Bank Transparency and Deposit Flows*

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Abstract: One of the most widely discussed issues in banking regulation and research is transparency. Yet, whether depositors – banks' most important claimholders – are affected by transparency, is an empirical open question. Analyzing US commercial banks from 1994-2019, we show that uninsured deposit flows are more sensitive to information about bank performance when banks are more transparent. We also link transparency to deposit rates, banks' investment funding patterns, and profitability. In addition, we find consistent evidence from a differences-in-difference analysis using the Sarbanes-Oxley Act of 2002 as a shock to transparency. Overall, our findings demonstrate that transparency is important in shaping depositors' behavior and highlight its potential costs.

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1. Introduction

The transparency of banks about the prospects of their risky loans is an issue of great importance in bank regulation.[1] A key component of the regulatory framework, Basel III, adopted after the 2008 crisis, is to strengthen transparency to allow various claimholders to better monitor banks' risks. Similarly, one development of financial regulation following the crisis, banks' stress tests, imposes substantial new disclosure requirements. Yet, recent theories, such as Dang et al. (2017), emphasize the benefit of opacity in allowing banks to provide liquidity to their depositors.

This active interest in bank transparency calls for empirical evidence on whether bank depositors are aware of the quality of information banks provide and whether it affects their behavior. Depositors are the prominent claimholders for banks; according to Hanson et al. (2015), they provide more than 70% of bank funding. They also play a key role in banking theory, whether it focuses on the role of depositors in disciplining bank lending activities (e.g., Calomiris and Kahn, 1991, or Diamond and Rajan, 2001) or on their demand for safe liquid assets (e.g., Gorton and Pennacchi, 1990, or Dang et al., 2017). Yet, depositors are commonly perceived as inattentive and/or lacking the incentives and expertise to understand the quality of bank information.[2] This is possibly because banks' disclosures – mainly Call Reports – are considerably long and complex (Morgan, 2002). A typical depositor may not be willing to invest the requisite time and resources to understand these disclosures, especially if they believe that government support will limit their losses in the event of bank failure.[3] Ultimately, whether bank transparency is an important factor in depositors' behavior is an open question. We address this question in this paper.

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[1] See reviews by Landier and Thesmar (2011), Goldstein and Sapra (2014), Acharya and Ryan (2016), and Bushman (2016).

[2] Drechsler et al. (2017) even argue that lack of depositor sophistication gives banks higher market power, which they use to earn higher spreads.

[3] Kelly et al. (2016) find that expectation of a government bailout significantly lowered the price of crash insurance for the entire financial sector during the Financial Crisis of 2007-08. Although not always, FDIC has occasionally protected uninsured depositors (Benston and Kaufman, 1997).

As a starting point, we need a measure of bank transparency. We construct such a measure to reflect the ability of banks' disclosures on performance to predict future realizations. In particular, for most of the analysis, we use bank earnings as the summary information for bank performance. This is the main metric used to assess banks' financial health, and there is considerable cross-bank variation in how informative it is about deteriorations in banks' asset quality (Ryan, 2012). The informativeness (transparency) of bank earnings is the adjusted R-squared from a regression of bank loan write-offs on the past components of the disclosed earnings (including loan loss provisions) and other key disclosure items that are shown in prior research to predict loan write-offs. We create this measure for every bank in every quarter based on recent history of disclosures and realizations. We refer to our measure as the *R2* measure and relegate a detailed description of its construction to Section 2. Everything else equal, banks with higher *R2*s are more transparent as their disclosures contain more information about their asset quality.

Our study is based on a large sample of U.S. commercial banks over the period 1994-2019 using Call Reports. We find that the *R2* measure varies substantially across banks. These differences cannot be explained, by and large, by observable differences in bank characteristics such as size or asset composition, suggesting that the *R2* measure captures a distinct bank characteristic and is largely determined by exogenous factors outside of banks' control. An advantage of the Call Reports data is that it includes both private and public banks. For the subsample of observations from public banks (about one sixth of the total sample), we can validate that *R2* captures an informational feature: stock returns are more sensitive to earnings news in banks with high *R2*.

Our main result is a highly statistically significant positive relation between the *R2* measure and the sensitivity of uninsured deposit flows to bank performance, particularly for poorly performing banks. The economic magnitude is also significant: a one-standard deviation increase in *R2* is associated with a 26% increase in the flow-performance sensitivity. These findings suggest that uninsured depositors are alert to the information about bank health and respond more strongly to it when this information becomes more precise. They also imply that any changes in banks' fundamental volatility would be met with even stronger changes in volatility in uninsured deposit flows at transparent banks. Indeed, we find that greater flow-performance sensitivity at high *R2* banks also manifests in unconditionally more volatile uninsured deposit flows.

Moving on to explore the behavior of insured depositors, we find, as expected, very different results. The sensitivity of insured deposit flows to bank performance is negatively related to the *R2* measure. This points to a substitution effect: insured deposits, which have much less to lose when banks perform poorly, substitute for the loss of uninsured deposits in poorly performing banks. This is consistent with recent evidence in Martin, Puri, and Ufier (2018). To better understand the mechanism, it is important to bring banks' deposit rates into the picture. As expected, we find that banks tend to increase deposit rates following poor performance in an attempt to keep depositors in. More interesting to our study, we find that deposit rates are more sensitive to bank performance in transparent banks. Hence, transparent banks act to substitute the outflow of uninsured deposits in times of poor performance by attracting insured deposits with higher rates. The substitution appears to be effective, as the sensitivity of total deposits to bank performance does not significantly vary by transparency. However, the substitution comes at a cost because of the higher deposit rates and insurance premium.

After establishing the importance of transparency in shaping the behavior of depositors, we explore its implications for banks' funding costs and performance. Consistent with transparent banks facing higher external funding costs, we find that they pay higher deposit rates and exhibit greater reliance on internally generated funds to support asset growth. We also find that the degree of transparency is negatively associated with profitability. These results provide support to the idea that transparency is costly, as articulated by Dang et al. (2017). According to this view, because informationally sensitive deposits are less effective in serving as a money-like claim, consumers may not be willing to pay a premium for holding these claims, pushing up the funding costs of transparent banks. This evidence is also consistent with recent work (Berger and Bouwman, 2009; Egan et al., 2021) that suggests that creation of money-like securities constitutes a major source of value creation in the banking business. We emphasize that our results do not imply that transparency does not yield monitoring benefits; the results only suggest that these monitoring benefits for an average bank are dominated by the costs of lower liquidity provision.[4]

Questions of causality may come up in interpreting our results. For the most part, our analysis aims to evaluate the link between transparency and various banks' outcomes in equilibrium, so our interpretation about the role played by transparency in deposit flows is not that affected by causality. In particular, whether uninsured depositors are more sensitive to performance because of the bank's transparency policy or the bank is transparent because depositors are more sensitive to performance, the overall message about the importance of transparency for uninsured deposit flows stays intact. There can of course always be omitted variables that are correlated with both our measure of transparency and with deposit-performance

[4] A natural question is why some banks are transparent given that, on average, transparency is associated with higher funding costs and lower profitability. The question relates to the broader literature in economics that seeks to understand the reasons for persistent differences in productivity across firms in the same industry (Syverson, 2011). As we discuss more in Section 4.3, one possibility is that a significant portion of transparency may be pre-determined by the nature of the local markets and borrowers served by banks. Evidence in Morgan (2002) indicates that a significant portion of bank transparency can be traced to the nature of banks' assets. That said, understanding sources of variation (exogenous and endogenous) in bank transparency is an open question that we do not address in this paper. Answers to this question in future research can yield insights into the sources of profitability dispersion in banking industry.

sensitivity, but the many controls and fixed effects we use and the validation of the transparency measure we conduct make this less likely. In addition, the differential response of uninsured and insured deposits mitigates concerns about omitted correlated variables. For example, one might be concerned that stickier uninsured flows at low *R2* banks may be a result of better service quality offered by such banks. To the extent that both uninsured and insured depositors are similarly affected by service quality, this analysis suggests that service quality, or other related unobserved bank characteristics, cannot explain our results.

With this in mind, to complete the analysis, we also look for additional evidence by utilizing a shock to transparency in our sample period. Specifically, we employ what is perhaps the most significant shock to transparency that occurred in a long time: The Sarbanes-Oxley Act of 2002 (SOX). As is well known, this has been a reform in disclosure standards for public firms following accounting scandals in the years that led to it. While SOX has been widely studied in finance and accounting, our dataset containing both public and private banks provides a unique angle, which, to the best of our knowledge, has not been exploited before. Because its provisions were mainly applicable to public banks, SOX introduces a natural opportunity for a difference-in-difference analysis in our study, by looking at the difference in behavior of public banks relative to private banks after vs. before the Act. Following this analysis, we confirm the qualitatively similar effect of a shock to transparency on all the major bank outcomes we explored in this paper. These include the sensitivity of uninsured deposit flows to performance, the sensitivity of illiquid asset growth to internal funds, deposit rates, and bank profitability. All respond to transparency in the same direction as in our main analysis and with high statistical significance. While these findings get us closer to a causal interpretation, the confounding potential of other concurrent events cannot be ruled out definitively. We therefore take a conservative approach and interpret these findings as additional evidence consistent with our main results.

In addition to the papers mentioned above, our paper contributes to several streams of literature. One stream documents that uninsured depositors are responsive to bank performance (Gorton, 1988; Goldberg and Hudgins, 1996; Saunders and Wilson, 1996; Calomiris and Mason, 1997; Martinez Peria and Schmukler, 2001; Iyer and Puri (2012); Berger and Turk-Ariss, 2015; Egan, Hortacsu and Matvos, 2017).[5] Our contribution to this literature is twofold. First, we establish such a result in a comprehensive sample covering almost the entire universe of U.S. banks over the last two and half decades. Second, and more importantly, we document that the response of uninsured depositors is sophisticated enough to consider differences in the quality of information across banks. This result is entirely novel and particularly important given the central role of transparency in recent banking theories (Dang et al., 2017) and in banking regulations.

Our paper also relates to several studies that yield evidence on the monitoring benefits of transparency for U.S. banks (e.g., Beatty and Liao, 2011; Bushman and William, 2015; and Ng and Rusticus, 2020).[6] These studies document that more transparent banks experience beneficial outcomes during periods of crises/recessions such as lower decline in lending, fewer loan defaults, or lower equity market illiquidity. Our study differs from this literature in several key respects. First, ours is the only study that explores the consequences of transparency through the lens of its effect on the performance sensitivity of uninsured deposits – as explained in Section 3, in leading

[5] Our paper is also related to studies that explore the link between performance and withdrawals in the context of money-market funds (MMFs). The evidence suggests that the response of claimholders in MMFs is sophisticated enough to consider differences in the quality of portfolio holdings. See, for example, McCabe (2010), Chernenko and Sunderam (2014), Strahan and Tanyeri (2015), and Schmidt et al. (2016).

[6] Another notable study on monitoring benefits for U.S. Banks is by Granja (2018), but the evidence from this study comes from the National Banking era of 1863-1914, which was characterized by a very different institutional environment. For evidence on monitoring benefits outside of the U.S., see, for example, Ertan et al. (2017) and Balakrishnan and Ertan (2019).

banking theories, this sensitivity is the key channel through which transparency affects banking business.[7] Second, our study speaks to the consequences of transparency *ex ante*, i.e., at the time funding is obtained before loan payoffs (fundamentals) are realized *ex post*. We find that transparent banks on average face higher external funding costs and lower profitability *ex ante*. In contrast, these three studies explore how outcomes differ between transparent and opaque banks after a large adverse macroeconomic shock materializes *ex post*. Viewed collectively, the evidence highlights a trade-off of transparency that features in recent models in Gorton and Ordonez (2014) and Dang et al. (2015): While opacity facilitates production of safe, money-like claims *ex ante* (which are valued by consumers, resulting in lower funding costs and higher profitability), it also results in stronger market freezes/credit busts in periods of economic downturns *ex post*.

Finally, our paper relates to the broader empirical work on the economic consequences of disclosure by non-financial firms in general. Prior works show that greater disclosure benefits firms by reducing information asymmetries and constraining managerial misbehavior (e.g., Leuz and Verrecchia 2000; Greenstone et al., 2006). Recent works also highlight the costs of greater disclosure in the form of distorted long-term decision making (Kraft et al., 2018; Agarwal et al., 2018), revelation of information to competitors (e.g., Bernard, 2016; Li et al., 2018), and crowding out of production of decision relevant information in stock prices (Jayaraman and Wu, 2019). As we highlight above, there are unique tradeoffs in banks, and, in particular, transparency can adversely affect their role in meeting depositors' demand for safe, money-like assets.

[7] In a follow-up study to ours, Nguyen (2020) documents a negative association between reporting opacity and quantity of uninsured deposit financing, which in the paper is interpreted as evidence of monitoring by uninsured depositors. As we explain in Section 3.1, however, it is performance sensitivity (and not the quantity of funding) that is the theoretically appropriate way to evaluate effects of transparency; theory offers no clear prediction with respect to the effect on quantity. If greater performance sensitivity of uninsured deposits sufficiently reduces their utility as a money-like claim, heightened depositor monitoring in a transparent regime can even result in lower quantity of funding (Dang et al., 2017).

2. Measuring transparency

2.1. Conceptual underpinnings and estimation methodology

We measure transparency by the ability of key accounting performance measures to reveal information about banks' asset quality. This approach is consistent with the theoretical framework in Dang et al. (2017) who model transparency as the ease (or cost) with which depositors can acquire information about the future performance of bank assets. Depositors' information acquisition costs are expected to be lower when disclosures are more informative and minimize the need for any additional investigations. Accounting disclosures are the key source of information for outside investors, particularly for private banks for which other information channels such as analyst reports, conference calls, and stock prices are not available.[8] Furthermore, many of the regulatory initiatives to boost transparency pertain to accounting disclosures.

Specifically, our measure captures the extent of uncertainty resolved by Call Reports about future defaults on a bank's loan portfolio. To illustrate the idea, consider a bank that holds a portfolio of fixed rate loans that will mature and pay P_{t+1} in the absence of defaults at *t+1*. Let random variable $\widetilde{D}_{t+1}$ denote the amount of defaults the bank will experience at *t+1*. At time *t*, the depositor decides whether to withdraw money now at *t* or wait till *t+1* to receive the proceeds when the loan portfolio matures, based on her assessment of the amount the bank can collect at *t+1* (i.e., $\tilde{V}_{t+1} = P_{t+1} - \widetilde{D}_{t+1}$). Let Ω_t be the information the depositor gleans from the Call

[8] To illustrate, requiring stock price data would result in 80% drop in our sample. CDS prices are another important source of information but is generally available for the 20 largest banks. Later, in Section 6, we evaluate the possibility of other information sources confounding our inferences. Several analyses reveal that this possibility is quite remote.

Reports at time *t* about $\tilde{V}_{t+1}$. The quality/informativeness of Ω_t can be measured by the proportion of uncertainty about $\tilde{V}_{t+1}$ (or equivalently, $\tilde{D}_{t+1}$) that it helps the depositor resolve:[9]

$$Information\ Quality \equiv \frac{Var(\tilde{V}_{t+1}) - Var(\tilde{V}_{t+1}|\Omega_t)}{Var(\tilde{V}_{t+1})} = \frac{Var(\tilde{D}_{t+1}) - Var(\tilde{D}_{t+1}|\Omega_t)}{Var(\tilde{D}_{t+1})} \quad (1)$$

Empirically, we estimate this measure as the (adjusted) R-squared from bank-specific regressions of future defaults on accounting disclosures in Call Reports relevant for predicting defaults.[10] The main accounting disclosure of focus is earnings, which is also the key performance metric we later use for examining depositor response to bank performance. Earnings number is the most widely used accounting output to assess the cash-flow generating ability of assets in any business, and not just from the standpoint of shareholders but also that of creditors. For example, popular textbooks on "Financial Statement Analysis" invariably include a chapter on credit risk analysis where earnings constitute an important input (e.g., Healy and Palepu, 2013; Wahlen, Baginski, and Bradshaw, 2014). Academic research shows that this focus on earnings when inferring credit risk is well justified.[11]

We decompose earnings into two components to account for their differential information content: loan loss provisions (*LLP*) and earnings before loan loss provisions (*EBLLP*). *LLP* directly pertains to defaults and represents a bank's estimate for credit losses attributable to originating and holding loans during the period and is recorded as an expense in the income statement. Several studies show that *LLP* is an important performance indicator for banks and there is considerable cross-bank variation in how effectively it captures current and future loan

[9] The second equality in (1) reflects the idea that once banks have determined the loan portfolio composition and set contractual terms (including interest rates), the bulk of the uncertainty regarding asset payoffs relates to future defaults.
[10] In information theory, how informative a random variable Y is about X is quantified by the amount of mutual information between Y and X, i.e., I(X,Y)=H(X) – H(X|Y) where H(X) is the marginal entropy for X and H(X|Y) is the conditional entropy (Cover and Thomas, 2012). Regression R-squared corresponds to a scaled version of mutual information (Veldkamp, 2011) and has been used in prior research (e.g., Roll, 1988; Chen et al., 2007).
[11] See, for example, reviews by Demirgüč-Kunt (1989) and Beaver, Correia, and McNichols (2011).

portfolio deteriorations (e.g., Wahlen, 1994, Bhat, Lee and Ryan, 2020). Prior work suggests that *EBLLPs* also contain incremental information about asset quality. Several theoretical and empirical studies show that periods of credit boom are followed by poor performance.[12] Thus, an aggressive growth in revenue (which would be captured by *EBLLP*) could indicate a decline in lending standards and more defaults. We include two lags of *EBLLPs* and *LLPs* after scaling them by lagged total loans.

