)	70385.6	209712.5	224.4	952.5	18900.0
LiqRat	0.081	0.171	0.022	0.043	0.100
$MortVol ($Thou)	5702.1	21138.6	479	1557	4718
Dep ($Thou)	54005.9	440233.8	11386	26236	51519
#Applications	66.6	195.6	9	24	60
#Branch	5.8	10.7	1	3	6
#CtyBranch	181.9	264.3	33	87	226
MortHERF	0.347	0.231	0.185	0.281	0.429
DepHERF	0.301	0.243	0.137	0.218	0.377

Table 2: Deposit Flow in Surviving, Litigated Banks

The dependent variable in the regression models are bank-county level deposit bases. Litigated banks included in this sample are those that remain in the sample after the litigation announcement. Models 1 and 2 provide estimates over the 1994 to 2007 period, models 3 and 4 provide estimates over the 2001 to 2007 period, and model 5 provide estimates over the 2005 to 2007 period. Year and county fixed effects are included in some of the specifications. Dummy variables are included that take value one if the bank was litigated by the FDIC in year t-1 (Past), t (Current), and t+1 (Prior). Controls include lagged deposits, total assets (TotAssets) and the number of branches of the bank in a given county (#Branches). Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	$\ln(\text{Deposits})_t$	$\ln(\text{Deposits})_t$	$\ln(\text{Deposits})_t$	$\ln(\text{Deposits})_t$	$\ln(\text{Deposits})_t$
$\text{Fraud}_{\text{Prior}}$	0.0014	-0.0013	0.0106	0.0086	0.0298
	(0.020)	(0.020)	(0.025)	(0.026)	(0.035)
$\text{Fraud}_{\text{Current}}$	-0.0502 ***	-0.0532 ***	-0.0621 ***	-0.0642 ***	-0.0415 ***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.008)
$\text{Fraud}_{\text{Post}}$	-0.0121	-0.0152 *	-0.0070	-0.0097	-0.0102
	(0.008)	(0.009)	(0.012)	(0.013)	(0.014)
$\ln(\text{Deposits})_{t-1}$	0.8768 ***	0.8730 ***	0.8858 ***	0.8820 ***	0.8613 ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
$\ln(\text{TotAssets})_{t-1}$	0.0177 ***	0.0180 ***	0.0141 ***	0.0144 ***	-0.3216 ***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.093)
$\ln(\text{\#Branches})_{t-1}$	0.0271 ***	0.0246 ***	0.0285 ***	0.0258 ***	0.0400 ***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	No	Yes	No	Yes	Yes
2001-2007 Period Only?	No	No	Yes	Yes	No
2005-2007 Period Only?	No	No	No	No	Yes
N	163060	163060	93429	93429	54530
R2	0.8993	0.9001	0.9075	0.9083	0.9339

