Liquidity Transformation and Fragility in the US Banking Sector *

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This Draft: February 2021

Abstract: We provide the first large-scale evidence that liquidity transformation by banks creates fragility, as uninsured depositors face an incentive to withdraw money before others (a so-called panic run). Such fragility manifests itself in stronger sensitivity of deposit flows to bank performance. The fragility is stronger when the aggregate conditions in the banking system deteriorate. Multiple analyses show that depositors' motives are not driven purely by fundamentals, but reflect an element of panic. We analyze the tradeoff banks face when setting their level of liquidity transformation, and show how they use deposit insurance to mitigate some of its negative effects.

JEL Classification: G21; M40

Key Words: Liquidity transformation; Bank runs; Strategic complementarity

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***** We benefited from comments by participants at Boston College, Chinese University of Hong Kong, Columbia Burton Conference, Dartmouth Summer Conference, Federal Reserve Board, Shanghai University of Finance and Economics, the 2nd Sun Yat-Sen University and Geneva Finance Research Institute Finance International Conference, Villanova University, University of Utah, Wuhan University, and Yale Accounting Summer Conference.

1. Introduction

One of the key functions of banks is liquidity transformation. Banks hold illiquid assets, such as loans and illiquid securities, and finance themselves with highly liquid liabilities, such as demand deposits and other forms of short-term debt. This liquidity transformation is thought to play a critical role in the economy, allowing the financing of long-term illiquid investments, while satisfying the demand for liquid money-like assets by investors. At the same time, such liquidity transformation can make banks inherently fragile: they do not hold sufficient liquid assets at all times to meet the immediate withdrawal demands by all depositors. This fragility can lead to runs, whereby depositors rush to withdraw their money from the bank only because they fear others will do the same and the bank will run out of resources. Such fears can then become self-fulfilling outcomes, so called panic-based runs.

The possibility of panic-based runs has been the foundation behind government policies enacted to alleviate banking fragility over the years, and shaping the banking industry to this day, such as deposit insurance or lender of last resort. The classic view goes back to Bagehot (1873) and has been thoroughly analyzed in recent years by Diamond and Dybvig (1983), Rochet and Vives (2004), Keister (2016), and Allen, Carletti, Goldstein, and Leonello (2018), among others. Yet, despite the long-lasting impact of these ideas on government policies, empirical evidence that clearly links depositors' behavior to liquidity mismatch-driven panic is hard to find in the literature. The goal of this paper is to provide such empirical evidence. We do so using a large sample of U.S. commercial banks over the period 1993-2016.

Our empirical analysis is guided by theories linking the degree of liquidity mismatch on banks' balance sheet to depositors' withdrawals through the channel of panic-based runs (e.g., Goldstein and Pauzner, 2005; Chen, Goldstein, and Jiang, 2010; Vives, 2014). In these theories, banks' liquidity mismatch creates strategic complementarities in depositors' payoffs which increase depositors' incentive to withdraw when they expect that other depositors will withdraw. Depositors make decisions based on signals they receive about the bank's fundamental strength. Due to strategic complementarities, these signals affect depositors' behavior not only because they update about the fundamentals of the bank, but also because they update about what other depositors know and what they are going to do. The key prediction that we take to the data is that the sensitivity of depositors' flows to news about bank performance will be stronger when the bank has a greater liquidity mismatch on its balance sheet and so depositors face stronger strategic complementarities.

Why is this type of analysis appropriate to provide a test of the panic-based-run channel?[1] The idea is that if withdrawals were purely based on fundamentals with no element of panic (as in theories of fundamental-based runs, e.g., Chari and Jagannathan, 1988; Jacklin and Bhattacharya, 1988; Allen and Gale, 1998), there would be no reason for the sensitivity of deposit flows to bank performance to increase in the level of liquidity mismatch (we address a key concern below). The panic manifests itself by increasing the sensitivity of flows to performance, due to the added element of depositors using the performance to form expectations about what other depositors will do. This type of analysis was first introduced to the literature for equity mutual funds in Chen, Goldstein, and Jiang (2010), and a variant of the model they provide applies to our setting. Similar analysis has been followed later in the context of money-market mutual funds in Schmidt, Timmerman, and Wermers (2016), corporate-bond mutual funds in Goldstein, Jiang, and Ng (2017), and Life-Insurance industry in Foley-Fisher, Narajabad, and Verani (2020). We are the first to conduct such analysis for banks, which is arguably where fragility has been most prominent over the years, and where it affected government policies most strongly.

We start our analysis with a basic diagnostic of the relation between uninsured deposit flows and bank performance (measured by the return on equity, *ROE*), and find that they are positively related. Interestingly, the relation appears to be non-linear, with uninsured deposits responding strongly to *ROE* for much of the range of the *ROE* distribution, but weakly for either

[1] Since the word "panic" may mean different things to different people, we note that its meaning here reflects the way it has been used in the bank-run literature, which often distinguishes between "panic-based" runs and "fundamentals-based" runs (see, e.g., Goldstein, 2013). Hence, panic does not reflect anything irrational, but rather it is group behavior leading to an inferior outcome, which is not fully justified by fundamentals, and is attributed to a coordination failure.

very high or very low realizations of *ROE*. This S-shaped relation is consistent with the Goldstein and Pauzner (2005) model of bank runs that combines fundamentals and panics as sources of runs and guides our analysis. Specifically, when the fundamentals are very high or very low, they are sufficient to determine the fate of the bank regardless of depositors' behavior. Hence, only in the intermediate range, where depositors' behavior is critical for determining the fate of the bank, the sensitivity of flows to performance is amplified through the channel of using bank performance as a signal on what other depositors will do.

We then move to our main analysis of the panic-run channel, inspecting the impact of bank liquidity mismatch on depositors' response to bank performance. We build on the liquidity mismatch measure (*CatFat*) from Berger and Bouwman (2009). The *CatFat* measure is designed to capture the extent to which banks employ short-term liquid funding sources to invest in illiquid long-term assets. We provide a detailed description of this measure and its use in our analysis in Section 2.[2] Our main result is to show large differences in depositors' response to bank performance across banks with different levels of liquidity mismatch. Quantitatively, a one standard deviation increase in liquidity mismatch would increase the sensitivity of uninsured deposit flows to an average bank's *ROE* by 20%. As mentioned above, these results indicate an element of panic in uninsured depositors' flows: depositors respond to bank performance not just because of its direct implications but also because of how it might affect the behavior of other depositors. Interestingly, we see these patterns in small, medium, and large banks.

An important dimension of the analysis involves the difference between insured and uninsured deposit flows. As deposit insurance is known to be one of the key tools used against panic runs, one would not expect insured depositors to care about the degree of liquidity mismatch on the bank's balance sheet. Indeed, we find that the results above are unique to uninsured deposit

[2] An alternative recent measure that builds on *CatFat* is the *LMIRisk* measure form Bai et al. (2018). This measure differs from *CatFat* by incorporating changes that happen over time in the liquidity of assets and liabilities based on changes in market conditions. As we discuss in detail in the paper, this measure is problematic for our purpose, because the same forces that change the liquidity conditions in the market can both affect and be affected by depositors' behaviors.

flows, and do not hold for insured deposit flows. But, our results go beyond that to establish stark differences between insured and uninsured deposits. Recent evidence suggests that banks attempt to deal with the fragility of their uninsured depositor base by actively attracting insured depositors in times of poor performance (Martin, Puri, and Ufier, 2018; Chen, Goldstein, Huang, and Vashishtha, 2020). Consistent with this, we find that the sensitivity of insured deposit flows to bank performance is in fact negatively related to the extent of liquidity mismatch. Hence, banks are actively utilizing deposit insurance to manage volatility in uninsured deposits caused by liquidity mismatch.

A key concern about our main result is that uninsured depositors respond more strongly to performance signals when liquidity mismatch is high, not because of the implications for the behavior of other uninsured depositors, but because high liquidity mismatch is correlated with the informativeness of the performance signal. In particular, this would be the case if banks with greater liquidity mismatch invested in assets with greater performance persistence, and so, for them, a given shock in *ROE* would lead to a larger revision in perceived value of bank assets. We address this concern with two different analyses. First, we show that our results do not significantly change after we control for the persistence of the bank's *ROE*. Second, we show that the effect of asset illiquidity on the sensitivity of deposit flow to performance gets stronger as the bank is financed with a higher fraction of uninsured deposits or when a higher fraction of the liabilities can be more easily and less costly withdrawn.[3] This analysis speaks directly to the strategic complementarity and panic elements in uninsured depositors' behavior: They care about asset illiquidity when they know that more of the other liabilities might be withdrawn either because they are uninsured or because they carry lower incentives to stay in the bank.

When thinking about bank fragility, the worry, heightened by the events of the 2008-2009 financial crisis, is mostly about the systemic fragility. Linking to the analysis conducted in our paper, it is thus important to ask whether deposit flows respond mostly to idiosyncratic or systematic shocks and to what extent strategic complementarities within a bank are magnified by systematic weaknesses. Decomposing banks' *ROE* into a systematic component and an

[3] Here, we follow the Berger and Bouwman (2009) measure of liability side liquidity creation.

idiosyncratic component, we show that uninsured deposits are more sensitive to the former than the latter. Furthermore, the sensitivity to *ROE* at banks with high liquidity mismatch is coming mostly from the systematic *ROE*. Moreover, we use the financial crisis of 2008 as a laboratory to observe the performance and response of banks with different levels of liquidity mismatch during an unexpected crisis episode. We find that during the crisis, banks with greater liquidity mismatch exhibit a greater erosion in their deposit base despite offering higher rates, lower growth in credit, and higher failure rates. Together, these results demonstrate how strategic complementarities within a bank are amplified by poor aggregate conditions; a feature shown in a recent model by Goldstein, Kopytov, Shen, and Xiang (2020). The incentive to run before others would be greater when depositors know that the bank will have greater difficulty in meeting short-term spikes in deposit withdrawals by accessing interbank markets and/or by liquidating assets. 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 others (Liu, 2016).[4]

Finally, we provide some basic tests to explore the implications of the above findings for different bank outcomes. Conditional on experiencing outflows, banks with greater liquidity mismatch see greater decline in future performance. This is consistent with the basic mechanism behind the panic run, as outflows are more damaging when the bank provides more liquidity transformation. We also find that unconditionally, liquidity mismatch is associated with stronger future performance after controlling for bank risk. This is consistent with the view that banks overall create value by performing liquidity transformation. Yet, liquidity mismatch comes with significant risks. In particular, it has strong predictive power for future bank failure. An interquartile increase in bank's liquidity mismatch is associated with a 6% increase in failure chance over the next 3 years. Collectively, these results highlight that liquidity transformation is a

[4] The sample used in this version ends in 2016, and so does not cover the more recent Covid-19 crisis. We intend to extend the sample and include this episode as well. However, emerging accounts of this crisis seem to suggest that the banking sector did not experience much turmoil so far, as the turmoil centered in the non-bank sectors.

double-edged sword in that it allows banks to earn higher profits at the cost of heightened fragility and failure risk.

Our paper is related to prior empirical work on bank runs. Many early studies focused on establishing a strong negative association between bank performance and consequent banking crises to argue that bank runs seem to be driven by fundamentals and not by panic (see, e.g., Gorton, 1988; Demirguc-Kunt and Detragiache, 1998, 2002; Schumacher, 2000). However, as argued by Goldstein (2013), this interpretation is problematic, since panic manifests itself empirically as a multiplier effect by amplifying depositors' response to bad news about bank fundamentals when strategic complementarities are strong. In this paper, we use exactly this insight to identify the effect of panic on bank deposit withdrawals.

There are several recent papers attempting to evaluate the forces behind bank runs empirically. Among them, Iyer and Puri (2012), Iyer et al. (2016), Egan et al. (2017), and Artavanis et al. (2019) are perhaps the most related. Iyer and Puri (2012) and Iyer et al. (2016) explore depositor responses in a case study of one bank run in India that arguably was triggered by panic. Similarly, taking advantage of a special sequence of events in Greece, Artavanis et al. (2019) document presence of panic in depositor behavior using micro-account level data at daily frequency from one large bank in Greece. Egan et al. (2017) study a sample of the 16 largest US retail banks and find that uninsured deposit elasticity to bank distress is sufficiently high to make banks fragile. While evidence of panic-based runs in specific episodes is extremely helpful for understanding bank fragility, it has always been a challenge to document broader evidence of the underlying mechanisms in large samples. Our study attempts to provide such evidence, building on the premise from the theory of bank runs that panic-based runs originate from liquidity mismatch and utilizing the heterogeneity across banks and over time in the degree of liquidity mismatch. The extant empirical literature has not built on this important link between liquidity mismatch and fragility and our paper fills this void.

