Earnings Information Spillovers and Depositor Contagion*

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Abstract: Understanding the nature of interconnections between banks is crucial to the knowledge of financial contagions and the appropriate policy response. We examine interconnections in the U.S. banking industry that stem from earnings information spillovers from local peers. Using a sample of nearly 8,800 commercial banks over three decades, we find that uninsured deposit flows respond strongly to the performance of peer banks – particularly when peers perform poorly but not when they perform well. Exploring the mechanisms, we find that the earnings information spillovers operate through both asset commonalities and panic-driven behaviors wherein depositors withdraw out of concerns about early withdrawals by other depositors. Our findings inform theories of contagion and their policy implications.

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1. Introduction

Contagion is a prominent phenomenon in the history of banking and financial crises. For example, the 2007-08 global financial crisis featured strong spillovers across different banks and financial institutions, magnifying the severity and magnitude of the crisis, and leading to major introspection, as part of the regulatory effort that followed the crisis, about the role of interbank connections. More recently, the failure of Silicon Valley Bank (SVB) in 2023 generated fears of a market-wide loss of depositor confidence and meltdown of the banking system. Regulators responded with unusual force to guarantee uninsured deposits across the banking system and cited the fear of contagion as the primary justification for this response.

Over the years, a large theoretical literature on contagion and spillovers in the banking system has been developed. Recent advancements in models by Liu (2023) and Goldstein, Kopytov, Shen, and Xiang (2024) suggest that three interacting features are at play underlying such phenomena. First, banks exhibit some correlation in their assets and business models. This is expected given that the performance of banks is affected by common factors reflecting the economy as a whole or the industries and regions they focus on. Beyond that, there is a tendency for banks to adopt excessively similar strategies and business models.[1] In the presence of such correlations, regardless of their source, a shock in one bank may contain adverse information about the conditions in other banks and trigger withdrawals from them.[2]

The second feature is panic, which can amplify fundamental shocks. Panic is defined as a case where depositors take their money out because of strategic complementarities, i.e., because of the fear that others will take their money out. Banking theory teaches us that panic is inherent

[1] See, for example, Shaffer (1994), Acharya and Yorulmazer (2008), Acharya (2009), Wagner (2011), Ibragimov, Jaffee, and Walden (2011), and Allen, Babus, and Carletti (2012), for models of banks' incentives to invest in similar assets more than what is socially desirable.

[2] See Chen (1999), Dasgupta (2004), Acharya and Yorulmazer (2008), and Allen, Babus, and Carletti (2012) for examples of models where contagion spreads from such information spillovers across banks holding similar assets.

in banks' business model. As banks perform liquidity transformation, financing illiquid assets with liquid deposits, they create an incentive for uninsured depositors to withdraw before others. Going back to Diamond and Dybvig (1983), it is well understood that this force can lead to bank runs, showing up in their framework as multiple equilibria. More recent works by Rochet and Vives (2004) and Goldstein and Pauzner (2005) show how panic manifests itself instead by amplifying the effect of fundamental shocks: depositors become increasingly concerned about fundamentals, their tendency to withdraw is strengthened by the fear that others will do so, more so when the liquidation values of bank assets decline. As a result, we might see excessive deposit withdrawals, i.e., withdrawals that would not have occurred had depositors not worried about the withdrawals of others, even in response to deteriorating fundamentals. Connecting this to contagion and spillovers, this feature implies that deteriorating fundamentals in some banks will cause depositors to withdraw in related banks more vigorously in the face of panic concerns.

The third feature is interbank connections and fire sales. Withdrawals in some banks are expected to worsen conditions for other banks. One reason this could happen is the presence of direct links, whereby banks have direct exposures to each other. Alternatively, this might happen because of indirect links, whereby banks share common markets for interbank lending and asset liquidation. When poorly performing banks are forced to prematurely liquidate assets to meet their depositors' withdrawal demand, they generate fire-sale discounts and worsen the liquidation/collateral values of other banks' assets (e.g., Shleifer and Vishny, 1992), which in turn can exacerbate panic concerns at other banks.

