# The role of accounting information in banks' access to funding and liquidity

A dissertation presented by

Sujesh P. Nambiar

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Dissertation committee:

Steven Monahan (chair)

Daniel Bens

Gavin Cassar

Thomas Keusch

**ABSTRACT**

I examine the relation between the quality of banks' reported accounting numbers and their ability to attract uninsured deposits and create liquidity. I find that banks with consistently higher accounting quality raise more uninsured deposits, pay a lower price for uninsured deposits and create more liquidity. These relations: (1) exist only during periods of banking crises, when uninsured deposits become information-sensitive and (2) are non-existent for insured deposits, which are not information-sensitive. Consistent with the difference in information-sensitivity between uninsured and insured deposits, I also find that banks on average pay a higher price for uninsured deposits vis-à-vis insured deposits only during periods of banking crises. I provide novel evidence on the positive role of accounting information in reducing financing frictions in one of the key financial intermediation channels in the economy.

**KEYWORDS:** accounting quality, bank transparency, deposit funding, uninsured deposits, bank liquidity

**JEL CLASSIFICATIONS:** G01, G21, G28, M41, M48

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## DEDICATION

I dedicate this dissertation to my wife, Sudeshna and to my children, Shreya and Mridula. They were my main motivation to undertake this journey. Their enthusiastic cooperation all along helped and inspired me to complete this journey successfully.

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## I. INTRODUCTION

Theories of financial intermediation posit that liquidity creation and risk transformation are the two primary functions of banks (Diamond and Dybvig 1983; Bhattacharya and Thakor 1993). A bank's access to deposit funding is crucial for liquidity creation (Berger and Bouwman 2009).[1] Financing frictions in deposit funding can also adversely affect the risk profile of a bank's assets and the stability of the bank (Cornett, McNutt, Strahan, and Tehranian 2011). Whether greater transparency reduces or enhances these frictions is open to debate. On the one hand, lack of bank transparency is often cited as a key cause of the financing frictions that contributed to the 2007 financial crisis (Barth and Landsman 2010; Acharya, Philipppon, Richardson, and Roubini 2009). On the other hand, some argue that higher transparency is undesirable as it inhibits a bank's ability to create liquidity (e.g., Dang, Gorton, Holmström, and Ordonez 2017; Dang, Gorton, and Holmstrom 2015). Following the above debate, in this paper I examine how the increased asset transparency resulting from higher accounting quality affects banks' access to uninsured deposit funding and banks' ability to create liquidity.

I focus on uninsured deposits for four reasons.[2] First, uninsured depositors, unlike insured depositors, are exposed to bank default risk and therefore care about the usefulness of accounting information for predicting bank default. Second, uninsured deposits are used as a marginal source of funding either for meeting short-

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[1] Banks create liquidity on both sides of the balance sheet through maturity transformation, i.e., by funding long-term loans with short-term deposits. While long-term loans create liquidity by funding investments in the economy, short-term deposits create liquidity by facilitating transactions in the economy. Higher the maturity transformation (short term liabilities funding long term assets), higher is the volume of liquidity created.

[2] Uninsured deposits are deposits that exceed the insurance threshold volume of USD 100,000. Unlike insured deposits, they are not insured against bank default by the Federal Deposit Insurance Corporation (FDIC).

run funding demands or during periods in which liquidity shocks occur, such as the 2007 financial crisis, which are when financing frictions matter the most (Holod and Peek 2007; Acharya and Mora 2015). Third, uninsured deposits form a significant proportion of bank funding with a total market volume of USD 2.7 trillion (FDIC 2008).[3] Finally, although uninsured deposits are an important source of funding, there is scant empirical evidence about their nature and the role that accounting quality plays in attracting them (Beatty and Liao 2014). Hence, my study fills an important gap in the literature.

Uninsured deposits are similar to unsecured debt, with the additional option to exit the investment on demand. Exercising a timely exit option or avoiding an untimely exit is crucial for uninsured depositors. Uninsured depositors are mainly comprised of sophisticated investors such as money market funds, other investment funds and corporate treasuries, who have the ability to process banks' accounting information (Perignon, Thesmar, and Vuillemey 2018; Whitledge and Winters 2015). Therefore, I expect a bank that provides credible and timely (i.e., high quality) accounting information, which allows its uninsured depositors to better predict its default risk, will raise a higher volume of deposits and at a lower price. Since uninsured deposits are used as a marginal source of funding, better access to uninsured deposits facilitates maturity transformation, and thus improves banks' ability to create liquidity. Therefore, I expect a positive association between a bank's accounting quality and the volume of liquidity the bank creates.

[3] This is based on FDIC aggregate US bank data 2008. For my sample, the average (median) percentage of total funding obtained from uninsured depositors is 20 (18) percent, which is approximately twice the average (median) percentage of total funding obtained from equity investors. Uninsured deposits are also more crucial for private and small banks, which form approximately 70 percent of total US banks and, unlike large, publicly listed banks, do not have equal access to alternate sources of marginal funding such as foreign deposits and interbank funding.

I also expect that the associations between a bank's accounting quality and its uninsured deposit price and volume, and the volume of liquidity it creates, will be stronger during periods of banking crises. The reason for this is that during normal times, when banks are far from default, uninsured deposits remain information-insensitive and informed depositors cannot benefit from their superior information (Holmstrom 2015). However, during periods of banking crises, the risk of bank default significantly increases. Hence uninsured deposits become information-sensitive, and the importance of a bank's accounting quality in predicting default also increases.

I begin my empirical analyses by estimating the accounting quality for a bank. I define accounting quality as the usefulness of a bank's quarterly report for predicting default.[4] I use forecasts of non-performing loans (NPLs hereafter) as an indicator of a bank's default potential, and I measure a bank's accounting quality as the *incremental* improvement in out-of-sample forecast accuracy that is attributable to including the bank's accounting information in the set of variables that I use to forecast NPLs. Therefore, higher accounting quality provides higher transparency regarding the asset quality of a bank.

The ex-post and endogenous nature of financial reports leads to reverse causality issues, which affect my ability to empirically establish a consistent direction of association between accounting quality and deposit parameters (Clinch and Verrecchia 2015). To mitigate this concern, I use the historic consistency in accounting quality as an empirical approximation for a bank's ex-ante commitment to accounting quality. I measure the consistency in accounting quality as the historical

[4] All US bank holding companies above the threshold asset size of USD 150 million are required to file consolidated FR Y-9C regulatory reports on a quarterly basis. Along with detailed financial statements, these reports provide incremental disaggregated information pertaining to loans, investments, deposits, equity and various other risk parameters.

reduction in root mean square forecast error (RMSE hereafter) of NPLs over the previous eight quarters. I then regress the key deposit-funding parameters (i.e., price and volume) and a measure of liquidity creation on the consistency in accounting quality measure and a set of control variables that include accounting quality in the contemporaneous quarter.[5] Using eight quarters of data also mitigates concerns relating to verifiability of signal.

I further address concerns about endogeneity and omitted correlated variables bias by exploiting a unique feature in my setting: In the case of banks, insured deposits mirror uninsured deposits on all relevant parameters (especially demand and maturity) except those that relate to risk.[6] I mitigate issues related to identification by exploiting this parallel trend between insured and uninsured deposit parameters and the shock to default risk that occurred at the beginning of the 2007 banking crisis, in a generalized difference-in-difference design. I also exploit the exogenous shock to accounting quality via the shock to financial performance caused by the 2007 banking crisis (Dechow, Ge, and Schrand 2010).

I use quarterly panel data from the FR Y-9C regulatory financial report for US bank holding companies for the period 1992 to 2014. My results show that controlling for bank risk, higher consistency in accounting quality has a negative association with the cost of uninsured deposits and a positive association with both the quarterly growth in the volume of uninsured deposits and with the volume of liquidity created. These associations are significantly larger in magnitude during the 2007 financial crisis and

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[5] I use the measure of liquidity creation described in Berger and Bowman (2009, page 3791, table 1). I reproduce the methodology in the Appendix C.

[6] To make them more comparable, within insured deposits I use only the time deposits and exclude transaction related deposits such as savings and checking accounts. This is because the incentives for transaction seeking depositors could be potentially different from those seeking investments through time deposits.

do not manifest during non-crisis quarters. In contrast, consistency in accounting quality does not have any incremental impact on insured deposit pricing or volume either during crises or non-crises periods. The results are robust to using an alternate, broader definition of crisis-quarters.

The economic magnitude of the impact of accounting quality is non-trivial. Moving from the low to the high consistency in accounting quality category implies a seven basis points (bps) reduction in the cost of uninsured deposits, a 90 bps increase in the quarterly growth rate in uninsured deposits and a 70 bps increase in liquidity created by the bank. For a typical bank in my sample this translates into a USD 80,000 reduction in interest expense or 13 bps increase in return on equity, ROE. It also translates into a USD 1 million increase in deposits, which is around 100 percent of quarterly growth in uninsured deposits, and a USD 4 million increase in liquidity creation, which equals 3.5 percent of the total liquidity created.

I also provide new evidence about time series trends in the cost of deposits. I show that banks on average pay more for insured than uninsured deposits during non-crisis periods. However, during periods of bank crises, the cost of uninsured deposits surpasses that of insured deposits. This reversal suggests that uninsured deposits become information-sensitive only during crises periods, when default risk is significantly higher and is priced-in by the depositors. Combining this result with the fact that my main results on the impact of accounting quality are present only during bank crises periods confirms the shift in information-sensitivity of uninsured deposits as posited in Holmstrom (2015) and Dang, Gorton, and Holmstrom (2015). Overall, I document positive effects of increased bank transparency and the results provide evidence in support of the monitoring hypothesis posited in Calomiris and Kahn (1991) and in Diamond and Rajan (2001).

To the best of my knowledge, I am the first to study the impact of banks' accounting quality on deposit funding and internal liquidity creation. Prior papers in the accounting literature have examined the impact of accounting quality on cost of funds and liquidity in the secondary equity and debt markets (Wittenberg-Moerman 2008; Bushman and Williams 2015; Beatty and Liao 2014). My results provide evidence on how accounting quality impacts financing frictions in a systemically important funding channel, especially during periods of market-wide liquidity crises, when financing frictions matter most. I also document novel evidence on the comparative time-series trends in the cost of insured deposits vis-à-vis uninsured deposits and compare them during crises vs. non-crises periods.

I also contribute to the debate about whether higher transparency assists or impairs banks' access to funding and their ability to create liquidity. In this regard, my paper is related to Balakrishnan and Ertan (2019). They study the impact of an exogenous increase in asset transparency of European banks and provide evidence of its positive impact on non-deposit funding and bank lending. My paper is also related to and builds on Perignon et al. (2018). They evaluate the European certificate of deposit (CD hereafter) market and show that more information on bank risk during periods of banking crises causes uninsured deposits to become information-sensitive. They also show that the presence of informed investors prevents market-wide funding failure and instead facilitates risk-based screening. I build on these findings and show that after controlling for default risk, consistency in accounting quality is positively associated with incrementally better access to uninsured deposits and higher liquidity creation.[7]

A concurrent working paper by Chen, Goldstein, Huang, and Vashishtha (2019) uses a setting similar to that in my paper, but explores how higher transparency increases the ex-post sensitivity of deposit flow to bank performance. My paper however differs from theirs on multiple counts, including the research design, the data set and the implications drawn. Though higher transparency may have negative ex-post consequences, I argue and show that there are ex-ante benefits as well, and that these benefits, which accrue in the form of better access to uninsured deposits and higher liquidity creation, are realized during crises periods – i.e., when they are needed most. Since the information sensitivity of uninsured deposits shift between normal and crises periods, I separately examine and compare the impact of transparency during both normal and crisis periods. This enables me to document more nuanced evidence that is also consistent with the shift in information-sensitivity of deposits documented in the literature. Finally, since it is the bank holding company's overall financial strength that matters when pricing bank default, I conduct all my analyses using holding-company-level data as opposed to the commercial-bank-level data used by Chen et al. (2019).

I also contribute to the literature on the role of accounting information in debt contracting. Specifically, I develop a decision-usefulness-based measure of accounting quality that addresses: (1) the criticism raised by Dechow et al. (2010) about accounting quality measures not being context and usage specific; (2) the

[7] I do not make a claim regarding optimality or overall cost and benefits of bank transparency and its market wide implications.

criticism raised by Armstrong, Guay, and Weber (2010) about accounting quality proxies being opaque about the mechanism that allows investors to benefit from higher values of the measured quality construct; and (3) the issues raised by Clinch and Verrecchia (2015) about the endogenous nature of accounting disclosure. Since deposit contracts are arm's length transactions, wherein price, volume and maturity are the only contract variables, I also avoid identification issues related to controlling for the impact of collateral and unobservable contract terms, which are generally used in debt contracts in order to mitigate information asymmetry (Bharath, Sunder, and Sunder 2008).

## II. HYPOTHESIS DEVELOPMENT

In this section, I discuss the importance of uninsured deposits by providing an overview of its role in the maturity transformation and liquidity creation functions of a bank. I then discuss why accounting quality matters for uninsured depositors and why it can affect the volume and prices of uninsured deposits, and a bank's capacity to create liquidity.

**Role of uninsured deposits in bank funding**

A central role of banks is to create liquidity in order to support economic growth (Berger and Bouwman 2009). Banks create liquidity by financing long-term loans and commitments, which are illiquid, with short-term deposits, which are liquid (Bryant 1980; Diamond and Dybvig 1983). Short-term deposits (broadly categorized as transaction deposits) are money-like instruments that help facilitate trade and transactions in the economy while long-term loans help fund investment and growth. The maturity and risk transformation between transaction deposits and long-term loans is achieved by actively managing what is called wholesale funding. Wholesale funding includes uninsured deposits, interbank funding and other short- and long-term funding sources (FDIC Risk Management Manual 2009). The smooth functioning of the wholesale funding channel is therefore crucial for banks (Feldman and Schmidt 2001). Wholesale funding also plays an important role in determining a bank's risk profile, stability, and profitability (Demirgüç-Kunt and Huizinga 2010; Beau et al. 2014).