2. Measurement of liquidity mismatch

Consistent with the conceptual notion of liquidity mismatch outlined in Brunnermeier, Gorton, and Krishnamurthy (2013), we are interested in measuring the extent to which a bank can satisfy the contractually promised cash available to its counterparties at short notice. A fundamentally solvent bank can be liquidity mismatched if the short-term liquidation value of its assets (due to fire sale discount) is less than the immediate cash promised to its depositors and other counterparties. Such a bank would operate without disruption under normal cash withdrawal patterns but would fail in the presence of a panic based run.

To illustrate, consider two banks A and B both holding \$100 dollars of assets with \$20 in treasury bills and \$80 in loans. They differ in their sources of funding: bank A funds its assets with \$100 of demand deposits and bank B with \$20 of demand deposits and \$80 of equity. Assuming that the liquidation value of loans is less than \$80, bank A in this example is liquidity mismatched as it would fail if all of its depositors demanded money immediately. In contrast, bank B is not liquidity mismatched as it can meet any demand for deposit withdrawals (a maximum of \$20) by liquidating treasury securities.

Our main measure of liquidity mismatch is the *CatFat* measure from Berger and Bouwman (2009). To calculate *CatFat*, Berger and Bouwman first classify each category of bank activity (both on and off-balance sheet assets and liabilities) 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 1 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.

We obtain the data on *CatFat* at bank-quarter level from Christa Bouwman's website (https://sites.google.com/a/tamu.edu/bouwman/data), and use *CatFat* per unit of total gross asset as our main measure of liquidity mismatch. Table 1, Panel A presents the summary statistics. The mean of *CatFat* is 0.33, indicating that an average bank creates $0.33 of liquidity with $1 of gross assets. *CatFat* exhibits significant variation with a standard deviation at 0.17. As shown in Figure A1 of the Online Appendix, the sample distribution of *CatFat* is similar to those shown in Berger and Bouwman (2009). It increased from 1994, peaked around the financial crisis period, and followed by a decline. This pattern holds for different percentiles of *CatFat*, suggesting that a significant portion of the sample variations in *CatFat* is driven by cross-bank differences. In fact, in Table A1 of the Online Appendix, we find that bank fixed effects explain 76% of the variations in *CatFat* whereas quarter fixed effects explain only about 7.5%.

We also considered an alternative measure of liquidity mismatch (*LMI*) developed in Bai et al. (2018). Conceptually, like *CatFat*, *LMI* also measures the extent to which banks can satisfy the contractually promised availability of cash at short notice to its counterparties using its assets. The key difference between the two measures is that, unlike *CatFat*, *LMI* takes into account over time changes in the liquidity of the balance sheet items based on changes in the market conditions. While this makes *LMI* more accurate in identifying periods of more vs less liquidity stress in the banking system, it makes *LMI* conceptually problematic for detecting depositor panic using our regressions. This is because deterioration in the liquidity of the markets for banks' assets itself can often be a result of panic among investors including depositors. Specifically, when panic ensues, there is less capital available to fund asset purchases, resulting in larger fire sale-discounts or increased hair-cuts on collateral assets, which would manifest in deteriorations in *LMI*. This suggests that panic-based deposit outflows and deteriorations in *LMI* may be affected by the same factors, [5] and the former may even precede the latter rather than the other way round. If so, *LMI* may not significantly predict future deposit flows, even if panic is an important aspect of depositor behavior. Overall, it is not clear if we can use *LMI* to assess whether it results in depositor panic when it itself might be affected by panic. The *CatFat* measure on the other hand poses no such interpretational difficulties as it does not take market changes in liquidity into account. While we also report results using the *LMI* measure in additional analyses (discussed later), these results should be interpreted with caution.

3. Empirical Specification and sample

3.1 Conceptual underpinnings of the specifications

Our specifications are guided by a simple model of depositor behavior used in prior studies (Egan et al., 2017; Chen et al., 2020). Banks attract greater deposit flows when they offer greater utility to depositors (compared to competing banks) and when there is greater aggregate demand for holding deposits. A depositor's utility from a bank depends on her perception of bank's default risk, the deposit rate offered, and service quality. Depositors update their views about default risk as they receive information about bank performance. Thus, deposit growth at a bank can be summarized as function of the following four factors:

$$Deposit\ growth = f(performance, rate, service\ quality, and\ aggregate\ deposit\ demand) \quad (1)$$

Under the above framework, strategic complementarities affect deposit flows by affecting depositors' beliefs about default risk from bank performance. Theory works (Goldstein and Pauzner, 2005; Vives, 2014) show that, in the presence of strategic complementarities, information

[5] Consistent with this conjecture, Figure A2 in the Appendix plots the average deposit growth and *LMIRisk* around the 2007-2009 crisis period and shows that uninsured deposits started to decline around the same time when *LMIRisk* started to deteriorate.

about bank fundamentals updates a depositor's view not only about banks' asset-payoffs (i.e., fundamental news), but also about the actions of other depositors. This in turn results in a larger sensitivity of deposit flows to the fundamental information than one would expect in the absence of strategic complementarities. This is the central prediction we take to the data by examining how the sensitivity of uninsured deposit growth to bank performance is affected by the extent of strategic complementarities among a bank's depositors as measured by *CATFAT*.

The measure of performance we use is accounting earnings scaled by lagged equity (*ROE*). Accounting earnings are the key summary performance measure widely used by investors as well as regulators to assess the health of financial institutions. In robustness tests reported later, we find that our inferences are robust to the use of several other measures of performance. Following Chen et al (2020), we measure deposit flows over the two quarters following the end of quarter *t-1* for which bank performance is measured. This is because banks typically file call reports with a delay of 30 days after the calendar quarter ending (Badertscher et al., 2018) and because the literature on post-earnings announcement drift suggests that investors respond to quarterly accounting reports with a delay of up to a quarter following the announcement (Bernard and Thomas, 1989).

A potential concern is that uninsured depositors are implicitly insured by the government, and therefore may not be responsive to bank performance. However, Benston and Kaufman (1997) 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 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."[6]

3.2. Control variables

Our specification includes a variety of controls to account for the effect of the three factors other than bank performance (rate, service quality, and aggregate deposit demand) that can affect deposit growth. Because Call reports do not separately report the interest expenses on insured and uninsured deposits, we follow Acharya and Mora (2015) and use the core deposit rate to proxy the rates offered on insured deposits and the rate on large time deposit to proxy the rates on uninsured deposits. We believe this is a reasonable approximation because core (large time) deposits are most likely to be insured (uninsured). We measure these rates as the quarterly interest expense on the deposits divided by the average quarterly deposits over the same period.

We use bank fixed effects in most analyses to eliminate any time-invariant differences across banks in service quality, and include several time-varying characteristics (e.g., bank size) to take into account the time-varying component of service quality. Following prior work (e.g., Acharya and Mora, 2015; Chen et al., 2020), we control for the following 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 loans (*RealEstate_Loans)*, (iii) capital ratio defined as book value of capital scaled by total assets (*Capital Ratio*), (iii) wholesale funding scaled by total assets (*Wholesale Funding*), and (v) the standard deviation of *ROE* over the preceding 12 quarters.

Our final set of controls relate to aggregate demand for deposits, which can, for example, shift if alternative asset classes offer better returns. Dreschler et al. (2017) and Lin (2020) find that deposits flow out of the banking system when treasury securities and stock markets offer better

[6] 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.

returns. We include contemporaneous and lagged fed funds rates and the value-weighted market returns to control for these opportunity costs of holding bank deposits.

While including time dummies can fully soak the effect of such aggregate demand shifts, it also precludes a study of the depositor response to changes in bank performance that result from common macroeconomic shocks. This is problematic not only because many significant performance swings in the cyclical banking industry are systematic, but also because we expect the incentive to run before other depositors to be greater when the entire industry is experiencing a performance decline than when the performance decline is idiosyncratic (Liu, 2016; Goldstein et al., 2020). In Section 4.4, we use this differential prediction for response to systematic versus idiosyncratic performance to provide an additional test of the presence of strategic complementarities and find that depositors are 8 times more responsive to systematic performance than to idiosyncratic performance shocks. For completeness, we present our main results including time dummies where the identification comes primarily from idiosyncratic performance shifts. We find our inferences hold but, as expected, with smaller economic magnitudes.

Following prior work (Egan et al., 2017; Chen et al., 2020), we also contrast the results for uninsured and insured depositors for two purposes. The first is to allay any residual concerns about imperfect controls. The idea is that while insured depositors care less about default risk and bank performance, they still are affected by service quality and any aggregate trends that affect the demand for holding deposits (e.g., attractiveness of competing asset classes that might satisfy their liquidity/investment needs). If our specifications are simply reflecting the effect of these factors instead of panic from concerns about bank default, we should find similar results for uninsured and insured deposits. However, as we show later, we find the opposite to be the case.

Furthermore, from a policy standpoint, the analysis on insured deposits can also provide evidence on the extent to which banks use deposit insurance to manage the fragility in their uninsured deposit base due to liquidity mismatch. Deposit insurance is one of the key tools to guard against panic runs. Recent evidence indeed suggests that banks actively attract insured deposits in times of poor performance to compensate for their loss of uninsured deposits. Thus, evidence on how banks' liquidity mismatch affects the sensitivity of insured deposit flows to bank performance can shed light on the effectiveness of deposit insurance in helping banks manage panic-driven runs from uninsured deposits.

3.3. Data and sample

Our sample is at commercial bank-quarter level. We obtain most of our bank-level variables from U.S. Call Reports as disseminated by the Wharton Research Data Services (WRDS).[7] Call reports contain quarterly data on all commercial banks' income statements and balance sheets. The Appendix provides all variable definitions and details which specific Call report items are used to measure these variables. To avoid the impact of mergers and acquisitions, we exclude bank-quarter observations with quarterly asset growth greater than 10%. We also exclude bank quarters with total assets smaller than 100 million and winsorize all continuous variables at 1% and 99%. These sample-selection and cleaning procedures are commonly used in prior work (e.g., Gatev and Strahan, 2006; Acharya and Mora, 2015). Our final sample spans January 1994 to December 2016 (the last quarter where the *CatFat* variable is available from Christa Bouwman's website) and contains a maximum of 287,018 bank-quarter observations representing 8,153 unique commercial banks.

Descriptive statistics in Table 1 show that the average (median) annualized *ROE* is 10.36% (11.05%) with a standard deviation of 10.37%. The average annualized growth in uninsured (insured) deposits is 2.11% (2.78%) of assets. The correlation (untabulated) between uninsured deposit flows and lagged *ROE* is much higher (at 0.17) than that between insured deposit flows and *ROE* (at 0.05), suggesting that uninsured deposit flows are more sensitive to bank performance. Furthermore, uninsured and insured deposit growth exhibit a strong negative correlation of -0.47, consistent with banks substituting for loss of uninsured deposits by insured deposits.

[7] Since the coverage of Call reports at WRDS is incomplete after 2014, we supplement the post-2014 data using S&P's SNL financial database.

4. Liquidity mismatch and deposit flow-performance sensitivity

4.1 Semi-parametric analyses

We begin by estimating semi-parametric regressions of deposit flows on bank performance, which allow for a flexible relation between deposit flows and performance. This approach allows us to explore any non-linearity in the relation that are predicted by the theory (Goldstein and Pauzner, 2005) in the presence of strategic complementarities. The specification takes the following general form:

$$\Delta Dep_{it} = f(ROE_{it-1}) + Control_{it-1} + \epsilon_{it} \qquad (2)$$

where ΔDep_{it} represents deposit flows, measured as the change in deposit balance scaled by lagged total assets as in Archarya and Mora (2015), $ROE_{i,t-1}$ is the bank's return on equity that depositors observe at the end of quarter *t-1*, and $Control_{it-1}$represents the set of time-varying control variables explained earlier. Following prior studies (e.g., Chevalier and Ellison, 1997; Chen et al., 2010; Goldstein et al., 2017) that estimate such flow-performance relations semi-parametrically in the context of mutual funds, we use the method from Robinson (1988) for estimation.

Figure 2, Panel A presents the semi-parametric plots of deposit flows as a function of *ROE* for the full sample. As expected, insured deposit flows are significantly less sensitive to *ROE* than uninsured deposit flows. More interestingly, uninsured deposit flows exhibit an S-shaped relation with *ROE*, wherein they respond strongly for the mid-range of *ROE* distribution, but much less so for very high or low realizations of *ROE*. The S-shaped relation is consistent with the three regions of fundamentals identified in Goldstein and Pauzner (2005) where depositors are expected to behave differently. When fundamentals are extremely bad, bank assets cannot generate enough cash to repay all depositors even in the long run, making it rational for all depositors to run, regardless of other depositors' behavior, resulting in a fundamental run characterized by a flat flow-performance relation.[8] When fundamentals are really good, banks' assets can generate

[8] Although in the model all depositors demand money in this region, we do not expect this to result in a deposit growth of -100% in data. Banks typically suspend convertibility of deposits when they face significant withdrawal pressure or they may be placed into receivership by the regulators during which access to uninsured deposits is

enough cash to pay all depositors even in short-term, minimizing running incentives by depositors, again resulting in a flat flow-performance relation. Thus, fundamentals fully determine the behavior of depositors for very high or very low realizations of performance signals. It is only when the fundamentals are in the intermediate range, the potential for panic-based runs kicks in. The fundamentals in this region are strong enough to repay all depositors if they behave patiently, but not if they demand funds immediately and the bank needs to liquidate assets at a discount. Thus, in this region depositors use performance signals not only to update banks' fundamental but also to infer what other depositors will do. A poorer signal makes a depositor believe that a larger portion of other depositors will run. This results in greater deposit outflows as the performance signal worsens, i.e., a positive flow-performance sensitivity.

