Deposit Insurance and Discretion in Loan Loss Provisioning

Abstract

Deposit insurance (DI) shifts claims on bank liabilities from depositors to the insurer. It also induces moral hazard, leading banks to take more risks. Both forces affect stakeholder incentives and, consequently, should influence bank accounting. This paper studies how a recent, substantial expansion in DI coverage impacts a key accounting policy: discretion in banks' loan loss provision (LLP). We compare affected and exogenously unaffected banks using propensity-score-matched difference-in-differences. Banks that experience an increased DI ceiling post more positive discretionary LLP, suggesting a capital-reducing or conservative bent. Results are strongest for banks most exposed to the shock, those subject to the most regulatory scrutiny, and those that increase risk most. Our findings are consistent with regulatory pressure to recognize losses proactively, suggesting regulatory preferences shape financial reporting. We are the first to estimate how DI impacts bank accounting.

Keywords: Deposit Insurance, Accounting Discretion, Conservatism, Loan Loss Provision, Emergency Economic Stabilization Act

JEL Codes: G18, G21, G38, M48

Data Availability: Data are available from the public sources cited in the text.

I. INTRODUCTION

Deposit insurance (DI) is an integral feature of nearly 150 countries' banking systems.[1] It protects small investors by converting their deposits into a risk-free asset. As depositors' stake in the bank shifts to the deposit insurer, they have less incentive to monitor banks, yielding two main outcomes. First, less depositor scrutiny pares the risk of bank runs, liquidity crises in which depositors push banks toward failure by withdrawing large sums (Diamond and Dybvig 1983). Second, less scrutiny allows banks to take more risk (Calomiris and Jaremski 2019). Because of its ubiquity and weighty consequences, DI's effect on banking sector risk has been studied extensively (e.g. Keeley 1990; Demirgüc-Kunt and Detragiache 2002). However, no paper we know of explores its impact on accounting policy. This is surprising because managers set accounting policies with stakeholder preferences in mind. By handing uninsured depositors' stake

[1] https://www.iadi.org/en/deposit-insurance-systems/dis-worldwide/

to the deposit insurer and by encouraging bank risk-taking, DI can change preferences of the marginal stakeholder and, thus, influence accounting. We contribute by showing for the first time how U.S. federal DI, a controversial form of government intervention, impacts bank accounting: It causes bankers to exercise conservative discretion in recognizing loan losses.

The last major change in U.S. DI was activated by the Emergency Economic Stabilization Act of 2008 (EESA), which increased the DI ceiling from $100,000 per account to $250,000. Lambert, Noth, and Schüwer (2017) estimate that EESA insured an additional $500 billion in deposits. As a sharp, unanticipated shock, EESA offers an ideal setting to study the relationship between DI and accounting policy. Nearly all U.S. banks were affected by the shock because they accepted deposits over $100,000. However, 126 Massachusetts state-chartered savings and cooperative banks were not: Their deposits were fully insured by a state-run DI scheme initiated in the 1930s (on top of FDIC insurance). These institutions serve as natural controls, against which we compare banks affected by EESA. Because assignment into treated and control groups occurs when banks incorporate – sometimes 200 years before EESA – our setting offers the plausible exogeneity needed for difference-in-differences (DID) estimation. So that treated banks better resemble controls, we reduce observable differences through propensity score matching. DID estimation mutes the impact of potential confounders like the financial crisis as long as they affect treated and control groups similarly. We provide empirical evidence that they do.

The accounting policy we focus on is loan loss provision (LLP), banks' largest accrual by far (Beatty and Liao 2014). U.S. Generally Accepted Accounting Principles require banks to recognize future loan loss if it is probable that the loans cannot be collected. Current accounting standards provide guidance for loan loss provisioning, but managers retain significant discretion in determining whether and when to recognize losses (SFAS 5 and 114).[2] Therefore, managerial discretion plays an integral role in banks' financial reporting decisions. Our paper studies whether exposure to the DI shock affects the level and nature of managers' LLP discretion.

To measure LLP discretion, we first model LLP as a function of its determinants, adopting an explanatory model from recent literature. Residuals capture the unexplained or discretionary, component of LLP. We track the absolute values of those residuals, as well as their signed values. A higher (lower) absolute value implies a greater (smaller) level of overall LLP discretion. Importantly, discretion can be used for different purposes. Within regulatory boundaries, managers may underestimate loan losses and consequently under-accrue for them. We consider such discretion 'opportunistic' because it inflates capital and earnings. Conversely, managers may overestimate losses and book more LLP, eroding capital and earnings. Doing so equates to 'conservative discretion'.[3] A more positive (negative) signed residual suggests that managers use discretion more conservatively (opportunistically).

We expect DI to affect bank accounting because it changes the composition of a bank's stakeholders, whose preferences and incentives are known to shape accounting policies (Ball, Robin, and Wu 2003; Beatty, Weber, and Yu 2008; Lafond and Roychowdhury 2008). DI reduces depositor claims on bank losses, leaving the deposit insurer more liable. If these two parties differ

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[2] Statement of Financial Accounting Standards (SFAS) No. 5 Accounting for Contingencies: https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1218220126761&acceptedDisclaimer=true
SFAS No. 114 Accounting by Creditors for Impairment of a Loan: https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1218220123941&acceptedDisclaimer=true;
SFAS No. 114 Accounting by Creditors for Impairment of a Loan an amendment of FASB Statements No. 5 and 15: https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1218220128771&acceptedDisclaimer=true

[3] In our study, references to conservatism relate to the conservative use of LLP discretion. That is, conservatism equates to income- and capital-decreasing actions. Such conservatism is related but not identical to the notion of "accounting conservatism" in the Basu (1997) sense, which reflects the asymmetry in the recognition of losses versus gains and is often measured using the Khan and Watts' (2009) C-Score. Lim, Lee, Kausar, and Walker (2014) provide evidence that C-Scores and discretionary LLP are related. Our study does not focus on C-Score or other classic measures of accounting conservatism because they can only be computed for public banks, a small part of our sample.

in their financial reporting preferences or abilities to enforce those preferences, handing depositors' stake to the insurer can cause bankers to adjust LLP discretion. How DI should affect discretion hinges on whether depositors or regulators, who enforce deposit insurer interests, tolerate more discretion and more opportunistic discretion.

DI can also influence financial reporting indirectly by increasing bank risk. Because uninsured depositors lose money when banks fail, they monitor and 'discipline' risky banks by demanding higher rate premiums, withdrawing funds, or both (Goldberg and Hudgins 2002). DI suppresses this mechanism by insulating depositors from risk and, therefore, bankers from depositor discipline (Demirgüc-Kunt and Huizinga 2004). Doing so allows banks to become riskier (Calomiris and Jaremski 2019), and riskier banks are known to use more accounting discretion (Huizinga and Laeven 2012; Ng and Roychowdhury 2014), likely because of higher capital management incentives (Beatty and Liao 2014). They also employ more conservative accounting policies (Beatty et al. 2008), consistent with creditor demand for conservatism when faced with greater risk. This indirect channel predicts that DI should increase LLP discretion and its conservative use. Still, we remain agnostic because the primary channel above allows for no directional hypotheses.

Our baseline findings suggest that DI does not affect banks' overall level of LLP discretion but changes how they use that discretion.[4] After EESA, banks with expanded DI coverage use LLP discretion more conservatively than do unaffected banks: When they 'under-accrue' for losses, they do so by less. These results hold using four different explanatory models to capture LLP residuals and three methods of matching treated to control banks.

[4] Although our baseline tests detect no effect of DI on overall LLP discretion, analysis using a larger subsample finds evidence of such an effect. Cross-sectional and robustness specification also hint at an effect. Nonetheless, we focus on our baseline results, which we believe to be the most econometrically sound.

We also test how DI affects the intensive margin of LLP discretion. We measure exposure to the DI shock as the fraction of bank deposits between $100,000 and $250,000 the quarter before EESA. Banks in the highest quintile of 'newly insured deposits' increase overall LLP discretion no differently than banks in other quintiles, but they use that discretion to book significantly more conservative LLP. This cross-sectional evidence echoes conclusions from our baseline tests.

Next, we examine the channels through which DI can impact accounting. We test whether the deposit insurer's greater stake and/or banks' increased risk drive our findings. Ceteris paribus, the deposit insurer should be more concerned with less capitalized banks, which face a greater probability of default, and with larger banks, which threaten greater losses given default.[5] Because regulators enforce deposit insurer interests, larger and less capitalized banks should experience more regulatory scrutiny. We partition banks into quintiles along these two dimensions and find that the least capitalized quintile increases conservative LLP discretion most, consistent with an effect of regulatory scrutiny. We find insignificant results when partitioning on bank size, though, this may reflect the fact that even the largest quintile in our sample is under $1 billion in assets and may not warrant extra scrutiny. FDIC-supervised banks drive this finding, which is reassuring because the insurer directly dictates regulatory scrutiny for this group. Subsetting banks by two proxies of risk, distance to default and nonperforming loans, we find that entities that increase risk most from the pre- to the post-shock period shift most toward conservative LLP discretion. These tests support both theoretical channels linking DI to bank accounting.

We generalize our findings into the larger (i.e. non-matched) set of banks. Beginning with all banks affected by EESA that meet our sample restrictions, we alternately designate 'treated' ones as the quintile most exposed to the DI shock, those subject to the most regulatory scrutiny, and

[5] The largest quintile of banks in our matched sample is still fairly small, with an average size of $909 million.

those that increase risk most. Other banks serve as controls. In this larger sample, we replicate the intensive margin and channel tests above. DI shock exposure continues to relate positively to both overall LLP discretion and LLP conservatism. Strong evidence of both theoretical channels for signed residuals and their absolute values also emerges in this larger subset, as well.

Although DI is well known to induce bank risk-taking (Martinez-Peria and Schmukler 2001; Demirgüc-Kunt and Huizinga 2004), its impact on accounting policies has not been studied to our knowledge. Because DI is a central tenet of banking systems worldwide, this gap poses a meaningful call for new research. The combination of a sudden, impactful shock to DI and a sub-sample of exogenously unaffected banks provides an ideal research laboratory to test how DI affects bank accounting. That test is our paper's main contribution.

We also advance the broader literature on how regulatory considerations impact accounting policy. Zang (2012) and Cunningham, Johnson, Johnson, and Lisec (2019) show that SEC scrutiny shapes firms' earnings management choices. Ramesh and Revsine (2000) find that less capitalized banks, subject to more regulatory scrutiny, select accounting policies that protect book capital. Our results complement this research by showing that enhanced regulatory pressure from a substantial increase in DI leads bankers to change how they use LLP discretion. Bushman (2016) raises the possibility that the moral hazard engendered by DI necessitates closer regulatory oversight. Is oversight enough to curb excessive risk-taking or does accounting policy also play a role? Our findings suggest the latter. We also present new, causal evidence that risk leads banks to report more conservatively, reinforcing Huizinga and Laeven's (2012) and Ng and Roychowdhury's (2014) conclusions. More generally, our work offers policy-makers and researchers an accounting perspective on DI, an important economic issue that has been analyzed from other perspectives.

II. HYPOTHESIS DEVELOPMENT

DI reconfigures the claims of depositors and the deposit insurer and, therefore, their incentives. It also encourages bank risk-taking. In this section, we expound on how DI can affect accounting policy through these two channels.