Table 3: Deposit Flow in Competing Banks

The dependent variable in these regressions are bank-county level deposit bases. Year and county fixed effects are included where indicated. Though not show, lagged total assets, the number of branches for a given bank in a county, and deposits are included as control variables in all specifications. Models 3 through 7 restrict the sample to counties that contain a bank litigated by the FDIC. Models 1 through 4 restrict the subperiod to the 1994 to 2007 period, models 5 and 6 to the 2001 to 2007 period, and model 7 to the 2005 to 2007 period. Dummy variables included as explanatory variables to denote if the minimum pairwise distance between the bank's branches and those of the litigated bank is between 0 and 5 miles, 5 and 10 miles, 10 and 15 miles, 15 and 20 miles, and 20 and 30 miles. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	$\ln(Deposits)_t$	$\ln(Deposits)_t$	$\ln(Deposits)_t$	$\ln(Deposits)_t$	$\ln(Deposits)_t$	$\ln(Deposits)_t$	$\ln(Deposits)_t$
$D_{[0mi,5mi),t}$	0.0926 ***	0.0854 ***	0.1124 ***	0.1095 ***	0.1008 ***	0.0994 ***	0.0883 ***
	(0.007)	(0.006)	(0.012)	(0.011)	(0.013)	(0.013)	(0.012)
$D_{[5mi,10mi),t}$	0.0431 ***	0.0369 ***	0.0612 ***	0.0573 ***	0.0399 ***	0.0378 **	0.0260
	(0.011)	(0.010)	(0.016)	(0.015)	(0.015)	(0.016)	(0.020)
$D_{[10mi,15mi),t}$	0.0067	0.0045	0.0248 **	0.0265 **	0.0177	0.0221	0.0095
	(0.008)	(0.008)	(0.011)	(0.012)	(0.013)	(0.014)	(0.017)
$D_{[15mi,20mi),t}$	-0.0022	-0.0010	0.0171	0.0212	-0.0102	-0.0005	-0.0152
	(0.012)	(0.011)	(0.016)	(0.016)	(0.014)	(0.016)	(0.019)
$D_{[20mi,30mi),t}$	-0.0206 *	-0.0189 *	-0.0017	0.0035	-0.0192	-0.0098	-0.0388 ***
	(0.012)	(0.011)	(0.016)	(0.015)	(0.022)	(0.021)	(0.014)
Full Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fraud County Subset?	No	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes
2001-2007 Period Only?	No	No	No	No	Yes	Yes	No
2005-2007 Period Only?	No	No	No	No	No	No	Yes
N	163060	163060	93429	93429	53264	53264	36908
R2	0.8993	0.9001	0.9075	0.9083	0.9071	0.908	0.9159

Table 4: Mortgage Originations

The dependent variables are constructed using mortgage origination volume. Total volume is used for models 1 through 5, and non-high-priced mortgage volume for model 6. Models 5 through 6 exclude subordinate lien mortgages, and are restricted to the 2005 to 2007 subperiod. The results are derived from difference-in-difference estimators around the litigation event years. Only competing banks located within a 5 mile radius of the litigated bank's branches and same county are used as the treatment group of banks. Control banks include those located outside a 10 mile radius, and are matched using mortgage volume share, deposit share and number of branches in the previous year. The text provide additional details. Total mortgage volume of the litigated bank ($Vol_Fraud), the Herfindahl index using mortgage volume across banks in a given county (MortHERF) and total number of mortgage applications (#Applications) are included as controls. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Mortgage Sale / Retained:	All	All	All	All	All	All
High Priced?	All	All	All	All	All	No HP
$\Delta\ln(Deposits)_t$	0.4165 ***	0.3528 ***	0.3230 ***	0.3214 ***	0.3239 ***	0.3540 ***
	(0.064)	(0.028)	(0.027)	(0.025)	(0.033)	(0.035)
$\Delta\ln(\$Vol)_{Fraud,t}$		-0.1214	-0.0908	-0.2370 **	-0.1028	-0.1029
		(0.091)	(0.077)	(0.107)	(0.109)	(0.087)
$\Delta\ln(MortHERF)_t$		0.8502	-0.4766	-0.4393	4.9296	3.7654 ***
		(2.496)	(1.686)	(1.300)	(1.521)	(0.976)
$\Delta\ln(\#Applications)_t$		15.0904 ***	14.0639 ***	13.7114 ***	20.5953 ***	22.6235 ***
		(2.231)	(1.871)	(2.750)	(3.002)	(2.597)
First Liens Only?	No	No	No	No	Yes	Yes
2005-2007 Period Only?	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
County Fixed Effects	No	No	Yes	Yes	Yes	Yes
N	2342	2342	2342	1549	1360	1360
R2	0.0969	0.187	0.2803	0.3391	0.3704	0.2244