To more directly examine whether the flow-performance sensitivity in the intermediate region reflects panic, we turn to our main prediction that the flow-performance sensitivity should increase with the extent of strategic complementarities. We do so in Panel B of Figure 2 by providing separate plots for banks with above and below sample median *CatFat*. While the flow-performance relation is flat when *ROE* is very high or very low for both subsamples of banks, the relation is significantly steeper in the intermediate range for the subsample of banks with above median *CatFat*. Thus, for the same decline in performance in this range, banks with more liquidity mismatch experience stronger outflows in uninsured deposits than banks with less liquidity mismatch. Overall, the evidence of an S-shaped relation, which becomes steeper in the intermediate range of *ROE*, for banks that engage in more liquidity transformation, maps well into the theoretical predictions about depositor behavior in the presence of strategic complementarities.

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restricted until a resolution is reached. Moreover, as modelled in Chen et al. (2010), some depositors may not run simply because they are not paying attention. Consistent with attention and awareness playing a role, in their case study of a bank run in India, Iyer and Puri (2012) and Iyer, Puri, and Ryan (2016) find that depositors are more likely to run when they are part of a social network. In the plot in this region, the uninsured deposit growth is around -3%, which falls within the bottom quartile of the uninsured deposit growth in our sample.

4.2 Linear Regression Analyses

To formally test the effects of liquidity mismatch on flow-performance sensitivity, we follow prior literature and estimate various versions of the following regression in our analyses:

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

where α_i represents fixed effect for bank i and other variables are as defined before. We estimate this equation using ordinary least-squares (OLS) and obtain standard errors after clustering at the bank-level. We use the demeaned version of *CatFat* (i.e., *CatFat* minus sample mean), so that the coefficient β_0 captures the flow-performance sensitivity for a bank with average *CatFat*.[9]

Table 2, Panel A presents the estimates. Since a significant portion of the variation in *CatFat* is cross-sectional, we first present estimates without including bank fixed effects in columns (1) – (3). Estimates in column (1) for the model of uninsured deposit flows show that coefficients for both *ROE* (coef=0.101) and for its interactive term with *CatFat* (coef = 0.120) are positive and statistically significant at less than 1% level. Consistent with our non-parametric analyses, these results indicate that the flow-performance sensitivity of uninsured deposits increases with a bank's liquidity mismatch. The magnitudes imply that one standard deviation increase in liquidity mismatch (0.17) from the sample average is associated with a 20% (=0.17*0.120/0.101) increase in flow-performance sensitivity of uninsured deposits.

Column (2) models insured deposit flows. As expected and consistent with the non-parametric analyses, we find that on average the flow-performance sensitivity of insured deposits (coef on *ROE* = 0.024; p-value<0.01) is less than a quarter of the sensitivity of uninsured deposits. More interestingly, the coefficient on *ROE*×*CatFat* is negative and significant (coef = -0.218; p-value<0.01), which suggests that high *CatFat* banks manage the additional loss of their uninsured depositors in times of poor performance by attracting insured depositors. That poorly performing banks make up for their loss of uninsured deposits by attracting insured deposits has also been documented in prior work (e.g., Martin et al., 2020; Chen et al., 2020). Estimates in column (3)

[9] Throughout the paper, we use demeaned value of a variable when it is interacted with *ROE* so that β_0 continues to represent the sensitivity for the average bank.

for total deposit (both uninsured and insured) flows suggest that the substitution is quite successful as the coefficient on the interactive term between *ROE* and *CatFat* is no longer positive and in fact turns negative; our next set of estimates, however, show that the significant, negative coefficient on interaction term is sensitive to inclusion of bank fixed effects and turns insignificant in their presence. Overall, the above results not only shed light on how liquidity mismatch makes uninsured depositors fragile, but also highlight the efficacy of deposit insurance as a tool in mitigating the effect of panic.

Columns (4) - (6) present the estimates after including bank fixed effects. We continue to find our inferences to be robust both in terms of statistical significance and economic magnitudes. Estimates imply that a one standard deviation increase in *CatFat* is associated with a 38% increase in the flow-performance sensitivity of uninsured deposits. We also continue to find a negative coefficient on *ROE×CatFat* when we model insured deposit flows. Finally, we find an insignificant coefficient estimate on *ROE×CatFat* when we model total deposit flows, suggesting that high *CatFat* banks are largely able to offset the additional sensitivity of their uninsured depositors by attracting insured depositors. Given the robustness of our results to inclusion of bank fixed effects, in the rest of the paper we only present results with bank fixed effects.

Next, for completeness, columns (7) – (9) present the robustness of our results to use of time dummies instead of macroeconomic-controls (fed-fund rate and stock returns) to absorb the effect of any secular trends in deposit growth. As discussed in detail in Section 3.2, this is not our preferred specification because it does not allow us to study the depositor response to systematic industry-wide declines in performance, which is when we expect the incentive for panic based running to be greater. Later in Section 4.4, we explore this differential prediction for response to systematic and idiosyncratic performance to provide an additional test of the presence of strategic complementarities. It can be seen that all of our inferences continue to hold but with smaller economic magnitudes. As an example, the flow-performance sensitivity of uninsured deposits at a bank with average *CatFat* in these specifications is nearly 40% lower than that documented in column (1). The smaller magnitude is as expected as including time dummies restricts the identification to come primarily from idiosyncratic performance shifts.

Finally, Panel B of Table 2 presents the results separately for subsamples of small, medium, and large banks, as defined earlier. First, the results show that uninsured deposit flows are significantly sensitive to bank performance across all three subsamples of banks, with the largest magnitude for large banks (coefficient on *ROE*=0.138 compared to those of 0.113 and 0.081 for medium and small banks). This result is particularly interesting because one might have expected the "too-big-to-fail" effect to have muted the sensitivity for large banks; this finding likely reflects the greater liquidity mismatch of large banks – the mean *CatFat* for large banks is 0.43 compared to 0.39 and 0.31 for medium and small banks. Furthermore, we continue to find that *CatFat* amplifies the uninsured deposit sensitivity to *ROE* with economically large magnitudes across the three subsamples, although the amplification is not statistically significant for large banks. However, given the large economic magnitude (one standard deviation increase in *CatFat* amplifies the average sensitivity for large banks by 11%), the lack of statistical significance is likely an artifact of low sample size for large banks: the sample of small (medium) banks is nearly 20 (3.7) times the size as that for large banks. Finally, we also find evidence of substitution between uninsured and insured deposits across the three subsamples with a negative and significant coefficient on *CatFat*×*ROE* for insured deposit flows.

4.3 Could the results reflect differences in fundamental information content of ROE?

A potential concern is that a unit of *ROE* for high *CatFat* banks may contain greater news about intrinsic value of banks' assets. If this is the case, a one unit change in *ROE* at a high liquidity mismatch bank would result in a larger revision in depositors' perceived value of bank assets, and consequently larger deposit flows. Thus, our results may be reflecting the response to the larger magnitude of fundamental news in earnings of high *CatFat* banks instead of the effect of panic. Such differences in informational properties of *ROE* can arise because banks with different *CatFat* invest in different types of assets, which may generate a sequence of profits with different statistical properties. Below, we conduct two different analyses to address this concern.

4.3.1 Controlling for differences in informational properties

We first use the historical realizations of *ROE* to measure and then control for the potential differences in statistical properties of *ROE* across banks. A unit increase in *ROE* can result in a larger upward revision of beliefs about asset values if it is more persistent (i.e., more likely to repeat in future) and/or if it measures changes in asset values with greater precision. The latter follows from the Bayesian updating rule based on which depositors put more weight on more precise signals to update their priors about asset values.

We measure earnings persistence (*Persistence*) for each bank-quarter as the slope coefficient from an AR(1) regression of ROE_t estimated over the previous 12 quarters.[10] Our measure of earnings precision (*Informativeness)* is based on Chen et al. (2020) which captures the ability of earnings and its components to predict future write-offs, as assessed by the R-squared of the prediction regressions estimated over the previous 12 quarters. We refer readers to the Appendix of this paper and to Chen et al. (2020) for greater details on methodology. Chen et al. (2020) find that uninsured deposit flows are indeed more responsive to earnings of bank with greater *Informativeness*.

Table 3 presents the results after including controls for the above informational properties and their interactions with *ROE*. The effect of *CatFat* in these regressions is identified by comparing banks that are observationally similar in terms of informational properties of *ROE*. Because the additional data requirements for this analysis reduce the sample size to 231,728, we first reproduce the estimates for the flow-performance sensitivity of uninsured deposits in column (1) for comparison purposes: Coefficients on *ROE* and *ROE*×*CatFat* are 0.081 and 0.203, compared to coefficients of 0.094 and 0.211 for the same specification in column 4 of Table 2A. Estimates in columns (2) – (3) show that, as expected, uninsured deposits exhibit greater sensitivity to performance for banks with greater persistence and informativeness. More importantly, our

[10] In untabulated analyses, we explore measures of persistence from up to fourth order auto-regressive models and find our inferences to be unchanged.

inference about the effect of *CatFat* remains robust as the coefficient on *CatFat*×*ROE* exhibits little change in both magnitude and statistical significance.

One may also wonder if high *CatFat* banks are riskier and if the greater flow-performance sensitivity to *ROE* reflects the greater volatility of *ROE* at such banks. To the extent depositors put a greater discount on a volatile sequence of profits, we would expect a unit change in *ROE* to result in smaller change in perceived value of future asset payoffs (and consequently smaller flows) at banks with greater volatility. This suggests that, if anything, a positive correlation between *CatFat* and riskiness should only bias us against finding our results. Standard deviation of *ROE* (*Std(ROE))* – measured over a rolling 12-quarter window – exhibits a modest but positive correlation of 0.07 in our sample, which mitigates concerns about the confounding effect of *ROE* volatility. Nevertheless, in column (4) we also include *Std(ROE)* and its interaction with *ROE*. As conjectured, we indeed find that uninsured deposit flows are less sensitive to performance in banks with greater volatility of *ROE*. More relevant to us, the addition of this control results in little change in the coefficient estimate on *CatFat*×*ROE*.

4.3.2 Exploiting variation in strategic complementarities on the liability side

One may still be concerned that high *CatFat* banks may invest in systematically different kind of assets (more illiquid and longer maturity assets) that generates a sequence of profits and cash flows with different informational properties not fully controlled for by our measures of earnings persistence, informativeness, and volatility. To address this concern, we next exploit variation in strategic complementarities that is unlikely to be associated with differences in informational properties of earnings. The basic idea is to compare depositor behavior at banks with similar asset compositions (from a liquidity creation perspective), but still provide different running incentives due to differences on the liability side. That is, we compare the incentives to withdraw by uninsured depositors in Bank A and Bank C in Figure 1 (recall both have identical assets). This comparison can provide evidence that should not be affected by differences in earnings properties. The rich variation in the source and extent of liquidity creation in our sample allows us to make such comparisons.

We exploit two sources of variation in strategic complementarities that result purely from differences in the structure of banks' liability side. The first is the composition of insured vs. uninsured deposits, as measured by the percentage of total deposits that are uninsured (*PctUninsured*). All else equal, an uninsured depositor has less incentive to withdraw when she knows that a large fraction of other depositors are insured and therefore have little or no incentive to run. The second variable measures differences across banks in the ease and cost with which customers can obtain funds from their bank. For example, while consumers holding transaction and savings deposits can withdraw money anytime without penalty, those holding time deposits need to pay a penalty for early withdrawal, and those holding equity cannot demand funds from the bank at all. Holding the asset side constant, a depositor has less incentive to run earlier for strategic reasons when she knows that a larger fraction of the customers cannot withdraw funds easily from the bank. We use the measure of liquidity creation on the liability side (*LiqCreation_Liab)* from Berger and Bouwman (2009) to capture this aspect of strategic complementarities. Recall that liquidity creation on asset and liability side together determine *CatFat*, which is our main measure of liquidity mismatch.

We estimate deposit flow regressions using a specification that allows all coefficient estimates to vary across the three subsamples of observations corresponding to the top, middle, and bottom terciles of *PctUninsured* or *LiqCreation_Liab*.[11] We replace *CatFat* by the measure of liquidity creation on the asset side (*LiqCreation_Asset*) in these regressions. A comparison of depositor behavior across the three-subsamples allows us to explore how, for a given asset liquidity profile, the depositor response depends on the differences in banks' liability side.

