Regulatory Monitoring, Information Asymmetry and Accounting Quality: Evidence from the Banking Industry

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This version: 15 January 2016

Abstract

We examine how the information environment influences bank regulatory monitoring. Using distance between banks and regulatory field offices as a proxy for information asymmetry, we show that increases in distance reduces the quality of financial reporting. To establish causality, we use a quasi-natural experiment in a difference-in-difference setting that exploits multiple exogenous shocks to distance, an instrumental variable approach, as well as the enactment of the FDICIA Act of 1991 as a shock to the information environment. Our identification strategy provides evidence that regulators make use of local informational advantages to demand a higher quality of bank financial reporting. We further show that despite informational advantages, regulators strategically choose when to increase regulatory scrutiny and choose not to do so during the financial crisis when the risk of contagion is high. Overall, our study underscores the importance of local information in regulatory monitoring.

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1.0 Introduction

Banks manipulate their financial statements to manage earnings and regulatory capital (Ahmed, Takeda and Thomas, 1999; Beatty, Ke and Petroni, 2002). Manipulations of bank financial statements can lead to increases in both bank and systemic risk (Bushman and Williams, 2012; 2015), reductions in loan supply (Beatty and Liao, 2011), and a decrease in the market valuation of banks (Huizinga and Laeven, 2012). More recently, commenters blame lax regulatory oversight and poor accounting disclosure practices as antecedents of the recent financial crisis. [1]

Given the complexity and opacity of a banks' loan portfolio and banks' incentives to manipulate their financial statements (Bushman, Forthcoming), would superior information on local economic conditions and bank specific knowledge improve regulatory monitoring and lead to better bank accounting quality? Do regulators always make use of superior local information? In this paper, we provide empirical evidence on the role of the informational environment on the efficacy of regulatory monitoring.

We use the physical distance between a banks' headquarters and its' nearest regulatory office field office as a proxy for information asymmetry. Prior studies have shown that physical distance matters for lowering the cost of collecting new and soft information and decreases information asymmetry (e.g. Coval and Moskowitz, 2001; Malloy, 2005; Kedia and Rajgopal, 2011, Kubick and Lockhart; 2015). As banking regulators conduct both on and off-site monitoring of banks, geographical proximity is likely to be associated with superior information regarding local economic conditions that are tied to the quality of a banks' loan books and improve the efficacy of monitoring.

[1] For e.g. see http://www.reuters.com/article/us-financial-crisis-report-gop-idUSTRE70Q11S20110127

We use two measures to construct our proxy for accounting quality. Our main measure focuses on loan loss provisions (LLPs), which are the most important bank accrual used for managing earnings and regulatory capital (Kanagaretnam, Krishnan and Lobo, 2010) An extensive literature constructs proxies of the quality of financial statements by first estimating a model of LLPs then using the absolute value of its' residuals as indicators of discretionary or abnormal LLPs (Beatty and Liao, 2014). We investigate both the absolute magnitude of abnormal LLPs (ALLP) as well as its' sign to further assess if discretionary accounting is used to increase or decrease reported earnings.

Our second measure of accounting quality relates to the timeliness and magnitude of recording LLPs relative to changes in non-performing loans (e.g. Nichols, Wahlen and Wieland, 2009; Kanagaretnam, Lim and Lobo, 2014). As LLPs are accrued expenses and reflect the *expected* future losses of the loan portfolio, delays in provisioning obscures the true financial position of the bank by overstating current income.

Using hand-collected data on 208 regulatory field office locations belonging to the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve (Fed) and the Office of the Comptroller of the Currency (OCC) and the universe of small and medium sized U.S. commercial banks from 1984 to 2013, our baseline results show that increases in a banks' distance to the nearest relevant regulatory field office is negatively related to accounting quality. Banks which are located further away from regulatory offices have larger absolute discretionary LLPs as well as lower and less timely recognition of expected losses onto their financial statements. Examining the direction of discretionary LLPs reveals that distant banks manipulate LLPs to under-provision for expected losses to increase current income. Our results remain consistent to a rich set of robustness tests. Taken together, we provide evidence that distance reduces information asymmetry between banks' and regulators, leading to increase in efficacy of monitoring and better bank accounting quality

One challenge in interpreting our baseline results is that the association between bank accounting quality and distance could be driven by concerns of endogeneity, specifically reverse causality and unobserved omitted variables. We partially address issues of reverse causality, where banks with worst accounting quality deliberately relocate to escape regulatory scrutiny (Calluzzo, Wang and Wu, 2015), by removing banks that have relocated their headquarters or changed charters. To further establish causality, we use three different identification strategies that generates plausibly exogenous variations in distance or the informational environment.

Our first identification strategy relies on a quasi-natural experiment, the *closures* of regulatory field offices to generate plausibly exogenous *increases* in distance in a Difference-in-Difference (DiD) approach. We construct banks in our control group using a Propensity Score Matching (PSM) method to ensure that control and treated banks (banks that experience an increase in distance to regulatory offices due to closures) are similar along most observable characteristics in the *pre-shock* period. A key advantage of this approach is that there are multiple shocks (i.e. regulatory office closures) affecting different banks in different geographical locations at different times which rules out the possibility of potential omitted variables coinciding with a single shock that could affect accounting quality (Atanasov and Black, Forthcoming). Consistent with our baseline results, we find that compared to banks that were not affected by regulatory field office closures, increases in distance to regulatory offices leads to a deterioration in accounting quality.

The second identification strategy uses a 2-Staged Least Squared-Instrumental Variable approach (2SLS-IV). After the Federal Reserve Act was signed into law in 1913, the Reserve Bank Organization Committee (RBOC) relied heavily on votes by national banks on which cities should be allocated Federal Reserve Banks. We use the total number of votes obtained for each city in 1914 as our instrument for distance. The intuition behind our instrument is that banks located in Core-Based Statistical Areas (which housed these cities) with a higher number of votes would have a lower distance to Fed offices than banks located in CBSAs with lower or no votes as the number of votes is positively related to the probability of actually establishing a Federal Reserve Bank. We defend the exclusion criteria by noting that voting patterns for cities were determined by inter-bank relationships to operate the payments system as banks were restricted to single geographical locales before deregulations started in the 1970s (Jaremski and Wheelock, 2015). It is thus not obvious how voting patterns in 1914 would affect current accounting quality except through distance *after* controlling for other variables. Our results of our 2SLS-IV analysis are consistent with our baseline and DiD analysis and support a causal link.

The last identification strategy exploits the heterogeneous effects of the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) as an exogenous shock to the information environment. The FDICIA Act was enacted to empower more stringent and timely regulatory monitoring and enforcement. We hypothesized that the Act would lead to an increase in accounting quality for more *distant* banks compared to proximate banks due to ex-ante information asymmetries. Consistent with our hypothesis, geographically distant banks show a larger improvement in accounting quality after FDICIA than proximate banks. The results of the three identification strategies are consistent with our baseline results, supporting a causal link that superior information empowers regulatory monitoring that leads to a higher quality of financial reporting by banks.

After establishing a causal link that regulators possess superior knowledge (due to less information asymmetries) on the true loan performance of the bank and that this translates into demands for a higher quality of financial reporting, we show that regulators do *not always* exercise this superior information in restraining earnings management. We limit our sample to the 2008 to 2009 financial crisis and find that geographical proximity to regulatory field offices has no (or a reduced) explanatory effect on accounting quality. This suggests that regulators enforce different levels of scrutiny at different points of the economy despite possessing superior information for proximate banks. In crisis times where the risk of financial contagion is high, regulators choose to practice increased levels of forbearance and demand lower levels of accounting quality.

Our study contributes to existing literature in a number of ways. First, we show that information asymmetry between regulators and banks' influences the intensity and consistency of monitoring. Agarwal, Lucca, Seru and Trebbi (2014) show that state level banking regulators rate banks more leniently than federal regulators due to concerns over the local economy. We add to this literature by showing that information asymmetry as proxied by distance influences regulators' *ability* to impose their monitoring through the demand of higher accounting quality.

Secondly, we find that federal regulators strategically choose *when* to decrease regulatory scrutiny. While regulatory forbearance during crisis's has been documented (e.g. Brown and Dinc, 2011), less is known about regulators *ability* to practice forbearance due to information asymmetries (Bushman, Forthcoming). In this regard, our results complements Gallemore (2013) who show that bank opacity leads to regulatory forbearance. We contribute by establishing that ex-ante, regulators have different information sets regarding proximate banks that should persist even in crisis. Our findings that distance does not have an effect on accounting quality in crisis suggests that regulators while possessing *superior information*, chose to relax regulatory monitoring in times of financial stress to prevent contagion.

