Liquidity Transformation and Fragility in the US Banking Sector

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ABSTRACT

A key role of banks is liquidity transformation, which is also thought to create fragility, as uninsured depositors face an incentive to withdraw money before others (a so-called panic run). Despite much theoretical work, there has not been much empirical evidence establishing this mechanism. In this paper, we provide the first large-scale evidence of this mechanism. Banks that perform more liquidity transformation exhibit higher fragility, manifested by stronger sensitivities of uninsured deposit flows to bank performance and greater levels of uninsured deposit outflows when performance is poor. We also explore the effects of deposit insurance and systemic risk.

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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 always hold sufficient liquid assets to meet the immediate withdrawal demands of 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.[1]

A large body of economic theory, going back to Diamond and Dybvig (1983), has been developed to understand banks' role in liquidity transformation and their resulting exposure to panic-based runs. This line of thinking also lies behind government policies shaping the banking industry over the years, trying to mitigate panics, such as deposit insurance and lender of last resort (these ideas go back to Bagehot (1873)). Yet, despite the long-lasting impact of these ideas, empirical evidence that 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 from 1993-2016.

[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 (Goldstein (2013)). Hence, panic does not reflect anything irrational, but rather it is group behavior resulting from coordination failures leading to an inferior outcome that is not fully justified by fundamentals.

Traditional bank-run models feature multiple equilibria, where bank runs can either occur or not occur, and so they are difficult to test in the data, as Gorton (1988) argued. Hence, our empirical analysis is guided by more recent theories, which preserve the panic-based feature but provide more precise predictions about when runs are going to occur (Goldstein and Pauzner (2005), Chen, Goldstein, and Jiang (2010), Vives (2014)). Specifically, just like in Diamond and Dybvig (1983), in these theories, banks' liquidity mismatch creates strategic complementarities in depositors' payoffs, increasing their incentive to withdraw when they expect that other depositors will withdraw. In addition, depositors receive slightly noisy signals about the bank's fundamentals and act according to them. These signals inform them directly about the fundamentals but also indirectly about what other depositors know and what they might do. The key equilibrium result of such models is that depositors will run when their signal is below a threshold and not when above. Moreover, the threshold increases in the degree of liquidity transformation provided by the bank. In this way, fundamentals and panic jointly determine the bank's fragility: depositors run when fundamentals are lower, but their proneness to run depends on the degree of liquidity transformation, which brings in the element of panic.

We start our analyses with a basic diagnostic of the relation between uninsured deposit flows and bank performance (measured by the return on assets, *ROA*) without making any functional form assumptions by using semi-parametric estimation. We find that banks start losing uninsured deposits in response to performance declines only when *ROA* realizations are sufficiently poor – this region seems to lie well below the median *ROA*. In the above-median region, this flow-performance relation is flat. This relation is consistent with the Goldstein and Pauzner (2005) model, where runs are triggered below a threshold of the fundamentals. The fact that the sensitive region lies well below the median indicates that banks are mostly stable, and the likelihood of fragility and runs is low, which is what we would expect from a well-functioning banking system.

We then turn to our main objective to examine whether the uninsured depositors' withdrawal behavior in poor-performance regions reflects an element of panic. Building on the key insight from the theory that the performance threshold for runs increases with the degree of liquidity transformation, we get two testable predictions that form the core of our empirical analyses. First, the average sensitivity of uninsured depositors' flows to news about bank performance will be stronger for banks that do more liquidity transformation. Intuitively, because of the higher run-threshold, a given bad performance shock is more likely to breach the run-threshold (and trigger panic-based withdrawals) of banks doing more liquidity transformation; this, in expectation, makes uninsured deposit flows of these banks more sensitive to performance. Second, conditional on a given level of poor performance, we also expect high liquidity transformation banks to have lower levels of uninsured deposit flows because of their greater chance of having already experienced panic-based withdrawals. We develop these predictions in detail in Section I based on the existing theories.

We emphasize that the way the degree of liquidity transformation affects uninsured deposit flows and their interaction with performance provides support to the panic-based run channel. 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 difference in the flow patterns between banks that perform more liquidity transformation and banks that perform less liquidity transformation (we address a key concern below). The degree of liquidity transformation affects uninsured depositors because it makes them more worried about what other uninsured depositors will do.

Implementing this empirical analysis requires us to have measures of liquidity transformation. Liquidity transformation can come from the asset-side, when banks hold more illiquid assets, and from the liability-side, when banks have higher amounts of uninsured deposits. We use the two measures separately to highlight the effect of the different dimensions of liquidity transformation and also interact them in later analysis. For asset-side illiquidity, we rely on the measure developed by Berger and Bouwman (2009). We provide a detailed description of this measure in Section II.[2] For the liability side, we use the bank's reliance on uninsured deposits, which captures the extent to which banks create liquidity on the liability side without the help of government-backed deposit insurance.[3] We refer to these measures as *Asset Illiquidity* and *%Uninsured*. Our main results confirm the above predictions. For both measures of liquidity transformation – *Asset Illiquidity* and *%Uninsured* – banks that create more liquidity exhibit a stronger sensitivity of uninsured deposit flows to performance: a one-standard-deviation increase in *Asset Illiquidity* (*%Uninsured*) is associated with more than 34% (43%) higher sensitivity of uninsured deposit flows to performance. Moreover, for both measures, conditional on below-median performance, banks that create more liquidity have a higher amount of uninsured deposit outflows: a one-standard-deviation increase in *Asset Illiquidity* (*%Uninsured*) is associated with about 35% (34%) more outflows of uninsured deposit when bank performance declines from above to below median.

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2 An alternative measure of liquidity transformation is available from Bai, Krishnamurthy, and Weymuller (2018). Unlike our measure, the Bai et al. measure incorporates changes in the liquidity of assets and liabilities based on changes in market conditions. As we discuss in detail in Section II, this makes the Bai et al. measure unsuitable for our purpose because the deterioration in the liquidity of markets for bank' assets itself can be a result of panic.

[3] We explain in Section II why the Berger and Bouwman (2009) liability-side liquidity measure is not suitable for our purposes.

A key concern is that the information content of *ROA* may vary with our measures of liquidity mismatch. Perhaps a decline in *ROA* (particularly from above- to below-median region) implies a larger reduction in the cash-generating potential of assets of banks with greater liquidity transformation. Thus, the stronger adverse reaction of uninsured depositors at these banks may reflect the effect of more fundamental news instead of panic.

We first note that this concern is mainly applicable to the analyses based on *Asset Illiquidity.* Banks with different asset illiquidity invest in different asset classes; these asset classes may differ in the statistical/informational properties of the profits they generate. The concern is less applicable to the analyses based on *%Uninsured* since it is not directly connected to the cash-generating potential of banks' different asset classes. That said, the concern for *%Uninsured* may arise indirectly if banks systematically adjust asset side liquidity based on the fragility of their liability side. However, our results for *%Uninsured* remain fully intact in a matched sample analysis in which we explicitly eliminate any observable differences in asset composition and illiquidity across banks with different *%Uninsured*. We believe this analysis yields some of the cleanest evidence on the effect of strategic complementarities.

We also provide several analyses that mitigate this concern for *Asset Illiquidity*. First, we explore variation in the effect of *Asset Illiquidity* based on the availability of capital from local peer banks. Granja, Seru, and Matvos (2017) show that assets of distressed banks are primarily sold to local peers, and these asset sales happen at a greater fire sale discount when local peer banks have less capital to buy those assets. We therefore expect uninsured depositors to be even more concerned about the illiquidity of their banks' assets when local peer banks have less capital. We show that the effects of asset illiquidity are indeed much stronger when local peer banks have lower capital. This is consistent with the panic channel, and, at the same time, there is no clear economic rationale for why the informativeness of a bank's *ROA* would depend upon the capital ratio chosen by peer banks. Second, following a similar logic, we show that the effect of *Asset Illiquidity* is stronger when the bank is financed with a higher fraction of uninsured deposits. This is precisely what one would expect under the panic channel, as an uninsured depositor would care a lot more about the illiquidity of the bank's assets when she/he is surrounded by many other uninsured depositors. This finding is again difficult to explain based on the informativeness of *ROA* as it is not clear why, holding the level of asset illiquidity constant, the information content of *ROA* would vary with the degree of uninsured deposit financing. Third, we explicitly measure and control for informational properties of *ROA* and find that our inferences remain virtually unchanged.

In our next set of analyses, we explore the role of deposit insurance – a policy tool introduced in 1934 to mitigate panics. Several theoretical studies analyze the role of deposit insurance.[4] We find that the results for insured deposit flows tend to go in the opposite direction to those for uninsured deposit flows regarding the effect of liquidity transformation. This suggests that banks actively utilize deposit insurance to manage volatility in uninsured deposits caused by liquidity mismatch. This is consistent with recent evidence by Martin, Puri, and Ufier (2023) and Chen et al. (2022) on how banks deal with the loss of uninsured depositors in times of poor performance by actively attracting insured deposits.

Can high liquidity transformation banks fully offset the loss of uninsured deposits by attracting insured deposits? The answer in general is no. We find that the substitution with insured deposits is only partial when using the *Asset Illiquidity* measure. The evidence is even stronger in the

[4] See Diamond and Dybvig (1983), Rochet and Vives (2004), Keister (2016), Allen et al. (2018), and Davila and Goldstein (2023), among others.

context of the 2008 financial crisis where using both *Asset Illiquidity* and *%Uninsured* we find that high liquidity transformation banks cannot fully offset the loss of uninsured deposits with insured deposits. It is also important to note that even when substitution with insured deposits is effective, it does not imply that panic stemming from liquidity transformation is costless – the banks end up paying higher deposit rates (as we show later) and insurance premiums. The substitution merely changes the nature of costs. Overall, our results indicate that deposit insurance plays an interesting role, but does not make the panic-based fragility irrelevant as one would hope.

Finally, we analyze the differences between idiosyncratic and systematic shocks and how they interact with the panic-based channel. This is important for two reasons. First, the worry of policymakers, heightened by the events of the 2008 financial crisis, is mostly about systematic fragility. Hence, it is important to explore our channel when banks experience systematic shocks. Second, contrasting the results for the two types of shocks provides another test of the strategic complementarities channel. Strategic complementarities are expected to be stronger following a systematic shock because a bank will have greater difficulty in meeting spikes in deposit withdrawals by accessing liquidity from other (also distressed) banks either by selling assets or through interbank borrowings (see models by Shleifer and Vishny (1992), Liu (2016), Goldstein et al. (2022)). Decomposing banks' *ROA* into a systematic component and an idiosyncratic component and interacting with liquidity mismatch, we show that the effects of liquidity mismatch are stronger when the shock is systematic than when it is idiosyncratic, both in terms of higher sensitivity to performance and in terms of lower levels of uninsured outflows conditional on low performance. 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, leading to a lower growth in credit. All these results provide additional evidence for the panic-based channel and call for more thinking among policymakers on how to control it.

Our paper is related to prior empirical work on bank runs. Many early studies establish a strong negative association between bank performance and subsequent banking crises to argue that bank runs seem to be driven by fundamentals and not by panic (e.g., Gorton (1988), Demirguc-Kunt and Detragiache (1998, 2002), Schumacher (2000)).[5] However, as argued by Goldstein (2013), this interpretation is problematic since panic manifests as a multiplier effect by amplifying depositors' response to bad news about bank fundamentals when strategic complementarities are strong. In this paper, we use precisely this insight to identify the effect of panic on bank deposit withdrawals.

This type of analysis was first introduced to the literature for equity mutual funds by Chen, Goldstein, and Jiang (2010). 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 the life insurance industry in Foley-Fisher, Narajabad, and Verani (2020). We are the first to conduct such analysis for banks, where fragility has been most prominent over the years and where it affected government policies most strongly. The fact that fragility is still present in the banking sector despite deposit insurance is also an important insight which could not be obtained in any of the other settings.

Several recent papers also attempt to evaluate the forces behind bank runs empirically. Among them, Iyer and Puri (2012), Iyer, Puri, and Ryan (2016), Egan, Hortaçsu, and Matvos (2017), and

[5] Chen et al. (2022) recently analyze the way that such fundamental-based flows are affected by the transparency of the bank about its performance. They do not examine how liquidity transformation affects bank fragility.

Artavanis et al. (2022) are perhaps the most related. Iyer and Puri (2012) and Iyer, Puri, and Ryan (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. (2022) document the presence of panic in depositor behavior using micro-account level data at a daily frequency from one large bank in Greece. Egan, Hortaçsu, and Matvos (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 challenging 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.

Finally, our paper has been written largely prior to the episode of bank fragility in March 2023. This episode centered on the run on Silicon Valley Bank (SVB), one of the biggest and fastest bank runs in history, that spread to some other banks and led to government interventions. This episode demonstrates the fragility that is brought upon by uninsured deposits, a key force highlighted in our empirical analysis. Indeed, Jiang et al. (2023) analyzed this episode and the strategic complementarities and fragility caused by the unusually large reliance of SVB on uninsured deposits. Hence, this episode can be seen as an out-of-sample confirmation of the forces we study in this paper and demonstrates how destructive they can be in some cases. Our paper can help guide the discussions of policy changes now underway following that episode.

The remainder of the paper is organized as follows. Section I lays out the theoretical underpinnings for the testable predictions we examine in data. Section II discusses our measurement of liquidity mismatch. Section III describes the empirical specifications and the sample we used in our analysis. Section IV presents our main results on how liquidity mismatch affects deposit flow-performance relations. Section V provides further tests to address the alternative explanation. Sections VI and VII examine the effects of deposit insurance and systematic risk, respectively. Section VIII concludes.

I. Theoretical Underpinnings

Since the seminal work by Diamond and Dybvig (1983), several studies have used global games techniques to show that the likelihood of panic-based runs increases in the degree of liquidity mismatch (e.g., Morris and Shin (2000), Goldstein and Pauzner (2005), Chen, Goldstein, and Jiang (2010); Vives (2014)). In this section, we use the set-up in Goldstein and Pauzner (2005; hereafter, GP) to lay out the theoretical underpinnings of our empirical tests to detect panic-based withdrawals.

GP consider a bank that issues deposit claims to a continuum of consumers at $t = 0$ backed by illiquid assets. The assets are illiquid in that their liquidation value at $t = 1$ is much lower than the return they generate if held till $t = 2$. Fraction λ of the consumers experience a liquidity shock (impatient consumers) and need to consume early at $t = 1$ while fraction $1 - \lambda$ can wait to consume later at $t = 2$ (patient consumers). The degree of liquidity mismatch of a bank is captured by the parameter r_1 which represents the amount that consumers are allowed to withdraw early at $t = 1$: all else equal, a larger r_1 implies a bank funds a larger portion of its (illiquid) assets through immediately demandable deposit claims.[6] Consumers make withdrawal decisions at $t = 1$ after observing a noisy, private signal about bank performance (i.e., asset payoffs) $P(\theta)$, which depends on the random state of the economy θ. $P(\theta)$ increases monotonically with θ: that is, assets are expected to generate more payoffs as the state of the economy improves. Because $P(\theta)$ is a monotonically increasing function of θ, from now on, we suppress θ and discuss all results by referencing performance P, which more directly corresponds to our empirical measure of bank performance (i.e., *ROA*).

As expected, impatient depositors always withdraw at $t = 1$, contributing to a deposit flow of $-\lambda$. Of more relevance to us, GP show that there is a unique performance threshold P^* below which patient depositors also withdraw even if the bank is financially solvent – that is, there is a panic-based run.[7] Because both patient and impatient depositors withdraw, the deposit flow in the

[6] Holding the amount of promised demandable claims (i.e., r_1) constant, liquidity mismatch could also be increased by increasing the illiquidity of assets. Chen, Goldstein, and Jiang (2010) and Vives (2014) model this aspect of liquidity mismatch and show that run threshold increases in the degree of asset illiquidity. Similar to these studies, asset illiquidity can be easily accommodated in Goldstein and Pauzner (2005), for example, by assuming that the liquidation value of assets decreases with a parameter γ such that for every r_1 dollar of payment to early withdrawers, the bank needs to liquidate $(1 + \gamma)r_1$ dollar assets. It follows from Theorem 2 of GP that the run threshold increases in γ. In our empirical tests, we explore variation in liquidity mismatch resulting from both asset illiquidity and the degree of reliance on uninsured demandable claims.

[7] We follow the global-games literature and consider the limit case where the noise in depositors' private signal is very small (i.e., $\varepsilon \rightarrow 0$). The limiting case leads to sharp run thresholds wherein all impatient depositors run just below the threshold. For larger noise, the transition from run to no-run will not be so abrupt, but it does not change our predictions (proof available upon request).

below-P^* region is -1. Figure 1, Panel A illustrates various regions of depositor behavior by showing the equilibrium relation between performance realizations and deposit flows.

[Insert Figure 1 here.]

The central prediction of GP we wish to test is that the performance threshold (P^*) below which panic-based withdrawals occur increases in the degree of a bank's liquidity mismatch, that is, $\frac{\partial P^*}{\partial r_1} > 0$. This comparative static implies that banks with higher liquidity mismatch are more fragile because it takes a smaller deterioration in performance to trigger panic-based withdrawals. In taking the result $\frac{\partial P^*}{\partial r_1} > 0$ to the data, we need to deal with the fact that the threshold P^* is not observable to us. Hence, what we do is to test the implications of the comparative static $\frac{\partial P^*}{\partial r_1} > 0$ for how the liquidity mismatch r_1 affects the relation between withdrawal decisions ($flow$) and performance realizations (P), both of which we have a proxy for. Our tests focus on two aspects of the flow-performance relation that are expected to vary with liquidity mismatch: (i) flow-performance sensitivity and (ii) level of flows.

