The decision relevance of loan fair values for depositors*

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Abstract: Using a large sample of U.S. commercial banks from 1994-2019, we find that loan fair value changes are highly relevant for depositor decision-making: a one-standard-deviation decrease in fair values is associated with 10% lower uninsured deposit flows than the sample average. However, the information in fair values about loan quality is limited and does not fully explain the relevance of fair values for depositors. Furthermore, the relevance manifests more strongly in banks where depositors' incentives to withdraw money before other depositors (i.e., strategic complementarities) are stronger. The findings inform the cost-benefit trade-off of reporting loan fair values.

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1. Introduction

We examine whether loan fair value disclosures contain information relevant for depositor decision-making. The objective is to inform the ongoing debate on the merits of using fair value accounting to report the value of banks' assets.[1] Much of the debate hinges on whether fair value contains decision-relevant information for banks' claimholders whose behaviors affect bank operations. A major group of bank claimholders is depositors, who provide more than 75% of bank funding (Hanson et al., 2015) and are portrayed in prominent banking theories as key claimholders whose behavior affects the efficiency and stability of banking business.[2] Yet, there has been no evidence on the relevance of asset fair values for depositors.

We focus on loan fair values.[3] Loans account for nearly two-thirds of total bank assets and are at the center of the debate about using fair value to measure bank assets.[4] Arguments on both sides of the debate rely on implicit assumptions about whether and how loan fair values may be of relevance to the decision-making of bank stakeholders including depositors. Supporters argue that by aggregating information from market participants, fair values provide an updated, forward-looking view of assets' credit quality that can allow better monitoring by bank claimholders such as depositors. Critics, including bank management, have expressed concerns that the lack of liquid markets for bank loans can result in loan fair values deviating below their fundamental values (i.e.,

[1] For different perspectives on the debate, see reviews by Barth and Landsman (2010), Laux and Leuz (2009, 2010), Goldstein and Sapra (2014), Beatty and Liao (2014), Acharya and Ryan (2016), and Bushman (2016).
[2] See Gorton and Winton (2003) and Diamond, Kashyap, and Rajan (2017) for reviews of relevant banking theories.
[3] Under U.S. GAAP, banks report values of loans they intend to hold to maturity at amortized cost (net of an allowance for credit losses) on the balance sheet and disclose loan fair values in the footnotes. Statement of Accounting Standards (SFAS) 157 emphasizes the notion of exit price in deriving fair values. See Section 2 for a detailed discussion of the accounting guidance, its application in practice, and the connection to the fair-value debate.
[4] In their analysis of the comment letters for the FASB's 2010 Exposure Draft on fair value measurement, Hodder and Hopkins (2014) find that 85% of the comment letters are from banks or their representatives, most of which oppose the use of the fair value measurement for loans.

their cash-generating ability when held to maturity),[5] which can in turn lead to a loss of depositor confidence and exacerbate instability in the banking business, especially in times of crisis.[6,7]

The debate raises two important, unanswered questions that we address in this paper. Do loan fair values summarize information of relevance to depositor behavior? If yes, to what degree does the relevance reflect the information in fair values about the cash-generating potential of loans?

We conduct our analyses on a large sample of bank-quarter observations from 1994 to 2019. We establish the relevance of loan fair values by examining associations between loan fair value changes and uninsured deposit flows. We focus on uninsured depositors because, unlike insured depositors, fluctuations in bank asset values directly affect their expected payoffs. We document a significant positive association between uninsured deposit flows and changes in loan fair values: a one-standard-deviation decrease in changes in loan fair values is associated with a 10% decline in uninsured deposit flows from their sample average. The association is little affected when we control for historical cost-based performance measures. These results indicate that loan fair values summarize information relevant to uninsured depositors' decision-making that is distinct from the information in historical cost-based measures. Unlike uninsured deposit flows, we do not find loan fair value changes to be positively associated with insured deposit flows. Because uninsured and

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[5] We use the terms "earnings potential of loans," "loan credit quality," "cash-generating ability of bank loans," "bank fundamentals," and "value-in-use" interchangeably to refer to the lifetime profits one would make by holding the loan portfolio until maturity.

[6] For example, in its comment letter to the FASB, HSBC, a major international bank, notes that "*during a period of market uncertainty or crisis, [under fair value accounting] banks would report write-downs to their published shareholders' equity bases thereby causing concern over the financial strength of these banks. This may also be accompanied by a loss of depositor confidence which could trigger a deepening of the crisis*."

[7] Because of these concerns, the Financial Accounting and Standards Board's (FASB's) 2010 proposal requiring recognition of all financial instruments (including loans) at fair values on the balance sheet received nearly universal criticism from banks as well as from organizations such as credit rating agencies, the Financial Stability Board, and the Federal Deposit Insurance Corporation (FDIC). These parties, while generally supportive of fair value recognition of non-loan assets, were uniformly critical of the recognition of loans using fair values (American Bankers Association, 2010; Standard and Poor's, 2010; Financial Stability Board, 2009).

insured depositors mainly differ in their exposure to banks' default risk, this result suggests that the information summarized by loan fair values pertains to default risk.

We next examine if loan fair value changes contain incremental information about loan credit quality and if it is this information that drives their association with uninsured deposit flows. Using a variety of measures for future performance over multiple horizons, we find that loan fair values are incrementally predictive of future performance, albeit with small economic magnitude: while the historical cost-based measure (i.e., ROE) explains nearly 21% of the variation in write-offs over the next year, loan fair value changes explain a mere 0.1%. Even this small information content vanishes when the fair values are derived in periods with heightened loan market illiquidity. Despite the lack of fundamental information content, the association of loan fair values with uninsured deposit flows in highly illiquid periods, if anything, is stronger than in other periods. This is consistent with the concerns raised by critics that loan fair values have little fundamental information content because of the illiquid nature of loan markets, yet their fluctuations may affect depositor behavior. Several additional tests further confirm that the fundamental information content of loan fair values explains only a small portion of their association with uninsured deposit flows.

Overall, the above results may appear puzzling when evaluated from the perspective of banks' equity and long-term bond holders, who invest in banks to earn risk-adjusted returns and who obtain liquidity from secondary markets for their claims, and not from banks. For these claimholders, the decision-relevance of loan fair values are expected to be driven by their information content about banks' loan quality. The objective of depositors is different, however: depositors entrust their money to banks primarily for the safety and liquidity services provided by their banks, i.e., the ability to withdraw their money at par value on demand.

Taking the objective of depositors into account, theories of bank fragility show that depositors can react strongly to public signals about bank performance even if they contain little to no fundamental information (e.g., Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005; Vives, 2014). This is because banks do not hold enough liquid assets to meet the immediate withdrawal demand from all depositors. This generates strategic complementarities in depositors' payoff in that a depositor would want to immediately withdraw her money when she expects other depositors will withdraw too, for the fear that the bank will run out of resources and default on her payment if she is late to withdraw.[8] In the presence of strategic complementarities, a depositor's view of a bank's default risk is shaped not only by the cash-generating potential of the bank's assets (i.e., loan quality) but also by her expectations of the actions of other depositors. Thus, she will find a public signal to be decision-relevant if it updates her expectation about the actions of other depositors, especially if the signal is informative about the bank's exposure to loan-market illiquidity and about the bank's ability to raise immediate cash to meet a large mass of withdrawals. To the extent that loan fair values contain such information, they can be of great relevance to depositors in updating beliefs about other depositors' behavior.

In our final analyses, we explore if strategic complementarities can indeed explain some of the relevance of fair values for depositors. Since we cannot directly test if uninsured depositors rely on information in loan fair values to update their beliefs about other depositors' behavior, we follow the approach in recent empirical works on fragility in financial institutions and examine whether the association between uninsured deposit flows and changes in loan fair values is stronger in banks where depositors' payoffs exhibit greater strategic complementarities.[9]

[8] In general, strategic complementarities exist when the marginal return from taking an action (e.g., withdrawing money from a bank) is higher when more of other agents take the same action (Carlsson and van Damme, 1993).
[9] See, for example, Chen, Goldstein, and Jiang (2010) for an analysis of strategic complementarities in mutual funds, Schmidt, Timmermann, and Wermers (2016) for money market funds, Goldstein, Jiang, and Ng (2017) for bond funds,

We use two measures for the strength of strategic complementarities. The first measure is from Berger and Bouwman (2009) and captures the extent of liquidity mismatch on a bank's balance sheet, i.e., the extent to which the bank employs short-term, liquid funding sources to invest in illiquid, long-term assets. When a bank has a high liquidity mismatch, the short-term liquidation value of its (primarily illiquid) assets may not be enough to meet the immediate withdrawal demand from its short-term claimholders. Thus, in banks with greater liquidity mismatch, an uninsured depositor has a stronger incentive to withdraw when she expects others to do so. Second, we explore the variation in strategic complementarities due to differences in banks' mix of uninsured and insured depositors. All else equal, an uninsured depositor would have a lower incentive to withdraw early when she knows that more of her bank's depositors have a low incentive to withdraw early because they are covered by deposit insurance.

Using both measures, we find strong evidence that uninsured deposit flows are more sensitive to loan fair value changes when strategic complementarities are greater. The economic magnitude of the effect is large: uninsured deposit flows are nearly 2.5 times more sensitive to loan fair value changes for banks in the top tercile of strategic complementarity measures than banks in the bottom tercile. These findings suggest that strategic complementarities in depositors' payoffs might lie at the root of the strong relevance of loan fair values despite their limited fundamental information content.

Our paper contributes to the growing body of empirical work (discussed in detail in Section 2) on the decision relevance and economic consequences of fair values. To our best knowledge, this paper is the first to provide large-sample evidence on the decision relevance of loan fair values for depositors. Our findings complement, and cannot be inferred from, findings in the existing

Foley-Fisher, Narajabad, and Verani (2020) in the life insurance industry, and Chen et al. (2021b) for the banking industry.

literature, which has examined the decision-relevance of fair values from the perspectives of bank equity and long-term bond holders, whose objectives, as discussed earlier, are different from those of depositors. Since managing deposit funding is a major part of bank operations, our focus on deposit flows also connects our paper to the literature on the economic consequences of fair values. The extant literature primarily focuses on how fair values affect bank operations via the regulatory channel. Our results suggest that loan fair values, which do not affect banks' regulatory capital, can influence bank operations via the deposit channel.

Our findings bring important, new evidence to the debate about loan fair values (discussed in detail in Section 2). Specifically, our findings suggest that the monitoring benefits of loan fair value estimates for depositors are likely to be limited, as the decision-relevance of loan fair values for depositors, while being high, is largely unexplained by the limited information in fair values about loan quality. Instead, our findings of stronger responses by uninsured depositors to information in loan fair values in more fragile banks, i.e., banks with stronger strategic complementarities in their depositors' payoffs, lend support to the concerns raised by critics about the potentially destabilizing effect of loan fair value information.

Lastly, our findings also add to the growing body of evidence on agents' amplified response to public signals in various settings that exhibit strategic complementarities (see footnote 9 for citations). In this regard, our work is closely related to Chen et al. (2021b) but with a different focus. Chen et al. (2021b) focus on establishing empirical support for the role of strategic complementarities in bank fragility by examining uninsured depositors' response to historical cost-based measures that are known to be informative about loan quality (e.g., earnings, loan loss provisions, etc.). Our focus is to examine whether loan fair values contain decision-relevant information to depositors, above and beyond that contained in historical cost-based measures. We provide the first empirical evidence that connects strategic complementarities in depositors' payoffs to the informational value of loan fair values. We believe the connection is important to bring to the debate on loan fair values, as the extant academic research has not considered the role of strategic complementarities in evaluating the costs and benefits of fair values.

2. Institutional background and related literature

2.1 Accounting background and the loan fair value debate

More than two-thirds of banks' assets are loans, almost all of which are held for investment and are recorded at amortized cost (net of an allowance for credit losses) on banks' balance sheet.[10] Starting in 1992, Statement of Financial Accounting Standards (SFAS) 107 (Financial Accounting Standards Board [FASB] 1991, codified in ASC 825-10) requires companies to disclose the fair values of their financial instruments, including loans, in the notes to the financial statements. SFAS 157 (Financial Accounting Standards Board [FASB] 2006, codified in ASC 820) issued in 2006 clarifies the definition of fair value and emphasizes the notion of "exit" price by defining fair value as "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date." Accordingly, practitioners estimate loan fair values using secondary market prices or valuation models with various inputs reflecting assumptions from market participants.

There has been an ongoing debate about the appropriate measurement basis (historical cost vs. fair value) for loans. Supporters of fair value argue that allowance for credit losses under the historical cost approach is backward-looking and vulnerable to managerial manipulation and thus, does not provide timely information about impending defaults. Because loan fair values by design

[10] Cantrell et al. (2014) find that loans held for sale account for only 0.75% of net loans.

reflect market participants' most recent expectations about credit losses, they would provide more timely information about loan credit quality.

The opposition stems primarily from the emphasis on the use of exit prices in deriving fair values and from the fact that the secondary markets for loans are inactive, exhibit little liquidity, and are characterized by severe information asymmetries. The concern is that the hypothetical exit prices derived from such markets may deviate significantly from the actual cash-generating potential of loans (i.e., value-in-use) for banks who tend to hold most loans till maturity. When markets are illiquid, loan exit values may reflect the amount of cash available to buy loans instead of their earnings potential (e.g., Shleifer and Vishny, 1992, 2011).