Lastly, we add to the literature on the effects of geographical proximity between economic agents and their outcomes (e.g. Coval and Moskowitz, 2001; Malloy, 2005). Most related to our paper is the study by Kedia and Rajgopal (2011). The authors find that firms which are closer to the U.S. Securities and Exchange Commission (SEC) are less likely to restate their financial statements. Our study differs to theirs in a number of ways. First, we show systemic evidence using multiple measures of accounting quality in a universe of banks while they study a relatively small sample of earnings restatements. Secondly, we establish causality using three different identification strategies. Lastly, we show that despite informational advantages, regulators actively choose when to decrease scrutiny.

2.0 Institutional Setting and Hypothesis Development

2.1 Institutional Setting and Bank Examinations

Commercial banks in the U.S. are supervised by one of three federal regulators depending on their charter. State-chartered banks that are members of the Federal Reserve (Fed) are regulated by the Fed while non-member banks are regulated by the Federal Deposit Insurance Corporation (FDIC). Nationally chartered banks are regulated by the Office of the Comptroller of the Currency (OCC).

Bank supervisors use both on and off-site monitoring as micro-prudential tools to assess the stability of a bank. Off-site monitoring requires banks to file quarterly Reports of Condition and Income (Call reports) that regulators use to monitor a banks' financial condition between on-site examinations. On-site "safety and soundness" examinations are conducted by teams of travelling examiners and are used to verify the accuracy of the contents of Call Reports, test and assess the validity of internal risk management processes and models, review loan portfolios and meet with and evaluate the management of the bank (Federal Deposit Insurance Corporation, 2015).

Examiners evaluate six main areas of a banks' financial position; capital adequacy, asset quality, management, earnings, liquidity and sensitivity to market risk and assign a composite CAMELS rating based on a 1 to 5 scale. Ratings of 1 and 2 are reserved for the banks with little or no regulatory concerns while ratings 3 to 5 are awarded to banks presenting moderate to high levels of risk and regulatory concerns.

2.2 Hypothesis Development

Given the complexity of a banks' loan portfolio, the efficacy of supervisory monitoring is then dependent on how much information a regulator has on the performance of banks and its' loans. The Federal Reserve Bank of St. Louis states "Gathering in-depth information for a district covering more than 180,000 square miles would be a challenging task to accomplish from a single location, especially given the diverse nature of the businesses and local economies in the Eighth District. Therefore, one of the key ways branches assist the St. Louis Fed is through the gathering of economic information from around their zones. Branches allow not only for a more efficient collection of information, but also for deeper relationships through staff involvement in their local economies, producing a depth and breadth of information not possible from hundreds of miles away."

We follow existing literature and use the distance between a banks' headquarters and regulatory field offices as a proxy for information asymmetry (e.g. Coval and Moskowitz, 2001; Malloy, 2005; Kedia and Rajgopal, 2011). Similarly, we hypothesize that proximity to bank headquarters proxies for the ease of collecting bank specific soft information. Additionally, as proximate banks and regulators share similar geographical locations, regulators are more likely to be aware of local economic conditions which would influence a banks' loan portfolio performance. As regulators have more information about a banks' true loan performance, banks are less likely to be able to manage earnings through loan loss provisions and are required to recognize timelier and larger provisions that are in line with its' true credit risk.

Hypothesis 1: Banks which are geographically proximate to banking regulatory offices have better accounting quality as regulators possess informational advantages which facilitates monitoring.

3. Data, Variables and Summary Statistics

3.1 Sample Selection

Our initial sample consist of all deposit taking U.S. commercial banks from 1984:Q1 to 2013:Q4. Financial data is obtained from quarterly filings of the Reports of Condition and Income for commercial banks (Call Reports) from the Federal Reserve Bank of Chicago. [2] We remove bank-quarter observations with missing or incomplete financial data for variables used in our regressions as well as banks with headquarters not in the 51 U.S. states. The geographical location of a banks' headquarters (zip codes) are available from Call Reports and is used to calculate the distance to regulatory offices.

Regulatory field office locations for the FDIC (available from 2002 to 2009), the Fed (1984 to 2013) and the OCC (2004 to 2013) are sourced from their respective websites, public documents and various sources. [3] We explain the data collection process of regulatory offices in greater detail in *Section 3.2.2*. Definition and sources of variables used in this study are described in Appendix A. Summary statistics of the variables are reported in Table 1. We limit our sample to small and medium sized banks with assets not exceeding 3 billion USD (after applying the 2009 GDP deflator) as regulatory discipline is likely to differ for large banks, who also have in-house regulators. We winsorize all bank financial variables at the 1% and 99%

[2] https://www.chicagofed.org/banking/financial-institution-reports/commercial-bank-data
[3] https://www.fdic.gov/about/contact/directory/#Field_Offices,
http://www.federalreserve.gov/otherfrb.htm and http://www.occ.treas.gov/about/who-we-are/district-and-field-offices/index-organization.html

percentile to prevent outliers from driving our results. Our final unbalanced sample consist of 9130 banks with 284,785 bank-quarter observations from 1984 to 2013.

3.2 Construction of Variables

3.2.1 Construction of Accounting Quality Variables

We describe the construction of abnormal LLPs in a two-step approach as our main proxy for accounting quality. LLPs are by far the largest and most important accrual for banks to manage earnings and regulatory capital (Kanagaretnam, Krishnan and Lobo, 2010; Beatty and Liao, 2014). In the first step, we estimate the nondiscretionary component of LLPs following Beatty and Liao (2014). The absolute values of the residuals of the LLP regression are the discretionary or abnormal LLPs (ALLP) and our proxy for the quality of accounting.

Interpreting abnormal LLPs as a proxy for accounting quality relies on the efficacy of the discretionary LLP model (Jiang, Levine and Lin, 2014). Beatty and Liao (2014) assess nine different models of LLP used in the banking literature and conduct factor analysis on these models. Beatty and Liao (2014) then construct four new models using results from the factor analysis and test their ability to predict earnings restatements and comment letters from the U.S. SEC. We use the two best performing models' (Model A and B) identified by Beatty and Liao (2014) to ensure that our results are not driven by the choice of a single model.

$$\begin{aligned} Model\ A: LLP_{i,t} &= \Delta NPA_{i,t+1} + \Delta NPA_{i,t} + \Delta NPA_{i,t-1} + \Delta NPA_{i,t-2} + Total\ Assets_{i,t-1} \\ &+ \Delta Loans_{i,t} + \Delta State\ GDP_{j,t} + \Delta State\ House\ Price\ Index_{j,t} \\ &+ \Delta State\ Unemployment\ Rate_{j,t} + Year\ Dummies \\ &+ State\ Dummies \qquad (1) \end{aligned}$$

$$Model\ B: LLP_{i,t} = \Delta NPA_{i,t+1} + \Delta NPA_{i,t} + \Delta NPA_{i,t-1} + \Delta NPA_{i,t-2} + Total\ Assets_{i,t-1} + \Delta Loans_{i,t} + \Delta State\ GDP_{j,t} + \Delta State\ House\ Price\ Index_{j,t} + ALW_{i,t-1} + \Delta State\ Unemployment\ Rate_{j,t} + Year\ Dummies + State\ Dummies \quad (2)$$

where i indexes bank, j indexes state, and t indexes time. The variables are defined as follows; LLP: loan loss provisions scaled by lagged total loans, ΔNPA: change in non-performing assets divided by lagged total loans, Total Assets: the natural logarithm of total assets, Δloans: change in total loans divided by lagged total loans, ΔState GDP: change in GDP of the state of the banks' headquarters, ΔState House Price Index: change in the return of the house price index provided by the Federal Housing Finance Agency of the state of the banks' headquarters, ΔState Unemployment Rate: change in the state unemployment rate of the state of the banks' headquarters, ALW: loan loss allowance divided by total loans. We also include state dummies to account for any time-invariant state characteristics that could influence loan loss provisioning and year dummies to capture changes in loan loss provisioning over time.

Current and future NPA reflects the possibility that banks could use forward-looking information on non-performing loans to estimate LLP (Bushman and Williams, 2012) and lags of NPA to control for the use of historical information in estimating LLP (Beatty and Liao, 2014). Total assets is included as banks of different sizes are subject to different levels of regulatory and market discipline (Jiang, Levine and Lin, 2014). We control for loan growth as increases in loans could reflect an increase in loans to less credit worthy borrowers which have higher default rates (Beatty and Liao, 2014). The inclusion of lagged ALW in Model B is to control for past values of loan loss allowance in setting this periods' LLP. High values of past ALW would result in requiring a lower LLP in the current period (Kanagaretnam, Krishnan and Lobo, 2010). State GDP, unemployment rate and the house price index capture macroeconomic conditions which could affect the default rate of loans and subsequently, LLP. We cluster standard errors at the bank level.