2.1 Stakeholder Claims and Accounting Policy

DI reduces depositors' stake in the bank and increases the deposit insurer's stake, thereby changing the incentives of these two parties. Specifically, depositors' (the insurer's) incentive for monitoring bank behavior and negotiating their preferences with the bank decreases (increases). If managers consider stakeholder preferences when preparing financial statements, this shift could influence reporting decisions. A well-developed literature relates accounting policies to the prevalence and preferences of various stakeholders. For example, debtholder representation affects accounting conservatism (Zhang 2008; Nikolaev 2010; Tan 2013) as does managerial ownership (Lafond and Roychowdhury 2008); accruals quality increases with demand for monitoring by shareholders, lenders, and suppliers (Hope, Thomas, and Vyas 2017). Internationally, managerial incentives related to stakeholders are more important than de facto accounting standards in determining accounting policy (Ball et al. 2003). Because financial reporting decisions shape key interactions with stakeholders, accounting policy becomes a strategic response to stakeholder incentives.

Several papers shed light on what stakeholders might value in our context. McIntyre and Zhang (2020) show that banks that use less LLP discretion attract more uninsured deposits. Bouther and Francis (2017) show that equity-holders and unsecured creditors also hold larger stakes in banks that use less accounting discretion. These associations imply that unsecured creditors shun high LLP discretion. Danisewicz, McGowen, Onali, and Schaek (2021) find that a regulatory shock that subordinated uninsured non-depositor claims to those of uninsured depositors begot less LLP discretion but led banks to exercise discretion more opportunistically.[6]

Regulators are another key stakeholder because they enforce the deposit insurer's interests. By substantially increasing insurer liabilities, EESA expanded regulatory incentive for diligence. Beatty and Liao (2014) and Jiang, Levine, and Lin (2016) show that discretionary provisioning positively predicts SEC comment letters and financial restatements, implying that regulators might punish banks for excessive discretion. From another standpoint, Moyer (1990), Ahmed, Thomas, and Takeda (1999), and Shrieves and Dahl (2003) show that banks use LLP to manage regulatory capital. In sum, by changing a bank's marginal stakeholder, DI can affect the optimal level and nature of LLP discretion, although the direction is unclear, a priori.

2.2 Bank Risk and Accounting Policy

Beyond DI's immediate impact of shifting stakeholders' claims, it indirectly increases bank risk. Uninsured depositors lose money if their bank defaults. This feature motivates them to monitor bank risk-taking and, if risks become excessive, discipline banks by withdrawing money, demanding higher deposit rate premiums, or both (Goldberg and Hudgins 2002; Flannery 1998; Bennett, Hwa, and Kwast 2015). By reducing uninsured depositors' stake, DI weakens this safety valve, allowing banks to take more risk. Empirical work consistently associates DI with bank risk-taking (e.g. Martinez-Peria and Schmukler 2001; Demirgüc-Kunt and Huizinga 2004).[7]

Given that DI leads to more bank risk, research relating risk to accounting discretion guides our analysis. Ng and Roychowdhury (2014) show that banks exercising less accounting discretion

[6] Though they use our same empirical construct, they interpret it as a measure of opacity.

[7] DI's effect on risk can be understood from another perspective, as well. Merton (1977) argues that DI equates to a put option on bank assets. The FDIC writes the option and bank owners hold it. If the bank performs well, managers let the option expire; if the bank defaults, equity-holders 'exercise the option' by letting regulators assume bank liabilities. Because option value increases in the volatility of the underlying (Black and Scholes 1973), managers can increase shareholder value by taking on more risk.

enjoy less default risk. Their interpretation is that accounting discretion increases default risk but Beatty and Liao (2014) and Bushman (2014) point out the potential for reverse causality: Riskier banks could choose to exercise more discretion to manage accounting numbers. Bushman and Williams (2012) document a positive association between LLP discretion and risk. Huizinga and Laeven (2012) show that when faced with mounting risks during the 2007-2009 financial crisis, banks used accounting discretion to inflate asset values. These studies suggest that by increasing risk, DI could compel banks toward more discretion.

Empirical work also establishes a positive link between risk and accounting conservatism, which relates to conservative LLP discretion. Zhang (2008), Nikolaev (2010), and Tan (2013) associate debt with conservative accounting. By recognizing timely losses, firms enable better creditor monitoring. Therefore, creditors demand conservatism from risky firms. Kim, Li, Pan, and Zoo (2013) and Balakrishnan, Watts, and Zhou (2016) posit that equity-holders also demand more conservative accounting in response to greater firm risk. Given these links between risk and accounting conservatism, generally, we expect DI to increase demand for conservative LLP discretion by increasing bank risk. Although this secondary risk channel provides directional predictions, the mechanism discussed in Section 2.1, changes to stakeholder claims, does not. Therefore, we avoid hypothesizing the direction that DI will affect bank discretion.

III. RESEARCH DESIGN

In this section, we present background information on EESA and detail our identification strategy. We then outline our sample selection methodology and key variables used in the paper.

3.1 Setting

On October 3, 2008, President Bush signed the Emergency Economic Stabilization Act (EESA) to combat the ongoing financial crisis. The Act was precipitated by catastrophic events such as the failure of a major investment bank (Lehman), the largest insurance company (AIG), and difficulties at other important financial institutions (Fannie Mae and Freddie Mac). Its main purpose was to arrest deteriorating credit market conditions. DI expansion was one tool in the EESA toolkit, which included troubled asset purchases, debt guarantees, and corporate governance reforms.[8] Fein (2008) provides the context for this legislation and discusses its features.

Section 136 of EESA increased the DI ceiling from \$100,000 to \$250,000 per account.[9] According to then-FDIC Chairman, Sheila Bair, the provision was meant to "help consumers maintain confidence in the banking system."[10] Although it applied to deposit accounts at all FDIC insured institutions, depositors of 126 Massachusetts state-chartered savings banks and cooperatives experienced no change in coverage. Their deposits were already fully insured through Massachusetts' state-run DI scheme, initiated during the Great Depression.

The presence of an unaffected group of banks enables our DID research design explained in Section 4.1. Not only were these banks insulated from the sudden, substantial DI increase, but their exclusion was exogenously pre-determined well before EESA.[11] One concern is that these

[8] Contemporaneous changes, like different EESA provisions or general economic turmoil, can potentially bias our results. We could mistakenly attribute changes in LLP discretion to the increased DI ceiling even if they actually resulted from other shocks. Our methodology is carefully selected to mitigate this concern. The DID framework nets out other shocks *as long as they affect treated and control groups similarly*. To help ensure they do, we match on banks' propensities to be 'control' banks. Our matched samples exhibit no significant differences along key determinants like participation in the troubled asset guarantee program (TARP) or charge-offs. We also show treated and control banks' pre-shock similarities across outcome variables, evidence of a parallel trend. Perhaps most convincingly, intensive margin tests show that specifically treated banks that were most exposed to the DI shock experience the strongest effects. It is difficult to attribute this result to contemporaneous shocks that affect all banks.
[9] Initially set to expire in 2009, the protection was extended in May 2009 for another four years and made permanent by the Dodd-Frank Act in July 2010. Although it took a year and half to establish permanence, lobbying to do so began immediately. Therefore, it is plausible that bankers and depositors adjusted to the new limit immediately.
[10] https://www.fdic.gov/news/news/press/2008/pr08093.html
[11] Some of the banks in our control group were incorporated in the early 1800s. Their choice to incorporate in MA as state-chartered savings banks could not have anticipated the state-run deposit insurance fund initiated in the Great

institutions may fundamentally differ from commercial banks, the bulk of our treated sample, and therefore provide poor counterfactuals. We address this concern in three ways. First, our primary tests use propensity score matching (PSM) to select a sample of treated banks that resemble control banks on a broad range of observable characteristics. Matched treated and control banks are statistically indistinguishable across important factors like size or risk. Second, in robustness analysis, we assemble a different subsample of treated banks that meet two of three conditions defining control banks: (1) *non-Massachusetts* state-chartered savings banks or cooperatives; (2) Massachusetts *federally chartered* savings banks or cooperatives; and (3) Massachusetts state-chartered *commercial banks*. This alternate treated sample approximates the niche characteristics of our control sample. Finally, we conduct cross-sectional tests on the full sample of DI-shocked banks, selecting those most affected as treated and all others as control. This fully eliminates the potential issue of Massachusetts state-chartered savings and cooperative bank peculiarity.

3.2 Measuring Discretionary LLP

Following a long stream of literature, we capture accounting discretion as the unexplained or discretionary portion of a bank-quarter's LLP. To measure it, we adapt Nicoletti's (2018) LLP prediction model to our setting. Her model builds on Beatty and Liao's (2014) suggested specification by including state and time fixed effects. We implement the model via ordinary least squares (OLS):

$$\begin{aligned} LLP_{b,t} = {} & \alpha_1 DNPL_{b,t+1} + \alpha_2 DNPL_{b,t} + \alpha_3 DNPL_{b,t-1} + \alpha_4 DNPL_{b,t-2} + \alpha_5 EBLLP_{b,t} \\ & + \alpha_6 TIER1_{b,t-1} + \alpha_7 SIZE_{b,t-1} + \alpha_8 DLOAN_{b,t} + \tau_t + \mu_s + \epsilon_{b,t} \qquad (1) \end{aligned}$$

Depression, let alone EESA. Even for subsequently incorporated control banks, the decision is likely exogenous to the 2008 shock, which followed an unforeseen financial crisis.

where subscripts b, t, and s index the bank, quarter, and bank headquarter state, respectively. LLP is multiplied by 1000 so that coefficients in subsequent regressions can be better interpreted. Each unit, therefore, represents 10 basis points of the bank's loan portfolio in the prior quarter. *DNPL* captures changes in the quality of the underlying loan portfolio. Earnings before LLP and taxes (*EBLLP*) and the Tier 1 risk-based capital ratio (*TIER1*) capture earnings and capital management incentives, respectively (Kanagaretnam, Lobo, and Yang 2004; Beatty, Chamberlain, and Magliolo 1995). Bank size (*SIZE*) and loan growth (*DLOAN*) provide key operational controls. Variables are defined further in Appendix A. We include quarter-fixed effects, τ_t, to account for macroeconomic events common to all banks in a particular period and bank headquarter state-fixed effects, μ_s, to absorb persistent regional differences. Appendix B, Column 1 reports coefficient estimates from this regression. Past, present, and future changes in nonperforming loans relate positively to LLP, as do earnings and size. Tier 1 capital and loan growth relate negatively. Column 2 shows that these relationships remain stable when adding the two DID variables that we use in subsequent regressions.

Residuals from Equation (1) measure the discretionary component of LLP. Again, each unit represents 10 basis points of the bank-quarter's loan portfolio. From these residuals, we construct two variables for subsequent analysis. The first is the residuals' absolute value, *ABSDLLP*, which captures the overall level of LLP discretion that management exercises in a quarter. Larger values denote more discretion. To measure how managers employ discretion, we use the residuals' signed values, *SIGNDLLP*. Positive (negative) signed residuals imply that managers take greater (lower) provisions than the explanatory model predicts, consistent with conservatism (opportunism).

3.3 Sample Selection and Descriptive Statistics

Our sample period extends from 4Q2005, twelve quarters before EESA, to 4Q2011, twelve quarters after. Data come mainly from the FDIC's Statistics on Depository Institutions dataset, which reports financial information for all U.S. banks and savings and loan associations. We supplement with several variables from the Census Bureau, Federal Housing Finance Agency, Treasury, and other FDIC datasets. To mitigate survival bias, we start with all banks that exist in both pre- and post-shocks periods. Those with 25 percent or more missing values for any variables in our study are discarded.[12] To avoid including unrepresentative banks, we eliminate those that, at any point in our sample period, report total assets under $25 million. We also drop banks that experience a quarterly change in total assets of 10 percent or more over our sample period; such changes likely reflect acquisitions, which skew operating performance. Both restrictions are common in the literature (e.g. Gatev and Strahan 2006). Finally, we use PSM to select treated banks that resemble controls. The PSM methodology, detailed in the next paragraph, helps ensure that treated and control banks are good counterfactuals. The final sample includes 7,968 (1,855) observations on 323 treated (75 control) banks. Table 1 summarizes these sample restrictions.

