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Bank financial reporting opacity and uninsured deposit financing

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BANK FINANCIAL REPORTING OPACITY AND UNINSURED DEPOSIT FINANCING

by

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ABSTRACT

This study examines the association between bank financial reporting opacity, measured by delayed expected loss recognition, and banks' uninsured deposit financing. In particular, following calls from prior research, I investigate the effects of reporting opacity on this critical source of bank financing, which represents over $5 trillion at 2019. Using quarterly regulatory filings of federally-insured US commercial banks, I confirm a predicted negative association between uninsured deposits and larger delays in expected loss recognition, my proxy for reporting opacity. I also document expected cross-sectional variation, with this negative association accentuated for banks that are not too-big-to-fail (as these lack the implicit government guarantees of too-big-to-fail banks), and some evidence for banks that are not publicly-traded (which have lower overall reporting and disclosure quality relative to publicly-traded banks). My findings contribute to the extant literature on bank opacity, uninsured deposit financing, and the consequences of loan loss provisioning by suggesting that delayed expected loss recognition affects uninsured deposit financing.

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1. INTRODUCTION

This study examines whether bank financial reporting opacity, as measured by delayed expected loss recognition, is associated with banks' uninsured deposit financing. Specifically, I exploit cross-sectional differences in the application of the incurred loss model to examine whether delays in expected loss recognition affect banks' uninsured deposit financing levels.

Deposits are the largest source of capital to banks, accounting for over 70% of bank total assets at 2019. Deposits can be decomposed into insured versus uninsured deposits. The US Federal government provides insurance through the Federal Deposit Insurance Corporation (FDIC), which protects depositors of insured US banks against the loss of their deposits up to a standard maximum if an insured bank fails. Any amount in excess of this threshold is uninsured. At 2019, out of total US domestic deposits of $13.2 trillion, $5.4 trillion or 41% are designated as uninsured (with $7.8 trillion or 59% insured by the FDIC). Of note, the ratio of uninsured to total deposits has increased over time, from 26% in 1999 to 41% in 2019. Despite the economic significance of this source of bank financing, the relation between bank financial reporting opacity and uninsured deposit financing is not clear, and little is known about how bank accounting information addresses bank creditors' information problems (Beatty and Liao 2014). Most prior research focuses on the perspectives of outside equity investors rather than creditors. While more recent studies have begun to investigate public debt market implications, we understand very little about a particular type of creditors – critical yet unexplored capital providers – uninsured depositors. While uninsured depositors may

provide more financing to opaque banks due to their demand for safe securities (whose value does not fluctuate with the underlying assets) that help them share liquidity risks and create medium of exchange without fear of adverse selection (Diamond and Dybvig 1983; Gorton and Pennacchi 1990; Goldstein and Pauzner 2005), such opacity could worsen the information asymmetry between depositors and banks managers about the bank's monitoring quality and performance, leading to less uninsured deposit financing (Diamond 1984; Calomiris and Kahn 1991; Diamond and Rajan 2001). Understanding how and why financial reporting opacity is associated with uninsured deposit financing is important because of the significant role of uninsured deposits in bank financing.

To study the relation between bank financial reporting opacity and uninsured deposit financing, I examine all U.S. commercial banks in 1994–2013. I choose the setting of uninsured deposits of US commercial banks for several reasons. First, uninsured deposits represent an economically significant, and growing, part in bank's funding. Second, relative to insured depositors, uninsured depositors face strong incentives to monitor bank activities, as their deposit amounts exceed those covered under explicit government insurance limits. Further, uninsured depositors represent the wealthiest individuals and/or businesses, suggesting relatively greater resources than typical depositors to directly or indirectly engage in bank monitoring.

To measure bank financial reporting opacity, I exploit variation in the timeliness of loan loss provisioning across banks. Loan loss provisioning represents the most important and discretionary accounting choice for banks, as it affects earnings and capital ratios, which banks' investors, creditors, and regulators use as signals of bank health

(Ryan 2011; Beatty and Liao 2014; Bushman and Williams 2012). Following prior research, I define and measure the timeliness of loan loss provisioning by the extent to which a bank delays recognizing current and future loan portfolio deteriorations when determining its loan loss provision in current period: this is referred to as delayed expected loan loss recognition, or *DELR* (Bushman and Williams 2012, 2015). Banks that are slower to incorporate loan deteriorations into the provision will exhibit financial statement indicators (such as earnings and capital) that are less timely signals of bank problems, creating uncertainty about the banks' fundamentals (Bushman and Williams 2015). Prior research suggests that *DELR* is a powerful measure of financial reporting opacity that can impair monitoring by bank stakeholders (Bushman and Williams 2012, 2015; Chen et al. 2020).

Financial reporting opacity, as measured by *DELR*, could be associated with uninsured deposit financing in several ways. Uninsured depositors could provide more financing to banks that appear slow to recognize expected loan loss, due to their demand for safe securities, leading to a positive association between financial reporting opacity and uninsured deposit financing. This perspective is consistent with the liability-based theories that emphasize depositors' demand for money-like safe and liquid assets and banks can meet this demand precisely because they are able to keep information about their assets hidden (Dang et al. 2017).

Alternatively, financial reporting opacity could lead to lesser uninsured deposit financing, due to the increased information asymmetry and agency cost between banks and depositors, leading to a negative association between financial reporting opacity and

uninsured deposit financing. This perspective is consistent with the asset-based and information asymmetry theories that highlight the value generated by banks on the asset side of their balance sheet. Under these theories, banks generate value by monitoring borrowers, addressing the information problems between depositors and borrowers, but are subject to agency problems in relation with their external creditors (Armstrong et al. 2010; Beatty and Liao 2014). Transparency makes it easy for the creditors to see what banks are doing and so facilitates the creditors' monitoring of banks. This perspective suggests that opaque provisioning inhibits uninsured depositor monitoring. To illustrate the idea, consider two banks with the same underlying fundamentals (e.g., prior capital and earnings) and that experience the same deteriorations in current and future loan portfolio quality, but that incorporate them into the current period's loan loss provision differently (i.e., different *DELR*). The bank with lower *DELR* is more timely: it recognizes the impact of these deteriorations in the current provision to a greater extent, and so they affect the current period's earnings and capital ratios. In contrast, the bank with higher *DELR* is less timely: it defers recognizing a larger portion of these loan deteriorations until a future period, and thus the deteriorations impact the bank's current earnings and capital to a lesser extent. Therefore, when *DELR* is higher, bank financial metrics will reflect deteriorations in the bank's condition with more delay, increasing uncertainty over bank fundamentals (Bushman and Williams 2015). Consequently, I predict that uninsured depositors are less likely to become aware of bank problems or more uncertain about bank performance and asset quality, and therefore less likely to provide financing, when *DELR* is greater.

Measuring uninsured deposit financing using both the level of uninsured deposit (using the natural log), and the ratio of uninsured deposits to total assets, I document a strong negative association between financial reporting opacity and uninsured deposit financing. I conduct several tests to corroborate the negative association and to mitigate specific sources of endogeneity in *DELR*. For example, I account for variation in banking regulations, effective federal funds rate and economic conditions via the inclusion of time fixed effect. Additionally, to address concerns about bank-level correlated omitted variables, I show that my findings are robust to including an extensive set of control variables. Furthermore, I find similar results when employing several alternative *DELR* and dependent variable measures.

I also examine whether the association between financial reporting opacity and uninsured deposit financing varies in the cross-section. I predict and find that the negative association between *DELR* and uninsured deposits is stronger in banks that are not perceived as too big to fail (i.e., those banks having no implied government insurance guarantee). I also find some support of a more negative association for banks that are private versus publicly-traded, consistent with the former having higher overall information asymmetry and lower information quality. Overall, these results are consistent with uninsured depositors responding more to bank financial reporting opacity in the subset of banks for which the benefits to those depositors are most likely to accrue.[1]

[1] I also perform two additional analyses. First, consistent with expectations from prior research (Beatty and Liao 2014), I find evidence that during recessionary periods (as defined by NBER), bank opacity has an incremental negative effect on uninsured deposits as compared to non-

My findings are subject to several important caveats. First, *DELR* is not randomly distributed across banks. While I employ several approaches to mitigate concerns about specific sources of endogeneity, I cannot account for all potential sources. It should also be noted that my analysis aims to evaluate the link between bank financial reporting opacity and various uninsured deposit financing outcomes in equilibrium. I do not rely on a shock to transparency. A couple of recent papers looked at such shocks using changes in regulatory disclosure regimes either during the national banking era (Granja 2018) or outside of the U.S. (Ertan et al. 2017) to address different questions. I do not think such clear changes in regulatory regimes for a broad base of banks are available for the last few decades in the U.S., which is where the sample for my analysis on uninsured deposits comes from. More importantly, I think that the ability to find shocks to transparency or timeliness in the data is more generally limited, since it is not at all clear that regimes requiring more disclosure necessarily result in more timely disclosure that uninsured depositors would respond to. Hence, in my approach, I just let the data speak to whether uninsured depositors respond to the reporting opacity (*DELR* in my case), which I measure using the timeliness of loan loss provisioning. The relations I uncover in the data between bank financial reporting opacity and uninsured deposit financing are quite informative for regulators, academics, and bank managers, even without insisting on a causal interpretation. By providing the first direct evidence on the association between timeliness loan loss provisioning and uninsured deposit financing,

recessionary periods. Second, I confirm that the negative *DELR*-uninsured deposits association occurs among the bottom three quartiles of bank size, but not within the top quartile, consistent with depositors perceiving bank size as a counter risk indicator.

my study offers a starting point for exploring how financial reporting affects uninsured depositor monitoring.

Another important point is that I take the level loan loss provision to construct the timeliness in loan loss recognition measure as given and do not examine what economic forces determine equilibrium differences in *DELR* measure across banks. Usual bank characteristics do not go very far in explaining the observed differences in opacity. My approach has little bearing on the interpretation of analysis of depositors' behavior: i.e., from the depositors' standpoint, the timeliness or extent of delays of a bank's financial reporting is an exogenous bank characteristic that they take into account when they respond to the reporting. Thus, regardless of the determinants of opacity, my main findings stand: uninsured depositors react more negatively to more delayed signals about bank asset quality, and the resulting effects are economically important and need to be taken into account when evaluating policies affecting banking loan loss provisioning model.

My study makes three contributions. First, my study is among the first to examine how the timeliness of loan loss recognition affects a key and unexplored provider of capital for banks—uninsured depositors. In particular, following calls for research on information asymmetry between banks and depositors (Beatty and Liao 2014; Bushman and Williams 2015), the paper confirms that bank reporting transparency, measured by timeliness of loan loss recognition, mitigates the information asymmetry problem for this important capital provider, which provides 70% of bank total assets (over $13 trillion in 2019), of which 40% is designated as uninsured (FDIC). Second, my

study contributes to the debate on the optimality of bank opacity. Extant research is mixed on whether opacity is sometimes desirable (Acharya et al. 2009; Dudley 2009; Bank for International Settlements 2012; Dang, Gorton, and Holmstrom 2012; Holmstrom 2012; Gorton 2014; Admati 2016; Dang et al. 2017). My findings suggest that lower reporting opacity helps banks attract more uninsured deposits, i.e. providing banks with more financing and liquidity hence enhancing stability (defined as the consistent ability for firms with positive net present value projects to obtain financing for those projects across the phases of the business or credit cycle (cycle) (Acharya and Ryan 2016)). Finally, this study contributes to research on the economic effects of loan loss provisioning by confirming that *DELR* can influence uninsured depositors' monitoring and discipline (Beatty and Liao 2011; Bushman and Williams 2012, 2015). Understanding the effect of provisioning on bank financing is also important because the Financial Accounting Standards Board recently issued a rule that will eventually require banks to replace the incurred loss model with an expected loss model, which is intended to increase loan loss provision timeliness (FASB ASU 2016-13).

Section 2 presents the background, prior literature, and hypothesis development. Section 3 details the research design. Section 4 presents descriptive statistics, and Section 5 the primary empirical results. Section 6 presents alternative analyses, and Section 7 concludes.