An important consideration at this stage pertains to whether we should include other non-earnings-related accounting measures that may contain incremental information about asset quality. The answer is not obvious. Because we later examine depositors' response to earnings performance, one approach would be to measure only the information content of earnings. The trade-off is that this approach may yield a transparency measure that underestimates the total information depositors can glean from Call Reports. Because there is no unambiguously superior approach, we use both. We present the analysis in the paper using the transparency measure that also considers information in relevant non-earnings variables. In the Internet Appendix (Table A3, Panel E), we present results using the transparency measure that only captures the information content of earnings. All inferences are robust to using either transparency measure.[13]

We consider two key non-earnings variables that are expected to contain information about asset quality: (i) changes in non-performing loans (ΔNPL) and (ii) book value of equity scaled by assets (*Capital*).[14] *NPL*s are typically defined by banking regulators to be loans that are 90-days

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[12] See, e.g., Baron and Xiong (2017); Jordà, Schularick, and Taylor (2013); Reinhart and Rogoff (2009); Schularick and Taylor (2012); and Fahlenbrach et al. (2018).

[13] Our inferences are also robust if we estimate *R2* using only *LLPs* as a predictor (Internet Appendix, Table A3, Panel D).

[14] We focus on non-earnings variables for which there is an economic rationale as well as empirical evidence for their predictive ability for future defaults. This helps minimize data mining bias and the risk of model overfitting - the latter is important to consider too as our estimation window of 12 quarters limits the number of predictors that can be included.

past due. An increase in *NPL* therefore indicates deterioration in loan quality. The reason *NPLs* may contain incremental information is that they are less vulnerable to managerial manipulation because of the mechanical definition; thus, *NPLs* may contain valuable information for depositors when they expect managers to manipulate earnings.[15] We include two lags of ΔNPL. Lastly, we include capital ratio because it affects managers' incentive for risk taking, and thus potentially contains information about asset quality and future defaults. Prior research finds that both ΔNPL and capital ratio have predictive power for future defaults (Wahlen, 1994).

We measure future defaults ($\widetilde{D}_{t+1}$) using gross loan write-offs (or charge-offs), which represent the dollar amount of gross loans that are deemed to be uncollectible by banks in a period. Intuitively, write-offs can be thought of as future realization of the estimated loan-losses recorded in previous periods in the form of *LLP*s. To allow for the possibility that past signals of loan quality deterioration (e.g., *LLPs* or *NPLs*) may not manifest immediately in the form of write-offs in the next quarter, we use the cumulative write-offs over the two quarters (*t and t+1)* following the end of quarter *t-1*.[16]

To summarize, our measure of the informativeness of bank earnings is the adjusted R-squared (henceforth referred to as *R2*) from Eqn. (2) below, estimated for each bank-quarter using observations over the previous 12 quarters:[17]

[15] During our sample period, banks are required to follow the incurred loss model specified under the U.S. generally accepted accounting principles (GAAP) for estimating *LLPs*. See Ryan (2012) for a detailed discussion of the discretion available in the application of the incurred loss model.
[16] This approach is consistent with the regulatory guidance that requires closed-end consumer loans (open-end consumer loans and residential mortgages) be written-off no later than 120 (180) days past due (see Federal Financial Institutions Examination Council's policy dated June 12, 2000). In sensitivity tests reported later, we obtain similar inferences when we measure write-offs over the next 4 quarters.
[17] We later show that our results are robust to extending the estimation period to 20 quarters.

$$WriteOff_t = \alpha_0 + \sum_{k=1}^{2}(\delta_k EBLLP_{t-k} + \beta_k LLP_{t-k} + \gamma_k \Delta NPL_{t-k}) + \rho Capital_{t-1} + \varepsilon_t \quad (2)$$

Two features of our transparency measure are worth emphasizing. First, low *R2* doesn't necessarily imply that banks are riskier (i.e., higher $Var(\widetilde{D})$). This is because the *R2* measures the proportion of the uncertainty that depositors can resolve about banks' future loan portfolio performance (i.e., $\frac{Var(\widetilde{D})-Var(\widetilde{D}|\Omega_t)}{Var(\widetilde{D})}$), not the unconditional uncertainty of default ($Var(\widetilde{D})$) itself. Indeed, we find that *R2* and write-off volatility exhibit a relatively modest correlation of 0.10 (Table 1, Panel B). Nevertheless, we control for inherent uncertainty in bank fundamentals to ensure that our results are not driven by any mechanical relation between *R2* and the fundamental uncertainty.

Second, a bank can have a low *R2* either because the bank holds more opaque assets whose defaults are inherently difficult to predict for bank management, or because the management strategically chooses not to fully reveal its private information in the estimates of *LLP*. We view this to be an appealing feature of the measure because, from the perspective of depositors' decision-making, it does not matter whether depositors' lack of information results from inherently opaque assets or strategic withholding of information.[18] Given that a significant portion of banks' opacity can be traced to banks' assets (Morgan, 2002), a bank can appear quite opaque to depositors even if the management largely reveals its private information. This makes it quite important to measure total information and not just the information revealed by management.

[18] The distinction becomes relevant if one wants to evaluate the effect of specific accounting and disclosure standards designed to alter the revelation of bank managers' private information. The purpose of this paper, however, is to study depositor behaviors (and their resulting consequences) when depositors can obtain more information, regardless of its source.

The above feature also distinguishes our transparency measure from the ones used in the prior accounting literature that are mainly designed to measure the degree to which managers reveal their private information. There are two common approaches to measure bank transparency in the accounting literature. In one approach, researchers measure the timeliness with which managers reveal their private information about loan quality in loan loss provisions (e.g., Beatty and Liao, 2011).[19] In the other approach, researchers use the incidence of restatement of financial statements to measure transparency (e.g., Ng and Rusticus, 2020). Both approaches are mainly designed to measure managerial willingness to reveal private information, which makes these measures suitable for studying the determinants and consequences of managerial disclosures incentives, as is generally the intent in this literature. Unlike *R2*, however, they do not measure total information, making them less suitable for our purpose. Nevertheless, in robustness tests discussed later, we find that our inferences are robust if we use a measure of managerial propensity to reveal private information.

2.2. Data sources, descriptive statistics and validation of R2

We obtain most of our bank-level variables from the U.S. Call Reports as disseminated by the Wharton Research Data Services (WRDS) and SNL database. Call Reports contain quarterly data on all commercial banks' income statements and balance sheets. Our sample period is from January 1994 to December 2019. Our bank-quarter observation is at commercial bank level.[20] To avoid the impact of mergers and acquisitions, we exclude bank-quarter observations with quarterly

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[19] A related variant is the loan provision estimation quality constructed in Ng and Rusticus (2020), which also focuses on the information conveyed in *LLP*s by bank managers. We thank an anonymous referee for bringing this measure to our attention.
[20] A priori, it is not clear whether depositors make withdrawal decisions based on the health of the top bank holding company or of the subsidiary commercial bank alone. We estimate our main specifications at commercial bank level because the insured deposits data are not available from Y9-C reports filed by bank holding companies. In sensitivity analyses (results not tabulated), we aggregate banks belonging to a common holding company to their top holder level and treat them as a single entity (following Kashyap, Rajan, and Stein 2002; Acharya and Mora, 2015), and find qualitatively similar results.

asset growth greater than 10%. We also exclude bank quarters with total assets smaller than 100 million and winsorize all continuous variables at 1% and 99%. These sample-selection and cleaning procedures are commonly used in prior work (Gatev and Strahan, 2006; Acharya and Mora, 2015). The final sample contains over 340,000 bank-quarter observations with 9,064 unique banks. 27% of the banks are publicly listed, accounting for 17% of the bank-quarter observations, and the rest are from private banks. All variables are defined in Appendix A and Table 1, Panel A and B present the summary statistics and correlations for all main variables.

Figure 1 plots the summary statistics for *R2* across all banks (Panel A) and for subsamples of banks by asset sizes (Panel B) from 1994Q1 to 2019Q4. We follow Beatty and Liao (2011) and use $500 million as the cutoff for small banks as this is the cutoff FDICIA uses for independent audit requirement. We classify banks with assets above 3 billion as large banks (Berger and Bouwman, 2009) and those with assets between $500 million and $3 billion as medium banks. All cutoffs are in real 2000 dollars. With a mean of 0.22 and a standard deviation of 0.45 (Table 1 Panel A), the *R2* measure exhibits substantial cross-bank variation.[21] Both panels show that *R2* is relatively stable over time except a sharp increase during the Financial Crisis of 2007-2008. Since *R2* is estimated with data from the preceding 12 quarters, the peak in *R2* around 2009Q3 suggests that Call Reports released during the financial crisis period (2007-2009) are highly predictive of future loan write-offs. This is consistent with recent theoretical work which predicts greater information revelation about asset quality during bad times (Gorton and Ordonez, 2014; Bouvard, Chaigneau, and de Motta, 2015). We later examine if our results are concentrated in the financial crisis and do not find this to be the case.

[21] Since *R2* is the adjusted R-squared from a regression of bank loan write-offs on components of bank disclosure over 12 quarters, it can be negative if the banks' disclosure is not informative and its write-off is not very predictable.

Table 1, Panel C explores the association between *R2* and a vector of variables that capture the bank's size and asset composition, with different combinations of bank and quarter fixed effects. It can be seen that *R2* is higher in larger banks and banks with more real estate loans. The latter finding is consistent with Bhat, Lee, and Ryan (2020) who attribute this to the relatively homogeneous nature of real estate loans (e.g., consumer mortgages) which makes it easier to predict future write-offs based on statistical analyses, compared to other types of loans (e.g., large, commercial loans) where write-off prediction involves greater judgment based on information from loan officers.

Panel C reveals that there is significant heterogeneity in *R2* that cannot be captured by observable bank characteristics such as size and asset composition: the regression R-squared without any fixed effects in column (1) is less than 1%. Time-invariant bank-specific factors account for the largest proportion of variation in *R2*, at about 11% (column (2)). These results suggest that banks that appear similar based on aggregate asset composition can still differ significantly in the inherent opacity of their loan portfolio, possibly due to differences in factors outside banks' control such as characteristics of the markets and borrowers that they serve. This highlights the advantage of our *R2* measure which allows us to sort banks into different levels of information quality using a parsimonious model without access to detailed data on bank characteristics.

We next exploit stock price data for the subset of public banks to validate that *R2* indeed measures earnings information quality. If *R2* measures information quality, we should observe stronger stock price responses to earnings news at banks with higher *R2*, because a unit increase in earnings of high quality should lead to a larger upward revision in beliefs about banks' future prospects. This idea underlies a large body of accounting literature in evaluating earnings informativeness (e.g., Kothari, 2001). Following this literature, we estimate the following standard earnings response coefficient equation for the publicly traded banks in our sample:

$$Abret_{it} = \beta_0 \Delta Earnings_{it} + \beta_1 R2_{it-1} * \Delta Earnings_{it} + \beta_2 R2_{it-1} + Control_{it} + \epsilon_{it}$$

where $Abret_{it}$ is the abnormal stock return for quarter *t* calculated as the difference between the cumulative return over the 5-day window centered on earnings announcement date and the equal-weighted market return over the same period. We obtain similar results (not reported) when using the returns from 3-day window. $\Delta Earnings_{it}$ is the change of earnings from four quarters ago, scaled by lagged total assets and $R2_{it-1}$ is the *R2* from the most recent quarter prior to the earnings announcement. Estimates in Table 2 show that both $\widehat{\beta_0}$ and $\widehat{\beta_1}$ are significantly positive across all specifications, suggesting that earnings of high *R2* banks are perceived to be of higher quality.[22]

3. Transparency and the sensitivity of deposit flows to performance

3.1. Motivation

Our main analysis explores the response of uninsured depositors to earnings information and whether it is affected by information quality. If uninsured depositors can properly understand the quality of bank earnings, we would expect their decisions to become more sensitive to earnings performance as the precision of the earnings signal (i.e., *R2)* increases. This follows from the Bayesian updating rule which specifies larger weights on information signals with greater precision.

Our focus on the performance sensitivity of uninsured deposits is motivated by two leading streams of banking theories. In one set of theories, sensitive uninsured depositors – who "vote with their feet" when unhappy with banks' actions/performance – emerge as the main monitoring

[22] In results reported in the Online Appendix, we obtain similar inferences when we validate the *R2* measure using credit default swap (CDS) price movements for a much smaller set of large banks where CDS price data is available.

mechanism to contain agency problems (e.g., Calomiris and Kahn, 1991).[23] To the extent that heightened sensitivity of uninsured depositors due to greater transparency makes this disciplining mechanism more effective, greater transparency may benefit banks by reducing agency costs.

The sensitivity of uninsured depositors to bank performance signals also features prominently in the other set of banking theories, although as an undesirable attribute, which makes transparency costly. These theories emphasize the role of banks in producing safe, informationally insensitive claims that serve as a medium of exchange and help customers share liquidity risk (e.g., Gorton and Pennacchi, 1990; Dang et al., 2017).[24] The literature highlights that the production of such claims by the private sector that are backed by risky assets is socially desirable because safe claims backed by the government's taxing authority (e.g., treasury bills, insured deposits) may not fully meet the demand.[25] Dang et al. (2017) show that when uninsured deposits serve as safe, money-like claims, greater transparency can hurt banks by making uninsured deposits more informationally sensitive, which reduces their appeal as a money-like claim.[26]

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[23] Specifically, Calomiris and Kahn (1991) show that depositors' right to withdraw at any time at par, together with the sequential service constraint, motivates depositors to expend costly resources to produce information about bank performance which in turn disciplines bankers' risk-taking activities.

[24] Consistent with uninsured deposits serving as safe, money-like claims, the Central Bank includes uninsured deposits in its definition of money (M1 Money Stock). Furthermore, research documents that the prices of these claims and other similar uninsured short-term debt includes a convenience-premium for their utility as money-like claims. See, for example, Kacperczyk, Perignon, and Vuillemey (2020), Sunderam (2015), Hanson et al. (2015), and survey by Gorton (2017). Finally, the empirical work that illustrates the benefit of corporate cash holdings in managing liquidity risk (e.g., Opler et al., 1999; Duchin, 2010; Harford et al., 2014) includes uninsured deposits in the definition of cash holdings. This evidence suggests that corporates consider uninsured deposits as a tool to manage liquidity risk – a key benefit of owning safe, money-like assets highlighted in the theoretical literature.

[25] Holmstrom and Tirole (1998, 2011) and Tirole (2011) argue that deadweight costs of distortionary taxes and consumer risk-aversion limit the supply of government-backed safe claims. Gorton et al. (2012) document that the demand for safe assets has never been fully met by government produced safe claims and bank deposits constitute a non-trivial share of the total safe asset supply. In our sample, uninsured deposits on average account for a substantial 33% of banks' total deposits and this share increases to 41% for large banks (which account for the vast majority of banking assets in the economy).

[26] While opacity facilitates production of informationally insensitive claims *ex ante*, this informational insensitivity is not always guaranteed *ex post*. A sufficiently large *ex post* adverse shock to the underlying collateral can stimulate information production and result in market freezes of the kind observed in the Financial Crisis (Dang, Gorton, and Holmstrom, 2015). While our focus is on the role of transparency in creation of informationally insensitive claims *ex ante*, some studies examine how to revive markets out of a freeze if it materializes *ex post* (e.g., Tirole, 2012).

Overall, both sets of banking theories suggest that the behavior of uninsured depositors is an important channel through which transparency affects banking business. Yet, virtually no evidence is available on whether uninsured depositors' response is sophisticated enough to reflect differences in information quality. Given the complexity of banks' disclosures and the perception that depositors are not always paying attention, this is ultimately an empirical question, which we explore here.

3.2. Empirical specification

We explore the relation between *R2* and deposit flow-performance sensitivity using a simple model of depositor behavior used in prior research (e.g., Egan et al., 2017). Banks attract greater deposit flows when they offer greater utility to depositors (compared to competing banks) and when there is greater aggregate demand for holding deposits. A depositor's utility from a bank depends on her perception of the bank's default risk, the deposit rate offered, and service quality. Depositors update their views about default risk as they receive periodic information about bank performance from Call Reports. Thus, deposit growth at a bank can be considered a function of four factors: (i) default risk, (ii) deposit rate, (iii) service quality, and (iv) changes in aggregate demand for deposit.