Before laying out the rationale for these two tests in two steps, we first highlight two descriptive facts regarding the distribution of performance and the flow-performance relation. As we will explain, these facts are relevant for the intuition underlying the sensitivity prediction and are needed to confirm the intuitive idea that panic-based withdrawals are likely to occur only in regions of sufficiently poor performance. In a well-functioning banking system, one would expect the likelihood of runs to be low and banks to be operating in the non-run region most of the time. We then build on insights from the theory to provide a rigorous rationale for the testable predictions.

The first empirical fact can be gleaned from Figure 3, Panel A, which presents the semiparametric plots of the relation between deposit flows and *ROA*. The figure shows that banks start losing uninsured deposits in response to performance declines only when ROA realizations are sufficiently poor – this region seems to lie below the median ROA. In the above-median region, this flow-performance relation is flat. Connecting this observation to the threshold in GP, we conclude that the panic-run thresholds P^* are located below median performance. Of course, different banks will have their thresholds at different levels, but they seem to be below median performance for at least the vast majority, if not all, of them.

This empirical fact – that withdrawals happen well below median performance – is not surprising. If the run threshold P^* was located above the sample median, it would mean that banks would be under runs from their depositors more often than not. This would go against the basic rationale offered for the existence of banks: their ability to produce generally stable money-like claims that facilitate risk sharing among consumers. It seems implausible that a banking system in equilibrium would be so often under stress and still provide liquidity and facilitate risk sharing. As in the GP model, banks can adjust the terms of the demand deposit contract to control the likelihood of runs. This is also reinforced by many government rules and regulations that are meant to keep banks reasonably safe most of the time.

[Insert Figure 2 here.]

The second empirical fact is available in Figure 2, which shows that the distribution of ROA is approximately symmetric and unimodal around the median. This distribution implies that the probability density function for performance ($f(P)$) is increasing, i.e., $f'(P) > 0$ in the below-median performance region. Since this is the region where the run thresholds P^* are located, it follows that banks with a higher run threshold are more likely to experience performance realizations in the region around their P^*, where flows become sensitive to performance due to panic-based withdrawals. As we formally show next, this intuition underlies the sensitivity prediction.

A. Sensitivity Prediction

Our first test examines whether the average flow-performance sensitivity of uninsured depositors is higher for banks with more liquidity mismatch. Prior studies have tested this implication of panic-run models in the context of mutual funds (e.g., Chen, Goldstein, and Jiang (2010), Goldstein, Jiang, and Ng (2017)). Figure 1, Panel A shows the intuition for how this prediction follows from $\frac{\partial P^*}{\partial r_1} > 0$. The flows exhibit sensitivity to performance only if the performance realization is bad enough to breach the run threshold: the flows decrease from $-\lambda$ to -1 as P decreases from just above to just below P^*. In normal times (i.e., when $P > P^*$), flows are not sensitive to performance and remain at $-\lambda$. Because the run threshold for a bank with a higher liquidity mismatch is greater, it is more likely to be breached, which makes the bank's flows, in expectation, more sensitive to performance.

To see this more formally, consider a continuum of banks of unit mass with liquidity mismatch r_1 and a run threshold of $P^*(r_1)$. These banks face a performance distribution characterized by pdf of $f(P)$ and CDF of $F(P)$. Consider a small negative perturbation of performance $-\Delta P < 0$ to this group of banks. Only banks with performance between $P^*(r_1) + \Delta P$ to $P^*(r_1)$ will experience a change in flows from $-\lambda$ to -1, because the perturbation will result in crossing the run threshold for these banks. The rest of the banks will experience no change in flows. Thus, the aggregate change in flows (denoted by $\Delta FLOW$) for this group of banks is:

$$\Delta FLOW(r_1) = -\left[F(P^*(r_1) + \Delta P) - F\big(P^*(r_1)\big)\right](1 - \lambda)$$

Dividing both sides by $-\Delta P$ and taking $\lim \Delta P \to 0$ yield the following expression for the average flow-performance sensitivity (*AvgFPS*) for this group of banks:

$$AvgFPS(r_1) = \frac{\partial FLOW(r_1)}{\partial P} = f\big(P^*(r_1)\big)(1-\lambda).$$

Taking the derivative with respect to r_1, we obtain:

$$\frac{\partial AvgFPS(r_1)}{\partial r_1} = (1-\lambda)f'(P^*)\frac{\partial P^*(r_1)}{\partial r_1}$$

Since $\frac{\partial P^*(r_1)}{\partial r_1} > 0$, it is easy to see that as long as $f'(P^*) > 0$, $\frac{\partial AvgFPS(r_1)}{\partial r_1}$ will be positive, and the average sensitivity will increase with the degree of liquidity mismatch. The condition $f'(P^*) > 0$ means that P^* is located in the portion of the performance distribution where the density is increasing in P. It ensures that as P^* increases due to the increase in liquidity mismatch, the breaching of the run threshold becomes more likely due to the greater density of P in that region. This, in expectation, increases the flow-performance sensitivity as r_1 increases. As discussed earlier, the condition $f'(P^*) > 0$ is consistent with the unimodal distribution of performance we observe in the data (Figure 2) and the fact that uninsured deposit flows become sensitive to performance only at below-median performance levels (Figure 3, Panel A).

A. Level Prediction

The comparative static $\frac{\partial P^*}{\partial r_1} > 0$ also leads to a prediction regarding the levels of deposit flows. Specifically, uninsured deposit flows at higher liquidity mismatch banks should be less than or equal to the flows at low mismatch banks for all levels of performance P:

$$flow\big(P, r_1^{High}\big) \leq flow(P, r_1^{Low}), \forall\, P \qquad .$$

with strict inequality when performance is in the region of $\left(P^*(r_1^{Low}), P^*\big(r_1^{High}\big)\right)$. This prediction can be seen in Figure 1, Panel B: when $P \in \left(P^*(r_1^{Low}), P^*\big(r_1^{High}\big)\right)$, only banks with high mismatch experience a run and, consequently, lower flows; everywhere else, either both types of banks experience a run, or they don't, and in both cases, they have the same level of flows.

The level prediction does not require that the run thresholds P^* be located below median performance so that $f'(P^*) > 0$. That said, since it predicts strict inequality only in the performance region where the run thresholds are located, we expect the negative relation between liquidity mismatch and the level of uninsured deposit flows to be more salient in the below-median performance region.

The sensitivity and the level tests explore different empirical implications of the central prediction from theory models (that the run threshold increases in the degree of liquidity mismatch). We believe there is value in having both, as the two sets of tests together strengthen the empirical analysis and the interpretation of the results.

B. The Role of Deposit Insurance

A final issue that deserves clarification pertains to how the availability of deposit insurance affects our predictions. Prior studies show that banks substitute the loss of uninsured deposits with insured deposits in times of poor performance (Billett, Garfinkel, and O'Neal (1998), Martin, Puri, and Ufier (2023), Chen et al. (2022)). If uninsured depositors anticipate that banks will be able to avoid asset liquidations by fully replacing any loss of uninsured deposits with insured deposits, they would lose the incentive to withdraw in anticipation of withdrawals by others, and we would not observe panic-based withdrawals in equilibrium.

We first note that this possibility is likely to reduce the power of our tests in detecting panic-based withdrawals, and the true effect of strategic complementarities (in the absence of deposit insurance) is likely to be larger than what we would find in our sample. We also emphasize that we do not expect deposit insurance to fully allay uninsured depositors' concerns about running by other depositors. The issue is that a bank's ability to attract insured deposits is not without constraints, and uninsured depositors cannot be certain that their banks will be able to attract a sufficient quantity of insured deposits in a timely manner to avoid asset liquidation.[8] Perhaps unsurprisingly, historically, uninsured deposits have not been fully immune to losses even in the era of deposit insurance and have lost money in bank failures (Benston and Kaufman (1997)). In a later section, we empirically explore this issue in our sample and find evidence that the substitution between uninsured and insured deposits is not perfect.

II. Measurement of Liquidity Mismatch

Banks undertake liquidity mismatch when they invest in illiquid assets (e.g., loans) using liquid liabilities (e.g., demand deposits). The mismatch exposes even solvent banks to panic-based runs, particularly if the deposit financing comes from uninsured depositors who stand to lose money in the event of default. This occurs because the short-term liquidation value of banks' illiquid assets (due to fire sale discount) may not satisfy a large spike in deposit withdrawals. Thus, an uninsured depositor would like to withdraw (even if she does not need the money for consumption) if she expects a sufficient mass of other depositors to withdraw, creating the possibility of a self-fulfilling panic run.

[8] There are many reasons for why banks' ability to attract insured deposits is likely to be constrained. Depositors at competing banks may not be willing to incur the costs of switching from their existing banks or may simply be unaware that other banks are offering higher rates (Drechsler, Savov, and Schnabl (2017)). Furthermore, competing banks may also respond by offering higher rates to retain their depositor base. Even if sufficient quantity of insured funding is available, it cannot be attracted instantaneously, and uninsured depositors could be concerned that their bank will not be able to attract insured deposits in time to avoid asset liquidation.

We use two measures of liquidity mismatch that capture the two sources of variation in banks' ability to satisfy immediate withdrawal demands from their uninsured depositors: (i) the degree of asset illiquidity (*Asset Illiquidity*) and (ii) the degree of reliance on uninsured deposit financing (*%Uninsured*). All else equal, a bank is more vulnerable to panic-based withdrawals when *Asset Illiquidity* and/or *%Uninsured* are higher.

Our measure of *Asset Illiquidity* comes from Berger and Bouwman (2009), who create a composite bank-level measure of liquidity transformation by combining measures of asset- and funding-side liquidity. To measure *Asset Illiquidity*, the authors classify all assets into three categories: (i) illiquid assets (e.g., commercial real-estate loans; commercial and industrial loans), (ii) semi-liquid assets (e.g., consumer loans; residential real-estate loans), and (iii) liquid assets (e.g., cash; securities; trading assets). They then assign a weight of +1/2, 0, and -1/2 to each dollar of illiquid, semi-liquid, and liquid assets, respectively. *Asset Illiquidity* is calculated as the weighted sum of all assets.

We measure *%Uninsured* as the fraction of banks' total deposits that are uninsured.[9] With this definition, the measure captures banks' reliance on uninsured- relative to insured-deposit funding. An alternative would be to measure reliance on uninsured deposits relative to all other forms of financing, including equity and subordinated debt. The latter choice is problematic for our purpose because the measure would also capture differences in the priority of claims on a bank's cash flows: compared to a bank with more equity, an uninsured depositor's claim in a bank with less equity is effectively more junior, and it would take a smaller decline in performance to impair that claim.

[9] We use the average value from the previous three years instead of the preceding quarter so that this variable is not simply reflecting any recent trend in the deposit flows. Robustness tests presented in the Online Appendix show that our inferences are qualitatively unchanged if we use *%Uninsured* from the preceding quarter.

Thus, uninsured depositors at banks with low equity are expected to react strongly to performance declines even in the absence of strategic complementarities.[10]

Our measure addresses this problem by allowing us to compare banks with different deposit compositions while holding the amount of total deposits, equity, and non-deposit funding sources constant, which we explicitly control for in our empirical specifications. Holding these capital structure features constant, a dollar of uninsured deposit claim in a bank with a high *%Uninsured* has the same priority over cash flows as in a bank with a low *%Uninsured*.[11] What differs, however, is the degree of strategic complementarities: an uninsured depositor has a larger incentive to withdraw when she knows that most fellow depositors are uninsured and thus more likely to run.

We also considered an alternative measure of liquidity mismatch (*LMI*) developed in Bai, Krishnamurthy, and Weymuller (2018). Unlike our measures, however, *LMI* considers changes in

[10] This is one of the reasons we do not use the measure of funding side liquidity creation from Berger and Bouwman (2009) because their measure considers a bank with less equity as creating more liquidity. Thus, it can also reflect the effect of claim priority as opposed to strategic complementarities because uninsured depositors' claim priority is effectively lower in banks with less equity. Another reason for us not to use this measure is that it doesn't make the distinction between uninsured and insured deposits. This distinction is crucial when it comes to exploring the implications for panic-based runs – a bank may rely a lot on deposit financing without facing much fragility if most of its deposits are insured.

[11] In the event of a bank failure, the FDIC immediately pays off the claims of insured depositors. In exchange for these payments, the FDIC acquires legal claims against the failed bank's assets. The priority of these acquired claims is same as that of uninsured deposit claims. Both FDIC and uninsured depositors pro rata share the proceeds from the liquidation of assets. Thus, a dollar of uninsured deposit claim has the same cash flow rights regardless of the deposit composition. For further institutional details on resolution of bank failures, see, for example, Herzig-Marx (1978).

the liquidity of the balance sheet items over time based on changes in the market conditions. While this makes *LMI* more accurate in identifying periods of more versus 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 can often result from panic among investors including depositors. When panic ensues, less capital is available to fund asset purchases, resulting in larger fire sale discounts or increased haircuts 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, [12] and the former may even precede the latter rather than the other way around. 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. Our measures do not pose such interpretational difficulties as they do not consider market changes in liquidity.

III. Empirical Specification and Sample

A. Conceptual Underpinnings of the Specifications

Our specifications are guided by a simple model of depositor behavior used in prior studies (e.g., Egan, Hortaçsu, and Matvos (2017), Chen et al. (2022)). Banks attract greater deposit flows when they offer greater utility to depositors (compared to competing banks) and when there is greater aggregate demand for holding deposits. A depositor's utility from a bank depends on her perception of the bank's default risk, the deposit rate offered, and service quality. Depositors

[12] Consistent with this conjecture, Figure A1 in the Online Appendix plots the average uninsured deposit flows 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.

update their views about default risk as they receive information about bank performance. Thus, deposit growth at a bank can be summarized as a function of the following four factors:

$$Deposit\ growth_t = f(performance_{t-1}, rate_{t-1}, service\ quality_{t-1}, aggregate\ demand_{t-1}) \quad (1)$$

Under the above framework, strategic complementarities affect deposit flows by affecting depositors' beliefs about default risk from bank performance. Because the performance threshold (P^*) for panic-based withdrawals increases in the degree of strategic complementarities, a decline in performance would cause a depositor to worry more about default risk at a bank with higher strategic complementarities due to heightened concerns about withdrawals by other depositors. As we discuss in Section I, this should manifest in (i) greater deposit flow-performance sensitivity and (ii) lower (or at best equal) level of deposit flows at banks with higher complementarities. These are the two central predictions we take to data using variation in strategic complementarities that results from banks' degree of liquidity mismatch.

We estimate the above specification using quarterly data from Call Reports. The measure of performance we use is accounting earnings scaled by lagged assets (*ROA*). Accounting earnings are the key summary performance measure widely used by investors and regulators to assess financial institutions' health. One issue that deserves clarification pertains to the possibility that *ROA* for period *t-1* could have been partly shaped (at least for banks with sufficiently poor past performance) by panic-based deposit withdrawals that occurred before period *t-1*, instead of purely reflecting fundamentals that are predetermined before depositors' withdrawal decisions. We do not expect this to affect the interpretation of our results. Regardless of how the fundamentals (*ROA*) got determined at time *t-1*, a rational depositor would need to consider what the current fundamentals imply regarding banks' future cash flow generating ability and the possibility of withdrawals by other depositors. Theory suggests that, for the same level of fundamentals, regardless of how a bank got there, a depositor's incentive to withdraw would be stronger at a bank with a greater liquidity mismatch.

Following Chen et al. (2022), we measure deposit flows as the change in deposit balances (scaled lagged assets) over the two quarters following the end of quarter *t-1* for which bank performance is measured.[13] This is because banks typically file Call Reports with a delay of 30 days after the calendar quarter ends (Badertscher, Burks, and Easton (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)).

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[13] An alternative is to scale deposit flows by the beginning balance of deposits such that uninsured deposit flows measure the percentage change in uninsured deposit base. However, we expect this measure to be less effective at capturing variation in panic-based withdrawals. To see this, consider two banks with high and low reliance on uninsured deposits to fund assets. For the bank with low reliance on uninsured deposits, even a high %loss in uninsured deposit base may not be too difficult to meet from liquid resources, leading to little threat of asset liquidation. Thus, for this bank even high %loss in uninsured deposits may not be indicative of panic-based withdrawals. In contrast, for the bank with heavy reliance on uninsured deposits, even a small %loss in uninsured deposits may be enough to necessitate asset liquidations. Thus, for this bank even small %loss in uninsured deposit base can be indicative of panic-based withdrawals. Therefore, in the cross section, %loss in uninsured deposits may exhibit little association with the degree of liquidity mismatch even if liquidity mismatch causes panic-based withdrawals. Scaling by assets addresses this issue by providing a measure that captures the importance of deposit outflows based on the amount of assets they are funding. Nevertheless, we present the robustness of our results to using lagged uninsured deposit base as scalar in Table AII of the Online Appendix. Our inferences hold at less than 1% level in six out of the eight specifications; the results are directionally similar in the remaining two specifications but with weaker statistical significance.

Because panic-based withdrawals can occur quickly (e.g., over a few days) in some cases, a natural question pertains to the nature of runs that can be detected using our quarterly data.[14] The only types of runs we cannot capture are those that occur and fully reverse before the deposit flow measurement period ends. Even if the panic-based withdrawals occur quickly, our data will allow us to detect them as long as the lowered deposit levels persist till the end of the measurement period. To the extent the adverse real effects of persistent runs are likely to be more severe, these runs are more important to capture and study.

An advantage of our data is that we can explore the incidence of panic-based withdrawals for a large sample of banks. Such evidence is currently missing in the literature but is important to document. Using quarterly data, we can examine whether there is an element of panic in smaller withdrawals (i.e., those that don't result in extreme outcomes of failure and don't get publicized) and how common they are. In addition, our data allow us to link panic-based withdrawals to the degree of liquidity mismatch, which is something that case studies of runs at individual banks cannot do. We later show that for banks that do relatively higher liquidity transformation, just a decline in performance to below median levels is enough to trigger panic-based withdrawals. These smaller but commonplace panic-based withdrawals could be indicative of non-trivial aggregate costs if a broad set of banks are taking subtle yet costly actions, such as curtailing loan growth, reducing their holdings of illiquid assets, or substituting uninsured with insured deposits, to contain the impact of these withdrawals.