2. BACKGROUND, PRIOR LITERATURE, AND HYPOTHESIS DEVELOPMENT

2.1 Background

Deposits can be decomposed into those insured by the Federal government, and those that are not. The US federal government provides insurance through the Federal Deposit Insurance Corporation, or FDIC. The FDIC protects depositors of insured banks located in the US against the loss of their deposits if an insured bank fails. FDIC insurance covers all deposit accounts, including checking and savings accounts, money market deposit accounts and certificates of deposit. Prior to 2009Q3, the standard insurance amount was $100,000 per depositor, per insured bank, for each account ownership category. However, on July 21, 2010, the signing of the Dodd-Frank Wall Street Reform and Consumer Protection Act permanently raised the standard maximum deposit insurance amount to $250,000. Deposit amounts exceeding these indicated thresholds are *uninsured deposits*: that is, not covered by the FDIC if an insured bank fails.[2] Of note, uninsured deposits have grown dramatically over the last twenty years, both in absolute and relative terms: after twenty years of generally steady growth, uninsured deposits in the US at 2019 sum to over $5.4 trillion, and comprise 41% of total bank deposits.[3]

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[2] For example, Jane Doe has four single accounts at the same insured bank, including one account in the name of her business, which is a sole proprietorship. The FDIC insures deposits owned by a sole proprietorship as the single account of the business owner. Thus, the FDIC combines the four accounts (for example, totaling $260,000), with the balance up to $250,000 being insured, and the remainder ($10,000) being uninsured.

[3] At 2019, total US domestic deposits were $13,220 billion, of which $7,818 billion (59%) were insured by the FDIC, and $5,402 billion (41%) were not. Note that the ratio of uninsured deposits to total domestic deposits has increased over the past two decades, from 26% in 1999 to 41% in 2019. The only exception to this temporal increase was in 2009-2012, likely reflecting the increase

Relative to insured depositors, uninsured depositors differ in two key ways. First, uninsured depositors face a lower likelihood of government guarantees, as their deposit amounts exceed the insurance limit set by the FDIC.[4] Second, uninsured depositors likely have a greater ability to incur the necessary costs in monitoring bank activities. Prior research shows that most US uninsured deposits are held by the top 10% wealthiest (Wolff 2014) depositors.[5] It is also likely that a large portion of uninsured deposits are held by businesses; I confirm this in my own conversations with bank officers. Collectively, these suggest that uninsured deposits (whether as wealthy individuals or businesses) are more likely to have both the incentives and resources to better monitor bank activities, as compared to insured depositors.

In the monitoring of bank activities, a key source of information are financial reports and regulatory filings, which provide bank-specific information to investors, creditors and regulators seeking to understand a bank's fundamentals in order to guide investment and lending decisions, discipline risk-taking, and thus enhance stability. Loan

in the standard maximum deposit insurance amount from $100,000 to $250,000 in response to the global financial crisis. Source: https://www.fdic.gov/bank/statistical/stats/2019dec/fdic.pdf

[4] Of course, recalibrations of the maximum insurance coverage can reflect both unexpected economic events (e.g., financial crises) and related stop-gap measures (e.g., so-called "too big to fail" coverage provided to large banks). While both suggest non-zero probabilities of potential government guarantees even if not explicitly covered by existing limits, I assume these probabilities remain below (likely substantially below) the effective 100% probability of governmental guarantees implied by explicit FDIC limits.

[5] For example, Wolff (2014) shows that about two-third of all deposits in the US are held by the top 10% wealthiest individuals. The paper also reveals that at 2013, liquid assets (bank deposits, money market funds, and cash surrender value of life insurance) account for 7.6% of total household wealth. Further, the 10% (1%) wealthiest households have a net worth of $980,900 ($7,766,500). In untabulated calculations, I estimate the average uninsured deposit account balance by dividing aggregate uninsured deposits dollars at all commercial banks by the number of uninsured deposit accounts after 2009Q3: this leads to an average uninsured deposit of over $1.3 million. Applying Wolff's estimated liquid asset percentage, this suggests such depositors having average net worth of $17.1 million ($1.3 million / 7.6%), or more than double that of the top 1%.

loss provisioning is a key accounting policy choice that directly affects the volatility and cyclicality of bank earnings, banks' regulatory capital, as well as loan portfolios' risk attributes. Of note, loan loss provisions are the largest component among accruals, averaging 56% of total accruals over 2005-2012 (Beatty and Liao, 2014). The Financial Accounting Standard Board (FASB) and International Accounting Standard Board (IASB) have until recently followed the incurred loss model, which specifies that loan losses are recognized only when a loss is probable based on past events and conditions existing at the financial statement date. However, the complexity of loan portfolios reporting suggests substantial scope for discretion within the prescribed rules. For example, Beatty and Liao (2014) concludes, in assessing nine different loan loss models, that there is no consensus in banking research on how to best model discretionary provisions. More recent studies on loan loss provisioning timeliness as a measure of bank opacity confirm its links with banks' risk-taking behavior (Beatty and Liao, 2011; Bushman and Williams, 2012, 2015; Iannotta and Kwan, 2014; Bushman et al., 2016; Jiang and Levine, 2016; Dou et al., 2017; Costello et al., 2019; Gallemore, 2020). I define and measure the timeliness of loan loss provisioning by the extent to which a bank delays recognizing current and future loan portfolio deteriorations when determining its loan loss provision (referred to as delayed expected loan loss recognition or *DELR*). If a bank is slower to incorporate loan deteriorations into the provision, financial statement indicators (such as earnings and capital) will be less timely signals of bank problems, creating uncertainty about the bank's fundamentals (Bushman and Williams 2015). Prior research suggests that *DELR* is a powerful measure of financial reporting opacity that can

impair monitoring by bank stakeholders (Bushman and Williams 2012, 2015; Chen et al. 2020; Gallemore 2020).

2.2 Prior Literature

Banks play a particular role as efficient allocators of capital in the economy and providers of liquidity. The asset side of the bank balance sheet reflects the supply of bank financing to the real economy, and is the product of private information collection, delegated monitoring activities, and capital allocation decisions (Bushman 2014). Loans average 60% of banks' total assets, and provide an important source of external financing to firms (Beatty and Liao 2014). In private debt contracts—wherein banks represent creditors (i.e., lenders or capital providers), and firms/households represent debtors (i.e., borrowers or capital recipients)—banks require firms to bear the cost of agency conflicts between firm managers and banks. When firms commit to timely and more transparent financial reporting and bond themselves against opportunistic discretion in the accounting rules, this leads to lower agency problem and thus lower financing costs for firms (Armstrong et al. 2010).

The liability and equity side of banks' balance sheets reflects banks' capital structure. Similar to other industries, banks must attract outside funding in competitive markets, and deal with corporate governance issues deriving from self-interest and asymmetric information (Bushman 2014). The most significant component of bank capital comes from deposits. At 2012, deposits comprised 70–90% of bank total assets.[6]

[6] Broadly, this includes 50–70% core deposits and 20% noncore funding (Beatty and Liao 2014). Noncore funding includes large time deposits, deposits in foreign offices and subsidiaries, federal funds purchased, commercial paper, and brokered deposits.

The large role of deposits within bank capital structure raises the question of whether the providers of this capital (i.e., the depositors) seek to monitor and discipline banks, relying on banks' financial reporting timeliness. Prior research documents that depositors, and in particular uninsured and brokered depositors, withdraw funds when the bank's condition deteriorates, consistent with monitoring (Goldberg and Hudgins 1996, 2002; Peria and Schmukler 2001; Davenport and McDill 2006; Iyer and Puri 2012; Iyer et al. 2013; Martin et al. 2018; Chen et al. 2020). The question this study raises is how and why financial reporting opacity, measured by delayed expected loan loss recognition is associated with uninsured deposit financing. Restated, does bank financial reporting opacity increases agency cost between bank managers and depositors?

Both theory and empirical research, which explore bank financial reporting opacity and its role in driving market discipline, present conflicting views. On the one hand, credible public information about individual banks can enhance regulator and market participants' ability to monitor and exert discipline on a bank's behavior. The positive effects of transparency include: better corporate governance (Bushman and Smith 2001; Armstrong et al. 2010); greater bank stability through enhanced market discipline of banks' risk-taking (Calomiris and Kahn 1991; Rochet 1992; Cordella and Yeyati 1998; Diamond and Rajan 2001; Blum 2002); mitigating depositors' and other short-term lenders' uncertainty about the solvency of individual banks (Gorton and Huang 2006; Ratnovski 2013); and reducing financing frictions created by asymmetric information between bank managers and investors (Beatty and Liao 2011; Bushman and Williams 2015). Alternatively, endogenous costs arising from transparency can be

detrimental to the banking system. These negative effects include: inefficient bank runs due to coordination failures (Morris and Shin 2002; Chen and Hasan 2006); reputational contagion in the bank regulators (Morrison and White 2013); adverse incentives of bank managers (Goldstein and Sapra 2014); restricting interbank risk-sharing arrangements (Goldstein and Leitner 2013); and undermining banks' ability to produce private money (Gorton 2014; Dang et al. 2017).

Beatty and Liao (2014) review the empirical research of how banks and accounting information address information problems in the economy, primarily focusing on asymmetric information between banks and equity investors, and those between banks and regulators. Of note, the paper calls for research on the information asymmetry between *depositors* (i.e., *creditors*) and *banks* (i.e., *borrowers*) about the bank's monitoring quality and performance, arguing that this information asymmetry arises due to banks' delegated monitoring role. This role leads to possible agency problems, to the extent banks fail to fully internalize either the cost of their risk-taking or the benefit of their monitoring efforts. This suggests opacity as a side effect of banks' lending activities, thereby leading to a potential role for accounting information in addressing bank-depositor information asymmetry. Bushman and Williams (2015) similarly calls for research on the possible negative relation between opacity and both the access to and terms demanded by credit funding (e.g., Kashyap and Stein 1995, 2000; Ratnovski 2013). Acharya and Ryan (2016) reviews the empirical literature on the relation between banks' financial reporting and financial system stability, and also calls for additional empirical research to determine when and how more transparent financial reporting enhances

stability.

Prior research examines depositor discipline, confirming that depositors punish banks' additional risks by withdrawing deposits and/or requiring higher interest rates (e.g., Berger 1991; Peria and Schmukler 2001). For example, prior papers document that large uninsured certificates of deposits reflect higher interest costs for banks exhibiting higher risk-taking (Brewer and Mondschean 1994; Cook and Spellman 1994; Francis et al. 2005). Prior work also shows that the amount of uninsured deposits declines as a bank's risk increases (e.g., Goldberg and Hudgins 1996, 2002; Billett et al. 1998; Park and Peristiani 1998; Maechler and McDill 2006; Hasan et al. 2013). Finally, Berger and Turk-Ariss (2015) documents significant depositor discipline preceding the 2008 global financial crisis in both the US and EU, and that discipline mostly decreases during the crisis.

While a potential consequence of reporting opacity is reduced market discipline of banks' risk-taking, little work examines the relation between bank financial reporting opacity and uninsured deposit financing. Most extant work either combines insured and uninsured deposits, examines sample periods preceding the 2010 insurance limit change from $100,000 to $250,000, or assesses bank transparency as quantity of disclosure, being listed, or various risk factors.[7] One exception is McIntyre and Zhang (2020), which uses US commercial banks' data from 2001 to 2010 and finds that depositors

[7] Risk factors include bank financial statement indicators such as leverage, non-performing loans, and volatility in ROA. They also include measures such as balance-sheet-based Z-scores, or market measures such as return volatility, Merton 1974 's distance-to-default, value-at-risk, or rating agencies' credit ratings.

withdraw deposits at banks engaging in discretionary accounting practices (measured by the estimates of discretionary loan loss provisions), consistent with the theory of positive effects of transparency on market discipline. My study differs from McIntyre and Zhang (2020) in that it focuses on the timeliness of loan loss recognition (*DELR* is a powerful measure of financial reporting opacity that impairs monitoring by bank stakeholders (Bushman and Williams 2012, 2015)). The second difference is my study is motivated by the differential incentives and resources between insured and uninsured depositors. A working paper (Chen et al. (2020)) uses data for US commercial banks from 1994 to 2013 and focuses on the information quality aspect of bank earnings transparency (measured as the ability of its main components to predict future bank loan write-offs which arguably a less discretionary measure of bank asset quality). The findings of the working paper suggest that depositors respond more strongly to the information quality of bank performance , consistent with the theory of optimal opacity of banks in creating private money and the endogenous cost of transparency (Dang et al. 2017). The conflicting views in both prior theory and empirical research of bank reporting opacity suggest a need for more research to reveal insights into whether and how bank opacity affects bank deposit financing (Bushman 2014; Acharya and Ryan 2016). Accordingly, my research aims to evaluate the link between bank reporting opacity and potential disciplining by the largest capital providers for banks—depositors (Beatty and Liao 2014; Bushman 2014; Bushman and Williams 2015).