In practice, due to the inactive nature of secondary loan markets, loan fair values are usually determined using valuation models that rely on unobservable level 3 inputs in accordance with SFAS 157.[11] SFAS 157, however, clarifies that "the fair value measurement objective remains the same, that is, an exit price from the perspective of a market participant that holds the asset or owes the liability. Therefore, unobservable inputs shall reflect the reporting entity's own assumptions about the assumptions that *market participants* would use in pricing the asset and liability (including assumption about risk)".[12] An important implication of this guidance is that it requires firms to consider the lack of liquidity in deriving fair values if there are reasons to believe that a market participant would apply a liquidity discount. The emphasis on exit values and the application of liquidity discount is echoed by auditors[13] and has been applied in practice.[14]

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[11] McInnis et al. (2018) report 85.6% of loan fair values are based on level 3 inputs.
[12] Para. 30, page FAS157-15, Statement of Financial Accounting Standards No. 157, Original Pronouncements, As Amended.
[13] See, for example, a white paper (available here) issued by Center for Audit Quality, an industry group formed by the Big 4 Accounting firms, for an elaboration of this point. Also see KPMG (2017) guide on fair value measurement.
[14] The following extract from Wells-Fargo's 10-K filing for 2014 illustrates how the application of SFAS 157 can result in liquidity discounts in fair values even when relying on valuation models and level 3 inputs: "*We incorporate lack of liquidity into our fair value measurement based on the type of asset or liability measured and the valuation methodology used. For example, for certain residential MHFS and certain securities where the significant inputs have*

Even when liquidity is not a problem, loans may sell at a discount because buyers may be concerned that privately informed banks may be selling a loan of poor quality (Akerlof, 1970). Furthermore, outside parties may not value the relationship-specific rents that the originating banks may derive from their information monopolies (Rajan, 1992; Sharpe, 1990) or from the opportunity to cross-market other products and services to borrowers. These scenarios raise concerns about unnecessary adverse reactions from banks' claimholders following loan fair value declines that may have nothing to do with the cash-generating potential of the banks' loan portfolios.

2.2 Related literature and contributions

Our study is related to two strands of empirical literature on fair values for banks. One strand evaluates the informational relevance of loan fair values either by their ability to explain security values or by their ability to predict performance.[15] The evidence on the former is mixed. Eccher, Ramesh, and Thiagarajan (1996) and Nelson (1996) find that loan fair values do not have incremental power in explaining equity valuations relative to book values; similarly, McInnis, Yu, and Yust (2018) find that the fair values of all assets (including loans) are less value relevant than historical cost-based values. In contrast, Barth et al. (1996) and Blankespoor et al. (2013) find that loan fair values have incremental explanatory power for equity valuations and bond yields, and Campbell, Davidson, and Shakespeare (2021) find that fair value changes (particularly, those coming from loan fair values) provide information complementary to GAAP-based earnings for stock returns. The literature on whether fair values can predict future fundamentals has also

become unobservable due to illiquid markets and vendor or broker pricing is not used, we use a discounted cash flow technique to measure fair value. This technique incorporates forecasting of expected cash flows (adjusted for credit loss assumptions and estimated prepayment speeds) discounted at an appropriate market discount rate to reflect the lack of liquidity in the market that a market participant would consider."

[15] There is also significant work that examines the value relevance of fair values of securities (e.g., available-for-sale and trading securities). See Barth, Beaver, and Landsman (2001), Landsman (2007), and Beatty and Liao (2014) for reviews of this work.

generated mixed evidence. Evans, Hodder, and Hopkins (2014) find that fair value information for banks' interest-bearing investment securities has predictive ability for future reported income from those securities. However, Cantrell et al. (2014) find that loan fair values contain less information than historical cost-based book values in predicting future defaults. Along similar lines, Bischof, Laux, and Leuz (2021) find that during 2007-2008, loan fair values did not incorporate the market's expectations of impending defaults.

We complement this research by examining the informational relevance of loan fair values for depositors who, on average, provide more than 75% of bank funding and who, in leading banking theories, are portrayed as the key claimholder whose behavior affects the stability and efficiency of banking business. More importantly, as we discussed in the introduction, since the objective of depositors differs significantly from those of bank equity and bond holders, whether and how loan fair values contain information relevant for depositors cannot be readily inferred from the existing findings on their relevance for equity and bond holders, and therefore warrants an investigation of its own.

Because managing deposit funding is a major part of bank operations, our focus on deposit flows also relates our paper to the literature on the real consequences of fair value accounting. This literature mainly examines how fair value accounting affects banks through regulatory capital requirements. Unlike loans, unrealized gains and losses on trading securities and a subset of AFS securities are included in regulatory capital adequacy ratios.[16] Therefore declines in market prices of these securities can affect banks' ability to meet regulatory capital requirements. Several studies examine whether this makes banks averse to holding AFS securities ex-ante or leads to other

[16] See Fig. 4 in Beatty and Liao (2014) and Laux and Rauter (2017) for details.

adverse effects such as pro-cyclicality in bank lending/leverage or fire-sale liquidation of bank assets.

Regarding the effects on ex-ante portfolio holdings, Beatty (1995), Hodder, Kohlbeck, and McAnally (2002), Bhat et al. (2011), Chircop and Novotny-Farkas (2016), and Kim, Kim, and Ryan (2019) find that the link between AFS unrealized gains and losses and capital adequacy ratios makes banks averse to holding AFS securities ex-ante. However, the evidence on whether this link has any aggregate adverse effects is mixed. While Khan (2019) finds this link introduces systemic risk in the banking industry, Xie (2016), Laux and Rauter (2017), and Amel-Zadeh, Barth, and Landsman (2017) find no evidence that it contributes to the pro-cyclicality of bank lending or leverage. Similarly, Badertscher et al. (2012) find no evidence of an economically significant sale of securities in response to capital depleting declines in fair values during 2007-2008. Consistent with the conclusions in Laux and Leuz (2009, 2010), the latter set of studies generally attribute the insignificant results to the limited impact of recognized fair values on capital adequacy ratios, with trading and AFS securities accounting for only about 0.2% and 18% of the banks' asset base. Finally, Bischof et al. (2021) find evidence of a beneficial real effect: they find that bank managers are less likely to take corrective actions when regulators allow the losses on AFS investments to be filtered out of capital adequacy ratio calculation.

Our contribution to this literature is twofold. First, while most prior work focuses on recognized fair values of securities with active and liquid markets, we focus on disclosed fair values of loans, which account for most bank assets and whose markets are largely inactive and illiquid. Second, we explore the implications of fair value through the lens of depositors. Our findings suggest that loan fair values can affect banks even without affecting their capital adequacy ratios and even when they reveal little about loan payoffs. These findings are consistent with theoretical predictions on how depositors respond to information signals in the presence of strategic complementarities and lend support to concerns expressed by bank practitioners and regulators about the potential adverse effect of loan fair value information on banking stability.

3. Empirical design

3.1 *Conceptual underpinnings*

To assess the informational relevance of loan fair values, we adopt the specification in prior studies that explore uninsured depositor behavior (e.g., Acharya and Mora, 2015; Chen et al., 2021a,b). This specification is based on a model of deposit flows from Egan, Hortaçsu, and Matvos (2017), in which a bank attracts greater deposit flows when the aggregate demand for deposit claims is higher and when the bank offers greater utility to depositors than competing banks. A depositor's utility from a bank depends on the bank's default risk, deposit rate, and service quality. Default risk depends on the expected cash flows from the bank's assets. Depositors periodically update their views about expected cash flows, and consequently default risk, as they receive measures of bank performance. Thus, deposit growth in any period is affected by new performance signals that update depositors' views about default risk as well as three factors unrelated to default risk, including (i) deposit rate, (ii) service quality, and (iii) aggregate demand for holding deposits.

With the above framework in mind, consider a bank that at $t = 0$ uses deposit financing to invest in a portfolio of loans that will mature and pay $\tilde{\theta}$ at $t = 2$. The initial amount contributed by depositors is based on their information about $\tilde{\theta}$ at $t = 0$, summarized by a normally distributed common prior with mean θ_0 and precision s: $\tilde{\theta} \sim N(\theta_0, \frac{1}{s})$. At $t = 1$, depositors obtain two additional signals about $\tilde{\theta}$: an amortized cost-based signal (*HC)* and a fair value-based signal (*FV*), where $HC = \tilde{\theta} + \tilde{\varepsilon}_h$ with $\tilde{\varepsilon}_h \sim N\left(0, \frac{1}{h}\right)$ and $FV = \tilde{\theta} + \tilde{\varepsilon}_f$ with $\tilde{\varepsilon}_f \sim N\left(0, \frac{1}{f}\right)$.

Depositors update their views about the bank's expected future cash flows to $E^{Dep}(\tilde{\theta}|FV, HC)$ upon observing HC and FV. If $E^{Dep}(\tilde{\theta}|FV, HC)$ is lower (higher) than the prior of θ_0, the depositors would lower (increase) their deposit balance at $t = 1$. Thus, the deposit growth (ΔDEP) at $t = 1$ can be expressed as

$$\Delta DEP = \alpha_0 + \beta\left[E^{Dep}(\tilde{\theta}|FV, HC) - \theta_0\right] + \Gamma X, \quad (1)$$

where $\beta > 0$ represents the sensitivity of the deposit growth to changes in depositors' expectations about the bank's future cash flows. The sensitivity would depend upon depositor characteristics such as risk-aversion.[17] X summarizes the non-default risk-related factors such as service quality that can affect deposit flows.

Using Bayes' rule, depositors' updated beliefs about the bank's expected future cash flows can be expressed as

$$E^{Dep}(\tilde{\theta}|\mathrm{FV}, \mathrm{HC}) = \rho_0\theta_0 + \rho_1 FV + \rho_2 HC, \quad (2)$$

where weights ρ_i reflect the relative precision of each information signal.[18] Substituting (2) into (1), deposit flows can be expressed as

$$\Delta DEP = b_0 + b_1 FV + b_2 HC + \Gamma X, \quad (3)$$

where $b_0 = \alpha_0 + \beta\theta_0(\rho_0 - 1)$, $b_1 = \beta\rho_1$ and $b_2 = \beta\rho_2$.

Eqn. (3) is the motivation for our empirical regression specification. If fair values contain information about the cash-generating of loans (i.e., $\rho_1 > 0$) and if depositors consider that information in forming expectations about default risk, we expect the estimate of the coefficient on FV (i.e., $\widehat{b_1}$) to be significantly different from zero.

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[17] A unit decline in expected cash flows would be more concerning for a depositor with greater risk-aversion, resulting in greater likelihood of withdrawal from such depositors.
[18] Specifically, $\rho_0 = \frac{s}{s+h+f}$, $\rho_1 = \frac{f}{s+h+f}$, and $\rho_2 = \frac{h}{s+h+f}$.

A potential concern is that uninsured depositors are implicitly insured by the government and thus may not care about bank performance. Benston and Kaufman (1997), however, note that FDICA effectively ended the FDIC's policy of protecting uninsured depositors, and they report evidence of increased incidence of FDIC leaving uninsured depositors unprotected in bank failures after 1991. Furthermore, even if uninsured depositors eventually recover their money from a bank failure, they are likely to incur a significant loss of liquidity as it often takes time before they get their money back. For example, the FDIC notes on its website: "Payments of uninsured funds only, called dividends, depend on the net recovered proceeds from the liquidation of the bank's assets and the payment of bank liabilities according to federal statute. While fully insured deposits are paid promptly after the failure of the bank, the disbursements of uninsured funds may take place over several years based on the timing in the liquidation of the failed bank assets."[19]

A related concern is that depositors may lack the sophistication and resources to be attentive to bank performance. Several studies, however, provide evidence of greater deposit withdrawals in banks with poorer performance.[20] This is perhaps not surprising based on survey evidence which suggests that the majority of deposits are held by corporate entities, which (compared to retail depositors) are likely to have greater incentives and resources to monitor bank performance.[21]

[19] See https://www.fdic.gov/consumers/banking/facts/priority.html. To mitigate loss of liquidity to uninsured depositors, FDIC sometimes provides advance payments based on estimates of recovered amounts. Kaufman (2004), however, finds that over the period 1992 to 2002, FDIC offered such advance payments only in 36% of the bank failure resolutions.

[20] See, for example, Gorton (1988), Goldberg and Hudgins (1996), Saunders and Wilson (1996), Calomiris and Mason (1994), Martinez Peria and Schmukler (2001), Egan, Hortaçsu, and Matvos (2017), and Chen et al. (2021a).

[21] 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 the extent corporations have more cash to deposit than consumers, they are likely to account for an even larger portion of uninsured deposits. To our knowledge, this survey is the only public source of data on deposit ownership pattern.

Finally, it is worth emphasizing that our inferences from estimating Eqn. (3) are not affected by the fact that depositors may also glean information from non-accounting sources that are not included in our regression (e.g., analyst reports and conference calls). This is because our objective is to inform the debate on the use of fair value vs. historical cost accounting by examining (i) whether loan fair values *contain* information of relevance to depositors' decision-making and (ii) if yes, whether the information is incremental to what is contained in historical cost-based measures. The objective is not to assess whether the accounting measures (either historical cost-based or fair value-based) are preempted or subsumed by non-accounting information sources. In fact, prior research suggests that information in accounting reports is largely preempted by other timelier information sources, with earnings announcements contributing to only 5%-9% of the total information incorporated in share prices annually (e.g., Ball and Shivakumar, 2008). While this evidence suggests that accounting reports may not be the primary source of *new* information, it does not imply they are redundant. Even without being a timely source of information, accounting reports can add value in many ways, including performing a "confirmatory role" by verifying *ex-post* the truthfulness of other disclosure channels,[22] by providing verifiable performance measures useful for writing contracts, and, in the context of the banking industry, by allowing regulators to implement banking regulation.