[14] Not all runs occur quickly and there have been several episodes of runs characterized by withdrawals over longer periods (Rose (2015)).

B. Control Variables

Control variables in our specifications serve two broad purposes. First, they help account for factors other than bank performance (rate, service quality, and aggregate deposit demand) that can affect deposit growth. Second, they help control for differences in the priority of depositors' claims on cash flows that can result from differences in funding structure. As discussed in Section II earlier, compared to a bank with more equity, an uninsured depositor's claim in a bank with less equity is effectively more junior, and it would take a smaller decline in performance to impair that claim. Thus, uninsured depositors at banks with low equity are expected to react strongly to performance declines even in the absence of strategic complementarities. Controlling for differences in funding structure allows us to better isolate the effect of strategic complementarities.

To account for time-varying differences in funding structure, we control for (i) capital ratio defined as the book value of capital scaled by total assets (*Capital Ratio*), (ii) wholesale funding scaled by total assets (*Wholesale Funding*), and (iii) total deposit funding scaled by total assets (*%Deposits*). Following prior work (e.g., Acharya and Mora (2015)), we also control for four additional variables that account for differences in size, asset composition, and risk: (iv) the logarithm of asset size (*Ln(Assets*), (v) real estate loan share calculated as the amount of loans secured by real estate divided by total loans (*RealEstate_Loans*), (vi) commercial and industrial loans scaled by total loans (*C&I_Loans*), and (vii) the standard deviation of *ROE* over the preceding 12 quarters.

We include bank-fixed effects in most of our analyses to control for unobservables such as time-invariant aspects of service quality. We also expect some of our time-varying controls (e.g., size) to mitigate concerns about differences in service quality.

Next, we account for differences in deposit rates. 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 deposits 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.

Our final set of controls relates to aggregate demand for deposits. Aggregate demand shocks can occur if, for example, consumers conclude that alternative asset classes (e.g., money-market/bond funds or stock markets) will better meet their liquidity/investment needs. Consistent with this, Drechsler, Savov, and Schnabl (2017) and Lin (2020) find that a smaller portion of wealth is allocated to deposits when treasury securities and stock markets offer higher returns. Because our main interest is in examining how deposit withdrawals vary within the banking system as a function of bank-specific liquidity mismatch, we do not expect aggregate trends in deposit growth to confound our inferences. However, absorbing variation in deposit flows unrelated to default risk can increase the power of our tests. We include both contemporaneous and lagged values of fed funds rates and the value-weighted market returns to control for these opportunity costs of holding bank deposits. We include two lags of these variables because we are agnostic about how long it takes for depositors to respond to changes in opportunity cost.

Alternatively, we can use time dummies to fully absorb the effect of aggregate demand shifts. However, this approach would preclude a study of depositor response to bank performance changes resulting 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 withdraw 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. (2022)). In Section VII.A, 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 the effect of strategic complementarities to be significantly stronger for systematic performance declines than for idiosyncratic declines. For completeness, we also present our main results after 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, Hortaçsu, and Matvos (2017), Chen et al. (2022)), we also contrast the results for uninsured and insured depositors to ease any residual concerns about imperfect controls. The idea is that while insured depositors care less about default risk and bank performance, they are still affected by service quality or other relevant bank attributes unrelated to default risk. If our specifications simply reflect the effect of these factors instead of panic from concerns about bank default, we should find similar results for uninsured and insured deposits. As we show later, we find the opposite to be the case.

One final issue that deserves discussion concerns the possibility of customer relationships as an omitted correlated variable. Because of greater switching costs, relationship depositors may exhibit stickier flows and thus low flow-performance sensitivity. We cannot explicitly control for such switching costs because data to identify depositor relationships are not publicly available.[15]

[15] The limited prior evidence on the connection between depositor relationships and fragility comes from case studies of either one or two banks (Iyer and Puri (2012), Iyer, Puri, and Ryan (2016), Martin, Puri, and Ufier (2023)) or from consumer finance survey of a limited number of households in Switzerland (Brown, Guin, and Morkoetter (2020)).

We, however, emphasize that this can confound inferences only if banks with high liquidity mismatch make systematically *fewer* investments in building depositor relationships. We are unaware of any theoretical or empirical research suggesting this to be the case. If anything, to the extent that relationships reduce depositor fragility, we would expect banks with higher liquidity mismatch to invest more to counter the fragility from strategic complementarities.[16] We also document (in Section V) cross-sectional patterns in the effects of liquidity mismatch that are consistent with panic and cannot be explained by customer relationships.

C. 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).[17] 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

[16] There is another reason why, if anything, liquidity mismatch and customer-relationships may be positively correlated. To the extent that relationship-based loans are more likely to be illiquid (due to outsiders' concern about information advantage held by relationship banks), and that relationship with borrowers is positively related to relationship with depositors, we would expect banks with higher *Asset Illiquidity* to have stronger relationship with depositors.

[17] 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.

December 2016 (the last quarter where the *Asset Illiquidity* 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 I show that the average (median) annualized *ROA* is 1% (1.08%) with a standard deviation of 0.90%. The average annualized growth in uninsured (insured) deposits is 2.12% (2.79%) of assets. The correlation between uninsured deposit flows and lagged *ROA* is much higher (at 0.14) than that between insured deposit flows and *ROA* (at 0.02), suggesting that uninsured deposit flows are more sensitive to bank performance. Furthermore, uninsured and insured deposit growth exhibit a strong negative correlation of -0.32, consistent with banks substituting for loss of uninsured deposits with insured deposits.

[Insert Table I here.]

IV. Liquidity Mismatch and Flow-Performance Relation

A. Semi-parametric Analyses

We begin with an exploratory analysis of the relation between deposit flows and bank performance using semi-parametric regressions to avoid making functional form assumptions. The specification takes the following general form:

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

where ΔDep_{it} represents deposit flows, measured as the change in deposit balance scaled by lagged total assets, ROA_{it-1} is the bank's return on assets 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, Goldstein, and Jiang (2010), Goldstein, Jiang, and Ng (2017)), we use Robinson's (1988) estimator implemented using Gaussian local kernel regressions.

We first contrast the flow-performance relation for insured and uninsured depositors. Figure 3, Panel A illustrates the estimated relation for the two types of depositors. Two patterns are noteworthy. First, as expected, in contrast to uninsured depositors, insured deposit flows exhibit a relatively flat relation with ROA over the entire range of performance. Second, while uninsured deposit flows are virtually indistinguishable from insured deposit flows when bank performance is (roughly) above median, they start declining steeply as performance deteriorates to below median levels. As discussed in Section II, this fact indicates that the panic-run thresholds (P^*) are located below the median performance for at least the vast majority of our sample banks. Together with the unimodal distribution of ROA for our sample banks shown in Figure 2, it supports the assumption underlying our sensitivity prediction (i.e., $f'(P^*) > 0$), and highlights the importance of focusing on regions of poorer performance when detecting panic-based withdrawals.

[Insert Figure 3 here.]

Next, we divide banks into terciles based on either the level of *Asset Illiquidity* or *%Uninsured*, the two main variables used in our empirical analysis to capture liquidity transformation, and then estimate the flow-performance relation separately for the bottom and the top terciles. Panels B and C present the plots for the terciles of *Asset Illiquidity* and *%Uninsured*, respectively. Compared to banks with low *Asset Illiquidity* and *%Uninsured*, banks with high *Asset Illiquidity* and *%Uninsured* have similar (Panel C) or slightly higher levels of (Panel B) uninsured deposit flows in the above-median region of performance. The two groups of banks, however, exhibit dramatically different outcomes in regions of poor, below-median performance: banks with higher *Asset Illiquidity* and *%Uninsured* exhibit a much sharper decline in uninsured deposits as *ROA* deteriorates in this region such that these banks eventually end up with much lower uninsured deposit flows. Overall, the above evidence suggests that uninsured depositors are significantly more fragile for banks that hold more illiquid assets and obtain a larger fraction of financing from uninsured depositors.

While Figure 3 provides an intuitive overview of the flow-performance relation, it is exploratory as it does not accommodate bank fixed effects, does not allow us to conduct formal tests of statistical differences in depositor behavior across banks of different levels of liquidity transformation, and does not accommodate variations of the analysis to rule out alternative explanations. We employ parametric regressions to address these issues in the rest of the paper.

B. Parametric Regressions

B.1. Liquidity Mismatch and Flow-Performance Sensitivity

We first examine how the flow-performance sensitivity of uninsured depositors varies with the degree of liquidity mismatch. As discussed in Section I, if strategic complementarities play a role in shaping uninsured depositors' withdrawals, we expect the average sensitivity to be higher for banks with more liquidity mismatch. We estimate various versions of the following specification:

$$\Delta Dep_{it}^{u} = \alpha_i + \beta_0 ROA_{it-1} + \beta_1 MisMatch_{it-1} * ROA_{it-1} + \beta_2 MisMatch_{it-1} + Control_{it-1} + \varepsilon_{it}, \quad (3)$$

where $MisMatch$ represents one of the two measures of liquidity mismatch (*Asset Illiquidity* or *%Uninsured*), α_i represents the fixed effect for bank i, and the control variables are as defined before. We estimate Eqn. (3) using ordinary least squares (OLS) and obtain standard errors after two-way clustering at the bank- and quarter-level. We use the demeaned version of *MisMatch* (i.e., *MisMatch* minus sample mean), so that the coefficient β_0 captures the flow-performance sensitivity for a bank with an average *MisMatch*.[18] In addition to the control variables we discussed

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

earlier, we also include the interaction terms between *ROA* and the demeaned values of the time-varying bank characteristics to ensure that β_1 is not picking up the effects of banks' funding structure or asset composition unrelated to strategic complementarities.

Table II, Panel A presents the results with *Asset Illiquidity* as the mismatch measure. Column (1) presents the estimates without bank-fixed effects to exploit time series and cross-sectional variation in our liquidity mismatch measure. The coefficient for *ROA* is significantly positive at less than 1% level (coef=1.158); the coefficient for the interactive term between *ROA* and *Asset Illiquidity* is also positive (coef = 2.721) and statistically significant at less than 5% level. Together, they indicate that the flow-performance sensitivity of uninsured deposits increases with a bank's asset illiquidity. The magnitude is economically meaningful: a one-standard-deviation increase in *Asset Illiquidity* is associated with a 33% (=.14*2.721/1.158) increase in the flow-performance sensitivity.

[Insert Table II here.]

In column (2), we examine if, as we found in semi-parametric analyses, differences in the sensitivity for banks with different asset illiquidity manifest mainly when banks experience below-median performance. We use a linear spline regression that fits two linear segments connected at the median *ROA* while allowing a different slope for each linear segment. The estimation involves replacing *ROA* in the regression with two vectors (*ROA1* and *ROA2*) whose coefficients capture the marginal effect of *ROA* in regions below and above the median *ROA*.[19] Estimates in column (2) confirm the findings from the semi-parametric plots: the coefficient on the interaction of *Asset Illiquidity* with below-median levels of *ROA* (*ROA1)* is statistically significant at 1% level

[19] Specifically, $ROA1_{it-1} = Min(ROA_{it-1}, ROAMedian)$ and $ROA2_{it-1} = Max(ROA_{it-1}, ROAMedian)$. For more details on the estimation procedure, see Greene (1993, pp. 235-238) and Seber and Wild (1989, pp. 481-489).

(coef=3.953) but with above-median levels of *ROA* (*ROA2)* is insignificant at conventional levels (coef=0.300).

Next, column (3) presents the estimates from our preferred specification that includes bank fixed effects. Inferences are robust. Both the coefficients on *ROA* and its interaction with *Asset Illiquidity* are statistically significant at less than 1% level, and the economic magnitude of the effect increases slightly: a one-standard-deviation increase in *Asset Illiquidity* is associated with a 34% increase in the flow-performance sensitivity. In the rest of the paper, we present estimates from this specification when examining the effects on sensitivity.

Finally, for completeness, column (4) presents the robustness of our results to the inclusion of time dummies instead of macroeconomic controls (fed funds rate and stock returns) to absorb the effect of any secular trends in deposit growth. As discussed in Section III, this is not our preferred specification because it does not allow us to study depositors' response to systematic industry-wide declines in performance, which is when we expect the incentive for panic-based withdrawal to be greater. Later in Section VII, we explore this differential prediction for response to systematic and idiosyncratic performance to provide an additional test for the effect of strategic complementarities. Estimates in column (4) show that all coefficients of interest are significant at less than 1% level although with smaller economic magnitude: a one-standard-deviation increase in *Asset Illiquidity* is now associated with a 25% increase in flow-performance sensitivity. The smaller magnitude is expected as including time dummies restricts the identification to come primarily from idiosyncratic performance shifts.

Table II, Panel B presents the results using *%Uninsured* as our proxy for liquidity mismatch. All of our inferences are robust and the coefficients on *ROA* and its interaction term with *%Uninsured* are significant at less than 1% level in all specifications. The economic magnitudes of the effects are also large. For example, estimates from the specification with bank fixed effects (column (3)) imply that a one-standard-deviation increase in *%Uninsured* is associated with a nearly 43% (=14.58*0.041/1.386) increase in the flow-performance sensitivity.

B.2. Liquidity Mismatch and Level of Uninsured Deposit Flows

We next present results from testing the second prediction that, all else equal, the level of uninsured deposit flows at banks with more liquidity mismatch should be less than or equal to the flows at banks with less liquidity mismatch for all performance levels and with strict inequality in regions where the run thresholds are located. Intuitively, this prediction results from the fact that at any level of performance, there is a greater chance that a bank with high liquidity transformation has already experienced panic-based withdrawals due to its higher run threshold.

To test this prediction, we first sort all observations into deciles of *ROA* and then examine, within each decile, how the level of uninsured deposit flow varies with the degree of liquidity mismatch. Specifically, we estimate the following regression:

$$\Delta Dep_{it}^{u} = \alpha_i + \beta_0 ROA_{it-1} + \sum_{d=1}^{10} \beta_d MisMatch_{it-1} \times I_{it}^{d} \quad + \sum_{d=1}^{10} \gamma_d I_{it}^{d} + Control_{it-1} + \varepsilon_{it}, \quad (4)$$

where I_{it}^{d} is the indicator variable for whether an observation's level of *ROA* belongs to the d^{th} decile of *ROA*. Coefficient β_d measures how the level of uninsured deposit flows within the d^{th} decile of *ROA* varies with the degree of liquidity mismatch.

Figure 4 visually illustrates the findings by plotting the coefficients β_d for all deciles. The results are consistent with our prediction and with what we found in the semi-parametric analyses. Panel A presents the results for *Asset Illiquidity*. The coefficient estimates for the top five deciles above median *ROA* are close to zero and not significantly different from zero. The picture changes dramatically when we look at the coefficient estimates for the bottom five deciles: The coefficient estimate becomes negative at −0.06 for the 5^{th} decile and decreases monotonically in magnitude to −14.06 for the 1st decile, with estimates for the bottom two deciles significantly different from zero. The average coefficient estimate for the above-median deciles is 1.437, compared to the average for the below-median deciles at −5.966. These results suggest that the level of uninsured deposit flows does not vary with asset illiquidity in the above-median performance region, but as performance deteriorates to below median, banks with greater asset illiquidity experience significantly larger outflows.

[Insert Figure 4 here.]

Equation (4) is quite demanding on data as it looks for differential effects of asset illiquidity within narrow bands (deciles) of bank performance. Therefore, based on the analysis above, we use a simpler regression that parsimoniously summarizes the differential effect of *Asset Illiquidity* on the level of uninsured deposit flows in the two regions of *ROA* performance. This parsimony not only provides greater statistical power to our tests but will also be helpful when we later explore the interactions of *Asset Illiquidity* with other variables. Specifically, we estimate the following modified version of Eqn. (4) where we replace the ten decile dummies with one indicator for below-median performance ($I_{ROA<Med}$):

$$\Delta Dep_{it}^{u} = \alpha_i + \beta_0 ROA_{it-1} + \beta_1 MisMatch_{it-1} * I_{ROA<Med} + \beta_2 * I_{ROA<Med} + Control_{it-1} + \varepsilon_{it}. \quad (5)$$

In addition to standard controls, we also include interactions of $I_{ROA<Med}$ with all time-varying bank characteristics to control for their differential impact across the two regions of bank performance. The coefficient of interest is on the interaction term $Asset\ Illiquidity * I_{ROA<Med}$ which captures the effect of asset illiquidity on uninsured deposit flows as performance deteriorates from above- to below-median.

Table III presents the results from estimating Eqn. (5). Column (1) presents the estimates with $Asset\ Illiquidity$ as the measure of liquidity mismatch. The coefficient on the interactive term

$Asset\ Illiquidity * I_{ROA<Med}$ is negative (coef=−5.281; p-value<0.01), implying that banks with higher asset illiquidity experience additional uninsured deposit outflows as the performance deteriorates from above to below the median. Regarding economic magnitude, the additional outflows resulting from a one-standard-deviation increase in asset illiquidity are equivalent to 35% (=0.14*5.281/2.12) of the mean uninsured deposit flows in our sample.

[Insert Table III here.]

We obtain even stronger inferences when we use *%Uninsured* to measure liquidity mismatch. Figure 4, Panel B visually illustrates the effect of *%Uninsured* for each decile of *ROA*. Unlike for asset illiquidity, the coefficients on *%Uninsured* are negative and statistically significant even for the five above median deciles, with the average value of coefficient being −0.205. A possible explanation for this result is that compared to banks with a low *%Uninsured*, concerns about panic-based running are heightened at banks with a high *%Uninsured* such that they either do not wish to attract or have trouble attracting more uninsured deposits even in times of good performance. It is worth noting that technically, this explanation is outside of the scope of traditional bank-run models (e.g., Goldstein and Pauzner (2005)) that feature only one bank with an exogenously given composition of depositors. More in line with the traditional run models and consistent with our results for asset illiquidity, we find that the coefficient on *%Uninsured* monotonically declines as one moves down to the below median deciles (coef for the 5th decile = −0.232 and for the 1st decile = −0.347); the average coefficient for the below median deciles is −0.271, which is nearly 33% greater in absolute magnitude than that for the above median deciles.