Uninsured deposits form a significantly large source of funding for banks and on average constitute more than 50 percent of a bank's wholesale funding. For a typical US bank, this translates into 20 percent of total bank funding and an aggregate market volume of USD 2.7 trillion (FDIC aggregate US bank data 2008). Uninsured deposits are also used as an important marginal source of funds whenever banks face sudden funding gaps (Holod and Peek 2007; Feldman and Schmidt 2001). This is because uninsured depositors mainly comprise of yield-seeking investors and these deposits can be raised on short notice by offering competitive rates (Acharya and Mora 2015). This is in contrast to growing the transaction deposit base, which though highly desirable, requires time and investment in building customer relationships.

**Accounting quality and uninsured deposit funding**

For accounting quality to matter to depositors, a maintained hypothesis is that both default risk and accounting quality are factored into deposit contract terms and therefore depositors are sophisticated enough to process accounting information. While for insured depositors this assumption may be less appropriate, for uninsured depositors this assumption is quite reasonable. Uninsured depositors are exposed to bank default and would care about accounting reports that provide information regarding the risk profile of the bank's assets. Uninsured depositors are mainly comprised of sophisticated investors such as money market funds, investment funds, corporate treasuries, other banks and portfolio managers who invest on behalf of high-net-worth individuals (Whitledge and Winters 2015).[8] These are yield-chasing investors who often do not have a relationship with the bank (Holod and Peek 2007). The FDIC describes these investors as capital providers who "closely track institutions' financial condition and may cease or curtail funding, increase interest rates if they determine an institution's financial condition is deteriorating" (FDIC 2009).[9] Perignon et al. (2018) also provide evidence supporting the presence of

[8] In 2008, money market prime funds alone contributed to around 20 percent of total uninsured deposit funding for US banks (Investment Company Institute Factbook 2018)
[9] FDIC Risk Management Manual, Section 6.1, page 9.

informed investors in the European CD market who are able to screen out low-risk banks from high-risk banks.

Although the literature on accounting quality and debt contracting provides evidence of a positive relation between accounting quality and favorable contract terms for the borrower (Armstrong et al. 2010), these results may not generalize to the case of deposit funding in banks. Rather, competing theories provide alternate views of the impact of asset transparency provided by higher accounting quality. On the one hand, the monitoring view (Diamond and Rajan 2001) deems higher transparency as *desirable*, as it helps depositors to check managerial risk taking. This goes back to Blackwell's (1951) theorem and builds on the idea that more precise information regarding the assets of a bank will be more useful for market participants and it would in turn improve monitoring and market discipline (Goldstein and Sapra 2014). On the other hand, the liquidity creation view (Dang et al. 2017) deems higher transparency as *undesirable*, as it exposes depositors to fluctuations in default risk of the bank and interferes with the creation of information-insensitive and stable deposits. This alternate idea goes back to the "Hirshleifer Effect" (Hirshleifer 1971) where in greater disclosure has the adverse effect of reducing risk sharing opportunities for economic agents. Specifically, Dang et al. (2017) posit that informed investors would have no incentive to expend effort in processing information regarding the risk profile of the bank's assets, if the cost of processing is higher than the expected loss in the downside scenario.

I argue that both the monitoring and liquidity creation effects exist, but either of them can be dominant depending on what the depositors seek from their investment. On the one hand, depositors seeking transaction services would prefer that these deposits remain information-insensitive in order to facilitate payments. This argument is supported by the fact that FDIC insures transaction deposits so as to make these deposits information-insensitive and therefore suitable for payments. On the other hand, depositors seeking investment and return opportunities would prefer greater transparency regarding the risk profile of the assets of the bank. Since uninsured depositors mostly comprise of yield seeking investors than transaction seeking depositors (Acharya and Mora 2015; Holod and Peek 2007), I expect the monitoring effect to dominate, wherein higher transparency about the banks' assets is deemed desirable.[10]

The monitoring role played by uninsured depositors as well as the reduction in monitoring due to the increase in deposit insurance has been documented (Berger and Turk-Ariss 2015; Goldberg and Hudgins 2002; Bliss and Flannery 2002; Benston 1995; Demirgüç-Kunt and Huizinga 2004). Regulators rely on uninsured depositors to control excessive risk taking and enable market discipline as a lever of prudential regulation (FDIC Risk Management Manual, Section 6.1, page 9). Uninsured depositors monitor banks through the return they demand, the volume of funding they provide or by exiting their investments (Peria and Schmukler 2001). Uninsured depositors have an option to exit their investment at any time after paying a minimal charge. To make an optimal exit choice, they need credible and timely (i.e. high quality) information about a bank's default potential. Hence, a straightforward prediction is that when a bank provides credible information that helps uninsured depositors to assess its default risk better, these depositors will be more willing to invest and will accept a lower interest rate on

[10] Money market funds, the largest proportion of investors in uninsured deposits, do provide checking accounts and similar banking services in order to cater to a set of clients seeking transaction facilities. Such funds could value opacity over transparency, though the overall effect is still open to empirical examination.

their deposits. Therefore, I predict that there is a positive relation between consistency in accounting quality and uninsured deposit parameters such as price and volume.

Chen et al. (2019) argue that higher asset transparency has adverse effects due to a stronger ex-post reaction from depositors to reported bank performance. Higher asset transparency can have negative ex-post consequences such as higher deposit flow sensitivity, but there are also potential ex-ante benefits related to lower adverse selection costs. For example, Balakrishnan and Ertan (2019) show that an exogenous increase in asset transparency for a bank reduces its non-deposit funding cost. Moreover, a stronger ex-post reaction to reported bank performance does not necessarily imply less favorable ex-ante deposit pricing and volume effects. Whether the overall impact of higher asset transparency is positive or negative is still an open empirical question.

The quarterly regulatory reports filed by US banks are the primary source of the banks' accounting information. Badertscher, Burks, and Easton (2018) document the vital and incremental role of these reports in a bank's information environment. A large majority (more than 70 percent) of US banks are private and, because they do not have access to public capital, these banks rely heavily on uninsured deposits. Since publicly available sources of information are more restricted in the case of private banks, their quarterly published regulatory reports are more relevant. To the extent these reports provide uninsured depositors with credible information regarding a bank's risk profile and default potential, they reduce both adverse selection and moral hazard costs. This implies a lower cost of uninsured deposits for banks with higher consistency in accounting quality, and it leads to my first hypothesis:

*H1a: Consistency in accounting quality is negatively associated with a bank's cost of uninsured deposits.*

Depositors monitor banks and respond to increases in risk via both price and the option to exit. The latter affects the ability of a less transparent bank to raise new deposits and to retain existing deposits. I therefore expect a positive association between consistency in accounting quality and growth in uninsured deposit volume. This leads to my second hypothesis:

*H2a: Consistency in accounting quality is positively associated with a bank's growth in uninsured deposits.*

Banks are highly regulated. Moreover, default events are rare and tend to happen during periods of severe economic downturns. During normal periods, bank deposits are considered and priced as a highly safe asset class and depositors (both insured and uninsured) do not necessarily differentiate between banks on the basis of default risk. In line with these reasons, Holmstrom (2015) uses CDs as an example of an information-insensitive security and Ben-David, Palvia, and Spatt (2017) argue that during normal times banks' demand for funding is the predominant factor driving deposit price.

However, during periods of banking crises, when the risk of bank default increases, I expect that uninsured depositors differentiate on the basis of default risk, and thus the usefulness of accounting information in predicting default and therefore its quality will affect uninsured deposit prices and volumes. Perignon et al. (2018) show that uninsured deposits shift from being information-insensitive during normal times to being information-sensitive during times of banking crises. Gallagher et al. (2019) describe a similar scenario in the case of money market funds. During normal times, money market investors remain information-insensitive and do not monitor fund risk. However, they become information-sensitive when events that significantly increase default risk occur. This implies that during banking crises there is a stronger (1) negative association between consistency in accounting quality and the price of uninsured deposits and (2) positive association between consistency in accounting quality and the volume of uninsured deposits. This leads to the following additional hypotheses regarding pricing and volume, respectively:

*H1b: The negative association between a bank's consistency in accounting quality and its cost of uninsured deposits is higher during periods of banking crises.*

*H2b: The positive association between a bank's consistency in accounting quality and its growth in uninsured deposits is higher during periods of banking crises.*

The above predictions also follow from the limiting conditions under which informed investors do not have an incentive to process information, as derived in Dang et al. (2017). During crisis periods the expected loss in the downside scenario rises significantly and it surpasses the cost of processing information to determine the true default risk of the bank, thus violating the limiting condition. Investors no more remain indifferent to the risk profile of the bank and uninsured deposits become information-sensitive. As a result, the usefulness of accounting information in predicting default also increases.

Since insured deposits are not exposed to bank default risk, I do not expect a negative association between accounting quality and cost of insured deposits. Similarly, I also do not expect a positive association between accounting quality and growth in insured deposits.

**Accounting quality and liquidity creation by banks**

As noted earlier, banks create liquidity in the economy by the maturity transformation between transaction deposits, which are liquid, and long-term loans and commitments, which are illiquid. A bank that is funded with a higher proportion of transaction deposits and that lends out a higher proportion of its assets as long-term loans, will create more liquidity. This also implies that when more liquidity is created, the maturity transformation risk borne by the bank is higher (Berger and Bouwman 2009). Maturity transformation risk arises from the need to constantly bring in additional short-term funding to manage the liability and asset maturity mismatch. Because there is a significant lead-time needed to raise transaction deposits, they cannot be used to meet short-run funding gaps. Therefore, alternate sources of wholesale funds, and uninsured deposits in particular, is necessary (Holod and Peek 2007). Potential friction in raising uninsured deposits will therefore negatively affect a bank's ability to take on maturity transformation risk and reduce its ability to create liquidity. To the extent that consistency in accounting quality mitigates uninsured-deposit-funding frictions, it will result in higher liquidity creation. This leads to my liquidity hypothesis:

*H3a: A bank's consistency in accounting quality is positively associated with the volume of liquidity created by the bank.*

Following from this and in the same vein as H1b and H2b, I state my final hypothesis as follows:

*H3b: The positive association between a bank's consistency in accounting quality and the volume of liquidity created by the bank is higher during periods of banking crises.*

## III. ACCOUNTING QUALITY MEASURES

Usefulness of accounting information, and thus its quality, is context specific (Dechow et al. 2010). Uninsured depositors monitor banks using the option to exit on demand (Diamond and Dybvig 1983; Diamond and Rajan 2001; Benston 1994). Consequently, these investors demand timely and credible information about a bank's default risk. For most banks, credit risk is the largest component of total default risk and it is highly idiosyncratic (Nichols et al. 2009). Since NPL changes best capture changes in bank credit risk, I measure the usefulness of a bank's accounting information for forecasting future NPLs.[11] Also, since NPL definitions are highly standardized, managerial discretion in measuring NPLs is relatively low.

Extant studies on the impact of accounting quality on debt contracting use disclosure or transparency indices (Sengupta 1998), accrual-based measures (Bharath, Sunder, and Sunder 2008) and conservatism-based measures (Zhang 2008). These studies, however, do not explicate the mechanisms through which variation in accounting quality measures specifically translate into actionable information for lenders. In their review of this literature, Armstrong et al. (2010) highlight that, at a minimum, it must be ensured that a measure of accounting quality can be used to predict the level of or change in credit quality. I address this issue by directly measuring the impact of accounting quality on the predictability of NPLs.

[11] Alternatively, I could measure accounting quality using a bank-level default model. However, doing this has several drawbacks. First, the threat of regulatory interventions in the case of potential default situations significantly alters banks' behaviour, depositors' behaviour and the banks' reported financial results (Chan-Lau and Sy 2007). Regulatory intervention causes a discontinuity in policy and business that is highly idiosyncratic and cannot be generalized to all banks during pre-intervention periods. Second, the limited number of actual defaults significantly reduces the accuracy of bank-level forecast models. Finally, stock price data cannot be included in the forecast model as most of the banks in my sample are private. By forecasting NPLs, I avoid these issues, while at the same time I control for key factors that drive bank default.

I define accounting quality as the usefulness of a bank's quarterly regulatory report for predicting default. I use forecasts of NPLs as the indicator of default risk and measure accounting quality for a bank as the incremental reduction in the out-of-sample NPL forecast error achieved by including the bank's accounting information in the set of non-accounting predictor variables that I use in my baseline NPL forecast model.[12] A higher accounting quality as per my measure implies higher transparency regarding the risk profile of a bank's assets.

Since the above measure (Current Accounting Quality) is based on quarter-end reported accounting numbers, the reduction in forecast error for each quarter is an ex-post measure of accounting quality. Ex-post measures involve strategic disclosure choices. Consequently, evidence based on such measures does not provide clear-cut inferences when compared to measures based on ex-ante commitments (Clinch and Verrecchia 2015). To mitigate this concern, I estimate a measure of historic consistency in accounting quality as an empirical proxy for commitment to accounting quality. I measure consistency in accounting quality as the historical reduction in RMSE of NPL forecast over the previous eight quarters achieved by including the bank's accounting information in the set of non-accounting predictor variables used in my baseline NPL forecast model.

Following Bushman and Williams (2012), I use the cross-sectional median of Consistency in Accounting Quality (Current Accounting Quality) for a given quarter to convert the bank-level measures for that quarter into a binary variable. I refer to this variable as $Consistency\_in\_Quality$ ($Current\_Quality$). When a bank's Consistency in

[12] The baseline model is a benchmark model for forecasting NPL changes using only non-bank specific and non-accounting predictor variables.