2.3 Hypothesis Development

The direction of the association between *DELR* and uninsured deposit financing is not clear ex ante. On the one hand, opaque financial reporting choices, and *DELR* specifically, could help banks in carrying out its role in creating safe, money-like securities − uninsured deposits demanded by depositors because such securities help depositors share liquidity risks and create medium of exchange without fear of adverse selection (Diamond and Dybvig 1983; Gorton and Pennacchi 1990; Goldstein and Pauzner 2005). Therefore, uninsured depositors may provide more financing to banks that appear slow to recognize expected loan losses, leading to a positive association between *DELR* and uninsured deposit financing.

Alternatively, the association between *DELR* and uninsured deposit financing can be negative, in that *DELR* reduces bank transparency which can impair monitoring by bank outsiders. A bank's primary asset is its loan portfolio, and therefore understanding a bank's performance and solvency depends on having accurate and timely information regarding loan losses. Uninsured depositors base their monitoring in part on signals, such as capital ratios and earnings, obtained from regulatory filings (Call Reports). Loan loss provisioning significantly impacts these key signals of bank health (Bushman and Williams 2012). *DELR* can negatively impact depositors' awareness of problems by reducing the extent to which capital and earnings reflect bank fundamentals in a timely manner. Furthermore, *DELR* can negatively impact how depositors interpret non-accrual measures such as non-performing loans and can create uncertainty over the ability of the bank's capital to cover unexpected losses (Bushman and Williams 2015). In sum, *DELR*

can negatively impact monitoring by depositors by creating uncertainty about the bank's fundamentals, resulting in a lower uninsured deposit financing.

Bank financial reporting opacity also relies on the active efforts of information receivers as dictated by their incentives to gather, interpret, and impound available information into decision-making processes (Freixas and Laux 2012; Mehran and Mollineaux 2012). Besides having significant incentives, uninsured depositors likely have an ability to incur the necessary costs to monitor bank activities. This is because uninsured depositors likely reflect either high net worth individuals, corporations, or institutions—all entities having greater resources to cover expected monitoring costs. This includes direct monitoring via analysis of bank disclosures and financial data, as well as indirect monitoring through proxy (such as via financial advisors).

Uninsured depositors may respond to elevated bank risk-taking by requiring higher interest rates or withdrawing deposits (Berger 1991; Peria and Schmukler 2001). Banks typically do not separately report interest rates on insured versus uninsured deposits; in addition, prior research documents that the quantity effect is stronger than interest rate effect (Park and Peristiani 1998). Accordingly, I focus on the quantity effect: that is, the amount of uninsured deposits and the ratio of uninsured deposits to total assets.

If bank financial reporting opacity inhibits uninsured depositor monitoring and discipline, I predict the following relation between the extent of delayed expected loss recognition (as a proxy for bank reporting opacity, with higher values suggesting higher opacity) and the level of uninsured deposit financing of banks:

H_1 Banks' reporting opacity (proxied via delays in expected loss recognition) is negatively associated with uninsured deposits financing.

Various characteristics (such as explicit or implicit government guarantees) can dampen the incentives for uninsured depositors to exercise monitoring (Nier and Baumann 2006; Furlong and Williams 2006; Acharya et al. 2016). Similarly, the costs associated with monitoring—such as information gathering and processing—may outweigh any perceived benefits. Combined, both issues should bias against the predicted negative association.

Next, I predict two cross-sectional bank attributes as leading to variation in the information environment across banks. First, I expect that the exercise of depositors' discipline will be stronger when implicit government guarantees are not perceived to exist (Kroszner 2016). Banks perceived as "too big to fail" (TBTF) are often viewed as having implicit government guarantees, suggesting a lower sensitivity of uninsured depositors to elevated bank risk. In contrast, for those banks falling outside of this designation (i.e., "non-TBTF"), I predict uninsured depositors will exhibit greater sensitivity to elevated risk. Furthermore, stress test requirement for banks designated as TBTF should increase depositors' confidence that these banks will be in a position to repay depositors.[8] Thus, I predict:

H_{2A} The effect of reporting opacity (proxied via delays in expected loss recognition) is more negative for non-TBTF banks relative to TBTF banks.

Second, I expect that private banks face higher information asymmetry between

[8] The Dodd-Frank Act in 2010 stipulates that banks with total assets exceeding $10 billion must conduct an annual stress test. On October 10, 2019, the Office of the Comptroller of the Currency (OCC) revised the minimum stress test threshold for national banks and Federal savings associations from $10 billion to $250 billion.

banks and depositors as compared to public banks, as the latter have richer reporting environments arising from mandated public filings. This suggests that private banks are less likely to overcome financial market imperfections, and thus lack access to external funds as compared to publicly-traded banks (Holod and Peek 2007). Accordingly, I also predict:

H_{2B} The effect of reporting opacity (proxied via delays in expected loss recognition) is more negative for private banks relative to public banks.

3. RESEARCH DESIGN

3.1 Dependent Variables: Uninsured Deposits

I define two dependent variables to measure the level of uninsured deposit financing. First, I use the natural log of quarterly uninsured deposits (*Ln(Uninsured_Deposits)*); logging minimizes the effects of outlier values. Second, I use the ratio of uninsured deposits to total assets (*Uninsured_Deposits%*); the scaled measure helps to address any effect of different bank sizes (Nier and Baumann 2006). These two measures capture the level of financing uninsured depositors provide to banks.

I focus on the level versus growth rate of uninsured deposits, as bank reporting opacity (proxied via my experimental variable of *DELR*) is likely time-invariant within banks: for example, no prior research using *DELR* as a proxy for bank opacity includes bank fixed effects. Accordingly, my measure plausibly captures the cross-sectional differences in financing across banks. I focus on uninsured (versus insured or total) deposits, as uninsured depositors are predicted to differ in terms of their incentives, costs, and benefits of monitoring and disciplining of banks' risk-taking. Following Berger and Turk-Ariss (2015), I calculate uninsured deposits by taking all funds in large deposit accounts that are partially insured, and subtracting any insured amounts. This latter calculation incorporates changes in the FDIC's insured deposit limit that occur during the sample period.[9]

[9] In particular, uninsured deposits is calculated as follows for the identified quarters:
(i) before 2006Q2: ($ Deposit Accts > $100 K) − $100 K * (# Deposit Accts > $100 K);
(ii) 2006Q2-2009Q2: ($ Deposit Accts > $100 K) − $100 K * (# Deposit Accts > $100 K) + ($ Retirement Deposit Accts > $250 K) − $250 K * (# Retirement Deposit Accts > $250 K);
(iii) 2009Q3 onward: ($ Deposit Accts > $250 K) − $250 K * (# Deposit Accts > $250 K) + ($ Retirement Deposit Accts > $250 K) − $250 K * (# Retirement Deposit Accts > $250 K).

3.2 Experimental Variable: Delayed Expected Loss Recognition (DELR)

Following Bushman and Williams (2015), the primary experimental variable to proxy for accounting transparency is delayed expected loss recognition (*DELR*). This measure reflects that more-timely banks recognize loan loss provisions *concurrently with or in advance* of loans becoming nonperforming; conversely, less-timely banks recognize loan loss provision *after* loans become nonperforming (Nichols et al. 2009; Beatty and Liao 2011; and Bushman and Williams 2012, 2015). Following prior research (Beatty and Liao 2011; Bushman and Williams 2015) I generate bank-quarter estimates of *DELR*. Bushman and Williams (2015) argues that *DELR* captures opportunistic loan provisioning behavior; as such, higher values of *DELR* reduce bank transparency, create expected loss overhangs, and increase creditors' information uncertainty about the future cash flows of the bank. Accordingly, for each bank-quarter, I estimate the following two equations using a 12-quarter rolling window (i.e., observations of the past 3 years), within which I require at least 8 observations to run each regression below.[10]

$$LLP_{it} = \beta_0 + \beta_1 \Delta NPL_{it-2} + \beta_2 \Delta NPL_{it-1} + \beta_3 Tier1_{it-1} + \beta_4 EBLLP_{it} + \beta_5 Size_{it-1} + \beta_6 RealEstate\%_{it} + \beta_7 CommIndust\%_{it} + \varepsilon_{it} \quad (1)$$

$$LLP_{it} = \beta_0 + \beta_1 \Delta NPL_{it-2} + \beta_2 \Delta NPL_{it-1} + \beta_3 Tier1_{it-1} + \beta_4 EBLLP_{it} + \beta_5 Size_{it-1} + \beta_6 RealEstate\%_{it} + \beta_7 CommIndust\%_{it} + \beta_8 \Delta NPL_{it} + \beta_9 \Delta NPL_{it+1} + \varepsilon_{it} \quad (2)$$

LLP_{it} is the loan loss provisions scaled by lagged total loans of bank i in quarter t; ΔNPL is the change in nonperforming loans scaled by lagged total loans; *Tier1* is the tier 1 capital ratio; *EBLLP* is earnings before loan loss provision scaled by lagged total loans;

[10] Results are robust to alternatively requiring at least 6 or 10 observations.

Size is the natural log of total assets; *RealEstate%* is real estate loans scaled by total loans; and *CommIndust%* is commercial and industrial loans scaled by total loans. (See Appendix A for definitions.)

Following Bushman and Williams (2015), I first compute the incremental R^2 by subtracting the adjusted-R^2 of Equation (1) (i.e., the "More Delay Model") from that of Equation (2) (i.e., the "Less Delay Model"). A negative (positive) incremental R^2 is consistent with more (less) delays in the recognition of expected losses. I categorize each bank quarter based on their incremental R^2; thus, *DELR* is an indicator variable equal to 1 for bank-quarter with negative incremental R^2, and 0 otherwise. That is, *DELR* equals 1 for those banks that most aggressively delay loss recognition, and thus exhibit higher reporting opacity.

My derivation also incorporates innovations recommended by Acharya and Ryan (2016), which raises several research design issues regarding the *DELR* measure and its use to examine bank financial reporting and stability. First, the paper argues that loan portfolio composition can affect the timeliness of provisions for loan losses. Bhat, Lee and Ryan (2019) finds that banks record less timely provisions for loan losses for commercial and industrial loans than for mortgages such as real estate loans, since the former are more heterogeneous. The paper also finds that banks record higher allowances for loan losses for uncollateralized loans (e.g., consumer loans) than for collateralized loans (e.g., real estate loans). Acharya and Ryan (2016) recommends incorporating two aspects of banks' loan portfolio composition: the proportions of heterogeneous versus homogenous loans, and of collateralized versus uncollateralized

loans. Therefore, I include *RealEstate%* and *CommIndust%* in Equations (1) and (2) to better capture the loan portfolio composition (and thus, the timeliness of banks' loan loss recognition). Second, I extend Beatty and Liao (2011)'s sample selection recommendation to include smaller banks: in particular, those having assets smaller than $500 million. These smaller banks constitute a significant part of the banking system (e.g., exceeding 79% of my sample observations); more importantly, such banks are likely more sensitive to external financing frictions. Third, I include two additional control variables as suggested by Acharya and Ryan (2016) in my main regression (discussed in Section 3.3 below).

3.3 Regression

To test whether bank reporting opacity affects uninsured deposit financing, I examine differences in the association between quarterly uninsured deposits and the extent of delays in expected loss recognition using the following OLS regression:

$$UnInsDepos_{it} = \beta_0 + \beta_1 DELR_{it-1} + \Sigma\, \gamma\, BankFundamentals_{it-1} + \beta_2 LargeDepositRate_{it} + \beta_3 \Delta Loan_{it} + \beta_4 Ln(StatePersonalInc)_{it} + Year\text{-}Quarter\ FE + \varepsilon_{it} \quad (3)$$

where the dependent variable, $UnInsDepos_{it}$, alternatively equals $Ln(Uninsured\_Deposits)_{it}$ or $Uninsured\_Deposits\%_{it}$, as defined above.