Under the above framework, information quality can affect deposit flows by changing how depositors use signals about bank performance to update their views about default risk. We focus on bank earnings scaled by equity (*ROE*) as the main measure of bank performance.[27] As discussed in Section 2 earlier, earnings is the most important accounting indicator of asset quality, which along with funding structure, determines default risk.[28] If depositors take information quality into

[27] The choice of scalar does not matter for our inferences. As we discuss later, all our inferences are robust to use of assets instead of equity as the scalar.
[28] We include controls to capture the effect of funding structure on default risk.

account, a dollar of earnings shock at a high *R2* bank (i.e., a bank whose earnings are more predictive about future default) should lead to a larger change in depositors' beliefs about default risk compared to the effect of the same earnings shock at a low *R2* bank. In other words, we expect the deposit flows to be more sensitive to earnings performance at high *R2* banks. We test this prediction using the following specification:

$$\Delta Dep_{it} = \alpha_i + \beta_0 ROE_{i,t-1} + \beta_1 R2_{i,t-1} * ROE_{it-1} + \beta_2 R2_{i,t-1} + \Gamma X + \varepsilon_{i,t} \quad (3)$$

where ΔDep_{it} represents deposit flows measured as the changes in bank *i*'s deposit balances over period *t* scaled by the beginning of period assets; $ROE_{i,t-1}$ is bank *i*'s earnings during period *t-1* scaled by book value of equity; $R2_{i,t-1}$ is the information quality measure discussed earlier and measured at the end of quarter *t-1*. The key coefficient of interest in Eqn. (3) is β_1, which measures how the sensitivity of deposit flows to bank performance varies by the informativeness of bank earnings.

We measure deposit flows as the changes in deposit balances over the two-quarter period following the end of quarter *t-1*, scaled by the asset value at the end of *t-1*. This is to account for the fact that most banks typically file Call Reports with a delay of 30 days after the calendar quarter ending (Badertscher et al., 2018) and to allow sufficient time for depositors to respond. We cluster standard errors at the bank level, which adjusts for arbitrary forms of correlations between observations for the same bank that might result from overlapping windows for flow measurement.

A natural question is how depositors extract information from Call Reports. In principle, they can read the Call Reports themselves, or gain the information indirectly by reading analyst reports or media articles and/or by communicating with, or observing the reaction of, other claimholders with greater incentives and ability to process financial information.[29] Regardless of how uninsured depositors extract such information, positive estimates for β_0 and β_1 in Eqn. (3) would indicate that they respond more strongly to earnings information at more transparent banks.

We also take into account the effect of the other three factors (deposit rate, service quality, and aggregate deposit demand shifts) that affect deposit growth. We directly control for the deposit rates offered at the bank level (*Deposit Rate*). Because the Call Reports do not separately report the interest expenses on insured and uninsured deposits, we use the core deposit rate to proxy the rates offered on insured deposits and the rate on large time deposit to proxy the rates on uninsured deposits. We believe this is a reasonable approximation because core (large time) deposits are most likely to be insured (uninsured).[30] We measure these rates as the quarterly interest expense on the deposits divided by the average quarterly deposits over the same period.

We include bank fixed effects (α_i) and several time-varying controls to help account for both the time-invariant and time-varying components of service quality.[31] Following prior work (e.g., Acharya and Mora, 2015), we control for: (i) capital ratio defined as book value of capital scaled by total assets (*Capital_Ratio*), (ii) wholesale funding scaled by total assets (*Wholesale_Funding*), (iii) the ratio of total unused commitments to the sum of total loans and unused commitments (*Unused_Commitments*), (iv) real estate loan share calculated as the amount

[29] For example, withdrawals by a few large, sophisticated corporate depositors may cause smaller depositors to withdraw even without any direct knowledge of information disclosed in Call Reports. Similarly, for public banks, a stock price decline triggered by a large shareholder can trigger deposit withdrawals. We do not have data from recent time-periods to directly assess what fraction of depositors have the sophistication and resources to process information on their own. Data from the last survey on deposit ownership patterns from Federal Reserve Bulletin (discontinued in 1990) suggest that individual depositors and non-financial corporate entities held 26% and 56% of the total deposits, respectively. To our knowledge, this survey is the only public source of data on deposit ownership patterns.

[30] Until March 31, 2011, core deposits were defined in the Uniform Bank Performance Report (UBPR) User Guide as the sum of demand deposits, all NOW and automatic transfer service (ATS) accounts, money market deposit accounts (MMDAs), other savings deposits, and time deposits under $100,000. As of March 31, 2011, the definition was revised to reflect the permanent increase to FDIC deposit insurance coverage from $100,000 to $250,000 and to exclude insured brokered deposits from core deposits.

[31] An alternative approach is to replace bank fixed effects with lagged dependent variable. As shown in the Online Appendix, our main results are robust to this alternative specification.

of loans secured by real estate divided by total loans (*RealEstate_Loans)*, (v) the logarithm of asset size (*Ln(Assets)*), and (vi) the standard deviation of write-offs (measured over the same time period as the *R2* measure).[32] Because our inferences relate to the coefficient on the interaction of *R2* with *ROE*, we include these controls both on their own, and interacted with *ROE,* in our regressions.

Lastly, we address the effect of shifts in aggregate demand for deposits. Aggregate demand for deposits can go up when corporates/individuals have greater aggregate wealth available for investments and/or when they allocate a larger portion of this wealth to deposits. Consistent with the latter, Drechsler et al. (2017) and Lin (2019) find that a smaller portion of wealth is allocated to deposits when treasury securities and stock markets offer higher returns. Because our main interest is in examining how depositor behavior varies within the banking system as a function of bank specific *R2*, aggregate trends in deposits growth are unlikely to confound our inferences. Nevertheless, we include contemporaneous and lagged fed funds rates and the value-weighted market returns to control for these opportunity costs of holding bank deposits. Although not our preferred specification, we also show that our results are robust to including time dummies, which flexibly absorb any secular trends in deposit growth.[33]

A potential related concern is that bank performance could be correlated with wealth shocks faced by its (likely local) depositor base; and thus, instead of reflecting concerns about bank health, the association between deposit flows and bank performance could simply reflect changes in wealth available for making deposits. We emphasize that this possibility can confound our inferences only if the wealth shocks are systematically correlated with the degree of transparency; we are unaware of any economic rationale to expect such a correlation. Further

[32] We also use the standard deviation of *ROE* in sensitivity analysis and find similar results (not tabulated).
[33] Inclusion of time dummies precludes a study of the depositor response to changes in bank performance that result from common macroeconomic shocks. This is problematic because many significant performance swings in the cyclical banking industry are systematic.

inconsistent with explanation, we later document that the response of insured depositors to bank performance is opposite to that of uninsured depositors. If bank performance were simply capturing wealth shocks, we should have found both uninsured and insured deposits to be increasing in bank performance.

A final issue that deserves clarification is whether the possibility of systematic matching between depositors and banks affects the interpretation of our regression estimates. Perhaps it is the case that certain types of depositors demand more transparency and their banks increase information quality in response or, equivalently, these depositors systematically select into banks with higher *R2*. We note that such matching in and of itself does not affect the interpretation of our results as long as depositors appropriately process information according to the quality that ultimately becomes available to them. The latter would naturally be expected as there would be little point in demanding higher quality earnings if one does not utilize its greater information content by putting a larger weight. Thus, even in the presence of matching based on depositor-preferences for transparency, the higher flow-performance sensitivity at transparent banks should reflect the effect of higher information quality.

3.3. Results

3.3.1 Effects on uninsured deposit flow-performance sensitivity

Table 3, Panel A presents results on the relation between *R2* and flow-performance sensitivity of uninsured deposits. To facilitate interpretation, we use the demeaned versions of *R2* (i.e., *R2* minus its sample mean) and other bank characteristics in the regressions. This way, the coefficient on *ROE* measures the flow-performance sensitivity for the bank with the average values for *R2* and other characteristics, and the coefficient on the interaction term between *R2* and *ROE* measures the change in flow-performance sensitivity as one deviates from the average *R2*.

We first present the results without including bank fixed effects to fully exploit both cross-sectional and time-series variation in *R2*. The coefficient estimate on *ROE* in column (1) is positive and significant at 1% level (Coef. = 0.096), suggesting that, on average, uninsured deposits are sensitive to earnings performance. The economic magnitude of the sensitivity is meaningful: a one-standard-deviation decline in *ROE* is associated with a decline in deposit growth that is equivalent to more than half (51%=0.096*10.34/1.96) of the average annual growth in uninsured deposits.

Our main focus is the coefficient for *R2×ROE*, which is positive and significant (Coef. = 0.056; p-val. < 0.01), suggesting that uninsured deposits are more sensitive to bank performance at banks with higher *R2*: a one-standard-deviation increase in *R2* amplifies the average sensitivity by 26% (=0.45*0.056/0.096). Column (1) also shows that the coefficient for *R2* is negative and significant, indicating that transparent banks experience slower growth in uninsured deposits: for a bank with average *ROE*, a one-standard-deviation increase in *R2* is associated with a reduction of 10% (= (-0.999 + 0.056*9.96) * 0.45/1.96) in uninsured deposit growth.

Column (2) shows that these inferences are robust to including bank fixed effects, with the estimates implying a 20% amplification of flow-performance sensitivity for a one standard deviation increase in *R2*. Finally, we present the robustness of our results to the inclusion of time-dummies in column (3). As discussed earlier, this is not our preferred approach because it precludes us from studying depositors' response to changes in bank performance that result from common macro-shocks. This is problematic because of the cyclical nature of the banking industry where many significant performance swings are from common macro-shocks. Nevertheless, we continue to find evidence of higher flow-performance sensitivity in high *R2* banks. The Online Appendix also shows that all our main results are robust to the use of time dummies.

In Panel B we explore if the above results are concentrated in a specific size group or during the 2007-2008 Financial Crisis. Columns (1)-(3) present estimates from a specification in which we allow all coefficients to vary by groups of small, medium, and large banks, as defined earlier. The results manifest across all bank groups, with the economic magnitudes somewhat smaller for large banks, possibly because of "too-big-to-fail" effect. Columns (4) and (5) present a similar analysis except we allow all coefficients to vary for the Financial Crisis period (defined as the eight quarters from 2007Q3 to 2009Q2) and non-crisis period. Our results are not driven by the Financial Crisis and, in fact, they do not manifest during the Crisis; the insignificance during the Crisis could be due to low power as this period covers only 2 out of the total 26 sample-years.

To tie the above evidence more closely to the effect of information quality, in Table 4 we examine whether the effect of *R2* is stronger when depositors have stronger incentives and ability to process bank information. We do this in two ways. We first examine if the effect of *R2* varies by bank performance. Because uninsured depositors care more about downside risks, we expect them to pay closer attention to banks performance (and consequently its information quality) when banks are performing poorly than when they are doing well. Consistent with this prediction, estimates in columns (1) and (2) show that the effect of *R2* on flow-performance sensitivity manifests only in the subsample of observations with below median *ROE*.

Second, we examine if the effect of *R2* on the sensitivity of uninsured depositors varies by their account size. Uninsured depositors with larger balances have more to lose and therefore would be more alert and sensitive to bank performance; furthermore, these depositors are more likely to be corporate entities with greater resources at their disposal to monitor bank performance. Because we do not have data on individual deposit balances, we conduct this test by exploiting differences across banks in the average size of their uninsured deposit balances. The average uninsured deposit balance exhibits considerable variation across banks, with a mean (median) and standard deviation of 367 (270) and 233 thousand dollars. Columns (3) and (4) present the results separately for subsamples of observations with above and below median levels of average uninsured deposit size. The effect of *R2* on the flow-performance sensitivity is more than twice in banks with uninsured depositors with larger balances.

The results related to account size also mitigate concerns about omitted correlated bank characteristics. For example, one may be concerned that if service quality is correlated with *R2* (although it is not clear why this may be the case) our results may reflect the presence of stickier deposits in banks with high service quality instead of the effect of information quality. But both small and large uninsured depositors should care about service quality (or other bank attributes beyond default risk). Therefore, if *R2* is simply capturing the effect of such omitted correlated factors, we should have found similar results for both large and small depositors.

<u>3.3.2 Evidence on substitution between uninsured and insured deposits</u>

The results thus far indicate that banks with high *R2* experience larger loss of uninsured depositors when their performance declines. In Table 5 we explore if high *R2* banks attempt to substitute the loss of uninsured depositors by attracting insured depositors. Martin et al. (2018) find evidence of this substitution between uninsured and insured depositors. Consistent with this substitution, estimates in column (1) show that the coefficient on *R2×ROE* turns negative and significant when we model insured deposit flows. Estimates in column (2) show that this substitution appears effective as the performance sensitivity of total deposits (i.e., the sum of uninsured and insured deposits) does not vary significantly with *R2*.

Two possible mechanisms can explain the substitution: when bank performance declines, either concerned uninsured depositors split deposit balances across different banks to ensure they fall within the deposit insurance limits, or banks offer higher interest rates to attract insured depositors to make up for the loss of uninsured depositors, or a combination of both. The deposit rate mechanism is testable and we explore it in columns (3) and (4) where we model large time- and core-deposit rates as the dependent variables. Because we are modelling banks' response in the form of deposit rates, we do not control for lagged deposit rates in these regressions. The coefficients on *ROE* are significantly negative in both columns, indicating that banks raise deposit rates following poor performance. In addition, the sensitivity of rate increases to declining bank performance is stronger in banks with higher *R2*: the coefficient estimate on *R2×ROE* is -0.005 for large time deposit rate and is -0.004 for core deposit rate, both significant at less than the 1% level. The economic magnitude is meaningful: for every interquartile decline in *ROE (14.89-6.44=8.45),* compared to a bank with average *R2*, a bank with a one-standard-deviation higher *R2* offers an additional 1.9 (*=0.5*0.45*8.45*) and 1.52 (*=0.4*0.45*8.45*) basis points on its rates for large time and core deposits, respectively.

3.3.3 Interpretation of results

Collectively, the analyses thus far yield two key insights. First and foremost, the results provide strong evidence that, on average, uninsured deposits' response to bank performance is sophisticated enough to reflect differences in information quality. This suggests that uninsured depositors' behavior can indeed constitute an important channel through which transparency affects banking business. We explore the implications of this finding for banks' funding costs and profitability in the next section. Second, the results also illustrate that any effects of transparency on banks through uninsured depositors' behavior cannot be costlessly neutralized by substitution between uninsured and insured depositors. While transparent banks can offset the sensitivity of uninsured depositors by attracting insured depositors such that the sensitivity of total deposits does not significantly vary by *R2*, they come at a price as these banks end up paying higher deposit rates and insurance premiums.

4. Transparency, banks' external funding costs and profitability

This section explores the implications of the effect of transparency on uninsured depositors' behavior for banks' external funding costs and, ultimately, profitability. The effects are, *ex ante*, ambiguous. On the one hand, the disciplining effect of sensitive depositors may decrease external funding costs of transparent banks by making capital providers less worried about agency problems. On the other hand, because of the reduced appeal of sensitive uninsured deposits as money-like claims, consumers may not be willing to pay a premium for holding these claims, pushing up the funding costs of transparent banks (Dang et al., 2017). Thus, the association between transparency and banks' funding costs, and consequently profitability, is ultimately an empirical question that we now explore.

4.1. Evidence on external funding costs

We use two approaches to explore the relation between *R2* and funding costs. We first examine the association between *R2* and deposit rates. Table 6, Panel A, presents the results from regressing deposit rates on *R2*, bank characteristics, and other control variables. Estimates show that *R2* is positively associated with both large time- and core-deposit rates (Coefficients=0.034 and 0.041, respectively) with significance at less than 1% levels. The estimates indicate that a one-standard deviation increase in *R2* is associated with a higher large time (core) deposit rate of about 1.53 (1.85) basis points.

In the second approach we use banks' dependence on internally generated funds to finance asset/credit growth as an indicator of funding constraints. An unconstrained bank would not exhibit this dependence because it can meet internal funding shortfalls by raising external funds such as deposits. As costs of external funding increase, some projects on the margin become unprofitable. These projects need a larger portion of funding from internal sources to become viable. Therefore, holding growth opportunities constant, an increase in external funding costs should result in greater reliance on the availability of internal funding to finance assets.

We estimate the following specification for this analysis:

$$AssetGrowth_{i,t} = \alpha_i + \beta_0 \Delta Internal\_Funds_{i,t-1} + \beta_1 R2_{i,t-1} * \Delta Internal\_Funds_{i,t-1} + \beta_2 R2_{i,t-1} + \Gamma X + \varepsilon_{i,t}, \quad (4)$$

where $AssetGrowth_{i,t}$ is the annualized growth rate in one of banks' asset classes scaled by beginning of quarter total assets, and $\Delta Internal\_Funds_{i,t-1}$ is measured as change in equity balances excluding stock issuance and adding back dividends and repurchases, scaled by total assets at the beginning of quarter.[34] Essentially, this measure captures changes in internally generated funds from making profits and excludes any form of external financing. Similar to our analysis of deposit flows, we measure asset growth over two quarters subsequent to quarter *t-1*. The coefficient of interest in Eqn. (4) is β_1, which measures how *R2* affects the relation between the availability of internal funds and asset investment decisions.

A potential concern is that positive shocks to internal funding may be correlated with the arrival of growth opportunities, particularly for transparent banks which makes their investments more sensitive to these shocks. While we cannot definitively rule this out, it is not clear *a priori* why shocks to internal funding will be more correlated with growth opportunities in transparent banks. In addition, we later show that all our results hold when we exploit exogenous variation in

[34] This definition of internal funds implicitly assumes that dividends are paid out from residual funds left after funding investment opportunities. In sensitivity analyses (results not reported), we find qualitatively similar results when we measure changes in internal funds after paying dividends.

transparency introduced by the Sarbanes-Oxley Act. To the extent that SOX is unrelated to changes in growth opportunities, the results from the SOX analysis also mitigate this concern.