Accounting Quality is higher (lower) than the quarterly median, the variable $Consistency\_in\_Quality$ takes on a value of 1 (0) and I classify that bank as having high (low) Consistency in Accounting Quality. Similarly, when a bank's Current Accounting Quality is higher (lower) than the quarterly median, the variable $Current\_Quality$ takes on a value of 1 (0) and I classify that bank as having high (low) Current Accounting Quality. I use $Consistency\_in\_Quality$ as my main measure of accounting quality in all subsequent regressions and I simultaneously use $Current\_Quality$ to control for the potential effect of contemporaneous disclosure.

My approach is similar to the measure of timeliness in loan loss provisioning used in the banking literature (e.g., Beatty and Liao 2011; Bushman and Williams 2015). However, there are three important differences between my measure and the timeliness measures. First, timeliness in loan loss provisioning is just one of the constructs captured by my measure. My measure also captures other broader aspects of a bank's accounting quality that affect the usefulness of its reported numbers for forecasting NPLs. Second, I use changes in out-of-sample forecast errors to measure usefulness, whereas the timeliness measures used in extant studies reflect in-sample differences in r-squareds. This makes my measure more aligned with the way information is likely used by depositors, i.e., to predict default. Finally, I use panel data as opposed to time-series data to estimate my forecasts. Consequently, I am able to incorporate information about cross-sectional variation. The use of panel data also addresses issues related to low degrees of freedom, which is an unavoidable drawback associated with time-series regressions that use low-frequency accounting data. Appendix B describes the NPL forecast models, the accounting quality variables, and related calculations in further detail.

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## IV. RESEARCH DESIGN FOR HYPOTHESIS TESTING

I test my three hypotheses by separately regressing the price of uninsured deposits, quarterly changes in uninsured deposit volume and the volume of liquidity created on the accounting quality measures, a set of control variables and a set of fixed effects. I also address potential confounding effects attributable to endogenous accounting choices and funding decisions or omitted variables that affect both deposit terms and accounting quality. In the subsequent sub-sections, I describe the research design for my main tests.

**Regression model**

I estimate alternative versions of the following model for my main tests:

$$\begin{aligned} Dependent\_Variable_{i,t} &= \beta_0 + \beta_1\, Consistency\_in\_Quality_{\,i,t-1} \\ &+ \beta_2\, Consistency\_in\_Quality_{\,i,t-1} * Crisis_t + \beta_3\, Current\_Quality_{i,t-1} \\ &+ \beta_4\, Current\_Quality_{i,t-1} * Crisis_t + \beta_5\, Control\_Main_{i,t} \\ &+ \beta_6(l_k)\Sigma\, Control\_Other_{i,t-1} + Firm\ FE_i + Quarter\ FE_t + \varepsilon_{i,t} \qquad [3] \end{aligned}$$

Subscripts *i* and *t* represent bank and quarter, respectively. $Dependent\_Variable_{i,t}$ is $Cost\_Uninsured_{i,t}$ for the pricing tests (H1a and H1b), $Uninsured\_Growth_{i,t}$ for the volume tests (H2a and H2b) and $Liquidity\_Generated_{i,t}$ for the liquidity tests (H3a and H3b). I define $Cost\_Uninsured_{i,t}$ as the average cost of uninsured time deposits for firm *i* during quarter *t*. I classify all time deposits equal to or above USD 100,000 in amount as uninsured. I calculate the cost of deposit as the ratio of annualized quarterly interest expense to the quarterly average deposit balance. I define $Uninsured\_Growth_{i,t}$ as the quarterly change in uninsured deposit volume divided by total uninsured deposit volume at the beginning of the quarter. I define $Liquidity\_Generated_{i,t}$ as the total liquidity created by a bank as measured using the quarter-end balance sheet. To calculate the total liquidity created, I follow Berger and Bouwman (2009) and classify all assets and liabilities into liquid, semi-liquid and illiquid categories.[13] I then calculate the liquidity created as ½(illiquid assets + liquid liabilities) – ½(liquid assets + illiquid liabilities + equity), divided by total assets at the beginning of the quarter. $Liquidity\_Generated_{i,t}$ measures the ability of a bank to create money-like securities for transactions on the liability side of the balance sheet while providing long-term funding to businesses and individuals on the asset side.

$Consistency\_in\_Quality_{\ i,t-1}$ and $Current\_Quality_{i,t-1}$ follow the definitions in Section III. $Crisis_t$ is a quarter indicator variable corresponding to the 2007 to 2009 financial crisis and takes the value of 1 for quarters from 2007 Q3 to 2009 Q2, and 0 otherwise (Acharya and Mora 2015).

$Control\_\ Main_{i,t}$ is $Cost\_Insured_{i,t}$ for the pricing tests (H1a and H1b), and $Ininsured\_Growth_{i,t}$ for the volume tests (H2a and H2b). $Cost\_Insured_{i,t}$ is the average cost of insured time deposits for firm *i* in quarter *t*. I classify all time deposits below USD 100,000 in amount as insured. I estimate the cost of deposit as the ratio of annualized quarterly interest expense to the quarterly average deposit balance. $Insured\_Growth_{i,t}$ is the quarterly change in insured deposit volume divided by the volume of insured deposits at the beginning of the quarter. Since both uninsured and insured deposits are time deposits, their flows will mirror each other on all relevant parameters, except risk. Hence, I use $Insured\_Growth_{i,t}$ to control for potentially correlated omitted variables.

[13] I reproduce the classification methodology from Berger and Bouwman (2009) in Appendix C.

For the pricing tests, $Control\_Other_{i,t-1}$ is a vector of bank-specific risk factors and other control variables. These include bank size, $Size$, change in market share for uninsured deposits, $MSChange\_Uninsured$, return on equity, $ROE$, tier 1 capital adequacy ratio, $Leverage$, proportion of non-performing loans, $NPL\_Ratio$, listing status, $Listed$, real estate loan proportion, $RealEst\_Prop$, unused commitments as a proportion of total loans, $Unused\_Commit$, loan to deposit ratio, $LDR$ and deposit funding proportion, $Deposit\_Prop$. These control variables are known drivers of bank risk and are used by regulators for calculating the bank's CAMELS rating.[14]

For the volume tests, $Control\_Other_{i,t-1}$ includes loan growth over last four quarters, $Loan\_Growth$, wholesale funding proportion, $Wholesale\_Fund\_Prop$, total deposit market share, $MS\_Deposit$, ratio of uninsured to insured time deposits, $Unins\_to\_Ins\_Ratio$, the quarterly increase in cost of uninsured deposit net of quarterly increase in cost of insured deposits, $Netchange\_Cost\_Uninsured$, and the change in non-performing loan coverage, $NPL\_Cover\_Change$. Apart from these, the remaining controls used in the pricing tests, except $MSChange\_Uninsured$, are also included. Control variables for deposit flows are based on Acharya and Mora (2015) and for risk are the same as used in the pricing tests.

For the liquidity tests, $Control\_Other_{i,t-1}$ includes $Unused\_Commit$, $Leverage$, $Size$, $NPL\_Ratio$, $ROE$, $Loan\_Growth$, $Wholesale\_Fund\_Prop$ and interest rate risk, $IntRate_{Risk}$ (Berger and Bouwman 2009). Liquidity creation involves risk taking in order to manage the maturity mismatch. Hence, I also use standard risk measures

[14] CAMELS stands for Capital, Asset quality, Management, Earnings, Liquidity and Sensitivity to market risk. It is a composite rating provided to a bank by a regulatory examiner and is based on both public and private bank information. The composite rating is arrived at by assessing the banks on each of the six components mentioned.

such as $Leverage$, $Size$ and $NPL\_Ratio$ as controls. Wholesale funding and unused loan commitments pose additional liquidity risk.

$Firm\ FE$ is the firm fixed effect and $Quarter\ FE$ is the time fixed effect in all the specifications. I cluster the standard errors by bank and quarter. Appendix A provides detailed definitions of each of the variables mentioned above.

**Endogeneity and omitted correlated variables**

The association between accounting quality and the cost of uninsured deposits could be the result of an endogenous bank choice. Banks that have a lower cost of deposits or lower business risk might improve accounting quality in anticipation of higher deposit funding demand or lower deposit supply. I address reverse causality and the presence of potential omitted correlated variables in three different ways.

First, in equilibrium, the cost and volume of uninsured deposits is a function of the bank's default risk, accounting quality, demand for deposits, the duration of its deposits, depositors' risk appetite and the contemporaneous supply of deposit funding. A unique feature of my setting is that insured deposits for a bank mirror the uninsured deposits on all relevant parameters (especially demand and maturity) except those that relate to risk. Hence, I use the insured deposit price and volume change for each bank quarter as a control variable in my estimations. I also control for unobservable, time-varying, bank-specific factors such as the bank's business model and its customer franchise. The 2007 financial crisis provides an exogenous shock to bank default risk. Using the crisis as a treatment, I address identification by exploiting the parallel trends between insured and uninsured deposit parameters in a difference-in-difference design. The variation in supply of capital is a temporal market-wide phenomenon and its variation is captured by the time fixed effects.

Second, I use the 2007 financial crisis as an exogenous shock to accounting quality. Dechow et al. (2010) highlight that accounting quality is a combined function of the set of allowed accounting rules, managerial discretion, and fundamental financial performance. The banking crisis provides an exogenous shock to the third determinant – i.e., financial performance. Since the $Consistency\_in\_Quality_{i,t-1}$ measure uses lagged accounting data, strategic reporting behavior on part of bank managers is unlikely. Specifically, assuming bank managers were *un*able to anticipate the crisis more than a year in advance, which is a plausible assumption, the accounting numbers reported during the pre-crisis period were not manipulated in order to mitigate the effects of the crisis.

Finally, since the crisis started with a severe liquidity shock to the short-term bank-funding market, it also provides an exogenous shock to bank's demand for funding (Acharya and Mora 2015). This shock was amplified and sustained until the end of 2008 as banks' borrowers anticipated a tightening of liquidity and drew down on committed lines of credit (Acharya and Mora 2015). The crisis therefore also helps disentangle the endogenous effect of demand for funding on accounting quality.

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## V. DATA

US banks are typically organized into bank holding companies with each holding company having one or more commercial banks under them. I estimate all my regressions at the bank-holding-company-quarter level as opposed to the commercial-bank-quarter level. This is because uninsured depositors consider the financial backing and reputation of the overall group (e.g., Citigroup as opposed to Citibank) when investing in a bank's deposits.[15]

For the NPL forecast models (Section III) as well as for hypothesis testing (Section IV), I use quarterly reported data for US bank-holding companies for the period 1992 to 2014 as provided in the FR Y-9C and the Bank Call Report regulatory filings. All US bank holding companies that have total assets of more than USD 150 million are required to file the FR Y-9C report on a quarterly basis. Beginning in 2006, the threshold was raised to USD 500 million. For tests involving panel data prior to 2006, I estimate alternate tests in which I remove the banks that dropped out of the sample post 2005. The un-tabulated results of these alternative tests are similar to my tabulated findings.

In the last quarter of 2009, the cap on deposit insurance was temporarily increased from USD 100,000 to USD 250,000. Banks, however, continued to report under the USD 100,000 category up until 2015. Although the increase was initially temporary, it was made permanent when the Dodd-Frank Act was passed. For this

[15] When the capitalization or solvency of individual banks is at risk, the group's financial backing is valuable. Further, under Federal Reserve policy and Reg. Y, § 225.4(a) and later under Section 38A(a) added by the Dodd-Frank Act, it is required that any company controlling an FDIC-insured depository institution must serve as a source of financial and managerial strength to that depository institution. For the US market, bank holding companies hold more than 95 percent of the total banking assets. Stand-alone banks, which are not part of any bank-holding company, account for less than one percent of the total market (Avraham, Selvaggi, and Vickery 2012).

reason, my ability to accurately identify uninsured deposits reduces after the second quarter of 2009. I therefore estimate alternate specifications with and without the period after the second quarter of 2009. This choice of sample period involves trade-offs between higher test power due to the availability of both pre-crisis and post-crisis quarters in my sample and an overall larger sample size versus lower test power due to noisy measurement. This constraint does not apply to the liquidity-creation tests.

I use 16 historic quarters of data on a rolling basis to estimate the coefficients of the NPL forecast models. Hence, I lose 16 quarters of data from the start of my sample. Even though the FR Y-9C data and the call report data are available, and most variables are reported, the uninsured deposit price data are reported only after the third quarter of 1996. The resulting sample from 1996 to 2014 has 64,564 observations and spans 75 bank quarters with an average of 860 banks per quarter.[16]

Within the post 1996 sample, NPL data are missing at the holding company level, prior to 2001. Hence, I link each bank holding company to the individual commercial banks under the holding company structure. I then use commercial bank call report regulatory filing data, and I aggregate the bank-level data to generate an alternate estimate of the holding-company-level NPL. Still, around 4,000 observations drop out of my sample due to missing NPL data. I further lose around 16,000 bank quarter observations in order to estimate the NPL forecast RMSE measure, which is estimated on a rolling basis using historic eight quarters of data. Finally, around 5,000 additional observations drop out of my sample due to missing regression variables. The final dataset used in the regressions tables has 39,266 bank quarter observations.

[16] Per standard practice in the literature, I identify all bank quarters that involve merger and acquisition transactions and I remove the five quarters of data relating to the three quarters immediately prior to the transaction, the quarter of the transaction and the quarter after the transaction. I do this to remove the impact of mergers on change in NPLs (Bushman and Williams 2015).

Following past studies in the literature (Acharya and Mora 2015), I winsorize all variables at the $1^{st}$ and $99^{th}$ percentile.