– INSERT TABLE 1 ABOUT HERE –

The variables used in our PSM reflect a broad range of operational and structural bank characteristics. To measure scale and performance, we include the natural log of the bank's assets, its equity-to-asset ratio, and return on assets before LLP. To measure deposit portfolio structure, we include core deposits, large deposits, and demand deposits, all deflated by total deposits. To measure loan portfolio structure, we include 1-4 family residential real estate loans and commercial real estate loans, both deflated by total loans. To measure risk, we include the natural

[12] Given the paucity of control banks in our setting, our tests are susceptible to statistical power issues and outlier problems. To avoid losing more observations, we interpolate missing values via cubic spline function. Before doing so, we winsorize continuous variables at their 1% tails to mitigate the impact of outliers.

logarithm of Z-score, LLP, nonperforming loans and write-offs, all but the first one deflated by total loans. To capture economic conditions of the bank's customers, we include the unemployment rate and log housing price index for the county of its main office. Finally, to capture regulatory and structural factors, we include four indicators, respectively set to one if the bank opted out of the Transaction Account Guarantee Program[13], if it received Troubled Asset Relief Program (TARP) funds, if it is publicly traded, and if it is owned by a bank holding company. Appendix A defines these variables in more detail. An alternative PSM scheme described in Section 5.1 supplements these variables with additional ones.

To execute the PSM, each variable is averaged over the pre-shock period (4Q2005-3Q2008) for each bank, except TAG opt-out and TARP receipt, which are one or zero for the entire sample period. An indicator that flags one for banks in the control sample, zero otherwise, is regressed on the averaged variables via logistic regression. Fitted values reflect probabilities of selection into the control group. We match each control bank to treated ones that have similar probabilities, selecting up to five treated bank matches for each control, without replacement. To ensure match quality, we require treated and control bank propensity scores differ by 1 percent or less.[14]

– INSERT TABLE 2 ABOUT HERE –

Table 2 summarizes PSM results. We begin with 3,722 treated and 95 control banks that meet our sample selection requirements. Two-sample t-tests identify significant pre-shock differences

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[13] The Troubled Asset Guarantee Program (TAGP) was implemented around the time of EESA. It included two components: the Temporary Liquidity Guarantee Program (TLGP), which fully insured noninterest-bearing transaction accounts and the Debt Guarantee Program (DGP), which insured bank-issued debt. 1,099 banks, including 42 treated and nine control banks in our final sample, opted out of TAGP. DID estimation specifically eliminates noise and bias from contemporaneous events like these, as long as they affect both treated and control groups similarly. Matching on the decision to opt out of the shock helps ensure they do. Unlike the DI shock we explore, the TAG program was discontinued in 2010. For this reason and also because firms could select into the TAG program, we choose not to integrate it into our quasi-experiment.

[14] Our results hold for one-to-three matching within a 5 percent caliper as well as matching with replacement.

in 14 of 18 matching variables. For example, the average treated bank is 40 percent smaller and three times more profitable than the average control bank.[15] After matching, significant differences dissipate across all variables except the housing price index for banks' main office counties. The $3,823 difference between housing price indexes, while significant at the 5 percent level, is economically small given a median housing price above $150,000 over our sample period.[16] Importantly, the proportion of large deposits (>$100,000) to total deposits is nearly identical for both groups, at about one third. This suggests that control banks did not have substantially more large deposits just because they were fully insured. Because our matched treated and control samples resemble each other on observable characteristics, macro-economic events around the time of the shock were likely to affect them similarly. For example, the U.S. was well into a mortgage crisis by 4Q2008, but because treated and control banks' average nonperforming loans that quarter were both 1 percent of total assets (unreported), it is unlikely that one group had significantly higher exposure to the crisis. Likewise, TARP was implemented in 2008 but we match on whether banks subsequently opted into TARP: Around 3 percent of both groups did. Given that confounding events likely affect both samples similarly, they should not threaten causal inference in a DID setting.[17]

To further check the comparability between treated and control banks, we examine their pre-shock trends along several key dimensions. Panels A, B, and C of Figure 1 respectively graph *LLP*, *ABSDLLP*, and *SIGNDLLP* differences between treated and control banks over our sample period.

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[15] Exp(12.02)/Exp(12.53)-1=-39.55% and 0.30/0.10-1=300%

[16] Exp(5.06)-Exp(5.03)=3.823

[17] We also examine the geographic distribution of matched treated banks (untabulated). Because controls are all in Massachusetts, it is reassuring that matched treated banks generally come from other Eastern states with large cities. Specifically, Illinois, New Jersey, Pennsylvania, Ohio, New York, and Connecticut contribute roughly half of our treated sample. Across treated banks, the weighted average housing price index fell by 13.93% from 2008 to 2011, compared to 10.83% for controls. The 3.1% difference is small relative to the both mean (-12.67%) and standard deviation (11.48%) across states, further evidence that the crisis affected treated and control samples similarly.

Differences are estimated by regressing *LLP*, *ABSDLLP*, and *SIGNDLLP* on an indicator equal to one for banks exposed to the DI shock, year dummies, and the interaction of that indicator with each dummy. We omit 2008, the year EESA was passed, as the reference year. Before the shock, both groups provision statistically indistinguishable amounts (Panel A), exercise similar levels of LLP discretion (Panel B), and exercise that discretion to increase earnings by similar amounts (Panel C). Pre-shock similarity suggests that the two groups are reasonable counterfactuals. After the shock, however, two key differences emerge. First, treated banks increase LLP by a larger amount (Panel A), consistent with the risk-inducing effects of DI documented in prior literature. Though the two groups continue to exercise similar levels of overall LLP discretion (Panel B), how they use that discretion also diverges. Panel C shows that treated banks use discretion to inflate LLP, reducing income and capital. These results preview our main findings in a univariate setting. Overall, Figure 1 suggests that the parallel trend assumption, crucial for DID identification, likely holds for our quasi-experiment.

– INSERT FIGURE 1 ABOUT HERE –

Table 3 describes our final sample. The mean bank-quarter's LLP is 9 basis points of its loan portfolio. Our measure of LLP discretion, the difference between LLP and its predicted value, is almost 14 basis points. On average, this discretion is used to increase income and capital by 5 basis points. The mean bank-quarter experiences an 8 basis point increase in nonperforming loans and a pre-LLP ROA of roughly a quarter of a percent. It holds almost a fifth of its risk-weighted assets in capital. Its asset portfolio approximates (EXP(12.45)=) $255 million and loans grow by 0.72 percent per quarter. Our sample is slightly larger, better capitalized, and more profitable than samples in related papers (e.g. Bushman and Williams 2015 or Nicoletti 2018) because we target a subset of the banking universe: Massachusetts state-chartered savings and cooperative banks and institutions that can be matched to them.

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IV. EMPIRICAL ANALYSIS

This section presents our main empirical tests. We then explore the intensive margin and the two theoretical channels through which our results could obtain.

4.1 DI and Discretionary LLP

To test how DI affects bank accounting, we adopt a DID research design. An indicator, *TREAT*, equals one for banks affected by the DI shock; zero, otherwise. An indicator, *POST*, equals one for each period after 3Q2008; zero, otherwise. Their interaction, *TREATPOST*, measures how DI-shocked banks change discretionary LLP relative to unaffected ones. Chen, Hribar, and Melessa (2018) highlight potential bias from using residuals as dependent variables. We adopt their suggested solution by including all control variables, including fixed effects, from the first-stage, Equation (1), in the following second-stage regression which we estimate via OLS:

$$
\begin{aligned}
(ABS|SIGN)DLLP_{b,t} = {} & \beta_1 TREAT_b + \beta_2 TREATEDPOST_{b,t} + \beta_3 DNPL_{b,t+1} \\
& + \beta_4 DNPL_{b,t} + \beta_5 DNPL_{b,t-1} + \beta_6 DNPL_{b,t-2} + \beta_7 EBLLP_{b,t} \\
& + \beta_8 TIER1_{b,t-1} + \beta_9 SIZE_{b,t-1} + \beta_{10} DLOAN_{b,t} + \tau_t + \mu_s + \epsilon_{b,t} \qquad (2)
\end{aligned}
$$

The dependent variable alternates between *ABSDLLP* and *SIGNDLLP*. Standard errors are clustered by bank due to the bank-specific, persistent nature of LLP (Nicoletti 2018). Time-fixed effects fully explain the *POST* indicator so it drops from the equation.

The coefficient of interest is β_2. For *ABSDLLP* regressions, a positive (negative) β_2 implies that treated banks increase LLP discretion more (less) than control banks from the pre- to the post-EESA period.[18] It measures how DI affects the overall level of LLP discretion. For *SIGNDLLP* regressions, a positive β_2 implies that treated banks shift toward income-decreasing LLP discretion more than control banks from the pre- to the post-shock period.[19] A negative coefficient implies the converse. Here, β_2 measures how DI affects the nature of LLP discretion.

Column 1 of Table 4 presents results for *ABSDLLP*. An insignificant β_1 implies that treated and control banks exercise similar levels of discretion pre-EESA. The coefficient of interest, β_2, is also insignificant: DI appears not to affect banks' level of LLP discretion.

-- INSERT TABLE 4 ABOUT HERE –

Column 2 speaks to DI's impact on *SIGNDLLP* and refines the story above. Again, an insignificant β_1 suggests that before EESA, treated and control banks exercise LLP discretion similarly. The coefficient of interest, β_2, is highly significant with a t-value of 3.757. Relative to unaffected controls, banks receiving more DI protection transition toward conservative LLP discretion, echoing Figure 1. This effect is economically meaningful. The average bank-quarter posts an LLP of 9.27 basis points of its loan portfolio in our sample period (Table 3). Column 2, β_3 suggests that the DI shock drives 49 percent (=0.450/0.927) higher LLP, ceteris paribus. This result complements Huang's (2021) main finding that deregulation caused public banks to use less accounting conservatism. We show the converse over a broader sample: When regulators' stake increase, bank accounting becomes more conservative.

[18] Alternatively, it could mean that they reduce discretionary LLP by less.
[19] Alternatively, it could mean that they shift toward income-increasing LLP discretion less than control banks.

As for control variables, *DNPL* correlates positively with *ABSDLLP* and negatively with *SIGNDLLP* ($\beta_{3\text{-}6}$) when significant. Bankers faced with deteriorating loan portfolios appear to exercise more LLP discretion (Column 1) to recognize fewer losses (Column 2), consistent with Huizinga and Laeven's (2012) findings. *EBLLP* relates insignificantly to both *ABSDLLP* and *SIGNDLLP* (β_7), echoing prior findings that bankers do not manage earnings with LLP (Ahmed et al., 1999; Beatty et al., 1995; and Collins et al., 1995). In contrast, higher capital levels do predict less discretion, overall (β_9, Column 1), but more conservative LLP discretion (β_9, Column 2). Larger banks use LLP discretion more opportunistically. Finally, *DLOAN* relates negatively (positively) to *ABSDLLP* (*SIGNDLLP*), consistent with loan growth curbing LLP discretion, overall, but encouraging more LLP conservative.