In the models of Liu (2023) and Goldstein et al. (2024), the features interact with each other in the following sense. Starting from some correlation or common exposure, problems tend to spill over across banks, but this is further amplified by the panic dynamics, which is further

amplified by the interconnections across banks in the interbank markets or asset markets. A vicious cycle then emerges as fire sales further aggravate panic, which further aggravates fire sales, and so on.

Thus far, the empirical literature has not examined key aspects of the theory regarding the sources and mechanisms of contagion. In this paper, we contribute by examining whether fundamental shocks at some banks – as measured by earnings – generate externalities on other banks by affecting their uninsured deposit flows. We further investigate how the effects on uninsured deposits with the degree of liquidity transformation, which is the underlying source of panic, and with the likely strength of externalities across banks due to interbank and asset-market connections. Detecting these mechanisms in the data is of first-order importance because when policymakers intervene out of concern for contagion, they are worried about potential inefficiencies stemming from panic and externalities, yet there is no direct evidence on the role that these forces play.

A key challenge in the empirical analysis is to capture the notion of panic withdrawals in the data. We build on the approach in the recent paper of Chen, Goldstein, Huang, and Vashishtha (2024) who find empirical support for this channel in data covering the universe of banks in the United States in the last three decades. Their paper does not look at interactions across banks but rather focuses on how a shock to the bank is amplified by the panic withdrawals of depositors in that bank. We extend their framework to a cross-bank setting to explore whether panic plays a role in generating contagion and how it interacts with other channels of contagion.

We use a sample of more than 360,000 bank-quarter observations in the United States, spanning the years 1994 to 2022 and containing 8,792 commercial banks. The core of our research design to detect spillovers of fundamental shocks involves examining how uninsured deposit flows

of a bank – the focal bank – respond to earnings (scaled by assets, i.e., ROA) of competing peer banks. For each focal bank in each year-quarter, we identify a set of peer banks that fall in the same size group and have geographic overlaps with the focal bank's counties of operations. We then derive an aggregate *ROA* of this peer set (*PeerROA*) that considers the intensity of each peer bank's operations in the counties where the focal bank operates. Thus, *PeerROA* is our summary earnings signal of banks that have similar size and operate in similar geographies as the focal bank.

Consistent with the presence of strong earnings performance spillovers, we find that uninsured deposit flows are positively associated with *PeerROA* after controlling for the focal bank's own *ROA*. Furthermore, we find that the association is statistically significant only when *PeerROA* is below the sample median and is insignificant otherwise. This is consistent with the premise in the contagion literature that these mechanisms operate mostly following adverse shocks. The economic magnitude of the spillover is quite large: a one-standard-deviation decrease in *PeerROA* is associated with a nearly 39% decrease in uninsured deposit flows from the sample average and is similar to the effect of a one-standard-deviation decline in the focal bank's own *ROA*.

After establishing the link between *PeerROA* and the bank's own uninsured deposit flows, we go deeper into the underlying mechanisms, starting with the role of correlated fundamentals across banks. For this purpose, we create a measure of peer earnings informativeness (*PeerROA_Inform*) by adapting the measure of informativeness from Chen et al. (2022), calculated as the adjusted R-squared from a bank-specific regression of the focal bank's write-offs on lagged components of peer banks' earnings using data from the prior 12 quarters. Consistent with spillovers at least partly being driven by correlated fundamentals, we find that uninsured depositors react more strongly to *PeerROA* when it is more predictive of the focal bank's asset quality. The

economic magnitude of the effect is large: a one-standard-deviation increase in *PeerROA_Inform* is associated with a 23% increase in the average uninsured deposit flow-to-peer performance sensitivity.