In the next step, we obtain the absolute value of the residuals (|ALLP A| and |ALLP B|) obtained from Equations 1 and 2 and use them as our proxy for the quality of accounting. The use of residuals as a proxy for accounting quality, earnings and capital management is standard in literature (see for e.g. Dechow, Ge and Schrand, 2010 and Beatty and Liao, 2014). In our main tests, we use the absolute values of the residuals. In further analysis, we investigate the sign of both negative abnormal LLPs (Neg ALLP) and positive ALLPs (Pos ALLP) that reflect income-increasing and decreasing discretionary uses of LLP respectively. Higher values of |ALLP| is associated with a lower quality of accounting.

3.2.2 Construction of Distance Variables

To construct our distance variable, we require panel data on the geographical locations of both the headquarters of the bank and federal regulatory field offices. Bank headquarter locations (zip codes) are obtained from quarterly Call Reports. We use a banks' headquarters when measuring its' distance to regulatory offices because on-site examinations involve discussion and evaluations of a banks' senior management and risk management units who often reside in the banks' headquarters.

We identify the location of regulatory field offices in a panel setting by consolidating data from multiple sources. To accurately construct our distance variable, we require historical data on all regulatory field offices which are not directly obtainable from regulatory websites as they only provide geographical information on current offices. To obtain historical locations of Federal Reserve Bank offices, we manually collect and verify regulatory office locations or relocations for the twelve Federal Reserve Banks and their branches from their Annual Reports, available from their respective websites or the Federal Reserve FRASER archive maintained by the Federal Reserve Bank of St. Louis. [4] When missing, we manually search and read through historical accounts detailing Federal Reserve Banks' histories which often include architectural descriptions as well as the physical location of buildings. [5] We are able to identify the exact geographical locations of all 37 unique Federal Reserve Banks and their branches from 1984 to 2013.

As the FDIC and OCC has considerably less information on the geographical locations of its' offices from their Annual Reports and websites due to its centralized structure as compared to the twelve Federal Reserve Banks, we rely on a different strategy to identify the historical locations of field offices belonging to the FDIC and OCC. We use Wayback Machine, a web archiving site (https://archive.org/web/) to access the websites of the FDIC and OCC at specific intervals across time. Accessing the regulatory websites across time enables us to obtain historical locations of FDIC and OCC field offices in a panel setting. One limitation of Wayback Machine however is that archiving of the FDIC and OCC websites began only in 1996 and 2004 respectively. Geographical locations of FDIC field offices are only available from the FDICs' website from 2002 to 2009 while data on OCC field office locations are available from 2004 to 2013. There are 93 unique FDIC and 78 OCC offices for the time periods listed above.

For each bank and field office, we obtain the pair of latitude and longitude coordinates corresponding to their zip codes from the U.S. Census Bureau Gazetteer. [6] We calculate the

[4] The links to the 12 Federal Reserve Banks can be obtained from: http://www.federalreserve.gov/otherfrb.htm. The Federal Reserve FRASER archive can be accessed from https://fraser.stlouisfed.org/search.php?q=annual%20report%20federal%20reserve

[5] An example would be from the Federal Reserve Bank of Boston; http://www.bostonfed.org/about/history/ "In 1977, the Boston Fed moved once more to its current site at 600 Atlantic Avenue in Dewey Square. The 1922 Reserve Building was declared a Boston Landmark in the 1980's and now serves as a luxury hotel, The Langham."

[6] https://www.census.gov/geo/reference/zctas.html

distance between a banks' headquarters to each regulatory field office using the Haversine Formula. The distance (in kilometres) between locations' 1 and 2 is computed as follows:

$$Distance_{12} = R\ x\ 2\ x \arcsin\left(\min\left(1, \sqrt{a}\right)\right)$$

$$where\ a = (\sin\left(\frac{lat2 - lat1}{2}\right))^2 + \cos(lat1)\ x \cos(lat2)\ x\ (\sin\left(\frac{lon2 - lon1}{2}\right))^2$$

$$and\ r \approx 6378\ km\ (the\ radius\ of\ the\ earth)$$

where Lat and Lon are the latitudes and longitudes of the 2 locations; the bank headquarters and regulatory field offices. We next identify the relevant federal regulator for each bank from their Call Reports to calculate the distance to the relevant regulatory office. Nationally chartered banks (NCB) are supervised by the OCC. State chartered banks who are not members of the Federal Reserve System are regulated by the FDIC while State chartered non-member banks are regulated by the Fed.

Our first distance measure *Distance* is the distance in km between a banks' headquarters to the nearest relevant federal regulator. The mean distance between a banks' headquarters and its' nearest relevant regulator is 121 kilometres. Our second measure is a dummy variable *Distance 100km Dummy* that equals to 1 if the distance to the nearest relevant regulator is more than 100km following Coval and Moskowtiz (2001), Malloy (2005) and Kedia and Rajgopal (2011).

4.0 Baseline Regression Results

4.1 Abnormal Loan Loss Provisions

To assess how monitoring intensity from banking regulators affects the quality of accounting of a bank via loan loss provisioning, we estimate the following model:

$$|ALLP|_{i,t} = Distance_{i,t} + Bank\ Controls_{i,t} + State\ Controls_{j,t} + County\ Controls_{k,t} + Regulator\ Dummies + Year\ Dummies \quad (3)$$

where i indexes bank, j indexes state, k indexes county and t indexes time. The dependent variable is the absolute value of the residuals in either Model A or B (Equation 1 or 2). The variable of interest is the banks' geographical distance in kilometres to the nearest relevant regulator. We standardize *Distance* for ease of interpretation. *Bank Controls* is a vector of bank characteristics that could affect ALLP. Following Ashbaugh, LaFond and Mayhew (2003) and Kanagaretnam, Krishnan and Lobo (2010), we include *Lag LLP, Loss, EBLLP, Total Assets, Equity* as well as *Total Deposits, Total Loans, Real Estate Loans, Commercial and Industrial Loans*, *Individual Loans* and *BHC*. *State controls* include Δ*State Unemployment Rate,* Δ*State House Price Index and* Δ*State GDP* while *Country Controls* is a vector consisting of *Log Income per County Capita, Log County Population, County HHI* and *County Density*. Refer to Appendix A for the definition and construction of these variables.

Table 2 presents the baselines regression results. Control variables are supressed for brevity and exhibit signs that are consistent with previous studies. The dependent variable for Columns (1) and (2) is the absolute value of the residuals obtained from Model A |*ALLP A*| while Columns (3) and (4) uses |*ALLP B*|. Both variants of our distance variable is significant at the 1% level in all columns. A one standard deviation increase in *Distance* is associated with a 5% increase in |*ALLP A*| in Column (1). These findings are consistent with our hypothesis that information asymmetry between regulators and banks decreases the efficacy of monitoring. Regulators with superior information demand higher levels of bank financial reporting.

4.2 Robustness Tests

We perform a number of additional tests to ensure the robustness of our baseline results. The results are displayed in Table 9. In Column (1), we exclude banks that are located in Alaska and Hawaii for general comparability with the other U.S. states. Our results remain statistically significant at the 1% level and the economic significance of *Distance* does not change as compared to our baseline regressions.

In Column (2), we re-run our baseline regression with only banks that have not relocated during our sample period. Banks who pursue aggressive earnings management might choose to relocate further away from regulatory offices to escape regulatory scrutiny; i.e. the reverse causality problem. We define relocations using two criteria's. The first criteria is that a relocation of a banks' headquarters results in a change in the county of the headquarters of the bank. This restriction prevents us from including banks that make small relocations within their default geographical locales due to reasons related to leasing or rent. Second, the change in location must not coincide with a merger or acquisition in the last four quarters. Banks that have undertaken M&A activities might choose to change the location of their headquarters for strategic reasons. Our results remain significant at the 1% level even after exclusion of these banks.

We next limit our sample to banks that have not changed their charters during our sample period. Similar to above, banks that changed their charters might do so to select their regulators, which could be related to ease of access. Our results remains robust as shown in Column (3).

Our last set of robustness tests is related to the geographical and urban clustering of banks. Banks could be clustered in economically important and populous cities and be driving our results. We exclude the Top 10 cities by population in 2010 (New York, Los Angeles, Chicago, Houston, Philadelphia, Phoenix, San Antonio, San Diego, Dallas and San Jose) in Column (4). We next include an interaction term *Distance x County Density* to further control for the effects of urban density in Column (5). Our results remain statistically significant at the 1% level in both tests.

5.0 Identification

In this section, we address potential concerns that our baseline results could be endogenous. Firstly, there could be concerns of reverse causality. Banks which are more likely to engage in earnings management could deliberately choose to locate further away from regulatory offices to escape scrutiny. We have partially addressed concerns of reverse causality in *Section 4.2* by running a sub-sample of banks that have not relocated or switched charters. Additionally, 75% (90%) of banks in our sample have 5(10) branches or less and are thus restrained by their deposit clientele and cannot choose to freely relocate, mitigating some concerns over reverse causality.