Column (2) of Table III presents the result from the parsimonious regression that summarizes the differential effect of *%Uninsured* in the two regions of *ROA* performance. The coefficient on $\%Uninsured \times I_{ROA<Med}$ is negative (coef=−0.049; p-value<0.01), implying that banks with a higher *%Uninsured* experience additional uninsured deposit outflows as the performance deteriorates from above- to below-median. In terms of economic magnitude, as one moves from above- to below-median *ROA*, a bank whose *%Uninsured* is one-standard-deviation higher experiences additional outflows that are equivalent to 34% (=14.58*0.049/2.12) of the mean uninsured deposit flows in our sample.

Table AI of the Online Appendix presents the results separately for subsamples of small, medium, and large banks. It shows that all of our results hold across all subsamples, except that the result on the level specification is insignificant for large banks when we use *%Uninsured* as the proxy for the mismatch. This could reflect the significantly smaller sample size, the effect of "too-big-to-fail" for large banks, or a combination of both.

V. Could the Results Reflect Differences in Information Content of ROA?

A potential concern is that the information content of *ROA* may vary with our measures of liquidity mismatch. Perhaps a decline in *ROA* (particularly from above- to below-median region) implies a larger reduction in the cash-generating potential of assets of banks with greater liquidity mismatch. Thus, the stronger adverse reaction of uninsured depositors at these banks may reflect the effect of more fundamental news instead of panic.

We first note that this concern is mainly applicable to the analyses based on *Asset Illiquidity.* Banks with different asset illiquidity invest in different asset classes; these asset classes may differ in the statistical/informational properties of the profits they generate. The concern is less applicable to the analyses based on *%Uninsured* since it is not directly connected to the cash-generating potential of banks' different asset classes. That said, the concern for *%Uninsured* may arise indirectly if banks systematically adjust asset side liquidity based on the fragility of their liability side. For example, a bank with significant liquid claims on the liability side may create less liquidity on the asset side to manage liquidity mismatch risk.

In this section, we first address this residual concern about *%Uninsured* by using a matched sample analysis to explicitly eliminate any observable differences in asset composition across banks with different *%Uninsured*. We believe this analysis yields some of the cleanest evidence on the effect of strategic complementarities. We then provide a variety of additional analyses that show our inferences from *Asset Illiquidity* are unlikely to be driven by differences in information content of *ROA*.

A. Matched Sample Analyses for %Uninsured

For this analysis, we start by sorting our sample observations by *%Uninsured* into terciles. For each bank-quarter observation in the top tercile, we try to find a propensity-score matched observation from the bottom tercile, based on variables that capture banks' asset illiquidity and asset composition (*Asset Illiquidity*, *RealEstate_Loans*, and *Commercial_Loans*) as well as *ROA* and other bank characteristics we included as control variables in the main regression. We identify the matched control observation as the nearest neighbor (without replacement) based on propensity scores. To ensure high match quality, we use a caliper of 0.005 and drop any matched pairs that fall outside the common support.

Table IV, Panel A presents the covariate balance and shows that the matching is quite successful: the mean values of all variables are very close for the top and bottom terciles of *%Uninsured,* and none of the differences are statistically significant. For example, the mean *Asset Illiquidity* for the top and bottom terciles is nearly identical at 0.077.

[Insert Table IV here.]

We estimate our prior regression specifications on the matched sample with an indicator variable ($I_{High\,\%Unin}$) for membership in the top tercile of *%Uninsured* as the measure of *MisMatch*. Panel B, column (1) presents the findings regarding the performance sensitivity of uninsured depositors. The coefficient estimates on both *ROA* and $ROA \times I_{High\,\%Unin}$ are positive and significant at less than 1% level. They imply that, compared to banks in the bottom tercile, the average sensitivity of uninsured deposit flows to *ROA* in banks in the top tercile of *%Uninsured* is three times higher (1.626 vs. 0.490).

Estimates shown in column (2) indicate that the effects of *%Uninsured* on the levels of uninsured deposit flows are similarly robust. The coefficient on $I_{High\,\%Unin} \times I_{ROA<Med}$ in column (2) is −2.039 (p-value<0.01), which implies that compared to a bank in the bottom tercile, a deterioration in performance from above- to below-median for a bank in the top tercile of *%Uninsured* results in additional outflows equivalent to 96% of the sample average level of uninsured flows.[20]

B. Mitigating Concerns Regarding Inferences from Asset Illiquidity

We provide two types of analyses to mitigate concerns about our inferences from the results on *Asset Illiquidity*. First, we present evidence of additional patterns in the effects of *Asset Illiquidity* that are consistent with the effect of strategic complementarities but are unlikely to be correlated with any differences in the informational properties of *ROA*. Second, we explicitly measure the informational properties and control for them in our regressions.

[20] While not a main concern for inferences from results on *%Uninsured*, for robustness, we also add to the matching covariate list the measure of earnings precision (*Informativeness*) from Chen et al. (2022) which captures the predictive ability of bank earnings for future defaults (see our discussion in Section VB2). Results, shown in Table AIII of the Online Appendix, are essentially unchanged.

B.1. Additional Patterns in the Effects of Asset Illiquidity

We explore two sources of variations in the effect of asset illiquidity. First, we explore the variations based on the availability of capital from local peer banks. Granja, Matvos, and Seru (2017) find that assets of failed banks are predominantly sold to banks with operations in the same geographic locations as the failed banks, consistent with local peer banks possessing better information to value assets originated in the same area. They further find that asset sales happen at a larger fire-sale discount when the peer banks have less free capital to buy those assets. We therefore expect uninsured depositors to be even more concerned about the illiquidity of their banks' assets when the peer banks have less free capital: the depositors know that their banks' illiquid assets will command much lower prices in case they need to be liquidated. Under the assumption that the informational properties of earnings generated by a bank's assets do not depend on the capital ratios chosen by its geographic peers, this analysis can mitigate concerns about the confounding effect of the differential information content of *ROA*.

Following the approach in Granja, Matvos, and Seru (2017), we measure local capital availability using the average capital ratio of all peer banks located in the same MSA (*PeerCapital*). We then estimate regressions that allow the effect of *Asset Illiquidity* to vary with the top, middle, and bottom terciles of *PeerCapital* and present the results in Table V, Panel A.

[Insert Table V here.]

Columns (1) to (3) show the results for the flow-performance sensitivity specification. The coefficient on *Asset Illiquidity*×*ROA* decreases monotonically as the availability of the peer capital increases from the bottom to the top tercile, and the difference in coefficients between the top and the bottom tercile is statistically significant at less than 5% level. The economic magnitude of the variation is also quite large: the effect of asset illiquidity on the flow-performance sensitivity in the bottom tercile is more than three times the effect in the top tercile (5.535 vs. 1.611).

Columns (4) to (6) show the results for the level analysis, which show a similar monotonic pattern. The magnitude of the coefficient estimate for $Asset\ Illiquidity\ \times I_{ROA<Med}$ increases nearly 2.5 times when we move from the top tercile of peer capital (coef=-2.941) to the bottom tercile (coef=-7.360). Overall, as expected, the results show that the effect of asset illiquidity on deposit fragility is much stronger when there is less capital available to buy those assets.

In our second analysis, we explore how the effect of asset illiquidity on deposit fragility varies with the degree of *%Uninsured*. We expect the effect of asset illiquidity to become stronger as *%Uninsured* increases. Intuitively, when financing mainly comes from insured depositors, there is little incentive to run even if the assets are highly illiquid: an uninsured depositor knows that even if other uninsured depositors withdraw, cash withdrawals will not be large enough to trouble even a bank with primarily illiquid assets. However, the depositor would increasingly get more concerned about the illiquidity of assets as there are more uninsured depositors.

Table V, Panel B presents evidence on how the effect of *Asset Illiquidity* varies for the three terciles of *%Uninsured*. As predicted, the effect of *Asset Illiquidity* monotonically increases as one moves from the bottom to the top tercile of *%Uninsured* for both the sensitivity and level of flows. The magnitude of the effect is large. The effect of asset illiquidity on flow-performance sensitivity in the top tercile of *%Uninsured* is nearly 2.5 times the effect in the bottom tercile, although the difference between the two terciles is significant at only 11% level. When it comes to the effects on the level, however, the differences are both economically large and statistically significant at traditional levels: the coefficient on $Asset\ Illiquidity\ \times I_{ROA<Med}$ for the top tercile is nearly four times the coefficient for the bottom tercile, with the difference significant at

less than the 5% level. These results again mitigate concerns about the confounding effect of information content of *ROA*: it is not clear why, holding the level of asset illiquidity constant, the information content of *ROA* would vary with the degree of uninsured deposit financing.

Finally, it is worth noting that the above two patterns also help confirm our earlier conjecture (see Section III) that customer relationships are unlikely to confound our inferences. Specifically, it is unclear why switching costs would matter more for depositors' withdrawal decisions when less peer capital is available or when *%Uninsured* is higher.

B.2. Controlling for Informational Properties of ROA

In our last set of analyses, we explicitly examine the informational property of bank performance and control for it in our regressions. A unit increase in *ROA* can result in a larger upward revision of beliefs about asset values if it provides a more precise signal about changes in asset values, as depositors would rationally put more weight on more precise signals to update their beliefs about asset values. Our earnings precision measure (*Informativeness*) comes from Chen et al. (2022). It captures the ability of earnings and its components to predict future write-offs, as assessed by the adjusted *R*-squared of the prediction regression estimated over the preceding 12 quarters. We refer readers to the Appendix of this paper and Chen et al. (2022) for more details on this measure. Chen et al. (2022) find that uninsured deposit flows are indeed more responsive to bank earnings with greater *Informativeness*.

[Insert Table VI here.]

Table VI, Panel A presents the results by including *Informativeness* and its interaction with *ROA* in the sensitivity specification. As expected, estimates in column (1) indicate that uninsured deposits exhibit greater sensitivity to performance for banks with more informative earnings. The coefficient on the interaction of *Asset Illiquidity* with *ROA* remains statistically significant at less than 1% level. The economic magnitude remains large: a one-standard-deviation increase in *Asset Illiquidity* is associated with a more than 30% increase in the flow-performance sensitivity.

Estimates in column (2) show that our inferences from the level specification are also similarly robust with the coefficient on $Asset\ Illiquidity\ \times I_{ROA<Med}$ remaining negative and significant (coef=-5.022; p-value<0.01). The magnitude implies that a bank with asset illiquidity higher by one standard deviation experiences additional outflows equivalent to 33% of the mean uninsured deposit flow when performance declines from above- to below-median.

We also confirm the above results in a matched-sample analysis which produces inferences more robust to functional form misspecification. Similar to our matched-sample analysis shown in Table IV earlier, we propensity-score match the subsamples of observations in the top and the bottom terciles of *Asset Illiquidity* based on bank characteristics including *Informativness*. The idea is to compare two sets of banks that are different in asset illiquidity but similar in all other observables. As before, we use nearest neighbor matching without replacement with a caliper of 0.005 and require common support for the propensity scores across the two groups.

Table VI, Panel B presents covariate balance and shows that the matching is quite successful with no statistically significant differences across all matched variables. Panel C presents the regression results on the matched sample with an indicator variable ($I_{High\ Asset\ Illiq}$) for membership in the top tercile of *Asset Illiquidity* as the measure of *MisMatch*. Columns (1) and (2) present the sensitivity and level analysis results, respectively. As expected, column (1) shows that the coefficient on $ROA_{it-1} \times I_{High\ Asset\ Illiq}$ remains positive and significant (Coef = 0.983, p-value<0.01). It implies that the flow-performance sensitivity for banks in the top tercile of *Asset Illiquidity* is more than double that for banks in the bottom tercile. Similarly, for the level prediction, estimates in column (2) imply that compared to a bank in the bottom tercile, a deterioration in performance from above- to below-median for a bank in the top tercile results in additional outflows equivalent to nearly 70% of the average uninsured flows.

VI. Does Deposit Insurance Help Mitigate the Uninsured Depositor Fragility?

Deposit insurance is a key policy tool introduced in 1934 to address panic. In this section, we explore the efficacy of deposit insurance in helping banks manage the fragility of their uninsured deposit base. There are two ways this can occur. When performance at a high *MisMatch* bank deteriorates, concerned uninsured depositors can split deposit balances across different banks to ensure they fall within the deposit insurance limits, increasing banks' insured deposit balances. The other possibility is that banks with high *MisMatch* offer higher rates in times of poor performance to attract insured deposits from other banks. Prior work suggests that banks indeed actively attract insured deposits in times of poor performance by offering higher rates (Billett, Garfinkel, and O'Neal (1998), Martin, Puri, and Ufier (2023), Chen et al. (2022)). It is worth noting that the deposit rate mechanism can even lead to an increase in total deposits at high *MisMatch* banks if a sufficiently large mass of insured depositors – unconcerned about the greater default risk at high mismatch banks – leaves low mismatch banks to chase higher rates; as we discuss below, we find some evidence of this phenomenon.

[Insert Table VII here.]

Table VII, Panel A presents the results of this analysis using the sensitivity specification. For ease of comparison, columns (1) and (4) reproduce the results for uninsured deposit flows using *Asset Illiquidity* and *%Uninsured* as the proxy for *MisMatch*. Columns (2) and (5) present the results with insured deposit flows as the dependent variable. Consistent with insured deposits serving as substitutes for uninsured deposits, the coefficient on *MisMatch*×*ROA* is negative and significant when using both *Asset Illiquidity* (coef=-2.234; p-value<0.1) and *%Uninsured* (coef=-

0.055; p-value<0.01) as measures of *MisMatch*. The next question is to what degree insured deposits offset the sensitivity of uninsured deposits. The evidence is mixed and depends on the measure of *MisMatch*. For *Asset Illiquidity,* the sensitivity is only partly offset: estimates in column (3) show that the sensitivity of total deposits continues to increase with the degree of *Asset Illiquidity* (coef=1.531; p-value<0.01), suggesting that despite their effort to substitute uninsured with insured deposits in times of poor performance, banks with more *Asset Illiquidity* still experience larger loss of total deposits. Estimates in column (6), however, show that insured deposits more than make up for the loss of uninsured deposits when we use *%Uninsured* as the mismatch measure: the coefficient on the interaction term is negative and significant (coef=-0.010; p-value<0.05). In Table AV of the Online Appendix, we present the level specification results and find similar inferences.

We next explore whether the above results, at least partly, reflect the effect of differential rate increases at high and low *MisMatch* banks. Panel B presents the results from the estimation of the sensitivity specification except with the natural logarithm of large time- and core-deposit rates as the dependent variables. Because we are modeling banks' responses in the form of deposit rates, we do not control for lagged deposit rates in these regressions. Across all specifications, we find strong evidence that banks with greater *MisMatch* increase rate more in response to the decline in performance. As in the deposit flows analysis, Table A5 of the Online Appendix shows that similar inferences can be drawn from the level specification.

Several remarks regarding the implications of the above results are in order. First, although banks are (at least partly) successful in substituting uninsured with insured deposits, the substitution is not costless as the banks end up paying higher deposit rates and insurance premiums – the substitution merely changes the nature of costs incurred because of strategic complementarities. Second, to our knowledge, the findings in Table VII provide the first micro-level large sample evidence on the efficacy of deposit insurance in mitigating the effects of panic-based withdrawals. The evidence is important considering the non-trivial costs of running a government-sponsored deposit insurance program in the form of underpriced insurance, administrative costs, and perhaps most importantly, the costs in the form of increased moral hazard in the banking industry (e.g., Billett, Garfinkel, and O'Neal (1998)). These costs would be lowered (if not eliminated) if panic-based uninsured deposit withdrawals were not an economically important phenomenon.

Finally, these results inform the growing body of work on the trade-offs of production of safe, money-like claims by the private (i.e., banks) versus the public (i.e., government) sector. As highlighted in Gorton and Metrick (2012) and Gorton (2017), safe, money-like claims could be produced either through the backing of the taxing authority of the government (e.g., treasury bills, insured deposits) or purely in the private sector (i.e., without any government support) through the backing of banks' assets (i.e., uninsured deposits). The literature highlights that there are costs associated with government production of safe claims and thus there is social value in the production of safe assets by the private sector.[21] Our findings indicate that strategic complementarities place economically important bounds on the private sector's ability to produce safe claims – for banks with high strategic complementarities, uninsured deposits lose their perceived safety more quickly (even if the bank is financially solvent) and get replaced by government-backed safe claims in the form of insured deposits. Given the costs to producing safe

[21] Holmstrom and Tirole (1998, 2011) argue that deadweight costs of distortionary taxes will limit the government supply of safe claims. Tirole (2010, Chapter 5) shows that consumer risk aversion will further limit the supply of government liquidity even in the absence of deadweight costs of taxation.

claims by the government, the substitution between uninsured and insured deposits is not expected to be welfare-neutral.

VII. Implications for Systemic Fragility

When considering the implications of liquidity mismatch, a key concern pertains to systemic fragility. We provide two analyses that show how liquidity mismatch can contribute to industry-wide fragility by magnifying the effect of systematic weaknesses – a feature shown in a recent model by Goldstein et al. (2022). The results from these analyses also support our earlier inferences regarding depositor behavior reflecting an element of panic.

A. Systematic and Idiosyncratic Earnings

We first explore whether the effect of the liquidity mismatch differs when the performance shock is systematic vs. when it is idiosyncratic. Holding the magnitude of the performance shock constant, we expect 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, banks will have more difficulty meeting short-term spikes in deposit withdrawals by accessing interbank markets or liquidating assets.