We then explore the role of panic, which is our main focus. Demonstrating the presence of panic withdrawals is more subtle, as the long empirical literature on financial crises reveals (see Goldstein, 2012), yet it is critical for policy implications. Following Chen et al. (2024), we introduce two proxies for the degree of liquidity transformation, which is the underlying source of panic. The first one is a bank's reliance on uninsured deposit financing (*%Uninsured*) and the second one is the illiquidity of a bank's assets (*Asset_Illiquidity)*.[3] Intuitively, with strategic complementarities in place, an uninsured depositor has little incentive to withdraw early when she knows that the bulk of her bank's depositors have a low incentive to withdraw early because they are covered by deposit insurance. Her fear of withdrawals by others would increase as *%Uninsured* increases. We also expect an uninsured depositor to be more fearful of withdrawals by fellow depositors when their banks' assets are more illiquid and likely to sell at a greater fire-sale discount in the event of liquidation. Our measure of the illiquidity of bank assets (*Asset Illiquidity*) comes from Berger and Bowman (2009), and it captures variation in illiquidity that comes from differences in banks' asset composition.

With these measures in place, we show that focal banks' uninsured depositor response to *PeerROA* also reflects an element of panic. We find that uninsured depositors respond more strongly to *PeerROA* declines when *%Uninsured* or *Asset Illiquidity* in their own bank is higher. The effect is economically large: a one-standard-deviation increase in *%Uninsured* (*Asset*

[3] Previous studies used a similar approach in contexts other than banks. See Chen, Goldstein, and Jiang (2010) for an analysis of mutual funds, Schmidt, Timmermann, and Wermers (2016) for money market funds, Goldstein, Jiang, and Ng (2017) for bond funds, and Foley-Fisher, Narajabad, and Verani (2020) for analysis in the life insurance industry.

Illiquidity) in the focal bank is associated with a 60% (40%) increase in the average flow-to-peer performance sensitivity. This adds to the results in Chen et al. (2024) about the presence of panic in deposit outflows, extending them to the case where the trigger for panic is not the bank's own performance decline, but rather that of its peers.

The analysis of cross-bank spillovers allows us to bring in other dimensions to establish the role of panic, which were not available in the own-bank effects explored in Chen et al. (2024). Specifically, we examine the degree of liquidity mismatch at the peer banks. Consistent with contagion via common exposure to interbank and/or asset liquidation markets, we find that peer banks' liquidity mismatch shapes the withdrawal of uninsured depositors at the focal bank in the same way: the positive relations between deposit flows and peer performance are stronger when peer banks are more liquidity mismatched.

Lastly, we conduct two analyses to explore the interactive effects of the above features on deposit contagion from peer earnings news. We first examine whether the effects of a focal bank's liquidity mismatch on its flow-to-peer performance relation are amplified by the peer banks' degree of liquidity transformation. We find strong evidence that they are. We also find that the degree of asset commonality between the focal and peer banks positively influences the effects of the liquidity mismatch at these banks. Hence, consistent with theory, the negative spillover on deposit flows from a peer bank's earnings shock is amplified by the degree of liquidity transformation in both the focal bank and the peer bank, their interactions, and the degree of asset commonality among local banks. Therefore, when policymakers decide whether to take actions to mitigate a crisis, they need to take into account the rich structure of the banking network and identify where panic is most pronounced.

Our evidence informs theories of contagion and the associated policy implications. Most importantly, existing theories (Liu, 2023; Goldstein et al., 2024) propose that contagion is propagated through panic withdrawals and fire-sale externalities, and our paper provides the first evidence that these are indeed at work in determining cross-bank depositor reaction to shocks. It also demonstrates the importance of the complex structure of interactions between liquidity transformation in different banks and fire sale externalities. Given that policymakers are usually motivated to respond quickly to the threat of crises because such mechanisms can amplify small shocks, our work establishes the benefits of policies such as deposit insurance, lender of last resort, or liquidity injections in secondary markets, which are meant to stem them.

Our work also has implications for the design of accounting rules and disclosure regulations. The presence of positive information externalities – through, for example, reduction in demand and cost uncertainty for the entire industry – is typically offered as a rationale for mandating accounting information disclosures (Admati and Pfleiderer, 2000; Leuz and Wysocki, 2016). Our work suggests that the banking industry may be unique because of the potential for negative information externalities due to panic withdrawals and fire-sale dynamics. This may provide a rationale for why banks are more opaque compared to firms in other industries (Morgan, 2002). Furthermore, given the importance of earnings information in shaping depositors' beliefs, our findings suggest that the regulators could try to mitigate contagion through the design of earnings measurement rules. For example, future research can assess the effect of the recent change in accounting rules about the loan loss provisions on information spillovers among banks.