Table 6, Panel B presents the estimates of Eqn. (4) for growth in different asset classes. Column (1) models loan growth. The coefficient on the interaction between $R2$ and $\Delta Internal\_Funds$ is 0.138 and significant at 1% level, suggesting that banks with higher $R2$ are less able to fund loans without the availability of internal funds. The effect is economically large: a one-standard-deviation increase in $R2$ would increase an average bank's sensitivity of funding loans to the availability of internal funds by 29% (=0.138*0.45/0.216). Estimates in column (2) show similar findings for growth in outstanding loan commitments (i.e., credit lines): a one-standard-deviation increase in $R2$ amplifies banks' sensitivity of loan commitments to $\Delta Internal\_Funds$ by about 19% (=0.45*0.07/0.164). Not surprisingly, inferences are similar when we model total credit in column (3), which includes both loans and commitments.

Finally, as a placebo test, we also model growth in liquid assets, measured as the sum of cash, federal funds sold and reverse repos, and securities excluding MBS/ABS securities. We expect no or little wedge between internal and external funding costs when it comes to financing liquid assets because there are little information asymmetries on the payoffs of these assets. We therefore do not expect the growth of these assets to be tied to availability of internal funding. Consistent with this prediction, column (4) shows that the coefficients on both $\Delta Internal\_Funds$ and its interaction with $R2$ are insignificant. Overall, these results suggest that the funding of illiquid loans at high $R2$ banks is more tied to the availability of internal funding.

4.2. Evidence on profitability

We next examine whether the adverse external funding costs at transparent banks also reflect in lower profitability. Table 7 presents results from regressions of ROA and ROE on $R2$ and other bank characteristics, both with and without bank fixed effects. We find that *R2* exhibits a significant negative association with *ROA* and *ROE* across all specifications. The coefficient estimates without the bank fixed effects indicate that a one-standard-deviation increase in *R2* is associated with nearly 0.046% (0.44%) decrease in *ROA* (*ROE*).

One may be concerned that these differences in profitability may reflect differences in risk. For example, if transparent assets also tend to be less risky, then the lower profitability of high *R2* banks may simply reflect the lower risk-premium commanded by their assets. Inconsistent with this explanation, however, we find that, if anything, the correlation between the volatility of profits generated by bank assets and their *R2* is positive, suggesting transparent banks are riskier.[35] We also note that our results obtain after controlling for bank fixed effects (which should fully absorb time-invariant differences in risk) as well as several time varying controls for bank characteristics including the standard deviation of *ROA* and *ROE* (measured over the last 12 quarters).

4.3. Interpretation of results

The above results indicate that on average transparent banks face greater funding costs and have lower profitability, lending support to the model in Dang et al. (2017) where transparency reduces banks' ability to produce money-like claims. The evidence is also consistent with recent work that finds that creation of money-like securities constitutes the major source of value creation in the banking business (Berger and Bouwman, 2009; Egan et al., 2021).

We emphasize that our results do not imply the absence of monitoring benefits of transparency, but only that the costs for an average bank are greater. Nonetheless it raises the question of why some banks are transparent. One possibility is that a significant portion of

[35] As noted in Section 2.1, *R2* is designed to measure the proportion of uncertainty resolved by Call Reports (i.e., $\frac{Var(\widetilde{D}_{t+1})-Var(\widetilde{D}_{t+1}|\Omega_t)}{Var(\widetilde{D}_{t+1})}$) and not the underlying volatility/risk ($Var(\widetilde{D}_{t+1})$) itself. There is a priori no compelling reason to expect a strong correlation between *R2* and risk. We find that *R2* exhibits a relatively modest correlation of 0.10 (0.07) with the volatility of write-offs (*ROE*).

transparency may be pre-determined by the nature of the local market and borrower characteristics. For example, loans in some areas may involve greater reliance on soft-information based lending because of differences in the underlying real economy, jobs, education levels, and cultural norms.[36] Difficulties in credibly communicating soft information to outsiders will make these banks opaque. On the other hand, information about banks with more hard information-based assets can be more easily collected and communicated. Management at these banks could attempt to become opaque by hiding information but regulators, reporting requirements, auditors, and other governance mechanisms will limit the degree to which this can be accomplished. Consistent with the above arguments, Morgan (2002) suggests that a larger portion of bank transparency can be traced to the nature of banks' assets.

That said, understanding sources of variation in bank transparency is an open question that we do not address in this paper. Answers to this question in future research can yield valuable insights into the sources of profitability dispersion in banking industry.

5. Evidence from Sarbanes-Oxley Act of 2002

The analysis thus far explores equilibrium differences across banks in depositor behavior and other outcomes to shed light on the effects of transparency. In this section, we use the Sarbanes-Oxley (SOX) Act of 2002 as a mandated shock to transparency to mitigate any residual concerns about omitted correlated variables. Enacted in July 2002 in response to major corporate accounting scandals (e.g., Enron and WorldCom), the SOX Act was designed to restore confidence in the reliability of financial reporting by strengthening companies' auditing and internal control

[36] This could occur if the pool of local corporate borrowers in some areas is dominated by small, private businesses or businesses that mainly have intangible assets. For retail borrowers such differences in reliance on soft-information can result from cultural and socioeconomic differences that may not be captured by credit score. For instance, certain cultures/religions place greater stigma on defaults/bankruptcy, which is known to affect borrowers' propensity for bankruptcy filing (e.g., Fay et al 2002).

systems (Coates and John, 2007). Highlighting the significance of the law, the then SEC chairman, William Donaldson said before Congress that "the Act represents the most important securities legislation since the original federal securities laws of the 1930s." As reviewed in Coates and Srinivasan (2014), a large body of academic research shows that SOX resulted in significant improvements in accounting quality. Furthermore, because provisions of SOX are mainly applicable to publicly listed firms, we can use private banks as a control group to implement a difference-in-differences (DiD) design. Despite the wide use of the SOX reform in the broader finance literature, we are not aware of other papers that conducted such DiD analysis. This is something we are able to do because of the unique data sources available for banks, covering both private and publicly listed entities.

We implement the DiD design using various versions of the following specification:

$$Outcome_{i,t} = \alpha + \beta_1 Public_i + \beta_2 Post_t + \beta_3 Public_i \times Post_t + \varepsilon_{it}$$

where $Outcome_{i,t}$ represents one of the several bank outcomes of interest; *Public* is an indicator variable that takes a value 1 for public and 0 for private banks; *Post* is an indicator variable for quarters that fall after the enactment of SOX in July 2002. Our key interest is in coefficient β_3, which measures the change in outcomes for public banks around SOX relative to the change in outcome for private banks. We do not include any controls for time-varying bank characteristics because they themselves are likely to be affected by the transparency shock and therefore their inclusion can bias and take away the effect of interest.[37]

To mitigate the concern that private banks may not form a good control group (i.e., may violate parallel trends assumption) because they are significantly smaller than public banks, we

[37] See Angrist and Pischke (2009, pp. 64-66) for a discussion of this issue. To illustrate with an example, suppose that the SOX shock increases the flow-performance sensitivity of uninsured deposits and suppose that banks counteract this increased instability in deposit funding by increasing equity capital ratio. In this scenario, controlling for capital ratio when examining the effect of SOX on the sensitivity of uninsured deposits can remove the effect of interest.

conduct this analysis on a propensity score matched sample of public and private banks based on size. Specifically, we conduct nearest neighbor matching based on bank size in the quarter just before SOX enactment (i.e., 2002Q2). We require a caliper of 0.01 and drop observations outside the common support to ensure high match quality. We start with a sample of 699 public and 2,683 private banks. Our final matched sample contains 592 public and 592 private banks. Figure 2 presents the size distribution of public and private banks before and after matching. In the matched sample, the size distribution of private banks closely mirrors that for public banks, indicating that the matching is quite successful.

We begin the analysis by examining the effect of SOX on our main outcome of interest: flow-performance sensitivity of uninsured depositors. We create a bank-specific measure of flow-performance sensitivity at a point in time by using up to 5 years of prior data as follows:

$$FlowSensitivity_{it} = \frac{1}{J}\sum_{j=1}^{J}\frac{Uninsured\ DepFlow_{i,t-j} - Uninsured\ DepFlow_{i,t-j-1}}{ROE_{i,t-j} - ROE_{i,t-j-1}} \quad (5)$$

where deposit flows and *ROE* are measured as before, and *J* represents the number of periods using up to 5 years of data. To obtain reasonably precise estimates, we require at least 12 quarters of data. The above approach is akin to the one used in the mutual fund literature for estimating fund specific flow-performance sensitivities (e.g., Chen et al., 2008). In our estimation sample, we drop the year of the shock (i.e., 2002) and include data up to 5 years before and 5 years after the shock. Because we require at least 12 quarters of data to estimate flow-performance sensitivities, the data in the post-shock period starts from year 2006 and runs until year 2010.

We use the above approach to examine the effects on flow-performance sensitivity for two reasons. First, using an explicit bank-quarter level measure of flow-performance sensitivity allows us to clearly plot the timing of changes in the outcome variable around the SOX Act shock. Second, because of its inherent nature, changes in flow-performance sensitivity cannot be observed immediately after the shock: a statistician needs to observe multiple data points on ROE and deposit flows in the post-shock period to measure the sensitivity in the new regime. Our design accommodates this requirement by including at least 12 quarters of data in the post-period to measure flow-performance sensitivity.

Table 8, Panel A presents the results. Estimates in column (1) show that the coefficient of $Public_i \times Post_t$ is positive and significant (Coef. = 0.049; p-val. < 0.01), indicating that the SOX shock resulted in an increase in the flow-performance sensitivity of uninsured depositors for public banks. The effect is economically large, representing a 25% increase over the pre-shock flow-performance sensitivity. We next replace the *Post* dummy with dummies for several individual years (and their interactions with $Public_i$ dummy) around the shock to examine the detailed timing of the changes around the SOX shock. The coefficients on these interaction terms measure the change in sensitivity for public banks relative to private banks around the respective years. Figure 3 visually illustrates the findings by plotting the coefficient estimates of the interaction terms of these year dummies with $Public_i$ dummy. In support of the parallel trends assumption, it can be seen that the flow-performance sensitivities do not exhibit significant changes for public relative to private banks in years prior to the shock. Furthermore, the increase in flow-performance sensitivity after the shock continues to persist and does not reverse over time.

We conduct two robustness checks on the above findings. First, we drop the quarters corresponding to the 2007-2008 Financial Crisis to see if the Crisis is driving our results. Estimates, presented in column (2), show that our results are not driven by the Crisis. Second, we explore the robustness of our results to including time-trends based on bank characteristics. Although our estimates show that public and private banks exhibit parallel trends in years prior to the SOX shock, a remaining concern (as with any DiD analysis) is that differences in characteristics of public and private banks cause the trends to diverge exactly around the SOX shock for reasons unrelated to increase in transparency caused by SOX. In column (3), we absorb such confounding trends by including pre-shock bank characteristics (measured in the quarter just prior to the shock) and their interactions with the *Post* dummy. This approach is essentially the same as the strategy of including group-specific time-trends used in prior studies (Card, 1992; Besley and Burgess, 2004). The results are robust to this specification change. Finally, in contrast to uninsured depositors, estimates in columns (4) - (6) reveal no evidence of changes in flow-performance sensitivity for insured deposits around SOX.

In Panel B, we explore the effect of SOX on deposit-rate levels, reliance on internal funds to finance asset growth, and profitability. For brevity, we present these results only using the conservative specifications where we control for trends based on pre-shock bank characteristics. In untabulated robustness tests, we confirmed that all tabulated results are robust to excluding the quarters during the Financial Crisis. To examine the reliance on internal funds to finance credit growth, we create measures of sensitivity of asset growth to changes in availability of internal funds using the approach similar to how we estimate the flow-performance sensitivities in Eqn. (5). We are unable to do this analysis for liquid asset growth because this variable is available only since year 2002 and therefore cannot be measured for the pre-SOX period. Overall, results shown in Panel B are qualitatively consistent with our main results discussed earlier: the increased uninsured deposit flow-performance sensitivity around SOX is also accompanied by increased deposit-rates, increased reliance on internal funds to finance credit growth, and lower profitability.

Collectively, we interpret the findings from the SOX analyses as providing additional evidence consistent with the effects of transparency on deposit flows and bank operations.

6. Additional analyses and robustness tests

6.1 Can information sources other than Call Reports affect our inferences?

A potential concern is that depositors at low *R2* banks make up for less information from Call Reports by relying more on alternative information sources such as analyst reports, information aggregated in stock prices or perhaps the soft information revealed by bank managers in conference calls. Thus, it is possible that the total information, and consequently the overall stability, of these depositors is similar to that of depositors of high *R2* banks. We first note that if this was the case, we should not observe our previous findings on the relations between *R2* and banks' deposit rate response, reliance on internal funds to finance loans, and profitability. All of these results rest on uninsured deposits being more sensitive at high *R2* banks. Nevertheless, we perform two additional analyses to address this concern.

First, we directly test whether uninsured deposits are unconditionally more volatile at high *R2* banks and present the results in Table 9, Panel A. The dependent variable is the logarithm of the standard deviation of uninsured deposit flows calculated over the same period that *R2* is estimated from Equation (2). Estimates in both columns (1) and (2) show that *R2* is significantly positively related to uninsured deposit flow volatility, indicating that transparency is associated with fragility in deposits. Second, we examine whether the association between *R2* and flow-performance sensitivity of uninsured deposits holds for the subset of private banks. To the extent that depositors at private banks have less access to alternative information sources and rely primarily on Call Reports to assess performance, evidence of a positive relation between transparency and flow-performance sensitivity for private banks would further address this concern. Table 9, Panel B shows the results from estimating Eqn. (3) separately for the subsamples of public and private banks. We find that greater *R2* is associated with higher uninsured deposit flow-performance sensitivity for both public and private banks.

6.2. Alternative measures of transparency and performance

In Table 10 we explore the robustness of our inferences to alternative measures of transparency and bank performance.[38] We first modify our *R2* measure by extending the window for measurement of write-offs in Eqn. (2) from two to four quarters to account for the fact that some loans may take longer than two quarters to be written off after becoming non-performing or part of loan loss provision (Bhat, Lee and Ryan, 2020). Column (1) shows that our main result of a positive relation between *R2* and the sensitivity of uninsured deposit flows to *ROE* is robust to this variation. Column (2) reports similar robustness result when we use the *R2* estimated over 20 (instead of 12) quarters.

As we discussed in Section 2.1, our *R2* measure is better suited for our purpose because it captures all sources of variations in bank opacity regardless of whether it is exogenously given or strategically chosen by bank managers (Huizinga and Laeven, 2012). Nonetheless, to examine whether our main finding is unique to our transparency measure, we construct the timeliness measure following Beatty and Liao (2011), as described in detail in the Appendix. The correlation coefficient between the timeliness measure and *R2* is 0.05 (shown in Table 1, Panel B). Results in column (3) of Table 10 show that our inferences are robust and the *Timeliness* of *LLP* has a significantly positive effect on uninsured deposit flow-performance sensitivities.[39]

[38] For brevity, we only present the results for uninsured deposit flow-performance sensitivity in Table 10. All other main results are robust to these variations, and are included in the Online Appendix.

[39] We do not examine the robustness to the restatement measure because of the rather low incidence of accounting restatement: in Ng and Rusticus (2020), only 13% of the banks exhibit restatements; the measure therefore classifies 87% of the banks as transparent (13% as opaque), throwing away large variation in transparency that we can capture using the *R2* measure.

Finally, in columns (4) to (7) of Table 10, we explore the sensitivity of our results to four alternative performance measures: (i) return on assets (ROA), (ii) change in internal equity capital ($\Delta Internal\_Equity$), (iii) the level of loan loss provisions (LLP), and (iv) non-performing loans (NPL).[40] It can be seen that the results using these measures are qualitatively similar to those using ROE. Specifically, columns (4) and (5) show that the sensitivity of uninsured deposits to ROA and to change in equity capital is increasing in *R2*. Columns (6) and (7) show a negative sensitivity of uninsured deposit flows to banks' non-performing loans and to loan loss provisions and more so for more transparent banks as measured by *R2*.

7. Conclusion

Transparency plays an important role in research and regulation of banks. Yet, little is known empirically about whether depositors are actually aware of the level of transparency and whether it affects their behavior. Such effects require depositors to have a considerable level of sophistication and incentives, which is often at odds with anecdotal accounts of depositors as inattentive and unsophisticated. Our paper tackles these issues empirically and finds that transparency is indeed consequential.

Using a large sample of US banks from 1994-2019 we find that uninsured depositors of more transparent banks are significantly more sensitive to their banks' performance in their withdrawal decisions. This sensitivity has implications for many aspects of banks' business, as transparent banks offer higher deposit rates, rely more strongly on internal funds to finance illiquid assets, and exhibit lower profitability. A difference-in-differences analysis around the Sarbanes-Oxley Reform of 2002 also generates results consistent with the broad sample analysis. Overall,

[40] Unlike *LLP*s, which convey information about the dollar value of credit losses by taking into account both the probability of default and the amount of loss given default, *NPLs* do not incorporate information about loss given default. Furthermore, unlike *LLPs*, *NPLs* (due to its mechanical definition) do not incorporate information about future credit losses that bank managers may be aware of for loans not 90-days past due yet.

the results point to a cost of bank transparency, consistent with theories where opacity helps banks in their liquidity provision role.