However, our results could also be biased by omitted variables that are correlated with both distance to regulatory offices and abnormal loan loss provisioning behaviour. To formally address concerns of endogeneity and establish causality, we use three different identification strategies.

5.1 Difference-in-Difference Approach

Our first identification strategy exploits closures of federal regulatory field offices to generate plausibly exogenous shocks in distance to relevant banking supervisors. Specifically, we compare the change in accounting quality for our sample of treated banks (banks that were affected by the closure of the regulatory field offices, and thus experienced an increase in distance to the next nearest relevant regulatory office) to a matched sample of control banks that were not affected by these closures.

While it can be argued that closures of regulatory field offices are not random and are based on strategic reasons to maximise supervisory efficiency and minimize costs, it is unlikely that these considerations are based on the characteristics of individual banks. Decisions to close regulatory offices are likely to be driven by *observable* geographical factors and the performance of banks under the field offices' jurisdiction. To ensure covariate balance, we use a propensity score matching (PSM) method to construct our sample of control banks before implementing the DiD analysis.

A key advantage of this identification strategy is that there are multiple shocks affecting different banks that are located in different geographical locations across time. This alleviates concerns of omitted variables coinciding with a single shock (field office closures) that could be correlated with bank accounting quality (Atanasov and Black, Forthcoming).

We identify regulatory office closures during the data collection process as explained in *Section 3.2.2*. We define a regulatory office as closed if an existing field office is not listed on the regulators' website in the following year. For example, the Federal Reserve Bank of New York Buffalo Branch last appeared in documents and its' website in 2008. We treat 2008 as *t-1* and 2009 as *t,* the event year. To ensure that field offices are not simply renamed following minor relocations, we manually check and compare the addresses of new field offices that appeared on regulatory websites after an existing field office disappears. If a new field office is listed following the disappearance of an existing field office remains in the same county, we do not include these instances as events of regulatory field office closures. In total, we are able to identify 11 (5 FDIC, 1 Fed and 5 OCC) events of field office closures.

The DiD analysis requires us to identify the treatment and control group. We classify a bank to be in the treatment group if the bank is affected by the regulatory office closure; i.e. the bank is under the jurisdiction of the field office that was subsequently closed. Additionally, the bank must not have relocated, not changed charters as well as have non-missing variables used in our baseline regression (Equation 3) for the periods *t-2, t-1, t, t+1 and t+2*. We choose a 5-year window as our FDIC sample period (2002 to 2009) is relatively short and extending the DiD window would result in us not being able to use all of the FDIC field office closures.

We construct our control group of banks by matching bank and geographical characteristics to those of the treatment group. Our matching procedure relies on a nearest-neighbour matching of propensity scores, developed by Rosenbaum and Rubin (1983) and used in recent studies such as Malmendier and Tate (2009) and Lemmon and Roberts (2010). The full sample of *potential* control banks are banks that were not affected by regulatory field office closures, did not relocate, did not change charters and have non-missing variables for the periods *t-2* to *t+2*.

In the first step, we run a Probit regression where the dependent variable *Pre-Match* is a dummy that equals one if the bank is in the treatment group (and zero if the bank is in the *potential* control group) for the years *t-1*. We include an additional control variable, *|Growth ALLP A|* alongside the bank and geographical variables used in our baseline regression as specified in Equation 3. As explained in Roberts and Whited (2012), the key identifying assumption of the DiD estimator is the parallel trends assumption. The parallel trends assumption requires any trends in outcomes (Abnormal LLPs) to be similar for both the control and treatment groups prior to the treatment. By including the growth of ALLP, we ensure satisfaction of this assumption.

The results of the Probit model are reported in Column (1) of Table 3. The specification has a pseudo-R^2 of 18.1% and a p-value of 0.00 for the Chi-squared test. This suggests that the model has significant explanatory power in predicting treatment. We next use the predicted probabilities, or propensity scores from the Probit model to perform a nearest-neighbour matching with replacement. We match each treatment bank with ten control banks with the nearest propensity score. [7] The process yields 238 unique treatment and 1344 control banks. We re-run our Probit model with our matched sample in Column (2) of Table 3. Most of the previously significant variables including |*Growth ALLP A*| in the Pre-Match equation are now insignificant. Furthermore, the pseudo-R^2 falls to 1.3% and the p-value for the Chi-squared test is now 0.8. This suggests that post-match and pre-shock, our control and treatment group of banks are now similar along many observable characteristics including the propensity to be treated.

Columns (3) and (4) of Table 3 report the results of our DiD analysis. Our variable of interest is the interaction term *Treated x Post*. It is equal to one for treated banks in periods *t+1* and *t+2*. The variable is statistically significant at the 5% level for both models A and B. Additionally, the economic effect is sizable; the coefficient on the DiD interaction term for Model A is 0.022. Interpreted, this means that relative to banks that were not affected by regulatory field office closures, treated banks increased the magnitude of their earnings management via LLP by 7% post-shock. In sum, the DiD analysis using exogenous shocks to distance provides similar results as our baseline analysis which allows us to infer causality.

5.2 Instrumental Variable Approach

Our second identification strategy uses a 2SLS-instrumental variable approach. After the enactment of the Federal Reserve Act in 1913, the Reserve Bank Organization Committee (RBOC) was tasked in determining the number of Federal Reserve Districts, the boundaries of each district, and the location of the Federal Reserve Banks. Jaremski and Wheelock (2015) show that the RBOC relied heavily on votes by national banks in selecting the cities for Federal

[7] We also perform a 1 to 5 matching and results remain quantitatively similar.

Reserve Banks, and that the number of votes were positively correlated to the probability of a city being selected to house Federal Reserve Banks.

We instrument distance using the number of votes received for each city in 1914 during the establishment of the Federal Reserve System. The intuition behind our instrument is that banks located in high vote Core-Based Statistical Areas (CBSAs) housing these cities would have a lower distance to Fed offices than banks located in CBSAs with lower or no votes as the number of votes is positively related to the probability of actually establishing a Fed Reserve Bank.

For our instrument to be valid, it must fulfil the exclusion criteria; that the instrument only affects abnormal LLPs through distance to regulatory offices *after* controlling for other factors. Because the exclusion criteria is untestable, we provide economic reasons to motivate our choice of instrument. To do so, we must understand the determinants of votes for particular cities by banks in 1914. Jaremski and Wheelock (2015) study the determinants of vote choices and find that bank correspondent links explained voting patterns. In 1914 (before banking deregulations began in 1970s), banks were limited to a single geographical location and that correspondent links to banks in large financial cities were necessary to operate the payment system, collect checks and drafts on distant locations and hold deposits. It is not obvious how correspondent links (which explained voting patterns), a necessity due to restrictions on bank branching and a less sophisticated payments system over a 100 years ago could affect current abnormal LLPs.

We construct our instrument using data provided in Jaremski and Wheelock (2015) and reproduced in Appendix B. We match the total number of votes for each city to the corresponding CBSA and subsequently, attribute it to the banks that are geographically located in that CBSA. For example, there were 673 votes for the city of New York. Following, banks that are geographically located in CBSA Code 35620 (New York-Newark-Jersey City) received a value of 673 for our instrument, the total number of votes. Comparatively, banks which are located in CBSAs without any votes received a value of 0. Thus, banks which are located in CBSAs with a larger number of 1914 votes are expected to have shorter distances to Fed offices due to these cities having a higher probability of being allocated Fed offices.

The results of the first and second-staged IV regressions are reported in Table 4. We restrict our sample to banks located in CBSAs. Banks not geographically located in CBSAs would naturally not be plausibly expected to be in or near any cities that would be candidates for Federal Reserve Banks. We limited our sample to Fed regulated banks. We include similar control variables as our baseline OLS regression as specified in Equation 3 but do not show them for brevity.

The first-staged result of our baseline IV regression is shown in Column (1) and the second-staged in Column (2) of Table 4. The *t-stat* of 13 on the instrument *First Choice Votes in 1914* in the first-staged coupled with a Kleibergen-Paap rK Wald F stat of 134 alleviates concerns that our instrument is weak. The coefficient on *First Choice Votes in 1914* is negative, suggesting that the number of first choice votes for cities is negatively related to distance to regulatory office in these cities, as predicted. In the second-staged, *Distance* remains positive and significant at the 1% level.

We test the robustness of our results to a number alternate specifications. In Columns (3) and (4), we exclude the state of New York and California. The cities of New York and San Francisco were important economic cities and were undoubtedly going to be allocated Federal Reserve Banks (Jaremski and Wheelock, 2015). Our results continue to remain statistically significant at the 1% level.

It can also be argued that banks with higher levels of earnings management could choose to relocate away from Fed offices after its establishment. As we are unable to observe bank addresses in 1914, we test for this by limiting our sample in Column (5) to small community banks with less than 5 or less branches. It is reasonable to assume that business decisions on where to headquarters and branch are driven by considerations of the local clientele and not related to the location of regulatory offices (DeYoung, Hunter and Udell, 2004). We report the results of the second-staged in Column (5). *Distance* continues to remain statistically significant at the 1% level.