Our paper contributes to the empirical literature on contagion in the banking industry,[4] which has largely focused on the spillover effects from isolated bank failures.[5] For example, Iyer and Peydró (2011) examine how interbank exposures propagated contagion following a bank failure in India. Beck, Nicoletti, and Stuber (2022) find that community banks sharing a common auditor with a failed bank experience lower deposit growth. More recently, studies of the failure of SVB in 2023 find that the failure prompted deposit withdrawals at other banks (Cipriani, Eisenbach, and Kovner, 2024; Caglio, Dlugose, and Rezende, 2024) and that social media hastened the contagion (Cookson et al., 2024). While these event-based studies provide valuable evidence on the presence of contagion, it is difficult to examine the underlying mechanisms in these settings. Our paper adds to these studies by providing the first large-sample evidence on depositor contagion triggered by peer banks' earnings – a key metric of fundamental performance. Unlike the event-based studies, our broad sample approach enables us to examine multiple contagion mechanisms, including asset commonality, panic-driven withdrawals, and fire-sale externalities. We further show how these mechanisms interact, highlighting features of the banking system that macroprudential policies can target to limit the spread of negative shocks.

Our focus on panic's role in contagion also connects our work to the literature on bank runs and banking crises. We build on Chen et al. (2024) and Chen, Vashishtha, and Wang (2025), who find evidence of panic-driven withdrawals in depositors' response to negative signals from their own banks about asset value-in-use (as captured by earnings) and liquidation values (as captured by loans' fair value losses). Applying the methodology in Chen et al. (2024), we find that negative

[4] We focus on contagion in the banking industry. The general literature on contagion, i.e., how adverse shocks at one place negatively affect outcomes at others, is too large for us review here.

[5] There is also a strand of studies using experiments to examine the likelihood and causes of contagions. For example, Chakravarty, Fonseca, and Kaplan (2014) and Brown, Trautmann, and Vlahu (2017) find evidence that withdrawals at peer banks can trigger panic-based withdrawals at focal banks.

earnings news from peer banks can trigger panic withdrawal, both by informing about the credit quality of focal bank assets and by implying declines in asset liquidation values via fire sale externality. Because banks have limited, if at all, control over their peers' performance and liquidity risk, relative to Chen et al. (2024) and Chen, Vashishtha, and Wang (2025), the findings from our cross-bank setting offer stronger inferences on panic's destabilizing role. To the extent that contagion amplifies idiosyncratic shocks into broader banking crises, our findings on panic's role in contagion complement those in Jamilov et al. (2025) that suggest panic contributed to past banking crises around the world.[6]

Lastly, our paper is also related to prior studies that examine contagion in the context of how shocks from the banking system spread to other markets, such as stock markets or the real economy. For example, several studies find that adverse shocks at one bank negatively impact equity investors of other banks (Docking, Hirschey, and Jones, 1997; Slovin, Sushka, and Polonchek, 1999; and more recently, Choi, Goldsmith-Pinkham, and Yorulmazer, 2024), and investments and employment in the real economy (e.g., Ivashina and Scharfstein, 2010; Campello, Graham, and Harvey, 2010; Chodorow-Reich, 2014). Our study complements this literature by directly examining the effects on depositors whose behavior is at the core of bank troubles in crises. Our focus on depositors also allows us to explore the role of panic – a key mechanism that is entirely unexplored in this literature.

2. Research design

[6] Correia, Luck, and Verner (2025) conclude that most bank failures accompanied by depositor runs reflected underlying insolvency, based on their findings that bank failures were predictable by fundamentals and that asset recovery rates in failed banks were low in the pre-FDIC era. However, as Goldstein (2012) notes, the association between weak fundamentals and failure does not rule out panic. We find that, in the presence of asset commonality and liquidity mismatch, poor peer performance can trigger panic-based withdrawals (which can push banks into insolvency) and large fire-sale discounts (which can lower recovery rates), even in the modern era with support from FDIC and the Federal Reserve. These findings highlight how contagion from peer banks' negative news complicates efforts to disentangle panic from fundamentals in banking crisis.