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Appendix: Variable Definition and Description

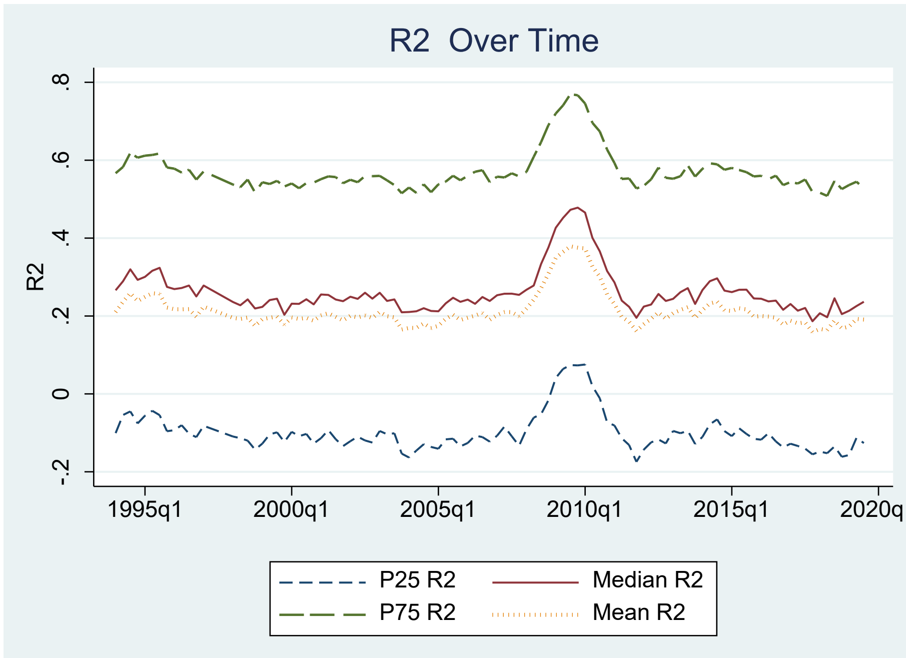
Variable Name	Definition
R2 $_{it-1}$	Adjusted R^2 for each bank-quarter from the regression $WriteOff_{[t,t+1]} = \alpha_0 + \sum_{j=1}^{2} \gamma_j LLP_{t-j} + \sum_{j=1}^{2} \beta_j EBLLP_{t-j} + \rho \Delta NPL_{t-1} + \delta Capital_{t-1} + \varepsilon_t$, estimated using the bank's observations from quarter $t-12$ to quarter $t-1$. $WriteOff_{t,t+1}$ is the sum of write-off (RIAD4635) in quarters t and $t+1$. LLP_{t-j} is loan loss provision (RIAD4230) and $EBLLP_{t-j}$ is earnings before loan loss provision (RIAD4301+RIAD4230) in quarter $t-j$, both reported as year-to-date and converted to within-quarter. ΔNPL is change in non-performing loan (RCFD1403+RCFD1407) in quarter $t-1$ from the previous quarter, $Capital$ is capital divided by total assets (RCFD3210/RCDF2170). All variables other than capital ratio are scaled by total loan (RCFD1400).
Liquid Assets $_{i,t-1}$	Liquid assets are the sum of cash (RCFD0010), federal funds sold & reverse repos [RCFD1350 (before 2002Q1) and RCONB987 + RCFDB989 (from 2002Q1)], and securities excluding MBS/ABS securities [before 2009Q2: RCFD1754+RCFD1773 - (RCFD8500+RCFD8504+RCFDC026+RCFD8503+RCFD8507+RCFDC027). And from 2009Q2: RCFD1754 + RCFD1773 - (RCFDG300 + RCFDG304 + RCFDG308 + RCFDG312 + RCFDG316 + RCFDG320 + RCFDG324 + RCFDG328 + RCFDC026 + RCFDG336 +RCFDG340 + RCFDG344 + RCFDG303 + RCFDG307 + RCFDG311 + RCFDG315 + RCFDG319 + RCFDG323 + RCFDG327 + RCFDG331 + RCFDC027 + RCFDG339 + RCFDG343 + RCFDG347)].
Commercial Loan $_{i,t-1}$	Commercial and industrial loan (RCFD1766), scaled by lagged total assets.
RealEstate_Loans $_{i,t-1}$	Loans secured by real estate (RCFD1410), scaled by total loans.
ROE $_{i,t-1}$	Annualized *ROE* (in %) in quarter t-1, calculated as net income (RIAD4300, adjust year-to-date reporting to within quarter) divided by beginning equity (RCFD3210).
Std_WriteOff $_{i,t-1}$	Standard deviation of write-offs measured over 12 rolling quarters (from Quarter $t-12$ to $t-1$).
Capital_Ratio $_{i,t-1}$	Total equity (RCFD3210) divided by total assets (RCFD2170).
Wholesale_Funding $_{i,t-1}$	Wholesale funds are the sum of following: large-time deposits (RCON2604), deposits booked in foreign offices (RCFN2200), subordinated debt and debentures (RCFD3200), gross federal funds purchased and repos [RCFD2800, or (RCONB993+RCFDB995 from 2002q1)], other borrowed money (RCFD3190). Scaled by total assets.
Ln(Assets) $_{i,t-1}$	Log of total assets (RCFD2170).
Unused_Commitments $_{it-1}$	Unused commitments (RCFD3814 + RCFD3816 + RCFD3817 + RCFD3818 + RCFD6550 + RCFD3411) divided by the sum of loans (RCFD1400) and unused commitments.
$\Delta Internal\_Funds_{i,t-1}$	Annualized growth rate in bank equity (RCFD3210) as a percentage of lagged assets. Dividends are added back (RIAD4460+RIAD4470), stock issuances, repurchases and treasury stock transactions are excluded (RIADB509+RIADB510, or RIAD4346 before 2001Q1), both adjusted from year-to-date to quarterly.
ΔDep_{it}^{Total}	Annualized growth in total deposits (RCFD2200) in quarter t and t+1 as a percentage of lagged assets (in %): $(Deposits_{i,t+1} - Deposits_{i,t-1})/Asset_{i,t-1} * 200\%$. The deposits follow the definition in Call reports and include transaction accounts (checking, NOW, etc.) and non-transaction accounts such as money market accounts, IRA, saving accounts, and time deposits (which include CDs with maturity dates).
ΔDep_{it}^{I}	Annualized growth rate in insured deposits as a percentage of lagged assets in quarter t and $t+1$ (in %): $(Insured\ Deposits_{i,t+1} - Insured\ Deposits_{i,t-1})/Asset_{i,t-1} * 200\%$. Insured deposits are accounts of \$100,000 or less. After 2006Q2, it includes retirement accounts of \$250,000 or less. From 2009Q3, reporting thresholds on non-retirement deposits increased from \$100,000 to \$250,000. Insured deposits: RCON2702 (before 2006Q2); RCONF049 + RCONF045 (from 2006Q2).

ΔDep^{U}_{it}	Annualized growth rate in uninsured deposits as a percentage of lagged assets (in %) in quarter t and $t+1$. Uninsured deposit is calculated as deposits (RCFD2200) – insured deposits.
ΔLoans$_{it}$	Annualized growth rate in total loans (RCFD1400) as a percentage of lagged assets in quarter t and $t+1$ (in %): $\left(Loan_{i,t+1} - Loan_{i,t-1}\right)/Asset_{i,t-1} * 200\%$.
ΔCommitments$_{it}$	Annualized growth rate in commitments in quarter t and $t+1$ as a percentage of lagged assets: $(Commitments_{i,t+1} - Commitments_{i,t-1})/Asset_{i,t-1} * 200\%$. Commitments = (RCFD3814 + RCFD3816 + RCFD3817 + RCFD3818 + RCFD6550 + RCFD3411)
$\Delta Credit_{it}$	Sum of *ΔLoans$_{it}$ and ΔCommitments$_{it}$.*
$\Delta Liquid\ Assets_{it}$	Annualized growth in liquid assets as a percentage of lagged assets in quarter t and $t+1$ (in %): $(Liquid\ assets_{i,t+1} - Liquid\ Assets_{i,t-1})/Asset_{i,t-1} * 200\%$.
Large Time Deposit Rate$_{i,t}$	Annualized average interest rate (in %) over the two quarters $t, t+1$ on large time deposits. Calculated as quarterly interest expense (RIADA517 (RIAD4174 before 1997Q1), adjusted year-to-date reporting to within quarter) divided by average balance of large time deposits (RCONA514 (RCON3345 before 1997Q1)): $(large\ time\ deposit\ interest\ expense\ in\ Qtr\ t\ and\ t+1)/$ $(Avg. large\ time\ deposit\ balance\ in\ Qtr\ t\ and\ t+1)\ ) * 400\%)$.
Core Deposit Rate$_{i,t}$	Annualized average interest rate (in %) over the two quarters $t, t+1$ on core deposits. Core deposits are the sum of transaction deposits, saving deposits, and small time deposits. The average balance items: transaction deposits: RCON3485; savings deposits: RCONB563 + (RCON3486 + RCON3487 before 2001Q1); small time deposits: RCONA529 (RCON3469 before 1997Q1). The interest expense items: transaction deposits: RIAD4508; saving deposits: RIAD0093 (RIAD4509 + RIAD4511 before 2001Q1); small time deposits: RIADA518 (RIAD4512 before 1997Q1), adjusted year-to-date reporting to within quarter.
Average Size of Uninsured Deposits$_{i,t}$	Uninsured deposit balance divided by the number of deposit accounts above insurance threshold (RCONF048+RCONF052; RCON2722 before 2006Q2)
Public $_{i,t-1}$	Indicator variable equal to 1 if in quarter $t-1$ the commercial bank is a public company or a subsidiary of a public company. That is, if a bank's Fed ID (RSSD9001), or its bank holding company (RSSD9348) can be linked to a PERMCO. The PERMCO-RSSD link table is from the website of Federal Reserve Bank of New York.
TimelinessLLP $_{i,t-1}$	The timeliness of LLP (LLP Timeliness) is an indicator variable that equals 1 (0) if the difference in the adjusted R-squared from the following two equations is above (below) sample median: both equations are estimated for each bank-quarter using the bank's observations from the previous 12 quarters: $LLP_t = \beta_0 + \sum_{j=-2}^{-1} \beta_j \Delta NPL_{t+j} + \gamma_1 Capital_{t-1} + \gamma_2 EBLLP_t + \varepsilon_t\ (a)$ and $LLP_t = \beta_0 + \sum_{j=-2}^{1} \beta_j \Delta NPL_{t+j} + \gamma_1 Capital_{t-1} + \gamma_2 EBLLP_t + \varepsilon_t\ \ (b)$.
Std_ROE $_{i,t-1}$	Standard deviation of *ROE* measured over 12 rolling quarters (from Quarter $t-12$ to $t-1$).
NPL $_{i,t-1}$	The percentage of non-performing loan (RCFD1403+RCFD1407) in total loan.
ROA $_{i,t-1}$	Annualized ROA (in %) in quarter t-1, calculated as net income (RIAD4300, adjust year-to-date reporting to within quarter) divided by beginning assets.
StockRet	Value weighted quarterly market return (includes distributions) retrieved from CRSP.
FedFundRate	Retrieved from Federal Reserve Bank of St. Louis website. Quarterly average of effective fed funds rate.

Figure 1: *R2* Over Time

Panel A plots the summary statistics for *R2* across banks in the sample over time. Panel B plots the average *R2* for three groups of banks over time. *R2* is the adjusted R-squared from estimating Equation (2) for each bank-quarter using 12 quarters rolling window. Small banks have assets below 500 million, large banks have assets above 3 billion, medium banks have assets between 500 million and 3 billion (measured in year 2000 real dollars).

Panel A: All banks



Panel B: By bank size

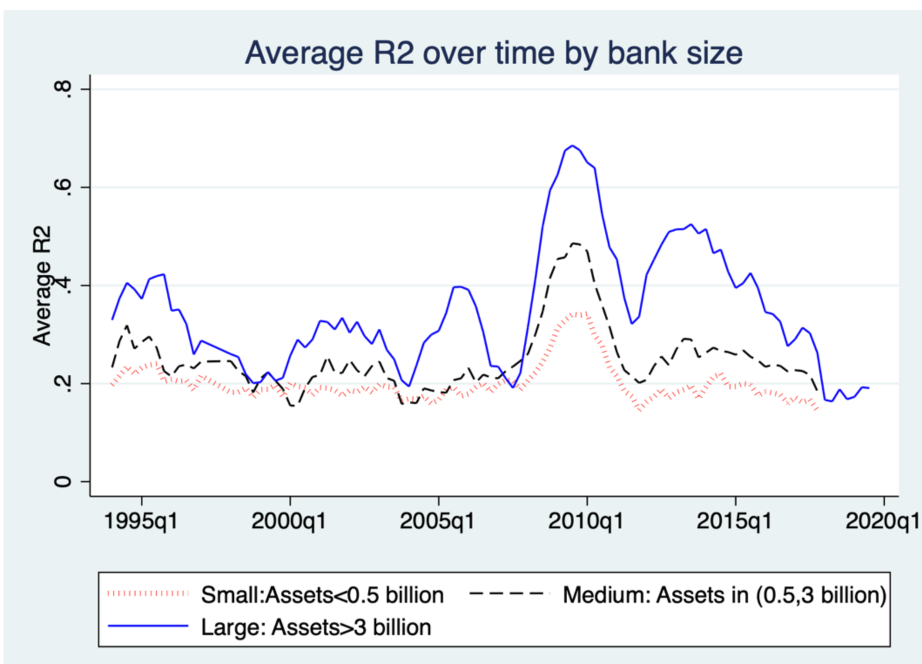


Figure 2: Size Distribution of Public and Private Banks

Figure 2 plots the size distribution of public banks and private banks based on the logarithm of their total asset values in the quarter prior to the enactment of Sarbanes-Oxley Act of 2002 (i.e, Q2, 2002). The top panel plots the distribution for the entire samples of public and private banks. The bottom panel plots the distribution for the matched sample of public and private banks, based on the propensity score matching requiring a caliper of 0.01 and dropping observations outside the common support.

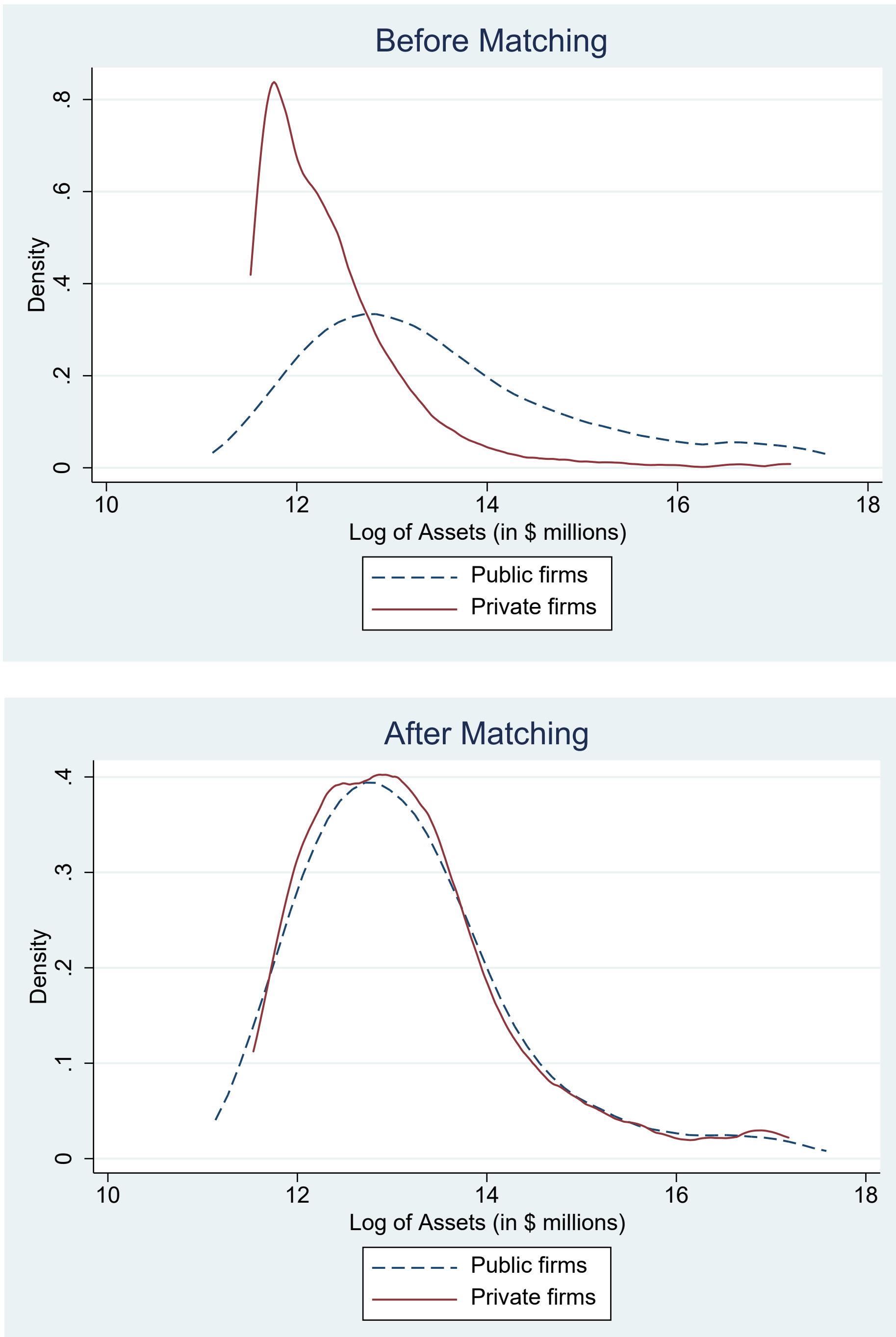


Figure 3: Timing of Changes in the Uninsured Deposit Flow-Performance Sensitivity Around the SOX Shock Between Private and Public Banks

Figure 3 plots the differences in uninsured deposit flow-performance sensitivities between public banks and private banks. The sensitivity measure is calculated for each bank quarter, as the average of the ratio of uninsured deposit flows to changes in *ROE* over the preceding 5-year period. The post-shock period covers 2006-2010 to allow sufficient observations to calculate the sensitivity after the SOX shock. The dot is the point estimate and the vertical bar plots the 95% confidence interval.