5.3 FDICIA as an Exogenous Shock

Our final identification strategy uses the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) as an exogenous shock and its' heterogeneous effects through distance on abnormal LLP. The FDICIA Act of 1991 was enacted to empower banking regulators to exercise more timely supervision and to resolve troubled financial institutions before failure.

Formally, the Act required regulators to increase the frequency of on-site examinations of banks to 12-18 month intervals, as compared to a mean on-site interval of 600 days before FDICIA (Kane, Bennett and Oshinsky, 2008). We hypothesize that FDICIA would have heterogeneous effects on banks that is dependent on their distance to regulatory offices. Banks which are located closer to regulatory offices should decrease the magnitude of their earnings management on the onset of more stringent supervision *less* than banks located further away. The underlying assumption is that if distance functions as a proxy for information asymmetry and the stringency of monitoring, geographically proximate banks would already be subject to more intense monitoring pre-FDICIA.

We report our results in Table 5. As before, we include all control variables used in our baseline regression in Equation 3 and suppress them for brevity. *Post FDICIA* is a dummy variable that equals to one for years 1992 to 1995 and 0 for years 1988 to 1991. We investigate the effects of FDICIA in an 8-year window. [8] Our variable of interest is the interaction term *Distance x Post FDICIA*. We limit our sample to Fed regulated banks as we do not have data on the distance to FDIC and OCC regulatory field offices for this time period.

The coefficient of the interaction term is negative and statistically significant at the 5% level in both Columns (1) and (2). This suggests that banks which are located *further* away from regulatory offices decreased their abnormal LLPs *more* than banks which are geographically proximate after the implementation of FDICIA. This interpretation is consistent with predictions.

Overall, the results of all three identification strategies are consistent with our baseline regressions and suggests a causal relationship between accounting quality and distance. This evidence supports our hypothesis that geographical proximity helps mitigate information asymmetries between banks and regulators and facilitates regulatory monitoring leading to a higher quality of bank financial reporting.

[8] Our results are similar when using a 6-year window (1989 to 1994) and a 10-year window (1988 to 1996).

6.0 Further Analysis

6.1 Signed Abnormal LLPs

In this section, we estimate the ALLP model separately for negative (income-increasing) and positive (income-decreasing) ALLP. Negative ALLPs are of particular interest as income-increasing manipulations of LLPs leads to an overstatement of earnings, which are part of Tier 1 capital. Additionally, LLPs are understated in relation to the riskiness of the loan credit portfolio. We use the same baseline equation as Equation 3 but replace the dependent variable with either the positive or negative ALLP. The results are displayed in Table 6. Columns (1) and (2) report estimates for negative ALLPs *Neg ALLP A* while Columns (3) and (4) show positive ALLPs *Pos ALLP A*, both from Models A. [9] The controls are similar to our baseline model in Equation 3 and are again supressed for brevity.

The coefficient on *Distance* and *Distance 100km Dummy* are negative and statistically significant at the 1% level in our regression when the dependent variable is income-increasing negative abnormal LLPs *Neg ALLP*. Interpreted, this means that the further the bank is from regulatory offices, the more negative is the negative ALLP. The economic significance is sizable. A one standard deviation increase in distance increases the magnitude of negative ALLP by 11% in Column (1).

The coefficients on both our distance measures are insignificant in Columns (3) and (4) where the dependent variable is *Pos ALLP*. These results suggest that our earlier findings of higher absolute abnormal LLPs are driven by income-increasing earnings management. Negative ALLPs represent an under-provisioning of loans relative to their credit risk and obscures the real risk and capital position of the bank.

[9] The results using Model B are similar and are not shown for brevity.

6.2 Conditional Conservatism

In a second related test, we follow Nichols, Wahlen and Wieland (2009) and Kanagaretnam, Lim and Lobo (2014) and investigate the timeliness and magnitude of loan loss provisioning with respect to non-performing loans. Loan loss provisions are accrued expenses and reflect the expected future losses of the loan portfolio. When banks' delay recognition of expected losses by under-provisioning in LLP, a current expense is not recorded for some losses expected to occur in the future. We show that consistent with evidence provided in this study, banks which are geographically proximate to regulators recognize timelier and larger provisions with respect to non-performing loans.

To estimate the timeliness and magnitude of loan loss provisioning, we follow Nichols, Wahlen and Wieland (2009) and Kanagaretnam, Lim and Lobo (2014) and estimate the model as:

$$\begin{aligned} LLP_{i,t} = {} & \Delta NPL_{i,t-1} + \Delta NPL_{i,t} + \Delta NPL_{i,t+1} + NCO_{i,t} + NCO_{i,t+1} + Distance_{i,t} \\ & + \Delta NPL_{i,t-1}\ x\ Distance_{i,t} + \Delta NPL_{i,t}\ x\ Distance_{i,t} \\ & + \Delta NPL_{i,t+1}\ x\ Distance_{i,t} + NCO_{i,t}\ x\ Distance_{i,t} \\ & + NCO_{i,t+1}\ x\ Distance_{i,t} + LLA_{i,t-1} + Indiv\ Loans_{i,t-1} + Tier1_{i,t} \\ & + Loan\ Growth_{i,t} + Total\ Assets_{i,t} + State\ Controls_{j,t} \\ & + County\ Controls_{k,t} + Regulator\ Dummies + Year\ Dummies \qquad (4) \end{aligned}$$

where *i* indexes bank, *j* indexes state, *k* indexes county and *t* indexes time. *State controls* include Δ*State Unemployment Rate,* Δ*State House Price Index and* Δ*State GDP* while *Country Controls* is a vector consisting of *Log Income per County Capita, Log County Population, County HHI* and *County Density*. Refer to Appendix A for the definition and construction of these variables.

Our variables of interest are the three interaction terms of $\Delta NPL_{i,t-1}$ *x Distance* , $\Delta NPL_{i,t}$ *x Distance* and $\Delta NPL_{i,t+1}$ *x Distance* in Columns (3) and (4) of Table 7. Control variables are suppressed for brevity. The coefficient on all three interaction terms are negative and statistically significant at the 1% level for both proxies of distance. These results indicate that as distance to regulatory offices increase, banks recognize *smaller* and *less timely* loan loss provisions. Similar to the consequence from income-increasing ALLP, a smaller loan loss provisioning masks' the true credit risk of the bank by not allowing for future expected losses.

Additionally, delaying expected losses which are expected to materialise in the future can lead to an overhang of unrecognized expected losses that can increase capital inadequacy concerns during economic downturns by compromising the ability of loan loss reserves to cover both unexpected recessionary losses and losses that are deliberately delayed (Bushman and Williams, 2015).

7.0 Financial Crisis

Lastly, we exploit differences in distance, our proxy for regulatory scrutiny due to informational advantages to explore the role of regulatory forbearance during the 2008 to 2009 financial crisis. Previous studies have shown that regulators are more like to practice forbearance when the economy is weak (Brown and Dinc, 2011; Morrison and White, 2013). There is however less evidence on a regulators' *ability* to practice forbearance (Bushman, Forthcoming).

We perform the same set of tests (Absolute ALLP, Signed ALLP and conditional conservatism) during the 2008 to 2009 financial crisis. Because we show that regulators have more information on proximate banks and that this leads to better accounting quality, we can now observe how accounting quality changes in the crisis conditional on distance. Our results are shown in Table 8. The coefficient on our variables of interest *Distance* and *Distance x*

$\Delta NPL_{i,t-1}$, *Distance x* $\Delta NPL_{i,t}$ and *Distance x* $\Delta NPL_{i,t+1}$ are all insignificant in Columns (1), (3) and (4). Although *Distance* is still significant at the 1% level in our Negative ALLP (income-increasing earnings management) regression in Column (2), the economic magnitude falls from 11% to 7% as compared to the full-sample test.

Interpreted, our results suggest that *despite* informational advantages of proximate banks in normal times, regulators do not or are unwilling to impose additional scrutiny in financial crisis. This result complements findings by Gallemore (2013) who show that opaque banks experienced greater forbearance and were less likely to fail during the crisis. We show that *despite* having the *ability* to more accurately assess and monitor proximate banks, regulators do not do in times of economic downturns.

8.0 Conclusion

This paper studies the relationship between geographical proximity to banking regulatory offices and the accounting quality of the bank. Using the universe of small and medium sized commercial banks in the U.S. in an unbalanced panel from 1984 to 2013, we find that increases in distance (information asymmetry) decreases the quality of accounting information disclosed in banks' financial reports. Specifically, distant banks manage earnings more through LLPs, (have larger absolute discretionary accruals), have larger income-increasing abnormal accruals (under-provisioning in LLPs) and recognize smaller and less timely LLPs coinciding with non-performing loans. We provide evidence that local informational advantages decreases the information asymmetry between regulators and banks. Decreases in information asymmetry increases the efficacy of regulatory monitoring leading to a higher quality of financial reporting by banks.