2.1 Identifying peer banks and measuring their earnings performance

Our paper focuses on earnings information spillover from local banks with similar business models. Local banking markets provide a natural setting to explore the spread of depositor contagion through earnings information. Since bank performance is shaped by local economic conditions, information spillovers from asset commonality will be more salient among local peers. Moreover, the spread of contagion through panic is also more likely to occur, at least initially, in local banking markets. Granja et al. (2017) document that because of informational frictions, most loan liquidations of failed banks tend to occur to local peers, suggesting fire-sale spillovers – which are at the heart of the spread of contagion through panic – are also likely to be felt first in local markets.

To capture business model similarities, we define peer banks as local banks in the same size group. This definition helps ensure that peer banks have similar business models as they serve similar local customers and face similar regulatory requirements. Similar definitions of peer banks are also adopted in prior studies (e.g., Silva, 2019). Following prior work (e.g., Berger and Bouwman, 2009; Beatty and Liao, 2011), we use 500 million dollars (measured in 2000 real dollars) as the cutoff for small banks, as it is the cutoff FDICIA uses for independent audit requirements. We classify banks with assets above 3 billion as large banks and banks with assets between 500 million and 3 billion as medium banks. Using these asset size cutoffs, we select peers (denoted with subscript j in the following equations) as the banks in the same size group and operating in the same geographic locations with a focal bank (subscript i is used to denote these banks). We identify banks' geographic operations using their annual branch and deposit information from the Summary of Deposit (SOD) data provided by the FDIC.

To detect earnings information spillover, we construct a summary measure of the earnings performance of peer banks (*PeerROA*) and examine whether depositors of a focal bank respond to this signal. For each focal commercial bank in our sample, we calculate *PeerROA* in two steps. First, in each local county *c* where the focal bank (denoted with subscript i) operates, we calculate the performance of its peers in the county, $CountyPeerROA_{c,t}$, as the weighted average *ROA* of peer banks (denoted with subscript j) weighed by their deposit-share in that county as follows:

$$CountyPeerROA_{c,t} = \sum_{j} w_{j,t}^{c}\, ROA_{j,t}\,, where\ w_{j,t}^{c} = \frac{Deposits_{j,t}^{c}}{\sum_{j} Deposits_{j,t}^{c}} \qquad (1)$$

We then derive $PeerROA_{i,t}$ at the focal-bank level by calculating the weighted average of $CountyPeerROA_{c,t}$ using the focal bank's deposit share in each local county as the weight, i.e.:

$$PeerROA_{i,t} = \sum_{c} \omega_{i,t}^{c}\, CountyPeerROA_{c,t}\,, where\ \omega_{i,t}^{c} = \frac{Deposits_{i,t}^{c}}{\sum_{c} Deposits_{i,t}^{c}} \qquad (2)$$

An advantage of the above aggregation approach is that it explicitly considers a peer bank's market share in deriving *PeerROA*: A peer bank's earnings are less likely to have a spillover effect in a market where it commands little deposit share. We consider *PeerROA* as the summary measure that is representative of the earnings performance of banks that have branches in the focal bank's areas of operations.[7]

2.2 Regression Specification

Our specifications to examine the effect of *PeerROA* on deposit flows are guided by a simple model of uninsured depositor behavior commonly assumed in prior work (e.g., Egan, Hortaçsu, and Matvos, 2017; Chen et al., 2022, 2024). Banks attract more deposits when they offer greater utility to depositors (compared to other banks) and when there is greater aggregate demand

[7] We include all banks that fit our peer bank criteria in the calculation as long as they have available data from Call Reports and SOD. Thus, a bank that later failed or merged with other banks would remain in our analysis (both as a member of the peer banks for a focal bank or as a focal bank itself) until it no longer files Call Reports or SOD.