The experimental variable is *DELR* as defined above. Consistent with recent research on market discipline and bank financial reporting, I measure *DELR* and bank-level control variables with a lag (Brown and Dinç 2005, 2011; Akins et al. 2016; Ng and Roychowdhury 2014; Balla et al. 2015; Bushman and Williams, 2015; Gallemore 2020). Following H_1, I predict a negative coefficient on *DELR* if uninsured deposits decline with banks' reporting opacity. Restated, a negative coefficient on *DELR* is consistent with

delayed expected loan loss recognition reflecting lower uninsured deposit financing. To mitigate the concern of banks with low previous uninsured deposit amounts having incentives to make themselves more attractive to such depositors by presenting loan loss provisions that are more timely, I use a lagged value of *DELR*.

I include a vector of control variables (*BankFundamentals*), following prior research (Peria and Schmukler 2001; Beyhaghi et al. 2014; Berger and Turk-Ariss 2015; Acharya and Mora 2015; McIntyre and Zhang 2020). All are defined as one-quarter-lagged bank risk characteristics. The variables reflect the so-called CAMELS rating system of banks, which stands for capital adequacy, asset quality, management, earnings, liquidity, and sensitivity. Deteriorating CAMELS indicators signal increased bank risk. Accordingly, I control for capital adequacy (*Tier1)*; as banks with lower risk (reflected in higher capital ratios) may be more attractive to uninsured depositors, the predicted sign is positive. Alternatively, banks with higher equity ratios are mechanically less funded with non-equity financing (including uninsured deposits); this suggests a negative predicted sign. Accordingly, I do not predict the sign for this risk proxy. I next control for asset quality using non-performing loans (*NPL*), with a negative predicted sign. I also control for: management quality using earnings before loan loss provisions (*EBLLP*), earnings performance (*ROA*), and liquidity (*Liquidity%*); all have positive predicted signs. Sensitivity with loan concentration is controlled for by including real estate lending (*RealEstate%*), with a negative predicted sign. Finally, I include *Size* (defined as the natural log of total assets) to control for unspecified bank scale effects, with a positive predicted sign.

I also include *LargeDepositRate* (measured as interest expense on large deposits divided by the quarterly average of large time deposits, expressed in annual percentage terms) to control for the level of interest paid on large time deposits. If banks are successful in attracting more uninsured deposits by raising interest rates, the predicted sign is positive. Alternatively, prior research suggests that larger banks can raise deposits at a lower cost (e.g., Acharya and Ryan 2016), consistent with perceptions of lower risk for such banks; this suggests a negative predicted sign. Accordingly, I do not predict the coefficient sign for *LargeDepositRate*. I also include two additional control variables suggested by Acharya and Ryan (2016): *ΔLoan* (change in the natural log of loans) to control for changes in the loan supply by banks; and *Ln(StatePersonalInc)* (natural log of real personal income for the bank's state of incorporation) to control for the demand for deposits and banks' economic aspects. Both have predicted positive signs. Finally, I include time-series quarter fixed-effects (*Year-QuarterFE*) to control for macroeconomic and banking sector developments common across banks. All continuous variables are winsorized at the top and bottom 1%.

3.4 Cross-Sectional Analyses

I test the cross-sectional hypotheses by assessing the incremental impact on the *DELR* coefficients for the respective partitions using the following regression:

$$UnInsDepos_{it} = \beta_0 + \beta_1 DELR_{it-1} + \beta_2 CrossSect_{it} + \beta_3 DELR_{it-1} * CrossSect_{it} + Controls + Quarter\ FE + \varepsilon_{it} \quad (4)$$

Specifically, I interact *DELR* with the two predicted cross-sectional bank characteristics (*CrossSect*), defined as the following two alternate indicator variables. I test H_{2A} using

NonTBTF, which equals 1 if the bank is not too-big to fail, and 0 otherwise (i.e., is too-big-to-fail). For each quarter-year, banks above the upper 10th percentile of total assets are designated as TBTF banks; the remainder are designated as *NonTBTF* banks. I test H_{2B} using *Private*, which equals 1 if the bank is not publicly-traded, and 0 otherwise (i.e., is publicly-traded). I use the PERMCO-RSSD link table from the Federal Reserve Bank of New York to identify public banks.[11]

Consistent with my cross-sectional predictions, I test H_{2A} by examining if the coefficient on *DELR*NonTBTF* is negative; and I test H_{2B} by examining if the coefficient on *DELR*Private* is negative.

4. SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

Table 1 Panel A presents the sample selection. I collect quarterly data for all US commercial banks from Bank Call reports in the Bank Regulatory Database for the period 1994Q1–2013Q4. I chose 1994 as the starting point as this is the first year after full implementation of both risk-based capital and the FDIC Improvement Act of 1991 (FDICIA). I obtain real personal income by state from the Bureau of Economic Analysis (BEA), adjusted for both inflation and using BEA's regional price parities to better

[11] This dataset links regulatory identification numbers (RSSD ID) from the National Information Center (NIC) to the permanent company number (PERMCO) used in the Center for Research in Security Prices (CRSP) from June 30, 1986 to December 31, 2018. The RSSD ID is a unique identifier assigned to commercial banks or bank holding companies by the Federal Reserve and is the primary identifier of entities in regulatory reports such as the Call Report (FFIEC031) and Y9-C. The PERMCO is a unique and permanent company identification number assigned to publicly-traded institutions in the CRSP database. While a company may change its name, ticker, exchange, or CUSIP, the PERMCO will remain the same. In CRSP, companies with multiple tranches of publicly traded stock will be assigned to multiple PERMNOs. These PERMNOs will be linked back to a single PERMCO. Linking the RSSD ID to PERMCO allows researchers to match bank regulatory data with financial market data.

compare the buying power of personal income across the 50 states and the District of Columbia. The initial sample consists of 713,228 bank-quarter observations.[12] The final sample after applying several filters is 149,330 bank-quarter observations, representing 7,185 distinct banks for the period 1994Q1–2013Q4.

Table 1 Panel B provides the distribution by three groups defined by bank total assets: "small banks" (those with assets from $100 million to $1 billion); "medium banks" (those with assets from $1 billion to $5 billion); and "large banks" (those with assets exceeding $5 billion). The small, medium, and large bank groupings account for 91%, 7% and 2% of the sample, and exhibit uninsured to total deposits of 19.4%, 27.5% and 31.7%, respectively.

Table 2 Panel A presents the descriptive statistics. Sample banks have average quarterly uninsured deposits of $125 million, representing 16.5% of total assets. On average, 29.2% of banks have negative incremental R^2 ($DELR$ = 1) in a quarter. Average tier 1 ratio (*Tier1*) is 14.4%, nonperforming loan ratio (*NPL*) is 1.3%, real estate loans (*RealEstate%*) account for 71.5% of total loans, and the liquid assets ratio (*Liquidity%*) is 26.6%. The average large deposit rate (*LargeDepositRate%*) in annual percentage term is 3.8%. 81.5% of my sample is private banks (*Private)* and 16.1% is stand-alone and not

[12] To derive the final sample, I exclude the following: (i) banks with 50% or greater foreign ownership, and not incorporated in the 50 states or District of Columbia; (ii) observations with total asset growth exceeding 10% in any quarter to mitigate effects that may be driven by mergers and acquisitions (Gatev and Strahan 2006); (iii) banks that are inactive in the loan market, defined as those with maximum loans-to-assets ratios of less than 5%; (iv) banks with assets of less than $100 million, which are likely viewed as the riskiest banks by uninsured depositors and have the smallest percentage of uninsured deposits (12%, as compared to 32% in largest bank group of more than $5 billion in assets); (v) banks lacking 8-quarters for each bank-quarter for the rolling window calculations; and (vi) observations with missing values for main regressions.

affiliated with a bank holding company (*StandAlone*). On average, banks in my sample have earnings ratio to total loans (*EBLLP*) of 0.9% and ROA (*ROA*) of 1%.

Table 2 Panel B partitions the sample into two groups *DELR*=1 and *DELR*=0 and compares variables across the groups. As compared to banks with less delays (*DELR* = 0), banks with more delays (*DELR* = 1) exhibit lower uninsured deposits (*Ln(Uninsured_Deposits)*) and lower percentage of uninsured deposits in total assets (*Uninsured_Deposits%*), higher tier 1 capital (*Tier1*), lower non-performing loan ratio (*NPL*), higher real estate loans ratio (*RealEstate%*), lower earnings before loan loss provisions (*EBLLP*), higher ROA (*ROA*), higher liquidity assets ratio (*Liquidity%*), smaller assets size (*Size*), lower interest rate (*LargeDepositRate%*), lower loan growth (*ΔLoan*), and lower state personal income (*Ln(StatePersonalInc)*). These mean comparisons suggest that the control variables differ significantly across the two DELR groups, further justifying their inclusion in my analyses.

Table 3 presents the correlations. Consistent with my hypotheses, both dependent variables (*Ln(Uninsured_Deposits)*, *Uninsured_Deposits%*) have significant negative correlations with delays in expected loss recognition (*DELR*). Further, the table confirms the expected negative correlations between my uninsured deposit variables with nonperforming loans (*NPL*), real estate loans (*RealEstate%*), and expected positive correlations with earnings (*EBLLP*), *ROA*, bank size (*Size*), loan growth (*ΔLoan*), and state personal income (*Ln(StatePersonalInc)*. The dependent variables have significant negative correlations with *Tier1* and *LargeDepositRate* in this univariate analysis.

Liquidity% is negatively correlated with *Ln(Uninsured_Deposits)* but positively correlated with *Uninsured_Deposits%*.

5. EMPIRICAL RESULTS

5.1 Bank Opacity and Uninsured Deposit Financing

Table 4 presents results examining uninsured deposit financing as related to opacity, proxied via *DELR* (delayed expected loss recognition). In Columns (1) and (2), the dependent variable is $Ln(Uninsured\_Deposits)_{it}$, the natural log of uninsured deposits of bank *i* in quarter *t*. Column (1) presents the univariate test, revealing the predicted significantly negative coefficient on *DELR* (–0.173, *t*-stat = 25.27). Column (2) presents the multivariate test with similar results (*DELR* = –0.037; *t*-stat = 6.43).

Control variables all obtain the predicted signs. This includes significantly negative coefficients for: *Tier1* (–2.389; *t*-stat = 15.19), suggesting a substitute financing between equity and non-equity; *RealEstate%* (–0.600; *t*-stat = 13.29), suggesting uninsured depositors monitor and are sensitive to banks' asset quality; and *LargeDepositRate* (–7.454; *t*-stat = 11.17), suggesting that uninsured depositors perceive banks having to pay higher interests (higher risk premium) as more risky. Similarly, I find the expected positive coefficients for: *EBLLP* (0.021; *t*-stat = 1.77), consistent with higher uninsured deposits for more profitable banks; *ROA* (7.934; *t*-stat =14.56), consistent with uninsured deposits increasing for better managed banks; and *Liquidity%* (0.533; *t*-stat = 9.07), consistent with higher uninsured deposits for more liquid banks. I also find higher uninsured deposits for banks that are larger (*Size* = 1.115; *t*-stat = 153.47), have higher loan growth ($\Delta Loan$ = 1.242; *t*-stat = 17.00), and operating in states with higher personal income (*Ln(StatePersonalInc)* = 0.044; *t*-stat = 5.69). The coefficient on *NPL* is negative but insignificant.

In Columns (3) and (4), the dependent variable is *Uninsured_Deposits%*$_{it}$, the ratio of uninsured deposits to the total assets of bank *i* in quarter *t*. Thus, these columns replicate the analyses now using a scaled version of uninsured deposits. Results are similar to those reported above. I find a significantly negative coefficient on *DELR* in the univariate analysis of Column (3) (–0.007, *t*-stat = 14.22), as well as in the multivariate analysis of Column (4) (–0.008; *t*-stat = 9.09). The association between *DELR* and uninsured deposits is also economically significant. Referring to Column (4), I find that banks with *DELR* = 1 (i.e., more delays) have 0.8 percentage points lower uninsured deposits to total assets, where the sample mean equals 16.5%. This represents $5 million less uninsured deposits in a quarter of the sample with mean assets of $625 million. Results on the control variables attain the same predicted positive and negative coefficients as discussed above.