We decompose each bank's ROA_{it} for every period into a systematic (ROA_Sys_t) and an idiosyncratic (ROA_Idio_{it}) component. ROA_Sys_t is calculated as the average *ROA* for the entire banking sector for quarter *t,* and ROA_Idio_{it} is the difference between ROA_{it} and ROA_Sys_t. We then estimate our flow-performance sensitivity regression after including the two components of *ROA* and their interactive terms with measures of mismatch separately. Table VIII, Panel A presents the results. Consistent with depositors being significantly more concerned about the illiquidity of their banks' assets when the performance shock is systematic, the coefficient on the interaction of *Asset Illiquidity* with *ROA_Sys* is more than seven times as large as that on the interaction with *ROA_Idio* (11.682 vs 1.581). The differential impact is similarly large when we use *%Uninsured* as the proxy for mismatch: the coefficient on interaction with *ROA_Sys* is eight times as large as that on the interaction with *ROA_Idio* (0.160 vs 0.020).

[Insert Table VIII here.]

To explore the effects on the level of deposit flows, we examine whether the adverse effect of *MisMatch* we found in below median region of performance (i.e., the coefficient on *MisMatch*$\times I_{ROA<Med}$ from Table III) is driven by periods of adverse systematic or idiosyncratic shocks. We rank observations in the below-median *ROA* region along two dimensions. We rank them based on the magnitude of *ROA_Sys*, and characterize them as having bad systematic shock if the *ROA_Sys* falls below a cutoff value (e.g., in the bottom 1/3, 1/4, or 1/5 of *ROA_Sys*). Similarly, we also rank them based on *ROA_Idio* and characterize them as having bad idiosyncratic shock if the *ROA_Idio* falls below its respective cut-off. We use indicator variables ($I_{PoorSys\,\&\,ROA<Med}$ or $I_{PoorIdio\,\&\,ROA<Med}$) to identify these observations and include them along with their interactions with *MisMatch.* The coefficients on these interactions measure how the outflows caused by *MisMatch* in the below-median *ROA* region vary with the intensity of the systematic and idiosyncratic shock.

Table VIII, Panel B presents the results for both *Asset Illiquidity* (columns (1)-(3)) and *%Uninsured* (columns (4)-(6)). Columns (1) and (4) present the results when we use the bottom tercile value as the cutoff to identify bad systematic and idiosyncratic shocks. As expected, the coefficients on interactions of both *MisMatch* proxies with $I_{PoorSys\,\&\,ROA<Med}$ and

$I_{PoorIdio\,\&\,ROA<Med}$ are negative and significant. More importantly, the magnitude of the effect of a poor systematic shock (compared to idiosyncratic shock) is nearly five times as large when we use *Asset Illiquidity* (-10.7 vs. -2.2) and more than six times when we use *%Uninsured* (-0.13 vs. -0.02) as the *MisMatch* measure. Estimates in the remaining columns show that these inferences are robust to using the bottom quartile or quintile as the cutoffs to identify bad shocks.

A potential concern is that periods of systematic distress may coincide with increased demand for liquidity by consumers. Perhaps it is the case that stronger withdrawals in response to systematic shocks reflect heightened liquidity needs and not panic. We emphasize that this possibility can account for these results only if crises systematically have a larger impact on the liquidity needs of individuals residing in regions where banks with more liquidity mismatch are located. We are unaware of any empirical finding or theoretical reason to expect this to be the case. Nevertheless, to mitigate this concern, we repeat the above analyses but restrict our sample to observations from single-state banks (i.e., banks with branches located in only one state). We use state×year-quarter interactive fixed effects to flexibly absorb any state-specific trends in liquidity demand that may coincide with systematic shocks. This way, we obtain estimates by comparing banks with varying levels of liquidity mismatch operating in the same state. Results presented in Table AVI of the Online Appendix show that our inferences remain intact.

B. Liquidity Mismatch and the 2008 Financial Crisis

We next use the 2008 Financial Crisis as a laboratory to observe the differential impact of an episode of a crisis on banks with varying levels of liquidity mismatch. We estimate the following difference-in-differences style specification:

$$\mathrm{Y_{it}} = \alpha_i + \beta_t + \gamma_1 MisMatch_i \times Crisis_t + \sum_j \delta_j BankChar_{ij} \times Crisis_t + \epsilon_{it}, \quad (6)$$

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 2007Q3-2009Q2. *MisMatch* and all the bank characteristics we control for (*BankChar*) are measured as of the quarter just before the onset of the crisis.[22] α_i and β_t represent bank and year-quarter fixed effects. Because *MisMatch* and *BankChar* are time-invariant, their main effects are subsumed by the bank-fixed effects. The coefficient of interest is γ_1 which measures the differential impact of the crisis on banks with varying levels of *MisMatch*. The estimation sample includes data for up to 5 years before the crisis period and ends with the crisis period. We examine three categories of outcomes: deposit flows, deposit rates, and growth in loans and credit commitments.

[Insert Table IX here.]

Table IX, Panels A and B present the results with *Asset Illiquidity* and *%Uninsured* as the *MisMatch* measure, respectively. Columns (1) - (3) in both panels present the results with uninsured, insured, and total deposit flows as the dependent variables. Coefficient estimates on *MisMatch* × *Crisis* show that banks with higher liquidity mismatch experience larger uninsured deposit outflows during the crisis, which they are unable to completely make up for using insured deposits, resulting in lower total deposit flows. Columns (4) and (5) model banks' deposit rate response and yield some evidence (the results are significant only for *Asset Illiquidity*) that the adverse deposit flow outcomes occur despite high *MisMatch* banks offering greater interest rates during the crisis. Finally, in columns (6) and (7), we model growth in loans and credit commitments to examine whether the funding pressure faced by high *MisMatch* banks manifests

[22] All controls are measured prior to the crisis to avoid the well-known "bad-control" problem (e.g., Angrist and Pischke (2009, pp. 64-66)). Because the controls are also affected by the crisis, introducing time-varying controls can bias estimates and even take away the effect of interest.

in lending outcomes. Both Panels A and B find strong evidence that banks with higher *MisMatch* experience slower growth in loans and commitments during the crisis: a one-standard-deviation increase in pre-crisis *Asset Illiquidity* (*%Uninsured*) is associated with an additional adverse impact of 2.8% (1.1%) on loan growth and 1.2% (1%) on commitments. As a benchmark, our sample's average growth in loans and commitments is 4.5% and 1%, respectively.

Overall, the above results support our earlier inferences and highlight how liquidity mismatch can magnify systemic weakness and contribute to industry-wide fragility.

VIII. Conclusions

In this paper, we examine the effect of the amount of liquidity transformation conducted by banks on the outflows of their uninsured deposits. Banks that provide more liquidity transformation experience higher sensitivities of uninsured deposit flows to performance and greater levels of uninsured deposit outflows when they perform poorly. Results from a battery of tests indicate that the withdrawal decisions of uninsured deposits are not purely driven by fundamentals but reflect an element of panic. While banks utilize deposit insurance to mitigate the impact of fragility – by raising deposit rates to attract insured deposits to substitute the loss of uninsured deposits when their performances decline – they are still prone to fragility. Finally, the effects of liquidity transformation are exacerbated when the aggregate conditions in the banking system are unfavorable. Our results are consistent with the theoretical predictions of Goldstein and Pauzner (2005). As in their model, we show that fundamentals are important for explaining bank runs, but in addition, an element of panic amplifies withdrawals due to the bank’s liquidity creation.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

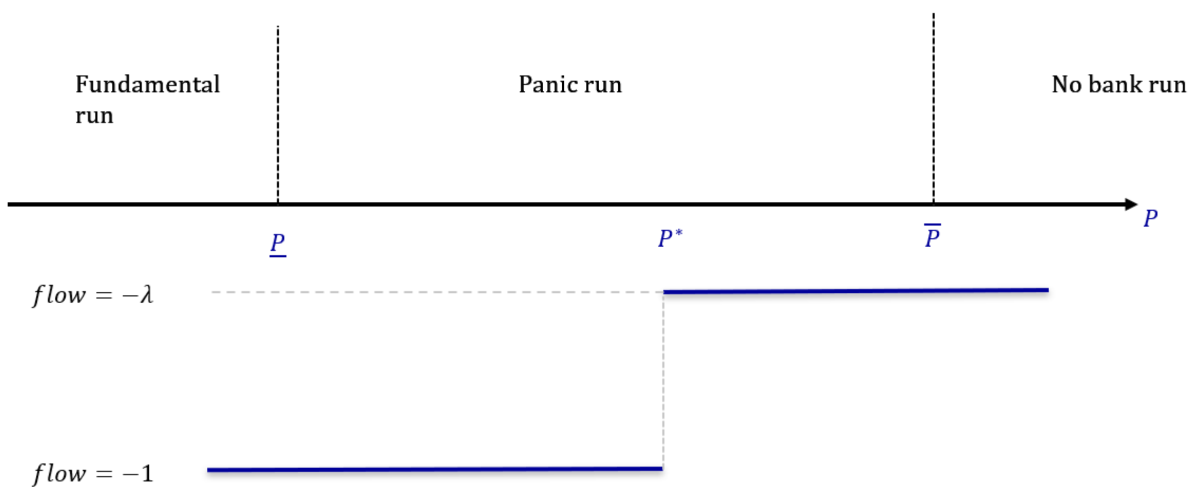
Appendix S1: Internet Appendix.

Replication Code.

Figure 1
Illustration of the Theoretical Underpinning

This figure summarizes the main result from Goldstein and Pauzner (2005) on the withdrawal decisions by depositors in equilibrium. Panel A shows that impatient depositors always withdraw to meet their liquidity needs regardless of bank performance, resulting in an outflow of deposits at the level of $-\lambda$. Patient depositors, contributing $1-\lambda$ portion of bank funding, withdraw when they observe a (noisy) signal that indicates the bank's performance is below a threshold of P^*. Panel B shows that the threshold for withdrawal is higher for banks with higher degree of liquidity mismatch (r_1).

Panel A: Illustration of Run Regions



Panel B: Comparison of Banks with High and Low Liquidity Mismatch

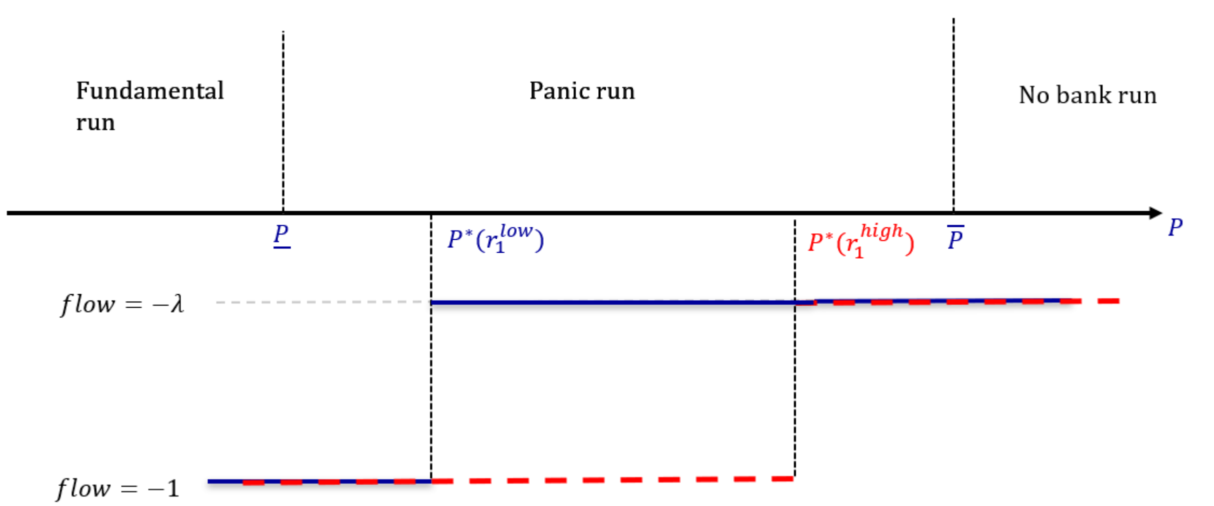


Figure 2
Distribution of *ROA* for our Sample Banks

This figure plots the distribution of *ROA* (centered on the sample median level) for our sample bank-quarter observations. Because *ROA* is winsorized at the 1st and 99th percentiles, the distribution in these tails is omitted.

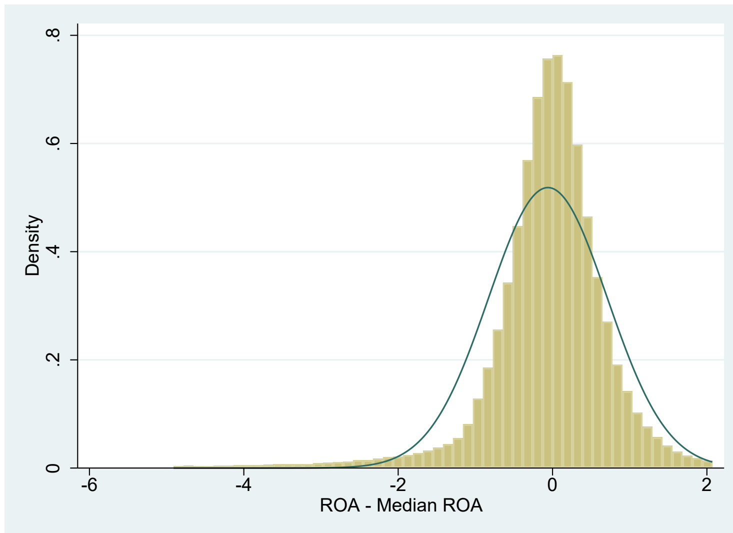
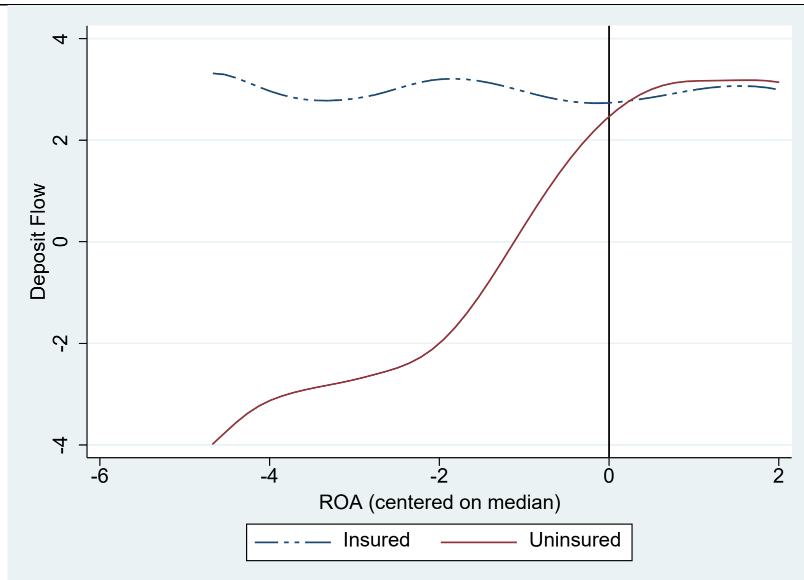


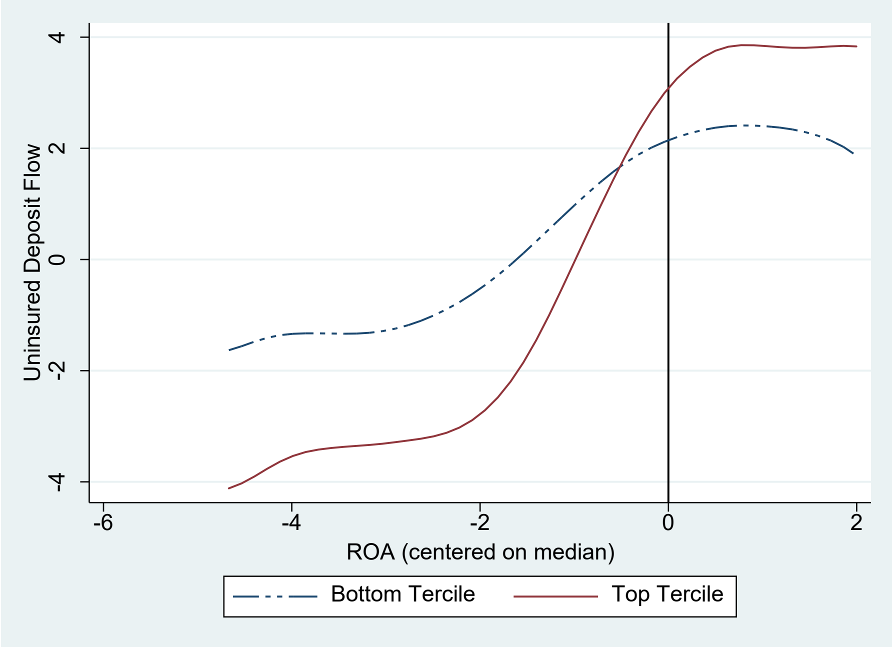
Figure 3
Semi-parametric Estimates of the Flow-Performance Relation

This figure illustrates the semi-parametric estimates of the flow-performance relation using the Robinson's (1988) estimator implemented using Gaussian local kernel regressions. Panels B and C plot the estimates for the uninsured deposit flows for banks in the top and bottom terciles of *Asset Illiquidity* and *%Uninsured*, respectively. The plots are based on deposit flows measured as the changes in deposit balances scaled by the beginning balance of total assets (see discussion in footnote 13 regarding appropriate scalar for deposit flows).