Most of the data restrictions are due to missing values or lack of reporting in early years of my sample period. Most of the deleted observation result in shortening of my sample period as opposed to banks dropping out of the sample. The few banks that do fall out of the sample are either foreign banks with US branches (since they have less stringent disclosure norms or have confidentiality clauses) or very small banks with sizes below the mandatory reporting threshold. Therefore, despite the reduction in sample size, there is still considerable variation across all variables in my sample, thus mitigating potential concerns about selection bias affecting the results. Most extant studies focus on listed banks, and thus have significantly smaller samples than mine.

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## VI. RESULTS

### Descriptive results

In Figure 1 and in Table 1, I provide descriptive data related to the accounting quality measure. Figure 1 plots the quarterly values for the 25$^{th}$ percentile, median and the 75$^{th}$ percentile of the absolute reduction in forecast error achieved by Model (2) over Model (1), and presents the time-series distribution of the improvement in forecast error achieved by accounting data. Table 1 provides the distribution for the quarterly RMSE of NPL forecast Model (1) (baseline model), Model (2) (baseline model with accounting data included) and the difference, as described in Section III. On average and also over the distribution, Model (2) provides a better forecast. Table 1 provides further evidence that Model (2) on average has both lower RMSE and lower variance compared to Model (1). Overall, the data shows that the usefulness of accounting information in predicting NPLs varies across business cycles, and accounting information becomes more valuable in forecasting NPLs during periods of banking crises. Since bank default risk and the ability of accounting information to predict default become crucial during periods of banking crises, accounting quality should matter most during these times.

In Figure 2, I plot the time-series trends in the average price paid by banks for time deposits, split by insured and uninsured. An interesting and novel observation is that the long-term average cost of insured deposits is higher than that of uninsured deposits, and that this pattern reverses only during periods of bank crises. A potential explanation is that during regular periods since bank default risk is relatively low, investors do not differentiate on the basis of default risk and as described by Holmstrom (2015), deposits remain information-insensitive. Since insured deposits are a more stable source of funding, during normal times, when funding demand is not very high, banks compete more for insured than uninsured deposits, which causes the observed price difference. Ben-David et al. (2017) argue that, contrary to popular belief, depositor monitoring and risk-based screening do not normally drive deposit rates. Instead, banks' loan growth and the resulting demand for funding is the main determinant. Although I confirm their findings, I also provide a more nuanced view on deposit price dynamics by splitting the data into crises and non-crises periods and by examining separately both insured and uninsured deposits. Figure 2 shows that the relative cost between insured and uninsured deposits reverses during crises periods as default risk selectively effects uninsured deposits and insured deposits alone are not able to meet the increased funding demand. This descriptive evidence is in line with a similar shift in information-sensitivity of uninsured deposits during the 2007 banking crisis reported in Perignon et al. (2018) using European bank data.

**Main regression results**

In Tables 3, 4 and 5, I report the results of tests of the relation between accounting quality and the cost of uninsured deposits, growth in uninsured deposit volume and liquidity creation, respectively. The structure of the three tables is similar and is explained in the next sub-section. $Consistency\_in\_Quality$, its interaction with $Crisis$ and their combined effect reported in the F-test are the main variables and results of interest in these tables.

**Tests and predictions**

For each of my dependent variables of interest, I estimate seven alternative versions of equation [3] and report the results in tables 3, 4 and 5, respectively. $Consistency\_in\_Quality$ is the main variable of interest, and the $Current\_Quality$

measure acts as a control. In each of these three tables, in the first column I exclude the $Crisis$ and the $Consistency\_in\_Quality$ interaction term and test only the overall effect of consistency in accounting quality. $\beta_1$ is the main coefficient of interest in column 1 and captures the average effect of consistency in quality without separately considering the effects during crisis and non-crisis periods. A significant negative value (positive value) in the pricing test (in the volume and liquidity tests) would provide evidence in support of H1a, H2a and H3a. The average effect could be insignificant despite the crisis period effect being significant, since the proportion of crisis quarters in my total sample is low.

In columns 2 to 5, I sequentially add $Current\_Quality$, its interaction with $Crisis$, $Firm\ FE$, $Quarter\ FE$ and $Control\_Other$. Column 5 provides the test results using the full specification. For each of columns 2 to 5, I also calculate an F statistic for the combined significance of the main and the interaction term ( $\beta_1 + \beta_2$), which measures the total effect.

In columns 2 to 5, I test whether the overall effect of consistency in quality on each of the dependent variables is driven by the crisis period, the non-crisis period or both. A significant negative value (positive value) for $\beta_1$ in the pricing test (in the volume and liquidity tests) would show that the effect of consistency in accounting quality exists even during the non-crisis periods. A significant result for the F-test for the combined value of $\beta_1 + \beta_2$ would show that the effect of consistency in accounting quality exists during the crises periods. Together, these tests would provide evidence in support of H1a, H1b and H1c and explain which period (crisis or non-crisis) is driving the results. Finally, a significant negative value (positive value) for $\beta_2$ in the pricing test (in the volume and liquidity tests) would provide evidence in support of H1b (H2b and H3b). Since I argue that bank default risk and the impact of accounting quality get factored in only during periods of banking crises, I predict $\beta_1$ to be *in*significant while $\beta_1 + \beta_2$ and $\beta_2$ to be significant.

I include firm fixed effects in my model to improve identification, but this restricts the identification to only the within-firm variation in consistency in accounting quality. To improve the generalizability of my results, I replace firm fixed effects with county fixed effects in column 6. My predictions for column 6 remain the same as those for columns 2 to 5.

The tests in columns 2 to 6 use the 2007 to 2009 banking crisis for the treatment effect- $Crisis$. In order to improve the generalizability of my results beyond the 2007 crisis and also to increase test power, I re-estimate the specification in column 5 by replacing the variable $Crisis$ with a continuous measure: the LIBOR-OIS (Overnight Interest Swap) spread, along with the continuous versions of the variables $Consistency\_in\_Quality$ and $Current\_Quality$. I report the results in column 7. The LIBOR–OIS spread is a commonly used leading indicator of increased bank default risk (Thornton 2009; Olson, Miller, and Wohar 2102; Michaud and Upper 2008). The reason for this is that the LIBOR-OIS spread captures both credit risk (counter party default) and liquidity risk (interbank funding friction). I predict $\beta_1$ to be *not* significant and $\beta_2$ to have a significant negative value (positive value) in the pricing test (in the volume and liquidity tests).

**Pricing test results**

The uninsured deposit pricing test results are reported in Table 3. In column 1, the full sample period average effect of $Consistency\_in\_Quality$ ($\beta_1$) is not significant. In all subsequent columns, once $Consistency\_in\_Quality$ is interacted with $Crisis$, the coefficient on the interaction term ($\beta_2$) is negative and significant. The combined value of $\beta_1 + \beta_2$ is also significant as indicated the F-test results. At the same time, $\beta_1$ is not significant in any of the columns. These results show that Consistency in Accounting Quality is negatively associated with cost of uninsured deposits, and only so during periods of banking crises. The positive significant coefficient for $Crisis$ in columns 2 and 3 shows that though during the crisis the cost of uninsured deposits is unconditionally higher, $Consistency\_in\_Quality$ helps mitigate this increase.

The average economic effect of having higher Consistency in Accounting Quality on the cost of uninsured deposits during crises periods is approximately 7 basis points. For a typical bank in my sample this translates into a reduction of USD 80,000 in interest expense and is equivalent to a 13 bps increase in ROE.

$Current\_Quality$ is not significant in any of the columns. The interaction of $Current\_Quality$ with $Crisis$ is significant with the expected negative sign only in column 5. This shows that vis-à-vis Current Accounting Quality, Consistency in Accounting Quality has a stronger impact on uninsured deposit pricing.

In column 6, I replace firm fixed effects with county fixed effects and the results remain unchanged. In column 7, I replace the variable $Crisis$ with a continuous variable LIBOR-OIS and I replace both quality measures with their respective continuous versions. The results become even stronger. The results in Column 7 help validate and generalize the results beyond the 2007 financial crisis.

**Volume test results**

In table 4, I present the results of the uninsured deposit volume tests. Overall, the findings are similar to but stronger than those reported in the pricing tests.[17] Unlike the pricing test results, in column 1, the coefficient on $Consistency\_in\_Quality$ ($\beta_1$) is positive and significant. This supports the view of an overall average positive association between consistency in quality and growth in uninsured deposit volume. It therefore provides evidence in support of H2a.

However, once $Consistency\_in\_Quality$ is interacted with $Crisis$ in columns 2 to 7, $\beta_1$ becomes insignificant. $\beta_2$, which captures the incremental impact of $Consistency\_in\_Quality$ on uninsured deposit volume, when moving from non-crises to crises periods, is significantly positive. Moreover, the F-test for $\beta_1 + \beta_2$, which captures the impact of higher $Consistency\_in\_Quality$ on uninsured deposit volume during periods of crises, is also significant. These results show that the overall average effect of $Consistency\_in\_Quality$ as seen in column 1 is driven only by the crises period and that consistency in quality does not affect uninsured deposit volume during non-crises periods. Together, these results provide evidence in support of H2a and H2b.

The negative significant coefficient for the variable $Crisis$ in columns 2 and 3 show that during the crisis the increase in uninsured deposit volume is unconditionally lower. However, the interaction of $Crisis$ with $Consistency\_in\_Quality$ has the

[17] The volume test results for accounting quality being stronger than the price test results is in line with the stronger volume based monitoring documented by Perignon et al (2018). In fact, Perignon et al (2018) do not find much evidence of price based monitoring for European banks. This could be because their price data is at the aggregate market level and not at the individual bank level (not available for European banks), and therefore not granular enough.

opposite sign. This shows that higher $Consistency\_in\_Quality$ helps mitigate the loss of uninsured deposits during periods of banking crises.

The economic effect of having higher Consistency in Accounting Quality on the growth in uninsured deposits during crises periods is approximately 90 basis points. This translates into approximately USD 1 million in extra deposits for a typical bank in my sample and is around 100 percent of the quarterly growth in uninsured deposits.

It is interesting to note that unlike the results of my pricing tests, the coefficient on $Control\_Main$ ($\beta_5$) is positive across all columns. This provides further assurance of a parallel demand trend between uninsured and insured deposits.

Taken together, the pricing and volume tests show that banks with higher Consistency in Accounting Quality are able to raise more uninsured deposits and at a lower price. The ability to raise a higher volume of deposits without having to pay a price premium, especially during periods of funding stress, provides consistent evidence of lower funding friction for banks with higher Consistency in Accounting Quality.

**Liquidity test results**

The results for the bank liquidity creation tests are reported in Table 5. Overall, the findings are similar to but weaker than those of the volume tests. $\beta_1$ is not significant in any of the specifications except in column 1 where there is no $Crisis$ interaction term. Both $\beta_2$ and $\beta_1 + \beta_2$ are significant with the expected signs across most specifications. Together, these results provide evidence in support of H3a and H3b.

The documented effect translates into a 70 basis points increase in the volume of liquidity created during periods of crises. For a typical bank in my sample, this corresponds to an additional liquidity creation of USD 4.2 million, which is approximately 3.5 percent of the total liquidity created by the median bank.

The liquidity test results differ from the price and volume tests in two ways. First, the interaction of $Current\_Quality$ and $Crisis$ ($\beta_4$) in the fully specified model in column 5 is significant with the correct sign. The economic magnitude of impact however is lower than that of $Consistency\_in\_Quality$. Also, the results in column 6, which use county fixed effects instead of firm fixed effect, are not significant in the case of the liquidity test.

**Additional test results: Differential impact on insured vs. uninsured deposits**

Hypotheses H1 and H2 explore the impact of Consistency in Accounting Quality on uninsured deposit parameters while using insured deposit parameters as controls. In this section, I conduct additional tests for the differential impact of Consistency in Accounting Quality on insured and uninsured deposit parameters. I exploit the parallel trends between insured and uninsured deposit price and volume in a generalized difference-in-difference design, with a three-way interaction. A generic difference-in-difference design in this setting would have an interaction term between insured status and crises quarters. Since I need to concurrently test the impact of Consistency in Accounting Quality as well, I introduce a three-way interaction between insured status, crises quarters and Consistency in Accounting Quality. I use the following model for this test:

$$Price_{i,t}\ or\ Deposit\_growth$$
$$= \beta_0 + \beta_1\, Uninsured_i + \beta_2\, Uninsured_i * Crisis_t + \beta_3\, Consistency\_in\_Quality_{\ i,t-1} + \beta_4\, Consistency\_in\_Quality_{\ i,t-1} * Crisis_t + \beta_5\, Uninsured_i * Consistency\_in\_Quality_{\ i,t-1} + \beta_6\, Uninsured_i * Consistency\_in\_Quality_{\ i,t-1} * Crisis_t + \beta_7(l_k)\Sigma\, Control_{i,t-1} + Firm\ FE_i + Time\ FE_t + \varepsilon_{i,t} \qquad [4]$$

$Uninsured_i$ is equal to 1 when the dependent variable measure is for uninsured deposits and equal to 0 when it is for insured deposits. $Price_{i,t}$ is $Cost\_Uninsured_{i,t}$ when $Uninsured_i = 1$ or $Cost\_insured_{i,t}$ when $Uninsured_i = 0$. $Deposit\_growth$ is $Uninsured\_growth_{i,t}$ when $Uninsured_i = 1$ or $Insured\_growth_{i,t}$ when $Uninsured_i = 0$. All the other variables are as defined for model 3. I exclude $Current\_Quality$ measure to avoid multiple three-way interactions, which would make the results difficult to interpret. However, its inclusion does not alter the results.

I estimate the above regression twice, once using $Price_{i,t}$ and then using $Deposit\_growth$, as the dependent variable. The control variables in each case are the same as those used in the previous pricing and volume tests respectively. The key identifying assumption for this test is that in the absence of an exogenous shock (i.e. the banking crisis), the parallel trend between insured and uninsured deposit parameters would continue.