The fact that DI leads banks toward conservative LLP discretion could reflect three possibilities. It could be that when managers exercise conservative discretion, they do so by more than they otherwise would. Conversely, they could be exercising smaller levels of opportunistic discretion when choosing to adjust LLP downwards. Finally, managers' propensity to choose conservative over opportunistic discretion could be increasing. To test the first two possibilities, we split the sample into observations with positive and negative *SIGNDLLP* (+*SIGNDLLP* and –*SIGNDLLP*). We re-estimate Equation (2) for each subsample. Here, β_2 reveals whether, conditional on choosing to exercise conservative or opportunistic discretion, treated bank managers do so by larger amounts, post-shock. To test for the third possibility, we create an indicator variable, *NEGDLLP*, that equals one when *SIGNDLLP* is negative and zero otherwise.

With *NEGDLLP* as the dependent variable in Eq. (2), β_2 measures a bank's likelihood to select opportunistic over conservative LLP discretion.[20]

Columns 3-5 of Table 4 report results. When choosing conservative LLP discretion, treated and control banks use similar amounts (β_2, Column 3). When, instead, bankers use LLP discretion to boost earnings and capital, treated banks do so by less than their matched controls, post-shock (β_2, Column 4). Finally, the likelihood to post earnings-increasing accruals does not change differentially for treated and control banks from the pre- to the post-shock period (β_2, Column 5). Overall, Columns 3-5 clarify the result in Column 2; they show that DI-shocked banks shift toward conservative LLP discretion by choosing smaller income- and capital-increasing accruals.

4.2 The Intensive Margin

We explore the intensive margin using the cross-section of LLP discretion. If differences in outcomes between treated and control banks stem from the increased DI ceiling, then banks more exposed to the shock should exhibit greater changes in LLP discretion. To test this, we drop control banks from our sample, as their exposure to the shock is zero, by definition. For remaining banks, we construct a variable, newly insured deposits (*NIDEP*), equal to the fraction 3Q2008 deposits in the \$100,000-\$250,000 range. Banks are sorted into *NIDEP* quintiles, with the largest quintile being most exposed to the shock.[21]

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[20] We choose a linear probability model over a logit or probit, because of our fixed effects structure. Logit and probit models poorly accommodate nonlinearities (Wooldridge 2010).

[21] Although deposits in the \$100K-\$250K range were fully insured as of 4Q2008, banks continued to report according to the old, \$100K insurance threshold through 2Q2009. We adopt Lambert et al.'s (2017) approach to estimating newly insured deposits, aware of this data limitation. We start with the amount of 3Q2009 deposits in accounts with balances above \$250K. We subtract from that value the number of deposit accounts with balances above \$250K times \$250K to capture only the uninsured portion (because the first \$250K is insured). Next, we track deposits in accounts with balances above \$100K as of 3Q2008, subtracting from that value \$100K times the number of deposit accounts above \$100K. We finally subtract 3Q2009 uninsured deposits at the larger threshold from 3Q2008 uninsured deposits at the smaller one. The resulting measure, divided by 3Q2008 total deposits, approximates the fraction of a bank's deposits exposed to the DI shock. Although we recognize the limitations from lagged reporting change, we see no reason for this noise to vary cross-sectionally, leaving our quintile designations unbiased.

Figure 2 illustrates how our dependent variables change from the pre- to the post-shock period for each quintile. Striped black (solid grey) bars denote average changes in *ABSDLLP* (*SIGNDLLP*) with values plotted along the y-axis. We report the average *NIDEP* for each quintile. This graph shows that *ABSDLLP* is highest at the highest *NIDEP* quintile: Banks more exposed to the DI shock increase discretion by more, consistent with an effect of DI on the intensive margin of LLP discretion. The *SIGNDLLP* results are even more intriguing: On average, banks in the first four *NIDEP* quintiles actually shift toward opportunistic discretion; only banks in the fifth quintile, those most exposed to the DI shock, transition more toward conservative LLP discretion.

-- INSERT FIGURE 2 ABOUT HERE –

To formalize this test, we create an indicator variable, *Q5NIDEP*, that equals one for the highest quintile of newly insured deposits. *ABSDLLP* and *SIGNDLLP* are regressed on *Q5NIDEP,* its interaction with *POST* (again, *POST* drops because of the quarter-fixed effects), and all controls from Equation (2):

$$\begin{aligned}(ABS|SIGN)DLLP_t = {} & \gamma_0 + \gamma_1 Q5NIDEP_t + \gamma_2 Q5NIDEPPOST_t + \gamma_3 DNPL_{t+1} \\ & + \gamma_4 DNPL_t + \gamma_5 DNPL_{t-1} + \gamma_6 DNPL_{t-2} + \gamma_7 EBLLP_t + \gamma_8 TIER1_{t-1} \\ & + \gamma_9 SIZE_{t-1} + \gamma_{10} DLOAN_t + \tau_t + \mu_s + \epsilon_t \qquad (3)\end{aligned}$$

The interaction coefficient, γ_2, measures whether banks with the greatest exposure to the DI shock adjust accounting discretion differently. One can consider this specification an alternative DID design, wherein the control group (Q1-4) comprises banks whose DI coverage increased *less* than the treated group's coverage (Q5). Coefficients of the same sign as those in Table 4 would imply stronger effects for banks more exposed to the shock.

Table 5 presents the results. In this specification, a significant γ_2 in Column 1 provides suggests that banks most exposed to the DI shock (with 27 percent more of their deposits now insured) increase LLP discretion significantly more than other banks. Unlike Table 4, Column 1, this result suggests that DI causes bankers to use more discretion. A positive γ_2 in Column 2 implies that banks most affected by the DI shock, shift more toward conservative LLP discretion than do banks less exposed to EESA, consistent with our previous results. Overall, Table 5 provides cross-sectional support that DI facilitates more conservative LLP discretion and may impact overall discretion, too. [22]

– INSERT TABLE 5 ABOUT HERE –

4.3 Possible Channels

Next, we explore the channels through which DI could affect LLP discretion. These tests resemble the ones in the previous subsection but use different variables to partition banks into quintiles. Section 2.1 established DI's immediate effect on bank accounting: It transfers depositor claims on bank losses to the deposit insurer. Because bankers factor stakeholder preferences into accounting decisions, adjusting the representation of different stakeholders could change optimal accounting policy. This channel predicts that our results should be strongest for banks that matter most to the deposit insurer because regulators will focus limited attention on these banks. Poorly capitalized banks likely face greater regulatory scrutiny because a smaller buffer separates them from default and, therefore, insurance payout. Larger banks also probably matter more because, conditional on default, the payout would be greater. Our first set of tests partitions banks into quintiles by average pre-shock *TIER1* and by *SIZE*.

[22] Identical conclusions hold when designating the highest tercile, quartile, and decile (instead of quintile) as the treated group and when using a continuous measure of *NIDEP*.

Section 2.2 outlines DI's indirect impact of increasing bank risk. DI shields depositors from loss, reducing their monitoring incentives. Lower depositor monitoring enables higher bank risk-taking. Riskier banks may prefer to report differently or stakeholders may demand different reporting from them. This channel predicts that our findings should be stronger for banks that increase risk more. We measure the change in risk as a bank's pre- to post-shock changes in z-score and in nonperforming loans. Changes are computed by averaging each variable in each of the pre- and post-shock periods and taking the difference. Our second tests partition banks into quintiles by these change-in-risk variables.

Figure 3 presents univariate evidence on both channels. Panel A shows that the least capitalized quintile of banks increases discretion by more than the next four quintiles and the only one to shift toward conservative discretion, on average. The cross-section of bank size (Panel B) presents somewhat mixed evidence as the middle quintile uses the most discretion and uses it least opportunistically, on average. Panels C and D relate LLP discretion to changes in z-score and nonperforming loans, respectively. Both panels present strong, nearly linear trends suggesting that across the change-in-risk distribution, higher values are associated with stronger effects for *ABSDLLP* and *SIGNDLLP*.

We confirm these results in multivariate tests. Table 6 shows results from estimating a modified Equation (3), where *Q5NIDEP* is replaced with indicators for the quintiles subject to the greatest regulatory scrutiny, *Q5REGSCRUT*, (Q1 for capitalization, Q5 for size) and the most risk-increasing quintiles, *Q5INCRISK*, (Q1 for change in z-score, Q5 for change in nonperforming loans). Interacting quintile indicators with *POST* follows our DID design. Covariates are included but unreported for brevity. Columns 1 and 2 show that DI-shocked banks, likely subject to the greatest regulatory scrutiny, adjust overall LLP discretion no differently than other banks. Column

5 shows that one likely proxy for regulatory scrutiny, capitalization, associates with more LLP conservatism. The other measure, size, in Column 6 does not support this interpretation. It is worth noting, however, that even the largest banks in our matched sample are under $1 billion in assets on average. To the extent that severe regulatory scrutiny might kick in at a higher threshold, it Q5 of size experiences no incremental change in *SIGNDLLP*. Columns 3 and 4 show that increased risk strongly predict more LLP discretion with t-statistics above 5, further evidence of an effect of DI on overall LLP discretion, despite our baseline test's insignificance. Finally, Columns 7 and 8 confirm that banks that increase risk most also transition most toward conservative discretion, showing that our baseline findings likely flow through the change-in-risk channel, as well.

– INSERT TABLE 6 ABOUT HERE –

In unreported analysis, we conduct another test of whether changing stakeholder claims explains the effect of DI on LLP discretion. This test leverages an institutional detail of the U.S. banking system. The FDIC not only manages the DI fund but also supervises – i.e. acts as the regulator for – a substantial fraction of U.S. banks, roughly half the banks in our PSM sample. As the deposit insurer, the FDIC has more incentive for scrupulous supervision and will thus exercise more diligence. If so, our results should be strongest for FDIC supervised banks, which is what we find. *TREATPOST* relates positively to *SIGNDLLP* for FDIC-supervised institutions but insignificantly for banks supervised by other regulators. The coefficient for FDIC-supervised banks is 0.571, substantially larger than our 0.450 estimate from Table 4, Column 2, while the coefficient for the other sample is insignificant. For both groups, tests of *ABSDLLP* continue to show insignificant results.

These tests contextualize our baseline results by tracing the channels through which DI affects bank accounting. As DI recalibrates the marginal stakeholder away from depositors and toward the deposit insurer, banks may cater to different net preferences. Regulators and depositors can also differ in ability to impose their preferences. We find that banks subject to the most regulatory scrutiny shift most toward conservative LLP discretion. This result supports a greater regulatory demand for LLP conservatism or a greater ability to secure it. We find an even stronger link between change in risk and LLP discretion. Banks that increase risk the most also increase LLP discretion and transition toward conservative LLP discretion significantly more than other banks. This is consistent with a stronger stakeholder demand for conservatism in the presence of greater risk and managers exercising more discretion to satisfy that demand.

V. ADDITIONAL ANALYSES

We conduct several supplemental analyses in this section. First, we confirm our baseline results' robustness by using three different LLP prediction models to estimate *ABSDLLP* and *SIGNDLLP* and by employing two alternate matching schemes between treated and control banks. Second, we replicate our analysis in a broader sample of treated banks.