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 periodically update their perceptions of their banks' default risks as they receive signals relevant for assessing the cash-generating potential of their banks' assets (i.e., asset quality). Thus, deposit growth in any period is affected by performance signals that update depositors' views about default risk as well as by factors unrelated to default risk, including (i) deposit rate, (ii) service quality, and (iii) aggregate demand for holding deposits.

Under the above framework, if *PeerROA* provides incremental information relevant to shaping depositors' perceptions about default risk, we expect it to be positively associated with deposit growth. We test for this earnings information spillover using various versions of the following regression specification:

$$\Delta Dep_{i,t}^{u} = \alpha_i + \beta_0 PeerROA_{i,t-1} + \beta_1 ROA_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

where $\Delta Dep_{i,t}^{u}$ represents uninsured deposit flows measured over periods subsequent to quarter *t-1*. Following prior studies (e.g., Chen et al., 2022, 2024), we measure uninsured deposit flows as the change of uninsured deposit balances scaled by lagged assets over two quarters following the end of quarter *t-1*, in which *PeerROA* and *ROA* are measured.[8] The reason is that banks typically file Call Reports up to 30 days after the calendar quarter ends, and the literature on post-earnings announcement drift suggests that investors can respond to quarterly earnings reports with delays up to a quarter after the earnings announcement (Bernard and Thomas, 1989); measurement of deposit flows over two future quarters provides sufficient time for depositors to respond to earnings information.

[8] An alternative is to scale by the beginning balance of uninsured deposits. We do not use this scaling in our main specifications because, as explained in Chen et al. (2024) (footnote 13 on page 4001), it is less effective in detecting panic-based withdrawals. In Table A3 of Appendix 1, we show that our main results are robust to this alternative scaling.

The control variables follow those in prior literature (Acharya and Mora, 2015; Chen et al., 2022, 2024) and account for factors other than default risk that affect deposit growth (i.e., deposit rate, service quality, and aggregate demand). We first control for deposit rates by using the rates offered on large-time deposits and core deposits as proxies for rates on different types of deposits.[9] We measure the rates as quarterly interest expenses on these deposits divided by average quarterly deposits over the same periods for which we measure deposit flows.

To account for differences in bank characteristics (including service quality), we include bank fixed effects (α_i) as well as several time-variant features of banks' business models used in prior work including: (i) capital ratio defined as capital scaled by assets (*Capital_Ratio*), (ii) wholesale funding scaled by assets (*Wholesale_Funding*), (iii) total deposit funding scaled by total assets (*%Deposits*), (iv) the logarithm of asset size (*Ln(Assets)*), (v) real estate loan share as the amount of loans secured by real estate scaled by total loans (*RealEstate_Loans*), (vi) commercial and industrial loan scaled by total loans (*C&I_Loans*) and (vii) the standard deviation of ROA in prior 12 quarters ending at *t-1* (*Std(ROA)*). Since our focus is on information spillover from local peers, we also control for the degree of competition in the local market faced by the focal bank, measured as the Herfindahl–Hirschman index of deposit shares across local peer banks (*ExpDepHHI*).

Finally, we account for aggregate fluctuations in the demand for holding deposit claims. Investors can choose alternative asset classes (e.g., money-market funds or stock markets) instead of bank deposits to meet their liquidity and investment needs. Accordingly, Drechsler, Savov, and Schnabl (2017) and Lin (2020) show that aggregate deposits decline when treasury securities and the stock market offer higher returns. Following Chen et al. (2022, 2024), we include both

[9] Ideally we would like to control for rates offered on insured and uninsured deposits. Unfortunately, Call Reports do not separately report interest expenses on insured and uninsured deposits.

contemporaneous and two lagged values of fed fund rates and the value-weighted stock market returns to control for opportunity costs of holding deposits. An alternative approach to control aggregate demand is to use year-quarter fixed effects. However, Chen et al. (2022, 2024) advise against this approach because it precludes the investigation of depositor response to performance shocks stemming from common macroeconomic shocks; this is problematic because many of the important performance swings in the cyclical banking industry tend to be systematic. This issue is even more relevant for our study because of our focus on depositor contagion, which we expect to be particularly severe when the banking industry is experiencing systematically adverse shocks.