Panel A: Insured versus Uninsured



Panel B: Subsamples of Asset Illiquidity



Panel C: Subsamples of %Uninsured

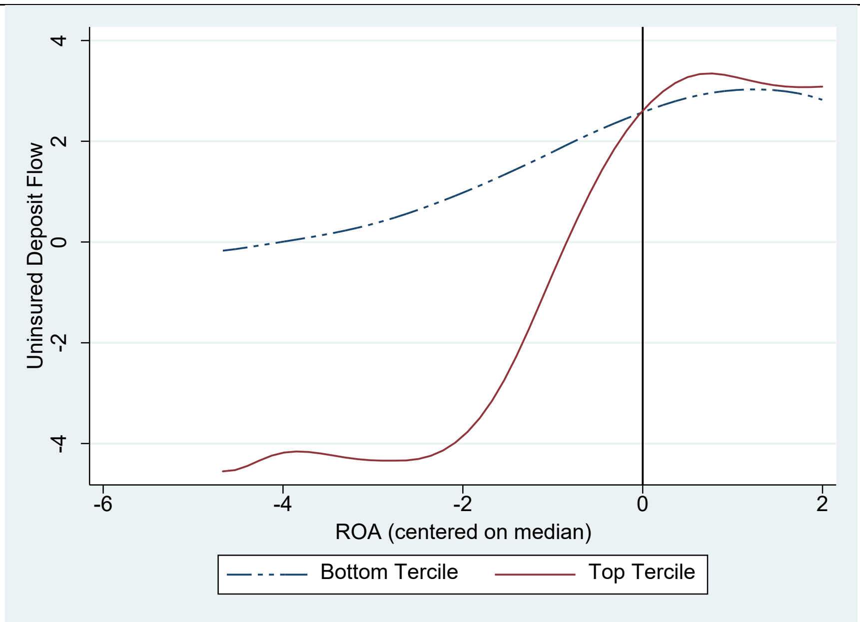
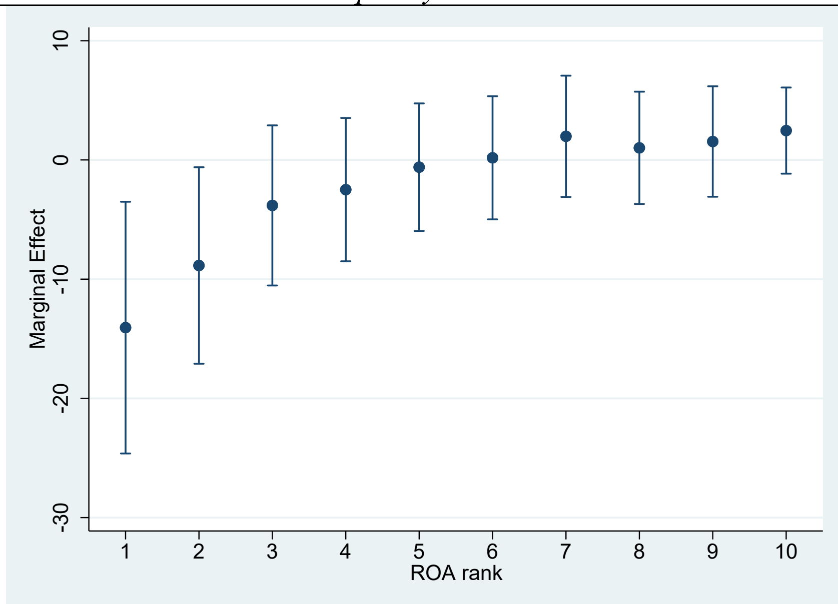


Figure 4
Effect of Liquidity Mismatch on Uninsured Deposit Flows by Deciles of *ROA*

This figure plots the coefficient estimates on *MisMatch* for each decile of *ROA* from estimating Eqn. (4). Panels A and B plot the estimates where the measure of *Mismatch* is *Asset Illiquidity* and *%Uninsured*, respectively. The vertical bar presents the 90% confidence intervals based on two-way clustered standard errors at the bank and year-quarter level.

Panel A: Asset Illiquidity as MisMatch Measure



Panel B: %Uninsured as MisMatch Measure

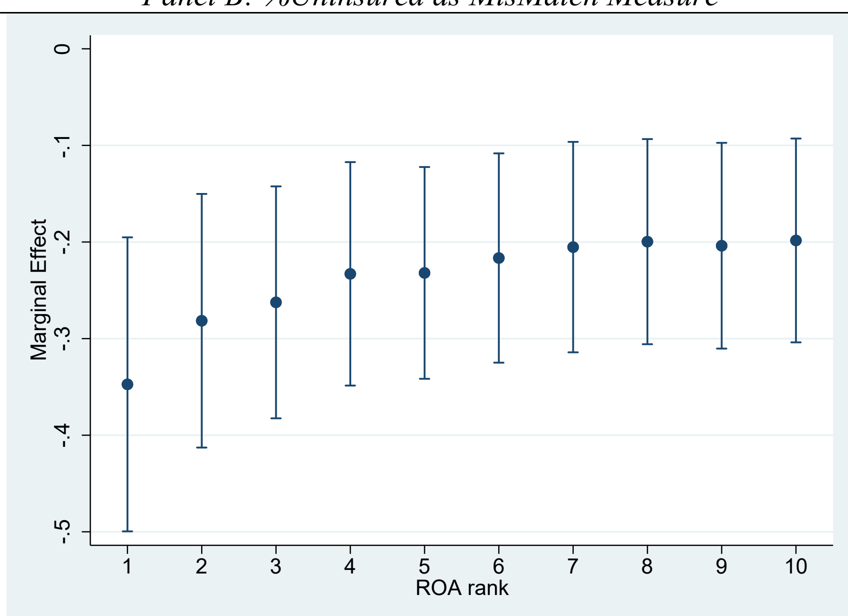


Table I
Summary Statistics

This table presents summary statistics for the key variables in our analyses. The Appendix contains a detailed description of the variable constructions. 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 the commercial bank-quarter level. The final sample includes 8,153 unique commercial banks over 1994-2016.

	N	Mean	Stdev	P25	P50	P75
ROA	287,018	1.00	0.90	0.70	1.08	1.44
Asset Illiquidity	287,018	0.07	0.14	-0.02	0.08	0.18
%Uninsured (in percentage)	284,352	33.90	14.58	23.55	31.40	41.47
ΔDep^{U}	287,018	2.12	9.92	-2.04	2.16	6.84
ΔDep^{I}	287,018	2.79	9.25	-1.63	1.32	5.00
ΔDep^{Total}	287,018	4.78	10.60	-1.48	3.87	9.93
Core Deposit Rate	281,816	2.21	1.40	0.98	1.96	3.40
Large Time Deposit Rate	281,798	3.33	1.68	1.90	3.22	4.80
Ln(Assets)	287,018	12.63	1.05	11.89	12.34	13.02
C&I_Loans	287,018	0.16	0.10	0.09	0.14	0.20
RealEstate_Loans	287,018	0.69	0.17	0.60	0.72	0.82
Wholesale_Funding	287,018	0.20	0.10	0.12	0.19	0.26
Capital_Ratio	287,018	0.10	0.03	0.08	0.09	0.11
%Deposits	287,018	0.83	0.07	0.80	0.85	0.88
Std(ROE)	287,018	5.30	5.82	1.93	3.21	6.07

Table II
Liquidity Mismatch and the Flow-Performance Sensitivity of Uninsured Deposits

This table presents evidence on how the flow-performance sensitivity of uninsured depositors is associated with the degree of their banks' liquidity mismatch. Panels A and B present results using *Asset Illiquidity* and *%Uninsured* as the respective measure of liquidity mismatch. Interactive controls include the interactive terms between *ROA* and the demeaned values of time-varying bank characteristics (*Ln(Size), C&I Loans, RealEstate_Loans, Wholesale_Funding, Capital_Ratio, %Deposits, and Std(ROE)*). Macro controls include current and lagged federal fund rates and stock market returns. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Asset Illiquidity

Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)
ROA $_{it-1}$ × *Asset Illiquidity* $_{it-1}$	2.721**		3.668***	1.383***
	(2.135)		(3.179)	(4.150)
ROA $_{it-1}$	1.158***		1.499***	0.787***
	(6.403)		(4.817)	(11.365)
Asset Illiquidity $_{it-1}$	-1.495	-1.671	-6.417	1.853***
	(-0.710)	(-0.817)	(-1.363)	(2.695)
ROA1 $_{it-1}$ × *Asset Illiquidity* $_{it-1}$		3.953***		
		(2.717)		
ROA2 $_{it-1}$ × *Asset Illiquidity* $_{it-1}$		0.300		
		(0.235)		
ROA1 $_{it-1}$		1.703***		
		(4.544)		
ROA2 $_{it-1}$		0.525***		
		(4.317)		
Control Variables				
Ln(Size) $_{it-1}$	0.014	0.002	-2.948***	-3.541***
C&I_Loans $_{it-1}$	5.280***	5.637***	1.285	0.239
RealEstate_Loans $_{it-1}$	1.724**	2.144***	-0.992	-1.089
Wholesale_Funding $_{it-1}$	0.331	0.753	3.840	9.863***
Capital_Ratio $_{it-1}$	13.588***	14.707***	49.220***	45.270***
%Deposits $_{it-1}$	6.376***	6.562***	12.705***	8.668***
Std(ROE) $_{it-1}$	-0.047***	-0.014	-0.053***	-0.056***
Large Time Deposit Rate $_{t}$	-0.333*	-0.336*	-0.333*	-0.039
Core Deposit Rate $_{t-1}$	-0.506	-0.503	-1.007*	0.159**
Interactive controls	Y	Y	Y	Y

Macro controls	Y	Y	Y	N
Bank fixed effects	N	N	Y	Y
Quarter fixed effects	N	N	N	Y
Observations	287,018	287,018	286,831	286,831
Adj. R-squared	0.067	0.068	0.106	0.283

Panel B: %Uninsured

Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)
ROA $_{it-1}$× %Uninsured$_{it-1}$	0.039***		0.041***	0.022***
	(3.699)		(3.800)	(4.817)
ROA $_{it-1}$	1.149***		1.386***	0.794***
	(6.757)		(5.059)	(11.127)
%Uninsured$_{it-1}$	-0.083**	-0.082**	-0.287***	-0.220***
	(-2.264)	(-2.291)	(-3.594)	(-12.423)
ROA1 $_{it-1}$× %Uninsured$_{it-1}$		0.055***		
		(4.002)		
ROA2 $_{it-1}$× %Uninsured$_{it-1}$		-0.004		
		(-0.478)		
ROA1 $_{it-1}$		1.555***		
		(4.813)		
ROA2 $_{it-1}$		0.697***		
		(6.027)		
Control Variables				
Ln(Size)$_{it-1}$	0.257**	0.229*	-1.919***	-2.735***
C&I_Loans $_{it-1}$	8.701***	8.794***	3.617***	2.493**
RealEstate_Loans $_{it-1}$	1.948**	2.211***	-0.740	-0.952
Wholesale_Funding $_{it-1}$	3.503***	3.541***	12.402***	13.326***
Capital_Ratio $_{it-1}$	16.895***	18.487***	50.050***	49.003***
%Deposits $_{it-1}$	6.177***	6.237***	10.089***	10.287***
Std(ROE) $_{it-1}$	-0.053***	-0.028*	-0.115***	-0.091***
Large Time Deposit Rate$_t$	-0.338*	-0.334*	-0.282*	-0.034
Core Deposit Rate$_{t-1}$	-0.544	-0.536	-0.962*	0.159**
Interactive controls	Y	Y	Y	Y
Macro controls	Y	Y	Y	N
Bank fixed effects	N	N	Y	Y
Quarter fixed effects	N	N	N	Y
Observations	284,352	284,352	284,158	284,158
Adj. R-squared	0.072	0.074	0.135	0.294

Table III
Liquidity Mismatch and the Level of Uninsured Deposit Flows

This table presents evidence on how the decline in uninsured deposit flows following poor performance varies with the degree of liquidity mismatch. $I_{ROA<Med}$ is an indicator variable that equals 1 for observations whose ROA_{it-1} is less than the sample median level of *ROA*, and equals 0 otherwise. Columns (1) and (2) use *Asset Illiquidity* and *%Uninsured* as the liquidity mismatch measure, respectively. Interactive controls include the interactive terms between $I_{ROA<Med}$ and the demeaned values of time-varying bank characteristics (*ROA, Ln(Size), C&I Loans, RealEstate_Loans, Wholesale_Funding, Capital_Ratio, %Deposits, and Std(ROE)*). Macro controls include current and lagged federal fund rates and stock market returns. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Liquidity mismatch measure	*Asset Illiquidity*	*%Uninsured*
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)
Liquidity MisMatch$_{it-1}$ × $I_{ROA<Med}$	-5.281***	-0.049***
	(-3.422)	(-3.682)
Liquidity MisMatch$_{it-1}$	0.189	-0.224***
	(0.063)	(-3.289)
$I_{ROA<Med}$	-1.167***	-0.843***
	(-3.571)	(-2.668)
Control Variables		
ROA_{it-1}	0.655***	0.763***
$Ln(Size)_{it-1}$	-2.618***	-1.773***
C&I_Loans $_{it-1}$	1.475	3.408***
RealEstate_Loans $_{it-1}$	-1.238	1.395
Wholesale_Funding $_{it-1}$	11.970***	20.109***
Capital_Ratio $_{it-1}$	43.749***	40.222***
%Deposits $_{it-1}$	18.926***	18.696***
Std(ROE) $_{it-1}$	-0.115***	-0.155***
Large Time Deposit Rate$_{t}$	-0.334*	-0.285*
Core Deposit Rate$_{t-1}$	-1.031*	-1.005*
Interactive controls	Y	Y
Macro controls	Y	Y
Bank fixed effects	Y	Y
Observations	286,831	284,158
Adj. R-squared	0.106	0.134

Table IV
Effects of *%Uninsured* on Matched Sample

This table explores the effects of *%Uninsured* on uninsured deposit flows on a matched sample of bank-quarter observations. We construct the matched sample by propensity-score matching bank-quarter obs. in the top and bottom terciles of *%Uninsured* based on values of covariates shown in Panel A. Panel A presents evidence on covariate balance of the matched sample. Columns (1) and (2) in Panel B present, respectively, the results for the sensitivity and the level analysis where $I_{High\ \%Unin}$ is an indicator variable for observations from the matched sample with top tercile value of *%Uninsured*. Controls include bank characteristics and the interaction terms of their demeaned values with *ROA* (in column (1)) or $I_{ROA<Med}$ (in column (2)), lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Covariate Balance of the Matched Sample

Subsample	Bottom Tercile of *%Uninsured*	Top Tercile of *%Uninsured*	
Covariates	Mean	Mean	t-stat of Diff.
ROA	0.970	0.977	0.141
C&I_Loans $_{it-1}$	0.152	0.153	0.326
RealEstate_Loans $_{it-1}$	0.710	0.709	-0.141
Wholesale_Funding $_{it-1}$	0.200	0.199	-0.249
Capital_Ratio $_{it-1}$	0.099	0.099	0.110
%Deposits $_{it-1}$	0.831	0.833	0.701
Ln(Size)	12.571	12.547	-0.916
Std(ROE) $_{it-1}$	5.744	5.715	-0.101
Asset Illiquidity	0.077	0.077	-0.097

Panel B: Matched Sample Results

	(1)		(2)
Dependent variable	ΔDep^U_{it}		ΔDep^U_{it}
ROA $_{it-1}$ × $I_{High\ \%Uninsured}$	1.626***	$I_{High\ \%Uninsured}$ × $I_{ROA<Med}$	-2.039***
	(4.175)		(-4.544)
ROA $_{it-1}$	0.490***	$I_{ROA<Med}$	0.665*
	(3.448)		(1.732)
$I_{High\ \%Uninsured}$	-5.876***	$I_{High\ \%Uninsured}$	-3.366***
	(-3.351)		(-2.539)
Controls	Y		Y
Bank fixed effects	Y		Y
Observations	92,319		92,319
Adj. R-squared	0.140		0.138

Table V
Variations in the Effect of *Asset Illiquidity*

This table presents evidence on how the effects of *Asset Illiquidity* vary by the availability of peer capital (Panel A) and by *%Uninsured* (Panel B). In Panels A and B we sort the sample into terciles by the amount of peer capital (calculated following the procedure in Granja, Matvos, and Seru (2017)) and by the bank's *%Uninsured*, respectively. Columns (1) to (3) in each panel present the results from a pooled estimation of Eqn. (3) while allowing the effects of *Asset Illiquidity* on flow-performance sensitivity to vary by tercile. Columns (4) to (6) in each panel present the results from a pooled estimation of Eqn. (5) while allowing the coefficients to vary by tercile. Controls include bank characteristics and the interaction terms of their demeaned values with either *ROA* or $I_{ROA<Med}$, lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: How the Effect of Asset Illiquidity Varies by the Availability of Peer Capital

	Sensitivity specification			Level specification		
Tercile rank of Peer Capital	1st	2nd	3rd	1st	2nd	3rd
	(1)	(2)	(3)	(4)	(5)	(6)
ROA $_{it-1}$ × *Asset Illiquidity*$_{it-1}$	5.535***	3.266**	1.611***			
	(3.008)	(2.529)	(2.781)			
ROA $_{it-1}$	2.014***	1.543***	1.105***			
	(3.768)	(4.270)	(6.381)			
Asset Illiquidity$_{it-1}$ × $I_{ROA<Med}$				-7.630***	-5.924***	-2.941***
				(-2.854)	(-2.926)	(-3.350)
$I_{ROA<Med}$				-1.680***	-1.295***	-0.278
				(-3.084)	(-3.491)	(-0.749)
Asset Illiquidity$_{it-1}$	-5.826	-6.915	-4.634	3.625	-0.517	-0.944
	(-1.082)	(-1.564)	(-1.539)	(1.254)	(-0.194)	(-0.364)
Controls		Y			Y	
Bank fixed effects		Y			Y	
Observations		214,029			214,029	
Adj. R-squared		0.122			0.121	
Test of difference: Top Tercile – Bottom Tercile						
		Diff		.	Diff	
ROA $_{it-1}$ × *Asset Illiquidity*$_{it-1}$		-3.924**				
		(2.056)				
Asset Illiquidity$_{it-1}$ × $I_{ROA<Med}$					4.688*	
					(1.746)	