[11] We form the portfolios based on the average values of *PctUninsured* or *LiqCreation_Liab* over the preceding three years instead of the preceding quarter so that the uninsured deposit flows in this quarter is not simply reflecting any recent trend in the sorting variable.

Table 4, Panel A presents the analysis for terciles partitioned based on *PctUninsured*. Since we use the demeaned version of *LiqCreation_Asset*, the coefficient on *ROE* captures the uninsured deposit sensitivity across the three terciles of *PctUninsured* for banks with average level of liquidity creation on the asset side. Columns (1) – (3) show that the sensitivity of uninsured deposits increases monotonically from the bottom to the top tercile of *PctUninsured*, with the sensitivity in the top-tercile much larger than that of the sensitivity in the bottom tercile.

We also expect the differences in the deposit sensitivity across terciles to get magnified as we compare banks with increasingly illiquid assets. Intuitively, when the assets are perfectly liquid, there is no incentive for a depositor to run before other depositors regardless of the composition of the liability side: because assets can be liquidated at their intrinsic value at any time, a solvent bank can pay all claim holders regardless of when they demand money. It is when assets need to be liquidated at a discount, the potential for panic based running kicks in with the incentives for running higher when liability side has higher *PctUninsured*. Consistent with this expectation, we find that the coefficient on *ROE×LiqCreation_Asset* also increases monotonically across the *PctUninsured* terciles, with the magnitude at the top tercile significantly higher than that at the bottom tercile

A concern is that the above effects could still reflect differences in asset side liquidity (and thus differences in earnings properties) across the different terciles of *PctUninsured*, if banks systematically adjust asset side liquidity based on their liability side liquidity or vice-versa. For example, a bank with significant liquid claims on the liability side might create less liquidity on the asset side to manage liquidity mismatch risk. In our sample, the asset side liquidity creation (*LiqCreation_Asset)* has a correlation of 0.16 with *PctUninsured* and -0.16 with *LiqCreation_Liab*.

To mitigate this concern, we conduct this analysis on a matched sample in which we explicitly eliminate any observable differences in asset side liquidity creation. For this analysis, we include the top and the bottom terciles of *PctUninsured* to focus on subsamples with the largest differences in the liability side. We then propensity-score match the top and the bottom terciles on *LiqCreation_Asset*. We implement this using nearest neighbor matching without replacement using a caliper of 0.005 and require common support for the propensity scores across the two groups. The matching is quite successful: on the matched sample, mean values of *LiqCreation_Asset* for the top and bottom terciles of *PctUninsured* (*LiqCreation_Liab*) are 0.071 and 0.070 (0.071 and 0.075), respectively, and the difference is not statistically significant.

Columns (4) - (5) of Panel A presents the results for the matched sample. They show that uninsured depositors of a bank with average asset side liquidity are significantly more sensitive at the top tercile of *PctUninsured* than at the bottom tercile. The differences in sensitivity are further magnified as one compares banks with more illiquid assets, as the coefficient for *ROE*×*LiqCreation_Asset* is also significantly higher in the top tercile than in the bottom tercile.

We have interpreted the higher coefficient on *ROE* in tercile 3 than in tercile 1 as consistent with panic-based run due to fragility on banks' funding/liability side. An alternative explanation is that banks with higher *PctUninsured* may simply have more dollar amount of uninsured deposits (relative to their asset size) to be withdrawn for the same decline in *ROE*. Since we scale the changes in deposits by total assets, this can result in higher coefficient for *ROE* across portfolios sorted by *PctUninsured*. To ensure that this alternative explanation is not driving the results, in Panel B, we repeat the analysis by replacing the dependent variable with $G\_Dep_{it}^{U}$, calculated as changes in the balances of uninsured deposit scaled by the beginning balance of uninsured deposits. As Panel B shows, we obtain qualitatively similar results. This is not surprising since the correlation coefficient between the two flow measures is higher than 0.9.

We note that scaling deposit flows by its own beginning balance (i.e., using $G\_Dep_{it}^{U}$) does not take into account the economic importance of uninsured deposits in banks' operations. A bank that relies primarily on insured deposits can have a near zero uninsured deposit balance and thus large swings in the percentage changes in its uninsured deposits that are economically unimportant. This makes $G\_Dep_{it}^{U}$ a weak variable to detect panic-runs in data because an uninsured depositor's tendency to run not only depends on the percentage of depositors that are uninsured but also on how important uninsured deposits are in funding banks' assets. For this reason, we do not use this scaling in our main analysis. Nonetheless, in the Online Appendix, we show that our main inferences remain unchanged with this alternative scaling.

Panel C of Table 4 presents the results from subsamples sorted using the measure of liquidity creation on the liability side (*LiqCreation_Liab).* As can be easily seen, the overall inferences are similar to those drawn from Panel A, although with relatively smaller economic magnitudes. In both the whole sample and matched sample analyses, the coefficient on *ROE* (*ROE*×*LiqCreation_Asset*) for the top tercile is higher than the coefficient for the bottom tercile, and significantly so for the coefficient for *ROE*. It is interesting to note that in both cases, the magnitudes of the difference are not as large as those for portfolios sorted by *PctUninsured*. This is perhaps not consistent with the fact that deposit insurance completely immunizes an insured depositor against losses and therefore would be much more effective in dampening the incentives to run than any costs imposed by banks on deposit withdrawals. This also suggests that *PctUninsured* provides a more powerful way to detect differences in strategic complementarities across banks than *LiqCreation_Liab*.

Overall, the above analyses illustrate how specific differences in the liability side structure contribute to depositor fragility; more importantly, these analyses mitigate concerns that our main results simply reflect differences in earnings properties of assets with different liquidity profile.

4.4 Systematic and idiosyncratic earnings

In this section we examine whether strategic complementarities in depositors' behavior are amplified by poor aggregate conditions, as modelled in Goldstein, Kopytov, Shen, and Xiang (2020). The motivation is to assess to what extent strategic complementarities within a bank can amplify the effect of any systemic weaknesses and, consequently, contribute to a systemic crisis. Holding the magnitude of the performance shock constant, we expect the depositors' incentive to run before others to be stronger in response to a systematic performance shock (i.e., when the entire industry is suffering) than when the shock is idiosyncratic. 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 the bank will have greater difficulty in meeting short-term spikes in deposit withdrawals by accessing interbank markets and/or by liquidating assets.

To test this prediction, for each bank we decompose its ROE_{it} for every period t into a systematic (ROE_Sys_t) and an idiosyncratic (ROE_Idio_{it}) component. ROE_Sys_t is calculated as the average *ROE* for the entire banking sector for quarter *t* and ROE_Idio_{it} is the difference between ROE_{it} and ROE_Sys_t. We then estimate our deposit flow regressions after including the two components of *ROE* separately and present the results in Table 5. The coefficients on both *ROE_Sys* and *ROE_Idio* are positive and significant, with the magnitude much larger for *ROE_Sys* (0.561 vs. 0.060). The difference in magnitudes is striking: for a bank with average *CatFat*, a systematic earnings decline results in 9 times larger the amount of uninsured-deposit outflows than that if the same earnings decline is idiosyncratic. We also expect the differential sensitivity to *ROE_Sys* and *ROE_Idio* to be magnified as banks' liquidity mismatch increases. This is because the adverse effect of a systematic performance decline should be stronger for such banks– their (more illiquid) assets will command an even larger fire-sale discount in the event of a liquidation; and, because of a larger liquid claimholder-base, their claimholders would have a greater incentive to run before others. Consistent with this prediction, we find that the coefficient on *ROE_Sys×CatFat* is nearly 5 times the coefficient on *ROE_Idio×CatFat*.

4.5 Liquidity mismatch and the 2007-2009 Financial Crisis

To further demonstrate the role of strategic complementarities in times of systematic shock, we next use the Financial Crisis of 2007-2009 as a laboratory to explore how liquidity mismatched banks perform and respond to an extreme systemic shock. We do so by estimating various versions of the following specification:

$$\mathrm{Y_{it}} = \beta_0 CatFat_{it-1} + \beta_1 CatFat_{it-1} \times Crisis_t + \beta_2 Crisis_t + Control_{it} + \epsilon_{it} \quad (4)$$

where Y_{it} represents an outcome variable for bank i at time t and $Crisis_t$ is an indicator variable for the crisis period of 2007Q3 to 2009Q2. We examine three categories of outcomes: deposit flows, deposit rates, and loan decisions. The estimation is done on the full sample we use for our main analyses before.

Panel B of Table 5 presents the results with uninsured, insured, and total deposit flows as the dependent variables in columns (1) - (3). Coefficient estimates on $CatFat_{it-1} \times Crisis$ show that banks with higher liquidity mismatch experience larger uninsured deposit outflows during the crisis, which they are unable to make up for using insured deposits flows, resulting in lower total deposit flows compared to banks with less liquidity mismatch. Columns (4) and (5) model banks' deposit rate response and the estimates show that banks with greater liquidity mismatch offer higher rates during the crisis. Together the above results imply that banks with higher *CatFat* experience adverse deposit flow outcomes during the crisis despite offering higher rates.

Lastly, in columns (6) and (7) we model growth in loans and credit commitments to examine whether the funding pressure faced by high *CatFat* banks manifests in adverse lending outcomes. The coefficient on *Crisis* is positive and significant in both columns, consistent with the finding in prior literature that banks act as liquidity providers to their borrowers during the crisis (e.g., Acharya and Mora, 2015). More relevant to us, the coefficient estimates for *CatFat* × *Crisis* are negative in both columns, although only statistically significant in column (7), indicating that banks with more liquidity mismatch increase their commitment less during the crisis period.[12] The economic magnitude of the effect is significant. The average annualized growth in commitment is 1.1%, whereas a one standard deviation increase in *CatFat* would lower growth in commitment during the crisis period by 1.0%. Furthermore, as we discuss next, more mismatched banks experience a higher failure rate during the crisis.

[12] In untabulated analysis, we follow Acharya and Mora (2015) and break the *Crisis* dummy into *Crisis1* dummy (defined as the period between 2007Q3 and 2008Q2) and *Crisis2* dummy (defined as the period between 2008Q3 and 2009Q2). We continue to find significant negative coefficients for both *CatFat*×*Crisis1* and *CatFat*×*Crisis2* when the dependent variable is growth in commitment. However, when we examine growth in loans, we find a significantly positive coefficient for *CatFat*×*Crisis1* but a negative coefficient for *CatFat*×*Crisis2*. These results suggest that borrowers draw down their commitment from banks during the first stage of the crisis, consistent with the findings from Ivashina and Scharfstein (2010) and Acharya and Mora (2015).

5 The relation between liquidity mismatch and bank performance

Our analyses thus far provide compelling evidence that liquidity mismatch results in significantly fragile uninsured deposit funding. We next explore the consequences of this finding for several bank outcomes including failure risk and overall profitability.

5.1.Liquidity mismatch and future bank failure

We first examine whether the increased funding fragility of liquidity mismatched banks are associated with higher failure risk using the following logit model for both the non-crisis and crisis periods:

$$BankFailure_{i,[t,t+j]} = \gamma_1 CatFat_{it-1} + \gamma_2 ROE_{it-1} + Controls + \epsilon_{it}, \quad (5)$$

where $BankFailure_{i,[t,t+j]}$ is an indicator variable that equals 1 if bank *i* appears on FDIC's failed bank list during the period spanning years t to $t + j$ where $j = \{1,2,3\}$. We estimate (5) using observations from non-crisis period and examine the failure incidence during the crisis period separately. To avoid double counting failures and underestimating standard errors, we use non-overlapping periods such that an observation for a bank failure appears only once in the sample. For example, when the dependent variable is failure within the next two year (i.e., [t, t+2]), we leave a two-year gap between successive observations by using observations from the first quarter of odd years, such as 1995Q1, 1997Q1, and 1999Q1, etc.

Columns (1) – (3) of Panel A of Table 6 present the results for the non-crisis period. To ease interpretation, we present the marginal effects at the means of the independent variables. The results show that liquidity mismatch is a significant predictor of bank failure over horizons 2 years or longer. For example, estimate from column (2) suggests that one standard deviation increase in bank's liquidity mismatch would increase the chance of bank failure over the next 2 years by 3.4 basis points (=0.2%*0.17), representing a 6.5% increase over the average failure rate of 52 basis points. In column (4), we also model failure risk during the Financial Crisis period by using a dummy for failure during the eight quarters from 2007Q3 to 2009Q2 as the dependent variable. Each bank contributes only one observation for this analysis and all bank characteristics are measured in the most recent quarter preceding the crisis. Naturally, all macroeconomic controls are excluded from this estimation. Estimates show that liquidity mismatch is a stronger predictor of failure during the crisis compared to the non-crisis period: A one standard deviation increase in *CatFat* is associated with a 21% increase over the average failure rate of 2.18% during the crisis.