In Table 6, columns 1 through 3 (4 through 6), I tabulate the results for the pricing (volume) tests. Column 1 (column 4) uses a binary version of the variable $Consistency\_in\_Quality$ and interacts it with the binary variable $Crisis$. Column 2 (column 5) uses the continuous version of the variable $Consistency\_in\_Quality$ and interacts it with the continuous variable LIBOR-OIS in place of $Crisis$. In column 3 (column 6) I repeat the specification in column 2 (column 5) after replacing firm fixed effects with county fixed effects.

To estimate the impact of Consistency in Accounting Quality on insured deposit parameters, I separately examine crises and non-crises periods. For non-crises periods $\beta_3$ measures the impact of $Consistency\_in\_Quality$ on both price and growth in insured deposit volume. Since $Consistency\_in\_Quality$ , $Crisis$ and $Uninsured$ are all binary variables, $\beta_3$ measures the impact of high $Consistency\_in\_Quality$ when both $Crisis$ and $Uninsured$ equal 0, which corresponds to the effect of $Consistency\_in\_Quality$ on insured deposit parameters during non-crises periods. Results in Table 6 show that $\beta_3$ is insignificant across all specifications for both price and volume tests.

Similarly, for the crises periods, $\beta_3$+$\beta_4$ measures the incremental effect of $Consistency\_in\_Quality$ on both price and volume growth of insured deposits. The second F-test at the bottom of Table 6 provides the results for this. $\beta_3$+$\beta_4$ is not significant for either the pricing or volume tests. Taken together, these results do not provide evidence of $Consistency\_in\_Quality$ being associated with insured deposit parameters.

The first F-test reported at the bottom of Table 6 tests the significance of the term $\beta_3$+$\beta_4 + \beta_5$+$\beta_6$. It measures the incremental impact of $Consistency\_in\_Quality$ on uninsured deposits during crises periods. The results show a significant association between $Consistency\_in\_Quality$ and uninsured deposit parameters during crises periods and confirms the F-test results provided in Tables 3 and 4.

The coefficient on the three-way interaction term $\beta_6$ is significant with the correct predicted sign in the case of pricing tests, only in columns 2 and 3, both of which use continuous version of $Consistency\_in\_Quality$ along with the LIBOR-OIS spread measure.

In the case of the volume tests, $\beta_6$ is significant with the correct predicted sign in all three columns. For the volume tests we can conclude that there is a stronger association between $Consistency\_in\_Quality$ and deposit volume growth for uninsured deposits during crises periods vis-à-vis non-crises periods. These results are consistent with hypotheses H1b and H2b.

It is also interesting to note that the sign of $\beta_1$ is the opposite of the sign of $\beta_2$ in both the pricing and volume tests and across all the three specifications. For the pricing tests, this implies that uninsured deposits are cheaper than insured deposits during normal periods but more expensive during periods of crises when default risk is manifest. For the volume tests this implies that uninsured deposit volume growth is unconditionally higher than insured deposits. This confirms that uninsured deposits are used as a marginal source of funds. The differences in the signs of $\beta_1$and $\beta_2$ in the volume tests signifies higher frictions in raising uninsured deposits during periods of crises.

**Alternate dependent variable measure for deposit price**

The deposit price I estimate is based on total outstanding volume and it reflects the average price as opposed to the marginal price paid by the bank to raise new deposits. As an alternative measure for cost of deposits, I calculate the change in the cost of uninsured deposits for the quarter and subtract from it the contemporaneous change in the cost of insured deposits. The second differencing helps control for changes in the cost of deposits that are not attributable to changes in risk. I then estimate a modified version of model 3 in which I use the variable described above as the dependent variable. I present the results in Table 7. Columns 1 to 3 use binary versions of the variables $Consistency\_in\_Quality$ and $Crisis$, while columns 4 to 6 use continuous version of both these variables. Columns 1 and 4 exclude all fixed effects. The results are similar to those for the main pricing tests in Table 3, except that the interaction of $Consistency\_in\_Quality$ and $Crisis$ is insignificant in column 3.

**Further robustness tests**

My main test results are based on the full sample starting in 1996 and ending in 2014. Beginning in the third quarter of 2009, the deposit insurance limit was increased from USD 100,000 to USD 250,000. However, the data provided by the banks in the regulatory reports were not updated until 2015. This weakens my empirical measures for uninsured and insured deposit parameters post 2009. Also, starting with the latter half of 2009, many regulatory changes were made in the banking sector. These could confound my results and are difficult to control for in my tests.

To address these concerns, I re-estimate the main tests after restricting my sample to all quarters prior to the third quarter of 2009. I provide the results of the main regressions using this smaller sample in Table 8. Columns 1, 3 and 5 use binary versions of the variables $Consistency\_in\_Quality$ and $Crisis$, while columns 2, 4 and 6 use continuous version of both these variables. All earlier results except those for the volume tests using the continuous version of $Consistency\_in\_Quality$ continue to hold when using this reduced sample. For completeness, I include all the control variables used in the respective models.

## VII. CONCLUSION

Banks perform an important role of creating liquidity in the economy through maturity transformation. Wholesale funding, of which uninsured deposits are a major part, plays a crucial role in managing maturity transformation and liquidity creation for the bank. This is even truer for a large majority of US banks that are small and private, and therefore have limited access to non-deposit sources of wholesale funding. Despite its crucial role and the ongoing debate regarding the need for higher transparency in banks, the role of accounting quality in uninsured deposit funding has not been examined.

Using a sample of US bank holding companies, I document a positive association between the usefulness of a bank's accounting information in predicting default (i.e., accounting quality) and the bank's ability to access uninsured deposits and create liquidity. I provide evidence of how accounting information can help reduce financing frictions in one of the important intermediation channels facilitated by banks and how it can help banks serve their role of creating liquidity. I only document the magnitude and direction of impact of higher accounting quality at an individual bank level. I do not make any claims on whether higher accounting quality is overall optimal or more efficient for the industry or the economy as a whole.

A key finding in my study is that accounting quality affects uninsured deposit funding only during periods of banking crises when such deposits shift from being information-insensitive to being information-sensitive. I also show that insured deposits continue to remain information-insensitive even through periods of banking crises. In fact, the price paid by a bank for insured deposits is on average marginally higher than that paid on average for uninsured deposits and this trend reverses only during periods of banking crises. This provides further evidence that during normal periods, default risk is not priced and deposits remain information-insensitive.

The results in my paper inform the ongoing debate on the role of transparency in banks by documenting evidence of a positive impact of accounting quality on deposit funding and liquidity creation. My results provide evidence of the monitoring hypothesis being more dominant than the liquidity hypothesis, in the case of uninsured deposits. The results also have implications for how bank managers could potentially trade off accounting quality with the volume of liquid assets, since both can be used to improve access to funding in times of financial distress (Ratnovski 2013). Since regulators can more effectively enforce changes in the required level of liquid assets than the required level of accounting quality, the trade-off could have unintended effects on accounting quality and the usefulness of accounting information.

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## APPENDIX A: VARIABLE DEFINITIONS

| | |
|---|---|
| ***Cost_Uninsured*** | Cost of uninsured deposits: annualized value of quarterly interest expense on uninsured deposits divided by the average of the beginning and ending quarter uninsured deposit volume<br><br>Uninsured deposits defined as all time deposits with size of USD 100,000 and above |
| ***Cost_Insured*** | Cost of insured deposits: annualized value of quarterly interest expense on insured deposits divided by the average of the beginning and ending quarter insured deposit volume<br><br>Insured deposits defined as all time deposits with size below USD 100,000 |
| ***Cost_Core_Deposits*** | Cost of core deposits: annualized value of quarterly interest expense on core deposits divided by the average of the beginning and ending quarter core deposit volume<br><br>Core deposits defined as total deposits less time deposits |
| ***Netchange_Cost_Uninsured*** | The quarterly change in Cost_Uninsured less the contemporaneous quarterly change in Cost_Insured: $[\boldsymbol{Cost\ Uninsured_{i,t}} - \boldsymbol{Cost\ Uninsured_{i,t-1}}] - [[\boldsymbol{Cost\ Insured_{i,t}} - \boldsymbol{Cost\ Insured_{i,t-1}}]$ |
| ***Uninsured_Growth*** | Quarterly change in Uninsured deposits scaled by quarter beginning total assets |
| ***Insured_Growth*** | Quarterly change in Insured deposits scaled by quarter beginning total assets |
| ***Liquidity_Generated*** | Volume of liquidity created as measured at the end of the quarter. Detailed definition available in Appendix C |
| ***Unins_to_Ins_Ratio*** | Ratio of total uninsured deposits to insured deposits |
| ***Current_Quality -* Continuous** | It measures the accounting quality of a firm for a particular quarter. It is calculated as the reduction in out of sample NPL forecast mean square error achieved using accounting data. Please refer to Section III for further details. |
| ***Current_Quality*** | It is a binary version of the variable Current_Quality - Continuous. It is an indicator variable which takes on the value of 1 for a bank classified as having high accounting quality and 0 otherwise. A bank is classified as having high accounting quality if in that |

| | |
|---|---|
| | quarter the value of Current_Quality - continuous is above the quarterly cross-sectional median. |
| ***Consistency_in_Quality* - Continuous** | It measures the consistency in accounting quality for a firm as measured in a particular quarter. It is calculated as the reduction in RMSE of NPL forecast achieved by Model (2) (accounting model) over Model (1) (baseline model) and measured over a period of trailing eight historic quarters. |
| ***Consistency_in_Quality*** | It is a binary version of the variable Consistency_in_Quality - Continuous. It is an indicator variable which takes on the value of 1 for a bank if the bank has high consistency in accounting quality and 0 otherwise. A bank is classified as having high consistency in accounting quality if in that quarter the value of Consistency_in_Quality - Continuous is above the quarterly cross-sectional median. |
| ***NPL_Ratio*** | The ratio of total non-performing loans to the total loans. Non-performing loans include both past due with and without accruing |
| ***RealEst_Prop*** | (Residential real estate loans + Commercial real estate loans ) / Total loans |
| ***ROE*** | Return on equity based on quarterly average equity |
| ***Leverage*** | Tier 1 Capital adequacy ratio |
| ***MSChange_Uninsured*** | Quarterly change in market share of uninsured deposits |
| ***NPL_Cover_Change*** | Net change in NPL coverage over last 4 quarters. NPL coverage is the ratio of total provisions for loan losses (balance sheet) to total Non-performing loans |
| ***IntRate_Risk*** | Absolute value of the difference between interest bearing assets and liabilities that are re-priceable within a year (Acharya and Mora 2015) |
| ***LDR*** | Loan to deposit ratio |
| ***Listed*** | An indicator variable which takes the value of 1 for banks with public securities |
| ***Size*** | Log of total assets |
| ***MS_Deposit*** | Market share of total deposits |
| ***Unused_Commit*** | Unused loan and other off-balance sheet commitments as a proportion of total loans |
| ***Wholesale_Fund_Prop*** | Wholesale funds as a proportion of total assets |
| ***Crisis*** | A quarter indicator variable corresponding to the 2007 to 2009 financial crisis and takes the value of 1 for the quarters from 2007 Q3 to 2009 Q2, and 0 otherwise |
| ***Crisis* – Alternate continuous measure** | It is an alternate and continuous variable measure for banking crisis. It is calculated as the quarterly average value of the LIBOR – OIS difference. LIBOR |

| | |
|---|---|
| | is the London interbank offered rate. OIS is the Overnight indexed swap rate. It is a benchmark for the US Fed fund rate. |
| ***Deposit_Prop*** | It is the proportion of total assets funded by deposits. |
| ***Loan_Growth*** | Growth in total loans over previous 4 quarters. |
| ***Uninsured*** | An indicator variable which takes on the value of 1 when the deposit rate corresponds to that of uninsured deposit. This variable is used only for the regressions with three-way interaction in table 6. |
| ***Price*** | Price is equal to Cost_Uninsured when Uninsured = 1 and equal to Cost_Insured otherwise. This variable is used only for the regressions with three-way interaction in table 6. |
| ***Unins_Ins_Ratio*** | The ratio of volume of uninsured to insured deposits |

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## APPENDIX B

Estimating the measure of accounting quality and the historic consistency in accounting quality for each bank involves two steps: (1) estimating the reduction in NPL forecast error and (2) converting the forecast error reduction into a measure of accounting quality.

**Estimating reduction in NPL forecast errors**

I estimate the reduction in NPL forecast error for each bank using the following two forecast models:

$$NPL_{i,t} = \beta_0 + \beta_1 NPL_{i,t-1} + \beta_2(l_2)\Sigma\, Macro_{it-1} + \varepsilon_{it} \quad [1]$$

$$NPL_{i,t} = \beta'_0 + \beta'_1 NPL_{i,t-1} + \beta'_2(l'_2)\, \Sigma Macro_{it-1} + \beta'_3(l'_3)\Sigma\, Accounting_{it-1} + \varepsilon'_{it} \quad [2]$$

Subscripts i and t represent bank and quarter, respectively. Model (1) only uses the macro variables observable in quarter *t-1* and $NPL_{i,t-1}$ to forecast the NPL in quarter t, $NPL_{i,t}$. I refer to Model (1) as the "baseline" model and I refer to the predictors used in it as "baseline" predictors. Model (2) uses the baseline predictors in Model (1) and bank-specific accounting variables. I discuss the baseline and bank-specific accounting variables and the model selection in the next sub-section named 'Forecast model selection'. When estimating Models 1 and 2, I use panel data that consists of 16 trailing bank quarters, and I estimate the coefficients using pooled ordinary least squares (i.e., OLS) regressions. I use the respective sets of coefficients to forecast one-quarter-ahead NPLs for each bank, and then I use these forecasts to determine bank-specific forecast errors for each model. I define my basic measure of accounting quality as the bank-specific difference between the forecast error for Model (1) and the forecast error for Model (2). The average NPL ratio for my sample is 160 bps with a standard deviation of 210 bps. The average forecast error of Model (1) is around 70 bps while the average improvement achieved by accounting information (Model (2)) is around 10 bps.