Overall, these results provide consistent support for H_1, and suggest banks with higher opacity (i.e., those exhibiting higher *DELR*) exhibit decreased levels of uninsured deposits, consistent with bank opacity reduces uninsured deposit financing.

5.2 Cross-Sectional Analyses

Table 5 presents the cross-sectional analyses of uninsured deposits, and thus my tests of H_{2A} and H_{2B}. Focusing on Column (1) using *Ln(Uninsured_Deposits)* and Column (3) using *Uninsured_Deposits%* as dependent variables to test H_{2A}, I find as predicted that the negative association between uninsured deposits and higher bank opacity is more prevalent among banks, which are not too big to fail (*NonTBTF*) (coefficient on *NonTBTF*DELR* = –0.045; *t*-stat = 2.12 in Column (1), –0.021; *t*-stat =

5.42 in Column (3)). All other coefficients on control variables are similar to the main regressions in Table 4.

Tests of H_{2B} are in Columns (2) and (4), using the same two alternative dependent variables. I only find a significantly negative effect on *Private*DELR* in Column (4), using *Uninsured_Deposits%* as dependent variable (–0.006; *t*-stat = 2.27). The coefficient on the interaction term in Column (2), using *Ln(Uninsured_Deposits)* as dependent variable, is positive but insignificant (0.017; *t*-stat = 1.12). These results provide limited evidence that the link between uninsured deposit to assets ratio and higher opacity is more prominent among private banks relative to publicly traded banks, partially supporting H_{2B}.

Overall, I conclude that the negative association between uninsured deposits and higher bank opacity exhibits predictable cross-sectional variation. Specifically, I find lower uninsured deposits for banks unlikely to be designated as too big to fail (consistent with H_{2A}); and some support for lower uninsured deposits for private banks (consistent with H_{2B}).

5.3 Sensitivity Analyses

I perform several sensitivity analyses to assess the robustness of my results to alternative research design choices. First, I examine an alternative proxy for my experimental variable, which is a regression-based DELR measure. In particular, I use a stock measure (*DELR_Stock1*) based on the ratio of the allowance of loan loss provisions divided by nonperforming loans (Beatty and Liao 2011). This ratio captures banks' recognition of expected risk in their performing loans, as well as incurred losses in their

nonperforming loans. While less intuitive in capturing the extent of delays in expected loss recognition, this measure does not require time-series data as the regression-based DELR measure does; this places fewer time-series imposed limitations on sample selection. I expect that banks with a smaller delay in expected loss recognition will recognize greater loan provisions relative to nonperforming loans. Accordingly, I designate banks with a lagged ratio higher (lower) than the median during the quarter as having a smaller (greater) delay in expected loss recognition. As a second measure, I follow Akins et al. (2017) and modify the Beatty and Liao (2011) stock measure by computing the ratio of the allowance of loan loss provisions at quarter *t* as a percentage of the nonperforming loans at quarter *t*+1 for each bank-quarter observation (*DELR_Stock2*).[13] The correlation between the two DELR stock measures is 70%. Table 6 presents results using *DELR_Stock1*, which are unchanged to my primary results using *DELR*.[14] Results using *DELR_Stock2* (Table 11) are virtually identical to those using *DELR_Stock1*, and continue to support the primary findings.

Second, I examine the sensitivity of my results to the time-series of observations used to define the primary experimental variable of *DELR*. The primary analyses use at least 8 previous quarters; I alternatively require at least 6 or 10 quarterly observations for Equations (1) and (2) to construct *DELR*. Table 7 presents the results, using the dependent variables of *Ln(Uninsured_Deposits)* in Columns (1) and (2), and

[13] This latter ratio captures the extent to which loan loss allowances at time *t* take into account the current levels of and future changes in nonperforming loans (since nonperforming loans at time *t*+1 equals nonperforming loans at time *t* plus the changes in nonperforming loans at time *t*+1).

[14] Note that *N* differs within this and the ensuring sensitivity analyses due to different data requirements. However, results for all sensitivity analyses are unchanged to using the same primary sample (i.e., *N* = 149,330).

Uninsured_Deposits% in Columns (3) and (4). Results are unchanged to using either 6 or 10 quarters: the coefficient on *DELR* is consistently significantly negative across all four specifications.

Third, I redefine my dependent variables to be the ratio of uninsured deposits to total deposits (*Uninsured/Total_Deposits*) (versus as a ratio of total assets in the primary analyses), and to be the natural log of the *change* in uninsured deposits (*Ln(ΔUninsured_Deposits)*) (versus the natural log of the *level* in uninsured deposits in the primary analyses). Results are presented in Table 8, and remain unchanged to the primary analyses: the coefficient on *DELR* remains significantly negative across all four specifications.

6. ADDITIONAL ANALYSES

6.1 Uninsured Deposit Financing during Recessionary Periods

Beatty and Liao (2011) provides evidence that banks with greater delays in expected loss recognition reduce their lending during recessions more than banks with smaller delays. Accordingly, I predict that the primary negative association between uninsured deposits and delays in expected loss recognition to be accentuated (i.e., more negative) during recessions, consistent with those banks being more financially constrained, less likely to meet their liquidity demand, and thus reducing lending more. Table 9 presents the results. Column (1) has the recession year observations for periods between 2001Q2–2001Q4 and 2008Q1–2009Q2, and Column (2) the non-recession year observations for periods other than recessionary periods; that is, I define recessions using data from the National Bureau of Economic Research. Results are consistent with expectations. In particular, the coefficient on *DELR* is –0.042 (*t*-stat = 4.86) in Column (1) for recessionary observations, and –0.029 (*t*-stat = 4.65) in Column (2) for non-recessionary observations (with the difference significant at $F = 8.52$, p-value < 0.001), suggesting a more negative effect on uninsured deposits at banks with more delays during recessionary periods.

6.2 Uninsured Deposit Financing by Bank Size Quartiles

Previously, I define TBTF banks as the upper 10^{th} percentile of total assets, with Table 5 results confirming the expected stronger negative relation between uninsured deposits and bank opacity for *NonTBTF* compared to TBTF banks. However, the distribution of my sample is heavily skewed to smaller banks: for example, 90% of my

sample includes banks smaller than $1 billion in total assets. Accordingly, I extend my analysis to examine the relation between uninsured deposits and bank reporting opacity across four equally-sized bank quartiles by total assets. Table 10 presents the results. The coefficients on *DELR* are significantly negative across the first three quartiles: from Column (1) (smallest banks) to Column (3), it is –0.074 (*t*-stat = 6.67), –0.027 (*t*-stat = 2.70), and –0.033 (*t*-stat = 3.19), respectively. In Column (4) for the largest bank quartile, the coefficient on *DELR* is negative but insignificant (–0.002; *t*-stat = 0.15). Collectively, these results are consistent with the TBTF hypothesis of implicit government guarantee lowering the sensitivity of uninsured depositors to banks' risk-taking for the largest banks. Further, the results confirm that the negative association between uninsured deposits and bank opacity appears consistent across the three bottom quartiles of banks: that is, it appears widely-distributed across banks below the largest grouping.

Finally, a potential concern is that the primary sample excludes the smallest banks with total assets less than $100 million, while those banks should be most sensitive to uninsured depositing funding. In untabulated analysis, I include all banks in my sample, confirming that the results are unchanged to my primary analyses (coefficients on *DELR* are –0.032 (*t*-stat = 6.39) and –0.008 (*t*-stat = 13.15) corresponding to the two dependent variables in primary analyses) (Table 12).

6.3 Uninsured Deposit Financing and Bank Holding Company

I examine the difference in bank affiliation with a parent holding company. Extant literature shows that such affiliations (i.e., a multibank-holding company) enhance

the availability of internal financing for operations relative to stand-alone banks (Houston et al. 1997; Campello 2002). This suggests that the effect of bank reporting opacity on uninsured deposits will be stronger for stand-alone banks as compared to banks affiliated with a multibank-holding company.

I test this prediction using *StandAlone*, defined as 1 if the bank is a stand-alone bank and not part of a bank holding company, and 0 otherwise. I follow Holod and Peek (2007) and separate banks into two categories in each quarter: stand-alone banks, and banks in bank-holding companies (or BHCs). I use the ID number of the highest holder for each bank in each quarter. Those banks having a highest holder ID equal to zero in any particular quarter are considered stand-alone banks in that quarter (and thus *StandAlone* = 1); otherwise, banks are considered to be operating under a BHC (and *StandAlone* = 0).

In untabulated results, I find an unexpected positive coefficient on *StandAlone*DELR* , using *Ln(Uninsured_Deposits)* as dependent variable. The coefficient on the interaction term using *Uninsured_Deposits%* as dependent variable, is negative as expected but insignificant (–0.002; *t*-stat = 0.64) (Table 13). Thus, relative to the bank holding status, standalone banks that delay more do not seem to be disadvantaged in attracting uninsured deposit financing.

7. CONCLUSION

This study provides evidence that uninsured deposit financing—a key and growing source of capital for banks over the past twenty years—are lower for banks exhibiting higher reporting opacity, consistent with uninsured depositors playing a monitoring role over banks' risk-taking. In particular, I find the both the level and percentage of uninsured deposits are negatively associated with my proxy for reporting opacity. My proxy is *DELR*, introduced by Bushman and Williams (2015) in which a larger value is consistent with lower quality reporting due to more delays in recognizing expected losses. These findings occur for a broad sample of US commercial banks during the period 1994-2013, and are robust to the inclusion of an extensive set of control variables and various research designs. Cross-sectional analyses confirm that these effects are accentuated for banks lacking the too-big to fail designation (and thus not having implicit government guarantees), provide some evidence of this effect being accentuated for private banks (which lack the more robust reporting of publicly-traded banks), and reveal the effect to be more prominent during recessionary periods. Combined, these results are consistent with a monitoring role played by uninsured depositors over banks' loan loss provisioning opacity. This role appears consistent with both the incentives uninsured depositors face due to a lack of governmental guarantees insuring their deposits, and from such depositors—who are comprised of very wealthy individuals or institutions—likely having the resources to engage in such monitoring. One primary caveat to these inferences is that uninsured depositors' direct actions are unobservable; thus, I infer them from banks' aggregate uninsured deposits. Nonetheless,

this study presents important new evidence consistent with accounting transparency, measured by timeliness of loan loss recognition, playing a role in uninsured deposit financing, consistent with prior research suggesting that transparency has a positive effect on monitoring and disciplining banks by outside stakeholders.

APPENDIX A

Variable Definitions

Dependent Variables

Uninsured_Deposits$_{it}$

Uninsured deposit amounts of bank *i* in quarter *t* is calculated as follows for the identified quarters:
(i) before 2006Q2 = ($ Deposit Accts > $100 K) − $100 K * (# Deposit Accts > $100 K);
(ii) 2006Q2-2009Q2 = ($ Deposit Accts > $100 K) − $100 K * (# Deposit Accts > $100 K) + ($ Retirement Deposit Accts > $250 K) − $250 K * (# Retirement Deposit Accts > $250 K);
(iii) 2009Q3 onward = ($ Deposit Accts > $250 K) − $250 K * (# Deposit Accts > $250 K) + ($ Retirement Deposit Accts > $250 K) − $250 K * (# Retirement Deposit Accts > $250 K).

Ln(Uninsured_Deposits)$_{it}$

Natural log of uninsured deposits of bank *i* in quarter *t*.

Uninsured_Deposits$_{it}$*%*

The ratio of uninsured deposits to total assets of bank *i* in quarter *t*.

Uninsured/Total_Deposits$_{it}$

The ratio of uninsured deposits to total deposits of bank *i* in quarter *t*.

Ln(ΔUninsured_Deposits)$_{it}$

Natural log of change in uninsured deposits of bank *i* from quarter *t-1* to quarter *t*.