5.2.Liquidity mismatch and profitability

We next explore profitability differences between banks with more and less liquidity mismatch. While liquidity mismatch exposes banks to risks associated with funding fragility, it should also allow banks to earn higher return for the liquidity services they provide both on the asset and liability side of the balance sheet. We examine this by regressing *ROE* and *ROA* on *CatFat* and other bank characteristics and present the results in Panel B of Table 6. The coefficient estimate on *CatFat* is positive and significant in all specifications with meaningful economic magnitude. For example, the estimate in column (1) suggests that a one-standard deviation increase in *CatFat* is associated with nearly 0.34% increase in annualized *ROE*. The estimate in column (2), where bank fixed effects are included, suggests that the effect is larger (at 0.5%)[13]. The positive relation between *CatFat* and bank profitability is consistent with Berger and Bouwman (2009)'s finding of a positive association between *CatFat* and the stock market valuations for the subsample of publicly traded banks. Overall, the analysis of economic consequences highlights that liquidity transformation is a double-edged sword in that it allows banks to earn higher profits at the cost of heightened fragility and failure risk.

5.3.Do greater deposit outflows hurt liquidity mismatched banks more?

The presence of strategic complementarities in banks with illiquid assets is based on the assumption that if a sufficiently large portion of depositors withdraw money, it will hurt bank value because the bank may be forced to inefficiently liquidate its assets at a loss and/or curtail its asset growth to meet deposit withdrawals, which can lead to further losses and higher chances of default. This is what gives a depositor the incentive to be in line before other depositors if she expects large

[13] This is calculated with the average value of the within bank standard deviation in *CatFat* (at 0.06), multiplied by 8.39.

withdrawals by other depositors. We next present evidence on this assumption by examining the implications of large deposit withdrawals on future asset growth and performance of banks with high *CatFat*. We do so by estimating various versions of the following specifications:

$$Y_{it+1} = \beta_1 Outflow_{it} + \beta_2 Outflow_{it} * CatFat_{it} + \sum_{j=0}^{4} \gamma_j ROE_{it-j} + Controls + \epsilon_{it}, \quad (6)$$

where $Outflow_{it}$ is a dummy variable that equals 1 if the total deposit outflows in the previous quarter is below 10th percentile of the total deposit flows (at -2.75% of total assets quarterly), and 0 otherwise.[14] Y_{it+1} represents either *ROE,* loan growth, or growth in credit commitments. Because we control for lagged performance, the coefficient on $Outflow_{it}$ estimates the effect of large outflows beyond what is predicted by past performances for banks with no liquidity mismatch (i.e., *CatFat*=0). If large deposit outflows hurt future performance and asset growth more for high *CatFat* banks, we should find the coefficient β_2 to be negative.

Table 7 presents the results. Column (1) shows a negative but insignificant coefficient estimate for *Outflow*, indicating that large deposit outflows are not significantly associated with poor future performance for banks with no liquidity mismatch. The coefficient estimate for *Outflow*CatFat*, however, is negative at -0.771 and significant at less than 10% level, suggesting that the future performance of banks with more liquidity mismatch is more adversely affected by large outflows of deposits. Columns (2) and (3) examine the effect of large outflows on banks' future growth in loan and in commitment/credit lines to borrowers, respectively. Column (2) shows that the coefficient estimate for *Outflow* is significantly negative for loan growth. This is expected because deposit outflows directly reduce banks' loanable funds, even for banks with no liquidity mismatch. In contrast, the coefficient on *Outflow* is statistically indistinguishable from zero for commitment growth, indicating that large outflows do not materially affect banks' willingness to make commitment to borrowers when they do not have any liquidity mismatch problem. More importantly for our analysis, the coefficients for the interactive term between *Outflow* and *CatFat*

[14] In untabulated analysis, we obtain qualitatively similar results when we use 5th percentile or 25th percentile as the cutoff point.

are significantly negative at less than 1% level in both columns, indicating that large deposit outflows have more adverse effects on banks' future loan and credit commitment growth when banks are more liquidity mismatched.

6. Robustness to alternative measures of liquidity mismatch and bank performance

We next present results for several robustness tests. We first examine the robustness of our results to using the alternative liquidity mismatch measure from Bai et al. (2018). As explained in Section 2 earlier, incorporation of market liquidity conditions in this measure poses interpretational problems and makes it harder to detect panic based running. We present these results mainly for completeness.

Bai et al. (2018) create liquidity mismatch index (*LMI*) to measure the difference between the market liquidity of assets and the funding liquidity of liabilities and compute it as follows: $LMI_{it} = \sum_k \lambda_{t,a_k} a_{t,k}^i + \sum_k \lambda_{t,l_{k'}} l_{t,k'}^i$, where $a_{t,k}^i$ ($l_{t,k'}^i$) is the share of assets (liability) category k (k') on bank i's balance sheet and λ_{t,a_k} ($\lambda_{t,l_{k'}}$) is the corresponding time-varying liquidity factors for the category. Bai et al. use repo market haircuts to extract the liquidity factors of different asset classes. For example, a haircut of 20% on corporate loans means that a bank can raise \$80 cash immediately using a repo transaction collateralized by \$100 of its loan portfolio. To assess time-variation in liquidity of its liabilities (i.e., $\lambda_{t,l_{k'}}$), Bai et al. use the spread between the Treasury bill rate and the Overnight Indexed Swap rate (hereafter, OIS-T-bill spread). The idea is that greater OIS-T-bill spread reflects a stronger market desire to own liquid assets and therefore it is indicative of increased likelihood that banks' liabilities will be redeemed.

The measure we actually use in our analysis is *LMIRisk,* which is based on *LMI* and designed by Bai et al. to directly measure the exposure of a bank to liquidity risk based on changes in market liquidity conditions. Specifically, *LMIRisk* is the decrease in *LMI* that would occur if the market and funding liquidity conditions (i.e., haircuts and OIS-T-bill spreads) deteriorated by 1 standard deviation; i.e., $LMIRisk = LMI_t - LMI_{t,1\sigma}$. We obtain the underlying data and code to construct the measure from Bai et al. who make them publicly available for years 2002 to 2014, resulting in a smaller sample than the one for *CatFat*. Panels C and D in Figure A1 in the Online Appendix plot the over-time changes in *LMIRisk* for the whole sample as well as for different bank size groups. It is noticeable that unlike *CatFat*, most of the variations in *LMIRisk* are time-series and not cross-sectional. This is further confirmed in Table A1 which shows that in contrast to *CatFat* where the majority of variations (76%) is explained by bank fixed effects, the lion's share of variations (92%) in *LMIRisk* is explained by quarter fixed effects.

Table 8, Panel A presents the results using the demeaned version of *LMIRisk*. Estimates in column (1) shows that the sensitivity of uninsured deposit flows to performance is significantly higher in banks with higher *LMIRisk*. Furthermore, consistent with our results for *CatFat*, estimates in column (2) show that insured deposit flows counter the higher sensitivity of uninsured deposits, resulting in an insignificant coefficient estimate on *ROE*×*LMIRisk* when we model total deposit flows in column (3).

In our final set of robustness tests presented in Panel B of Table 8, we explore the sensitivity of our results to two alternative performance measures: return on assets (*ROA*) and non-performing loans (*NPL*). The results using these measures are qualitatively similar to those using *ROE*. Specifically, column (1) shows that the sensitivity of uninsured deposit to *ROA* is increasing in liquidity mismatch measured as *CatFat.* Column (4) shows uninsured deposit flows is negatively associated with banks' non-performing loans, and more so for banks with more liquidity mismatch.

7. Conclusion

In this paper we examine the relation between liquidity mismatch on bank's balance sheet and depositors' response to bank performance. We find that the sensitivity of uninsured deposit flows to bank performance is higher for banks with more liquidity mismatch on their balance sheet, especially for banks with intermediate level of performance. The effects are present in banks of all sizes and significantly so in small and medium banks that arguably have fewer access to alternative financing channels. The effects of liquidity mismatch are robust to control for the informational properties of bank earnings and are exacerbated when the aggregate conditions in the banking system are unfavorable. Evidence also suggests that the deposit fragility associated with liquidity mismatch can result in bank instability, as we find a positive association between bank's liquidity mismatch and their future failure, especially during the financial crisis of 2008. Banks with more liquidity mismatch also experience more deposit withdrawals and lending reduction during the crisis. Our results are consistent with the theoretical prediction of Goldstein and Pauzner (2005) where liquidity mismatch can generate strategic complementarities in depositors' payoff and induce panic-based runs due to coordination failure among depositors. While our results emphasize the importance of fundamentals in bank runs, they also support the idea that liquidity creation by banks comes at the cost of fragility.

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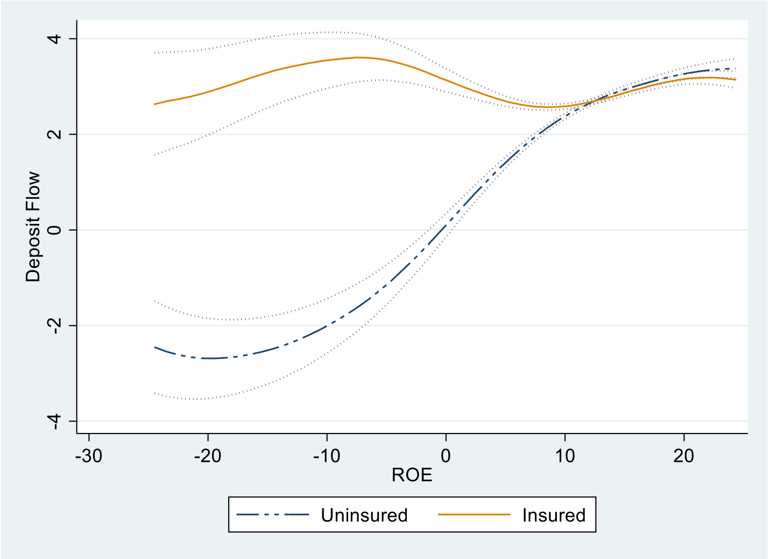
Figure 1: Examples for calculating the Berger and Bouwman measure of bank liquidity creation

		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

Figure 2: Sensitivity of deposit flows to bank performance

Panel A: Insured vs. uninsured



Panel B: Uninsured for subsamples by Catfat

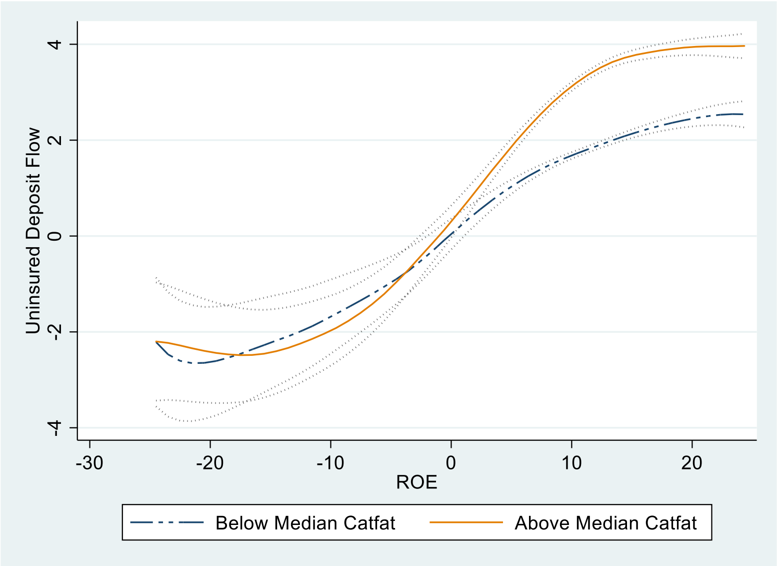


Table 1. Summary statistics

This table presents summary statistics for the main regression variables calculated over the regression sample. To avoid the impact of mergers and acquisitions, we exclude bank-quarter observations with quarterly asset growth greater than 10%. We also exclude observations with total assets less than 100 million. The unit of observation is at commercial bank-quarter level. The final sample includes 8,153 unique commercial banks from 1994 to 2016. The Appendix provides detailed information for variable definitions.