2.3 Mechanisms of deposit contagion

Theoretical work on contagion identifies several features that can make adverse earnings shocks at one bank generate negative externalities for others. The first pertains to asset commonality, referring to the situation where banks share some correlation in their asset payoffs (see Chen, 1999; Dasgupta, 2004; Acharya and Yorulmazer, 2008; Allen, Babus, and Carletti, 2012 for examples). Asset commonality is expected, as the performance of banks is affected by common factors reflecting the economy as a whole or the industries and locations they focus on. The literature has also identified several reasons that banks may choose to adopt similar strategies and business models at a level that is more than socially desirable (Shaffer, 1994; Acharya and Yorulmazer, 2008; Acharya, 2009; Wagner, 2011; Ibragimov, Jaffee, and Walden, 2011; and Allen et al., 2012). When banks hold assets with correlated payoffs, poor earnings shocks at peer banks can reveal adverse information about the credit quality of the focal bank's assets and trigger withdrawals by the focal bank's depositors. Empirically, this mechanism implies that the sensitivity of uninsured deposit flow-to-peer earnings is higher when the peer earnings are more informative about the focal bank's fundamentals.

The second feature underlying contagion is panic, under which depositors withdraw out of the fear of early withdrawals by fellow depositors. Economic theory, going back to Diamond and Dybvig (1983), has for long shown that banks' role in liquidity transformation – i.e., funding illiquid assets with liquid demand deposit claims – makes them vulnerable to panic-based bank runs: because banks do not hold enough liquid assets, depositors may rush to withdraw their money only because they fear others will do the same and the bank will run out of resources. Later theory works show that panic manifests by raising the performance threshold under which depositors withdraw, thus rendering the banks more vulnerable to run-induced failure (e.g., Rochet and Vives, 2004; Goldstein and Pauzner, 2005). Chen et al. (2024) show that panic-based withdrawals empirically manifest as an amplified response to adverse fundamental shocks by depositors at more liquidity mismatched banks.

The third feature is interbank connections. The connections can be direct, whereby banks hold positions in each other. When this is the case, deteriorating performance at peer banks directly reduces focal banks' performance. They can also be indirect, whereby banks participate in the same asset markets (e.g., markets for bank asset liquidation, repo markets, or inter-banking lending markets) and compete for the common pool of liquidity. When peer banks suffer adverse shocks, they demand more liquidity to meet withdrawals by their own depositors, which can depress asset prices in these markets, generating fire-sale discounts, and increasing the costs of focal banks to access external liquidity (e.g., Shleifer and Vishny, 1992; Diamond and Rajan, 2005). As a result, panic elements can kick in as depositors at focal banks withdraw out of fear of early withdrawals by their fellow depositors.

Recent theory works show that these three features can intertwine to generate contagion in the banking system in which problems at some banks spill over to others, first due to correlation

in asset returns, followed by the amplification caused by panic concerns at these banks, which is then further magnified by the interconnections across banks in the interbank markets or asset markets (e.g., Liu, 2023; Goldstein et al., 2024). A vicious cycle can then emerge as fire sales further exacerbate panic, which further aggravates fire sales, and so on. Our empirical analysis aims to examine whether these features are present in data. Below we explain the tests used to detect these features.

2.3.1 Asset commonality

We explore the asset commonality mechanism by exploiting cross-market variation in the predictive ability of *PeerROA* for the focal bank's fundamentals. The idea is that if *PeerROA* triggers deposit withdrawals at the focal bank by providing incremental information about the asset quality at the focal bank, the spillovers on deposit withdrawals would be stronger when *PeerROA* is more predictive of the focal bank's asset quality. Empirically, we modify the earnings informativeness measure in Chen et al. (2022) and use *PeerROA_Inform* to capture variations in the predictive ability of peer earnings. Specifically, for each focal bank-quarterly observation, we calculate *PeerROA_Inform* as the adjusted R-squared from a bank-specific regression of the focal bank's future loan write-offs on the components of peer banks' earnings using data from prior 12 quarters ending at *t-1* (see Appendix 2 for details of all variable constructions). Higher *PeerROA_Inform* suggests that *PeerROA* has greater information content for the credit quality of the focal bank's assets. With this measure, we estimate the following flow-to-peer performance specification:

$$\Delta Dep^{u}_{i,t} = \alpha_i + \beta_0 PeerROA_{i,t-1} + \beta_1 PeerROA_Inform_{i,t-1} * PeerROA_{i,t-1} + \beta_2 PeerROA_Inform_{i,t-1} + \beta_3 ROA_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