5.1 Robustness Checks

To test for our results' robustness, we vary our measure of discretionary LLP and matching methods. Results are reported in Table 7, though control variables are unreported for brevity. In Columns 1, 2, and 3 (6, 7, and 8), we measure *ABSDLLP* (*SIGNDLLP*) as residuals from three different models in the literature instead of Nicoletti's (2018) adapted specification. The first uses Kangaretnam, Krishnan, and Lobo's (2010) prediction model, which additionally controls for loan loss reserves and the composition of banks' loan portfolios. The next employs Bushman and Williams' (2012) model, which factors in changes in local economic conditions. The final one uses Basu, Vitanza, and Wang's (2020) specification, which includes the effects of charge offs and recoveries when estimating discretionary LLP. Each model includes core concepts in Nicholetti's (2018) specification – changes in nonperforming loans, profitability, capitalization, size, and loan growth – though precise measurement and fixed effects differ. We refer the reader to the original papers for these models' full rationale. Controlling for different potential LLP determinants helps ensure that model residuals actually capture managerial discretion and not just omitted factors. Re-estimating Equation (2) yields β_2 coefficients with the same sign as our baseline ones in five of six cases. The exception is Column 2, Bushman and Williams' (2012) *ABSDLLP* regression. Here, a positive β_2 implies that treated banks use more discretion overall, post-shock, providing another of several clues that DI may actually cause bankers to increase LLP discretion, despite our baseline results' insignificance.

– INSERT TABLE 7 ABOUT HERE –

We also test whether our results are sensitive to the particular subset of treated banks selected via PSM. One may argue that our treated and control banks inherently differ and those differences persist even after matching on observables. If such differences interact with discretionary provision, estimates may be biased. To address this concern, we implement an alternative empirical design where we match control banks to treated banks that share two of three defining characteristics. Recall that control banks are (1) Massachusetts-headquartered, (2) state-chartered, (3) savings or cooperative banks. For these tests, our revised sample of treated banks constitute:

1. *Non-Massachusetts*, state-chartered savings banks,
2. Massachusetts, *federally-chartered* savings banks, and
3. Massachusetts, state-chartered *commercial* banks.[23]

Our mixed counterfactual should improve internal validity (Roberts and Whited 2013).

[23] Massachusetts is the only state with state-chartered cooperative banks.

Additionally, Caliendo and Kopeinig (2008) suggest that that PSM is more accurate with more covariates. We augment our baseline PSM model by including eleven additional controls: cash/assets and securities/assets, which measure liquidity; deposits/loans, which measures interest rate risk; loans/assets, commercial and industrial loans/loans and loans to individuals/loans which reflect additional loan portfolio characteristics; savings deposits/deposits and certificates of deposits/deposits which reflect additional deposit portfolio characteristics; tier 1 capital/assets, risk-weighted assets/assets, and allowance for loan and lease losses/loans which reflect additional aspects of risk. The cost of matching on more covariates is fewer matches. Instead of 323 treated (75 control) banks, this matching routine produces 216 (58) within the 1 percent caliper. In Table 7, we refer to the first matching scheme as "Alt Match" and the expanded PSM as "Alt PSM." For both dependent variables under both matching schemes (Columns 5, 6, 9, and 10), β_3 resembles estimates in the first two columns of Table 4. Overall, Table 7 shows that our baseline results are robust to different discretionary LLP constructs and to different matching schemes.

5.2 Tests over a Broader Sample

Finally, we turn to the external validity of our findings. Intensive margin tests in Sections 4.2 discard Massachusetts state-chartered savings and cooperative banks, which have no newly insured deposits by definition. For continuity, Section 4.3 employs the same sample. The control group is no longer *fully insulated* from the shock as in Section 4.1, but rather *more insulated* from it. However, if these tests exclude Massachusetts state-chartered savings and cooperative banks, they can be run over the full sample, not just the PSM sample. We re-estimate Equation (2) on the sample of treated banks before matching and present results in Table 9. In Column 1 (6), we test whether banks' change in *ABSDLLP* (*SIGNDLLP*) relates to their levels of newly insured deposits. In Columns 2 and 3 (7 and 8), we test whether it relates to bank capitalization and size, proxies for regulatory scrutiny. In Columns 4 and 5 (9 and 10), we test whether it relates to changes in z-score and nonperforming loans, measures of bank risk. Again, controls are unreported for brevity. These tests have the advantage of greater statistical power but the disadvantage of self-selection into treated and control groups. Unlike Massachusetts state-chartered savings and cooperative banks, control banks in these tests are endogenously determined by operating characteristics. Therefore, we lean less on these tests for causal inference and more to check robustness of our main findings.

– INSERT TABLE 9 ABOUT HERE –

Unlike our baseline analysis, Columns 1-5 suggest DI *does* affect overall LLP discretion. Column 1 shows that banks most exposed to the DI shock increased LLP discretion significantly more than other banks from the pre- to the post-shock period. Columns 2 and 3 show that this effect varies predictably by regulatory scrutiny: The least capitalized and largest banks, likely subject to greater scrutiny, increase LLP discretion more. Columns 4 and 5 show that banks that increase risk the most also increase LLP discretion by more. Columns 6-10 reaffirm our findings on LLP conservatism from Tables 5 and 6 in the larger sample, providing external validity. Overall, Table 8 adds evidence of a link between DI and overall LLP discretion and solidifies the case that DI causes a shift toward conservative LLP discretion.

VI. CONCLUSION

Since its adoption by the U.S. in 1933, DI has spread around the world, becoming an integral feature of most banking systems. In the U.S., EESA further entrenched DI by raising the insured deposit limit from $100,000 to $250,000. Given the banking sector's importance to market economies and DI's centrality to the banking ecosystem, research has studied various DI-related issues. To our knowledge, however, DI's impact on accounting policy has not been examined.

This is surprising given that most analyses of DI focus on issues like risk-taking and monitoring, to which financial reporting choices are central.

Our study uses EESA as a quasi-experiment to examine the effect of DI on accounting discretion. EESA diminished the role of uninsured depositors as bank monitors, often identified as an unintended consequence of DI. Would less monitoring drive banks to act opportunistically about accounting choices, or would regulators' stronger role constrain accounting discretion? Would the additional risks taken by banks in response to DI influence accounting discretion?

We explore these issues by focusing on the discretionary component of the most important bank accrual, the loan loss provision. We find that affected banks increase overall discretion and that they exercise discretion more conservatively. That is, bankers subject to more DI use this important accrual to reduce income and capital. This consequence of DI has not been discussed by previous literature.

In their review and analysis of DI, Demirgüc-Kunt and Kane (2002) discuss the risk-taking consequence of DI and the critical role of regulators in monitoring banks to ensure that the system does not collapse from the moral hazard. From the accounting angle, our results suggest that regulators in the U.S. provide the proper oversight and monitoring to limit banks' opportunistic reporting, especially when the moral hazard from DI incentivizes greater risk.

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APPENDIX A: Variable Definitions.

This table defines the variables in our analysis. Unless otherwise specified, variables come from the FDIC's statistics on depository institutions dataset; their names in that data are included in parentheses. All income statement items are annualized.

Dependent Variables	Definitions
LLP	Loan loss provision (elnatr) times 1000 divided by lagged total loans (lnlsgr).
SIGNDLLP	Discretionary loan loss provisions measured as residuals from Nicoletti's (2018) model: LLP(t) = f(EBLLP(t), DNPL(t+1), DNPL(t), DNPL(t-1), DNPL(t-2), DLOAN(t), TIER1(t-1), SIZE(t-1), quarter and state fixed effects). Variables from Nicoletti's model are defined below.
ABSDLLP	Absolute value of SIGNDLLP, defined above.
NEGDLLP	An indicator equal to 1 if SIGNDLLP, defined above, is negative, 0 otherwise.

Independent Variables	Definitions
TREAT	An indicator equal to 0 for Massachusetts state-chartered savings and cooperative banks, 1 otherwise.
POST	An indicator equal to 1 for observations after 3Q2008, 0 otherwise. Omitted in regressions because of quarter-fixed effects.
TREATPOST	TREAT times POST, both defined above.
Q5NIDEP	An indicator equals 1 if a bank was in the fifth quintile of newly insured deposits as of 3Q2008 and 0 otherwise. A bank's newly insured deposits are measured as the fraction of its deposits between $100,000 and $250,000 at 3Q2008. Because banks continued to report according to $100K insurance threshold up to 3Q2009, we adopt Lambert, Noth, and Schüwer's (2017) approach to estimate shocked deposits, aware of this data-driven limitation. We start with the amount of 3Q2009 deposits in deposit accounts with balances above $250K (iddeplam). We subtract from that value the number of deposit accounts with balances above $250K (iddeplgb) times $250K to capture only the uninsured portion (because the first $250K is insured). Next, we track deposits in accounts with balances above $100K (deplgamt) as of 3Q2008, subtracting from that value $100K times the number of deposit accounts above $100K (deplgb). We finally subtract 3Q2009 uninsured deposits at the larger threshold from 3Q2008 uninsured deposits at the smaller one. The resulting measure, divided by 3Q2008 total deposits, approximates the fraction of a bank's deposits exposed to the DI shock.
Q5NIDEPPOST	Q5NIDEP*POST, both defined above.
Q5REGSCRUT	An indicator equal to 1 for banks likely to receive more regulatory scrutiny, 0 otherwise. In some specifications, Q5REGSCRUT equals 1 if a bank's tier 1 capital ratio (rbc1rwaj) is in the lowest quintile of our sample; in others, it equals 1 if the bank's size (at) is in the highest quintile of our sample. Both measures are based on average values over 3Q2005-3Q2008.
Q5REGSCRUTPOST	Q5REGSCRUT*POST, both defined above.
Q5INCRISK	An indicator equal to 1 for banks likely to receive more regulatory scrutiny, 0 otherwise. In some specifications, Q5INCRISK equals 1 if a change in z-score (defined below) is in the lowest quintile of our sample; in others, it equals 1 if the change in nonperforming loans (nclnls) is in the highest quintile of our sample. Both measures are based on average values over 3Q2005-3Q2008.
Q5 INCRISKPOST	Q5 INCRISK *POST, both defined above.

APPENDIX A (Continued)

Control Variables	Definitions
DNPL	Quarterly change in nonperforming loans (nclnls) divided by lagged total loans (lnlsgr).
EBLLP	Net income before extraordinary items (ibefxtr) minus LLP (elnatr) divided by lagged total loans (lnlsgr).
TIER1	Tier 1 risk-adjusted capital ratio (rbc1rwaj).
SIZE	Natural logarithm of total assets (at).
DLOAN	Quarterly change in total loans (lnlsgr) divided by lagged total loans (lnlsgr).

Matching Variables	Definitions
SIZE	The natural logarithm of total assets (at).
BV	Book equity (eq) divided by total assets (at).
CDEPOSIT	Core deposits (coredep) divided by total deposits (dep).
LDEPOSIT	Large deposits, those above $100,000 (deplgamt), divided by total deposits (dep).
DDEPOSIT	Demand deposits (ddt) divided by total deposits (dep).
RRELOAN	1-4 family real estate loans (lnreres) divided by total loans (lnlsgr).
CRELOAN	Commercial real estate loans (lncres) divided by total loans (lnlsgr).
LZSCORE	Natural logarithm of z-score, which is computed as the sum of net income (netinc) and book equity capital (eq), each scaled by total assets (at), divided by the 12-quarter rolling standard deviation of net income (netinc) divided by total assets (at).
NPL	Nonperforming loans (nclnls) divided by total assets (at).
WOFF	Loan and lease charge-offs (ntlnls) divided by total loans (lnlsgr).
UNEMP	Quarter-end unemployment rate for the county of the bank's headquarters. Source: Census Bureau.
HPI	Quarter-end housing price index for the county of the bank's headquarters. Source: Federal Housing Finance Agency.
TAG OO	An indicator equal to 1 if the bank opted out of the FDIC's 2008 Transaction Account Guarantee Program, 0 otherwise. Source: FDIC.
TARP	An indicator equal to 1 if the bank received funds through the Capital Purchase Program, 0 otherwise. Source: U.S. Treasury.
PUBLIC	An indicator equal to 1 if the bank is publicly traded, 0 otherwise. Source: Federal Reserve Bank of New York
HC	An indicator equal to 1 if the bank is part of a holding company structure (hcmult), 0 otherwise.