Table 5: Private Mortgage Securitizations

The dependent variables are constructed using private securitization volume. Models 1 through 5 use mortgages privately securitized, model 6 uses non-high-priced mortgages privately securitized, and model 7 uses high-priced mortgages privately securitized to construct the dependent variable. Models 3 through 7 restrict the sample to the 2005 through 2007 period. Models 5 through 7 excludes subordinate lien mortgages. Year and county fixed effects are included when specificied. All specifications include the full set of control variables used in Table 4. Additional control variables included in some specifications include: retained mortgages or mortgages sold to GSEs ($Vol_Agency) and high-priced private securitization volume ($Vol_Sold&HP). Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Mortgage Sale / Retained:	Private	Private	Private	Private	Private	Private
High Priced?	All	All	All	All	No HP	HP
$\Delta\ln(Deposits)_t$	0.0927 *	0.1233 **	0.0674 *	0.1267 ***	0.1354 ***	-0.0008
	(0.049)	(0.055)	(0.038)	(0.030)	(0.025)	(0.021)
$\Delta\ln(\$Vol)_{Agency,t}$			0.1701 **	0.0811	0.0767	0.0107
			(0.077)	(0.108)	(0.104)	(0.021)
$\Delta\ln(\$Vol)_{Private\&HP,t}$					0.2793 ***	
					(0.047)	
Full Controls?	Yes	Yes	Yes	Yes	Yes	Yes
First Liens Only?	No	No	No	Yes	Yes	Yes
2005-2007 Period Only?	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2342	1549	1549	1360	1360	1360
R2	0.15	0.2205	0.2442	0.276	0.2938	0.1901

Table 6: Jumbo Mortgage Originations and Sales

The dependent variables are jumbo mortgages volume. Models 1 through 3 use jumbo mortgages volume, and models 4 through 6 use private jumbo securitization volume as the dependent variables. Inclusion of year and county fixed effects, as well as restriction to the 2005 through 2007 subperiod, apply where indicated. All specifications include the full set of control variables used in Table 4. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Mortgage Sale / Retained:	All	All	All	Private	Private	Private
$\Delta\ln(\text{Deposits})_t$	0.3924 ***	0.3656 ***	0.3291 ***	0.1587 ***	0.1283 ***	0.1399 ***
	(0.053)	(0.029)	(0.030)	(0.034)	(0.029)	(0.021)
Full Controls?	Yes	Yes	Yes	Yes	Yes	Yes
2005-2007 Period Only?	No	No	Yes	No	No	Yes
Year Fixed Effects	No	Yes	Yes	No	Yes	Yes
County Fixed Effects	No	Yes	Yes	No	Yes	Yes
N	2342	2342	1549	2342	2342	1549
R2	0.0875	0.2006	0.2282	0.0999	0.1894	0.2294

Table 7: Financial Constraints and Securitization

The dependent variables are constructed using first-lien mortgage volume. Model 1 uses retained non-high-priced mortgages or mortgages sold to GSEs; models 2 and 3 use non-high-priced mortgages privately securitized; and model 4 uses high-priced mortgages privately securitized to construct the dependent variables. All specifications include year and county fixed effects, as well as the full set of control variables used in Table 4. On-balance sheet liquidity ratio (LiqRat) is defined as the sum of cash and liquid securities, quantity scaled by total assets for the parent bank. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Mortgage Sale / Retained:	Non-Private	Private	Private	Private
High Priced?	No HP	No HP	No HP	HP
$\Delta\ln(\text{Deposits})_t$	0.2412 ***	0.1112 ***	0.1131 ***	-0.0044
	(0.039)	(0.036)	(0.031)	(0.012)
$\ln(\text{LiqRat})_{t-1}$	-2.1797	0.1873	0.0838	0.3639
	(1.871)	(1.348)	(0.941)	(1.767)
$\ln(\text{LiqRat})_{t-1}$ x $\Delta\ln(\text{Deposits})_t$	-0.7698 ***	0.0210	-0.0078	0.0980
	(0.092)	(0.275)	(0.245)	(0.224)
$\Delta\ln(\$Vol)_{Agency,t}$		0.0780 ***	0.0755	
		(0.108)	(0.103)	
$\Delta\ln(\$Vol)_{Private\&HP,t}$			0.2733 ***	
			(0.047)	
Full Controls?	Yes	Yes	Yes	Yes
First Liens Only?	Yes	Yes	Yes	Yes
2005-2007 Period Only?	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
N	1341	1341	1341	1341
R2	0.317	0.2599	0.277	0.1967