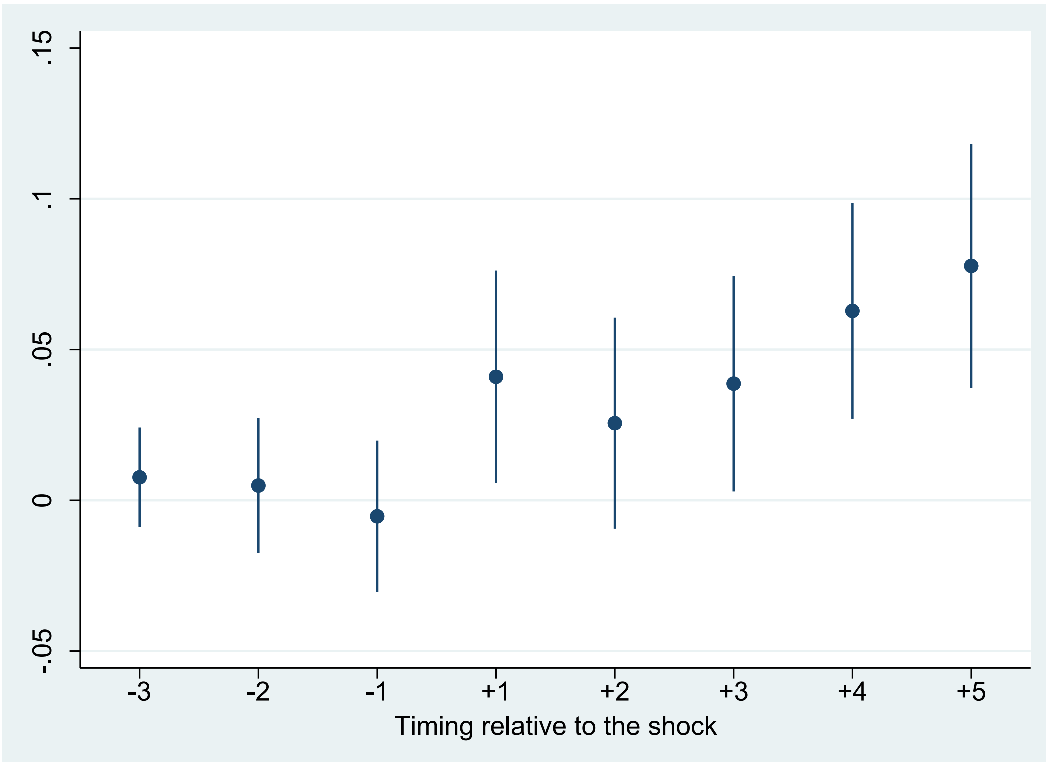


Table 1. Descriptive Analyses

Panel A presents summary statistics and Panel B presents the correlation table for the main regression variables. These statistics are calculated over the regression sample. To avoid the impact of mergers and acquisitions, we exclude bank-quarter observations with quarterly asset growth greater than 10%. We also exclude bank quarters with total assets smaller than 100 million. See the Appendix for variable definitions.

Panel A: Summary statistics

	N	Mean	Std. Dev.	p10	p25	Median	p75	p90
$R2_{it-1}$	341334	0.22	0.45	-0.43	-0.10	0.26	0.58	0.78
ROE_{it-1}	341334	9.96	10.34	2.40	6.44	10.49	14.89	19.63
ROA_{it-1}	341334	0.98	0.89	0.25	0.67	1.05	1.41	1.82
ΔDep_{it}^{U}	341334	1.96	9.45	-6.81	-1.86	2.03	6.36	11.80
ΔDep_{it}^{I}	341334	2.59	8.79	-4.80	-1.60	1.27	4.79	10.39
ΔDep_{it}^{total}	341334	4.55	10.30	-6.51	-1.41	3.68	9.48	16.39
$Capital\_Ratio_{it-1}$	341334	0.10	0.03	0.07	0.08	0.10	0.11	0.14
$Wholesale\_Funding_{it-1}$	341334	0.20	0.11	0.08	0.12	0.18	0.26	0.34
$RealEstate\_Loans_{it-1}$	341334	0.71	0.18	0.47	0.61	0.74	0.85	0.92
$Ln(Assets)_{it-1}$	341334	12.70	1.09	11.68	11.92	12.41	13.12	14.07
$Unused\_Commitments_{it-1}$	341334	0.14	0.07	0.06	0.09	0.13	0.18	0.23
Large Time Deposit Rate$_{it}$	335527	3.36	1.73	1.14	1.92	3.22	4.78	5.65
Core Deposit Rate$_{it}$	335595	2.17	1.40	0.51	0.96	1.89	3.31	4.21
$\Delta Loans_{it}$	341334	4.11	8.99	-5.33	-0.81	3.50	8.43	14.27
$\Delta Commitments_{it}$	336217	0.98	4.75	-3.92	-1.37	0.57	3.03	6.36
$\Delta Liquid\ Assets_{it}$	264544	1.01	8.61	-8.79	-3.79	0.53	5.43	11.41
$\Delta Internal\_Funds_{i,t-1}$	336348	1.07	1.47	-0.22	0.51	1.06	1.64	2.35
$Std\_WriteOff_{it-1}$	341334	0.71	0.92	0.08	0.17	0.37	0.83	1.74
Std_ROE_{it-1}	341334	5.04	5.71	1.20	1.81	3.02	5.66	10.89
Std_ROA_{it-1}	341334	0.53	0.75	0.12	0.17	0.28	0.54	1.14
$Ln(Vol(\Delta Dep_{it}^{U}))$	224435	1.78	0.60	1.01	1.39	1.79	2.21	2.58
Public	341334	0.17	0.38	0.00	0.00	0.00	0.00	1.00
$Timeliness_{it-1}$	334376	0.51	0.50	0.00	0.00	1.00	1.00	1.00
LLP_{it-1}	341326	0.11	3.80	0.00	0.01	0.05	0.11	0.25
NPL_{it-1}	341333	1.44	1.92	0.10	0.33	0.80	1.73	3.41

Panel B: Pairwise correlation for main variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	*R2* $_{it-1}$	1.00																				
2	*ROE* $_{it-1}$	-0.08	1.00																			
3	ΔDep_{it}^{U}	-0.04	0.15	1.00																		
4	ΔDep_{it}^{I}	0.03	0.07	-0.46	1.00																	
5	ΔDep_{it}^{total}	-0.01	0.21	0.57	0.47	1.00																
6	*Capital_Ratio* $_{it-1}$	-0.02	0.01	0.03	-0.02	0.01	1.00															
7	*Wholesale_Funding* $_{it-1}$	0.04	-0.10	-0.04	0.05	0.01	-0.17	1.00														
8	*RealEstate_Loans* $_{it-1}$	0.01	-0.18	-0.04	-0.01	-0.05	-0.01	0.00	1.00													
9	*Ln(Assets)* $_{it-1}$	0.11	0.01	0.03	0.02	0.04	-0.05	0.13	-0.03	1.00												
10	*Unused_Commitments* $_{it-1}$	0.02	0.15	0.09	0.04	0.12	-0.12	-0.08	-0.19	0.41	1.00											
11	*Large Time Deposit Rate* $_{it}$	-0.01	0.12	0.01	0.08	0.08	-0.07	0.12	-0.03	-0.05	0.02	1.00										
12	*Core Deposit Rate* $_{it}$	0.00	0.09	0.00	0.10	0.08	-0.10	0.23	-0.07	-0.12	-0.08	0.79	1.00									
13	*ΔLoans* $_{it}$	-0.04	0.29	0.21	0.24	0.43	0.01	-0.03	-0.03	0.06	0.22	0.14	0.11	1.00								
14	*ΔCommitments* $_{it}$	-0.02	0.11	0.12	0.05	0.17	0.01	-0.04	-0.04	0.04	-0.03	-0.01	-0.03	0.15	1.00							
15	$\Delta Liquid\ Assets_{it}$	0.01	0.02	0.33	0.24	0.55	0.03	0.00	-0.03	-0.01	-0.04	-0.02	-0.01	-0.23	0.06	1.00						
16	$\Delta Internal\_Funds_{i,t-1}$	-0.04	0.59	0.09	0.05	0.14	0.15	-0.06	-0.13	0.02	0.08	0.10	0.09	0.16	0.06	0.02	1.00					
17	*Std_WriteOff* $_{it-1}$	0.10	-0.43	-0.10	-0.11	-0.20	-0.05	0.09	0.01	-0.03	-0.13	-0.22	-0.17	-0.30	-0.07	0.00	-0.23	1.00				
18	*Ln(Vol(* ΔDep_{it}^{U} *))*	0.03	-0.11	-0.12	0.13	0.00	-0.14	0.11	-0.09	-0.09	0.02	-0.15	-0.08	-0.13	-0.06	0.06	-0.03	0.19	1.00			
19	*Public*	0.06	0.02	0.03	0.02	0.04	-0.07	0.10	-0.04	0.44	0.24	0.03	0.00	0.05	0.03	0.00	0.02	0.00	-0.01	1.00		
20	*Timeliness* $_{it-1}$	0.05	-0.04	-0.02	0.01	-0.01	0.00	0.01	0.00	0.03	0.01	-0.01	-0.01	-0.03	-0.01	0.01	-0.02	0.07	0.02	0.03	1.00	
21	*LLP* $_{it-1}$	0.00	-0.02	-0.01	0.01	0.00	-0.01	0.01	-0.01	0.00	0.00	0.00	0.01	-0.02	-0.01	0.00	-0.01	0.02	0.02	0.00	0.01	1.00
22	*NPL* $_{it-1}$	0.07	-0.50	-0.15	-0.10	-0.24	-0.05	0.12	0.13	0.00	-0.21	-0.21	-0.15	-0.38	-0.11	0.00	-0.28	0.58	0.19	-0.02	0.04	0.02

Panel C: R2 and Banks' Asset Side Characteristics

Panel C presents the association between *R2* and banks' asset side characteristics. The dependent variable is the adjusted R-squared from estimating Equation (2) for each bank-quarter using a 12-quarter rolling window. *Real Estate Loan* $_{it}$ is the ratio of real estate loans to total assets. *Commercial Loan* $_{it}$ is the ratio of commercial and industrial loans to total assets. *Liquid Assets* $_{it}$ is the ratio of liquid assets to total assets. *Ln(Assets)* $_{it}$ is the log of total assets. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	$R2_{it}$	$R2_{it}$	$R2_{it}$	$R2_{it}$
RealEstateLoan $_{it}$	0.125***	0.130***	0.116***	0.072***
	(0.013)	(0.025)	(0.013)	(0.026)
Commercial Loan $_{it}$	0.020	-0.078	0.007	-0.065
	(0.026)	(0.049)	(0.026)	(0.049)
Other Loan $_{it}$	0.110***	0.008	0.089***	-0.008
	(0.024)	(0.046)	(0.024)	(0.047)
Ln(Assets) $_{it}$	0.037***	0.012***	0.039***	0.024***
	(0.002)	(0.005)	(0.002)	(0.007)
Bank fixed effects	No	Yes	No	Yes
Quarter fixed effects	No	No	Yes	Yes
No. of observations	317,851	317,851	317,851	317,851
Adjusted R-squared	0.009	0.113	0.021	0.123

Table 2: Validating *R2* Using Public Banks

This table shows the results from regressing abnormal stock returns over the banks' quarterly earnings announcement dates on earnings news and its interaction term with *R2* (entered as its demeaned value). Abnormal return is calculated as the difference between the cumulative return for the bank over the 5-day window centered on the earnings announcement dates and the equal-weighted market return over the same period. *Earnings News* is the changes in earnings from four quarters ago, scaled by lagged total assets. Bank characteristics include *Std_Writeoff, Capital_Ratio, Wholesale_Funding, RealEstate_Loans, Ln(Assets)* and *Unused_Commitments.* Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	*Abret(-2,2)*	*Abret(-2,2)*	*Abret(-2,2)*	*Abret(-2,2)*
Earnings News	0.016***	0.010**	0.015***	0.009*
	(0.006)	(0.005)	(0.005)	(0.005)
R2×Earnings News	0.030***	0.025**	0.025**	0.019**
	(0.011)	(0.010)	(0.010)	(0.010)
R2	-0.002**	-0.003***	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Bank characteristics	No	No	Yes	Yes
Bank fixed effects	No	Yes	No	Yes
No. of observations	45,174	45,135	45,021	44,981
Adjusted R-squared	0.003	0.022	0.005	0.024

Table 3. Transparency and Uninsured Deposit Flow-Performance Sensitivity

Panel A: Full Sample Results

Panel A presents ordinary least-squares estimates of Equation (3) over various specifications. The dependent variable is ΔDep_{it}^{U}, calculated as the changes in the uninsured deposits scaled by beginning value of total assets. *R2* is measured as the deviation from sample mean. Bank fixed effect is included throughout except in column (1). Macro-control variables (contemporaneous and lagged fed fund runs and S&P stock returns) are included in all columns except column (3). Interactive terms between bank characteristics (*Std_Writeoff, Capital_Ratio, Wholesale_Funding, RealEstate_Loans, Ln(Assets) and Unused_Commitments),* measured as the deviations from their respective sample means and *ROE*, are included in all columns. The Appendix contains detailed descriptions for the independent variables. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
ROE_{it-1}	0.096***	0.114***	0.057***
	(0.003)	(0.004)	(0.003)
$R2_{it-1} \times ROE_{it-1}$	0.056***	0.051***	0.016***
	(0.005)	(0.005)	(0.004)
$R2_{it-1}$	-0.999***	-0.994***	-0.210***
	(0.065)	(0.069)	(0.056)
	-0.279***	-0.300***	-0.469***
$Std\_WriteOff_{it-1}$	(0.029)	(0.038)	(0.032)
	7.344***	34.177***	31.838***
$Capital\_Ratio_{it-1}$	(1.047)	(1.910)	(1.705)
	-0.526	-2.145***	5.980***
$Wholesale\_Funding_{it-1}$	(0.327)	(0.527)	(0.524)
	0.165	-2.695***	-1.384***
$RealEstate\_Loans_{it-1}$	(0.200)	(0.386)	(0.358)
	-0.134***	-2.243***	-2.666***
$Ln(Assets)_{it-1}$	(0.033)	(0.093)	(0.112)
	7.609***	7.249***	7.026***
$Unused\_Commitments_{it-1}$	(0.576)	(0.853)	(0.765)
	-0.029	-0.019	-0.003
Large Time Deposit $Rate_{it-1}$	(0.018)	(0.013)	(0.005)
	-0.617***	-1.112***	0.159***
Core Deposit $Rate_{it-1}$	(0.040)	(0.064)	(0.034)
	0.096***	0.114***	0.057***
*Bank characteristics * ROE_{it-1}*	Yes	Yes	Yes
Bank fixed effects	No	Yes	Yes
Macro-variable controls	Yes	Yes	No
Quarter fixed effects	No	No	Yes
No. of observations	341,334	341,334	341,334
Adj. R-squared	0.061	0.096	0.282

Panel B: Main results by subsamples of size and by crisis and non-crisis periods

Panel B explores the effect of transparency on flow-performance sensitivity for subsamples by bank asset size (columns (1)-(3)) and by non-crisis and crisis period (columns (4)-(5)). Small banks are defined as those with total assets below 500 million, large banks have assets above 3 billion, and medium banks have assets between 500 million and 3 billion (measured in 2000 real dollars). All regressions include bank-fixed effects, demeaned bank-year specific controls and their interactive terms with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Small banks Asset $\in (0.1, 0.5)$\$bil	Medium banks Assets $\in (0.5, 3)$\$bil	Large banks Assets > 3 \$bil	Non-Crisis Period	Crisis Period (2007Q3-2009Q2)
	(1)	(2)	(3)	(4)	(5)
Dependent variable	ΔDep^U_{it}	ΔDep^U_{it}	ΔDep^U_{it}	ΔDep^U_{it}	ΔDep^U_{it}
ROE_{it-1}	0.116***	0.132***	0.054***	0.103***	0.073***
	(0.005)	(0.018)	(0.013)	(0.004)	(0.013)
$R2_{it-1} \times ROE_{it-1}$	0.044***	0.075***	0.034*	0.050***	-0.005
	(0.006)	(0.013)	(0.018)	(0.005)	(0.015)
$R2_{it-1}$	-0.909***	-1.399***	-0.608**	-0.784***	-0.391*
	(0.077)	(0.179)	(0.234)	(0.066)	(0.205)
Bank characteristics		Yes			Yes
Bank characteristics $\times$ ROE_{it-1}		Yes			Yes
Bank fixed effects		Yes			Yes
Macro controls		Yes			Yes
No. of observations		341,334			341,334
Adj. R-squared		0.100			0.181