**Forecast model selection**

In this subsection I describe the procedure and choices involved in choosing Model (1) and Model (2) for NPL forecast. Model selection involves choosing on three different dimensions: (1) the measure of model fit; (2) the choice of the macro variables and firm-specific accounting variables for predicting NPLs; and, (3) whether to use a cross-sectional or a time-series model.

I use out-of-sample mean-squared error (MSE) as my primary measure of model fit. As discussed in Gerakos and Gramacy (2013), MSE embeds the same loss function as OLS, which I used as my in-sample estimator. Consequently, MSE is the most logical and consistent criterion for evaluating out-of-sample fit.

For variable selection, I draw from the banking literature on NPL forecasting (Harris, Khan, and Nissim 2018; Beatty and Liao 2015) to create my list of macro variables and bank-specific accounting variables. I use different combinations of these predictors and I evaluate different versions of Model (1) (Model (2)) separately. I calculate the MSE for each version of Model (1) (Model (2)) for each quarter. Among the set of alternative versions of Model (1) (Model (2)), I then select the version of Model (1) (Model (2)) with the lowest average MSE across all quarters in my full sample. Across all quarters, I use the same version of Model (1) (Model (2)) for forecasting and do not carry out the model selection for each quarter separately. Since I use the full sample for model selection, it does induce some hindsight bias.

Each model is chosen independent of the other because the version of Model (1) that best fits the data need not necessarily be a nested version of Model (2). For example, the interaction effect between macro variables and bank-specific accounting variables could affect the prediction. Hence, by choosing each model separately, I ensure that the macro-only baseline model (i.e., Model (1)) is given its best chance at prediction.

The reduction in forecast error achieved by using the best version of Model (2) vis-à-vis the best version of Model (1) reflects the effect of using bank-specific accounting variables on forecast accuracy. The main macro variables include lagged aggregate loan growth, change in bankruptcy filings, nominal GDP growth for the US and its lags, level and changes in unemployment, stock market performance, changes in market-wide interest rate and quarter indicators. The main bank-specific metrics include loan charge-off proportion, loan loss provisions, NPL coverage ratio, change in net interest margin, loan growth, the risk-weighted asset proportion, the capital adequacy ratio, asset market share, consumer loan proportion and real estate loan proportion. All quarterly data points are seasonally adjusted.

Regarding the choice between using a time-series model and using a cross-sectional model, I estimate a single pooled time series regression using the full cross section of banks. Hence, I assume that the best version of Model (1) (Model (2)) does not vary across banks. Since accounting standards are the same for all of the banks in my sample and there is no cross-industry variation, the key factor that might cause this “homogeneity” assumption to be violated is variation in the loan portfolio mix. Harris, Khan, and Nissim (2018) find that the proportion of real estate and consumer loans are the key determinants of credit losses. Based on their findings, I incorporate these two loan composition variables in my forecast model. Since both Model (1) and Model (2) are estimated using the full cross section, differencing the magnitude of the forecast error limits the impact of any potential cross-sectional difference.

Though time-series models are simpler and capture idiosyncratic factors well, Mark and Sul (2011) highlight that when the cross-sectional heterogeneity is not too high, panel-data forecasts incorporate additional information in the cross section and therefore work better than time-series forecasts.

**Measures of accounting quality**

For every quarter *t* in my sample, I estimate two separate regressions: one using Model (1) and one using Model (2). I estimate the regression coefficients using 16 trailing quarters of data starting from quarter *t-18* to quarter *t-3*. I then apply the estimated coefficients from the regressions to the data for quarter *t-2* and determine the out-of-sample NPL forecasts from Model (1) and Model (2) for the quarter *t-1*. I calculate the NPL forecast errors for quarter *t-1* for each model. Finally, I use the two forecast errors to derive two separate measures of accounting quality: (1) Current Accounting Quality and (2) Consistency in Accounting Quality.

I measure Current Accounting Quality as the difference in squared forecast errors between Model (1) and Model (2) for each bank. Since the quality observed at the end of a quarter will impact the investment decision of the depositors during the subsequent quarter, in my hypothesis tests, I use the Current Accounting Quality measured at the end of quarter *t-1* to regress the deposit parameters observed at the end of quarter *t*. In total, there is a lag of three (two) quarters between the deposit parameters used in the hypothesis testing regressions and the data used to estimate the forecast model coefficients (data used to estimate the NPL forecast).

Clinch and Verrecchia (2015) note that a reduction in the variance of the measurement error of an unbiased signal is synonymous with a stronger commitment to disclose. Building on this, for the quarter *t-1*, I calculate the RMSE in NPL forecast over the previous eight quarters (quarters t-9 to t-2) for both Model (1) and Model (2). I measure Consistency in Accounting Quality for quarter *t-1* as the reduction in RMSE achieved by Model (2) over Model (1) (RMSE [Model (1)] – RMSE [Model (2)]). Hence, the measure captures the extent to which a bank's past accounting information helped reduce forecast errors, and thus allowed depositors to forecast NPLs better. In the case where the signal is unbiased, a reduction in standard deviation alone would result in a stochastically superior forecast. However, I use RMSE instead of standard deviation as it also includes the effect of bias as well, and therefore holds even if the signal is biased. Similar to how I use Current Accounting Quality in my hypothesis tests, I use the Consistency in Accounting Quality measured at the end of quarter *t-1* to regress the deposit parameters observed at the end of quarter *t*.

In order to rule out the possibility that my measure is mechanically capturing some spurious effect, I carry out falsification tests by using non-optimal pairs of Model (1) and (2), and then use the resulting quality measure to test my hypotheses. The results do not hold when I use alternate pairs of Model (1) and Model (2). I also investigate whether the errors from Model (1) are mechanically correlated with the improvement in errors achieved when using Model (2) and find no evidence to support such an association. Absence of correlation helps rule out the possibility that my model choice is spuriously driving the results.

Since my measure is for a single industry, I use a common pooled cross-sectional model to estimate NPL forecast coefficients for the entire cross-section.

This could induce cross-sectional variation in my quality measures due to business model specific variations. There are three aspects in my research design which address this concern. First, I use business model specific variables such as proportion of different types of loans that have been show in the literature to be the key drives in cross-sectional variation in NPLs. Second, since I difference out the effect of non-accounting variables on NPL forecast error using the baseline model, to the extent the cross-sectional variation in forecast error is similar for both accounting and non-accounting variables, the differencing addresses the issue. Finally, and most importantly, I use bank fixed effects for the hypothesis testing regressions in the next stage to control for business model specific factors that could drive cross-sectional variation in NPL forecast errors.[18]

[18] The variation in accounting quality does however include the variation in the ability of managers to forecast NPLs and this cannot be separated out from the measure. It does not affect my conclusions since what matters to the depositor is the overall resultant quality and usefulness of the accounting information.

## APPENDIX C

### METHODOLOGY FOR ESTIMATING VOLUME OF LIQUIDITY CREATED

The below table has been reproduced as is from Berger and Bouwman (2009), Table 1: page 3791. The second part of the table on page 3792 containing a similar breakup for off balance sheet items has been excluded.

| Illiquid assets (weight = 1/2) | Semi-liquid assets (weight = 0) | Liquid asset (weight = - 1/2) |
|---|---|---|
| Commercial real estate loans (CRE) | Residential real estate loans (RRE) | Cash and due from other institutions |
| Loans to finance agricultural production | Consumer loans | All securities (regardless of maturity) |
| Commercial and industrial loans (C&I) | Loans to depository institutions | Trading assets |
| Other loans and lease financing receivables | Loans to state and local governments | Fed funds sold |
| Other real estate owned (OREO) | Loans to foreign governments | |
| Customers' liability on bankers acceptances | | |
| Investment in unconsolidated subsidiaries | | |
| Intangible assets | | |
| Premises | | |
| Other assets | | |

| Liquid Liabilities (weight = 1/2) | Semi-liquid liabilities (weight = 0) | Illiquid Liabilities plus equity (weight = - 1/2) |
|---|---|---|
| Transactions deposits | Time deposits | Bank's liability on banker's acceptances |
| Savings deposits | Other borrowed money | Subordinated debt |
| Overnight federal funds purchased | | Other liabilities |
| Trading liabilities | | Equity |

I then measure the liquidity created as ½ (illiquid assets + liquid liabilities) – ½ (liquid assets + illiquid liabilities + equity), scaled by quarter beginning total assets. I do not include the off-balance sheet items for my liquidity creation measurement. This approach is defined as the CAT – NOFAT measure in Berger and Bouwman (2009, page 3792)

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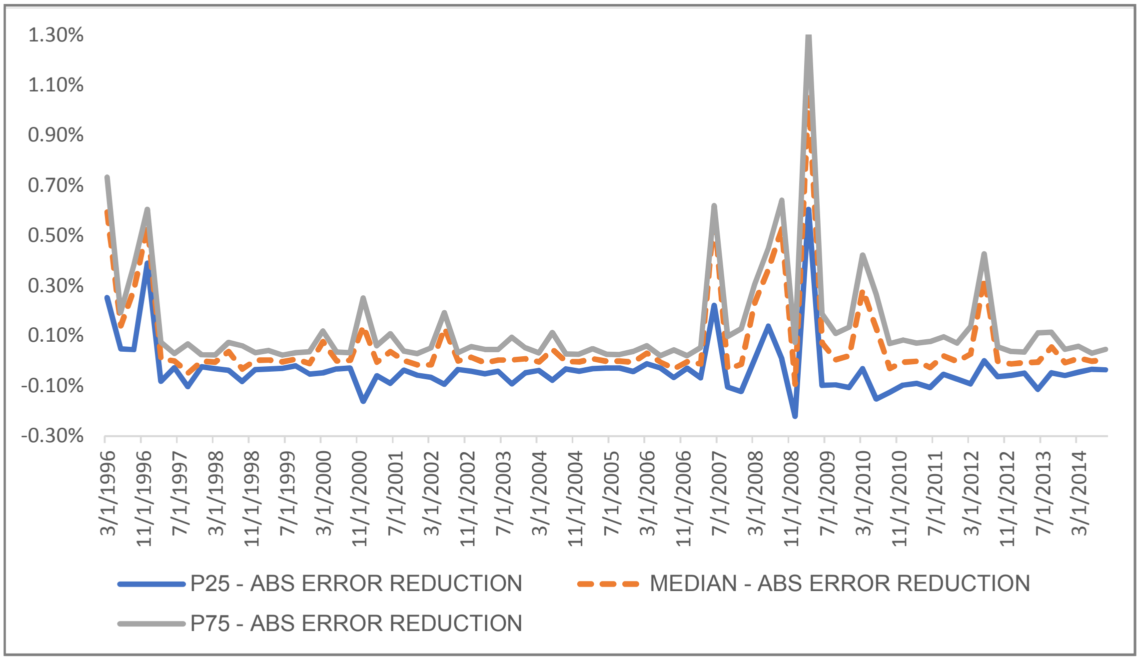
**FIGURE 1**
**Absolute forecast error reduction: Model (2) (Baseline + Accounting) over Model (1) (Baseline)**




Note: Figure 1 plots the quarterly 25th, 50th and 75th percentile of square error reduction achieved by using Model (2) (NPL forecast model using both macro and banks specific accounting data) over Model (1) (Baseline NPL forecast model using only macro data), while forecasting NPL data.

**TABLE 1**
**Descriptive statistics for forecast error and reduction in error measures**

| Variables | Units | Mean | Stdev | Min | p25 | Median | p75 | Max | Nobs |
|---|---|---|---|---|---|---|---|---|---|
| Quarterly RMSE for Model (1) (Baseline) | % | 0.648 | 0.286 | 0.350 | 0.445 | 0.536 | 0.834 | 1.859 | 75 |
| Quarterly RMSE for Model (2) (Baseline + Accounting) | % | 0.608 | 0.236 | 0.356 | 0.434 | 0.504 | 0.773 | 1.157 | 75 |
| Quarterly median difference in absolute error (Model (1) - Model (2)) | % | 0.072 | 0.185 | -0.093 | 0.035 | 0.060 | 0.117 | 1.049 | 75 |

Note: Table 1 provides the descriptive statistics for the quarterly forecast error of Model (1) and Model (2) and their difference. The sample covers 75 quarters from 1996 to 2014.