Table 8: Conditional Securitization Rates

The dependent variables are private securitization rates conditional on acceptance. Private securitization rates (SecRat) is calculed as the number of mortgages that are privately securitized scaled by the total number of mortgages originated. Exclusion of subordinate lien mortgages and restriction to the 2005 through 2007 subperiod are indicated when applicable. The full set of control variables used in Table 4 are included in all specifications. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	$\Delta SecRat_t$	$\Delta SecRat_t$	$\Delta SecRat_t$	$\Delta SecRat_t$
$\Delta \ln(Deposits)_t$	-0.0011	-0.0024	0.0010	-0.0025
	(0.004)	(0.006)	(0.002)	(0.002)
$\Delta \ln(\$Vol)_{Agency,t}$				-0.0197 ***
				(0.006)
$\Delta \ln(\$Vol)_{Private\&HP,t}$				0.0125 ***
				(0.001)
Full Controls?	Yes	Yes	Yes	Yes
First Liens Only?	No	No	Yes	Yes
2005-2007 Period Only?	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
N	2342	1549	1341	1341
R2	0.1764	0.3301	0.3491	0.409

Table 9: Integration in Securitization Activities

The dependent variables are constructed using first lien, mortgage volume excluding high-priced mortgages over the 2005 through 2007 subperiod. Models 1 and 2 use retained mortgages or mortgages sold to GSEs; and models 3 through 6 use mortgage volume privately securitized to construct the dependent variables. Broker is a dummy variable that takes value one if the bank belongs to a holding company that owns a securities dealer as a subsidiary, and zero otherwise. All specifications include the full set of control variables used in Table 4; and county and year fixed effects. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Mortgage Sale / Retained:	Non-Private	Non-Private	Private	Private	Private	Private
High Priced?	No HP	No HP	No HP	No HP	No HP	No HP
$\Delta\ln(\text{Deposits})_t$	0.3535 ***	0.3601 ***	0.0891 ***	0.0536 ***	0.0563 *	0.0224
	(0.022)	(0.024)	(0.029)	(0.017)	(0.031)	(0.040)
Broker_{t-1}		-0.4290			-0.5060	-0.4268
		(0.369)			(0.556)	(0.554)
$\text{Broker}_{t-1} \times \Delta\ln(\text{Deposits})_t$		-0.0227			0.1683 *	0.1618 **
		(0.110)			(0.087)	(0.082)
$\Delta\ln(\$Vol)_{Agency,t}$				0.0912		0.0900
				(0.062)		(0.062)
$\Delta\ln(\$Vol)_{Private\&HP,t}$				0.1474 ***		0.1410 ***
				(0.041)		(0.039)
Full Controls?	Yes	Yes	Yes	Yes	Yes	Yes
First Liens Only?	Yes	Yes	Yes	Yes	Yes	Yes
2005-2007 Period Only?	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1260	1260	1260	1260	1260	1260
R2	0.3316	0.3324	0.313	0.3238	0.3165	0.3267

Table 10: Alternative Matching Criteria

The dependent variables are private securitization volume in Panel A, and retained mortage volume or mortgages sold to GSEs in Panel B over the 2005 through 2007 subperiod. The dependent variables exclude subordinate lien mortgages. For each year and county, banks are divided into three bins according to rankings based on number of branches operated (#Branches), the proportion of deposits to total deposits (DepShare), and the proportion of mortgage applications to total mortgage applications (AppShare) in a given county. Only banks in the treatment group that can be matched to a bank in the control group within a similar bin based on #Branches (model 1), DepShare (model 2), AppShare (model 3) or all groups (model 4) are used for the specification. Standard errors are clustered on the bank and year levels, which are displayed below the coefficients in parentheses. Statistical significance levels of 10%, 5% and 1% are denoted by *, ** and ***, respectively.