Panel B: How the Effect of Asset Illiquidity Varies by %Uninsured

	Sensitivity specification			Level specification		
Tercile rank of *%Uninsured*	1^{st}	2^{nd}	3^{rd}	1^{st}	2^{nd}	3^{rd}
	(1)	(2)	(3)	(4)	(5)	(6)
$ROA_{it-1} \times Asset\ Illiquidity_{it-1}$	1.593***	2.348***	4.045**			
	(3.199)	(3.608)	(2.432)			
ROA_{it-1}	0.752***	1.220***	2.003***			
	(4.921)	(4.621)	(5.002)			
$Asset\ Illiquidity_{it-1} \times I_{ROA<Med}$				-2.017***	-3.563***	-7.949***
				(-3.369)	(-3.578)	(-2.837)
$I_{ROA<Med}$				-0.252	-0.775**	-1.890***
				(-0.806)	(-2.499)	(-4.133)
$Asset\ Illiquidity_{it-1}$	0.112	-0.711	-6.035	3.252*	3.821	1.966
	(0.054)	(-0.233)	(-1.336)	(1.786)	(1.650)	(0.970)
Controls		Y			Y	
Bank fixed effects		Y			Y	
Observations		284,158			284,158	
Adj. R-squared		0.124			0.122	
Test of difference: Top Tercile – Bottom Tercile						
		Diff		.	Diff	
$ROA_{it-1} \times Asset\ Illiquidity_{it-1}$		2.452				
		(1.560)				
$Asset\ Illiquidity_{it-1} \times I_{ROA<Med}$					-5.932**	
					(-2.073)	

Table VI
Controlling for Differences in Informational Properties of *ROA*

This table explores whether the effect of asset illiquidity on uninsured deposit fragility is robust to controlling for the precision of *ROA*. Columns (1) and (2) of Panel A present the results from the sensitivity and the level specifications for the full sample, respectively. Panels B and C present the results on the matched sample. Panel B lists the matching covariates and presents evidence on the covariate balance of the matched sample. Columns (1) and (2) in Panel C present, respectively, the results for the sensitivity and the level analysis where $I_{High\ Asset\ Illiq}$ is an indicator variable for observations from the matched sample with top tercile value of *Asset Illiquidity*. Controls include bank characteristics and the interaction terms of their demeaned values with *ROA* (in column (1)) or $I_{ROA<Med}$ (in column (2)), lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Full Sample Results

	(1)		(2)
Dependent variable	ΔDep_{it}^{U}		ΔDep_{it}^{U}
ROA $_{it-1}$ × *Asset Illiquidity* $_{it-1}$	3.321***	*Asset Illiquidity* $_{it-1}$ × $I_{ROA<Med}$	-5.022***
	(3.292)		(-3.483)
ROA $_{it-1}$	1.432***	$I_{ROA<Med}$	-1.131***
	(5.040)		(-3.614)
Asset Illiquidity $_{it-1}$	-6.098	*Asset Illiquidity* $_{it-1}$	-0.035
	(-1.353)		(-0.012)
ROA $_{it-1}$ × *Informativeness* $_{it-1}$	0.452**	*Informativeness* $_{it-1}$ × $I_{ROA<Med}$	-0.437*
	(2.246)		(-1.950)
Informativeness $_{it-1}$	-0.921**	*Informativeness* $_{it-1}$	-0.265**
	(-2.492)		(-2.283)
Controls	Y		Y
Bank fixed effects	Y		Y
Observations	282,293		282,293
Adj. R-squared	0.107		0.106

Panel B: Covariate Balance for the Matched Sample

Subsample	Bottom Tercile of *Asset Illiquidity*	Top Tercile of *Asset Illiquidity*	
Covariates	Mean	Mean	t-stat of Diff.
ROA	1.062	1.073	0.316
C&I_Loans	0.160	0.160	0.068
RealEstate_Loans	0.689	0.692	0.459
Wholesale_Funding	0.203	0.199	-1.077
Capital_Ratio	0.100	0.100	0.520
%Deposits	0.827	0.828	0.648
Ln(Size)	12.643	12.617	-0.771
Std(ROE)	4.944	4.891	-0.374
Informativeness	0.211	0.208	-0.481
%Uninsured	34.612	33.974	-1.188

Panel C: Matched Sample Results

	(1)		(2)
Dependent variable	ΔDep_{it}^{U}		ΔDep_{it}^{U}
$ROA_{it-1} \times I_{High\ Asset\ Illiq}$	0.983***	$I_{High\ Asset\ Illiq} \times I_{ROA<Med}$	-1.465***
	(3.552)		(-3.491)
ROA_{it-1}	0.837***	$I_{ROA<Med}$	0.036
	(5.685)		(0.090)
$I_{High\ Asset\ Illiq}$	-1.320	$I_{High\ Asset\ Illiq}$	0.476
	(-1.521)		(1.022)
Controls	Y		Y
Bank fixed effects	Y		Y
Observations	99,580		99,580
Adj. R-squared	0.105		0.104

Table VII
Substitution Between Uninsured and Insured Deposits

This table explores whether insured deposits help make up for the additional loss of uninsured deposits experienced by high liquidity mismatch banks using the sensitivity specification. Panel A examines the effects on deposit flows and Panel B examines whether deposit rates can, at least partly, explain the substitution between uninsured and insured deposits. Controls include bank characteristics and the interaction terms of their demeaned values with *ROA*, and macro controls. Lagged deposit rates are also included as controls in Panel A. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Deposit Flows Results

MisMatch measure	*Asset Illiquidity*			*%Uninsured*		
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}
	(1)	(2)	(3)	(4)	(5)	(6)
$ROA_{it-1} \times MisMatch_{it-1}$	3.668***	-2.234*	1.531***	0.041***	-0.055***	-0.010**
	(3.179)	(-1.686)	(3.372)	(3.800)	(-4.007)	(-2.336)
ROA_{it-1}	1.499***	-0.330	1.192***	1.386***	-0.081	1.316***
	(4.817)	(-0.970)	(12.513)	(5.059)	(-0.284)	(13.682)
$MisMatch_{it-1}$	-6.417	17.271***	9.869***	-0.287***	0.336***	0.040***
	(-1.363)	(3.376)	(8.269)	(-3.594)	(3.713)	(2.640)
Controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Observations	286,831	286,831	286,831	284,158	284,158	284,158
Adj. R-squared	0.106	0.108	0.165	0.135	0.142	0.162

Panel B: Deposit Rate Results

MisMatch measure	*Asset Illiquidity*		*%Uninsured*	
Dependent variable	$\text{Log}(\text{RateCore}_{it})$	$\text{Log}(\text{RateLT}_{it})$	$\text{Log}(\text{RateCore}_{it})$	$\text{Log}(\text{RateLT}_{it})$
	(1)	(2)	(3)	(4)
$ROA_{it-1} \times MisMatch_{it-1}$	-0.311***	-0.165***	-0.002***	-0.001***
	(-7.516)	(-4.985)	(-6.355)	(-4.508)
ROA_{it-1}	-0.007	-0.005	-0.004	-0.000
	(-0.528)	(-0.524)	(-0.272)	(-0.042)
$MisMatch_{it-1}$	1.142***	0.812***	0.012***	0.010***
	(6.449)	(5.681)	(4.567)	(4.251)
Controls	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y
Observations	284,675	284,478	281,991	281,804
Adj. R-squared	0.783	0.706	0.786	0.710

Table VIII
Systematic versus Idiosyncratic Performance Shocks

This table explores if the effect of liquidity mismatch on uninsured depositors depends on whether the performance shock is systematic or idiosyncratic. Panel A presents the results from the sensitivity specification where ROA_Sys_t is the average ROA for all banks in a given quarter, and ROA_Idio_{it} is the difference between ROA_{it} and ROA_Sys. Panel B presents the results for level specifications where $I_{ROA<Med}$ is the indicator variable for whether the bank has below sample median *ROA* performance, $I_{PoorSys\,\&\,ROA<Med} = I_{ROA<Med} * I(ROA\_Sys_t < Cutoff_{sys})$ where $Cutoff_{sys}$ is equal to the bottom 1/3, 1/4, and 1/5 values of sample ROA_Sys in columns (1) and (4), in columns (2) and (5), and in columns (3) and (6), respectively. Similarly, $I_{PoorIdio\,\&\,ROA<Med} = I_{ROA<Med} * I(ROA\_Idio_{it} < Cutoff_{idio})$ where $Cutoff_{idio}$ is set to equal to the bottom 1/3, 1/4, and 1/5 of sample ROA_Idio in columns (1) and (4), in columns (2) and (5), and in columns (3) and (6), respectively. Controls include bank characteristics and the interaction terms of their demeaned values with either *ROA_Sys and ROA_Idio* in Panel A or with the performance indicator variables in Panel B, lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Results from the Sensitivity Specification

MisMatch measure	*Asset Illiquidity*	*%Uninsured*
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)
$ROA\_Sys_{t-1} \times MisMatch_{it-1}$	11.682**	0.160***
	(2.189)	(2.638)
$ROA\_Idio_{it-1} \times MisMatch_{it-1}$	1.581***	0.020***
	(3.078)	(4.122)
ROA_Sys_{t-1}	6.753***	5.436**
	(2.732)	(2.172)
ROA_Idio_{it-1}	0.884***	0.909***
	(8.087)	(9.357)
$MisMatch_{it-1}$	-13.042*	-0.373***
	(-1.703)	(-3.421)
Controls	Y	Y
Bank fixed effects	Y	Y
Observations	286,831	284,158
Adj. R-squared	0.128	0.150

Panel B: Results from the Level Specification

MisMatch measure	*Asset Illiquidity*			*%Uninsured*		
Poor shock cut-off	Bottom 1/3rd	Bottom 1/4th	Bottom 1/5th	Bottom 1/3rd	Bottom 1/4th	Bottom 1/5th
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)	(6)
$MisMatch_{it-1}$ × $I_{PoorSys\,\&\,ROA<Med}$	-10.709**	-9.641*	-9.180*	-0.130***	-0.141**	-0.151***
	(-2.621)	(-1.966)	(-1.746)	(-2.782)	(-2.515)	(-2.723)
$MisMatch_{it-1}$ × $I_{PoorIdio\,\&\,ROA<Med}$	-2.181***	-2.485***	-2.764***	-0.022***	-0.025***	-0.031***
	(-2.917)	(-3.131)	(-3.308)	(-3.382)	(-3.419)	(-3.833)
$MisMatch_{it-1}$ × $I_{ROA<Med}$	-0.453	-1.768**	-2.084***	0.010	0.001	0.000
	(-0.526)	(-2.621)	(-3.208)	(0.708)	(0.082)	(0.006)
$I_{ROA<Med}$	0.088	0.009	0.036	0.238	0.052	-0.015
	(0.162)	(0.016)	(0.059)	(0.445)	(0.096)	(-0.027)
$I_{PoorSys\,\&\,ROA<Med}$	-2.941**	-3.249**	-3.729*	-2.445**	-2.318	-2.214
	(-2.323)	(-1.989)	(-1.910)	(-2.191)	(-1.647)	(-1.338)
$I_{PoorIdio\,\&\,ROA<Med}$	0.066	-0.080	-0.196	-0.064	-0.092	-0.136
	(0.289)	(-0.344)	(-0.618)	(-0.279)	(-0.397)	(-0.449)
$MisMatch_{it-1}$	0.472	0.703	1.090	-0.211***	-0.210***	-0.207***
	(0.165)	(0.255)	(0.421)	(-3.375)	(-3.454)	(-3.519)
Controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Observations	286,831	286,831	286,831	284,158	284,158	284,158
Adj. R-squared	0.116	0.116	0.117	0.143	0.142	0.142

Table IX
Liquidity Mismatch and the 2008 Financial Crisis

This table explores how the effects of the 2008 Financial Crisis vary with the degree of a bank's pre-crisis liquidity mismatch. Panels A and B present results with *Asset Illiquidity* and *%Uninsured* as the mismatch measure. $Crisis_t$ is an indicator variable for the crisis period of 2007Q3 to 2009Q2. *MisMatch* and all the bank characteristics we control for are measured as of the quarter just before the onset of the crisis. The estimation sample contains data for up to 5 years before the crisis period and ends with the crisis period. Controls include the bank characteristics (measured at the quarter before the crisis) and their interaction terms with $Crisis_t$. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. $\text{Ln}(\text{RateCore}_{\text{it}})$

Panel A: Results for Asset Illiquidity

Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	Log(RateCore$_{it}$)	Log(RateLT$_{it}$)	$\Delta Loan_{it}$	$\Delta Commit_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Crisis_t \times MisMatch_i$	-10.406***	-0.736	-11.570***	0.201***	0.069**	-20.776***	-8.766***
	(-6.906)	(-0.424)	(-6.151)	(4.195)	(2.744)	(-8.993)	(-8.298)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89,011	89,011	89,011	88,795	88,844	89,011	89,011
Adj. R-squared	0.294	0.336	0.152	0.827	0.716	0.271	0.102

Panel B: Results for %Uninsured

Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	Log(RateCore$_{it}$)	Log(RateLT$_{it}$)	$\Delta Loan_{it}$	$\Delta Commit_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Crisis_t \times MisMatch_i$	-0.118***	0.051*	-0.074***	-0.001	0.000	-0.081***	-0.073***
	(-4.591)	(2.045)	(-3.489)	(-0.769)	(0.242)	(-4.467)	(-9.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88,439	88,439	88,439	88,231	88,287	88,439	88,439
Adj. R-squared	0.292	0.335	0.148	0.826	0.717	0.253	0.096

Appendix
Variable Definitions

Variables	Definitions
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.
$I_{ROA<Med}$	An indicator variable that equals 1 for observations where *ROA* $_{i,t-1}$ is below the sample median level of *ROA*, and 0 otherwise.
Asset Illiquidity	The measure of 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 on a bank's asset side (including off-balance-sheet activity) as liquid, semi-liquid, or illiquid based on product category. Step 2: Assign weights to the activities classified in Step 1. Illiquid assets get ½, semi-liquid assets get 0, and liquid assets get -1/2. Step 3: Combine bank asset activities as classified in Step 1 and as weighted in Step 2 to construct the asset illiquidity measure.
%Uninsured	The fraction of deposits that are uninsured (shown in percentage terms) averaged over the preceding 12 quarters with a minimum of six observations available.
ΔDep_{it}^{U}	Annualized growth rate in uninsured deposits as a percentage of lagged assets (in %) in quarters t and $t+1$. Uninsured deposit is calculated as total deposits (RCFD2200) – insured deposits.
Ln(Assets)	Log of total assets (RCFD2170).
C&I Loan $_{i,t-1}$	Commercial and industrial loans (RCFD1766), scaled by lagged total assets.
RealEstate_Loan	Loans secured by real estate (RCFD1410) scaled by total loans (RCFD1400).
Wholesale_Funding	Wholesale funds are the sum of the 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.
Capital_Ratio	Total equity (RCFD3210) divided by total assets (RCFD2170).
%Deposits	The ratio of total deposits to assets.
Std(ROE) $_{i,t-1}$	The standard deviation of ROE measured over 12 rolling quarters (from Quarter $t-12$ to $t-1$).
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.
Large Time Deposit Rate $_{i,t}$	Annualized average interest rate (in %) over the two quarters $t, t+1$ on savings deposits: $(larget\ timedeposit\ interest\ expense\ in\ Qtr\ t\ and\ t+1)/(Avg.\ large\ time\ deposit\ balance\ in\ Qtr\ t\ and\ t+1)\ )*400\%)$.
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.
ΔDep_{it}^{I}	The annualized growth rate in insured deposits as a percentage of lagged assets in quarters 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}^{Total}	Sum of ΔDep_{it}^{I} and ΔDep_{it}^{U}

Internet Appendix for

"Liquidity Transformation and Fragility in the US Banking Sector"*

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Figure A1: Changes Around the Financial Crisis of 2008

This figure plots the quarterly sample average values of *LMIRisk* from Bai et al. (2018) and of uninsured deposit flows around the 2008 Financial Crisis period.