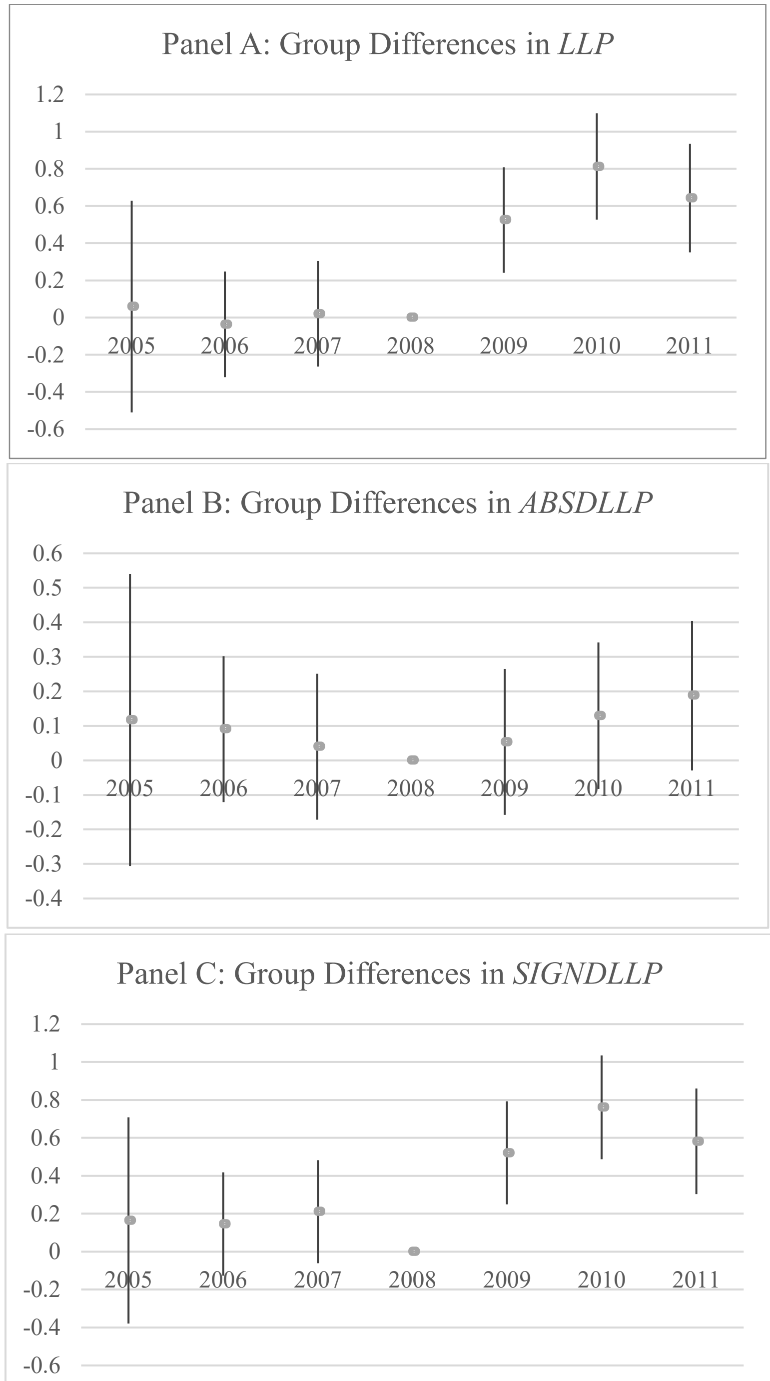
APPENDIX B: Explanatory Model to Obtain Discretionary LLP

Variable	(1) LLP_t	(2) LLP_t
$TREAT_t$		***-0.198***
		(-1.179)
$TREATPOST_t$		***0.464******
		(3.866)
$DNPL_{t+1}$	7.659***	-10.789*
	(3.566)	(-1.762)
$DNPL_t$	26.109***	9.384
	(10.754)	(1.329)
$DNPL_{t-1}$	39.645***	32.565***
	(17.621)	(5.327)
$DNPL_{t-2}$	39.184***	39.039***
	(17.115)	(6.157)
$EBLLP_t$	40.999***	32.033
	(4.406)	(1.221)
$TIER1_{t-1}$	-3.665***	-2.945***
	(-15.163)	(-7.279)
$SIZE_{t-1}$	0.302***	0.095**
	(13.292)	(2.302)
$DLOAN_t$	-15.381***	-8.978***
	(-28.517)	(-6.409)
Observations	93,897	9,823
Adjusted R-squared	0.206	0.173
Fixed Effects	State+Qtr	State+Qtr
SE Clusters	RSSD	RSSD

This table reports coefficients from an OLS regression of Equation 1. The dependent variable is LLP, loan loss provision. DNPL is the quarterly change in nonperforming loans. EBLLP is earnings before loan loss provision. TIER1 is the ratio of Tier 1 capital to risk-weighted assets. Size is the natural logarithm of total assets. DLOAN is the quarterly change in loans. All variables are scaled by prior quarter's total loans except TIER1, in which the denominator is risk-weighted assets. Column 1 is our prediction model. Residuals from this model are our dependent variables in subsequent regressions. Column 2 augments this model with the three difference-in-differences variables: TREAT, an indicator equal to 0 for Massachusetts state-chartered savings banks and cooperatives and 1 otherwise; POST, an indicator equal to 1 for all observations after 3Q2008 and 0 otherwise; and TREATPOST, the interaction of those two indicators. Refer to Appendix A for further variable definitions. Models include state and quarter fixed effects. Standard errors are clustered by bank. *, **, *** Denote two-tailed significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

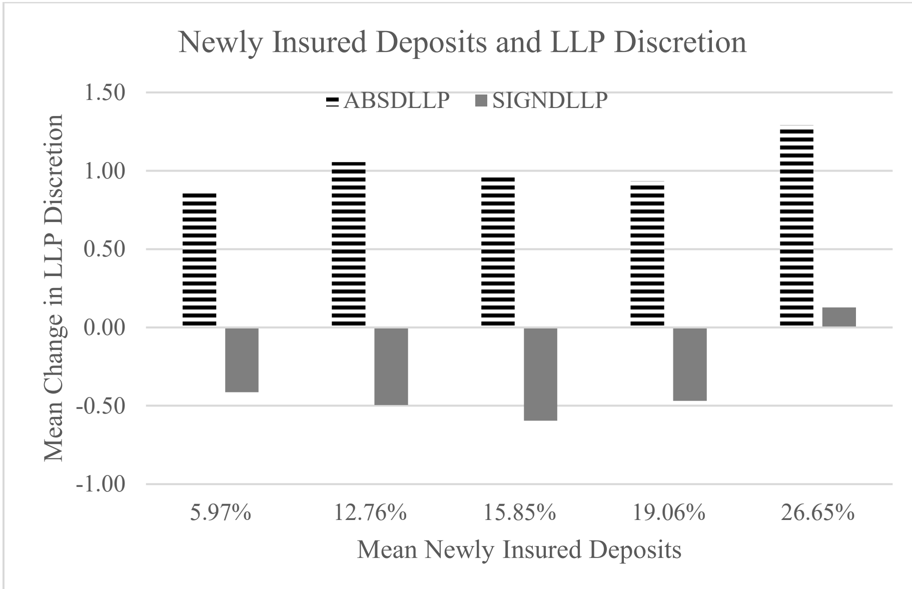
Figures and Tables

Figure 1: Treated and control bank trends in LLP, ABSDLLP, and SIGNDLLP.



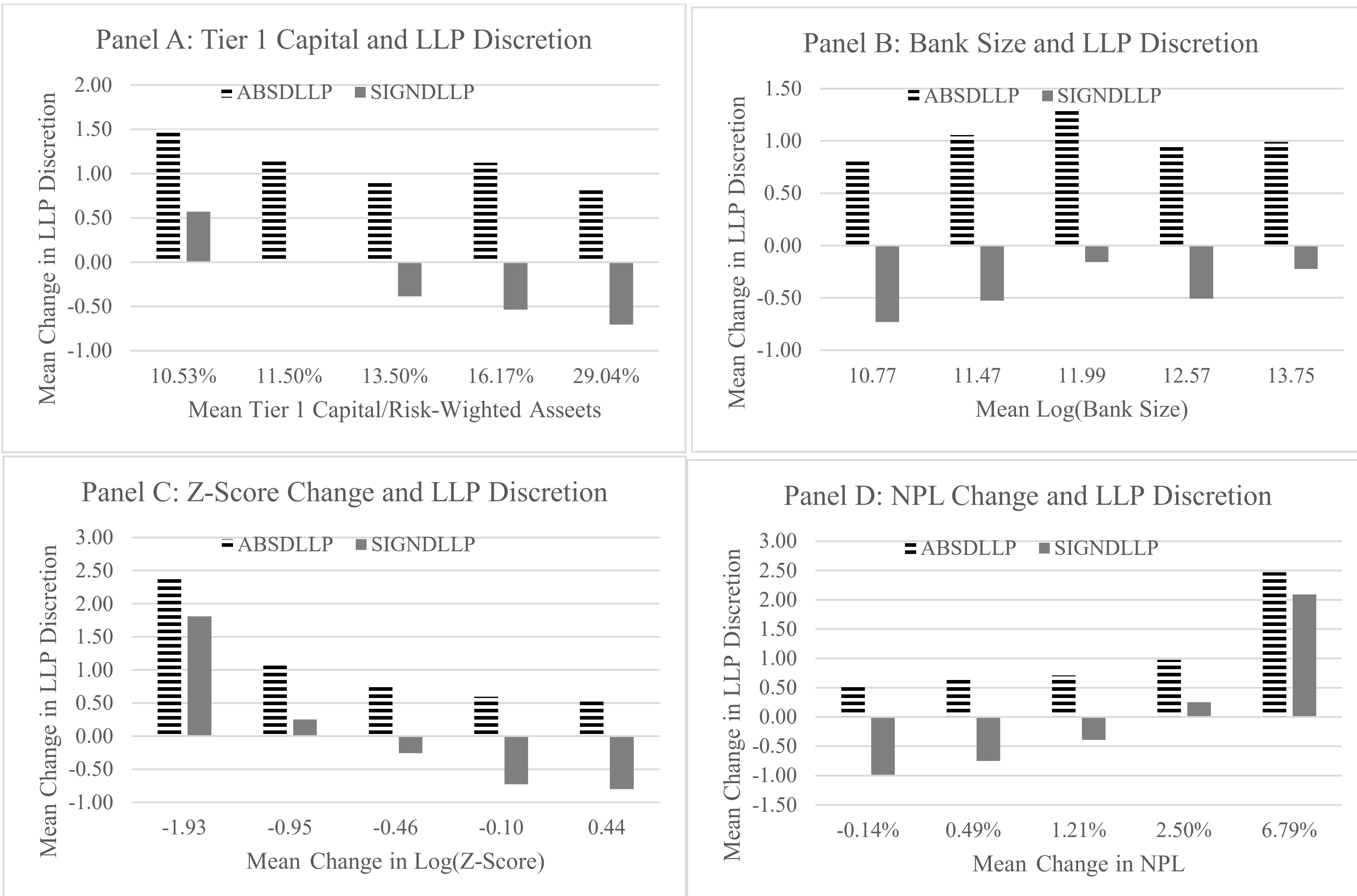
This figure plots coefficients and their 95% confidence intervals from regressions tracking treated-control differences in LLP discretion by year. The dependent variable is LLP (*ABSDLLP, SIGNDLLP*) in Panel A (B, C). The independent variables are an indicator, *TREAT*, equal to one for treated banks, year dummies, and these dummies' interaction with *TREAT*, excluding the benchmark year, 2008, when EESA was passed.