Panel A: Retained Mortgages / Sales to GSEs

	(1)	(2)	(3)	(4)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Match:	# $Branches_{t-1}$	$DepShare_{t-1}$	$AppShare_{t-1}$	All
$\Delta\ln(Deposits)_t$	0.2591 ***	0.2278 ***	0.1763 ***	0.3452 ***
	(0.033)	(0.050)	(0.065)	(0.030)
First Liens Only?	Yes	Yes	Yes	Yes
2005-2007 Period Only?	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
N	777	772	753	163
R2	0.2912	0.3561	0.2793	0.5286

Table 10 (Continued)

Panel B: Private Securitizations				
	(1)	(2)	(3)	(4)
Dependent Variable:	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$	$\Delta\ln(\$Vol)_t$
Match:	# $Branches_{t-1}$	$DepShare_{t-1}$	$AppShare_{t-1}$	All
$\Delta\ln(Deposits)_t$	0.0932 ***	0.0949 ***	0.1046 ***	0.0492
	(0.008)	(0.019)	(0.019)	(0.043)
$\Delta\ln(\$Vol)_{Agency,t}$	0.0518	0.0618	0.0289	0.0738
	(0.137)	(0.124)	(0.127)	(0.135)
$\Delta\ln(\$Vol)_{Private\&HP,t}$	0.2486 ***	0.3235 ***	0.2132 ***	0.3719
	(0.076)	(0.067)	(0.057)	(0.314)
First Liens Only?	Yes	Yes	Yes	Yes
2005-2007 Period Only?	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
N	777	772	753	163
R2	0.2338	0.2626	0.307	0.3604

Figure 1: Number of Matched FDIC Litigations

The bar graph plots the number of FDIC orders by year from 1994 through 2007 used in the analysis.

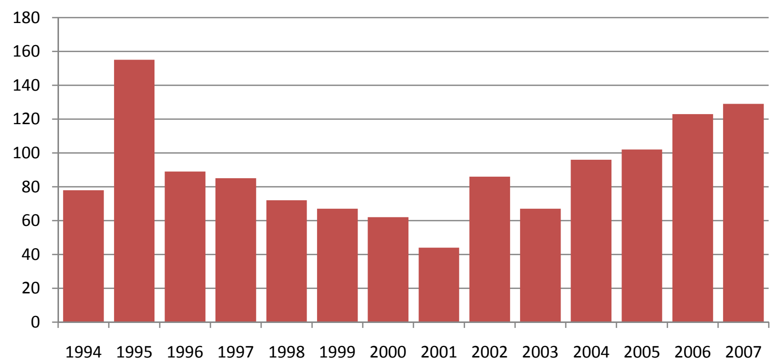
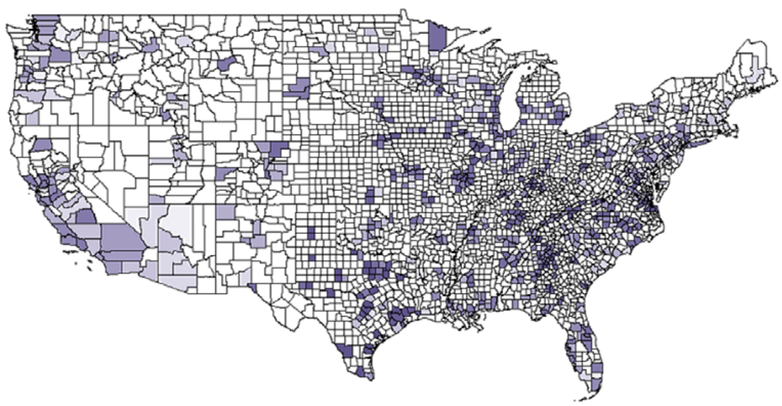


Figure 2: FDIC Litigations by County

The following figures plot surface graphs by county for the number of FDIC orders (Panel A) and number of bank branches (Panel B) for the 2001 through 2007 period. Darker colors denote larger values.