UnInsDepos$_{it}$

Dependent variable alternatively equals *Ln(Uninsured_Deposits)*$_{it}$ or *Uninsured_Deposits%*$_{it}$, as defined above.

Experimental Variables

DELR$_{it-1}$ *(Flow Measure)*

An indicator variable equal to 1 if the lagged delay measure of bank *i* is negative during the quarter, and 0 otherwise, where the delay measure is the difference in adjusted-R^2 (Equation (2) - Equation (1)) from the following two rolling regressions for each bank-quarter using the observations of the past 3 years. I require at least 8 observations to run each regression.

$$LLP_{it} = \beta_0 + \beta_1 \Delta NPL_{it-2} + \beta_2 \Delta NPL_{it-1} + \beta_3 Tier1_{it-1} + \beta_4 EBLLP_{it} + \beta_5 Size_{it-1} + \beta_6 RealEstate\%_{it} + \beta_7 CommIndust\%_{it} + \varepsilon_{it} \quad (1)$$

$$LLP_{it} = \beta_0 + \beta_1 \Delta NPL_{it-2} + \beta_2 \Delta NPL_{it-1} + \beta_3 Tier1_{it-1} + \beta_4 EBLLP_{it} + \beta_5 Size_{it-1} + \beta_6 RealEstate\%_{it} + \beta_7 CommIndust\%_{it} + \beta_8 \Delta NPL_{it} + \beta_9 \Delta NPL_{it+1} + \varepsilon_{it} \quad (2)$$

where

LLP_{it} is loan loss provisions scaled by lagged total loans of bank *i* in quarter *t*.

ΔNPL is change in nonperforming loans divided by lagged total loans.

Tier1 is Tier 1 capital divided by risk-weighted assets.

EBLLP is earnings before loan loss provision, scaled by lagged total loans.

Size is the natural log of total assets.

RealEstate% is the amount of loans secured by real estate, scaled by total loans.

CommIndust% is the amount of commercial and industrial loans, scaled by total loans.

$DELR6_{it-1}$ (Flow Measure)

Requiring 6 observations in Equations (1) and (2) above to construct the delay measure.

$DELR10_{it-1}$ (Flow Measure)

Requiring 10 observations in Equations (1) and (2) above to construct the delay measure.

$DELR\_Stock1_{it-1}$ (Stock Measure)

An indicator variable equal to 1 if the lagged delay measure of bank *i* is below the median during the quarter, and 0 otherwise, where the delay measure is the ratio of loan loss allowance on balance sheet divided by nonperforming loans in current period (LLA_{it}/NPL_{it}).

$DELR\_Stock2_{it-1}$ (Stock Measure)

An indicator variable equal to 1 if the lagged delay measure of bank *i* is below the median during the quarter, and 0 otherwise, where the delay measure is the ratio of loan loss allowance on balance sheet divided by nonperforming loans in future period (LLA_{it}/NPL_{it+1}).

NonTBTF

An indicator variable equal to 1 if the bank is not TBTF, and 0 otherwise. For each quarter-year, banks above the upper 10th percentile of total assets are designated as TBTF banks; the remainder are designated as NonTBTF banks.

Private

An indicator variable equal to 1 if the bank is not publicly traded, and 0 otherwise.

StandAlone

An indicator variable equal to 1 if the bank is a stand-alone bank and not part of a bank holding company, and 0 otherwise.

Control Variables

NPL

Nonperforming loans divided by total loans.

ROA

Annualized ROA, calculated as net income adjusted year-to-date reporting to within quarter, divided by beginning total assets.

Liquidity%

Liquid assets to assets, excludes MBS/ABS securities. Liquid assets are cash, federal funds sold and reverse repos, and securities excluding MBS/ABS securities.

LargeDepositRate

Implicit rate, calculated as interest expense on large time deposits (adjusted year-to-date reporting to within quarter) divided by quarterly average of large time deposits.

ΔLoan

Change in natural log of loans.

Ln(StatePersonalInc)

Natural log of real personal income by state where the bank is incorporated, adjusted for both inflation and using BEA's regional price parities to better compare the buying power of personal income across 50 states and the District of Columbia.

Recession

An indicator variable equal to 1 for periods between 2001Q2 and 2001Q4, and periods between 2008Q1 and 2009Q2, and 0 otherwise, as defined by NBER.

TABLES

Table 1: Sample Selection and Distribution

Panel A: Sample Selection

	Banks	Quarterly Observations
All Commercial Banks on the Bank Regulatory database, during 1994-2013, quarterly data	15,538	713,228
Less banks:		
not in 50 states and DC	–39	–1,782
with foreign ownership > 50%	–792	–33,775
with total assets growth > 50% or = -100% in a quarter	–0	–46,262
with total loans to assets < 5% (inactive in loan market)	–240	–5,091
smaller than $100 million in assets	–5,153	–318,478
with less than 8-quarter data to calculate DELR	–314	–84,840
with missing data for regressions	–1,815	–73,670
Final Sample	**7,185**	**149,330**

Panel B: Distribution of Observations by Total Assets

Bank Group	Average Total Assets ($ millions)	Uninsured Deposits / Total Deposits	Sample Banks	Sample Quarterly Observations
Small Banks	278.0	0.194	6,415	135,392
Medium Banks	1,933.0	0.275	564	10,652
Large Banks	10,664.6	0.317	206	3,286
Final Sample	**624.6**	**0.203**	**7,185**	**149,330**

Panel A presents for the sample selection. Panel B presents the distribution by total assets, using three groupings: *Small Banks* include banks with assets from $100 million to $1 billion; *Medium Banks* include banks with assets from $1 billion to $5 billion; and *Large Banks* include banks with assets of greater than $5 billion.

Table 2: Descriptive Statistics

Panel A: Pooled Sample

Variables (*N* = 149,330)	**Mean**	**St Dev**	**p10**	**p25**	**Median**	**p75**	**p90**
Ln(Uninsured_Deposit)$_{it}$	10.622	1.207	9.315	9.830	10.446	11.209	12.140
Uninsured_Deposit%$_{it}$	0.165	0.089	0.065	0.101	0.150	0.213	0.286
Assets ($ '000)	624,574	1,658,716	117,438	147,118	228,935	431,230	941,067
Uninsured_Deposits ($ '000)	124,862	392,962	11,105	18,585	34,419	73,795	187,256
TBTF	0.100	0.300	0.000	0.000	0.000	0.000	0.000
Private	0.815	0.389	0.000	1.000	1.000	1.000	1.000
StandAlone	0.161	0.368	0.000	0.000	0.000	0.000	1.000
DiffR2	0.029	0.402	–0.392	–0.059	0.000	0.131	0.497
DELR$_{it-1}$	0.292	0.455	0.000	0.000	0.000	1.000	1.000
Tier1$_{it-1}$	0.144	0.062	0.095	0.105	0.126	0.161	0.214
NPL$_{it-1}$	0.013	0.020	0.001	0.003	0.007	0.016	0.031
RealEstate%$_{it-1}$	0.715	0.170	0.489	0.618	0.737	0.837	0.919
EBLLP$_{it-1}$	0.009	0.324	0.003	0.005	0.006	0.008	0.011
ROA$_{it-1}$	0.010	0.009	0.002	0.007	0.011	0.015	0.019
Liquidity%$_{it-1}$	0.266	0.133	0.115	0.169	0.245	0.341	0.449
Size$_{it-1}$	12.560	0.912	11.662	11.886	12.328	12.962	13.742
LargeDepositRate$_{it}$	0.038	0.014	0.019	0.026	0.037	0.049	0.057
ΔLoan$_{it}$	0.013	0.036	–0.029	–0.008	0.013	0.034	0.056
Ln(StatePersonalInc)$_{it}$	12.306	0.901	11.131	11.725	12.300	12.948	13.461

Panel B: Descriptive Statistics by *DELR* Partition

	Less Delayed Banks *DELR = 0* (*N* = 105,755)			More Delayed Banks *DELR = 1* (*N* = 43,575)			*Test of Mean Differences*
Variables	**Mean**	**Median**	**St Dev**	**Mean**	**Median**	**St Dev**	
Ln(Uninsured_Deposit)	10.673	10.477	1.263	10.500	10.377	1.046	–0.1732 ***
Uninsured_Deposit%	0.167	0.152	0.092	0.160	0.147	0.082	–0.0072 ***
$Tier1_{it-1}$	0.143	0.124	0.063	0.147	0.130	0.058	0.0035 ***
NPL_{it-1}	0.013	0.007	0.021	0.013	0.007	0.018	–0.0006 ***
$RealEstate\%_{it-1}$	0.712	0.734	0.175	0.724	0.743	0.156	0.0120 ***
$EBLLP_{it-1}$	0.010	0.006	0.385	0.007	0.006	0.005	–0.0035 *
ROA_{it-1}	0.010	0.011	0.010	0.010	0.011	0.009	0.0004 ***
$Liquidity\%_{it-1}$	0.264	0.242	0.134	0.272	0.252	0.130	0.0075 ***
$Size_{it-1}$	12.602	12.346	0.962	12.459	12.288	0.765	–0.1436 ***
$LargeDepositRate_{it}$	0.038	0.038	0.014	0.037	0.036	0.014	–0.0014 ***
$\Delta Loan_{it}$	0.013	0.013	0.036	0.012	0.012	0.033	–0.0014 ***
$Ln(StatePersonalInc)_{it}$	12.308	12.302	0.913	12.299	12.296	0.871	–0.0087 *

This table presents descriptive statistics. Panel A presents those for the full sample, and Panel B for the sample partitioned into two groups: those with *DELR* = 0 and those with *DELR* = 1. *DELR* is an indicator variable equal to 1 if *DiffR2* is negative (indicating low timeliness), and 0 otherwise. The last column is a standard *t*-test comparing mean differences across the *DELR = 1* and *DELR = 0* bank groupings. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Table 3: Correlations

Variables (*N* = 149,330)		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Ln(Uninsured\_Deposit)_{it}$	(1)	**1**											
$Uninsured\_Deposit\%_{it}$	(2)	**0.637**	**1**										
$DELR_{it-1}$	(3)	**–0.065**	**–0.037**	**1**									
$Tier1_{it-1}$	(4)	**–0.257**	**–0.192**	**0.026**	**1**								
NPL_{it-1}	(5)	**–0.046**	**–0.106**	**–0.014**	**–0.056**	**1**							
$RealEstate\%_{it-1}$	(6)	**–0.060**	**–0.126**	**0.032**	**0.062**	**0.079**	**1**						
$EBLLP_{it-1}$	(7)	0.003	**0.014**	–0.005	**0.051**	**–0.006**	**–0.011**	**1**					
ROA_{it-1}	(8)	**0.045**	**0.124**	**0.021**	**0.132**	**–0.486**	**–0.173**	**0.022**	**1**				
$Liquidity\%_{it-1}$	(9)	**–0.089**	**0.034**	**0.026**	**0.536**	**–0.120**	**–0.102**	**0.026**	**0.136**	**1**			
$Size_{it-1}$	(10)	**0.866**	**0.223**	**–0.072**	**–0.193**	**0.034**	**0.034**	–0.001	**–0.047**	**–0.149**	**1**		
$LargeDepositRate_{it}$	(11)	**–0.094**	**–0.063**	**–0.045**	0.003	**–0.201**	**–0.095**	**0.006**	**0.155**	**–0.033**	**–0.090**	**1**	
$\Delta Loan_{it}$	(12)	**0.043**	**0.108**	**–0.018**	**–0.018**	**–0.303**	**–0.020**	0.004	**0.222**	**0.051**	**–0.029**	**0.158**	**1**
$Ln(StatePersonalInc)_{it}$	(13)	**0.104**	**0.105**	–0.004	–0.002	**0.059**	**0.202**	**–0.011**	**–0.121**	**0.026**	**0.094**	**–0.098**	–0.005

This table presents Pearson correlations. Bolded values indicate correlations significant at the 5% level. *N* = 149,330 bank-quarter observations. All variables are defined in Appendix A.