3.2 *Empirical regression specification*

We estimate the following empirical counterpart to Eqn. (3):

$$\Delta Dep_{i,t+1}^{u} = \alpha_0 + \beta_1 FVG\&L_{i,t} + \beta_2 ROE_{i,t} + \Gamma X_{i,t} + \varepsilon_{i,t+1}, \qquad (4)$$

[22] See, for example, Gigler and Hemmer (1998), Stocken (2000), Lundholm (2003), and Ball, Jayaraman, and Shivakumar (2012).

where $\Delta Dep_{i,t+1}^{u}$ represents the uninsured deposit flows measured as the change in bank i's uninsured deposit balance over period $t+1$ scaled by assets at the beginning of the period. We measure deposit flows over the two quarters following the end of quarter *t*, for which *ROE* and *FVG&L* are measured to allow 6 months for uninsured deposit flows to respond to quarter *t* information. This is to accommodate the fact that banks file Call Reports and quarterly financial statements with a lag after a quarter ends and that depositors may react with a delay as well (Chen et al., 2021a). [23] We cluster standard errors at the bank level. $X_{i,t}$ is a vector of controls for factors unrelated to bank performance that may also affect deposit flows. We discuss these controls in the next section.

Our main variable of interest is the measure of loan fair value changes: *FVG&L*. We follow Hodder, Hopkins, and Wahlen (2006) and calculate *FVG&L* as the change in the excess of fair value over book value of financial assets net of tax scaled by the beginning value of equity. Because there is no difference in fair value and book value for assets recognized at fair value on the balance sheet (e.g., AFS and trading securities), *FVG&L* includes changes only in unrealized fair-value gains and losses on assets recognized at historical cost (mostly loans) for quarter *t*.[24] We apply 35% as the effective tax rate before 2017 and 21% after 2017. We compute the after-tax measure to be consistent with *ROE* which is based on after-tax net income. A higher *FVG&L* indicates greater (lower) unrealized fair-value gains (losses) for loans bank *i* experiences in period

[23] In untabulated sensitivity tests, we obtain qualitatively similar results when we measure deposit flows over the next quarter.
[24] We calculate *FVG&L* using fair values and books values of total financial assets instead of only loan-related fair values and book values because loan fair value data are not available before 2005 on SNL. This approach allows us to speak to our research question for a much longer time horizon. The measures (*FVG&L*) calculated under the two methods are highly correlated (with a correlation coefficient of 96%) during 2005-2019. Since HTM securities account for only 4% of total assets on average in our sample (versus 67% for loans), the effect of other assets measured at historical cost (mostly HTM securities) on our measure would be negligible. In untabulated robustness tests, we obtain similar results when we restrict our sample period to 2005-2019 and use *FVG&L* based on the fair values and book values of loans.

t and an improvement in bank fundamentals. The coefficient of interest is β_1, which measures the extent to which loan fair value changes contain information relevant to depositors' decisions.

We also include *ROE* in the regression, which captures changes in loan fundamentals based on the historical-cost accounting method.[25] Furthermore, *ROE* captures value creation from non-lending activities. Thus, with both *ROE* and *FVG&L* together in the regression, we comprehensively capture summary signals of asset value changes banks are required to disclose in accounting reports.

3.3 Accounting for non-default risk-related factors

As discussed earlier in Section 3.1, in addition to expected default risk, deposit flows are also affected by (i) deposit rates, (ii) service quality, and (iii) aggregate demand for holding deposit claims. We include control variables based on prior work (Acharya and Mora, 2015; Egan et al., 2017, Chen et al., 2021a,b) to account for these factors.

First, we control for deposit rate. Because Call Reports do not separately report interest expense on insured vs. uninsured deposits, we calculate *Deposit Rate* as the interest expense on total deposits, scaled by the average balance of total deposits. In untabulated analyses, we create separate proxies for deposit rates on uninsured and insured deposits by assuming interest expense on large-time deposits and core deposits corresponds mainly to uninsured and insured deposits, respectively. We find that the rates on large time deposits (core deposits) exhibit a correlation of 88% (99%) with our main *Deposit Rate* variable. Using them instead of *Deposit Rate* leads to virtually no change in our estimates.

[25] Strictly speaking, *ROE* includes unrealized gains and losses on trading/marketable securities. In robustness tests, we separate unrealized gains and losses on trading/marketable securities out from *ROE* and include it along with unrealized gains and losses on AFS securities in the regression. Our results on *FVG&L*, which only captures changes in fair values of HTM investments (primarily loans), are not sensitive to this change.

We include bank-fixed effects and several time-varying controls for bank characteristics to absorb differences in banks' service quality. Specifically following Acharya and Mora (2015) and Chen et al. (2021a), we include six time-varying controls for bank characteristics: (i) the logarithm of asset size (*Ln(Assets)),* (ii) real estate loan share calculated as the amount of loans secured by real estate divided by total assets (*Real Estate Loan*), (iii) capital ratio defined as the book value of capital scaled by total assets (*Capital*), (iv) wholesale funding scaled by total assets (*Wholesale Fund*), (v) the ratio of total unused commitments divided by the sum of total loans and unused commitments (*Unused Commitments*), and (vi) the standard deviation of write-offs over the preceding 12 quarters (*Std Writeoff*).

Finally, we address the effect of shocks to the aggregate demand for holding deposit claims. Such aggregate demand shocks can occur if, for example, consumers conclude that alternative asset classes (e.g., money-market/bond funds or stock markets) will better meet their liquidity/investment needs. Consistent with this, Drechsler, Savov, and Schnabl (2017) and Lin (2020) find that a smaller portion of wealth is allocated to deposits when Treasury securities and stock markets offer higher returns. We include contemporaneous and lagged federal funds rates and the value-weighted market returns to control for these opportunity costs of holding bank deposits.

An alternative approach to control for demand shocks is to use time dummies. However, as explained in Chen et al. (2021a,b), this approach precludes us from studying the depositor response to bank performance changes resulting from common macroeconomic shocks. This is an important issue not only because many important performance swings in the highly cyclical banking industry are systematic, but also because theory shows that depositors' incentive to withdraw before other depositors is expected to be stronger when the performance decline is common to the entire industry than when it is idiosyncratic to the bank.[26] Consistent with this argument, Chen et al. (2021b) show that depositors are nearly 8 times more responsive to systematic than to idiosyncratic *ROE* changes. For completeness, however, we also present the results after augmenting our main specifications with time dummies wherein the estimates are obtained only from idiosyncratic performance changes. We continue to find that fair value changes are informationally relevant, but as expected, with smaller economic magnitudes.

To further allay concerns about imperfect controls, we follow prior work (e.g., Egan et al., 2017; Chen et al., 2021a,b) and contrast our results for uninsured deposit flows with those for insured deposit flows. Because their payoffs are protected by government-backed insurance, insured depositors would not be expected to care about bank performance but are still affected by all other factors, including service quality or aggregate changes in demand for holding deposit claims due to, for example, increased attractiveness of money-market funds. Therefore, if our results for uninsured deposit flows reflect the effect of such omitted factors, we should find similar results for insured deposit flows. As we show later, this is not the case.

4. Data and descriptive statistics

Our sample consists of all public banks in the U.S. from 1994 to 2019. We obtain most bank-level variables from the U.S. Call Reports provided by Wharton Research Data Services (WRDS) for the pre-2014 periods, and from the SNL database for 2014-2019 when WRDS's coverage of Call Reports is incomplete. We obtain bank financial asset fair value disclosures from the SNL database. Except for stand-alone commercial banks that file financial statements, fair

[26] This is because when the entire industry is experiencing poor performance, assets sell at a higher fire-sale discount (Shleifer and Vishny, 1992) and banks are less likely to lend to other banks (Liu, 2016). Therefore, depositors know that in periods of systematic distress banks will have greater difficulty in meeting short-term spikes in deposit withdrawals by accessing interbank markets and/or by liquidating assets. See the model in Goldstein et al. (2020) for a formal illustration of how poor aggregate conditions amplify strategic complementarities.

value data are available only at the bank holding company level. In contrast, Call Reports are available at the commercial bank level, even for banks that belong to a bank holding company. Therefore, for consistency, we aggregate Call Report data to the holding company level for banks that belong to a holding company.[27] For stand-alone commercial banks that file financial statements, we maintain the unit of analysis at the bank level. We merge the Call Report data with the SNL fair value data, yielding a financial-statement-filer level sample consisting of bank holding companies and stand-alone commercial banks that disclose fair value information.[28]

The frequency of data availability differs across banks and periods. Specifically, OTC banks without SEC-registered securities follow the OTC market disclosure guidelines and disclose fair values annually (during the fourth quarter) throughout our sample period. All other banks disclose fair values annually before 2009 and quarterly after 2009. For observations with annual disclosures, we construct their quarterly fair value measures by assuming the annual change occurs evenly throughout the year. In sensitivity analyses (not tabulated), we find that our main results are robust if we use only Q4 data for these observations.

Following common practice in the literature (e.g., Acharya and Mora, 2015; Gatev and Strahan, 2006), we exclude bank-quarter observations with quarterly asset growth greater than 10% to avoid the impact of business combinations. We winsorize all continuous variables at 1% and 99%. Our final sample consists of 43,922 bank-quarter observations, with 1,334 unique banks. Table 1, Panels A and B, present the summary statistics and correlations for the main variables used in our analyses. Panel A shows that both the average and median values of *FVG&L* are small

[27] The alternative is to use data from Y9-C reports filed by bank holding companies (BHC) instead of the Call report data. However, Y9-C does not contain information about insured vs. uninsured deposits. Following prior literature (Goetz, Laeven, and Levine, 2013; Plosser, 2014), we aggregate bank call report data to the holding company level using code RSSD9364 (or RSSD9379 when RSSD9364 is not available) in the Y-9C reports to link bank subsidiaries to the parent BHCs.

[28] This sample structure is consistent with that in prior studies analyzing fair value disclosures (e.g., Cantrell et al., 2014).

and negative, at -0.45% and -0.44%, respectively, while ROE has a mean and median of 9.3% and 10.1%, respectively. The standard deviation of $FVG\&L$, however, is more than 60% larger than that of ROE (13.8% vs. 8.4%).

Consistent with the findings in Chen et al. (2021a), uninsured deposit flows are highly positively correlated with ROE (correlation coefficient = 0.15). They are also positively correlated with changes in loan fair values, albeit at a smaller magnitude of 0.03. Insured deposit flows are negatively correlated with changes in loan fair values (at -0.02).

Panel C of Table 1 provides a preliminary analysis to shed light on the sources of variation in $FVG\&L$. Column (1) shows that observable bank characteristics such as capital ratio, bank size, and asset compositions explain a small amount of variation in $FVG\&L$, with an adjusted R-squared of less than 1%. The inclusion of bank-fixed effects only marginally improves the R-squared, suggesting little time-invariant bank-specific component in $FVG\&L$. These patterns are in contrast with the historical cost-based performance measure ROE, for which time-varying bank characteristics and bank-fixed effects each explain more than 20% of the variations (in columns (4)-(5)). Both $FVG\&L$ and ROE, however, exhibit significant variations over time. The quarter-fixed effects explain about 18% (7%) variations in $FVG\&L$ (ROE). In light of these results, it is not surprising that the correlation between ROE and $FVG\&L$ is only 0.01 (Panel B of Table 1), indicating that $FVG\&L$ contains information (or noise) that is orthogonal to that in ROE.

5. Evidence on decision-relevance of loan fair values to depositors

Table 2, Panel A presents the main results for the associations between uninsured deposit flows and loan fair value changes. Column (1) presents the results from a univariate regression of uninsured deposit flows on $FVG\&L$. Consistent with fair values containing information of relevance to uninsured depositors, the coefficient on $FVG\&L$ is positive and significant

(Coef=0.024; p-value<0.01). In column (2), we include *ROE* as an additional explanatory variable to gauge the extent of information overlap between loan fair value changes and *ROE*. Confirming the informational relevance of *ROE*, the coefficient on *ROE* is positive and significant (Coef=0.167; p-value<0.01). More importantly, after including *ROE,* the coefficient on *FVG&L* only marginally decreases from 0.024 to 0.022 and remains statistically significant (p-value<0.01). This suggests that from the perspective of depositor decision-making, most of the information content of fair value changes is orthogonal to that of *ROE.*

We next assess the informational relevance of *FVG&L* and *ROE* for economically similar banks by first including controls for time-varying bank characteristics (column (3)) and then further augmenting it with bank-fixed effects (column (4)). There is little change in inferences. For example, in column (4), the coefficient on *FVG&L* marginally increases back to the original magnitude of 0.024, and the coefficient on *ROE* declines slightly to 0.147, with both staying significant at less than 1% level.

We present our main specification in column (5), where we add macro-economic controls, i.e., contemporaneous and lagged values of federal funds rates and stock market returns, to account for any shocks to the aggregate demand for holding deposit claims. We find that the coefficient on *FVG&L* increases to 0.027 (p-value<0.01), about 11% higher than the coefficient estimated in column (4) (at 0.024). This result also provides an important, initial insight into the source of informational relevance of fair values: that it does not derive from the fair values' ability to summarize loan-value changes based on market-wide changes in interest rates that are unrelated to loans' credit quality. This result is consistent with the idea that market-wide interest rate changes unrelated to credit quality provide little information about the cash-generating potential of loans, the majority of which are fixed rates and are expected to be held by banks till maturity. We later explore if the informational relevance derives from the information in fair values about changes in loan portfolios' credit quality.

The above results indicate that the informational relevance of fair values is economically meaningful. For example, estimates from our main specification in column (5) indicate that a within-bank one-standard-deviation decline in *FVG&L* is associated with a 0.37% (=0.027*13.52) decrease in uninsured deposit flows, which represents nearly 10% of the sample average. In contrast, a within-bank one-standard-deviation change in *ROE* (at 6.93) results in a change in uninsured deposit flows that is equivalent to 27% of the sample mean.