Figure 2: Mean change in *ABSDLLP* and *SIGNDLLP* by newly insured deposit quintiles.



This figure plots mean change in *ABSDLLP* (black striped bars) and *SIGNDLLP* (solid grey bars) from the pre- to the post-shock period for banks in various quintiles of newly insured deposits. A bank's newly insured deposits are measured as the fraction of its deposits between $100,000 and $250,000 at 3Q2008. Refer to Appendix A for our methodology in estimating newly insured deposits. The y-axis measures the average change in *ABSDLLP* and *SIGNDLLP*; the x-axis plots the average level of newly insured deposits for banks in each quintile.

Figure 3: Mean change in *ABSDLLP* and *SIGNDLLP* by regulatory scrutiny and change-in-risk quintiles.



This figure plots mean change in *ABSDLLP* (black striped bars) and *SIGNDLLP* (solid grey bars) from the pre- to the post-shock period for banks in various quintiles of four variables. We include two measures of concern to the deposit insurer, and thus regulatory scrutiny, tier 1 capital (Panel A) and bank size (Panel B), and two measures of change in risk, change in z-score (Panel C), and change in nonperforming loans (Panel D). The y-axis measures the average change in *ABSDLLP* and *SIGNDLLP*; the x-axis measures the average values of the partitioning variable for each quintile.

Table 1: Sample Selection

	Treated		Control		Total	
Condition	Banks	Obs.	Banks	Obs.	Banks	Obs.
Full sample, 4Q2005 - 4Q2011	7,915	191,576	124	3,061	8,039	194,637
Less than 25% missing values	7,847	190,087	124	3,061	7,971	193,148
Over $25mm	6,957	169,767	123	3,036	7,080	172,803
No merger activity	3,722	91,552	95	2,345	3,817	93,897
Propensity score matched	323	7,968	75	1,855	398	9,823

This table outlines our sample selection procedures. We begin with the full universe of bank-quarter observations in the FDIC's Statistics on Depository Institutions dataset between 4Q2005 and 4Q2011. Banks with 25 percent or more missing values for any variable in our study are dropped, as are those with under $25 million in total assets in any quarter within the sample period, and those that experience quarterly growth in assets of 10 percent or more, as this proxies for merger activity. Finally, the remaining banks in the control subsample are propensity score matched to those in the treated subsample.

Table 2: Propensity Score Matching

	Before Matching					After Matching				
	Banks		Means			Banks		Means		
Variable	Treatment	Control	Treatment	Control	p-value	Treatment	Control	Treatment	Control	p-value
SIZE	3,722	95	12.02	12.53	(0.00)	323	75	12.40	12.45	(0.70)
BV	3,722	95	10.69%	10.66%	(0.93)	323	75	11.03%	10.99%	(0.94)
EBLLP	3,722	95	0.30%	0.10%	(0.00)	323	75	0.13%	0.12%	(0.21)
CDEPOSIT	3,722	95	81.47%	81.30%	(0.76)	323	75	81.98%	81.72%	(0.74)
LDEPOSIT	3,722	95	34.66%	33.75%	(0.24)	323	75	32.33%	32.76%	(0.71)
DDEPOSIT	3,722	95	12.13%	6.82%	(0.00)	323	75	7.12%	6.60%	(0.35)
RRELOAN	3,722	95	34.19%	67.68%	(0.00)	323	75	64.96%	66.75%	(0.48)
CRELOAN	3,722	95	21.13%	15.65%	(0.00)	323	75	16.96%	16.09%	(0.56)
LZSCORE	3,722	95	4.99	5.32	(0.00)	323	75	5.32	5.33	(0.85)
LLP	3,722	95	0.05%	0.02%	(0.00)	323	75	0.02%	0.02%	(0.18)
NPL	3,722	95	0.98%	0.52%	(0.00)	323	75	0.62%	0.58%	(0.65)
WOFF	3,722	95	0.04%	0.01%	(0.00)	323	75	0.01%	0.01%	(0.68)
UNEMP	3,722	95	4.97%	4.62%	(0.00)	323	75	4.72%	4.70%	(0.83)
HPI	3,363	95	4.93	5.05	(0.00)	323	75	5.03	5.06	(0.02)
TAG OO	3,722	95	14.86%	9.47%	(0.08)	323	75	13.31%	10.67%	(0.54)
TARP	3,722	95	7.05%	2.11%	(0.00)	323	75	3.15%	2.67%	(0.82)
PUBLIC	3,722	95	5.84%	4.21%	(0.50)	323	75	4.49%	5.33%	(0.74)
HC	3,722	95	74.05%	24.12%	(0.00)	323	75	26.60%	25.22%	(0.80)

This table summarize our propensity score matching procedure. Banks are matched along log (total assets) (*SIZE*); book value of equity (BV); earnings before loan loss provision (*EBLLP*); core deposits (*CDEPOSIT*); large deposits (*LDEPOSIT*); demand deposits (*DDEPOSIT*); residential real estate loans (*RRELOAN*); commercial real estate loans (*CRELOAN*); the natural logarithm of z-score (*LZSCORE*); loan loss provision (*LLP*); nonperforming loans (*NPL*); write-offs (*WOFF*); unemployment rate and housing price index at the bank's main office county (*UNEMP*, *HPI*); whether the bank opted out of the TAG program (*TAG OO*); whether it accepted TARP funds (*TARP*); whether it is publicly traded (*PUBLIC*); and whether it is owned by a holding company (*HC*). Refer to Appendix A for further variable definitions. The number of banks and their mean values for each variable are reported before and after matching as are p-values from two-tailed t-tests on mean differences. Continuous variables are winsorized at their 1 percent tails.

Table 3: Descriptive Statistics

		Mean	St. Dev.	25%	Median	75%
Dependent Variables:	LLP	0.927	2.344	0.000	0.247	0.832
	ABSDLLP	1.380	1.779	0.465	0.997	1.761
	SIGNDLLP	-0.492	2.197	-1.502	-0.704	0.069
Independent Variables:	DNPL	0.08%	0.67%	-0.11%	0.00%	0.21%
	EBLLP	0.23%	0.31%	0.11%	0.22%	0.34%
	TIER1	19.15%	9.67%	12.55%	16.12%	22.01%
	SIZE	12.45	1.05	11.66	12.44	13.14
	DLOAN	0.72%	3.01%	-1.11%	0.56%	2.36%

This table describes the sample we use through our baseline empirical analysis. Dependent variables include loan loss provision (*LLP*), the absolute values of discretionary loan loss provision (*ABSDLLP*), and the signed value (*SIGNDLLP*), measured as residuals from Equation (1). Independent variables include the quarterly change in nonperforming loans (*DNPL*), earnings before loan loss provision (*EBLLP*), the Tier 1 risk-based capital ratio (*TIER1*), log(total assets) (*SIZE*), and quarterly change in loans (*DLOAN*). All variables are computed over a sample of 10,019 and winsorized at their 1 percent tails. Refer to Appendix A for further variable definitions.

Table 4: Change in DI and Discretionary LLP

Variable	(1) ABSDLLP	(2) SIGNDLLP	(3) *+SIGNDLLP*	(4) *-SIGNDLLP*	(5) *NEGDLLP*
$TREAT_t$	0.196	-0.200	0.783	0.137**	0.032
	(1.591)	(-1.261)	(1.478)	(2.498)	(0.794)
$TREATPOST_t$	***-0.066***	***0.450****	***0.330***	***-0.170****	***-0.024***
	(-0.829)	***(3.757)***	***(0.852)***	***(-4.381)***	***(-0.794)***
$DNPL_{t+1}$	-5.685	-19.430***	-12.665	4.900***	2.629***
	(-1.321)	(-3.425)	(-1.150)	(3.944)	(3.978)
$DNPL_t$	6.215	-17.100**	3.993	15.616***	3.406***
	(1.183)	(-2.509)	(0.314)	(10.477)	(4.473)
$DNPL_{t-1}$	23.385***	-8.073	34.564***	24.342***	3.424***
	(5.096)	(-1.396)	(3.096)	(16.169)	(4.896)
$DNPL_{t-2}$	27.658***	-1.081	46.689***	22.685***	3.332***
	(5.419)	(-0.177)	(3.928)	(13.251)	(4.614)
$EBLLP_t$	4.853	-10.429	2.855	13.422**	1.911
	(0.270)	(-0.417)	(0.084)	(2.159)	(0.672)
$TIER1_{t-1}$	-1.558***	1.571***	-1.997***	-2.442***	-0.918***
	(-5.320)	(3.969)	(-3.574)	(-16.850)	(-11.212)
$SIZE_{t-1}$	0.038	-0.187***	-0.107	0.132***	0.056***
	(1.324)	(-4.653)	(-1.210)	(10.000)	(7.615)
$DLOAN_t$	-10.774***	7.396***	-15.261***	-13.247***	-4.013***
	(-9.503)	(5.385)	(-5.405)	(-35.217)	(-19.691)
Observations	9,823	9,823	2,622	7,201	9,823
Adjusted R-squared	0.234	0.112	0.241	0.679	0.232
Fixed Effects	State+Qtr	State+Qtr	State+Qtr	State+Qtr	State+Qtr
SE Clusters	RSSD	RSSD	RSSD	RSSD	RSSD

This table reports coefficients from OLS estimates of Equation 2. The dependent variable is absolute value of discretionary loan loss provision in Column 1 (*ABSDLLP*) and the signed value (*SIGNDLLP*) in Column 2. Dependent variables alternate between *SIGNDLLP* in Columns 3 and 4 and an indicator equal to 1 if *SIGNDLLP* is negative and 0 otherwise (*NEGDLLP*) in Column 5. Columns 3 and 4 separately estimate Equation 2 for subsamples with positive and negative *SIGNDLLP*, respectively, whereas Column 5 includes the full sample. *TREAT* is an indicator equal to 0 for Massachusetts state-chartered savings banks and cooperatives and 1 otherwise. *POST,* an indicator equal to 1 for all observations after 3Q2008 and 0 otherwise, is dropped because of the quarter-fixed effects. *TREATPOST* is the interaction of those two. *DNPL* is the quarterly change in nonperforming loans. *EBLLP* is earnings before loan loss provision. *TIER1* is the ratio of Tier 1 capital to risk-weighted assets. *SIZE* is the natural logarithm of total assets. *DLOAN* is the quarterly change in loans. All variables are scaled by prior quarter's total loans except *TIER1*, in which the denominator is risk-weighted assets. Refer to Appendix A for further variable definitions. Continuous variables are winsorized at their 1 percent tails. Models include state and quarter fixed effects. Standard errors are clustered by bank. *, **, *** denote two-tailed significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 5: Newly Insured Deposits and LLP Discretion