	N	Mean	Stdev	P25	P50	P75
ROE (in %)	287,018	10.36	10.37	6.94	11.05	15.44
CatFat	287,018	0.33	0.17	0.22	0.34	0.45
ΔDep^{U}	287,018	2.11	9.88	-2.04	2.16	6.84
ΔDep^{I}	287,018	2.78	9.18	-1.63	1.32	5.00
ΔDep^{Total}	287,018	4.76	10.42	-1.48	3.87	9.93
Ln(Assets)	287,018	12.63	1.05	11.89	12.34	13.02
RealEstate_Loans	287,018	0.69	0.17	0.60	0.72	0.82
Capital_Ratio	287,018	0.10	0.03	0.08	0.09	0.11
Wholesale_Funding	287,018	0.20	0.10	0.12	0.19	0.26
Std(ROE)	287,018	5.29	5.79	1.93	3.21	6.07
Large Time Deposit Rate	287,018	3.39	1.73	1.89	3.37	4.90
Core Deposit Rate	287,018	2.29	1.42	1.03	2.12	3.51
Persistence	233,270	0.16	0.38	-0.11	0.13	0.42
Informativeness	282,480	0.22	0.45	-0.10	0.27	0.58
LiqCreation_Asset	287,018	0.08	0.14	-0.02	0.08	0.18
LiqCreation_Liab	287,018	0.19	0.07	0.14	0.19	0.24
PctUninsured	265,846	33.69	14.50	23.18	31.44	41.73
LMIRisk	164,198	0.10	0.09	0.03	0.10	0.13
ROA	287,018	1.00	0.90	0.70	1.08	1.44
Pct_NPL	287,017	1.50	1.97	0.34	0.83	1.80

Table 2. Liquidity mismatch and sensitivity of deposit flows to bank performance

Panel A: Main Results

This table presents OLS estimates of Equation (3). The dependent variables are changes in the uninsured, insured, and total deposits scaled by the beginning value of total assets. *CatFat* is demeaned when interacted with *ROE*. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ROE $_{it-1}$	0.101***	0.024***	0.126***	0.094***	0.007**	0.106***	0.061***	0.045***	0.109***
	(35.458)	(7.628)	(34.967)	(28.275)	(2.124)	(29.736)	(21.139)	(16.133)	(30.406)
ROE $_{it-1}$ × *CatFat* $_{it-1}$	0.120***	-0.218***	-0.093***	0.211***	-0.176***	0.030	0.110***	-0.076***	0.027
	(7.032)	(-11.628)	(-4.182)	(10.114)	(-8.058)	(1.282)	(5.871)	(-4.223)	(1.155)
CatFat $_{it-1}$	3.204***	7.298***	10.228***	3.144***	11.550***	14.033***	5.500***	8.449***	13.512***
	(12.389)	(25.984)	(30.117)	(6.555)	(22.450)	(26.071)	(13.661)	(21.099)	(23.534)
Control Variables									
Ln(Size) $_{it-1}$	-0.074**	-0.298***	-0.399***	-3.213***	-2.769***	-5.656***	-3.592***	-3.020***	-6.163***
RealEstate_Loans $_{it-1}$	-0.471***	1.350***	0.773***	-2.813***	-0.106	-3.025***	-1.478***	-2.197***	-3.505***
Capital_Ratio $_{it-1}$	8.685***	0.073	9.652***	37.892***	29.249***	66.983***	39.114***	23.167***	62.738***
Wholesale_Funding $_{it-1}$	1.129***	6.464***	7.704***	1.000*	20.156***	20.140***	9.617***	9.909***	18.746***
Std(ROE) $_{it-1}$	-0.066***	-0.143***	-0.211***	-0.076***	-0.135***	-0.210***	-0.064***	-0.157***	-0.219***
Large Time Deposit Rate $_{t}$	-0.358***	0.327***	-0.044	-0.352***	0.283***	-0.077**	-0.039*	-0.057***	-0.094***
Core Deposit Rate $_{t-1}$	-0.485***	0.977***	0.448***	-0.987***	1.312***	0.294***	0.205***	0.210***	0.398***
Bank fixed effects	N	N	N	Y	Y	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y	Y	Y	N	N	N
Quarter fixed effects	N	N	N	N	N	N	Y	Y	Y
Observations	287,018	287,018	287,018	286,831	286,831	286,831	286,831	286,831	286,831
Adj. R-squared	0.064	0.055	0.066	0.102	0.102	0.166	0.282	0.330	0.188

Panel B: Main results in subsamples by bank asset size

This panel explores whether the effect of liquidity mismatch on flow-performance sensitivity differs by bank asset size. Columns (1) - (2), columns (3) - (4), and columns (5) - (6) present the results for deposit flow-performance sensitivity using ordinary least-squares estimates of Equation (3) for the subsample of small, medium, and large banks, respectively. Small banks are defined as those with total assets below 500 million, large banks have assets above 3 billion, and medium banks have assets between 500 million and 3 billion (measured in 2000 real dollars). *CatFat* is demeaned within each subsample when interacted with *ROE*. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Small banks: Assets $\in$ (0.1, 0.5 billion)		Medium banks: Assets $\in$ (0.5, 3 billion)		Large banks: Assets $>$ 3 billion	
	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{U}	ΔDep_{it}^{I}
	(1)	(2)	(3)	(4)	(5)	(6)
ROE_{it-1}	0.081***	0.013***	0.113***	-0.015*	0.138***	-0.058***
	(22.563)	(3.473)	(12.363)	(-1.770)	(8.920)	(-4.212)
$ROE_{it-1} \times CatFat_{it-1}$	0.193***	-0.130***	0.258***	-0.228***	0.088	-0.202***
	(8.413)	(-5.269)	(4.739)	(-4.210)	(1.100)	(-2.669)
$CatFat_{it-1}$	4.370***	12.099***	3.163***	14.198***	-0.382	7.534***
	(7.809)	(20.595)	(2.642)	(11.534)	(-0.237)	(4.037)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231,860	231,860	43,169	43,169	11,678	11,678
Adj. R-squared	0.103	0.115	0.154	0.106	0.108	0.066

Table 3: Controlling for differences in informational properties of *ROE*

This table presents ordinary least-squares estimates of Equation (3) after controlling for the effect of performance persistence. Variables are entered as their demeaned value when interacted with *ROE*. We measure *Persistence* as the AR(1) coefficient from a time-series regression of banks' *ROE* on its lagged value over the 12-quarters and *Informativeness* as the transparency measure in Chen et al (2020). T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)
ROE_{it-1}	0.081***	0.074***	0.075***	0.135***	0.126***
	(23.390)	(21.962)	(21.843)	(27.557)	(26.032)
$ROE_{it-1} \times CatFat_{it-1}$	0.203***	0.185***	0.191***	0.198***	0.172***
	(9.264)	(8.483)	(8.777)	(8.965)	(7.885)
$CatFat_{it-1}$	1.348***	1.643***	1.520***	1.135**	1.531***
	(2.926)	(3.596)	(3.313)	(2.445)	(3.336)
$ROE_{it-1} \times Persistence_{it-1}$		0.068***			0.058***
		(10.616)			(8.940)
$Persistence_{it-1}$		-1.686***			-1.499***
		(-16.666)			(-14.666)
$ROE_{it-1} \times Informativeness_{it-1}$			0.037***		0.028***
			(6.926)		(5.087)
$Informativeness_{it-1}$			-0.847***		-0.644***
			(-10.772)		(-8.019)
$ROE_{it-1} \times Std(ROE)_{it-1}$				-0.005***	-0.005***
				(-15.550)	(-16.024)
$Std(ROE)_{it-1}$				-0.051***	-0.048***
				(-7.048)	(-6.791)
Bank characteristics	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y	Y
Observations	231,728	231,728	231,728	231,728	231,728
Adj. R-squared	0.104	0.106	0.104	0.105	0.108

Table 4. Effects of liability side variation in strategic complementarities

This table presents OLS estimates of Equation (3) for subsamples partitioned by the percentage of uninsured deposits for panels A and B, and by the liquidity creation on the liability side for panel C, where the portfolio sorting variables are averaged over the preceding 3 years. *ROE* is interacted with the (demeaned) measure of liquidity creation on the asset side. The dependent variable is the changes in uninsured deposit levels as a percentage of beginning balance of uninsured deposits ($G\_Dep_{it}^{U}$) in panel B, and as a percentage of beginning balance of total assets (ΔDep_{it}^{U}) in panels A and C. In all panels, the matched samples are based on liquidity creation on the asset sides. All regressions include bank-fixed effects and the controls for time-varying bank characteristics and macro-conditions where coefficients are allowed to vary by subsamples. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Subsamples partitioned by the percentage of uninsured deposits with ΔDep_{it}^{U} as the dependent variable

	Full Sample			Matched Sample	
Tercile rank (low to high)	1st	2nd	3rd	1st	3rd
	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)
ROE_{it-1}	0.035***	0.068***	0.103***	0.040***	0.110***
	(11.094)	(13.36)	(14.870)	(8.439)	(14.81)
ROE_{it-1} × $LiqCreation\_Asset_{it-1}$	0.128***	0.164***	0.342***	0.148***	0.387***
	(4.904)	(4.634)	(8.542)	(4.227)	(7.728)
$LiqCreation\_Asset_{it-1}$	0.077	0.132	-4.312***	0.971	-5.217***
	(0.147)	(0.207)	(-5.552)	(1.311)	(-5.171)
Observations		277,462		142,348	
Adj. R-squared		0.134		0.131	
Test of difference: Top Tercile – Bottom Tercile					
	Diff.	(t-stat.)		Diff.	(t-stat.)
ROE_{it-1}:	0.068***	(8.837)		0.070***	(8.086)
ROE_{it-1} × $LiqCreation\_Asset_{it-}$:	0.214***	(4.558)		0.239***	(4.017)

Panel B: Subsamples partitioned by the percentage of uninsured deposits with $G\_Dep_{it}^{U}$ as the dependent variable

	Full Sample			Matched Sample	
Tercile rank (low to high)	1st	2nd	3rd	1st	3rd
	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{U}$

	(1)	(2)	(3)	(4)	(5)
ROE_{it-1}	0.204***	0.238***	0.267***	0.214***	0.284***
	(9.569)	(12.46)	(14.66)	(8.433)	(14.53)
ROE_{it-1} × LiqCreation_Asset $_{it-1}$	0.578***	0.653***	0.813***	0.506***	0.929***
	(4.114)	(4.884)	(7.747)	(2.958)	(7.314)
LiqCreation_Asset $_{it-1}$	1.590	0.174	-12.24***	3.450	-14.59***
	(0.658)	(0.0756)	(-5.855)	(1.127)	(-5.442)
Observations		277,462		142,348	
Adj. R-squared		0.102		0.103	
Test of difference: Top Tercile – Bottom Tercile					
	Diff.	(t-stat.)		Diff.	(t-stat.)
ROE_{it-1}:	0.063**	(2.299)		0.070***	(2.266)
ROE_{it-1} × LiqCreation_Asset $_{it-}$:	0.235	(1.375)		0.422**	(2.077)

Panel C: Subsample partitioned by liquidity creation on the liability side

	Full Sample			Matched Sample	
Tercile rank (low to high)	1st	2nd	3rd	1st	3rd
	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)
ROE_{it-1}	0.074***	0.089***	0.095***	0.071***	0.089***
	(13.393)	(16.31)	(15.48)	(12.675)	(13.04)
ROE_{it-1} × LiqCreation_Asset $_{it-1}$	0.231***	0.454***	0.313***	0.199***	0.359***
	(6.109)	(11.05)	(7.406)	(5.093)	(7.525)
LiqCreation_Asset $_{it-1}$	-6.451***	-6.163***	-3.765**	-4.801***	-4.627**
	(-8.997)	(-9.023)	(-4.979)	(-5.663)	(-5.033)
Observations		286,831		163,039	
Adj. R-squared		0.107		0.112	
Test of difference: Top Tercile – Bottom Tercile					
	Diff.	(t-stat.)		Diff.	(t-stat.)
ROE_{it-1}:	0.021**	(2.564)		0.018**	(2.036)
ROE_{it-1} × LiqCreation_Asset $_{it-}$:	0.082	(1.472)		0.161***	(2.645)

Table 5: Systematic vs. idiosyncratic performance shocks

Panel A presents OLS estimates of a modified version of Equation (3). *ROE_Sys* is the average *ROE* for all banks in a given quarter and *ROE_Idio* is the difference between *ROE* and *ROE_Sys*. Panel B presents OLS estimates of Equation (4) where Crisis is the period from 2007Q3-2009Q2. *CatFat* is demeaned when interacted with *ROE* or its components. All regressions include the same set of control variables and bank fixed effects as those in Table 2. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Systematic vs. idiosyncratic performance shocks

	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}
	(1)	(2)	(3)
ROE_Sys $_{it-1}$	0.561***	-0.519***	0.063***
	(60.068)	(-49.670)	(5.761)
ROE_Sys $_{it-1}$**CatFat* $_{it-1}$	0.593***	-0.222***	0.409***
	(13.052)	(-4.907)	(7.293)
ROE_Idio $_{it-1}$	0.060***	0.045***	0.108***
	(18.344)	(13.850)	(29.991)
ROE_Idio $_{it-1}$**CatFat* $_{it-1}$	0.121***	-0.131***	-0.022
	(5.730)	(-6.111)	(-0.896)
CatFat $_{it-1}$	-1.360**	12.262***	9.751***
	(-2.185)	(20.054)	(12.498)
Controls	Y	Y	Y
Observations	286,831	286,831	286,831
Adj. R-squared	0.118	0.124	0.167