Lastly, column (6) explores an alternative approach to account for the effect of aggregate demand shocks by including time dummies instead of macroeconomic control variables. Time dummies flexibly absorb the variation in *FVG&L* that results from common macroeconomic changes, and thus the estimates are derived purely from bank-specific idiosyncratic changes. As previously discussed, this is not our preferred specification because many performance changes in the cyclical banking industry are systematic, and also because depositors' incentive to withdraw before other depositors is expected to be stronger when the entire industry is experiencing a performance decline than when the performance shock is idiosyncratic. It can be seen that both *FVG&L* and *ROE* continue to be informationally relevant but, as expected, with smaller economic magnitudes (coefficients = 0.010 and 0.074).

In Table 2, Panel B, we present estimates from specifications that model insured deposit flows. The main objective is to address any residual concerns about the confounding effect of the three non-credit risk-related factors that affect deposit flows (deposit rates, service quality, and aggregate demand shocks). In contrast to our results for uninsured deposit flows, the estimates show that insured deposit flows exhibit a significant negative association with both *FVG&L* and

ROE. The negative association is consistent with prior evidence that poorly performing banks offset a loss of uninsured depositors by attracting insured depositors (e.g., Martin, Puri, and Ufier, 2018; Chen et al., 2021a). More importantly, this finding mitigates concerns about omitted-correlated variables. While insured depositors are not exposed to bank default risk, they should still be affected by deposit rates, service quality, or any aggregate demand shocks unrelated to banks' credit conditions (e.g., better services or lower fees at money-market/bond funds). Therefore, if the coefficients on *FVG&L* in our uninsured deposit regressions simply capture the effect of these other factors, we should have found similar results for insured deposits.

Finally, Table 2, Panel C presents the results of estimating Eqn. (4) separately for small, medium, and large banks. The motivation partly is to check if the "too big to fail" effect eliminates the informational relevance of fair value changes in large banks. Following Beatty and Liao (2011), we classify banks with total assets less than \$500 million (measured in year 2000 dollars) as small banks, banks with total assets more than \$3 billion as large banks, and all other banks as medium banks. Fair value changes are informationally relevant for all bank groups, albeit the coefficients on *FVG&L* decline slightly from 0.030, 0.025, to 0.022 for small, medium, and large banks, respectively. These results are consistent with prior evidence that uninsured depositors are responsive to bank performance even in large banks (e.g., Chen et al., 2021a,b).

6. Can information about loan quality explain fair value relevance for depositors?

Our results thus far provide evidence that loan fair values summarize information relevant to depositor decision-making, and that this information is largely orthogonal to the historical cost-based information about loan value changes contained in *ROE*. In this section, we examine if the informational relevance of loan fair values reflects their information content about the cash-flow generating potential of loan portfolios (i.e., $\tilde{\theta}$ in Section 3.1).

Loan fair values can change when loan credit risk changes or when market-wide interest rate unrelated to credit risk changes. As discussed earlier, our evidence (Table 2, Panel A) suggests that depositors do not find loan fair value changes resulting from market-wide interest rates to be relevant because controlling for these rates leads to little change in the coefficient on *FVG&L*. This is possibly because most loans are held till maturity, and market-rate changes unrelated to credit quality have no bearing on the cash-generating potential of these loans.[29] We now examine if loan fair value changes contain information about loan credit quality (Section 6.1) and if this information can explain their decision relevance for uninsured depositors (Section 6.2).

6.1 Information content of loan fair values for loan credit quality

We examine whether loan fair values contain information about credit quality by estimating various versions of the following regression specification:

$$Future\ Defaults_{[t+h,t+m]} = \gamma_0 + \gamma_1 Performance\ Measure_t + \Gamma X_t + \varepsilon_{[t+h,t+m]} \quad (5)$$

Table 3, Panel A presents the main results from this analysis with average future write-offs over four quarters (i.e., t+1 to t+4) scaled by lagged equity as the dependent variable. Column (1) presents the results with only *FVG&L* as an independent variable to explore its unconditional predictive power. The coefficient on *FVG&L* is statistically insignificant, and the adjusted R^2 is 0.0%. One possibility for this result is that the predictive ability of *FVG&L* for future defaults is impaired by movements in *FVG&L* that result from market-wide interest rate changes unrelated to credit risk. To address this issue, we remove the variation in *FVG&L* that results from market interest rate changes by creating a new variable (*FVG&L_RES*), estimated as the residuals from a regression of *FVG&L* on lagged and contemporaneous federal fund rates. Estimates in column (2)

[29] Kirti (2020) reports that less than 25% of bank loans are floating rate loans. Furthermore, the findings in Drechsler, Savov, and Schnabl (2021) indicate that banks adjust deposit rates to minimize exposure to interest rate risks.

show that *FVG&L_RES* has statistically significant predictive power (Coef=-0.016; p-value<0.01) but with a modest adjusted R^2=0.1%.

For comparison, column (3) presents the results for the unconditional predictive ability of *ROE*. The coefficient on *ROE* is statistically significant (Coef. = -0.291; p-value<0.01) with a much larger adjusted R^2 of 20.6%. However, despite the large explanatory power of *ROE*, column (4) shows that even after controlling for *ROE,* the coefficient estimate on *FVG&L_RES* remains significant with about 75% of the magnitude (-0.012 vs. -0.016 in column (2)). This indicates that most of the information in loan fair values is orthogonal to that in *ROE*. This point is further strengthened in column (5), where we decompose *ROE* and include loan loss provisions (*LLP*)—the component of *ROE* directly relevant for defaults—separately along with earnings before loan loss provisions (*EBLLP*). The adjusted R^2 more than doubles to 45.6% in column (5). Yet, at the same time, the coefficient on *FVG&L_RES* remains significant with a magnitude comparable to that in column (4). Similar inference can be drawn from column (6), where we include the full set of control variables from our deposit flow regressions. In the Appendix (Table A1), we obtain very similar inferences, if instead of write-offs, we use future *LLPs* or changes in *NPL* to measure credit losses. Overall, these results suggest that *FVG&L* has some information content for future defaults, but the economic magnitude, at least relative to *ROE,* is quite modest. [30]

In Table 3, Panel B, we present a similar analysis using future *ROE* as the dependent variable to explore if using a more comprehensive measure that incorporates aspects of

[30] Cantrell et al. (2014) find that the *level* of loan fair values (i.e., a stock variable) has no incremental predictive ability over historical cost-based loan book values. Using the level implicitly assumes that all past loan fair value changes have the same predictive power. We examine the predictive ability of *changes* in loan fair values, which allow for more powerful tests by focusing on the predictive power of the most recent loan fair value changes. Cantrell et al. (2014) also include current write-offs and non-performing loans as independent variables. We find that the coefficient on *FVG&L* remains unchanged when we include these two variables.

performance beyond credit losses increases the information content of $FVG\&L$. We obtain similar inferences.

In the Appendix (Tables A2 and A3), we also explore the relative information content of $FVG\&L$ and ROE over longer horizons up to 3 years in the future. We continue to find evidence of $FVG\&L$ having predictive power that is statically significant but quite modest in magnitude relative to the predictive power of ROE.

Finally, we explore how the information content of loan fair values varies with the degree of liquidity in the secondary market for loans. The objective is to assess the validity of the opponents' argument against fair values, which contends that loan fair values will have little fundamental information content because of the illiquid nature of loan markets. Our measure of the liquidity condition in loan markets comes from Bai, Krishnamurthy, and Weymuller (2018), who create a time-varying liquidity weight (λ_t) for each asset class held by banks. These liquidity weights are designed to capture the amount of cash a bank could raise on an immediate basis by, for example, selling the asset or using it as collateral in repo markets. For liquid assets such as cash or treasury securities, λ would be equal to 1; for loans, it would be less than 1. Bai et al. (2018) calibrate the liquidity weights for bank loans using bid prices from secondary loan markets. The data on liquidity weights from Bai et al. (2018) are available for 2002 to 2015, reducing the sample size for this analysis. Highlighting the illiquidity of loans as an asset class, the average liquidity weights on loans (λ_{loans}) for our sample is 0.75. It also exhibits significant temporal variation with a standard deviation of 0.11.

Table 3, Panel C presents the results for this analysis for both future write-offs (columns (1)-(4)) and ROE (columns (5)-(8)) as dependent variables. Because of the smaller sample for this analysis, we first estimate Eqn. (5) on the subsample of observations where λ_{loans} is not missing.

We include both *FVG&L* and *ROE* in the specifications. Because we present specifications with all control variables (including federal funds rates), the coefficient on *FVG&L* is obtained after controlling for the effect of market-wide interest rate changes. We, therefore, do not need to include *FVG&L_Res* explicitly (like we did in the previous panel) to focus on the predictive ability of loan fair value changes. Columns (1) and (5) of Panel C show that the coefficients and significance levels on *FVG&L* are close to the results in Panel A and B. We next estimate this specification separately for the three terciles of λ_{loans} to assess the impact of the degree of loan market liquidity. As discussed in Section 2.1, although the majority of loan fair values are level 3 estimates, the emphasis on exit values by SFAS 157 and the application of liquidity discount in practice suggest that the fundamental information content of fair values can be affected by market liquidity. Consistent with this conjecture, estimates show that *FVG&L* exhibits no predictive ability in the bottom tercile of λ_{loans}.[31] We obtain similar patterns in untabulated analyses when we examine future performance over longer horizons (up to 12 quarters) and consider alternative measures of credit losses, including future *LLPs* and changes in *NPL*.

Viewed collectively, the above results suggest that loan fair values contain some information for future fundamentals, but the economic magnitude is small. Furthermore, even this small fundamental information content vanishes when the generally illiquid loan markets go through periods of heightened illiquidity.

6.2 Does the information content of loan fair values explain the deposit flow-fair value association?

[31] Panel C also shows a non-linear relation between market liquidity and fair values' predictive ability: the predictive ability is higher in the second tercile of market liquidity than in the top tercile. We are not aware of any theory that predicts such a non-linear relation.

We conduct three complementary analyses to test if the fundamental information content of loan fair values – even if small – can explain the uninsured deposit flow-fair value association. The results are difficult to reconcile with this explanation for the association.

6.2.1 Partition by loan market liquidity

To start, we examine if the association of loan fair values with uninsured deposit flows also manifests in periods of heightened illiquidity in secondary loan markets (i.e., bottom tercile of λ_{loan}) where we earlier found that loan fair values contain virtually no fundamental information. Table 4, Panel A presents estimates of deposit flow regressions separately for periods of low loan market liquidity (where loan fair values contain no fundamental information) and other periods where we found evidence of loan fair values having some fundamental information. *FVG&L* continues to exhibit a significant association (Coef=0.030; p-value<0.01) even in periods of extremely low liquidity. Although the difference between periods is not statistically significant, the coefficient on *FVG&L* in low liquidity periods is nearly 20% greater than the coefficient for other periods (Coef=0.025; p-value<0.01). At the very least, the evidence suggests that factors beyond the fundamental information content of *FVG&L* are playing an important role.

6.2.2 Controlling for future realizations of fundamentals

Second, we explore the association between loan fair values and uninsured deposit flows after controlling for the future cash-generating ability of banks' loan portfolios. If the association between uninsured deposit flows and *FVG&L* is primarily driven by the information in *FVG&L* about loan quality, then the coefficient on *FVG&L* should attenuate or even become insignificant when we control for *ex-post* realizations of future performance in our deposit flow regressions. In spirit, this test is akin to the Mishkin (1983) test used in accounting literature to assess whether equity investors' reactions can be justified based on the fundamental information content of earnings numbers. Kraft, Leone, and Wasley (2007) show that the Mishkin test can be equivalently conducted by estimating linear regressions after controlling for future fundamentals.[32]

Table 4, Panel B presents the detailed estimation results. As a benchmark, in column (1), we reproduce the main result from Table 2, Panel A using the most comprehensive specification wherein the coefficients on *FVG&L* and *ROE* equal 0.027 and 0.139, respectively. In column (2), we control for the average future write-offs and *ROE* for the next 4 quarters. While the coefficient on *ROE* declines by nearly 81% (from 0.139 to 0.027), the coefficient on *FVG&L* decreases by only 15% (from 0.027 to 0.023). This is consistent with our earlier finding that *FVG&L* contains little information content for loan performance over the next 4 quarters relative to *ROE*. The result also suggests that the information content of *FVG&L* for loan performance over the next 4 quarters cannot explain the bulk (nearly 85%) of its association with uninsured deposit flows.

We next explore if accounting for the information content over longer horizons can explain the association. Because requiring data for future write-offs and *ROE* for up to 12 quarters reduces the sample size, in column (3), we first replicate the result in column (2) on the smaller sample where future write-offs and *ROE* for up to 12 quarters are not missing. The coefficients on *FVG&L* and *ROE* are 0.024 and 0.034. Column (4) shows that including controls for average write-offs and *ROE* for 2 additional future years (for a total of 3 years) only marginally reduces the magnitude of the coefficient on *FVG&L* from 0.024 to 0.022. Finally, column (5) also includes controls for average *LLPs* and changes in *NPL* for each of the three future years to allow for the possibility that write-offs and *ROE* may not fully capture the information in loan fair values. The coefficient on *FVG&L* remains unchanged at 0.022. Overall, the results suggest that while fundamental information content can account for a significant portion (81%) of the association of *ROE* with

[32] See, also, Lewellen (2010) for a detailed elaboration of the assumptions and trade-offs of this test.

uninsured deposit flows, the bulk (about 85%) of the association of loan fair values remains unexplained.