Variable	(1) ABSDLLP	(2) SIGNDLLP
$Q5NIDEP_t$	-0.065	0.021
	(-0.840)	(0.177)
$Q5NIDEPPOST_t$	***0.282****	***0.614*****
	(1.809)	***(2.441)***
$DNPL_{t+1}$	-6.158	-20.238***
	(-1.273)	(-3.133)
$DNPL_t$	1.679	-19.269**
	(0.281)	(-2.469)
$DNPL_{t-1}$	22.454***	-7.154
	(4.220)	(-1.056)
$DNPL_{t-2}$	27.683***	1.490
	(4.482)	(0.209)
$EBLLP_t$	-0.182	-15.011
	(-0.009)	(-0.526)
$TIER1_{t-1}$	-1.480***	1.670***
	(-4.641)	(3.953)
$SIZE_{t-1}$	0.031	-0.157***
	(0.937)	(-3.492)
$DLOAN_t$	-10.551***	6.963***
	(-8.032)	(4.549)
Observations	7,968	7,968
Adjusted R-squared	0.213	0.101
Fixed Effects	State+Qtr	State+Qtr
SE Clusters	RSSD	RSSD

This table reports coefficients from OLS estimates of a modified Equation (3). The sample excludes control banks. The dependent variable is absolute value of discretionary loan loss provision in Column 1 (*ABSDLLP*) and the signed value (*SIGNDLLP*) in Column 2. *Q5NIDEP* is an indicator that equals 1 if a bank was in the fifth quintile of newly insured deposits as of 3Q2008 and 0 otherwise. A bank's newly insured deposits are measured as the fraction of its deposits between $100,000 and $250,000 at 3Q2008. Refer to Appendix A for our methodology in estimating newly insured deposits. *POST,* an indicator equal to 1 for all observations after 3Q2008 and 0 otherwise, is dropped because of the quarter-fixed effects. *Q5NIDEPPOST* is the interaction between these two indicators. *DNPL* is the quarterly change in nonperforming loans. *EBLLP* is earnings before loan loss provision. *TIER1* is the ratio of Tier 1 capital to risk-weighted assets. *SIZE* is the natural logarithm of total assets. *DLOAN* is the quarterly change in loans. All variables are scaled by prior quarter's total loans except *TIER1*, in which the denominator is risk-weighted assets. Refer to Appendix A for further variable definitions. Continuous variables are winsorized at their 1 percent tails. Models include state and quarter fixed effects. Standard errors are clustered by bank. *, **, *** denote two-tailed significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 6: Potential Channels for LLP Discretion Effects

	ABSDLLP				SIGNDLLP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Capital	Size	LZSCORE	NPL	Capital	Size	LZSCORE	NPL
$Q5REGSCRUT_t$	-0.088	0.139			-0.310**	-0.038		
	(-0.937)	(1.529)			(-2.117)	(-0.279)		
$Q5REGSCRUTPOST_t$	***0.342***	***-0.075***			***1.135******	***0.149***		
	(1.559)	***(-0.712)***			***(3.846)***	***(0.884)***		
$Q5INCRISK_t$			0.162**	0.102			0.130	-0.027
			(2.304)	(1.076)			(1.204)	(-0.213)
$Q5INCRISKPOST_t$			***0.927******	***1.085******			***1.349******	***2.292******
			(5.153)	***(5.953)***			***(4.992)***	***(9.317)***
Fixed Effects	State+Qtr	State+Qtr	State+Qtr	State+Qtr	State+Qtr	State+Qtr	State+Qtr	State+Qtr
S.E. Clusters	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,091	8,091	8,091	8,091	8,091	8,091	8,091	8,091
Adjusted R-squared	0.220	0.099	0.219	0.220	0.248	0.240	0.096	0.096

This table reports coefficients from OLS estimates of a modified Equation (3), where *Q5NIDEP* and *Q5NIDEPPOST* are replaced with *Q5REGSCRUT* and *Q5REGSCRUTPOST* in Columns 1,2,5, and 6, and with *Q5INCRISK* and *Q5INCRISKPOST* in Columns 3,4,7, and 8. The sample excludes control banks. Dependent variables are the absolute value of discretionary loan loss provision (*ABSDLLP*) in columns 1-4 and the signed value (*SIGNDLLP*) in columns 5-8. *Q5REGSCRUT* is an indicator that equals 1 if a bank was in the most extreme quintile of risk to the deposit insurer and 0 otherwise. This is defined as Q1 for capitalization in Columns 1 and 5 and as Q5 for size in Columns 2 and 6. *Q5INCRISK* is an indicator that equals 1 if a bank was in the most extreme quintile of increase in risk and 0 otherwise. This is defined as Q1 for change in log z-score in Columns 3 and 7 and as Q5 for change in nonperforming loans in Columns 4 and 8. All specifications include controls from Equation 2, which are unreported for brevity. Refer to Appendix A for further variable definitions. Continuous variables are winsorized at their 1 percent tails. Models include state and quarter fixed effects. Standard errors are clustered by bank. *, **, *** denote two-tailed significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 7: Robustness Tests – Alternative Specifications of Discretionary LLP and Sample Matching Criteria

			ABSDLLP					SIGNDLLP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	KKL10	BW12	BVW20	Alt Match	Alt PSM	KKL10	BW12	BVW20	Alt Match	Alt PSM
$TREAT_t$	-0.009	0.047	-0.001	0.115	-0.010	0.081	-0.200	0.088	-0.253	-0.444***
	(-0.144)	(0.353)	(-0.007)	(0.736)	(-0.121)	(1.144)	(-1.253)	(0.800)	(-1.580)	(-3.042)
$TREATPOST_t$	***-0.034***	***0.205*****	***-0.002***	***-0.093***	***0.024***	***0.171******	***0.451******	***0.208******	***0.438******	***0.483******
	(-0.593)	***(2.273)***	***(-0.022)***	***(-1.087)***	***(0.226)***	***(3.895)***	***(3.779)***	***(4.073)***	***(3.349)***	***(3.080)***
Fixed Effects	State+Qtr	State+ Qtr	State+ Qtr	State+ Qtr	State+ Qtr	State+ Qtr	State+ Qtr	State+ Qtr	State+ Qtr	State+ Qtr
S.E. Clusters	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,823	9,823	9,823	7,743	6,754	9,823	9,823	9,823	7,743	6,754
Adj. R-squared	0.186	0.115	0.176	0.285	0.242	0.044	0.147	0.041	0.153	0.107

This table reports coefficients from OLS estimates of Equation (2). In Columns 1 and 2, dependent variables are the absolute and signed values of discretionary loan loss provision (DLLP) computed as residuals from Kanagaretnam, Lim, and Lobo's (2010) model (KKL10). In Columns 3 and 4, dependent variables are the absolute and signed values of DLLP computed as residuals from Bushman and Williams' (2012) model (BW12). In Columns 5 and 6, dependent variables are the absolute and signed values of DLLP computed as residuals from Basu, Vitanza, and Wang (2020) model (BVW20). In Columns 7 and 8, a treated subsample is selected to include all Massachusetts state-chartered commercial banks, Massachusetts federally-chartered savings banks, and non-Massachusetts state-chartered savings banks. Columns 9 and 10 use an alternate propensity score matching scheme that includes additional matching variables listed in Section 4.2. Dependent variables for columns 7-10 mirror our baseline variables: *ABSDLLP* in Columns 7 and 9, *SIGNDLLP* in Columns 8 and 10. *TREAT* is an indicator equal to 0 for Massachusetts state-chartered savings banks and cooperatives and 1 otherwise; *POST,* an indicator equal to 1 for all observations after 3Q2008 and 0 otherwise, is dropped because of the quarter-fixed effects; and *TREATPOST*, the interaction of those two indicators. All controls from Equation (2) are included in this test but unreported here for brevity. Refer to Appendix A for further variable definitions. Continuous variables are winsorized at their 1 percent tails. Models include state and quarter fixed effects. Standard errors are clustered by bank. *, **, *** Denote two-tailed significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 8: Cross-sectional Analysis over Full Sample

Variable	ABSDLLP					SIGNDLLP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile Measure	NIDEP	Capital	Size	LZSCORE	NPL	NIDEP	Capital	Size	LZSCORE	NPL
$Q5NIDEP_t$	0.033					0.052				
	(1.140)					(1.244)				
$Q5NIDEPPOST_t$	***0.302****					***0.500****				
	(5.296)					***(6.060)***				
$Q5REGSCRUT_t$		-0.021	0.102**				-0.065	-0.202***		
		(-0.705)	(2.205)				(-1.420)	(-2.959)		
$Q5REGSCRUTPOST_t$		***0.289****	***0.171****				***0.798****	***0.840****		
		(5.048)	***(3.129)***				***(9.634)***	***(10.454)***		
$Q5INCRISK_t$				0.301***	0.228***				0.287***	0.228***
				(8.891)	(6.635)				(6.138)	(4.786)
$Q5INCRISKPOST_t$				***1.458****	***1.424****				***2.345****	***2.658****
				(19.970)	***(21.178)***				***(23.376)***	***(30.667)***
Fixed Effects	St+Qtr	St+Qtr	St+Qtr	St+Qtr	St+Qtr	St+Qtr	St+Qtr	St+Qtr	St+Qtr	St+Qtr
S.E. Clusters	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD	RSSD
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,552	91,552	91,552	91,552	91,552	91,552	91,552	91,552	91,552	91,552
Adjusted R-squared	0.194	0.193	0.193	0.228	0.224	0.032	0.034	0.034	0.084	0.097

This table reports coefficients from OLS estimates of Equation (3) or a modified Equation (3) using all treated banks in our sample before PSM-driven exclusions. Dependent variables are the absolute value of discretionary loan loss provision (*ABSDLLP*) in columns 1-5 and the signed value (*SIGNDLLP*) in columns 6-10. Indepenedent variables of interest in Columns 1 and 6 include *Q5NIDEP* and *Q5NIDEPPOST*, but these variables are replaced with *Q5REGSCRUT* and *Q5REGSCRUT* in Columns 2, 3, 7, and 8, and with *Q5INCRISK* and *Q5INCRISKPOST* in Columns 4, 5, 9, and 10. *Q5NIDEP* is an indicator that equals 1 if a bank was in the fifth quintile of newly insured deposits as of 3Q2008 and 0 otherwise. A bank's newly insured deposits are measured as the fraction of its deposits between $100,000 and $250,000 at 3Q2008. Refer to Appendix A for our methodology in estimating newly insured deposits. *POST,* an indicator equal to 1 for all observations after 3Q2008 and 0 otherwise, is dropped because of the quarter-fixed effects. *Q5NIDEPPOST* is the interaction between these two indicators variables. *Q5REGSCRUT* is an indicator that equals 1 if a bank was in the most extreme quintile of regulatory scrutiny and 0 otherwise. This is defined as Q1 for capitalization in Columns 2 and 6 and as Q5 for size in Columns 3 and 7. *Q5INCRISK* is an indicator that equals 1 if a bank was in the most extreme quintile of increase in risk and 0 otherwise.

Table 8 (continued)

This is defined as Q1 for change in log z-score in Columns 4 and 9 and as Q5 for change in nonperforming loans in Columns 5 and 10. All specifications include controls from Equation (2) which are unreported for brevity. Refer to Appendix A for further variable definitions. Continuous variables are winsorized at their 1 percent tails. Models include state and quarter fixed effects. Standard errors are clustered by bank. *, **, *** denote two-tailed significance at the 10 percent, 5 percent, and 1 percent levels, respectively.