Table 4: Variation by Depositors' Incentives and Ability to Monitor

This table presents the results for deposit flow-performance sensitivity using ordinary least-squares estimates of Equation (3) separately for subsamples of bank-quarters where *ROE* is above and below sample median (in columns (1) and (2)) and where the average uninsured deposit account is above and below sample median size (about $270,350) (in columns (3) and (4)), respectively. The Appendix contains detailed descriptions for all variables. All regressions include bank-fixed effects, demeaned bank-year specific controls and their interactive terms with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Partition variable	ROE		Average account size	
Subsample	Below Median	Above Median	Below Median	Above Median
	(1)	(2)	(3)	(4)
Dependent variable	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$
ROE_{it-1}	0.116***	0.059***	0.114***	0.109***
	(0.006)	(0.007)	(0.005)	(0.005)
$R2_{it-1} \times ROE_{it-1}$	0.059***	0.000	0.023***	0.048***
	(0.007)	(0.012)	(0.008)	(0.006)
$R2_{it-1}$	-1.006***	-0.134	-0.633***	-0.886***
	(0.071)	(0.203)	(0.112)	(0.078)
Bank characteristics	Yes		Yes	
Bank characteristics $\times$ ROE_{it-1}	Yes		Yes	
Bank fixed effects	Yes		Yes	
Macro controls	Yes		Yes	
No. of observations	341,334		337,219	
Adj. R-squared	0.102		0.112	

Table 5. Substitution Between Uninsured and Insured Depositors

This table presents ordinary least-squares estimates of Equation (3) with deposit rates as the dependent variable. Columns (1) and (2) model $\Delta \mathrm{Dep}_{\mathrm{it}}^{\mathrm{I}}$ and $\Delta \mathrm{Dep}_{\mathrm{it}}^{T}$, calculated as the changes in the insured and total deposits, respectively, scaled by beginning value of total assets. Columns (3) and (4) model rate on large time deposits and rate on core deposits, respectively. The Appendix contains detailed descriptions for the independent variables. All regressions include bank-fixed effects, demeaned bank-year specific controls and their interactive terms with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	(1) $\Delta \mathrm{Dep}_{\mathrm{it}}^{\mathrm{I}}$	(2) $\Delta \mathrm{Dep}_{\mathrm{it}}^{\mathrm{T}}$	(3) Large time deposit $\mathrm{rate}_{\mathrm{it}}$	(4) Core deposit $\mathrm{rate}_{\mathrm{it}}$
ROE_{it-1}	-0.016***	0.099***	-0.002***	-0.004***
	(0.004)	(0.004)	(0.000)	(0.000)
$R2_{it-1} \times ROE_{i,t-1}$	-0.051***	-0.000	-0.005***	-0.004***
	(0.005)	(0.005)	(0.001)	(0.000)
$R2_{it-1}$	1.019***	0.025	0.086***	0.083***
	(0.074)	(0.072)	(0.009)	(0.006)
$Std\_WriteOff_{it-1}$	-0.925***	-1.225***	-0.110***	-0.068***
	(0.041)	(0.046)	(0.005)	(0.004)
$Capital\_Ratio_{it-1}$	24.626***	58.803***	-0.854***	-3.032***
	(1.937)	(2.601)	(0.296)	(0.226)
$Wholesale\_Funding_{it-1}$	16.260***	14.115***	-0.045	0.045
	(0.593)	(0.667)	(0.080)	(0.060)
$RealEstate\_Loans_{it-1}$	0.419	-2.276***	-0.561***	-0.963***
	(0.414)	(0.543)	(0.067)	(0.051)
$Ln(Assets)_{it-1}$	-1.787***	-4.030***	0.087***	-0.204***
	(0.086)	(0.126)	(0.015)	(0.012)
$Unused\_Commitments_{it-1}$	10.934***	18.183***	-0.550***	-1.934***
	(0.886)	(1.097)	(0.114)	(0.096)
Large Time Deposit Rate$_{it-1}$	0.018	-0.001		
	(0.014)	(0.005)		
Core Deposit Rate$_{it-1}$	1.264***	0.152***		
	(0.059)	(0.038)		
Bank characteristics × ROE_{it-1}	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
No. of observations	341,334	341,334	335,520	335,520
Adj. R-squared	0.094	0.152	0.705	0.852

Table 6: Transparency and External Funding Costs

Panel A: Deposit rate levels

Panel A presents ordinary least-squares estimates of Equation (3) with deposit rates as the dependent variable. Column (1) models rates on large time deposits and column (2) models rates on core deposits. The Appendix contains detailed descriptions for the independent variables. All regressions include bank-fixed effects, demeaned bank-year specific controls and their interactive terms with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	(1) Large time deposit rate$_{it}$	(2) Core deposit rate$_{it}$
R2 $_{it-1}$	0.034***	0.041***
	(0.007)	(0.004)
ROE$_{it-1}$	-0.003***	-0.004***
	(0.000)	(0.000)
Std_WriteOff $_{it-1}$	-0.110***	-0.067***
	(0.006)	(0.004)
Capital_Ratio $_{it-1}$	-1.188***	-3.381***
	(0.282)	(0.214)
Wholesale_Funding $_{it-1}$	-0.164**	-0.055
	(0.076)	(0.055)
RealEstate_Loans $_{it-1}$	-0.604***	-0.981***
	(0.064)	(0.049)
Ln(Assets) $_{it-1}$	0.088***	-0.217***
	(0.015)	(0.012)
Unused_Commitments $_{it-1}$	-0.615***	-2.102***
	(0.104)	(0.088)
Bank fixed effects	Yes	Yes
Macro controls	Yes	Yes
No. of observations	335,520	335,520
Adj. R-squared	0.704	0.851

Panel B: Reliance on internal funds for growth

Panel B presents ordinary least-squares estimates of Equation (6). The dependent variable is changes in the balance of total loans in column (1), the changes in the balance of total commitments in column (2), the changes in the sum of loans and commitment in column (3), and changes in the balances of liquid assets in column (4). All dependent variables are scaled by lagged total assets. The Appendix contains detailed descriptions for the independent variables. All regressions include bank-fixed effects, demeaned bank-year specific controls and their interactive terms with $\Delta Internal\_Funds$, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	$\Delta \mathrm{Loan}_{it}$	$\Delta \mathrm{Commitment}_{it}$	$\Delta \mathrm{Credit}_{it}$	$\Delta \mathrm{Liquid\ Assets}_{it}$
$\Delta Internal\_Funds_{i,t-1}$	0.216***	0.164***	0.379***	0.011
	(0.015)	(0.008)	(0.019)	(0.017)
$R2_{it-1} \times \Delta Internal\_Funds_{i,t-1}$	0.138***	0.070***	0.200***	-0.047
	(0.028)	(0.014)	(0.035)	(0.030)
$R2_{it-1}$	-0.383***	-0.280***	-0.649***	0.133**
	(0.057)	(0.029)	(0.071)	(0.057)
$Std\_WriteOff_{it-1}$	-1.941***	-0.567***	-2.491***	-0.246***
	(0.047)	(0.021)	(0.056)	(0.034)
$Capital\_Ratio_{it-1}$	10.427***	5.474***	14.917***	40.731***
	(2.377)	(1.114)	(2.747)	(2.041)
$Wholesale\_Funding_{it-1}$	-7.222***	-1.940***	-9.145***	7.348***
	(0.573)	(0.279)	(0.678)	(0.480)
$RealEstate\_Loans_{it-1}$	-0.768	-2.742***	-3.672***	-1.161***
	(0.538)	(0.254)	(0.603)	(0.411)
$Ln(Assets)_{it-1}$	-3.472***	-0.205***	-3.575***	-1.589***
	(0.122)	(0.056)	(0.140)	(0.082)
$Unused\_Commitments_{it-1}$	51.789***	-29.620***	19.220***	-20.347***
	(1.147)	(0.684)	(1.230)	(0.881)
Bank characteristics $\times \Delta Internal\_Funds_{i,t-1}$	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
No. of observations	336,348	331,231	331,231	264,544
Adj. R-squared	0.262	0.101	0.222	0.026

Table 7: Transparency and Profitability

This table explores the association between transparency and bank performance. The dependent variable is return on assets (*ROA*) in columns (1) and (2) and return on equity (*ROE*) in columns (3) and (4). The Appendix contains detailed descriptions for the independent variables. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	(1) ROA_{it}	(2) ROA_{it}	(3) ROE_{it}	(4) ROE_{it}
$R2_{it}$	-0.086***	-0.103***	-0.839***	-0.981***
	(0.004)	(0.006)	(0.050)	(0.064)
$Capital\_Ratio_{it}$	5.353***	4.646***	-24.703***	-51.480***
	(0.260)	(0.230)	(2.661)	(2.065)
$Wholesale\_Funding_{it}$	-0.468***	-0.652***	-3.361***	-6.359***
	(0.056)	(0.053)	(0.625)	(0.566)
$RealEstate\_Loans_{it}$	-0.477***	-0.855***	-3.972***	-8.870***
	(0.046)	(0.035)	(0.506)	(0.361)
$Ln(Assets)_{it}$	-0.209***	0.007	-2.935***	0.063
	(0.009)	(0.006)	(0.103)	(0.058)
$Unused\_Commitments_{it}$	1.910***	0.473***	18.837***	6.142***
	(0.090)	(0.086)	(0.992)	(0.920)
Std_ROA_{it}	-0.373***	-0.376***		
	(0.010)	(0.009)		
Std_ROE_{it}			-0.755***	-0.742***
			(0.013)	(0.012)
Bank fixed effects	Yes	No	Yes	No
No. of observations	341,334	341,334	341,334	341,334
Adj. R-squared	0.439	0.177	0.450	0.220

Table 8: Evidence from Sarbanes-Oxley Act of 2002

This table reports the results from the difference-in-differences (DiD) analysis using Sarbanes-Oxley Act of 2002 as a shock to transparency to publicly traded banks. The sample contain quarterly observations from 592 public and 592 private banks propensity score matched based on asset size in the quarter before SOX enactment over 5 years before and 5 years after the SOX enactment. The dependent variables in Panel A are the flow-performance sensitivities, calculated as the average of the ratio of changes in deposit flows to changes in *ROE* over the preceding 5-year period. Similar approach is used to calculate the dependent variables in columns (3) to (5) of Panel B. *Public* is an indicator for public banks; *Post* is an indicator variable quarters from 2006-2010 to accommodate the fact that the sensitivity measures require at least 12 quarters of data to calculate. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: SOX and deposit flow-performance sensitivities

Dependent Variable	Flow-Performance Sensitivity					
	Uninsured Deposits			Insured Deposits		
	(1)	(2)	(3)	(4)	(5)	(6)
Public×Post	0.049***	0.063***	0.035**	0.010	-0.013	0.013
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Public	-0.004	-0.004	-0.013	-0.025**	-0.025**	-0.021*
	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)
Post	-0.011	-0.027***	-0.048	-0.045***	-0.024**	0.399***
	(0.009)	(0.009)	(0.111)	(0.011)	(0.011)	(0.121)
Trends based on Pre-Shock bank characteristics included?	No	No	Yes	No	No	Yes
Crisis quarters excluded?	No	Yes	No	No	Yes	No
No. of observations	29,984	24,140	29,984	29,984	24,140	29,984
Adj. R-squared	0.006	0.007	0.047	0.010	0.008	0.058

Panel B: Effect of SOX on external funding constraints and profitability

Dependent Variable	Deposit rates		Sensitivity of asset growth to availability of internal funds			Profitability	
	Large time	Core	Loans	Commitments	Total Credit	ROA	ROE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Public×Post	0.214***	0.258***	0.501***	0.080	0.586**	-0.080*	-1.197**
	(0.040)	(0.043)	(0.190)	(0.067)	(0.231)	(0.048)	(0.557)
Public	-0.106***	-0.255***	-0.294*	-0.042	-0.371*	0.076***	1.003***
	(0.030)	(0.039)	(0.157)	(0.049)	(0.191)	(0.028)	(0.311)
Post	-1.078***	-1.471***	1.581	0.835*	2.506	1.277***	15.131***
	(0.335)	(0.308)	(1.391)	(0.470)	(1.690)	(0.349)	(4.193)
No. of observations	28,197	28,213	29,398	29,398	29,398	29,984	29,984
Adj. R-squared	0.415	0.490	0.093	0.168	0.103	0.119	0.133

Table 9: Are the Inferences Confounded by Information Sources Other Than Call Reports?

Panel A: Unconditional variation in uninsured deposit flows

Panel A examines how the unconditional volatility of uninsured deposit flows varies with the level of bank transparency. The dependent variable is the logarithm of the standard deviation of uninsured deposit flows during the 12-quarter periods over which *R2* is estimated. The Appendix contains detailed descriptions for the independent variables. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	$\mathrm{Log}(\sigma(\Delta \mathrm{Dep}^{\mathrm{U}}))$	
	(1)	(2)
R2 $_{it}$	0.024***	0.021***
	(0.005)	(0.006)
Std_ROE $_{it}$	0.015***	0.015***
	(0.001)	(0.001)
Capital_Ratio $_{it}$	-1.368***	-1.852***
	(0.263)	(0.190)
Wholesale_Funding $_{it}$	1.722***	0.876***
	(0.068)	(0.048)
RealEstate_Loans $_{it}$	-0.208***	-0.452***
	(0.052)	(0.032)
Ln(Assets) $_{it}$	-0.068***	-0.115***
	(0.012)	(0.005)
Unused_Commitments $_{it}$	-0.215**	1.280***
	(0.087)	(0.073)
Bank fixed effects	Yes	No
Macro controls	Yes	Yes
No. of observations	224,435	224,435
Adj. R-squared	0.475	0.153

Panel B: Exploring effects separately for public and private banks

Panel B explores the effect of transparency as measured by *R2* within the subset of private (column (1)) and public banks (column (2)) separately. A commercial bank is classified as public if its Fed ID (RSSD9001), or its bank holding company (RSSD9348) can be linked to a PERMCO using the PERMCO-RSSD link table from the website of Federal Reserve Bank of New York. The Appendix contains detailed descriptions for all variables. All regressions include bank-fixed effects, demeaned bank-year specific controls and their interactive terms with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Private Banks	Public Banks
	(1)	(2)
Dependent variable	$\Delta \mathrm{Dep}_{\mathrm{it}}^{\mathrm{U}}$	$\Delta \mathrm{Dep}_{\mathrm{it}}^{\mathrm{U}}$
ROE $_{it-1}$	0.112***	0.104***
	(0.004)	(0.011)
R2 $_{it-1}$ × *ROE* $_{it-1}$	0.049***	0.057***
	(0.005)	(0.013)
R2 $_{it-1}$	-0.960***	-1.191***
	(0.073)	(0.197)
Bank characteristics	Yes	Yes
Bank characteristics × *ROE*	Yes	Yes
Bank fixed effects	Yes	Yes
Macro controls	Yes	Yes
No. of observations	283,409	57,925
Adj. R-squared	0.099	0.103

Table 10: Sensitivity to Alternative Transparency and Performance Measures

This panel explores the robustness of our main results to alternative transparency and performance measures. The dependent variable is uninsured deposit flows. Columns (1) to (3) use *ROE* as the performance measure with different transparency measures. *R2(4 quarters of writeoff)* is the adjusted R-squared from estimating Equation (2) using write-off in the leading 4 quarters as the dependent variable. *R2 (20 quarters)* is the adjusted R-squared from estimating Equation (2) over previous 20 quarters. *Timeliness of LLP* is an indicator variable that equals 1(0) if the incremental adj. R-squared from estimating equations (a) and (b), as outlined in the Appendix, is above (below) the sample median. Columns (4) to (7) use *R2* as the transparency measure with different performance measures. The Appendix contains detailed descriptions for all variables. All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Alternative Transparency Measures			Alternative Performance Measures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{U}$
Performance measure	*ROE*	*ROE*	*ROE*	*ROA*	*Changes in internal equity*	*Loan Loss Provisions*	*Non-performing loans*
Transparency measure	*R2(4 quarters of write-off)*	*R2(20 quarters)*	*Timeliness of LLP*	*R2*	*R2*	*R2*	*R2*
Perf $_{it-1}$	0.114***	0.111***	0.118***	1.186***	0.223***	-0.718***	-0.623***
	(0.004)	(0.004)	(0.004)	(0.040)	(0.016)	(0.276)	(0.024)
Transparency $_{it-1}$ × *Perf* $_{it-1}$	0.049***	0.079***	0.020***	0.592***	0.221***	-0.242**	-0.351***
	(0.005)	(0.008)	(0.004)	(0.055)	(0.031)	(0.108)	(0.027)
Transparency $_{it-1}$	-1.113***	-1.668***	-0.362***	-1.066***	-0.799***	-0.514***	-0.017
	(0.069)	(0.109)	(0.061)	(0.074)	(0.058)	(0.047)	(0.055)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × *ROE*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,222	330,693	334,376	341,334	336,348	341,326	341,333
Adj. R-squared	0.096	0.094	0.097	0.096	0.091	0.090	0.096