We establish the causality of our results using three different identification strategies. Our first identification strategy uses a quasi-natural experiment, the closure of regulatory field offices, in a DiD approach that generates exogenous increases in distance. The second identification strategy uses a 2SLS-IV approach. We instrument distance using the number of votes received for each city in 1914 during the establishment of the Federal Reserve System. The intuition behind our instrument is that banks located in Core-Based Statistical Areas (which housed these cities) with a higher number of votes would have a lower distance to Fed offices than banks located in CBSAs with lower or no votes as the number of votes is positively related to the probability of actually establishing a Fed Reserve Bank. The last identification strategy exploits the implementation of the FDICIA Act of 1991 as an exogenous shock to the information environment. The FDICIA Act empowered regulators to conduct more timely and stringent supervisions of banks. We show that banks which are located further away from regulatory offices show a greater increase in accounting quality after FDICIA, consistent with our hypothesis that information asymmetry increases alongside distance and that this impedes monitoring.

Our paper provides an empirical study on how the information environment can affect regulatory monitoring. Additionally, we show that regulators do not always make use of local information. In times of financial crisis, distance to regulators has no predictive power on accounting quality. This suggests that despite geographical informational advantages and having the ability to more accurately evaluate proximate banks' financial reports, regulators strategically choose when to decrease regulatory scrutiny to avoid contagion when the economy is weak. We shed light on the how information asymmetry can affect regulatory monitoring and how regulators make use of superior information in their demand for higher accounting standards by banks.

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Table 1: Summary Statistics

This table reports summary statistics for the variables used in this study. Refer to Appendix A for the construction and definition of these variables. The sample consists of U.S. commercial banks with assets not exceeding 3 billion USD (using the 2009 GDP deflator) for the period 1984 to 2013. Bank financial variables are winsorized at the 1% and 99% levels. N is the number of bank-quarter observations.

Variables	(1) N	(2) Mean	(3) Std. Dev	(4) p1	(5) p25	(6) p50	(7) p75	(8) p99
Distance	284,785	121.712	128.72	0	50.77	99.1	160.81	469.9
Distance 100km	284,785	0.494	0.500	0	0	0	1	1
First Choice Votes in 1914	284,785	72.83	194.7	0	0	0	0	906
Reg by FDIC	284,785	0.489	0.500	0	0	0	1	1
Reg by Fed	284,785	0.321	0.467	0	0	0	1	1
Reg by OCC	284,785	0.190	0.392	0	0	0	0	1
BHC	284,785	0.811	0.392	0	1	1	1	1
Total Deposits	284,785	0.839	0.0685	0.580	0.808	0.855	0.888	0.932
Total Loans	284,785	0.628	0.156	0.186	0.532	0.648	0.744	0.888
Loan Growth	284,785	1.024	0.0680	0.879	0.989	1.016	1.045	1.298
Equity	284,785	0.105	0.0354	0.0547	0.0829	0.0966	0.118	0.246
Tier 1	249, 234	0.102	0.353	0.057	0.09	0.092	0.113	0.243
EBLLP	284,785	0.00736	0.00598	-0.0104	0.00344	0.00662	0.0108	0.0254
Loss	284,785	0.0900	0.286	0	0	0	0	1
Total Assets	284,785	11.58	1.128	9.138	10.80	11.52	12.30	14.42
Real Estate Loans	284,785	0.631	0.198	0.0811	0.507	0.663	0.783	0.944
Agri Loans	284,785	0.0857	0.136	0	0	0.0172	0.117	0.586
CI Loans	284,785	0.160	0.105	0.00686	0.0869	0.138	0.208	0.547
Indiv Loans	284,785	0.102	0.0992	0.00114	0.0338	0.0727	0.137	0.491
|A LLP A |	284,785	0.312	0.460	0.00443	0.0927	0.191	0.350	2.936
|A LLP B |	284,785	0.309	0.439	0.00385	0.0843	0.186	0.363	2.742
Neg ALLP A	193,383	-0.236	0.185	-0.861	-0.317	-0.190	-0.102	-0.00600
Pos ALLP A	91,402	0.482	0.784	0.00276	0.0726	0.194	0.491	4.216
LLP	284,785	0.00310	0.00621	-0.00159	0.000272	0.00121	0.00315	0.0356
Lag LLP	284,785	0.00188	0.00368	-0.000829	0.000163	0.000752	0.00197	0.0216
Lag LLA	284,785	0.0151	0.00799	0.00453	0.0105	0.0130	0.0170	0.0509
Forward NCO	284,785	0.00233	0.00565	-0.00289	0	0.000507	0.00216	0.0326
NCO	284,785	0.00225	0.00551	-0.00287	0	0.000478	0.00209	0.0314
Δ Lag NPL	284,785	0.000375	0.00948	-0.0273	-0.00199	0	0.00211	0.0331
Δ NPL	284,785	0.000415	0.00960	-0.0275	-0.00200	0	0.00215	0.0338
Δ Forward NPL	284,785	0.000424	0.00973	-0.0277	-0.00203	0	0.00219	0.0342
Δ State House Price Index	284,785	0.00691	0.0166	-0.0448	0.000593	0.00844	0.0144	0.0520
Δ State GDP	284,785	0.0443	0.0341	-0.0591	0.0298	0.0459	0.0635	0.112
Δ State Unemployment Rate	284,785	0.0596	0.213	-0.211	-0.0862	0	0.135	0.730
County HHI	284,785	1,172	709.1	190.7	650.6	996.7	1,485	2,526
County Density	284,785	0.000314	0.00177	7.14e-07	1.12e-05	2.75e-05	0.000131	0.00359
Log Income per County Capita	284,785	3.414	0.329	2.537	3.240	3.434	3.619	4.157
Log County Population	284,785	4.287	1.749	1.258	3.005	3.851	5.494	8.581

Table 2: Baseline Analysis of Accounting Quality and Distance to Regulator

This table reports estimates of Absolute Abnormal LLPs on Distance (Equation 3) using pooled-OLS regressions. The sample period is an unbalanced panel from 1984:Q1 to 2013:Q4 (bank-quarter observations). Refer to Appendix A for construction and definition of variables. The dependent variable in Column (1) and (2) is the ALLP from Model A (Equation 1) while Columns (3) and (4) uses ALLP from Model B (Equation 2). Bank controls includes: Lag LLP, Loss, EBLLP, Total Assets, Equity, Real Estate Loans, Agri Loans, CI Loans, Indiv Loans, Total Deposits, Total Loans and BHC. County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) |ALLP A|	(2) |ALLP A|	(3) |ALLP B|	(4) |ALLP B|
Distance	0.015***		0.010***	
	[5.942]		[3.840]	
Distance 100km Dummy		0.014***		0.012***
		[5.229]		[4.283]
Bank controls	Yes	Yes	Yes	Yes
County/State controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regulator fixed effects	Yes	Yes	Yes	Yes
Observations	284,785	284,785	284,785	284,785
Adj. R-squared	0.432	0.432	0.425	0.425