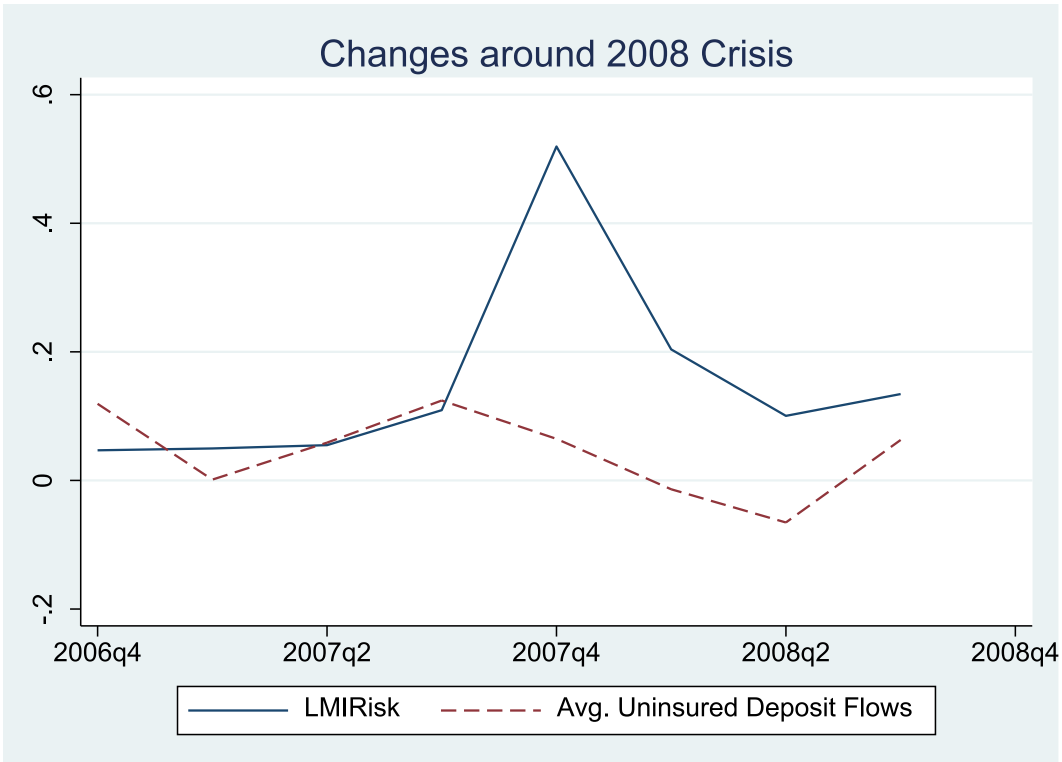

Table AI: Main Results in Subsamples by Bank Asset Size

This table explores whether the effect of liquidity mismatch on deposit flows differs by bank asset size for the sensitivity specification (Panel A) and the levels specification (Panel B). 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). Controls include time-varying bank characteristics and the interaction terms of their sample demeaned values with either *ROA* or $I_{ROA<Med}$, lagged deposit rates, and macro controls. T-statistics, reported in parentheses, are based on standard error estimates two-way clustered at the bank and year-quarter level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Sensitivity Specification

	Small banks: Assets $\in (0.1, 0.5$ billion$)$		Medium banks: Assets $\in (0.5, 3$ billion$)$		Large banks: Assets > 3 billion	
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)	(6)
$ROA_{it-1} \times Asset\ Illiquidity_{it-1}$	3.237***		3.804***		4.778**	
	(2.841)		(2.891)		(2.096)	
$ROA_{it-1} \times \%Uninsured_{it-1}$		0.041***		0.037***		0.019**
		(3.332)		(3.612)		(2.222)
ROA_{it-1}	1.481***	1.407***	1.063***	1.092***	1.393**	1.961***
	(4.438)	(4.585)	(3.292)	(3.193)	(2.134)	(2.703)
$Asset\ Illiquidity_{it-1}$	-5.496		-7.831		-7.783*	
	(-1.153)		(-1.427)		(-1.822)	
%Uninsured		-0.310***		-0.288***		-0.179***
		(-3.458)		(-3.861)		(-5.991)
Controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Observations	231,860	229,753	43,169	42,757	11,678	11,531
Adj. R-squared	0.106	0.137	0.161	0.187	0.117	0.134

Panel B: Level Specification

	Small banks: Assets $\in (0.1, 0.5$ billion)		Medium banks: Assets $\in (0.5, 3$ billion)		Large banks: Assets $>$ 3 billion	
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{ROA<Med} \times$ *Asset Illiquidity*$_{it-1}$	-4.777***		-7.725***		-6.868**	
	(-3.258)		(-3.620)		(-2.184)	
$I_{ROA<Med} \times$ *%Uninsured*$_{it-1}$		-0.047***		-0.056***		-0.007
		(-3.285)		(-3.206)		(-0.360)
$I_{ROA<Med}$	-1.149***	-1.016***	0.340	0.778	-3.526**	-3.725**
	(-3.360)	(-2.891)	(0.556)	(1.326)	(-2.306)	(-2.350)
Asset Illiquidity $_{it-1}$	0.484		-0.294		0.254	
	(0.156)		(-0.074)		(0.085)	
%Uninsured $_{it-1}$		-0.249***		-0.230***		-0.151***
		(-3.228)		(-3.494)		(-5.366)
Controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Observations	231,860	229,753	43,169	42,757	11,678	11,531
Adj. R-squared	0.106	0.136	0.160	0.185	0.117	0.134

Table AII. Robustness to Alternative Scaling of Dependent Variable

This table presents evidence on the robustness of our results when we calculate the dependent variable as changes in uninsured deposit balances scaled by the beginning balance of uninsured deposits. Columns (1) to (4) present the results for both the sensitivity and level specifications for the whole sample and columns (5) to (8) present the results for the matched samples. Controls include time-varying bank characteristics and the interactive terms of their sample demeaned values with either ROA or $I_{ROA<Med}$, lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Whole sample analysis					Matched sample analysis			
Mismatch measure	*Asset Illiquidity*		*%Uninsured*			*Asset Illiquidity*		*%Uninsured*	
Specification	Sensitivity	Level	Sensitivity	Level		Sensitivity	Level	Sensitivity	Level
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
$ROA_{it-1} \times MisMatch_{it-1}$	10.374***		0.036*		$ROA_{it-1} \times I_{MisMatch}$	3.517***		2.730***	
	(3.391)		(1.802)			(4.420)		(3.013)	
ROA_{it-1}	4.244***		3.916***		ROA_{it-1}	2.110***		2.294***	
	(4.787)		(4.835)			(4.227)		(4.544)	
$MisMatch_{it-1} \times I_{ROA<Med}$		-16.073***		-0.035	$I_{MisMatch} \times I_{ROA<Med}$		-4.972***		-3.815***
		(-3.779)		(-1.565)			(-3.976)		(-3.573)
$I_{ROA<Med}$		-4.322***		-2.904***	$I_{ROA<Med}$		0.074		0.028
		(-4.695)		(-3.214)			(0.057)		(0.024)
$MisMatch_{it-1}$	-22.738*	-3.309	-1.041***	-0.991***	$I_{MisMatch}$	-5.270**	1.010	-22.628***	-18.195***
	(-1.682)	(-0.364)	(-5.312)	(-5.212)		(-1.999)	(0.663)	(-4.885)	(-4.754)
Controls	Y	Y	Y	Y		Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y		Y	Y	Y	Y
Observations	286,830	286,830	284,157	284,157		99,580	99,580	92,319	92,319
Adj. R-squared	0.073	0.073	0.109	0.109		0.074	0.073	0.126	0.125

Table AIII. Robustness to Matching on *Informativeness* on the Matched Sample Analysis for *%Uninsured*

This table shows the matched sample analysis similar to that shown in Table IV of the main text, with the only exception that we add the measure of earnings precision (*Informativeness*) from Chen et al. (2022) to the matching covariate. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Covariate Balance

Subsample	Bottom Tercile of *%Uninsured*	Top Tercile of *%Uninsured*	
Covariates	Mean	Mean	t-stat of Diff.
ROA	0.973	0.981	0.151
C&I_Loans $_{it-1}$	0.151	0.152	0.287
RealEstate_Loans $_{it-1}$	0.711	0.710	-0.159
Wholesale_Funding $_{it-1}$	0.201	0.199	-0.252
Capital_Ratio $_{it-1}$	0.099	0.099	0.227
%Deposits $_{it-1}$	0.832	0.833	0.799
Ln(Size)	12.575	12.551	-0.874
Std(ROE) $_{it-1}$	5.714	5.708	-0.018
Asset Illiquidity	0.077	0.077	0.016
Informativeness	0.218	0.217	-0.180

Panel B: Matched Sample Results

	(1)		(2)
Dependent variable	ΔDep_{it}^{U}		ΔDep_{it}^{U}
ROA $_{it-1}$ × $I_{High\,\%Uninsured}$	1.592***	$I_{High\,\%Uninsured} \times I_{ROA<Med}$	-1.842***
	(4.257)		(-4.151)
ROA $_{it-1}$	0.555***	$I_{ROA<Med}$	0.300
	(3.973)		(0.780)
$I_{High\,\%Uninsured}$	-5.695***	$I_{High\,\%Uninsured}$	-3.326***
	(-3.345)		(-2.598)
Controls	Y		Y
Bank fixed effects	Y		Y
Observations	89,945		89,945
Adj. R-squared	0.136		0.134

Table AIV. Alternative Specification for the Matched Sample Analysis with the Sensitivity Analysis

This table shows the results for an alternative specification for the matched sample analysis with the sensitivity analysis. Specifically, for each bank-quarter in the matched pairs, we calculate a bank-quarter-specific flow-performance sensitivity as in $FlowSensitivity_{it} = \frac{1}{J}\sum_{j=1}^{J}\frac{\Delta Dep_{i,t-j}^{U}-\Delta Dep_{i,t-j-1}^{U}}{ROA_{i,t-j}-ROA_{i,t-j-1}}$, using data from preceding twenty quarters. We then regress $FlowSensitivity_{it}$ on the matched sample, with the indicator variable for the treatment observations. Column (1) presents the result from this analysis for the same matched sample of *%Uninsured* used in Table IV, and column (2) presents the results for the same matched sample of *Asset Illiquidity* used in Table VI Panels B and C. The number of observations is smaller here because we require at least twelve preceding quarters to calculate $FlowSensitivity_{it}$. Controls include the matching covariants and bank fixed effects. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)		(2)
Dependent variable	$FlowSensivity_{it}$		$FlowSensivity_{it}$
$I_{High\ \%Uninsured}$	1.412***	$I_{High\ Asset\ Illiq}$	0.206*
	(11.656)		(1.960)
Controls	Y		Y
Bank fixed effects	Y		Y
Observations	68,559		75,834
Adj. R-squared	0.590		0.557

Table AV: Substitution Between Uninsured and Insured Deposits with the Level Analysis

This table explores whether insured deposits help make up for the additional loss of uninsured deposits experienced by high liquidity mismatch banks using the level specification. Panel A explores the effects on deposit flows and Panel B explores whether deposit rates can, at least partly, explain the substitution between uninsured and insured deposits. Controls include bank characteristics and the interaction terms of their demeaned values with $I_{ROA<Med}$, and macro controls. Lagged deposit rates are also included as controls in Panels A. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Results on Deposit Flows

MisMatch measure	*Asset Illiquidity*			*%Uninsured*		
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}	ΔDep_{it}^{U}	ΔDep_{it}^{I}	ΔDep_{it}^{Total}
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{ROA<Med}$ × *MisMatch$_{it-1}$*	-5.281***	2.416	-2.895***	-0.049***	0.075***	0.023***
	(-3.422)	(1.404)	(-4.357)	(-3.682)	(4.470)	(3.140)
$I_{ROA<Med}$	-1.167***	-0.178	-1.352***	-0.843***	-0.243	-1.107***
	(-3.571)	(-0.527)	(-6.120)	(-2.668)	(-0.797)	(-5.283)
MisMatch$_{it-1}$	0.189	13.697***	13.028***	-0.224***	0.247***	0.018
	(0.063)	(4.433)	(11.287)	(-3.289)	(3.374)	(1.071)
Controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Observations	286,831	286,831	286,831	284,158	284,158	284,158
Adj. R-squared	0.106	0.107	0.165	0.134	0.139	0.162

Panel B: Results on Deposit rates

MisMatch measure	*Asset Illiquidity*		*%Uninsured*	
Dependent variable	$\text{Log}(\text{RateCore}_{\text{it}})$	$\text{Log}(\text{RateLT}_{\text{it}})$	$\text{Log}(\text{RateCore}_{\text{it}})$	$\text{Log}(\text{RateLT}_{\text{it}})$
	(1)	(2)	(3)	(4)
$I_{ROA<Med}$ × *MisMatch$_{it-1}$*	0.382***	0.205***	0.003***	0.001**
	(5.812)	(4.014)	(4.941)	(2.126)
$I_{ROA<Med}$	0.059***	0.037***	0.057***	0.034***
	(3.626)	(2.965)	(3.788)	(2.952)
MisMatch$_{it-1}$	0.622***	0.535***	0.009***	0.008***
	(4.837)	(5.189)	(3.587)	(3.833)
Controls	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y
Observations	284,675	284,478	281,991	281,804
Adj. R-squared	0.783	0.705	0.786	0.710

Table AVI: Systematic versus Idiosyncratic Performance Shocks Using Single State Banks Only

This table repeats the analyses in Table VIII of the main draft except we restrict the sample to be banks that operate in only one state. In addition to bank fixed effects, we also include the interactive fixed effects of state and year-quarter to flexibly absorb any state-specific responses to systematic shocks. Panel A presents the results from the sensitivity specification where ROA_Sys is the average ROA for all banks in a given quarter and ROA_Idio is the difference between ROA and ROA_Sys. Panel B presents the results for level specifications where $I_{ROA<Med}$ is the indicator variable for whether the bank has below sample median ROA performance, $I_{PoorSys\,\&\,ROA<Med} = I_{ROA<Med} * I(ROA\_Sys_t < Cutoff_{sys})$ where $Cutoff_{sys}$ is set to equal to the bottom 1/3, 1/4, and 1/5 of sample ROA_Sys in columns (1) and (4), in columns (2) and (5), and in columns (4) and (6), respectively. Similarly, $I_{PoorIdio\,\&\,ROA<Med} = I_{ROA<Med} * I(ROA\_Idio_{it} < Cutoff_{idio})$ where $Cutoff_{idio}$ is set to equal to the bottom 1/3, 1/4, and 1/5 of sample ROA_Idio in columns (1) and (4), in columns (2) and (5), and in columns (4) and (6), respectively. Controls include bank characteristics and the interaction terms of their demeaned values with either *ROA_Sys and ROA_Idio* in Panel A or the performance indicator variables in Panel B, lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A: Sensitivity Specification

MisMatch measure	*Asset Illiquidity*	*%Uninsured*
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)
$ROA\_Sys_{t-1} \times MisMatch_{it-1}$	7.105***	0.069***
	(3.853)	(4.382)
$ROA\_Idio_{it-1} \times MisMatch_{it-1}$	0.374	0.017***
	(1.117)	(4.236)
ROA_Idio_{it-1}	0.660***	0.667***
	(10.294)	(9.823)
$MisMatch_{it-1}$	-2.954	-0.289***
	(-1.532)	(-14.705)
Controls	Y	Y
Bank fixed effects	Y	Y
*State*Qtr fixed effects*	Y	Y
Observations	260,279	257,619
Adj. R-squared	0.315	0.326

Panel B: Level Specification

MisMatch measure	*Asset Illiquidity*			*%Uninsured*		
Poor shock cut-off	Bottom 1/3rd	Bottom 1/4th	Bottom 1/5th	Bottom 1/3rd	Bottom 1/4th	Bottom 1/5th
Dependent variable	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}	ΔDep_{it}^{U}
	(1)	(2)	(3)	(4)	(5)	(6)
$MisMatch_{it-1} \times I_{PoorSys\ \&\ ROA<Med}$	-4.872***	-4.296***	-3.938***	-0.037***	-0.035**	-0.039***
	(-4.457)	(-3.317)	(-2.638)	(-2.985)	(-2.626)	(-2.652)
$MisMatch_{it-1} \times I_{PoorIdio\ \&\ ROA<Med}$	-1.837***	-1.958***	-2.231***	-0.021***	-0.023***	-0.025***
	(-3.084)	(-2.897)	(-3.062)	(-3.383)	(-3.189)	(-3.428)
$MisMatch_{it-1} \times I_{ROA<Med}$	0.627	0.007	-0.262	0.002	-0.003	-0.005
	(1.142)	(0.015)	(-0.527)	(0.373)	(-0.435)	(-0.802)
$I_{ROA<Med}$	-0.561***	-0.611***	-0.666***	-0.524***	-0.580***	-0.635***
	(-3.403)	(-3.903)	(-4.363)	(-3.168)	(-3.666)	(-4.142)
$I_{PoorSys\ \&\ ROA<Med}$	-0.139	-0.094	0.062	-0.114	-0.035	0.234
	(-0.930)	(-0.527)	(0.311)	(-0.700)	(-0.167)	(0.975)
$I_{PoorIdio\ \&\ ROA<Med}$	-0.290***	-0.286***	-0.259**	-0.333***	-0.312***	-0.304***
	(-3.155)	(-2.970)	(-2.260)	(-3.556)	(-3.189)	(-2.687)
$MisMatch_{it-1}$	4.977***	4.978***	4.970***	-0.213***	-0.213***	-0.213***
	(8.518)	(8.546)	(8.521)	(-13.075)	(-13.047)	(-13.009)
Controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
State*Qtr fixed effects	Y	Y	Y	Y	Y	Y
Observations	260,279	260,279	260,279	257,619	257,619	257,619
Adj. R-squared	0.314	0.314	0.314	0.325	0.325	0.325

Table AVII. Robustness to Using *%Uninsured* Measured at the End of the Preceding Quarter

This table presents evidence on the robustness of our results when we measure *%Uninsured* at the end of the previous (instead of the average over the previous three years). Columns (1) to (2) present both the sensitivity and levels specifications for the whole sample and columns (3) to (4) present the results for the matched samples. Controls include time-varying bank characteristics and the interactive terms of their sample demeaned value with either *ROA* or $I_{ROA<Med}$, lagged deposit rates, and macro controls. T-statistics, based on two-way clustered standard errors at the bank and year-quarter level, are presented in the parenthesis below. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Sample	Whole sample			Matched sample	
Specification	Sensitivity	Levels		Sensitivity	Levels
	(1)	(2)		(3)	(4)
ROA_{it-1} × $MisMatch_{it-1}$	0.048***		ROA_{it-1} × $I_{MisMatch}$	2.205***	
	(3.351)			(3.519)	
ROA_{it-1}	1.714***		ROA_{it-1}	0.291	
	(5.742)			(1.420)	
$MisMatch_{it-1}$ ×$I_{ROA<Med}$		-0.047**	$I_{MisMatch}$ × $I_{ROA<Med}$		-2.308***
		(-2.327)			(-2.903)
$I_{ROA<Med}$		-1.097***	$I_{ROA<Med}$		0.316
		(-3.500)			(0.608)
$MisMatch_{it-1}$	-0.366***	-0.299***	$I_{MisMatch}$	-9.200***	-6.130***
	(-4.610)	(-4.853)		(-4.134)	(-4.261)
Controls	Y	Y		Y	Y
Bank fixed effects	Y	Y		Y	Y
Observations	284,158	284,158		98,955	98,955
Adj. R-squared	0.170	0.168		0.175	0.172