6.2.3 Weight on loan fair values relative to historical cost-based accounting measures

In our third and final analysis, we triangulate the above inferences using an alternative approach to assess whether the weight uninsured depositors put on *FVG&L* reflects its fundamental information content. To see the rationale for this test, recollect from Section 3.1 that a rational (Bayesian) depositor would make a forecast of banks' future fundamentals ($\tilde{\theta}$) using Eqn. (2) as follows: $E^{Dep}\left(\tilde{\theta}\middle|\mathrm{FV},\mathrm{HC}\right)=\rho_0\theta_0+\rho_1 FV+\rho_2 HC,$ where the weights on FV ($\rho_1 = \frac{f}{s+h+f}$) and HC ($\rho_2 = \frac{h}{s+h+f}$) reflect the precision of the signals relative to the total precision of all information available to the Bayesian forecaster. Our test is based on the observation that if depositors make withdrawal decisions based only on the fundamental information content of *FVG&L*, then the weight ρ_1 should also reflect in the uninsured deposit flow specification. This can be seen more clearly from Eqn. (3) from Section 3.1, which lays out how Bayesian weights ρ_i relate to withdrawal decisions: $\Delta DEP = b_0 + b_1 FV + b_2 HC + \Gamma X$, where, $b_1 = \beta\rho_1$ and $b_2 = \beta\rho_2$. Thus, conceptually, an empirical estimate of weight on information in *FV* from Eqn. (2) – i.e., the forecasting equation – should equal the estimate of the *implied* weight on information in *FV* from Eqn. (3) – the deposit flow equation, with both weights being equal to $\rho_1 = \frac{f}{s+h+f}$.

We estimate the information weights from the forecasting equation using OLS estimates of the empirical counterpart of Eqn. (2):

$$\theta_{t+h} = a_0 + a_1 FV_t + a_2 HC_t + \Gamma\mathrm{X} + \tilde{\eta}, \quad (6)$$

Where θ_{t+h} represent *ex post* realizations of future fundamentals measured over different horizons; X represents control variables included to ensure the weights are derived from observationally similar banks. Under standard assumptions for consistency of OLS estimates, $\widehat{a_1} \rightarrow \rho_1$ and $\widehat{a_2} \rightarrow \rho_2$, where $\rightarrow$ denotes asymptotic convergence.

One complication with this test is that we cannot estimate the implied weights on information in *FV* from the deposit flow equation: As Eqn. (3) illustrates, the coefficient on *FV* does not estimate ρ_1 but $\beta\rho_1$. As discussed in Section 3.1, β captures depositors' sensitivity to changes in default risk and would depend on factors such as depositors' risk aversion. Thus, to separately identify the information weight on *FV*, we would need to make additional assumptions about depositor characteristics that determine β. To avoid this problem, instead of focusing on the absolute weight on *FV*, we design our test using weight on *FV* relative to the weight on *HC*, which does not depend on β. Specifically, Eqn. (3) shows that the ratio of the coefficient estimates on *FV* and *HC* from the deposit flow equation, $\frac{\hat{b}_1}{\hat{b}_2} \rightarrow \frac{\rho_1}{\rho_2} = \frac{\rho_1}{\rho_2} = \frac{f}{h}$, does not depend on β and simply reflects the ratio of the precision of the information in *FV* and *HC*. Similarly, Eqn. (6) shows that the ratio of coefficient estimates on *FV* and *HC* from the forecasting equation $\frac{\hat{a}_1}{\hat{a}_2} \rightarrow \frac{\rho_1}{\rho_2} = \frac{f}{h}$. Thus, under the null hypothesis that depositors' decisions are based on fundamental information content of *FV* and *HC*, we would expect $\frac{\hat{a}_1}{\hat{a}_2} = \frac{\hat{b}_1}{\hat{b}_2}$. And, $\frac{\hat{b}_1}{\hat{b}_2} > (<) \frac{\hat{a}_1}{\hat{a}_2}$ would indicate that the weights depositors put on *FV* relative to *HC* is higher (lower) than what is justifiable based on the information content of *FV* relative to *HC*.

Table 4, Panel C provides the results of this test. Column (1) reproduces the results from column (5) of Table 2, Panel A, which models our main specification for uninsured deposit flows. The ratio of the coefficients on *FVG&L* and *ROE* (i.e., $\frac{\hat{b}_1}{\hat{b}_2}$) is 0.197. Columns (2) and (3) present the results from OLS estimates of the forecasting equation (6) with *Future Writeoff* and *Future ROE* over the next four quarters as the dependent variables. The ratio of the two coefficient estimates (i.e., $\frac{\hat{a}_1}{\hat{a}_2}$) is about 0.04 in both columns, which is about 20% of the ratio obtained in column (1). The differences in the ratios are also statistically significant at less than 1% level. Consistent with our earlier inferences, these results suggest that the weight depositors puts on loan fair values relative to historical cost-based accounting measures is more than justifiable based purely on the information content of fair values for loan quality.

7. Role of strategic complementarities

In our final set of analyses, we explore if the concern for other depositors' behaviors due to banks' liquidity mismatch can explain the decision relevance of loan fair values despite the limited fundamental information content. A major portion of bank assets are illiquid (e.g., loans), which banks primarily finance using highly liquid liabilities such as deposits. As a result, a bank does not have enough liquid resources to repay all depositors if they withdraw at once. This generates strategic complementarities in depositors' payoffs in that a depositor would want to immediately withdraw her money when she fears other depositors will withdraw too and the bank will run out of resources. Thus, in the presence of strategic complementarities, a depositor's view of default risk is shaped not only by the cash-generating potential of banks' assets (i.e., loan quality) but also by her expectations of other depositors' actions. Theory shows that this can cause depositors to react strongly to public signals even with little to no fundamental content.[33] This multiplier effect emerges because of the dual role a public signal serves in the presence of strategic complementarities: the signal updates depositors not only about banks' asset quality but also about the actions of other depositors.

[33] See Morris and Shin (2002) and Angeletos and Pavan (2004) for this prediction in general settings and Goldstein and Pauzner (2005) and Vives (2014) for this prediction in the case of bank depositors. For an exploration of strategic complementarities outside the context of depositors, see Plantin, Sapra, and Shin (2008), who examine the pros and cons of fair values when bank managers are concerned about the negative valuation consequences of loan liquidation decisions by other banks.

The arguments made by critics suggest that loan fair value declines stemming from loan market illiquidity could be quite relevant in amplifying such concerns about withdrawals by other depositors even if these declines carry little information about the prospects of loans: such loan fair value declines indicate banks' exposure to loan-market illiquidity and thus can raise concerns about banks' ability to raise immediate cash to meet a large mass of withdrawals.

To test for this possibility, we follow recent empirical work that documents the importance of strategic complementarities in various financial institutions, including banks (see footnote 9 for citations). Specifically, we examine if the relevance of loan fair values is stronger in banks where uninsured depositors' payoffs exhibit greater strategic complementarities.

We use two approaches to measure the strength of strategic complementarities. The first is the measure from Berger and Bouwman (2009), labeled *CATFAT,* which captures the extent of liquidity mismatch on a bank's balance sheet, i.e., the extent to which banks employ short-term, liquid funding sources to invest in illiquid, long-term assets.[34] When a bank has a high liquidity mismatch, the short-term liquidation value of its (primarily illiquid) assets may not be enough to meet the immediate demand for liquidity from its large base of short-term claimholders. This in turn gives its depositors stronger incentives to withdraw early when they expect others to do so. Second, we exploit variation in strategic complementarities that result from differences across banks in their mix of uninsured and insured depositors. All else equal, an uninsured depositor would have lower (higher) incentive to withdraw early when she knows that more (fewer) of the remaining depositors have less incentive to withdraw early because they are covered by deposit insurance.

[34] We refer readers to Chen et al. (2021b) for a simple example to illustrate the intuition and construction of *CATFAT*. This example is replicated in the Online Appendix for reference.

We estimate deposit flow regressions in which we allow all coefficient estimates to vary across the terciles of either *CATFAT* or the percentage of uninsured deposits (*%Uninsured*). Table 5 presents the results from this analysis. Columns (1)-(3) show that the coefficient on *FVG&L* increases monotonically from the bottom to the top tercile of *CATFAT*, with the coefficients being statistically significant in each tercile. The magnitude of the amplification is striking: uninsured deposit flows are nearly 2.5 times more sensitive to a unit change in *FVG&L* at a bank in the top tercile of *CATFAT* than a bank in the bottom tercile, and the difference in sensitivity is significant (p-value<0.05).[35] We obtain similar inferences when we use *%Uninsured* to measure the strength of strategic complementarities in columns (4)-(6): The sensitivity of uninsured deposit flows to loan fair value changes in the top tercile of *%Uninsured* is again nearly 2.5 times that of the sensitivity in the bottom tercile.

8. Conclusion

Using a large sample of U.S. commercial banks from 1994 to 2019, we provide the first large sample evidence on the decision-relevance of disclosed loan fair values for bank depositors. Consistent with loan fair values summarizing information of relevance to depositors, we find a significant association between loan fair value changes and uninsured deposit flows. The information content of loan fair values for credit quality accounts for only a small portion of the association. We also find that the association manifests primarily in banks where depositors' incentives to withdraw money before other depositors (i.e., strategic complementarities) are stronger. Our findings are consistent with theoretical predictions that strategic complementarities

[35] As in Chen et al. (2021b), we also find that the uninsured deposit flows are more sensitive to *ROE* in banks with a higher level of liquidity mismatch as measured by *CATFAT*, indicating that strategic complementarities also explain some of the relevance of *ROE* to depositors. This result reconciles our finding in Table 4, Panel B that uninsured deposit flows exhibit some sensitivity to *ROE* (although the magnitude is significantly smaller) even after we explicitly control for future fundamentals.

in depositors' payoffs can make them respond strongly to information signals with little fundamental information content and lend support to concerns about the destabilizing effect of information contained in loan fair values on banks.

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Appendix: Variable Definitions

	Definitions	**Sources**
$FVG\&L_{i,t}$	Change in unrealized fair-value gains or losses on financial assets (in %, annualized). Calculated as the change in the excess of fair value over book value of financial assets net of tax scaled by beginning equity. We apply a tax rate of 35% before 2017 and 21% after 2017. When fair value data is available on a quarterly basis on SNL, $FVG\&L_{i,t}$ for bank i in quarter t is calculated as: $[(Fair\ Value\ of\ Assets_{i,t} - Book\ Value\ of\ Assets_{i,t}) - (Fair\ Value\ of\ Assets_{i,t-1} - Book\ Value\ of\ Assets_{i,t-1})]/Equity_{i,t-1} * 400\% * (1 - Tax\ Rate_t)$. When fair value data is available on an annual basis on SNL, $FVG\&L_{i,t}$ for bank i in quarter t of year T is calculated as: $[(Fair\ Value\ of\ Assets_{i,T} - Book\ Value\ of\ Assets_{i,T}) - (Fair\ Value\ of\ Assets_{i,T-1} - Book\ Value\ of\ Assets_{i,T-1})]/Equity_{i,T-1} * 100\% * (1 - Tax\ Rate_t)$. Fair value and book value of financial assets are obtained from SNL.	SNL
$ROE_{i,t}$	ROE in quarter t (in %, annualized): $Net\ Income_{i,t}/Equity_{i,t-1} * 400\%$. Net income: RIAD4300, adjust year-to-date reporting to within quarter. Equity: RCFD3210.	Call Reports[36]
$Std\ Writeoff_{i,t}$	Standard deviation of write-off to lagged equity ratio over quarter t-11 through quarter t. Loan write-offs: RIAD4635, adjust year-to-date reporting to within quarter. Equity: RCFD3210.	Call Reports
$Capital_{i,t}$	Equity to asset ratio. Equity: RCFD3210. Total assets: RCFD2170.	Call Reports
$Wholesale\ Fund_{i,t}$	Wholesale funds divided by total assets. Wholesale funds: RCON2604+RCFN2200+RCFD3200+RCFD2800 (RCONB993+RCFDB995 from 2002q1)+RCFD3190. Total assets: RCFD2170.	Call Reports
$Real\ Estate\ Loan_{i,t}$	Loans secured by real estate divided by total assets. Loans secured by real estate: RCFD1410. Total assets: RCFD2170.	Call Reports
$Ln(Assets)_{i,t}$	Log of total assets (RCFD2170).	Call Reports
$Unused\ Commitment_{i,t}$	Unused commitments divided by the sum of loans and unused commitments. Unused commitments: RCFD3814 + RCFD3816 + RCFD3817 + RCFD3818 + RCFD6550 + RCFD3411. Total loans: RCFD1400.	Call Reports

[36] We first aggregate Call Report data to financial-statement-filer level and then compute the variables for analyses. See Section 4.