Table 3: DiD Analysis of Accounting Quality and Distance to Regulator

This table reports the diagnostics and results of the DiD tests. Refer to Appendix A for construction and definition of variables. The dependent variable *Pre-Match* in Column (1) is a dummy variable that = 1 if banks are in the treatment group and 0 if otherwise. We define banks in the treatment group as banks that have been affected by regulatory field office closures. Column (1) is a Probit regression for t-4 quarters before the closure of a regulatory office and shows the pre-matched differences between treatment and pre-matched non-treated banks. *Post-Match* in Column (2) is a dummy variable that = 1 if banks are in the treatment group and 0 if banks are in the control group. Banks in the control group are matched to treatment banks using the Probit model specification specified in Column (1) to their nearest neighbour. We match each treatment bank with ten control banks with the nearest propensity score. Column (2) shows the post-matched differences between treatment and post-matched control banks for t-4 quarters before the closure of a regulatory office. Columns (3) and (4) show estimates of the DiD analysis using Absolute ALLP from Models A and B(Equation 1 and 2) respectively. The DiD analysis is carried out over a 5-year window (t-2, t-1, t, t+1 and t+2) where t is the year of regulatory office closure. *Treated* is a dummy variable that = 1 if a bank is in the treated group and 0 if the bank is in the group as matched in Column (2). *Treated x Post* is a dummy variable that = 1 if the bank is in the treatment group and in years t+1 or +2. *Treated x Post* is our DiD interaction term of interest. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) Pre-Match	(2) Post-Match	(3) |ALLP A|	(4) |ALLP B|
Treated			-0.013	-0.018*
			[-1.559]	[-1.875]
Treated x Post			0.022**	0.024**
			[2.145]	[2.297]
Distance	-0.057	0.074		
	[-0.801]	[0.685]		
|Growth ALLP A|	0.001	0.003		
	[0.377]	[1.071]		
Lag LLP	0.255	6.123	50.066***	48.734***
	[0.023]	[0.357]	[31.319]	[34.538]
Loss	-0.211	-0.156	0.524***	0.494***
	[-1.223]	[-0.602]	[17.830]	[18.801]
EBLLP	-6.489	-4.849	9.815***	8.392***
	[-1.149]	[-0.632]	[12.771]	[12.080]
Total Assets	0.069*	0.027	-0.007**	-0.009**
	[1.800]	[0.513]	[-2.158]	[-2.262]
Equity	1.109	0.987	-0.206**	0.322***
	[1.000]	[0.665]	[-2.485]	[2.674]
BHC	-0.116	-0.003	-0.004	-0.003
	[-1.446]	[-0.030]	[-0.553]	[-0.297]
Real Estate Loans	-0.312	-0.255	-0.108	-0.184*
	[-0.371]	[-0.225]	[-1.536]	[-1.878]
Agri Loans	-2.335**	-0.752	-0.008	-0.049
	[-2.511]	[-0.589]	[-0.094]	[-0.439]
CI Loans	-0.49	-0.449	-0.058	-0.065
	[-0.545]	[-0.366]	[-0.778]	[-0.622]
Indiv Loans	-0.547	-0.63	-0.131	-0.263**
	[-0.574]	[-0.506]	[-1.514]	[-2.393]
Total Deposits	1.544***	0.639	0.057	0.048
	[2.674]	[0.808]	[1.414]	[1.078]
Total loans	-0.560***	-0.028	-0.304***	-0.357***
	[-2.592]	[-0.097]	[-18.491]	[-14.829]
Log Income per County Capita	-0.359*	0.083	-0.01	-0.041**
	[-1.794]	[0.296]	[-0.651]	[-2.145]
Log County Population	-0.051	-0.069	0.004	0.003
	[-1.422]	[-1.288]	[1.206]	[0.618]
Δ State Unemployment Rate	-1.229***	-1.405**	0.117***	0.168***
	[-3.398]	[-2.259]	[4.963]	[7.366]
Δ State House Price Index	-28.002***	0.213	-2.385***	-1.607***
	[-8.133]	[0.029]	[-10.696]	[-7.493]
Δ State GDP	0.402	0.355	-0.700***	-0.526***
	[0.273]	[0.149]	[-6.696]	[-5.017]
County HHI	-0.0001***	-0.00008	0	0
	[-2.653]	[-1.019]	[-0.600]	[1.120]
County Density	-142.291	657.237**	26.356	44.241*
	[-0.923]	[1.966]	[1.142]	[1.866]
Year fixed effects	Yes	Yes	Yes	Yes
Regulator fixed effects	No	No	Yes	Yes
Observations	14,322	1,560	41,566	41,566
Psuedo/Adj. R-squared	0.181	0.013	0.428	0.411
P-value of Chi-squared	0.000	0.800	-	-

Table 4: IV-2SLS Analysis of Accounting Quality and Distance to Regulator

This table reports estimates of Absolute Abnormal LLPs on Distance (Equation 3) using an IV-2SLS approach. The sample period is from 1984:Q1 to 2013:Q4 (bank-quarter observations). Refer to Appendix A for construction and definition of variables. We restrict our sample to banks restricted by the Federal Reserve and banks located in CBSAs. The dependent variable in Columns (1) and (3) is *Distance* (1st-Staged) and *|ALLP A|* (2nd-Staged) in Columns (2), (4) and (5). Bank controls includes: Lag LLP, Loss, EBLLP, Total Assets, Equity, Real Estate Loans, Agri Loans, CI Loans, Indiv Loans, Total Deposits, Total Loans and BHC. County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	All CBSAs'		Excluding NY and Cali		<5 Branch
	(1)	(2)	(3)	(4)	(5)
	1st-Staged	2nd-Staged	1st-Staged	2nd-Staged	2nd-Staged
	Distance	|ALLP A|	Distance	|ALLP A|	|ALLP A|
First Choice Votes in 1914	-0.001***		-0.001***		
	[-13.008]		[-11.891]		
Distance		0.072***		0.065***	0.079***
		[4.742]		[3.716]	[3.66]
Bank controls	Yes	Yes	Yes	Yes	Yes
County/State controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	64,654	64,654	59,298	59,298	26,384
Adj. R-squared	0.316	0.432	0.31	0.435	0.411
Kleibergen-Paap rK Wald F stat.	-	134.01	-	141.4	94.173
Stock-Yogo weak ID critical Value (10%)	-	16.38	-	16.38	16.38

Table 5: FDICIA, Accounting Quality and Distance to Regulator

This table reports estimates of Absolute Abnormal LLPs on Distance and a Post FDICIA Dummy using pooled-OLS regressions. The sample period is from 1988:Q1 to 1995:Q4 (bank-quarter observations). Post FDICIA is a dummy variable that equals to one for years 1992 to 1995 and 0 for years 1988 to 1991. Refer to Appendix A for construction and definition of variables. We restrict our sample to banks restricted by the Federal Reserve. The dependent variable in Column (1) is the ALLP from Model A (Equation 1) while Column (2) uses ALLP from Model B (Equation 2). Bank controls includes: Lag LLP, Loss, EBLLP, Total Assets, Equity, Real Estate Loans, Agri Loans, CI Loans, Indiv Loans, Total Deposits, Total Loans and BHC. County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) |ALLP A|	(2) |ALLP B|
Distance	0.016*	0.013
	[1.669]	[1.358]
Post FDICIA	-0.081***	-0.033**
	[-5.236]	[-2.088]
Distance x Post FDICIA	-0.020**	-0.018**
	[-2.243]	[-1.972]
Bank controls	Yes	Yes
County/State controls	Yes	Yes
Year fixed effects	Yes	Yes
Observations	25,942	25,942
Adj. R-squared	0.395	0.401

Table 6: Signed Accruals and Distance to Regulator

This table reports estimates of the signed Abnormal LLPs on Distance (Equation 3) using pooled-OLS regressions. The sample period is an unbalanced panel from 1984:Q1 to 2013:Q4 (bank-quarter observations). Refer to Appendix A for construction and definition of variables. The dependent variable in Column (1) and (2) is the Negative ALLP from Model A (Equation 1) while Columns (3) and (4) uses the Positive ALLP from Model A (Equation 1). Bank controls includes: Lag LLP, Loss, EBLLP, Total Assets, Equity, Real Estate Loans, Agri Loans, CI Loans, Indiv Loans, Total Deposits, Total Loans and BHC. County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) Neg ALLP A	(2) Neg ALLP A	(3) Pos ALLP A	(4) Pos ALLP A
Distance	-0.026***		-0.004	
	[-12.506]		[-0.824]	
Distance 100km Dummy		-0.024***		-0.001
		[-11.116]		[-0.261]
Bank controls	Yes	Yes	Yes	Yes
County/State controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regulator fixed effects	Yes	Yes	Yes	Yes
Observations	193,383	193,383	91,402	91,402
Adj. R-squared	0.474	0.472	0.585	0.585

Table 7: Conditional Conservatism and Distance to Regulator

This table reports estimates of LLPs on Distance and interaction terms of Δ NPL (Equation 4) using pooled-OLS regressions. The sample period is an unbalanced panel from 1984:Q1 to 2013:Q4 (bank-quarter observations). Refer to Appendix A for construction and definition of variables. The dependent variable in Columns (1) to (4) LLP from Equation 4. Bank controls includes: Lag LLA, Lag Indiv Loans, Tier 1, Total Assets, Loan Growth, and BHC. County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) LLP	(2) LLP	(3) LLP	(4) LLP
Distance	0.000***		0.000***	
	[5.862]		[5.307]	
Distance 100km Dummy		0.000***		0.000***
		[4.115]		[4.512]
Δ Lag NPL	0.050***	0.050***	0.049***	0.055***
	[29.222]	[29.236]	[28.807]	[22.686]
Δ NPL	0.063***	0.063***	0.062***	0.068***
	[33.718]	[33.733]	[33.337]	[26.616]
Δ Forward NPL	0.029***	0.029***	0.029***	0.032***
	[19.356]	[19.373]	[19.189]	[15.399]
NCO	0.917***	0.917***	0.914***	0.932***
	[154.838]	[154.812]	[150.037]	[123.724]
Forward NCO	0.020***	0.020***	0.023***	0.008
	[4.654]	[4.670]	[5.360]	[1.425]
Distance x Δ Lag NPL			-0.008***	
			[-3.189]	
Distance x Δ NPL			-0.009***	
			[-3.326]	
Distance x Δ Forward NPL			-0.006**	
			[-2.523]	
Distance x NCO			-0.026***	
			[-2.676]	
Distance x Forward NCO			0.027***	
			[4.049]	
Distance 100km Dummy x Δ Lag NPL				-0.011***
				[-3.123]
Distance 100km Dummy x Δ NPL				-0.011***
				[-3.065]
Distance 100km Dummy x Δ Forward NPL				-0.008***
				[-2.599]
Distance 100km Dummy x Δ NCO				-0.037***
				[-3.156]
Distance 100km Dummy x Δ Forward NCO				0.028***
				[3.244]
Bank controls	Yes	Yes	Yes	Yes
County/State controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regulatory fixed effecs	Yes	Yes	Yes	Yes
Observations	249,234	249,234	249,234	249,234
Adj. R-squared	0.721	0.721	0.721	0.721