**FIGURE 2**
**Cost of time deposits: Insured vs. Uninsured**

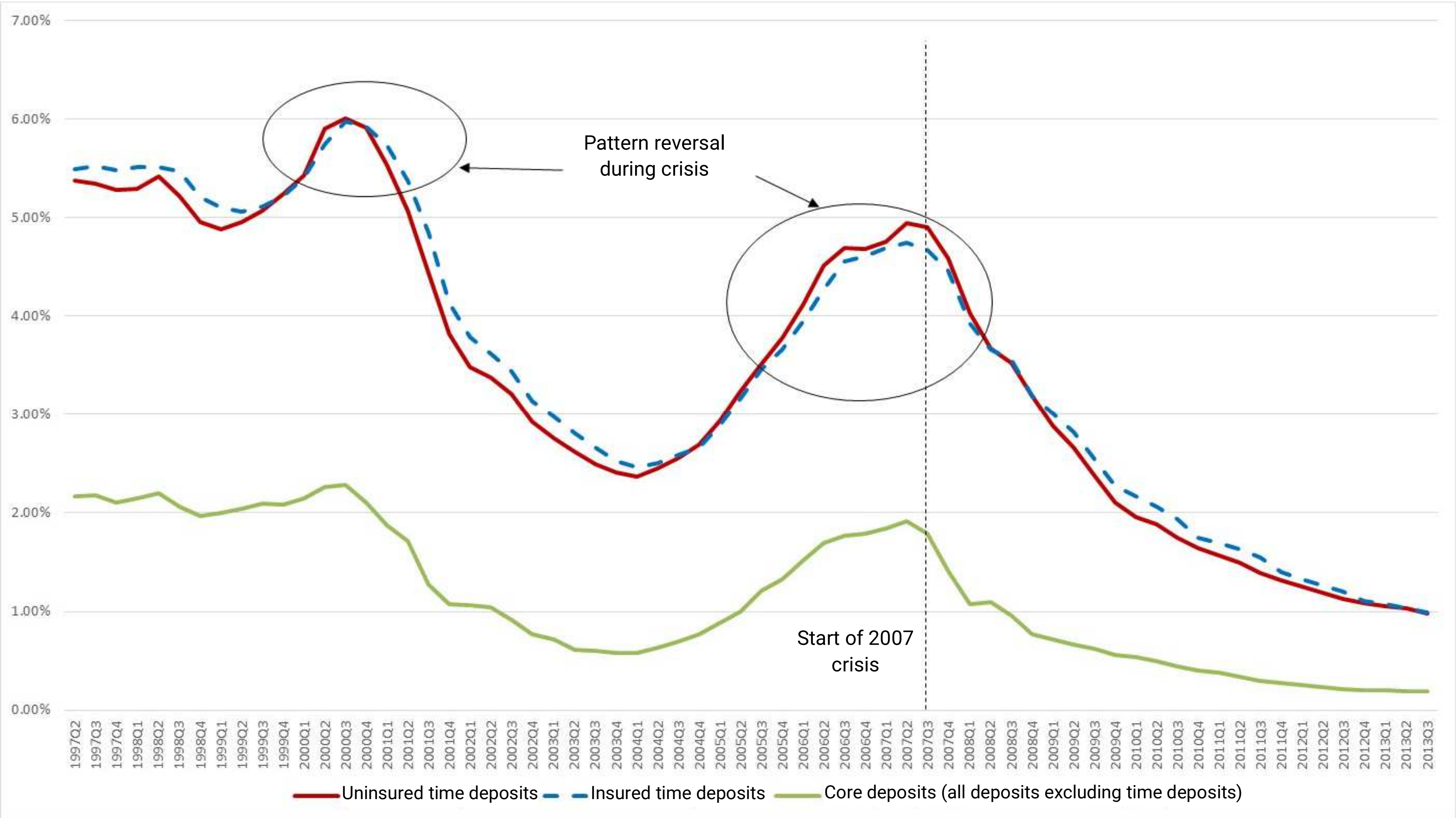


**TABLE 2**
**Descriptive statistics for all variables used in hypothesis testing**

| Variables | Units | Mean | Stdev | min | P5 | P25 | Median | P75 | P95 | max | Nobs |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Cost_Uninsured | % | 3.4 | 1.5 | 0.6 | 1.0 | 2.2 | 3.2 | 4.6 | 5.9 | 6.7 | 39,266 |
| Cost_Insured | % | 3.4 | 1.5 | 0.5 | 1.0 | 2.3 | 3.2 | 4.7 | 5.9 | 6.7 | 39,266 |
| Cost_Core _Deposits | % | 1.1 | 0.8 | 0.1 | 0.2 | 0.5 | 0.9 | 1.6 | 2.6 | 3.5 | 39,266 |
| Netchange_Cost_Uninsured | % | 0.0 | 0.8 | -3.7 | -1.0 | -0.1 | 0.0 | 0.1 | 1.0 | 3.8 | 39,266 |
| Uninsured_Growth | % | 2.4 | 12.5 | -30.1 | -14.7 | -4.1 | 0.8 | 7.1 | 24.9 | 53.2 | 39,266 |
| Insured_Growth | % | 0.3 | 7.2 | -17.8 | -8.7 | -2.9 | -0.5 | 2.2 | 11.9 | 36.4 | 39,266 |
| Liquidity_Generated | % | 19.4 | 15.1 | -20.8 | -7.0 | 10.0 | 19.9 | 29.4 | 44.2 | 54.6 | 39,266 |
| Unins_to_Ins_Ratio | % | 85.8 | 108.6 | 12.1 | 18.8 | 35.7 | 56.0 | 91.7 | 240.1 | 831.6 | 39,266 |
| Current_Quality_Cont | % | 0.000 | 0.003 | -0.009 | -0.002 | 0.000 | 0.000 | 0.000 | 0.005 | 0.018 | 39,266 |
| Current_Quality | % | 50 | 50 | 0 | 0 | 0 | 0 | 100 | 100 | 100 | 39,266 |
| Consistency_in_Quality_Cont | % | 0.05 | 0.11 | -0.18 | -0.08 | -0.01 | 0.02 | 0.08 | 0.31 | 0.45 | 39,266 |
| Consistency_in_Quality | % | 49 | 50 | 0 | 0 | 0 | 0 | 100 | 100 | 100 | 39,266 |
| NPL_Ratio | % | 1.6 | 2.1 | 0.0 | 0.1 | 0.4 | 0.9 | 1.8 | 5.8 | 12.0 | 39,266 |
| RealEst_Prop | % | 72.7 | 15.9 | 20.3 | 43.3 | 63.6 | 74.9 | 84.1 | 95.0 | 101.2 | 39,266 |
| ROE | % | 2.4 | 3.4 | -18.7 | -1.9 | 1.8 | 2.8 | 3.8 | 6.0 | 9.5 | 39,266 |
| Leverage (Tier 1 ratio) | % | 13.2 | 4.4 | 4.5 | 7.9 | 10.4 | 12.2 | 14.9 | 21.7 | 31.2 | 39,266 |
| MSChange_Uninsured | bps | -0.01 | 0.23 | -1.31 | -0.22 | -0.04 | 0.00 | 0.03 | 0.22 | 1.12 | 39,266 |
| NPL_Cover_Change | x | 0.0 | 7.0 | -35.3 | -5.8 | -0.6 | 0.0 | 0.6 | 5.5 | 39.6 | 39,266 |
| IntRate_Risk | % | 15 | 12 | 0 | 1 | 5 | 12 | 21 | 39 | 54 | 39,266 |
| LDR | % | 84 | 17 | 42 | 56 | 73 | 84 | 94 | 111 | 130 | 39,266 |
| Listed | % | 28 | 45 | 0 | 0 | 0 | 0 | 100 | 100 | 100 | 39,266 |
| Size | $ bn | 3.2 | 27.0 | 0.0 | 0.2 | 0.3 | 0.6 | 1.1 | 5.4 | 953.6 | 39,266 |
| MS_Deposit | % | 0.02 | 0.06 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.07 | 0.53 | 39,266 |
| Unused_Commit | % | 15.9 | 7.0 | 2.5 | 5.7 | 10.9 | 15.1 | 20.0 | 28.6 | 38.2 | 39,266 |
| Wholesale_Fund_Prop | % | 23.0 | 10.3 | 5.6 | 9.0 | 15.6 | 21.5 | 28.5 | 41.8 | 60.1 | 39,266 |
| Crisis_Alt | bps | 25 | 29 | 6 | 8 | 11 | 16 | 22 | 72 | 204 | 39,266 |
| Deposit_Prop | % | 80 | 8 | 51 | 65 | 76 | 82 | 86 | 90 | 91 | 39,266 |
| Loan_Growth | % | 7 | 12 | -21 | -11 | 1 | 7 | 14 | 28 | 49 | 39,266 |

**TABLE 3**
**Uninsured deposit pricing test**

| Cost_Uninsured | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Consistency_in_Quality | -0.00008 | 0.00003 | 0.00003 | 0.00011 | 0.00014 | 0.00008 | 0.05134 |
| | (-0.91) | (0.29) | (0.31) | (1.06) | (1.33) | (0.66) | (0.56) |
| Consistency_in_Quality x Crisis | | -0.0009*** | -0.0009*** | -0.00109*** | -0.00087** | -0.00078** | -0.00451*** |
| | | (-3.37) | (-3.34) | (-2.81) | (-2.55) | (-2.39) | (-2.89) |
| Current_Quality | | | -0.00006 | 0 | 0.00002 | 0.00001 | -0.3448 |
| | | | (-0.72) | (-0.01) | (0.39) | (0.14) | (-0.23) |
| Current_Quality x Crisis | | | -0.00034 | -0.00039 | -0.00038* | -0.00035 | -0.02167 |
| | | | (-1.26) | (-1.61) | (-1.69) | (-1.49) | (-1.39) |
| Crisis | | 0.00395*** | 0.00411*** | | | | |
| | | (20.97) | (17.96) | | | | |
| Cost_Insured | 0.81815*** | 0.81446*** | 0.81443*** | -0.05347* | -0.05213* | 0.02274 | -0.05224* |
| | (295.78) | (296.62) | (296.61) | (-1.99) | (-1.95) | (0.71) | (-1.95) |
| # of Observations | 39,266 | 39,266 | 39,266 | 39,188 | 39,188 | 39,236 | 39,188 |
| Adjusted R-Square | 0.69 | 0.696 | 0.696 | 0.892 | 0.894 | 0.86 | 0.894 |
| Controls | No | No | No | No | Yes | Yes | Yes |
| Firm FE | No | No | No | Yes | Yes | No | Yes |
| Quarter FE | No | No | No | Yes | Yes | Yes | Yes |
| County FE | No | No | No | No | No | Yes | No |
| Clustered Std Err. | No | No | No | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| p-value: F-test for $\beta_1 + \beta_2 = 0$ | | 0.000*** | 0.000*** | 0.012** | 0.031** | 0.028** | |

Notes: Table 3 presents results from a generalized difference-in-difference OLS regression of Cost of Uninsured deposits (Cost_Uninsured) on accounting quality, cost of insured deposits and various other bank variables based on model 3. Consistency_in_Quality is the key quality measure and its interaction with Crisis is the key term. Column 1 excludes interaction of quality with crisis quarters, while column 2 includes it. Thereafter, columns 3 to 5 progressively include additional controls and fixed effects. Column 5 has the full specification. Column 6 repeats column 5 with county fixed effects while column 7 repeats column 5 using continuous versions of both the quality and crisis variables. The F-test at the bottom tests the impact of accounting quality on uninsured deposit price during crisis period. t-statistics are presented in parentheses. *** denotes two-tailed statistical significance at 1%, ** at 5% and * at 10%. All variable definitions are provided in Appendix A.

**TABLE 4**
**Uninsured deposit volume test**

| Uninsured_Growth | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Consistency_in_Quality | 0.00247** | 0.0013 | 0.00127 | -0.00068 | -0.00078 | -0.0015 | -1.18518 |
| | (2.00) | (0.99) | (0.97) | (-0.54) | (-0.57) | (-1.25) | (-1.16) |
| Consistency_in_Quality x Crisis | | 0.01056*** | 0.01046*** | 0.00999*** | 0.00974*** | 0.00766*** | 0.04258*** |
| | | (2.67) | (2.65) | (3.12) | (3.10) | (2.65) | (2.83) |
| Current_Quality | | | 0.00149 | 0.00097 | 0.00101 | 0.00031 | 52.45367 |
| | | | (1.13) | (0.66) | (0.69) | (0.22) | (1.61) |
| Current_Quality x Crisis | | | 0.00584 | 0.00475 | 0.00504 | 0.00506 | -0.62123** |
| | | | (1.48) | (0.83) | (0.86) | (0.83) | (-2.11) |
| Crisis | | -0.00573** | -0.00855** | | | | |
| | | (-2.07) | (-2.54) | | | | |
| Insured_Growth | 0.31007*** | 0.31015*** | 0.31028*** | 0.21488*** | 0.19949*** | 0.20564*** | 0.19951*** |
| | (35.90) | (35.85) | (35.86) | (4.09) | (4.04) | (4.04) | (4.04) |
| # of Observations | 39,266 | 39,266 | 39,266 | 39,188 | 39,188 | 39,236 | 39,188 |
| Adjusted R-Square | 0.0319 | 0.032 | 0.0321 | 0.0699 | 0.117 | 0.0901 | 0.117 |
| Controls | No | No | No | No | Yes | Yes | Yes |
| Firm FE | No | No | No | Yes | Yes | No | Yes |
| Quarter FE | No | No | No | Yes | Yes | Yes | Yes |
| County FE | No | No | No | No | No | Yes | No |
| Clustered Std Err. | No | No | No | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| p-value: F-test for $\beta_1 + \beta_2 = 0$ | | 0.001*** | 0.001*** | 0.004*** | 0.004*** | 0.0302** | |

Notes: Table 4 presents results from a generalized difference-in-difference OLS regression of Uninsured deposits growth (Uninsured_Growth) on accounting quality, cost of insured deposits and various other bank variables based on model 3. Consistency_in_Quality is the key quality measure and its interaction with Crisis is the key term. Column 1 excludes interaction of quality with crisis quarters, while column 2 includes it. Thereafter, columns 3 to 5 progressively include additional controls and fixed effects. Column 5 has the full specification. Column 6 repeats column 5 with county fixed effects while column 7 repeats column 5 using continuous versions of both the quality and crisis variables. The F-test at the bottom tests the impact of accounting quality on uninsured deposit price during crisis period. t-statistics are presented in parentheses. *** denotes two-tailed statistical significance at 1%, ** at 5% and * at 10%. All variable definitions are provided in Appendix A.