$\Delta Dep^{I}_{i,t+1}$	Change in insured deposits from quarter *t* to *t+2* as a percentage of total assets (in %, annualized): $(Insured\ Deposits_{i,t+2} - Insured\ Deposits_{i,t})/Asset_{i,t} * 200\%$. Insured deposits: RCON2702 (before 2006Q2); RCONF049 + RCONF045 (from 2006Q2). Total assets: RCFD2170.	Call Reports
$\Delta Dep^{U}_{i,t+1}$	Change in uninsured deposits from quarter *t* to *t+2* as a percentage of total assets (in %, annualized). Uninsured deposits: RCFD2200 – insured deposits.	Call Reports
$Deposit\ Rate_{i,t}$	Average interest rate on total deposits over the two quarters *t*, *t+1* (in %, annualized): $(Deposit\ interest\ expense\ in\ Qtr\ t\ and\ t+1)/(Avg.deposit\ balance\ in\ Qtr\ t\ and\ t+1)\ ) * 400\%)$. Deposit quarterly interest expense: RIADA517 (RIAD4174 before 1997Q1) + RIAD4508 + RIAD0093 (RIAD4509 + RIAD4511 before 2001Q1) + RIADA518 (RIAD4512 before 1997Q1), adjust year-to-date reporting to within quarter. Deposit balance: RCONA514 (RCON3345 before 1997Q1)+ RCON3485 + RCONB563 (RCON3486 + RCON3487 before 2001Q1) + RCONA529 (RCON3469 before 1997Q1).	Call Reports
$CatFat_{i,t}$	The preferred liquidity creation measure ("cat fat") per Berger and Bouwman (2009) divided by gross total assets ("GTA"). "cat fat" and "GTA" are first aggregated to the financial-statement-filer level.	https://sites.google.com/a/tamu.edu/bouwman/data
$\%Uninsured_{i,t}$	Ratio of uninsured deposits to total deposits.	Call Reports
$Future\ Writeoff_{[t+h,t+m]}$	Average write-off to lagged equity ratio over quarters *t+h* through *t+m*.	Call Reports
$Future\ ROE_{[t+h,t+m]}$	Average *ROE* over quarters *t+h* through *t+m*.	Call Reports
$Market\ Return_{i,t}$	Average value-weighted return (include distributions) in quarter *t*.	CRSP
$Market\ Return_{i,t+1}$	Sum of average value-weighted return (include distributions) in quarter *t+1* and quarter *t+2* to match the period over which deposit flows are measured.	CRSP
$Fed\ Funds\ Rate_{i,t}$	Average federal funds rate in quarter *t*.	WRDS
$Fed\ Funds\ Rate_{i,t+1}$	Sum of average federal funds rate in quarter *t+1* and quarter *t+2* to match the period over which deposit flows are measured.	WRDS
$FVG\&L\_RES_{i,t}$	Residuals from a regression of *FVG&L* on $Fed\ Funds\ Rate_{i,t}$ and $Fed\ Funds\ Rate_{i,t+1}$.	N/A
$LLP_{i,t}$	Scaled LLP in quarter *t* (in %, annualized): $LLP_{i,t}/Equity_{i,t-1} * 400\%$. LLP: RIAD4230, adjust year-to-date reporting to within quarter. Equity: RCFD3210.	Call Reports
$EBLLP_{i,t}$	Difference between $ROE_{i,t}$ and $LLP_{i,t}$.	N/A
λ_{loans}	Liquidity weights for loans from Bai, Krishnamurthy, and Weymuller (2018).	http://www.jenniebai.com/data.html
$Future\ LLP_{[t+h,t+m]}$	Average LLP to lagged equity ratio over quarters *t+h* through *t+m*.	Call Reports
$Future\ \Delta NPL_{[t+h,t+m]}$	Average change in NPL to lagged equity ratio over quarters *t+h* through *t+m*. NPL (non-performing loans): RCFD1403+RCFD1407.	Call Reports

Table 1: Summary Statistics

This table presents summary statistics (Panel A) and correlation table (Panel B) for our main variables. These statistics are calculated over the regression sample. To avoid the impact of business acquisitions, we exclude bank-quarter observations with quarterly asset growth greater than 10%. We define all variables in the Appendix.

Panel A: Summary Statistics

VARIABLES	N	Mean	SD	P25	P50	P75
$\Delta Dep^{U}_{i,t+1}$	43,922	3.61	9.99	-0.82	2.84	7.60
$FVG\&L_{i,t}$	43,922	-0.45	13.75	-5.33	-0.44	4.78
$ROE_{i,t}$	43,922	9.29	8.35	6.73	10.11	13.72
$Deposit\ Rate_{i,t}$	43,922	2.18	1.40	0.96	1.91	3.31
$Std\ Writeoff_{i,t}$	43,922	3.11	4.62	0.68	1.46	3.30
$Capital_{i,t}$	43,922	0.10	0.02	0.08	0.10	0.11
$Wholesale\ Fund_{i,t}$	43,922	0.08	0.07	0.03	0.07	0.12
$Real\ Estate\ Loan_{i,t}$	43,922	0.51	0.14	0.41	0.51	0.61
$Ln(Assets)_{i,t}$	43,922	6.77	1.40	5.78	6.51	7.50
$Unused\ Commitment_{i,t}$	43,922	0.17	0.07	0.12	0.16	0.20
$Market\ Return_{i,t}$	43,922	1.56	3.81	0.05	2.45	3.46
$Fed\ Funds\ Rate_{i,t}$	43,922	4.18	4.25	0.30	2.45	8.44
$CatFat_{i,t}$	37,277	0.38	0.15	0.27	0.38	0.48
$\%Uninsured_{i,t}$	43,922	0.36	0.15	0.25	0.34	0.46
$\Delta Dep^{I}_{i,t+1}$	43,922	4.06	10.52	-1.09	1.74	5.81
$Future\ ROE_{[t+1,t+4]}$	43,922	9.05	8.39	6.82	9.98	13.47
$Future\ Writeoff_{[t+1,t+4]}$	43,922	3.38	5.35	0.68	1.64	3.54
λ_{loans}	25,870	0.75	0.11	0.63	0.69	0.87

Panel B: Pearson Correlation

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	$\Delta Dep^{U}_{i,t+1}$	1.00																
2	*FVG&L*$_{i,t}$	**0.03**	1.00															
3	*ROE*$_{i,t}$	**0.15**	*0.01*	1.00														
4	*Deposit Rate*$_{i,t}$	**0.03**	**0.08**	**0.18**	1.00													
5	*Std Writeoff*$_{i,t}$	**-0.09**	0.00	**-0.35**	**-0.12**	1.00												
6	*Capital*$_{i,t}$	**0.03**	0.00	**-0.13**	**-0.27**	**-0.14**	1.00											
7	*Wholesale Fund*$_{i,t}$	**-0.01**	0.00	**0.07**	**0.15**	**-0.11**	**-0.17**	1.00										
8	*Real Estate Loan*$_{i,t}$	**0.02**	0.00	**-0.14**	**-0.06**	**0.02**	**0.07**	-0.01	1.00									
9	*Ln(Assets)*$_{i,t}$	*-0.01*	**-0.02**	**0.14**	**-0.19**	**-0.10**	**0.10**	**0.33**	**-0.17**	1.00								
10	*Unused Commitment*$_{i,t}$	**0.13**	0.00	**0.15**	**-0.10**	**-0.12**	**0.01**	**0.02**	**-0.23**	**0.35**	1.00							
11	*Market Return*$_{t}$	**-0.13**	**-0.08**	0.00	**-0.14**	**0.07**	**0.02**	**-0.08**	**-0.03**	0.01	**-0.02**	1.00						
12	*Fed Funds Rate*$_{t}$	**0.06**	0.01	**0.32**	**0.80**	**-0.16**	**-0.24**	**0.08**	**-0.18**	**-0.10**	**0.05**	**-0.05**	1.00					
13	*Future ROE*$_{[t+1,t+4]}$	**0.18**	0.01	**0.68**	**0.12**	**-0.28**	**-0.16**	**0.04**	**-0.17**	**0.13**	**0.14**	**0.06**	**0.29**	1.00				
14	*Future Writeoff*$_{[t+1,t+4]}$	**-0.20**	0.00	**-0.45**	**0.03**	**0.47**	**-0.17**	**0.05**	**0.03**	**0.05**	**-0.11**	**-0.03**	**-0.12**	**-0.61**	1.00			
15	*CatFat*$_{i,t}$	**0.13**	-0.01	**-0.03**	**-0.29**	**0.06**	**0.08**	**-0.16**	**0.37**	**0.22**	**0.50**	**-0.02**	**-0.20**	**-0.05**	**0.06**	1.00		
16	*%Uninsured*$_{i,t}$	**0.10**	0.00	**0.09**	**-0.07**	**-0.13**	**0.04**	**0.04**	**-0.11**	**0.23**	**0.43**	**-0.06**	**0.02**	**0.05**	**-0.05**	**0.41**	1.00	
17	$\Delta Dep^{I}_{i,t+1}$	**-0.06**	**-0.02**	0.00	**0.10**	**-0.11**	**0.04**	**0.01**	**0.08**	**-0.04**	**0.05**	**0.09**	**0.03**	**-0.02**	*-0.01*	**0.06**	**0.12**	1.00

Correlation coefficient in bold: p-value < 0.01
Correlation coefficient in italics: p-value < 0.05

Panel C: FVG&L (ROE) and bank characteristics

This table presents the association between *FVG&L* (*ROE*) and bank characteristics. We define all variables in the Appendix. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) $FVG\&L_{i,t}$	(2) $FVG\&L_{i,t}$	(3) $FVG\&L_{i,t}$	(4) $ROE_{i,t}$	(5) $ROE_{i,t}$	(6) $ROE_{i,t}$
Deposit Rate$_{i,t}$	0.910***	1.525***	-0.117	0.802***	0.320***	-0.646***
	(17.415)	(17.134)	(-0.669)	(11.823)	(4.336)	(-4.490)
Std Writeoff$_{i,t}$	0.035**	0.105***	0.008	-0.619***	-0.603***	-0.512***
	(2.013)	(4.324)	(0.390)	(-19.141)	(-18.249)	(-16.203)
Capital$_{i,t}$	14.368***	21.060***	-6.737	-60.263***	-29.726***	-24.374***
	(5.172)	(3.593)	(-1.382)	(-11.225)	(-4.064)	(-3.804)
Wholesale Fund$_{i,t}$	-1.098	-0.646	-3.233*	-6.572***	-3.022	0.744
	(-1.120)	(-0.336)	(-1.916)	(-4.072)	(-1.533)	(0.360)
Real Estate Loan$_{i,t}$	0.158	-0.614	-1.179	-4.537***	-1.193	5.224***
	(0.343)	(-0.511)	(-1.041)	(-5.415)	(-0.855)	(3.763)
Ln(Assets)$_{i,t}$	0.007	0.858***	-0.266	0.810***	-2.186***	-0.200
	(0.137)	(3.690)	(-1.127)	(8.071)	(-8.654)	(-0.583)
Unused Commitment$_{i,t}$	1.229	-2.831	0.760	7.172***	17.613***	11.936***
	(1.298)	(-1.311)	(0.399)	(3.868)	(6.005)	(3.974)
Observations	43,922	43,892	43,892	43,922	43,892	43,892
Adjusted R-squared	0.007	0.015	0.195	0.200	0.401	0.471
Bank FE	N	Y	Y	N	Y	Y
Quarter FE	N	N	Y	N	N	Y

Table 2: Sensitivity of Deposit Flows to Changes in Loan Fair Values

Panel A: Uninsured Deposit Flows

This table presents ordinary least-squares estimates of Eqn. (4) for uninsured deposit flows. The dependent variable is the change in the uninsured deposits scaled by the beginning value of total assets. We define all variables in the Appendix. Column (1) presents the results from a univariate regression of uninsured deposit flows on *FVG&L*. Column (2) includes *ROE* as an additional explanatory variable. Columns (3)-(6) add controls for time-varying bank characteristics. Column (4)-(6) further include bank-fixed effects, column (5) contemporaneous and lagged federal funds rates and stock market returns, and column (6) quarter-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) $\Delta Dep^U_{i,t+1}$	(2) $\Delta Dep^U_{i,t+1}$	(3) $\Delta Dep^U_{i,t+1}$	(4) $\Delta Dep^U_{i,t+1}$	(5) $\Delta Dep^U_{i,t+1}$	(6) $\Delta Dep^U_{i,t+1}$
$FVG\&L_{i,t}$	0.024***	0.022***	0.021***	0.024***	0.027***	0.010***
	(5.528)	(5.317)	(5.046)	(5.921)	(6.833)	(2.842)
$ROE_{i,t}$		0.167***	0.157***	0.147***	0.139***	0.074***
		(15.452)	(13.991)	(13.349)	(12.665)	(7.759)
$Deposit\ Rate_{i,t}$			0.111*	-0.805***	-1.343***	0.565***
			(1.913)	(-10.832)	(-9.672)	(3.391)
$Std\ Writeoff_{i,t}$			-0.059***	-0.105***	-0.086***	-0.084***
			(-3.301)	(-5.088)	(-4.378)	(-4.594)
$Capital_{i,t}$			23.940***	58.115***	58.160***	63.342***
			(4.982)	(9.229)	(9.406)	(10.624)
$Wholesale\ Fund_{i,t}$			0.872	12.281***	9.844***	23.535***
			(0.744)	(6.789)	(5.446)	(12.251)
$Real\ Estate\ Loan_{i,t}$			3.854***	6.635***	5.769***	10.458***
			(5.825)	(4.941)	(4.291)	(7.768)
$Ln(Assets)_{i,t}$			-0.552***	-4.590***	-4.751***	-6.041***
			(-6.682)	(-16.496)	(-17.238)	(-16.428)
$Unused\ Commitment_{i,t}$			21.072***	22.661***	19.326***	17.318***
			(12.333)	(9.105)	(7.558)	(6.392)
$Market\ Return_t$					-0.271***	
					(-15.222)	
$Market\ Return_{t+1}$					-0.413***	
					(-24.111)	
$Fed\ Funds\ Rate_t$					-1.063***	
					(-7.199)	
$Fed\ Funds\ Rate_{t+1}$					0.672***	
					(10.907)	
Observations	43,922	43,922	43,922	43,892	43,892	43,892
Adjusted R-squared	0.001	0.021	0.044	0.137	0.162	0.298
Bank FE	N	N	N	Y	Y	Y
Quarter FE	N	N	N	N	N	Y