Online Appendix

Table A1. Robustness to Alternative Specifications

Panel A: Robustness to Including Time Dummies

Panel A presents the robustness of our main results to inclusion of time dummies instead of contemporaneous macro-controls. All other specifications are the same as their counterparts shown in the main draft.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{I}$	Large time deposit rate_{it}	Core deposit rate_{it}	$\Delta \mathrm{Loan}_{it}$	ΔCommit ment_{it}	$\Delta \mathrm{Credit}_{it}$	ΔLiquid Assets_{it}	ROA_{it}	ROE_{it}
ROE_{it-1}	0.057***	0.042***	-0.001***	-0.004***						
	(0.003)	(0.003)	(0.000)	(0.000)						
$R2_{it-1} \times ROE_{it-1}$	0.016***	-0.012***	-0.001	-0.000						
	(0.004)	(0.004)	(0.000)	(0.000)						
$\Delta Internal\_Fund_{i,t-1}$					0.341***	0.143***	0.481***	0.016		
					(0.017)	(0.009)	(0.021)	(0.018)		
$R2_{it-1} \times \Delta Internal\_Fund_{i,t-1}$					0.112***	0.033**	0.137***	-0.024		
					(0.028)	(0.014)	(0.034)	(0.030)		
$R2_{it-1}$	-0.210***	0.186***	0.007	0.008*	-0.269***	-0.106***	-0.359***	0.051	-0.055***	-0.548***
	(0.056)	(0.057)	(0.007)	(0.004)	(0.056)	(0.028)	(0.069)	(0.057)	(0.004)	(0.047)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,334	341,334	335,527	335,595	336,348	331,231	331,231	264,544	341,334	341,334
Adj. R-squared	0.282	0.315	0.771	0.899	0.287	0.133	0.254	0.063	0.486	0.485

Panel B. Robustness to Use of Lagged Dependent Variable

Panel B reports the robustness of our main results to a variation of our basic specification by replacing bank fixed effects with the lagged dependent variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	$\Delta\mathrm{Dep}_{it}^{U}$	$\Delta\mathrm{Dep}_{it}^{I}$	Large time deposit rate_{it}	Core deposit rate_{it}	$\Delta\mathrm{Loan}_{it}$	$\Delta\mathrm{Commitment}_{it}$	$\Delta\mathrm{Credit}_{it}$	$\Delta\mathrm{Liquid\ Assets}_{it}$	ROA_{it}	ROE_{it}
ROE_{it-1}	0.071***	0.019***	-0.001***	-0.001***						
	(0.003)	(0.002)	(0.000)	(0.000)						
$R2_{it-1} \times ROE_{it-1}$	0.034***	-0.026***	-0.000	0.000						
	(0.004)	(0.004)	(0.000)	(0.000)						
$\Delta Internal\_Fund_{i,t-1}$					0.076***	0.123***	0.161***	-0.010		
					(0.011)	(0.007)	(0.013)	(0.015)		
$R2_{it-1} \times \Delta Internal\_Fund_{i,t-1}$					0.083***	0.039***	0.085***	-0.050*		
					(0.022)	(0.012)	(0.025)	(0.027)		
$R2_{it-1}$	-0.607***	0.533***	0.001	0.000	-0.197***	-0.152***	-0.264***	0.102**	-0.054***	-0.563***
	(0.051)	(0.050)	(0.004)	(0.002)	(0.035)	(0.021)	(0.041)	(0.044)	(0.003)	(0.036)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	317,851	317,851	312,465	312,515	314,695	309,741	309,741	248,776	317,851	317,851
Adj. R-squared	0.172	0.216	0.845	0.943	0.441	0.153	0.431	0.116	0.443	0.444

Table A2: R2 and CDS Spread Response to Bank Earnings

In this table we examine whether the association between the credit default swap (CDS) spread and bank earnings is related to the banks' *R2*. CDS spread reflects the market's best estimate of the credit risk associated with the firm issuing the debt. We retrieve the CDS spread information for debts by our sample banks from Markit (via WRDS) and estimate the following regression:

$$CDS\_Spread_{it} = \beta_0 ROE_{it-1} + \beta_1 R2_{it-1} * ROE_{it-1} + \beta_2 R2_{it-1} + Control_{it} + \epsilon_{it}$$

where CDS_Spread_{it} is the average weekly 5-year CDS spread over quarter t for a bond issued by bank i and ROE_{it-1} is bank i's return on equity in the previous quarter. Following prior literature[$], we use the CDS quotations for senior unsecured debt with a modified restructuring (MR) clause and denominated in US dollars to ensure comparability across banks/bonds. We use the 5-year spreads because they are the most liquid and constitute over 85% of the entire CDS market, although we obtain qualitatively similar results (untabulated) using 1-year or 7-year spreads. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	CDS Spread	CDS Spread	CDS Spread	CDS Spread
ROE	-0.024***	-0.021***	-0.021***	-0.017**
	(0.006)	(0.006)	(0.006)	(0.007)
R2×ROE	-0.025***	-0.024***	-0.024***	-0.025***
	(0.008)	(0.009)	(0.007)	(0.008)
R2	0.797***	0.701***	0.650***	0.620***
	(0.128)	(0.122)	(0.123)	(0.120)
Bank characteristics	No	No	Yes	Yes
Bank fixed effects	No	Yes	No	Yes
No. of observations	1,191	1,191	1,191	1,191
Adjusted R-squared	0.283	0.394	0.356	0.457

[$]Jorion, P. and Zhang, G., 2007. Good and bad credit contagion: Evidence from credit default swaps. *Journal of Financial Economics*, *84*(3), pp.860-883.

Table A3: Robustness to Alternative R2 Measures

Panel A: Robustness to R2 Estimated with Estimated Over 20 Quarters

Panel A explores the robustness of our main results to measuring transparency with the adjusted *R2* from estimating Equation (2) with 20 quarters: *R2(20 quarters).* All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	ΔDep^{U}_{it}	ΔDep^{I}_{it}	Large time deposit $rate_{it}$	Core deposit $rate_{it}$	$\Delta Loan_{it}$	$\Delta Commit ment_{it}$	$\Delta Credit_{it}$	$\Delta Liquid Assets_{it}$	ROA_{it}	ROE_{it}
ROE_{it-1}	0.111***	-0.014***	-0.002***	-0.004***						
	(0.004)	(0.004)	(0.000)	(0.000)						
R2(20 quarters) × ROE_{it-1}	0.079***	-0.057***	-0.008***	-0.007***						
	(0.008)	(0.008)	(0.001)	(0.001)						
$\Delta Internal\_Fund_{i,t-1}$					0.196***	0.156***	0.350***	0.007		
					(0.015)	(0.008)	(0.019)	(0.017)		
R2(20 quarters) × $\Delta Internal\_Fund_{i,t-1}$					0.384***	0.152***	0.519***	-0.037		
					(0.046)	(0.022)	(0.056)	(0.044)		
R2(20 quarters)	-1.668***	1.239***	0.104***	0.105***	-1.609***	-0.798***	-2.414***	0.380***	-0.249***	-2.563***
	(0.109)	(0.121)	(0.015)	(0.010)	(0.102)	(0.051)	(0.126)	(0.092)	(0.010)	(0.104)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	330,693	330,693	325,042	325,101	325,977	320,861	320,861	255,547	330,693	330,693
Adj. R-squared	0.094	0.091	0.707	0.852	0.257	0.101	0.218	0.028	0.442	0.453

Panel B: Robustness to R2 Estimated with Four quarters of Write-offs

Panel B explores the robustness of our main results to measuring transparency with the adjusted *R2* from estimating Equation (2) with four quarters ahead of writeoffs as the dependent variable (*R2(4 quarters of write-off)).* All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	ΔDep^{U}_{it}	ΔDep^{I}_{it}	Large time deposit $rate_{it}$	Core deposit $rate_{it}$	$\Delta Loan_{it}$	ΔCommit $ment_{it}$	$\Delta Credit_{it}$	ΔLiquid $Assets_{it}$	ROA_{it}	ROE_{it}
ROE_{it-1}	0.114***	-0.016***	-0.002***	-0.004***						
	(0.004)	(0.004)	(0.000)	(0.000)						
R2(4 quarters of write-off) × ROE_{it-1}	0.049***	-0.056***	-0.006***	-0.005***						
	(0.005)	(0.005)	(0.001)	(0.000)						
$\Delta Internal\_Fund_{i,t-1}$					0.215***	0.164***	0.377***	0.010		
					(0.015)	(0.008)	(0.019)	(0.017)		
R2(4 quarters of write-off) × $\Delta Internal\_Fund_{i,t-1}$					0.168***	0.073***	0.230***	-0.019		
					(0.030)	(0.015)	(0.036)	(0.030)		
R2(4 quarters of write-off)	-1.113***	1.169***	0.090***	0.082***	-0.388***	-0.304***	-0.674***	0.100*	-0.077***	-0.106***
	(0.069)	(0.076)	(0.009)	(0.006)	(0.060)	(0.030)	(0.073)	(0.059)	(0.004)	(0.006)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,222	341,222	335,416	335,483	336,238	331,121	331,121	264,442	341,222	341,222
Adj. R-squared	0.096	0.094	0.705	0.852	0.262	0.101	0.222	0.026	0.439	0.178

Panel C: Robustness to R2 Estimated as Timeliness

Panel C explores the robustness of our main results to measuring transparency with the timeliness measure from Beatty and Liao (2011) (*Timeliness LLP*). All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	ΔDep^{U}_{it}	ΔDep^{I}_{it}	Large time deposit $rate_{it}$	Core deposit $rate_{it}$	$\Delta Loan_{it}$	$\Delta Commitment_{it}$	$\Delta Credit_{it}$	$\Delta Liquid Assets_{it}$	ROA_{it}	ROE_{it}
ROE_{it-1}	0.118***	-0.020***	-0.002***	-0.005***						
	(0.004)	(0.004)	(0.000)	(0.000)						
Timeliness LLP × ROE_{it-1}	0.020***	-0.023***	-0.002***	-0.001***						
	(0.004)	(0.005)	(0.001)	(0.000)						
$\Delta Internal\_Fund_{i,t-1}$					0.219***	0.166***	0.384***	0.019		
					(0.016)	(0.008)	(0.019)	(0.016)		
Timeliness LLP × $\Delta Internal\_Fund_{i,t-1}$					0.090***	0.028**	0.113***	-0.049*		
					(0.026)	(0.013)	(0.032)	(0.027)		
Timeliness LLP	-0.362***	0.389***	0.043***	0.035***	-0.283***	-0.106***	-0.382***	0.230***	-0.030***	-0.037***
	(0.061)	(0.063)	(0.007)	(0.004)	(0.048)	(0.024)	(0.059)	(0.049)	(0.003)	(0.004)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	334,376	334,376	328,755	328,818	329,494	324,627	324,627	259,264	334,376	334,376
Adj. R-squared	0.097	0.093	0.706	0.852	0.263	0.100	0.223	0.027	0.438	0.177

Panel D: Robustness to Alternative Specification for R2 Estimation with LLP

Panel D explores the robustness of our main results to estimating R2 from a modified version of Eqn. (2) where we include only two lagged values of *LLP* as the independent variable. We refer to this R2 as *R2(LLP)*. All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	ΔDep^{U}_{it}	ΔDep^{I}_{it}	Large time deposit $rate_{it}$	Core deposit $rate_{it}$	$\Delta Loan_{it}$	ΔCommit $ment_{it}$	$\Delta Credit_{it}$	ΔLiquid $Assets_{it}$	ROA_{it}	ROE_{it}
ROE_{it-1}	0.112***	-0.013***	-0.002***	-0.004***						
	(0.004)	(0.004)	(0.000)	(0.000)						
$R2(LLP) \times ROE_{it-1}$	0.098***	-0.100***	-0.008***	-0.006***						
	(0.009)	(0.009)	(0.001)	(0.001)						
$\Delta Internal\_Fund_{i,t-1}$					0.212***	0.162***	0.372***	0.013		
					(0.015)	(0.008)	(0.019)	(0.017)		
$R2(LLP) \times \Delta Internal\_Fund_{i,t-1}$					0.398***	0.190***	0.558***	-0.130***		
					(0.050)	(0.026)	(0.062)	(0.048)		
R2(LLP)	-2.130***	2.157***	0.110***	0.115***	-1.191***	-0.679***	-1.818***	0.393***	-0.186***	-1.907***
	(0.124)	(0.128)	(0.014)	(0.010)	(0.104)	(0.054)	(0.132)	(0.097)	(0.009)	(0.105)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,101	341,101	335,299	335,366	336,116	331,009	331,009	264,333	341,101	341,101
Adj. R-squared	0.097	0.095	0.705	0.852	0.262	0.101	0.223	0.026	0.440	0.451

Panel E: Robustness to Alternative Specification for R2 Estimation with Earnings Components

Panel E explores the robustness of our main results to estimating R2 from a modified version of Eqn. (2) where we include only two lagged values of the components of earnings ($EBLLP$ and LLP) as the independent variable. We refer to this R2 as *R2(Earnings)*. All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	$\Delta \mathrm{Dep}^{\mathrm{U}}_{\mathrm{it}}$	$\Delta \mathrm{Dep}^{\mathrm{I}}_{\mathrm{it}}$	Large time deposit $rate_{it}$	Core deposit $rate_{it}$	$\Delta \mathrm{Loan}_{\mathrm{it}}$	ΔCommit$ment_{it}$	$\Delta \mathrm{Credit}_{\mathrm{it}}$	ΔLiquid $Assets_{it}$	ROA_{it}	ROE_{it}
ROE_{it-1}	0.110***	-0.012***	-0.002***	-0.004***						
	(0.004)	(0.004)	(0.000)	(0.000)						
$R2(Earnings) \times ROE_{it-1}$	0.083***	-0.082***	-0.007***	-0.006***						
	(0.006)	(0.006)	(0.001)	(0.000)						
$\Delta Internal\_Fund_{i,t-1}$					0.213***	0.162***	0.374***	0.011		
					(0.015)	(0.008)	(0.019)	(0.017)		
$R2(Earnings) \times \Delta Internal\_Fund_{i,t-1}$					0.251***	0.126***	0.350***	-0.057		
					(0.037)	(0.018)	(0.045)	(0.036)		
R2(Earnings)	-1.701***	1.619***	0.109***	0.104***	-0.758***	-0.478***	-1.184***	0.204***	-0.130***	-1.314***
	(0.086)	(0.091)	(0.010)	(0.007)	(0.074)	(0.038)	(0.093)	(0.070)	(0.006)	(0.069)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,101	341,101	335,299	335,366	336,116	331,009	331,009	264,333	341,101	341,101
Adj. R-squared	0.097	0.095	0.705	0.852	0.262	0.101	0.223	0.026	0.440	0.451

Table A4: Robustness to Alternative Performance Measures

This table explores the robustness of our main results (the sensitivity of deposit flows and of deposit rates to bank performance) to four alternative measures of performance: *Return on Assets (ROA), Changes in Internal Equity*, *LLP*, and *NPL*. All regressions include bank-fixed effects, bank-year specific controls and their demeaned values interacted with *ROE*, and controls for macro conditions. Standard error estimates, reported in parentheses, are clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Performance measures	*ROA*				*Changes in Internal Equality*			
Dependent variable	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{I}$	Large time deposit rate_{it}	Core deposit rate_{it}	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{I}$	Large time deposit rate_{it}	Core deposit rate_{it}
$Perf_{it-1}$	1.186***	-0.157***	-0.008	-0.031***	0.223***	0.150***	-0.035***	-0.026***
	(0.040)	(0.040)	(0.010)	(0.006)	(0.016)	(0.015)	(0.004)	(0.002)
R2 × $Perf_{it-1}$	0.592***	-0.629***	-0.086***	-0.066***	0.221***	-0.184***	-0.015*	-0.020***
	(0.055)	(0.060)	(0.016)	(0.006)	(0.031)	(0.030)	(0.008)	(0.004)
R2	-1.066***	1.127***	0.127***	0.105***	-0.799***	0.740***	0.060***	0.066***
	(0.074)	(0.081)	(0.024)	(0.007)	(0.058)	(0.058)	(0.018)	(0.006)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
and interaction w. perf	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,334	341,334	341,334	341,334	336,348	336,348	336,348	336,348
Adj. R-squared	0.096	0.094	0.170	0.796	0.091	0.092	0.166	0.791

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Performance measures	*LLP*				*NPL*			
Dependent variable	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{I}$	Large time deposit rate_{it}	Core deposit rate_{it}	$\Delta \mathrm{Dep}_{it}^{U}$	$\Delta \mathrm{Dep}_{it}^{I}$	Large time deposit rate_{it}	Core deposit rate_{it}
$Perf_{it-1}$	-0.718***	0.528**	0.007	0.045**	-0.623***	-0.151***	-0.022***	0.012***
	(0.276)	(0.220)	(0.012)	(0.018)	(0.024)	(0.024)	(0.005)	(0.003)
R2 × $Perf_{it-1}$	-0.242**	0.230	0.026*	0.018*	-0.351***	0.325***	0.045***	0.036***
	(0.108)	(0.160)	(0.014)	(0.010)	(0.027)	(0.029)	(0.005)	(0.003)
R2	-0.514***	0.488***	0.043***	0.041***	-0.017	0.040	-0.018	-0.010*
	(0.047)	(0.048)	(0.016)	(0.005)	(0.055)	(0.054)	(0.022)	(0.005)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
and interaction w. Perf	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	341,326	341,326	341,326	341,326	341,333	341,333	341,333	341,333
Adj. R-squared	0.090	0.092	0.170	0.795	0.096	0.095	0.170	0.796