## TABLE 5
## Liquidity creation test

| Liquidity_Generated | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Consistency_in_Quality | 0.00275* | -0.00008 | -0.00015 | 0.00119 | -0.0007 | -0.00141 | -0.58369 |
| | (1.80) | (-0.05) | (-0.09) | (0.65) | (-0.49) | (-0.72) | (-0.48) |
| Consistency_in_Quality x Crisis | | 0.02567*** | 0.02581*** | 0.00975* | 0.00766** | 0.00675 | 0.03396** |
| | | (5.28) | (5.31) | (1.99) | (2.21) | (1.49) | (2.21) |
| Current_Quality | | | 0.0034** | 0.00119 | 0.00037 | -0.00006 | 10.24451 |
| | | | (2.10) | (1.61) | (0.60) | (-0.07) | (0.49) |
| Current_Quality x Crisis | | | -0.00747 | 0.0062** | 0.00487*** | 0.00198 | 0.17974** |
| | | | (-1.54) | (2.23) | (3.14) | (1.33) | (0.81) |
| Crisis | | 0.0033 | 0.00693* | | | | |
| | | (0.97) | (1.67) | | | | |
| Observations | 39,266 | 39,266 | 39,266 | 39,188 | 39,188 | 39,236 | 39,188 |
| Adjusted R-Square | 5.70E-05 | 0.0018 | 0.00189 | 0.826 | 0.867 | 0.687 | 0.867 |
| Controls | No | No | No | No | Yes | Yes | Yes |
| Firm FE | No | No | No | Yes | Yes | No | Yes |
| Quarter FE | No | No | No | Yes | Yes | Yes | Yes |
| County FE | No | No | No | No | No | Yes | No |
| Clustered Std Err. | No | No | No | Firm, Qtr | Firm, Qtr | Firm, Qtr | Firm, Qtr |
| p-value: F-test for $\beta_1 + \beta_2 = 0$ | | 0.000*** | 0.000*** | 0.020** | 0.035** | 0.216 | |

Notes: Table 5 presents results from an OLS regression of Liquidity created (Liquidity_Generated) on accounting quality, cost of insured deposits and various other bank variables based on model 3. Consistency_in_Quality is the key quality measure and its interaction with Crisis is the key term. Column 1 excludes interaction of quality with crisis quarters, while column 2 includes it. Thereafter, columns 3 to 5 progressively include additional controls and fixed effects. Column 5 has the full specification. Column 6 repeats column 5 with county fixed effects while column 7 repeats column 5 using continuous versions of both the quality and crisis variables. The F-test at the bottom tests the impact of accounting quality on uninsured deposit price during crisis period. t-statistics are presented in parentheses. *** denotes two-tailed statistical significance at 1%, ** at 5% and * at 10%. All variable definitions are provided in Appendix A.

**TABLE 6**
**Impact of Consistency in Quality on Insured vs. Uninsured deposits**

| | (1) Price | (2) Price | (3) Price | (4) Volume | (5) Volume | (6) Volume |
|---|---|---|---|---|---|---|
| Uninsured | -0.00113*** | -0.00151*** | -0.00151*** | 0.0216*** | 0.0214*** | 0.0214*** |
| | (-3.93) | (-3.66) | (-3.63) | (9.21) | (5.45) | (5.42) |
| Uninsured x Crisis | 0.0034*** | 0.00003** | 0.00003** | -0.01477 | -0.00003 | -0.00003 |
| | (4.55) | (2.31) | (2.30) | (-1.23) | (-0.19) | (-0.19) |
| Consistency_in_Quality | 0.00002 | -0.06999 | -0.07912 | -0.00108 | 1.5961 | 1.05446 |
| | (0.18) | (-0.60) | (-0.66) | (-1.40) | (1.57) | (1.04) |
| Consistency_in_Quality x Crisis | -0.00023 | 0.00159 | 0.00224 | -0.00155 | -0.0482** | -0.0504** |
| | (-0.81) | (0.98) | (1.30) | (-0.56) | (-2.39) | (-2.44) |
| Consistency_in_Quality x Uninsured | 0.00002 | 0.16 | 0.16 | 0.00073 | -2.89493* | -2.89493* |
| | (0.13) | (0.87) | (0.86) | (0.59) | (-1.89) | (-1.88) |
| Consistency_in_Quality x Uninsured x Crisis | -0.00072 | -0.00924*** | -0.00924*** | 0.00959*** | 0.09128*** | 0.09128*** |
| | (-1.22) | (-2.77) | (-2.75) | (2.68) | (2.68) | (2.66) |
| Observations | 78,532 | 78,532 | 78,532 | 78,532 | 78,532 | 78,532 |
| Adjusted R-Square | 0.866 | 0.865 | 0.846 | 0.105 | 0.105 | 0.0894 |
| Firm FE | Yes | Yes | No | Yes | Yes | No |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County FE | No | No | Yes | No | No | Yes |
| p-value: F-test for $\beta_3 + \beta_4 + \beta_5 + \beta_6 = 0$ | 0.034** | | | 0.015** | | |
| p-value: F-test for $\beta_3 + \beta_4 = 0$ | 0.432 | | | 0.33 | | |

Notes: Table 6 presents results from generalized difference-in-difference OLS regression of deposit price (columns 1-3) and deposit volume growth (columns 4-6) on accounting quality, banking crisis and various other bank variables based on model 4. A three-way interaction term between Consistency_in_Quality, Crisis and Uninsured (indicator variable for insured status) is the key term of interest. It simultaneously tests the differential impact of high consistency in accounting quality on uninsured deposits during times of banking crisis. Column 1 and 4 uses binary version of Consistency_in_Quality and Crisis variables, while columns 2, 3, 5 and 6 use continuous versions of Consistency_in_Quality and Crisis variables. Column 3 and 6 are respectively similar to column 2 and 5, except that the firm fixed effect is replaced with county fixed effect. The first F-test at the bottom checks the incremental impact of Consistency_in_Quality on both price and volume growth of uninsured deposits during crisis periods. The second F-test checks the incremental impact of consistency in quality on both price and volume growth of insured deposits. Standard errors are clustered by firm and quarter. t-statistics are presented in parentheses. *** denotes two-tailed statistical significance at 1%, ** at 5% and * at 10%. All variable definitions are provided in Appendix A.

## TABLE 7
## Alternate measures of cost of Uninsured Deposits

| Netchange_Cost_Uninsured | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Consistency_in_Quality | -0.00001 | 0.00001 | -0.00001 | -0.02788 | 0.07549 | 0.0778 |
| | (-0.13) | (0.12) | (-0.06) | (-0.55) | (1.52) | (1.14) |
| Consistency_in_Quality x Crisis | -0.00055** | -0.00039** | -0.00029 | -0.00469*** | -0.0031*** | -0.00283*** |
| | (-2.10) | (-2.32) | (-1.24) | (-3.74) | (-4.47) | (-3.39) |
| Current_Quality | -0.00007 | -0.00006 | -0.00009 | -2.18791 | -1.35433 | -0.4395 |
| | (-0.81) | (-0.77) | (-1.17) | (-1.10) | (-0.78) | (-0.25) |
| Current_Quality x Crisis | 0.00021 | 0.00018 | 0.00027 | 0.01648 | 0.01642 | 0.0115 |
| | (0.81) | (0.56) | (0.83) | (0.66) | (1.25) | (0.74) |
| Crisis | -0.00008 | | | 0** | | |
| | (-0.36) | | | (1.96) | | |
| Cost_Insured | -0.0708*** | -0.32488*** | -0.54149*** | -0.07249*** | -0.32486*** | -0.54147*** |
| | (-24.85) | (-10.44) | (-12.07) | (-25.33) | (-10.44) | (-12.07) |
| Observations | 39,266 | 39,266 | 39,188 | 39,266 | 39,266 | 39,188 |
| Adjusted R-Square | 0.0157 | 0.0681 | 0.0835 | 0.0163 | 0.0682 | 0.0836 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | No | No | Yes | No | No | Yes |
| Quarter FE | No | Yes | Yes | No | Yes | Yes |
| Std Err. clustered by | None | Firm, Qtr | Firm, Qtr | None | Firm, Qtr | Firm, Qtr |

Notes: Table 7 presents results from a generalized difference-in-difference OLS regression of an alternate measure of Cost of Uninsured deposit (Netchange_Cost_Uninsured) on accounting quality, cost of insured deposits and various other bank variables based on model 3. Consistency_in_Quality is the key quality measure and its interaction with Crisis is the key term. Columns 1 to 3 use binary version of both Consistency_in_Quality and Crisis variables, while columns 4 to 6 use continuous versions for both these variables. Columns 1 and 4 do not include any fixed effects. Columns 2 and 5 include quarter fixed effects while columns 3 and 6 use both firm and quarter fixed effects. t-statistics are presented in parentheses. *** denotes two-tailed statistical significance at 1%, ** at 5% and * at 10%. All variable definitions are provided in Appendix A.

**TABLE 8**
**Robustness tests: Alternate sample period**

| | (1) Price | (2) Price | (3) Volume | (4) Volume | (5) Liquidity | (6) Liquidity |
|---|---|---|---|---|---|---|
| Consistency_in_Quality | 0.00011 | -0.00094 | -0.00097 | -1.96432 | -0.00035 | -1.57597 |
| | (0.85) | (-0.01) | (-0.59) | (-1.02) | (-0.24) | (-0.90) |
| Consistency_in_Quality x Crisis | -0.00068* | -0.00395* | 0.007* | 0.03467* | 0.00859** | 0.04062** |
| | (-1.78) | (-2.00) | (1.90) | (1.49) | (2.21) | (2.09) |
| Current_Quality | 0.00009 | -0.8163 | -0.00058 | 34.11318 | 0.00026 | 22.05618 |
| | (1.49) | (-0.30) | (-0.33) | (0.64) | (0.38) | (0.74) |
| Current_Quality x Crisis | -0.00049** | -0.02643 | 0.00688 | -0.49618 | 0.00574*** | 0.1711 |
| | (-2.02) | (-1.17) | (1.16) | (-1.55) | (2.70) | (0.76) |
| Cost_Insured | -0.07728*** | -0.07733*** | | | | |
| | (-2.73) | (-2.74) | | | | |
| Insured_Growth | | | 0.17725*** | 0.17732*** | | |
| | | | (3.14) | (3.14) | | |
| MSChange_Uninsured | -21.34576*** | -21.34882*** | | | | |
| | (-4.82) | (-4.82) | | | | |
| Unused_Commit | -0.00566** | -0.00555** | 0.12682*** | 0.12877*** | 0.09598*** | 0.0972*** |
| | (-2.33) | (-2.29) | (3.35) | (3.38) | (2.80) | (2.83) |
| RealEst_Prop | -0.00382** | -0.00391** | 0.03247* | 0.0322* | | |
| | (-2.50) | (-2.58) | (1.95) | (1.94) | | |
| Size | 0*** | 0*** | 0*** | 0*** | 0*** | 0*** |
| | (5.58) | (5.55) | (-3.08) | (-3.11) | (-43.13) | (-38.58) |
| Leverage | -0.00999** | -0.00988** | -0.1268** | -0.12722** | -0.70584*** | -0.70584*** |
| | (-2.30) | (-2.26) | (-2.12) | (-2.12) | (-9.93) | (-9.92) |
| NPL_Ratio | 0.03158*** | 0.0289*** | -0.14077 | -0.15713 | -0.6015*** | -0.60422*** |
| | (3.16) | (2.87) | (-1.17) | (-1.26) | (-6.11) | (-5.99) |
| ROE | -0.00363 | -0.00308 | 0.09789 | 0.10069 | 0.11515*** | 0.11253*** |
| | (-1.24) | (-1.05) | (1.57) | (1.57) | (3.24) | (3.14) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Deposit_Prop | -0.00238 | -0.00235 | -0.92511*** | -0.92553*** | | |
| | (-0.90) | (-0.89) | (-11.90) | (-11.91) | | |
| Listed | -0.0002 | -0.00017 | 0.00531 | 0.00523 | | |
| | (-0.36) | (-0.30) | (0.51) | (0.50) | | |
| LDR | -0.00261* | -0.0026* | 0.15535*** | 0.15525*** | | |
| | (-1.74) | (-1.74) | (6.80) | (6.82) | | |
| NPL_Cover_Change | | | 0.00018 | 0.00018 | | |
| | | | (1.66) | (1.67) | | |
| Loan_Growth | | | 0.0661*** | 0.06598*** | 0.09662*** | 0.09665*** |
| | | | (6.41) | (6.40) | (10.35) | (10.33) |
| Netchange_Cost_Uninsured | | | -0.37981*** | -0.37779*** | | |
| | | | (-3.04) | (-3.02) | | |
| MS_Deposit | | | -48.61442*** | -48.49198*** | | |
| | | | (-2.76) | (-2.74) | | |
| Unins_to_Ins_Ratio | | | -0.00016 | -0.00011 | | |
| | | | (-0.04) | (-0.03) | | |
| Wholesale_Fund_Prop | | | -0.83432*** | -0.83447*** | -0.44575*** | -0.44575*** |
| | | | (-12.98) | (-13.01) | (-12.60) | (-12.64) |
| IntRate_Risk | | | | | 0.06167*** | 0.06198*** |
| | | | | | (4.35) | (4.37) |
| Observations | 30,747 | 30,747 | 30,747 | 30,747 | 30,747 | 30,747 |
| Adjusted R-Square | 0.848 | 0.848 | 0.104 | 0.104 | 0.885 | 0.885 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |

Note: Table 8 provides results for robustness tests. Columns 5 and 7 from each of the pricing, volume and liquidity tests are repeated for a shorter sample period ending in the 2nd quarter of 2009. Columns 1, 3 and 5 in table 8 use binary version of Consistency_in_Quality and Crisis variables, while columns 2, 4 and 6 use continuous version for both the variables. Standard errors are clustered by firm and quarter. t-statistics are presented in parentheses. *** denotes two-tailed statistical significance at 1%, ** at 5% and * at 10%. All variable definitions are provided in Appendix A.