Panel B: Insured Deposit Flows

This table presents ordinary least-squares estimates of Eqn. (4) for insured deposit flows. The dependent variable is the change in the insured deposits scaled by the beginning value of total assets. We define all variables in the Appendix. Column (1) presents the results from a univariate regression of insured deposit flows on *FVG&L*. Column (2) includes *ROE* as an additional explanatory variable. Column (3)-(6) add controls for time-varying bank characteristics. Column (4)-(6) further include bank-fixed effects, column (5) contemporaneous and lagged federal funds rates and stock market returns, and column (6) quarter-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) $\Delta Dep^{I}_{i,t+1}$	(2) $\Delta Dep^{I}_{i,t+1}$	(3) $\Delta Dep^{I}_{i,t+1}$	(4) $\Delta Dep^{I}_{i,t+1}$	(5) $\Delta Dep^{I}_{i,t+1}$	(6) $\Delta Dep^{I}_{i,t+1}$
$FVG\&L_{i,t}$	-0.012**	-0.012**	-0.019***	-0.018***	-0.012***	-0.003
	(-2.520)	(-2.519)	(-4.199)	(-3.925)	(-2.774)	(-0.735)
$ROE_{i,t}$		0.000	-0.056***	-0.084***	-0.060***	0.015
		(0.009)	(-5.126)	(-7.376)	(-5.321)	(1.421)
$Deposit\ Rate_{i,t}$			0.897***	0.282***	2.395***	1.036***
			(14.224)	(3.637)	(17.023)	(6.128)
$Std\ Writeoff_{i,t}$			-0.222***	-0.233***	-0.257***	-0.214***
			(-11.199)	(-9.403)	(-10.407)	(-9.226)
$Capital_{i,t}$			21.753***	55.713***	62.259***	55.565***
			(4.598)	(7.212)	(7.927)	(7.907)
$Wholesale\ Fund_{i,t}$			1.560	18.218***	20.137***	19.308***
			(1.356)	(9.227)	(9.960)	(9.273)
$Real\ Estate\ Loan_{i,t}$			6.845***	11.188***	11.840***	5.456***
			(10.447)	(7.973)	(8.393)	(3.779)
$Ln(Assets)_{i,t}$			-0.376***	-3.459***	-3.563***	-5.562***
			(-5.319)	(-12.621)	(-12.244)	(-13.885)
$Unused\ Commitment_{i,t}$			14.666***	15.021***	21.391***	19.548***
			(10.013)	(5.892)	(8.249)	(7.649)
$Market\ Return_{t}$					0.148***	
					(7.868)	
$Market\ Return_{t+1}$					0.341***	
					(18.710)	
$Fed\ Funds\ Rate_{t}$					-1.205***	
					(-7.543)	
$Fed\ Funds\ Rate_{t+1}$					-0.089	
					(-1.318)	
Observations	43,922	43,922	43,922	43,892	43,892	43,892
Adjusted R-squared	0.000	0.000	0.039	0.106	0.134	0.263
Bank FE	N	N	N	Y	Y	Y
Quarter FE	N	N	N	N	N	Y

Panel C: Sensitivity of Uninsured Deposit Flows to Loan Fair Value Changes by Bank Asset Size

This table presents ordinary least-squares estimates of Eqn. (4) for the subsample of small, medium, and large banks, respectively. We classify banks with total assets less than $500 million (measured in year 2000 dollars) as small banks, banks with total assets more than $3 billion as large banks, and all other banks as medium banks. All regressions include the control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) Small $\Delta Dep^U_{i,t+1}$	(2) Medium $\Delta Dep^U_{i,t+1}$	(3) Large $\Delta Dep^U_{i,t+1}$
$FVG\&L_{i,t}$	0.030***	0.025***	0.022**
	(4.596)	(4.253)	(2.493)
$ROE_{i,t}$	0.092***	0.169***	0.206***
	(6.084)	(10.621)	(7.511)
Deposit Rate$_{i,t}$	-1.774***	-1.362***	-1.232***
	(-8.821)	(-6.787)	(-3.476)
Std Writeoff$_{i,t}$	-0.072**	-0.082***	-0.124**
	(-2.348)	(-2.891)	(-2.305)
Capital$_{i,t}$	74.341***	45.552***	23.789*
	(7.634)	(4.611)	(1.786)
Wholesale Fund$_{i,t}$	15.042***	9.820***	5.455
	(4.599)	(3.643)	(1.459)
Real Estate Loan$_{i,t}$	10.119***	3.831*	2.179
	(5.248)	(1.773)	(0.501)
Ln(Assets)$_{i,t}$	-6.830***	-4.090***	-3.802***
	(-12.466)	(-9.126)	(-7.004)
Unused Commitment$_{i,t}$	18.708***	15.577***	9.968*
	(4.839)	(4.295)	(1.783)
Market Return$_t$	-0.278***	-0.261***	-0.268***
	(-9.612)	(-9.755)	(-6.873)
Market Return$_{t+1}$	-0.447***	-0.404***	-0.313***
	(-17.096)	(-16.595)	(-7.208)
Fed Funds Rate$_t$	-0.665***	-0.970***	-0.908**
	(-3.136)	(-4.653)	(-2.257)
Fed Funds Rate$_{t+1}$	0.583***	0.631***	0.555***
	(5.917)	(7.060)	(3.565)
Observations	19,853	17,386	6,625
Adjusted R-squared	0.195	0.180	0.134
Bank FE	Y	Y	Y

Table 3: Predictive Ability of Loan Fair Value Changes for Future Fundamentals

Panel A: Predictive Ability of Loan Fair Value Changes for Future Write-offs

This table presents ordinary least-squares estimates of Eqn. (5). The dependent variable is the average write-off to lagged equity ratio over quarters t+1 through t+4. We define all variables in the Appendix. Column (1)-(3) explore the ability of *FVG&L, FVG&L_RES,* and *ROE* to predict future write-offs, respectively. Column (4) regresses future write-offs on *FVG&L_RES* and *ROE*. Column (5) regresses future write-offs on *FVG&L_RES, LLP,* and *EBLLP*. Column (6) includes the full set of control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) *Future Writeoff* *[t+1,t+4]*	(2) *Future Writeoff* *[t+1,t+4]*	(3) *Future Writeoff* *[t+1,t+4]*	(4) *Future Writeoff* *[t+1,t+4]*	(5) *Future Writeoff* *[t+1,t+4]*	(6) *Future Writeoff* *[t+1,t+4]*
$FVG\&L_{i,t}$	0.001					
	(0.368)					
$FVG\&L\_RES_{i,t}$		-0.016***		-0.012***	-0.010***	-0.009***
		(-5.884)		(-5.575)	(-5.566)	(-5.842)
$ROE_{i,t}$			-0.291***	-0.290***		
			(-21.086)	(-21.077)		
$LLP_{i,t}$					0.492***	0.272***
					(23.915)	(14.754)
$EBLLP_{i,t}$					-0.078***	-0.089***
					(-8.353)	(-10.290)
Observations	43,922	43,922	43,922	43,922	43,922	43,892
Adjusted R-squared	-0.000	0.001	0.206	0.207	0.456	0.601
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Panel B: Predictive Ability of Loan Fair Value Changes for Future ROE

This table presents ordinary least-squares estimates of Eqn. (5). The dependent variable is the average future *ROE* over four quarters (i.e., t+1 to t+4). We define all variables in the Appendix. Columns (1)-(3) explore the ability of *FVG&L, FVG&L_RES,* and *ROE* to predict future *ROE,* respectively. Column (4) regresses future *ROE* on *FVG&L_RES* and *ROE*. Column (5) regresses future *ROE* on *FVG&L_RES, LLP,* and *EBLLP*. Column (6) includes the full set of control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) Future $ROE_{[t+1,t+4]}$	(2) Future $ROE_{[t+1,t+4]}$	(3) Future $ROE_{[t+1,t+4]}$	(4) Future $ROE_{[t+1,t+4]}$	(5) Future $ROE_{[t+1,t+4]}$	(6) Future $ROE_{[t+1,t+4]}$
$FVG\&L_{i,t}$	0.004					
	(0.974)					
$FVG\&L\_RES_{i,t}$		0.026***		0.018***	0.017***	0.018***
		(6.239)		(5.649)	(5.629)	(6.571)
$ROE_{i,t}$			0.685***	0.684***		
			(53.610)	(53.585)		
$LLP_{i,t}$					0.601***	0.208***
					(21.083)	(7.347)
$EBLLP_{i,t}$					0.662***	0.371***
					(46.302)	(24.706)
Observations	43,922	43,922	43,922	43,922	43,922	43,892
Adjusted R-squared	0.000	0.002	0.465	0.466	0.467	0.592
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Panel C: Predictive Ability of Loan Fair Value Changes for Future Fundamentals by Degree of Liquidity in Loan Markets

Panel C explores how the predictive ability of loan fair value changes varies with the degree of liquidity in loan markets. Columns (1)-(4) (Columns (5)-(8)) examine the predictive ability of loan fair value changes for future write-offs (future *ROE*). We perform the analyses on the sample where the liquidity weights on loans (λ_{loans}) from Bai, Krishnamurthy, and Weymuller (2018) are not missing. Columns (1) and (5) estimate Eqn. (5) for this sample. We then sort bank-quarter observations into terciles by λ_{loans} and estimate the same regressions for each tercile. Columns (2)-(4) and columns (6)-(8) present the results for each tercile. All regressions include the control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) *Future Writeoff* *[t+1,t+4]*	(2) *Future Writeoff* *[t+1,t+4]*	(3) *Future Writeoff* *[t+1,t+4]*	(4) *Future Writeoff* *[t+1,t+4]*	(5) *Future ROE* *[t+1,t+4]*	(6) *Future ROE* *[t+1,t+4]*	(7) *Future ROE* *[t+1,t+4]*	(8) *Future ROE* *[t+1,t+4]*
Sort by λ_{loans}	Full Sample	High market liquidity	Moderate market liquidity	Low market liquidity	Full Sample	High market liquidity	Moderate market liquidity	Low market liquidity
$FVG\&L_{i,t}$	-0.009***	-0.007**	-0.024***	0.001	0.021***	0.020***	0.038***	0.003
	(-3.680)	(-2.157)	(-4.927)	(0.464)	(5.246)	(3.317)	(4.472)	(0.648)
$ROE_{i,t}$	-0.266***	-0.157***	-0.164***	-0.150***	0.431***	0.335***	0.277***	0.202***
	(-24.956)	(-8.369)	(-10.029)	(-11.501)	(24.928)	(9.652)	(10.890)	(9.099)
Observations	25,844	9,170	8,080	8,510	25,844	9,170	8,080	8,510
Adjusted R-squared	0.579	0.537	0.568	0.764	0.596	0.669	0.585	0.727
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 4: Does Loan Fair Value Relevance Reflect Fundamental Information Content

Panel A: Loan Fair Value Relevance during Low Liquidity Periods

This table examines whether the association of loan fair values with uninsured deposit flows manifests in periods of low liquidity in secondary loan markets (i.e., bottom tercile of λ_{loan}) where we in Table 3, Panel C find no evidence of fundamental information content. All regressions include control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) $\Delta Dep^{U}_{i,t+1}$	(2) $\Delta Dep^{U}_{i,t+1}$
Sort by λ_{loans}	Low liquidity periods	Other periods
$FVG\&L_{i,t}$	0.030***	0.025***
	(3.813)	(3.668)
$ROE_{i,t}$	0.053***	0.098***
	(3.438)	(5.853)
Observations	25,844	
Adjusted R-squared	0.259	
Control variables	Y	
Bank FE	Y	
Difference in *FVG&L*	0.005	
	(0.464)	

Panel B: Controlling for Future Fundamentals

This table presents estimates from Eqn. (4) after controlling for future fundamentals. Column (1) replicates the main result from column (5) of Table 2, Panel A. In column (2), we control for the average future write-offs and *ROE* for the next 4 quarters. Column (3) replicates the result in column (2) on the smaller sample where future write-offs and *ROE* for up to 12 quarters are not missing. Column (4) presents the results for controlling for future write-offs and *ROE* for up to 12 quarters. Column (5) adds controls for average *LLPs* and changes in *NPL* for each of the 3 future years. All regressions include control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) $\Delta Dep^U_{i,t+1}$	(2) $\Delta Dep^U_{i,t+1}$	(3) $\Delta Dep^U_{i,t+1}$	(4) $\Delta Dep^U_{i,t+1}$	(5) $\Delta Dep^U_{i,t+1}$
$FVG\&L_{i,t}$	0.027***	0.023***	0.024***	0.022***	0.022***
	(6.833)	(5.742)	(5.242)	(4.882)	(4.873)
$ROE_{i,t}$	0.139***	0.027**	0.034***	0.034***	0.032**
	(12.665)	(2.482)	(2.724)	(2.724)	(2.522)
$Future\ Writeoff_{[t+1,t+4]}$		-0.202***	-0.198***	-0.129***	-0.171***
		(-7.810)	(-6.761)	(-4.562)	(-3.902)
$Future\ ROE_{[t+1,t+4]}$		0.140***	0.143***	0.097***	0.112***
		(7.902)	(6.844)	(4.566)	(4.684)
$Future\ Writeoff_{[t+5,t+8]}$				-0.146***	-0.196***
				(-5.250)	(-4.622)
$Future\ Writeoff_{[t+9,t+12]}$				-0.051*	-0.024
				(-1.823)	(-0.603)
$Future\ ROE_{[t+5,t+8]}$				0.014	0.016
				(0.790)	(0.816)
$Future\ ROE_{[t+9,t+12]}$				0.009	-0.002
				(0.588)	(-0.092)
$Future\ LLP_{[t+1,t+4]}$					0.046
					(0.897)
$Future\ LLP_{[t+5,t+8]}$					0.026
					(0.665)
$Future\ LLP_{[t+9,t+12]}$					-0.019
					(-0.558)
$Future\ \Delta NPL_{[t+1,t+4]}$					0.011
					(0.903)
$Future\ \Delta NPL_{[t+5,t+8]}$					-0.041***
					(-3.601)
$Future\ \Delta NPL_{[t+9,t+12]}$					-0.010
					(-0.914)
Observations	43,892	43,892	35,961	35,961	35,961
Adjusted R-squared	0.162	0.180	0.184	0.189	0.190
Control variables	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y