Panel A: FDIC Litigations by County



Panel B: Bank Branches by County

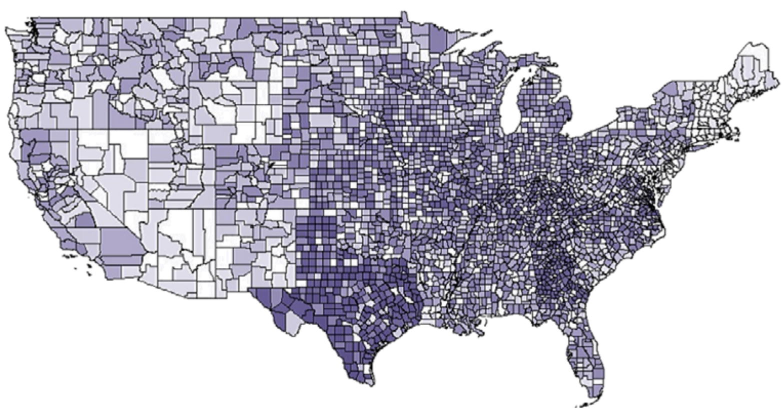
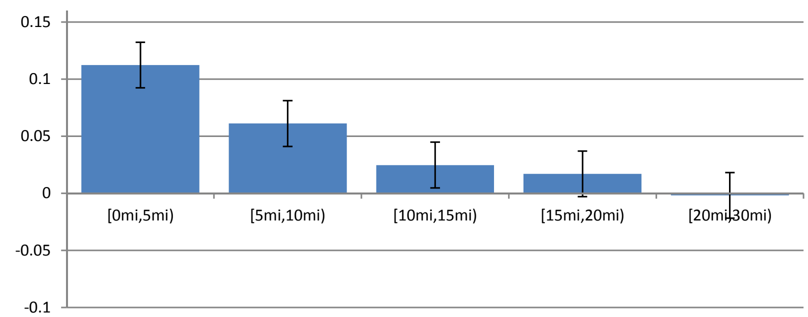


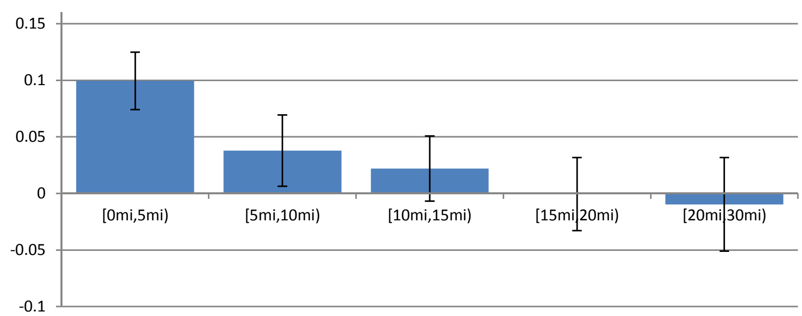
Figure 3: Impact of FDIC Litigation on Competitor Deposit Bases

The figures plot the dummy variable coefficients from Table 2 for models 2 (Panel A), 4 (Panel B), and 5 (Panel C). The coefficients are associated with dummy variables that denote banks located between 0 to 5 miles, 5 to 10 miles, 10 to 15 miles, 15 to 20 miles, and 20 to 30 miles from the litigated bank's branches. for each bar, the associated 99% confidence interval is also plotted.

Panel A: 1994-2007 Period



Panel B: 2001-2007 Period



Panel C: 2005-2007 Period