Table 4: Opacity and Uninsured Deposit Financing

Variables	Predicted Sign	*Ln(Uninsured_Deposits)$_{it}$* Coeff (*t*-stat)		*Uninsured_Deposits%$_{it}$* Coeff (*t*-stat)	
		(1)	(2)	(3)	(4)
DELR$_{it-1}$	**–**	**–0.173 (25.27) *** **	**–0.037 (6.43) *** **	**–0.007 (14.22)*** **	**–0.008 (9.09) *** **
Tier1$_{it-1}$	+ / –		–2.389 (15.19) ***		–0.286 (16.58) ***
NPL$_{it-1}$	–		–0.136 (0.50)		0.054 (1.55)
RealEstate%$_{it-1}$	–		–0.600 (13.29) ***		–0.073 (11.71) ***
EBLLP$_{it-1}$	+		0.021 (1.77) *		0.005 (2.16) **
ROA$_{it-1}$	+		7.934 (14.56) ***		1.023 (12.56) ***
Liquidity%$_{it-1}$	+		0.533 (9.07) ***		0.062 (7.09) ***
Size$_{it-1}$	+		1.115 (153.47) ***		0.017 (15.15) ***
LargeDepositRate$_{it}$	+ / –		–7.454 (11.17) ***		–1.135 (11.42) ***
ΔLoan$_{it}$	+		1.242 (17.00) ***		0.163 (15.79) ***
Ln(StatePersonalInc)$_{it}$	+		0.044 (5.69) ***		0.010 (7.97) ***
Fixed Effects			Year-quarter		Year-quarter
N		149,330	149,330	149,330	149,330
Adj. R^2		0.004	0.814	0.001	0.259

This table presents results from analyses examining the association between uninsured deposits and opacity. The sample includes 149,330 quarterly observations representing 7,185 individual banks. In Columns (1) and (2) the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. In Columns (3) and (4) the dependent variable is *Uninsured_Deposits$_{it}$%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. Across all columns, the experimental variable is *DELR$_{it-1}$*, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 5: Cross-Sectional Analyses

Variables	Pred Sign	*Ln(Uninsured_Deposits)$_{it}$* Coeff	(*t*–stat)	Coeff	(*t*–stat)	*Uninsured_Deposits%$_{it}$* Coeff	(*t*–stat)	Coeff	(*t*–stat)
		(1)		(2)		(3)		(4)	
NonTBTF$_{it–1}$	?	0.042	(1.46)			0.007	(1.64)		
NonPublic$_i$	?			–0.031	(1.68) *			–0.004	(1.25)
DELR$_{it–1}$	?	0.005	(0.23)	–0.050	(3.62) ***	0.011	(3.01) ***	–0.003	(1.19)
NonTBTF$_{it–1}$* DELR$_{it–1}$	**–**	**–0.045**	**(2.12) ****			**–0.021**	**(5.42) *****		
Private$_i$* DELR$_{it–1}$	**–**			**0.017**	**(1.12)**			**–0.006**	**(2.27) ****
Tier1$_{it–1}$	+ / –	–2.384	(15.14) ***	–2.373	(15.14) ***	–0.285	(16.53) ***	–0.283	(16.38) ***
NPL$_{it–1}$	–	–0.135	(0.49)	–0.125	(0.46)	0.054	(1.57)	0.055	(1.59)
RealEstate%$_{it–1}$	–	–0.606	(13.39) ***	–0.599	(13.29) ***	–0.074	(11.82) ***	–0.073	(11.75) ***
EBLLP$_{it–1}$	+	0.021	(1.76) *	0.021	(1.77) *	0.005	(2.14) **	0.005	(2.15) **
ROA$_{it–1}$	+	7.922	(14.52) ***	7.945	(14.56) ***	1.022	(12.55) ***	1.025	(12.55) ***
Liquidity%$_{it–1}$	+	0.532	(9.05) ***	0.536	(9.09) ***	0.061	(7.04) ***	0.062	(7.14) ***
Size$_{it–1}$	+	1.124	(112.99) ***	1.110	(138.34) ***	0.018	(11.91) ***	0.016	(13.21) ***
LargeDepositRate$_{it}$	+ / –	–7.467	(11.20) ***	–7.409	(11.12) ***	–1.134	(11.42) ***	–1.126	(11.36) ***
ΔLoan$_{it}$	+	1.241	(16.99) ***	1.248	(17.10) ***	0.163	(15.77) ***	0.164	(15.85) ***
Ln(StatePersonalInc)$_{it}$	+	0.044	(5.71) ***	0.043	(5.59) ***	0.010	(7.98) ***	0.009	(7.84) ***
Fixed Effect		Year–quarter		Year–quarter		Year–quarter		Year–quarter	
N		149,330		149,330		149,330		149,330	
Adj. R^2		0.814		0.814		0.260		0.259	

This table presents results examining variation in uninsured deposits and bank opacity conditional on two cross-sectional bank characteristics. In Columns (1) and (3), it is *NonTBTF* (an indicator variable equal to 1 if the bank is not designated as too-big to fail, and 0 otherwise); in Columns (2) and (4), it is *Private* (an indicator variable equal to 1 if the bank is not publicly-traded,

and zero otherwise). In Columns (1)–(2), the dependent variable is *Ln(Uninsured_Deposits)*$_{it}$, the natural log of uninsured deposits of bank *i* in quarter *t*. In Columns (3)–(4), the dependent variable is *Uninsured_Deposits*$_{it}$*%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. Across all columns, the experimental variable is *DELR*$_{it-1}$, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 6: Sensitivity Analyses−DELR-Stock Measures and Uninsured Deposit Financing

Variables	Predicted Sign	*Ln(Uninsured_Deposits)$_{it}$* Coeff	(*t*-stat)	*Uninsured_Deposits%$_{it}$* Coeff	(*t*-stat)
		(1)		(2)	
DELR_Stock1$_{it-1}$	**–**	**–0.024**	**(2.81)** ***	**–0.004**	**(3.34)** ***
Tier1$_{it-1}$	+ / –	–3.162	(18.68) ***	–0.374	(20.29) ***
NPL$_{it-1}$	–	–0.180	(0.47)	0.033	(0.64)
RealEstate%$_{it-1}$	–	–0.556	(12.24) ***	–0.063	(10.09) ***
EBLLP$_{it-1}$	+	14.486	(6.14) ***	2.659	(7.96) ***
ROA$_{it-1}$	+	3.011	(4.32) ***	0.104	(1.03)
Liquidity%$_{it-1}$	+	0.570	(8.89) ***	0.055	(6.13) ***
Size$_{it-1}$	+	1.092	(142.75) ***	0.012	(11.39) ***
LargeDepositRate$_{it}$	+ / –	–6.908	(11.20) ***	–1.068	(11.40) ***
ΔLoan$_{it}$	+	1.436	(19.09) ***	0.184	(17.83) ***
Ln(StatePersonalInc)$_{it}$	+	0.057	(7.68) ***	0.012	(10.37) ***
Fixed Effect		Year-quarter		Year-quarter	
N		191,335		191,399	
Adj. R^2		0.807		0.254	

This table presents results from sensitivity analyses using an alternative *DELR* stock measure to examine uninsured deposits and bank opacity. In Column (1) the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. In Column (2) the dependent variable is *Uninsured_Deposits$_{it}$%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. Across both columns, the experimental variable is *DELR_Stock1*, an indicator variable equal to 1 if lagged *LLA$_{it}$/NPL$_{it}$* is smaller than the median during the quarter, and 0 otherwise. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 7: Sensitivity Analyses−Alternative Time-series Related DELR Measures and Uninsured Deposit Financing

Variables	Predicted Sign	*Ln(Uninsured_Deposits)$_{it}$* Using 6 Quarters Coeff	(*t*-stat)	*Ln(Uninsured_Deposits)$_{it}$* Using 10 Quarters Coeff	(*t*-stat)	*Uninsured_Deposits%$_{it}$* Using 6 Quarters Coeff	(*t*-stat)	*Uninsured_Deposits%$_{it}$* Using 10 Quarters Coeff	(*t*-stat)
		(1)		(2)		(3)		(4)	
DELR$_{it-1}$	**–**	**–0.039**	**(6.77)** ***	**–0.013**	**(2.32)** **	**–0.009**	**(9.96)** ***	**–0.004**	**(5.17)** ***
Tier1$_{it-1}$	+ / –	–2.896	(17.39) ***	–2.784	(15.62) ***	–0.355	(18.94) ***	–0.337	(16.96) ***
NPL$_{it-1}$	–	–0.314	(0.91)	–0.098	(0.25)	–0.007	(0.15)	0.020	(0.39)
RealEstate%$_{it-1}$	–	–0.570	(12.74) ***	–0.564	(11.59) ***	–0.064	(10.13) ***	–0.068	(9.97) ***
EBLLP$_{it-1}$	+	18.384	(7.89) ***	18.490	(7.20) ***	2.923	(8.74) ***	2.865	(7.97) ***
ROA$_{it-1}$	+	3.027	(4.37) ***	3.697	(4.48) ***	0.206	(2.00) **	0.262	(2.24) **
Liquidity%$_{it-1}$	+	0.455	(7.47) ***	0.459	(6.86) ***	0.048	(5.45) ***	0.047	(4.95) ***
Size$_{it-1}$	+	1.104	(153.02) ***	1.106	(147.15) ***	0.014	(12.70) ***	0.017	(13.67) ***
LargeDepositRate$_{it}$	+ / –	–7.185	(11.20) ***	–6.999	(9.39) ***	–1.091	(11.39) ***	–1.035	(9.65) ***
ΔLoan$_{it}$	+	1.256	(17.59) ***	1.326	(15.58) ***	0.162	(15.88) ***	0.169	(14.37) ***
Ln(StatePersonalInc)$_{it}$	+	0.046	(6.12) ***	0.039	(4.71) ***	0.010	(8.64) ***	0.009	(7.07) ***
Fixed Effect		Year-quarter		Year-quarter		Year-quarter		Year-quarter	
N		162,663		113,555		162,703		113,584	
Adj. R^2		0.815		0.802		0.264		0.269	

This table presents results from sensitivity analyses to using alternative time-series to define *DELR* to examine uninsured depositors and bank opacity. In Columns (1) and (2) the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. In Columns (3) and (4) the dependent variable is *Uninsured_Deposits$_{it}$%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. The experimental variable is *DELR*, a proxy for bank financial reporting opacity. *DELR* is alternatively defined requiring 6 quarters in Columns (1) and (3), and 10 quarters in Columns (2) and (4). *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 8: Sensitivity Analyses−Alternative Dependent Variables

Variables	Predicted Sign	*Uninsured/Total_Deposits*$_{it}$ Coeff	(*t*-stat)	Coeff	(*t*-stat)	*Ln(ΔUninsured_Deposits)*$_{it}$ Coeff	(*t*-stat)	Coeff	(*t*-stat)
		(1)		(2)		(3)		(4)	
DELR$_{it-1}$	**–**	**–0.006**	**(5.47)** ***	**–0.011**	**(9.96)** ***	**–0.030**	**(2.82)** ***	**–0.044**	**(4.15)** ***
Tier1$_{it-1}$	+ / –	–0.411	(16.36) ***	–0.329	(13.18) ***	–2.826	(13.39) ***	–2.688	(12.46) ***
NPL$_{it-1}$	–	–0.385	(6.72) ***	0.001	(0.01)	–1.117	(2.24) **	–0.237	(0.45)
RealEstate%$_{it-1}$	–	–0.072	(9.12) ***	–0.090	(11.13) ***	–0.566	(11.17) ***	–0.595	(11.39) ***
EBLLP$_{it-1}$	+	1.571	(3.83) ***	4.128	(9.20) ***	13.318	(4.58) ***	17.934	(5.78) ***
ROA$_{it-1}$	+	0.911	(7.15) ***	0.115	(0.85)	3.818	(3.58) ***	3.116	(2.79) ***
Liquidity%$_{it-1}$	+	0.098	(9.41) ***	0.024	(2.15) **	0.057	(0.84)	–0.033	(0.44)
Size$_{it-1}$	+	0.033	(21.16) ***	0.029	(19.25) ***	0.929	(106.18) ***	0.924	(104.75) ***
LargeDepositRate$_{it}$	+ / –	–0.619	(13.51) ***	–1.291	(10.68) ***	–4.631	(12.10) ***	–6.640	(7.49) ***
ΔLoan$_{it}$	+	0.231	(17.08) ***	0.209	(15.93) ***	2.056	(13.76) ***	2.310	(15.35) ***
Ln(StatePersonalInc)$_{it}$	+	0.012	(7.99) ***	0.010	(6.63) ***	0.040	(4.79) ***	0.034	(4.02) ***
Fixed Effects		No		Year-quarter		No		Year-quarter	
N		149,361		149,361		83,151		83,151	
Adj. R^2		0.178		0.295		0.324		0.332	