Panel C: Relative Weights Depositors Place on Fair Values and Historical Cost-based Measures

This table examines whether depositors' weights on loan fair values and historical cost-based accounting measure are consistent with the Bayesian weights by testing if the ratio of the coefficient on *FVG&L* to that on *ROE* (*FVG&L/ROE*) from estimating Eqn. (4) is the same as that from estimating Eqn. (6). Column (1) presents the ratio (*FVG&L/ROE*) from estimating Eqn. (4) for uninsured deposit flows. Columns (2) and (3) present the ratio (*FVG&L/ROE*) from estimating Eqn. (6) for predicting future write-offs and future *ROE*, respectively. In columns (2) and (3), we also present the differences in the ratios (*FVG&L/ROE*) between columns (1) and (2) and between columns (1) and (3) and the corresponding chi-squared statistics. A statistically significant positive value would indicate the predictive ability of loan fair value changes explains some, but not the entirety, of the uninsured deposit flows' response to fair values. All regressions include control variables and bank-fixed effects. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

VARIABLES	(1) $\Delta Dep^{U}_{i,t+1}$	(2) *Future Writeoff*$_{[t+1,t+4]}$	(3) *Future ROE*$_{[t+1,t+4]}$
FVG&L$_{i,t}$	0.027***	-0.010***	0.018***
	(6.833)	(-5.530)	(6.522)
ROE$_{i,t}$	0.139***	-0.246***	0.443***
	(12.665)	(-23.212)	(29.616)
Observations	43,892	43,892	43,892
Adjusted R-squared	0.162	0.535	0.586
Control variables	Y	Y	Y
Bank FE	Y	Y	Y
FVG&L/ROE	0.197***	0.039***	0.041***
(Chi-squared)	(56.2)	(51.6)	(82.3)
Differences in FVG&L/ROE		0.158***	0.156***
(Chi-squared)		(26.4)	(25.6)

Table 5: Loan Fair Value Relevance and Strategic Complementarities

This table explores whether the sensitivity of uninsured deposit flows to loan fair value changes we document varies with the degree of strategic complementarities. We sort bank-quarter observations into terciles by *CatFat* in columns (1)-(3) and by *%Uninsured* in columns (4)-(6), and estimate Eqn. (4) for uninsured deposit flows for each tercile. We also present the differences in the coefficients on *FVG&L* between the highest tercile and the lowest tercile and the corresponding t-statistics in columns (2) and (5). All regressions include the control variables and bank-fixed effects, and all coefficient estimates are allowed to vary by subsamples. *, **, and *** represent statistical significance (two-sided) at the 10%, 5%, and 1% level, respectively. T-statistics calculated using standard error estimates clustered at the bank level are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable		$\Delta Dep_{i,t+1}^{U}$			$\Delta Dep_{i,t+1}^{U}$	
		Sort by CatFat			Sort by %Uninsured	
	Tercile 3	Tercile 2	Tercile 1	Tercile 3	Tercile 2	Tercile 1
$FVG\&L_{i,t}$	0.045***	0.021***	0.018***	0.037***	0.015**	0.015***
	(4.800)	(2.761)	(2.614)	(3.784)	(2.129)	(3.977)
$ROE_{i,t}$	0.211***	0.108***	0.083***	0.228***	0.121***	0.052***
	(11.235)	(7.163)	(4.376)	(8.619)	(7.237)	(4.023)
Observations		39,211			43,892	
Adjusted R-squared		0.176			0.182	
Control variables		Y			Y	
Bank FE		Y			Y	
Quarter FE		N			N	
Difference in *FVG&L* T3-T1		0.027**			0.022**	
		(2.307)			(2.127)	

Online Appendix

Table A1: Robustness to Choices of Future Fundamental Variables

This table presents the robustness of our main results to different choices of future fundamental variables. All other specifications are the same as their counterparts shown in the main draft.

Panel A: Predictive Ability of Loan Fair Value Changes for Future LLP

VARIABLES	(1) Future LLP $_{[t+1,t+4]}$	(2) Future LLP $_{[t+1,t+4]}$	(3) Future LLP $_{[t+1,t+4]}$	(4) Future LLP $_{[t+1,t+4]}$	(5) Future LLP $_{[t+1,t+4]}$	(6) Future LLP $_{[t+1,t+4]}$
$FVG\&L_{i,t}$	0.007***					
	(2.737)					
$FVG\&L\_RES_{i,t}$		-0.019***		-0.016***	-0.014***	-0.012***
		(-6.177)		(-5.860)	(-6.042)	(-5.892)
$ROE_{i,t}$			-0.247***	-0.246***		
			(-19.506)	(-19.504)		
$LLP_{i,t}$					0.560***	0.345***
					(32.616)	(17.504)
$EBLLP_{i,t}$					-0.027***	-0.057***
					(-3.747)	(-6.201)
Observations	43,922	43,922	43,922	43,922	43,922	43,892
Adjusted R-squared	0.000	0.002	0.141	0.142	0.393	0.517
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Panel B: Predictive Ability of Loan Fair Value Changes for Future Changes in ΔNPL

VARIABLES	(1) Future $\Delta NPL_{[t+1,t+4]}$	(2) Future $\Delta NPL_{[t+1,t+4]}$	(3) Future $\Delta NPL_{[t+1,t+4]}$	(4) Future $\Delta NPL_{[t+1,t+4]}$	(5) Future $\Delta NPL_{[t+1,t+4]}$	(6) Future $\Delta NPL_{[t+1,t+4]}$
$FVG\&L_{i,t}$	0.011***					
	(2.897)					
$FVG\&L\_RES_{i,t}$		-0.022***		-0.023***	-0.023***	-0.017***
		(-5.121)		(-5.335)	(-5.300)	(-4.562)
$ROE_{i,t}$			0.072***	0.073***		
			(5.736)	(5.807)		
$LLP_{i,t}$					0.187***	0.131***
					(6.405)	(4.059)
$EBLLP_{i,t}$					0.104***	0.061***
					(7.688)	(4.139)
Observations	43,922	43,922	43,922	43,922	43,922	43,892
Adjusted R-squared	0.000	0.001	0.006	0.007	0.010	0.200
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Table A2: Robustness to Future ROE over Longer Horizons

This table presents the robustness of our main results to predicting future *ROE* over longer horizons. All other specifications are the same as their counterparts shown in the main draft.

Panel A: Predictive Ability of Loan Fair Value Changes for Future ROE over Quarters t+5 to t+8

VARIABLES	(1) Future $ROE_{[t+5,t+8]}$	(2) Future $ROE_{[t+5,t+8]}$	(3) Future $ROE_{[t+5,t+8]}$	(4) Future $ROE_{[t+5,t+8]}$	(5) Future $ROE_{[t+5,t+8]}$	(6) Future $ROE_{[t+5,t+8]}$
$FVG\&L_{i,t}$	-0.006*					
	(-1.708)					
$FVG\&L\_RES_{i,t}$		0.025***		0.019***	0.019***	0.021***
		(5.834)		(4.908)	(4.946)	(6.324)
$ROE_{i,t}$			0.501***	0.500***		
			(30.668)	(30.649)		
$LLP_{i,t}$					0.531***	0.065**
					(14.077)	(1.996)
$EBLLP_{i,t}$					0.508***	0.190***
					(26.096)	(11.324)
Observations	40,050	40,050	40,050	40,050	40,050	40,021
Adjusted R-squared	0.000	0.001	0.224	0.225	0.225	0.494
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Panel B: Predictive Ability of Loan Fair Value Changes for Future ROE over Quarters t+9 to t+12

VARIABLES	(1) Future $ROE_{[t+9,t+12]}$	(2) Future $ROE_{[t+9,t+12]}$	(3) Future $ROE_{[t+9,t+12]}$	(4) Future $ROE_{[t+9,t+12]}$	(5) Future $ROE_{[t+9,t+12]}$	(6) Future $ROE_{[t+9,t+12]}$
$FVG\&L_{i,t}$	-0.005					
	(-1.327)					
$FVG\&L\_RES_{i,t}$		0.008**		0.004	0.005	0.008**
		(2.068)		(1.203)	(1.358)	(2.537)
$ROE_{i,t}$			0.343***	0.343***		
			(19.200)	(19.200)		
$LLP_{i,t}$					0.524***	0.039
					(13.884)	(1.130)
$EBLLP_{i,t}$					0.392***	0.083***
					(19.123)	(4.516)
Observations	36,001	36,001	36,001	36,001	36,001	35,972
Adjusted R-squared	0.000	0.000	0.100	0.100	0.105	0.471
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Table A3: Robustness to Future Write-offs over Longer Horizons

This table presents the robustness of our main results to predicting future write-offs over longer horizons. All other specifications are the same as their counterparts shown in the main draft.

Panel A: Predictive Ability of Loan Fair Value Changes for Future Write-offs over Quarters t+5 to t+8

VARIABLES	(1) *Future Writeoff* $_{[t+5,t+8]}$	(2) *Future Writeoff* $_{[t+5,t+8]}$	(3) *Future Writeoff* $_{[t+5,t+8]}$	(4) *Future Writeoff* $_{[t+5,t+8]}$	(5) *Future Writeoff* $_{[t+5,t+8]}$	(6) *Future Writeoff* $_{[t+5,t+8]}$
$FVG\&L_{i,t}$	0.007***					
	(2.939)					
$FVG\&L\_RES_{i,t}$		-0.023***		-0.020***	-0.018***	-0.016***
		(-7.450)		(-7.400)	(-7.037)	(-7.156)
$ROE_{i,t}$			-0.211***	-0.210***		
			(-14.558)	(-14.565)		
$LLP_{i,t}$					0.413***	0.196***
					(18.554)	(9.981)
$EBLLP_{i,t}$					-0.044***	-0.068***
					(-4.373)	(-6.607)
Observations	40,050	40,050	40,050	40,050	40,050	40,021
Adjusted R-squared	0.000	0.003	0.094	0.096	0.238	0.483
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Panel B: Predictive Ability of Loan Fair Value Changes for Future Write-offs over Quarters t+9 to t+12

VARIABLES	(1) *Future Writeoff* $_{[t+9,t+12]}$	(2) *Future Writeoff* $_{[t+9,t+12]}$	(3) *Future Writeoff* $_{[t+9,t+12]}$	(4) *Future Writeoff* $_{[t+9,t+12]}$	(5) *Future Writeoff* $_{[t+9,t+12]}$	(6) *Future Writeoff* $_{[t+9,t+12]}$
$FVG\&L_{i,t}$	0.005**					
	(2.188)					
$FVG\&L\_RES_{i,t}$		-0.016***		-0.015***	-0.014***	-0.011***
		(-6.018)		(-5.810)	(-5.299)	(-4.948)
$ROE_{i,t}$			-0.114***	-0.114***		
			(-8.520)	(-8.513)		
$LLP_{i,t}$					0.318***	0.120***
					(13.266)	(5.712)
$EBLLP_{i,t}$					0.003	-0.033***
					(0.232)	(-2.901)
Observations	36,001	36,001	36,001	36,001	36,001	35,972
Adjusted R-squared	0.000	0.001	0.025	0.026	0.087	0.464
Control variables	N	N	N	N	N	Y
Bank FE	N	N	N	N	N	Y

Figure B1: Examples for calculating the Berger and Bouwman measure of bank liquidity creation

		Bank A		Bank B		Bank C	
	Weight (a)	$ amount (b)	$ liquidity created (c=a*b)	$ amount (b)	$ liquidity created (c=a*b)	$ amount (b)	$ liquidity created (c=a*b)
Assets							
Cash	-0.5	0	0	100	-50	0	0
Residential loan	0	100	0	0	0	100	0
Commercial loan	0.5	200	100	200	100	200	100
Liquidity creation on asset side (LC_A)			100		50		100
Liabilities and Equities							
Demand deposits	0.5	200	100	200	100	100	50
Equity	-0.5	100	-50	100	-50	200	-100
Liquidity creation on liability side (LC_L)			50		50		-50
Total Liquidity Created (LC_A+LC_L)			150		100		50
Scaled by total assets (*CatFat*)			0.5		0.33		0.17

To calculate *CatFat*, Berger and Bouwman first classify each category of bank activity (both on and off-balance sheet) into liquid, semi-liquid, or illiquid, and then assign a weight to each. They assign a weight of 1/2 to each dollar of illiquid assets (e.g., commercial loans) and liquid liabilities (e.g., demand deposits), zero to semi-liquid assets (e.g., residential loans) and liabilities (e.g., time deposits), and -1/2 to liquid assets (cash) and illiquid liabilities (debt) and equities. Banks's liquidity creation or *CatFat* is the weighted sum of all the items. The idea is that a bank creates liquidity (i.e., exposes itself to liquidity mismatch) when it transforms liquid liability into illiquid loans, and destroys liquidity when it uses illiquid funding to purchase liquid assets.

Figure B1 provides a simple illustration of the Berger and Bouwman liquidity creation score for three hypothetical banks of the same size (total assets of $300). It shows that bank A invests more in illiquid loans and less in cash than bank B, so it creates more liquidity on the asset sides ($100 vs. $50). At the same time, both banks have the same funding structure and thus create the same amount of liquidity at $50 on the liability side. In total, bank A creates more liquidity (at $150) than bank B (at $100) and therefore is more liquidity mismatched, which is reflected by its higher *CatFat* per unit of total asset (0.5 vs. 0.33). Similarly, between bank B and C, while bank C holds the same assets as bank A and therefore creates more liquidity on the asset side than bank B, it relies on more stable, illiquid equity funding than bank B such that its *CatFat* score is lower than that of bank B (0.17 vs. 0.33), indicating that it is less liquidity mismatched than bank B.