Panel B: Effect of the Financial Crisis of 2007-09

	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	*Core Deposits rate*	*Large Time Deposits*	$\Delta Loan$	$\Delta Commit$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Crisis	-10.612***	17.535***	5.846***	0.464***	0.703***	5.230***	9.332***
	(-9.450)	(16.045)	(4.427)	(5.608)	(6.706)	(4.284)	(14.122)
Crisis× *CatFat* $_{it-1}$	-5.424***	1.314***	-3.950***	0.511***	0.317***	-0.020	-5.965***
	(-9.789)	(2.578)	(-6.483)	(13.126)	(6.838)	(-0.035)	(-20.689)
Catfat $_{it-1}$	8.220***	8.525***	16.074***	-0.983***	0.066	17.400***	1.960***
	(21.936)	(22.160)	(32.317)	(-23.223)	(1.359)	(35.866)	(10.785)

Controls	Y	Y	Y	Y	Y	Y	Y
*Controls*Crisis*	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	287,018	287,018	287,018	281,816	281,798	287,018	287,018
Adj. R-squared	0.204	0.211	0.188	0.892	0.813	0.275	0.099

Table 6: Liquidity mismatch and performance

Panel A. Liquidity mismatch and bank failure

Panel A shows the estimates of the marginal effects from a logit regression that explores the association between liquidity mismatch and bank failure. In columns (1) to (3), the dependent variable is an indicator variable that the bank fails within the next 1, 2, and 3 years during the non-crisis period, respectively. In column (4), the dependent variable is an indicator variable that the bank failed during the financial crisis period. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Failure in next year	*Failure in next two years*	*Failure in next three year*	*Failure during crisis*
	(1)	(2)	(3)	(4)
CatFat $_{it}$	0.001	0.002**	0.002*	0.027***
	(0.984)	(2.151)	(1.851)	(3.108)
ROE $_{it}$	-0.000***	-0.000***	-0.000***	0.000
	(-2.900)	(-2.764)	(-3.073)	(0.940)
In(Assets) $_{it}$	0.000*	0.000	0.000	0.005***
	(1.825)	(1.470)	(1.378)	(4.555)
RealEstate_Loans $_{it}$	-0.002*	-0.001	-0.001	0.035***
	(-1.656)	(-1.118)	(-0.477)	(3.852)
Capital Ratio $_{it}$	-0.048***	-0.047***	-0.074***	0.049
	(-3.407)	(-2.834)	(-4.276)	(1.298)
Wholesale_Funding $_{it}$	0.003	0.005***	0.006***	0.038***
	(1.621)	(2.799)	(3.182)	(3.382)
Core Deposit Rate $_{it}$	0.000**	0.000	0.000	0.009***
	(2.152)	(0.278)	(1.256)	(4.776)
Large Time Deposit Rate $_{it}$	-0.000	-0.000	0.000***	0.003**
	(-0.212)	(-0.473)	(2.904)	(2.113)
FedFundRate $_{t}$	-0.000	-0.001**	-0.001	
	(-1.054)	(-2.064)	(-0.813)	
StockRet $_{t}$	0.005**	0.011***	0.007**	
	(2.282)	(3.111)	(2.319)	
FedFundRate $_{t-1}$	0.000	0.001*	-0.000	
	(0.315)	(1.707)	(-0.001)	
StockRet $_{t-1}$	-0.001	0.003*	-0.002	
	(-0.813)	(1.879)	(-0.548)	
Observations	62,428	27,822	21,984	3,532
Pseudo. R-squared	0.242	0.278	0.388	0.207

Panel B: Liquidity mismatch and bank profitability

Panel B explores the association between liquidity mismatch and bank performance. The dependent variable is return on equity (*ROE*) for columns (1) and (2), and ROA for columns (3) and (4). T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	ROE	*ROE*	*ROA*	*ROA*
	(1)	(2)	(3)	(4)
CatFat $_{it}$	1.966***	8.390***	0.162***	0.857***
	(5.139)	(16.278)	(4.585)	(17.609)
In(Assets) $_{it}$	0.190***	-3.319***	0.011**	-0.265***
	(3.237)	(-27.123)	(2.063)	(-23.125)
RealEstate_Loans $_{it}$	-7.624***	-5.145***	-0.709***	-0.631***
	(-19.700)	(-8.848)	(-19.532)	(-12.036)
Capital Ratio $_{it}$	-59.299***	-26.221***	5.096***	6.115***
	(-24.044)	(-9.138)	(19.607)	(21.583)
Wholesale_Funding $_{it}$	-7.814***	-1.257*	-0.769***	-0.197***
	(-12.444)	(-1.831)	(-13.495)	(-3.169)
Std(ROE) $_{it-1}$	-0.782***	-0.768***		
	(-62.123)	(-58.471)		
Std(ROA) $_{it-1}$			-0.438***	-0.408***
			(-45.576)	(-42.127)
Constant	24.220***	60.012***	1.186***	4.165***
	(31.312)	(47.326)	(15.940)	(34.696)
Bank fixed effects	N	Y	N	Y
Observations	287,018	286,831	287,018	286,831
Adj. R-squared	0.232	0.461	0.194	0.445

Table 7. Do large deposit outflows hurt liquidity-mismatched banks more?

This table presents the OLS estimates for Equation (6). The dependent variable is return on equity (ROE_{it+1}) for period $t+1$. $Outflow_{it}$ is a dummy variable that equals 1 if the bank's total deposit flows as a percentage of lagged total assets is below the 10th percentile value of the sample, and 0 otherwise. All regressions include both current and lagged *ROEs* in previous four quarters. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	$ROE_{i,t+1}$	$\Delta Loan_{i,t+1}$	$\Delta Commit_{i,t+1}$
	(1)	*(2)*	*(3)*
$Outflow_{it}$	-0.188	-0.690***	0.000
	(-1.344)	(-4.163)	(0.001)
$Outflow_{it}$ *$CatFat_{it}$	-0.771*	-1.370***	-0.956***
	(-1.939)	(-3.092)	(-3.670)
$CatFat_{it}$	2.832***	15.854***	0.483**
	(8.751)	(32.116)	(2.309)
$Ln(Assets)_{it}$	-1.460***	-3.524***	-0.899***
	(-15.720)	(-22.699)	(-14.683)
Real_estate_loans	-0.580*	-0.335	-2.784***
	(-1.747)	(-0.603)	(-11.618)
$Capital\_Ratio_{it+1}$	-42.476***	18.203***	4.038***
	(-21.809)	(6.852)	(3.778)
$Wholesale\_Funding_{it+1}$	-7.228***	-5.154***	-2.103***
	(-14.357)	(-7.336)	(-7.515)
Lagged ROEs	Y	Y	Y
Macro control	Y	Y	Y
Bank fixed effects	Y	Y	Y
Observations	202,773	216,283	216,283
Adj. R-squared	0.577	0.307	0.096

Table 8. Robustness to alternative measures of liquidity mismatch and bank performance

Panel A explores the robustness of our main results to using *LMIRisk* as the liquidity mismatch measure. Panel B explores the robustness to two alternative bank performance measures– *ROA* (return on assets) in columns (1) - (3) and Non-performing Loan (*NPL*) in columns (4) - (6). T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Robustness to using LMIRisk as liquidity mismatch measure

	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}
	(1)	(2)	(3)
ROE_{it-1}	0.064***	0.032***	0.099***
	(11.165)	(5.316)	(23.113)
ROE_{it-1} * $LMIRisk_{it-1}$	0.499***	-0.557***	-0.005
	(8.472)	(-8.577)	(-0.128)
$LMIRisk_{it-1}$	-32.855***	36.338***	1.431**
	(-39.434)	(42.526)	(2.264)
Bank characteristics	Y	Y	Y
Macro controls	Y	Y	Y
Bank fixed effects	Y	Y	Y
Observations	164,081	164,081	164,081
Adj. R-squared	0.179	0.180	0.184

Panel B: Robustness to alternative performance measures

	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}
Performance measure		*ROA*			*%NPL*	
	(1)	(2)	(3)	(4)	(5)	(6)
$BankPerf_{it-1}$	1.126***	-0.086**	1.084***	-0.405***	-0.219***	-0.642***
	(29.458)	(-2.205)	(26.418)	(-21.240)	(-11.038)	(-27.543)
$BankPerf_{it-1}$ * $CatFat_{it-1}$	2.412***	-1.564***	0.841***	-1.395***	0.338***	-1.104***
	(10.117)	(-6.619)	(3.142)	(-13.183)	(3.196)	(-9.436)
$CatFat_{it-1}$	2.813***	11.410***	13.520***	7.041***	8.578***	14.957***
	(5.733)	(22.068)	(24.304)	(14.822)	(16.648)	(30.596)
Bank characteristics	Y	Y	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Observations	286,831	286,831	286,831	286,830	286,830	286,830
Adj. R-squared	0.103	0.102	0.165	0.101	0.103	0.170

Appendix: Variable definitions

Variables	Definitions
ROE $_{I,t-1}$	Annualized ROE (in %) in quarter t-1, calculated as net income (RIAD4300, adjust year-to-date reporting to within quarter) divided by beginning equity (RCFD3210).
CatFat	The preferred measure of Bank liquidity creation per unit of gross total assets, by Berger and Bouwman (2009) and downloaded from https://sites.google.com/a/tamu.edu/bouwman/data. Step 1: Classify all bank activities (asset, liability, and off-balance-sheet) as liquid, semi-liquid, or illiquid based on product category. Step 2: Assign weights to the activities classified in Step 1. Illiquid assets, liquid liabilities get ½, Liquid assets, illiquid liabilities and equities get -1/2. Certain loans and liabilities are classified as semi-liquid and get 0. Step 3: Combine bank activities as classified in Step 1 and as weighted in Step 2 to construct our liquidity creation measure.
ΔDep_{it}^{I}	Annualized growth rate in insured deposits as a percentage of lagged assets in quarter t and $t+1$. (in %): $(Insured\ Deposits_{i,t+1} - Insured\ Deposits_{i,t-1})/Asset_{i,t-1} * 200\%$. Insured deposits are accounts of $100,000 or less. After 2006Q2, it includes retirement accounts of $250,000 or less. From 2009Q3, reporting thresholds on non-retirement deposits increased from $100,000 to $250,000. Insured deposits: RCON2702 (before 2006Q2); RCONF049 + RCONF045 (from 2006Q2).
ΔDep_{it}^{U}	Annualized growth rate in uninsured deposits as a percentage of lagged assets (in %) in quarter t and $t+1$. Uninsured deposit is calculated as total deposits (RCFD2200) – insured deposits.
ΔDep_{it}^{Total}	Sum of ΔDep_{it}^{I} and ΔDep_{it}^{U}
G_Dep^{k}	Annualized growth rate of deposit category $k \in \{U, I, Total\}$, similar to ΔDep^{k} except scaled by beginning balance of the respective deposit level.
Ln(Assets)	Log of total assets (RCFD2170).
RealEstate_Loan	Loans secured by real estate (RCFD1410) scaled by total loans (RCFD1400).
Capital_Ratio	Total equity (RCFD3210) divided by total assets (RCFD2170).
Wholesale_Funding	Wholesale funds are the sum of following: large-time deposits (RCON2604), deposits booked in foreign offices (RCFN2200), subordinated debt and debentures (RCFD3200), gross federal funds purchased and repos [RCFD2800, or (RCONB993+RCFDB995 from 2002q1)], other borrowed money (RCFD3190). Scaled by total assets.
Std(ROE) $_{i,t-1}$	Standard deviation of ROE measured over 12 rolling quarters (from Quarter $t-12$ to $t-1$).

Large Time Deposit Rate$_{i,t}$	Annualized average interest rate (in %) over the two quarters $t, t+1$ on savings deposits: $(larget\ timedeposit\ interest\ expense\ in\ Qtr\ t\ and\ t+1)/(Avg.\ large\ time\ deposit\ balance\ in\ Qtr\ t\ and\ t+1)\ ) * 400\%)$.
Core deposit Rate$_{i,t}$	Core deposits include transaction, saving, and small time deposits, and core deposit rate is the average interest rate paid on the three.
Failure in n year	An indicator variable that equals 1 if the bank fails in the next n years, measured as 1 if the bank is on the FDIC failed banks list on https://www.fdic.gov/bank/individual/failed/
CatNonFat	The same as *CatFat*, but does not include off-balance sheet items.
LMI_Risk	$LMI\_RIsk_{it} = \max(LMI_{it} - LMI_{it}^{1\sigma}, 0)$. The liquidity risk of a bank is the exposure of that bank to a 1σ unfavorable change in both market and funding liquidity conditions. LMI_{it} is constructed following Bai et al. (2018) and its online appendix for a sample of commercial banks. Specifically, LMI_{it} for bank *i* at time *t* is computed as the net of the asset and liability liquidities: $LMI_{it} = \sum_k \lambda_{t,a_k} a_{t,k}^i + \sum_k \lambda_{t,l_{k'}} l_{t,k'}^i$.where λ_{t,a_k} is time varying asset liquidity factor that was backed out from haircuts in repo market; $\lambda_{t,l_{k'}}$ is the liability liquidity factor that calculated recursively using the maturity and liquidity cost. The parameters on liquidity factors are from Bai et al. (2018).
ROA $_{i,t-1}$	Annualized ROA (in %) in quarter t-1, calculated as net income (RIAD4300, adjust year-to-date reporting to within quarter) divided by beginning assets.
NPL $_{I,t-1}$	The percentage of non-performing loan (RCFD1403+RCFD1407) in total loan.
Informativeness	The adjusted R-squared from the following regression $WriteOff_t = \alpha_0 + \sum_{k=1}^{2}(\delta_k EBLLP_{t-k} + \beta_k LLP_{t-k} + \gamma_k \Delta NPL_{t-k}) + \rho Capital_{t-1} + \varepsilon_t$, estimated for each bank-quarter using the bank's observations over the previous 12 quarters.
Persistence $_{it-1}$	The slope coefficient β_1 in $ROE_t = \alpha_0 + \beta_1 ROE_{it-1} + \epsilon$, estimated for each bank-quarter using the bank's observations over the previous 12 quarters.