This table presents results from sensitivity analyses using alternative dependent variables to examine uninsured deposits and bank opacity. In Columns (1) and (2), the dependent variable is *Uninsured/Total_Deposits*$_{it}$, the ratio of uninsured deposits to total deposits of bank *i* in quarter *t*. In Columns (3) and (4), the dependent variable is *Ln(ΔUninsured_Deposits)*$_{it}$, the natural log of change in uninsured deposits of bank *i* in quarter *t*. The experimental variable is *DELR*$_{it-1}$, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 9: Additional Analyses−Uninsured Deposit Financing During Recession versus Non-Recession Periods

		Ln(Uninsured_Deposits)$_{it}$			
		Recession Periods		**Non-Recession Periods**	
Variables	**Predicted Sign**	**Coeff**	**(*t*-stat)**	**Coeff**	**(*t*-stat)**
		(1)		(2)	
DELR$_{it-1}$	**–**	**–0.042**	**(4.86) *****	**–0.029**	**(4.65) *****
Tier1$_{it-1}$	+ / –	–2.715	(14.43) ***	–2.860	(16.63) ***
NPL$_{it-1}$	–	1.334	(3.26) ***	–0.618	(1.63)
RealEstate%$_{it-1}$	–	–0.475	(8.59) ***	–0.577	(12.72) ***
EBLLP$_{it-1}$	+	19.697	(6.24) ***	18.708	(7.79) ***
ROA$_{it-1}$	+	0.832	(0.93)	3.890	(5.06) ***
Liquidity%$_{it-1}$	+	0.351	(4.43) ***	0.465	(7.35) ***
Size$_{it-1}$	+	1.073	(117.45) ***	1.110	(149.93) ***
LargeDepositRate$_{it}$	+ / –	–7.446	(8.78) ***	–7.239	(10.58) ***
ΔLoan$_{it}$	+	1.170	(9.01) ***	1.273	(16.33) ***
Ln(StatePersonalInc)$_{it}$	+	0.052	(6.13) ***	0.041	(5.27) ***
Fixed Effect		Year-quarter		Year-quarter	
N		26,744		122,586	
Adj. R^2		0.823		0.809	

This table presents results from additional analyses examining uninsured deposits and bank opacity during recession and non-recession periods. Columns (1) and (2) present results using recession, and non-recession subsamples, respectively. Recession periods between 2001Q2– 2001Q4 and 2008Q1–2009Q2 (i.e., those quarters defined by NBER as recessionary quarters). In all Columns, the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. The experimental variable is *DELR$_{it-1}$*, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A

Table 10: Additional Analyses−Uninsured Deposit Financing across Bank Size Quartiles

		Ln(Uninsured_Deposits)$_{it}$							
		Quartile 1 (smallest banks)		**Quartile 2**		**Quartile 3**		**Quartile 4 (largest banks)**	
Variables	**Predicted Sign**	**Coeff**	**(*t*-stat)**	**Coeff**	**(*t*-stat)**	**Coeff**	**(*t*-stat)**	**Coeff**	**(*t*-stat)**
		(1)		(2)		(3)		(4)	
DELR$_{it-1}$	**–**	**–0.074**	**(6.67)** ***	**–0.027**	**(2.70)** ***	**–0.033**	**(3.19)** ***	**–0.002**	**(0.15)**
Tier1$_{it-1}$	+ / –	–2.129	(9.00) ***	–2.206	(8.17) ***	–3.569	(11.11) ***	–3.882	(10.53) ***
NPL$_{it-1}$	–	–0.056	(0.09)	–0.414	(0.70)	–0.569	(0.90)	–0.048	(0.06)
RealEstate%$_{it-1}$	–	–0.294	(3.69) ***	–0.449	(6.35) ***	–0.598	(7.29) ***	–0.842	(8.80) ***
EBLLP$_{it-1}$	+	22.440	(4.56) ***	16.711	(4.11) ***	20.939	(5.08) ***	14.423	(3.15) ***
ROA$_{it-1}$	+	0.644	(0.43)	3.206	(2.72) ***	4.429	(3.61) ***	4.473	(2.87) ***
Liquidity%$_{it-1}$	+	0.553	(5.53) ***	0.485	(4.61) ***	0.329	(3.21) ***	0.425	(3.07) ***
Size$_{it-1}$	+	1.139	(16.68) ***	1.019	(17.09) ***	1.020	(21.98) ***	1.076	(66.99) ***
LargeDepositRate$_{it}$	+ / –	–7.942	(7.43) ***	–6.473	(5.95) ***	–6.135	(5.07) ***	–7.256	(4.75) ***
ΔLoan$_{it}$	+	0.978	(8.92) ***	1.148	(9.42) ***	1.289	(9.94) ***	1.654	(8.21) ***
Ln(StatePersonalInc)$_{it}$	+	0.022	(1.72) *	0.036	(2.94) ***	0.038	(2.96) ***	0.065	(4.35) ***
Fixed Effect		Year-quarter		Year-quarter		Year-quarter		Year-quarter	
N		35,857		38,195		38,480		36,793	
Adj. R^2		0.279		0.320		0.405		0.789	

This table presents results from additional analyses examining the uninsured deposits and bank opacity across different bank size quartiles. In all columns, the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*, and the experimental variable is *DELR$_{it-1}$*, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 11: Sensitivity Analyses−DELR-Stock Measures and Uninsured Deposit Financing

Variables	Predicted Sign	*Ln(Uninsured_Deposits)$_{it}$* Coeff	(*t*-stat)	*Uninsured_Deposits%$_{it}$* Coeff	(*t*-stat)
		(1)		(2)	
DELR_Stock2$_{it-1}$	**–**	**–0.017**	**(2.15)** **	**–0.002**	**(1.96)** *
Tier1$_{it-1}$	+ / –	–3.165	(18.69) ***	–0.375	(20.32) ***
NPL$_{it-1}$	–	–0.375	(1.07)	–0.010	(0.22)
RealEstate%$_{it-1}$	–	–0.556	(12.24) ***	–0.063	(10.09) ***
EBLLP$_{it-1}$	+	14.645	(6.20) ***	2.693	(8.07) ***
ROA$_{it-1}$	+	2.927	(4.20) ***	0.087	(0.87)
Liquidity%$_{it-1}$	+	0.570	(8.88) ***	0.055	(6.13) ***
Size$_{it-1}$	+	1.092	(142.55) ***	0.012	(11.38) ***
LargeDepositRate$_{it}$	+ / –	–6.899	(11.18) ***	–1.067	(11.38) ***
ΔLoan$_{it}$	+	1.436	(19.09) ***	0.184	(17.82) ***
Ln(StatePersonalInc)$_{it}$	+	0.057	(7.67) ***	0.012	(10.36) ***
Fixed Effect		Year-quarter		Year-quarter	
N		191,335		191,399	
Adj. R^2		0.807		0.254	

This table presents results from sensitivity analyses using an alternative *DELR* stock measure to examine uninsured deposits and bank opacity. In Column (1) the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. In Column (2) the dependent variable is *Uninsured_Deposits$_{it}$%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. Across both columns, the experimental variable is *DELR_Stock2*, an indicator variable equal to 1 if lagged *LLA$_{it}$/NPL$_{it+1}$* is smaller than the median during the quarter, and 0 otherwise. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 12: DELR and Uninsured Deposit Financing–All Banks

Variables	Predicted Sign	*Ln(Uninsured_Deposits)$_{it}$* Coeff	(*t*-stat)	*Uninsured_Deposits%$_{it}$* Coeff	(*t*-stat)
		(1)		(2)	
DELR$_{it-1}$	**–**	**–0.032**	**(6.39)** ***	**–0.008**	**(13.35)** ***
Tier1$_{it-1}$	+ / –	–1.661	(14.67) ***	–0.162	(14.37) ***
NPL$_{it-1}$	–	–0.033	(0.15)	0.008	(0.37)
RealEstate%$_{it-1}$	–	–0.323	(9.47) ***	–0.044	(11.71) ***
EBLLP$_{it-1}$	+	–0.017	(4.08) ***	–0.001	(1.62)
ROA$_{it-1}$	+	7.063	(16.28) ***	0.664	(12.82) ***
Liquidity%$_{it-1}$	+	0.546	(11.63) ***	0.055	(10.23) ***
Size$_{it-1}$	+	1.210	(214.72) ***	0.027	(40.87) ***
LargeDepositRate$_{it}$	+ / –	–4.820	(10.72) ***	–0.666	(12.69) ***
ΔLoan$_{it}$	+	0.874	(19.95) ***	0.089	(17.89) ***
Ln(StatePersonalInc)$_{it}$	+	0.027	(4.23) ***	0.006	(7.69) ***
Fixed Effect		Year-quarter		Year-quarter	
N		296,727		296,727	
Adj. R^2		0.860		0.299	

This table presents results from analyses examining the association between uninsured deposits and opacity. The sample includes all banks, including those with total assets of less than $100 million, i.e. 296,727 quarterly observations representing 11,933 individual banks. In Columns (1) the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. In Columns (2) the dependent variable is *Uninsured_Deposits$_{it}$%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. Across all columns, the experimental variable is *DELR$_{it-1}$*, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

Table 13: Cross-Sectional Analysis−BHC and Stand-Alone Banks

Variables	Predicted Sign	*Ln(Uninsured_Deposits)$_{it}$* Coeff	(*t*-stat)	*Uninsured_Deposits%$_{it}$* Coeff	(*t*-stat)
		(1)		(2)	
StandAlone$_i$	?	–0.151	(6.93) ***	–0.011	(3.60) ***
DELR$_{it-1}$	?	–0.044	(7.81) ***	–0.008	(8.61) ***
StandAlone$_i$*DELR$_{it-1}$	**–**	**0.036**	**(1.85) ***	**–0.002**	**(0.64)**
Tier1$_{it-1}$	+ / –	–2.123	(13.63) ***	–0.265	(15.05) ***
NPL$_{it-1}$	–	–0.227	(0.83)	0.046	(1.34)
RealEstate%$_{it-1}$	–	–0.545	(12.19) ***	–0.069	(10.77) ***
EBLLP$_{it-1}$	+	0.022	(1.91) *	0.005	(2.21) **
ROA$_{it-1}$	+	7.296	(13.70) ***	0.973	(12.14) ***
Liquidity%$_{it-1}$	+	0.498	(8.66) ***	0.059	(6.78) ***
Size$_{it-1}$	+	1.115	(154.18) ***	0.017	(15.16) ***
LargeDepositRate$_{it}$	+ / –	–7.403	(11.20) ***	–1.131	(11.41) ***
ΔLoan$_{it}$	+	1.281	(17.58) ***	0.166	(16.08) ***
Ln(StatePersonalInc)$_{it}$	+	0.049	(6.42) ***	0.010	(8.34) ***
Fixed Effect		Year-quarter		Year-quarter	
N		149,330		149,330	
Adj. R^2		0.816		0.261	

This table presents results examining variation in uninsured deposits and bank opacity conditional on one cross-sectional bank characteristic, i.e. *StandAlone* (an indicator variable equal to 1 if the bank is not a bank holding company BHC, and 0 otherwise). In Column (1), the dependent variable is *Ln(Uninsured_Deposits)$_{it}$*, the natural log of uninsured deposits of bank *i* in quarter *t*. In Column (2), the dependent variable is *Uninsured_Deposits$_{it}$%*, the ratio of uninsured deposits to total assets of bank *i* in quarter *t*. Across all columns, the experimental variable is *DELR$_{it-1}$*, a proxy for bank financial reporting opacity. *t*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels for the indicated one- or two-tailed tests of significance. Standard errors are clustered by banks. All variables are defined in Appendix A.

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