Table 8: Financial Crisis

This table reports estimates of Absolute Abnormal LLPs, Signed Abnormal LLPS and LLP on Distance (Equation 3, 3, 3 and 4 respectively) using pooled-OLS regressions. The sample period is an unbalanced panel from 2008:Q1 to 2009:Q4 (bank-quarter observations). Refer to Appendix A for construction and definition of variables. The dependent variable in Column (1), (2) and (3) is the Absolute ALLP, Negative ALLP and Positive ALLP from Model A (Equation 1) while Column (4) uses LLP from Equation 4. Bank controls for Columns (1) to (3) includes: Lag LLP, Loss, EBLLP, Total Assets, Equity, Real Estate Loans, Agri Loans, CI Loans, Indiv Loans, Total Deposits, Total Loans and BHC. Bank controls for Column (4) includes: Lag LLA, Lag Indiv Loans, Tier 1, Total Assets, Loan Growth, and BHC.County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) |ALLP A|	(2) Neg ALLP A	(3) Pos ALLP A	(4) LLP
Distance	0.006	-0.029***	-0.02	0
	[1.169]	[-9.525]	[-1.371]	[1.437]
Δ Lag NPL				0.057***
				[18.902]
Δ NPL				0.072***
				[22.720]
Δ Forward NPL				0.024***
				[9.832]
NCO				1.021***
				[150.510]
Forward NCO				0.015**
				[2.408]
Distance x Δ Lag NPL				0.005
				[1.114]
Distance x Δ NPL				0.009*
				[1.772]
Distance x Δ Forward NPL				0.002
				[0.418]
Distance x NCO				-0.007
				[-0.684]
Distance x Forward NCO				0.017*
				[1.704]
Bank controls	Yes	Yes	Yes	Yes
Country/State Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regulator fixed effects	Yes	Yes	Yes	Yes
Observations	51,317	37,332	13,985	51,317
Adj. R-squared	0.445	0.406	0.573	0.795

Table 9: Baseline Robustness Tests

This table reports estimates of Absolute Abnormal LLPs on Distance (Equation 3) using pooled-OLS regressions. The sample period is an unbalanced panel from 1984:Q1 to 2013:Q4 (bank-quarter observations). Refer to Appendix A for construction and definition of variables. The dependent variable in Columns (1) to (25) is the ALLP from Model A (Equation 1). Bank controls includes: Lag LLP, Loss, EBLLP, Total Assets, Equity, Real Estate Loans, Agri Loans, CI Loans, Indiv Loans, Total Deposits, Total Loans and BHC. County/State controls include: Δ State House Price Index, Δ State GDP, Δ State Unemployment Rate, County HHI, County Density, Log Income per County Capita and Log County Population. Standard errors are clustered at the bank level. t-statistics are reported in parenthesis. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Excluding Alaska & Hawaii (1) |ALLP A|	No Relocation (2) |ALLP A|	No Charter Change (3) |ALLP A|	Excluding Top 10 Pop. Cities (4) |ALLP A|	County Pop. Density Interaction (5) |ALLP A|
Distance	0.015***	0.014***	0.016***	0.013***	0.016***
	[5.909]	[5.347]	[5.867]	[5.32]	[6.036]
County Density	-1.493*	-1.125	-0.939	13.53***	-10.046
	[-1.754]	[-1.227]	[-1.061]	[4.08]	[-1.064]
Distance x County Density					-10.665
					[-0.919]
Bank controls	Yes	Yes	Yes	Yes	Yes
Country/State controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Regulator fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	284,537	261,521	235,750	257,669	284,785
Adj. R-squared	0.432	0.432	0.431	0.43	0.432

Appendix A: Definition of Variables

Variables	Definition	Source
Distance	Distance in km between a banks' headquarters to the nearest relevant regulatory field office	Call Report, Regulatory Websites, Public Documents
Distance 100km	Dummy variable that = 1 if the distance is more than 100km and 0 otherwise	Call Report, Regulatory Websites, Public Documents
First Choice Votes in 1914	Total number of votes by national banks for which cities should be allocated Fed Reserve Banks	Jaremski and Wheelock (2015)
Reg by FDIC	Dummy variable that =1 if the bank is regulated by the FDIC and 0 otherwise	Call Report
Reg by Fed	Dummy variable that =1 if the bank is regulated by the Fed and 0 otherwise	Call Report
Reg by OCC	Dummy variable that =1 if the bank is regulated by the OCC and 0 otherwise	Call Report
BHC	Dummy variable that = 1 if a bank is part of a Bank Holding Company	Call Report
Total Deposits	Total Deposits divided by Total Assets	Call Report
Total Loans	Total Loans divided by Total Assets	Call Report
Loan Growth	Total Loans divided by Lag Total Loans	Call Report
Equity	Total Equity divided by Total Assets	Call Report
Tier 1	Tier 1 Capital divided by Total Assets	Call Report
EBLLP	(Net Income before Extraordinary Items + Loan Loss Provisions) divided by Total Assets	Call Report
Loss	Dummy variable that = 1 if Net Income is negative and 0 otherwise	Call Report
Total Assets	Natural Logarithm of Total Assets	Call Report
Real Estate Loans	Real Estate Loans divided by Total Loans	Call Report
Agri Loans	Agricultural Loans divided by Total Loans	Call Report
CI Loans	Commercial and Industrial Loans divided by Total Loans	Call Report
Indiv Loans	Individual Loans divided by Total Loans	Call Report
|A LLP A |	Absolute value of the residuals of Model A (Equation 1) of the LLP regression	Authors calculation
|A LLP B |	Absolute value of the residuals of Model B (Equation 2) of the LLP regression	Authors calculation
Neg ALLP A	Negative residuals of Model A (Equation 1) of the LLP regression	Authors calculation
Pos ALLP A	Positive residuals of Model A (Equation 1) of the LLP regression	Authors calculation
LLP	Loan Loss Provisions divided by Lag Total Loans	Call Report
Lag LLP	Lag of (Loan Loss Provisions divided by Lag Total Loans)	Call Report
Lag LLA	Lag of (Loan Loss Allowance divided by Total Loans)	Call Report
Forward NCO	Forward of Net Charge Offs	Call Report
NCO	Net Charge Offs	Call Report
Δ Lag NPL	Lag of Change in (Bad Loans divided by Total Loans))	Call Report
Δ NPL	Change in (Bad Loans divided by Total Loans)	Call Report
Δ Forward NPL	Forward of Change in (Bad Loans divided by Total Loans)	Call Report
Δ State House Price Index	Change in the return of the House Price Index (All transactions index)	Website of Federal Housing Finance Agency
Δ State GDP	Change in State GDP	Website of Bureau of Economic Analysis
Δ State Unemployment Rate	Change in State Unemployment rate	Website of Bureau of Labor Statitics
Log Income per County Capita	Natural Logarithm of income per capita of the county	Website of Bureau of Economic Analysis
County HHI	HHI index using the deposits of banks which are headquartered in the county	Call Report
County Density	Population of the county divided by area of the county	U.S. Census Bureau
Log County Population	Natural Logarithm of the population of the county	U.S. Census Bureau

Appendix B: First Choice Votes for Federal Reserve Bank City

First Choice Votes received by city	Total first choice votes for city (Official)
Chicago	906
New York/Brooklyn	673
Minnealpolis/St Paul	508
Philadelphia	508
Kansas City	506
Pittsburgh	355
Dallas/Forth Worth	321
St. Louis	299
Cincinnati	299
Boston	290
San Francisco	259
Omaha	218
Richmond	170
Baltimore	141
Denver	136
Atlanta	124
Lousivlle	116
Cleveland	110
Houston	97
Portland	75
Birmingham	55
New Orleans	51
Seattle	40
Columbus	36
Salt Lake City	31
Spokane	30
Columbia	28
Washington DC	28
Los Angelas	26
Nashville	25
Savannah	24
Detroit	23
Lincoln	22
Charlotte	19
Indianapolis	19
Des Moines	17
Memphis	16
Jacksonville	14
Bufffalo	14
Milwaukee	13
Chattanooga	11
Albany	10
Sioux City	10