Online Appendix for

Liquidity Transformation and Fragility in the US Banking Sector

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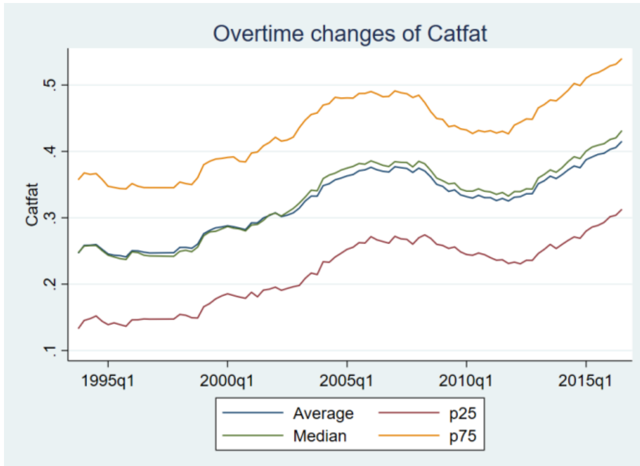
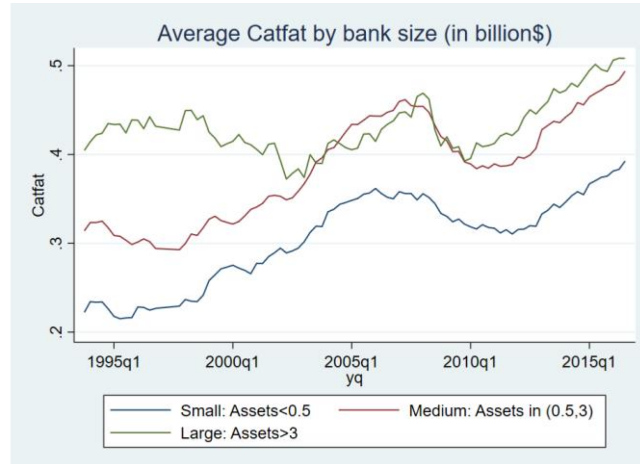
This Draft: February 2021

Figure A1: Over time changes in *CatFat and LMIRisk*

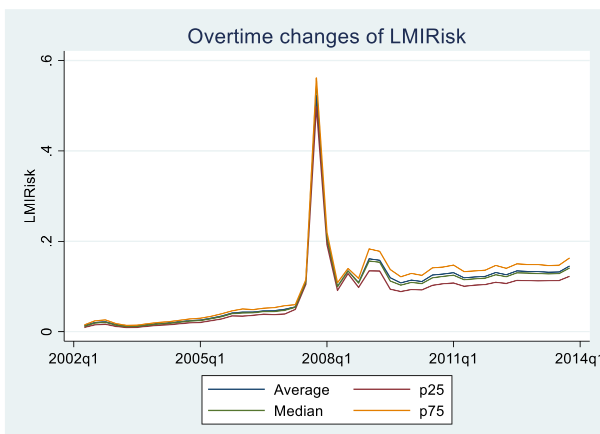
Panel A: Full Sample for CatFat



Panel B: Subsample by bank size for CatFat



Panel C: Full Sample for LMIRisk



Panel D: Subsample by bank size for LMIRisk

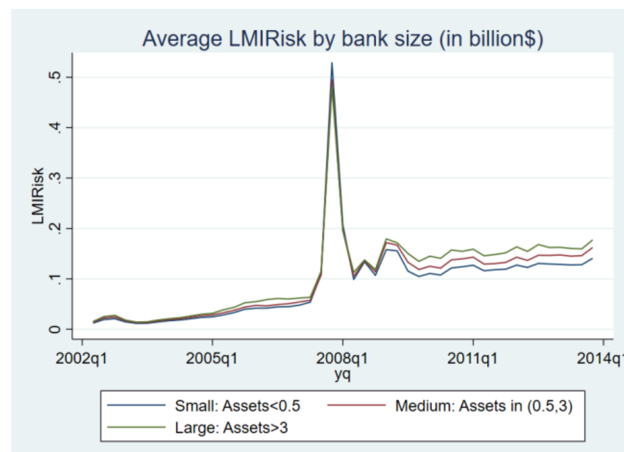


Figure A2: Changes around the Financial Crisis of 2008

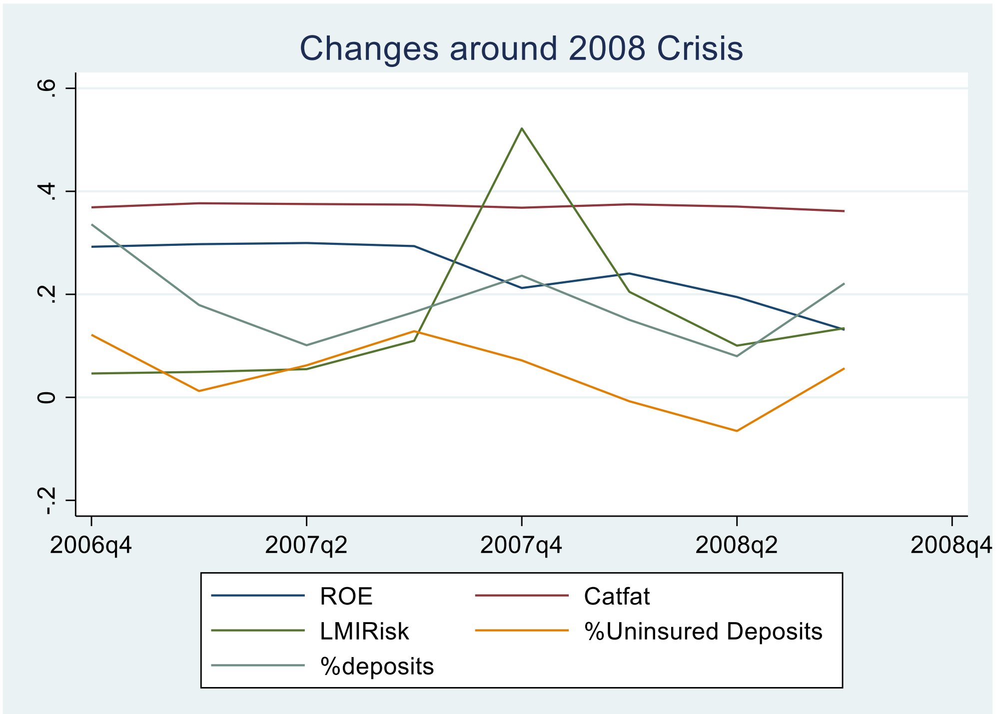


Table A1: Variations in liquidity mismatch variables

This panel presents to what extent bank fixed effects and quarter fixed effects explain liquidity mismatch variables. Columns (1) and (4) includes both bank and quarter fixed effects, columns (2) and (5) include only bank fixed effects, and columns (3) and (6) include only quarter fixed effects.

		$CatFat_{it}$			$LMIRisk_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank fixed effects	Yes	Yes	No	Yes	Yes	No
Quarter fixed effects	Yes	No	Yes	Yes	No	Yes
Observations	286,831	287,018	287,018	164,081	164,198	164,198
Adjusted R-squared	0.832	0.762	0.075	0.956	0.087	0.921

Table A2. Liquidity mismatch and sensitivity of deposit flows to bank performance

Panel A: Main Results

This table presents OLS estimates of Equation (3). The dependent variables are percentage changes in the uninsured, insured, and total deposits, **each scaled by their respective beginning value**. *CatFat* is demeaned when interacted with *ROE*. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{I}$	$G\_Dep_{it}^{Total}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{I}$	$G\_Dep_{it}^{Total}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{I}$	$G\_Dep_{it}^{Total}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ROE $_{it-1}$	0.349***	0.021***	0.149***	0.311***	-0.001	0.125***	0.219***	0.074***	0.129***
	(34.376)	(3.399)	(34.889)	(26.688)	(-0.158)	(29.527)	(20.257)	(13.202)	(30.069)
ROE $_{it-1}$ × CatFat$_{it-1}$	0.107*	-0.471***	-0.121***	0.361***	-0.373***	0.021	0.118*	-0.169***	0.019
	(1.900)	(-11.464)	(-4.581)	(5.500)	(-7.587)	(0.728)	(1.910)	(-4.090)	(0.684)
CatFat$_{it-1}$	6.802***	17.685***	12.233***	5.426***	25.083***	16.833***	15.611***	17.842***	16.297***
	(8.528)	(28.787)	(30.218)	(3.652)	(23.044)	(26.285)	(11.843)	(20.625)	(23.875)
Control Variables									
Ln(Size)$_{it-1}$	-0.867***	-0.312***	-0.337***	-11.754***	-4.916***	-6.653***	-12.961***	-5.334***	-7.119***
RealEstate_Loans $_{it-1}$	-1.584***	2.378***	0.731**	-7.022***	0.299	-3.568***	-3.205**	-4.039***	-3.850***
Capital_Ratio $_{it-1}$	42.050***	9.432***	16.577***	163.138***	60.946***	83.877***	162.742***	49.070***	79.513***
Wholesale_Funding $_{it-1}$	0.748	22.555***	12.785***	6.208***	50.378***	28.312***	34.452***	27.879***	26.810***
Std(ROE) $_{it-1}$	-0.180***	-0.238***	-0.247***	-0.197***	-0.248***	-0.249***	-0.236***	-0.278***	-0.255***
Large Time Deposit Rate$_{t}$	-0.924***	0.639***	-0.053	-1.069***	0.618***	-0.098***	-0.135	-0.106**	-0.125***
Core Deposit Rate$_{t-1}$	-0.766***	1.722***	0.518***	-2.510***	2.561***	0.347***	0.767***	0.263***	0.439***
Bank fixed effects	N	N	N	Y	Y	Y	Y	Y	Y
Macro controls	Y	Y	Y	Y	Y	Y	N	N	N
Quarter fixed effects	N	N	N	N	N	N	Y	Y	Y
Observations	287,017	287,017	287,018	286,830	286,830	286,831	286,830	286,830	286,831
Adj. R-squared	0.042	0.059	0.068	0.070	0.104	0.164	0.203	0.340	0.186

Panel B: Main results in subsamples by bank asset size

This panel explores whether the effect of liquidity mismatch on flow-performance sensitivity differs by bank asset size. The dependent variables are percentage changes in the uninsured, insured, and total deposits, each scaled by their respective beginning value. Columns (1) - (2), columns (3) - (4), and columns (5) - (6) present the results for deposit flow-performance sensitivity using ordinary least-squares estimates of Equation (3) for the subsample of small, medium, and large banks, respectively. Small banks are defined as those with total assets below 500 million, large banks have assets above 3 billion, and medium banks have assets between 500 million and 3 billion (measured in 2000 real dollars). *CatFat* is demeaned within each subsample when interacted with *ROE*. T-statistics, reported in parentheses, are based on standard error estimates clustered at the bank level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Small banks: Assets $\in (0.1, 0.5$ billion)		Medium banks: Assets $\in (0.5, 3$ billion)		Large banks: Assets $>$ 3 billion	
	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{I}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{I}$	$G\_Dep_{it}^{U}$	$G\_Dep_{it}^{I}$
	(1)	(2)	(3)	(4)	(5)	(6)
ROE_{it-1}	0.276***	0.015**	0.349***	-0.049***	0.412***	-0.161***
	(20.858)	(2.036)	(12.610)	(-2.622)	(7.743)	(-4.405)
$ROE_{it-1} \times CatFat_{it-1}$	0.329***	-0.253***	0.385**	-0.489***	0.147	-0.564***
	(4.392)	(-4.947)	(2.236)	(-3.527)	(0.509)	(-2.730)
$CatFat_{it-1}$	9.710***	25.489***	6.645*	32.750***	-4.261	16.627***
	(5.554)	(21.542)	(1.736)	(12.032)	(-0.868)	(3.189)
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231,859	231,859	43,169	43,169	11,678	11,678
Adj. R-squared	0.068	0.119	0.125	0.110	0.093	0.054