We use demeaned versions of *PeerROA_Inform* (*PeerROA_Inform* minus its sample mean) so that the coefficient estimate of β_0 denotes the flow-to-peer performance sensitivity for a bank with average *PeerROA_Inform*. In addition to the control variables discussed earlier, we include the interaction terms between *PeerROA* and the demeaned versions of time-varying characteristics of focal banks to ensure results do not reflect differences in business models. If *PeerROA* relates to uninsured deposit flows through information about future cash flows from focal banks' assets, we expect the coefficient estimates of β_0 and β_1 to be positive.

2.3.2 Panic-based deposit withdrawals

To detect if there is an element of panic in depositors' response to negative earnings news from peer banks, we modify the tests developed in Chen et al. (2024) in providing evidence of panic in depositor-response to their own banks' performance. The tests are derived based on the framework of panic run models with strategic complementarity (e.g., Goldstein and Pauzner, 2005) and explore how the degree of liquidity mismatch on banks' balance sheets affects the relation between uninsured deposit flows and bank performance. In the models, the likelihood of a panic run at a bank is characterized by a performance threshold below which depositors make withdrawals. A key comparative static from the model is that the run threshold is increasing in the degree of a bank's liquidity mismatch. This implies that banks with higher liquidity mismatch are more vulnerable to panic runs because it takes a smaller deterioration in performance to breach the higher threshold and trigger deposit withdrawals.

As explained in Section I of Chen et al. (2024), this leads to two testable predictions. First, the average sensitivity of uninsured deposit flows to news about bank performance is stronger for banks with more liquidity mismatch (i.e., the sensitivity test). 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); this, in expectation, makes uninsured deposit flows of these banks more sensitive to performance. [10] Second, conditional on a given level of poor performance, we expect high mismatch banks to have lower levels of uninsured deposit flows because of their greater chance of having already experienced panic-based withdrawals (i.e., the levels test).

Adapting their tests to our setting, we examine whether panic features in depositors' response to peer bank performance using the specifications in (5a) and (5b), respectively:

$$\Delta Dep^{u}_{i,t} = \alpha_i + \beta_0 PeerROA_{i,t-1} + \beta_1 MisMatch_{i,t-1} * PeerROA_{i,t-1} + \beta_2 MisMatch_{i,t-1} + \beta_3 ROA_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t} \quad (5a: sensitivity\ test)$$

$$\Delta Dep^{u}_{i,t} = \alpha_i + \gamma_0 I_{PeerROA<Med} + \gamma_1 MisMatch_{i,t-1} * I_{PeerROA<Med} + \gamma_2 MisMatch_{i,t-1} + \gamma_3 PeerROA_{i,t-1} + \gamma_4 ROA_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t} \quad (5b: levels\ test)$$

where *MisMatch* is one of the two measures of liquidity mismatch that we will discuss next. The control variables and the interactive controls are similar to those in equation (4). In all our analyses, we use the demeaned versions of *MisMatch* to facilitate interpretations of the coefficients.

For the sensitivity test in equation (5a), the coefficient of interest is the one on the interaction term between *MisMatch* and *PeerROA*, β_1, which captures how the flow-to-peer performance sensitivity varies with the degree of the focal bank's liquidity mismatch. A significantly positive β_1 is consistent with panic-based withdrawals. For the levels test in equation (5b), $I_{PeerROA<Med}$ is an indicator variable for when *PeerROA* is below the sample median and the coefficient of interest is the interaction term between $MisMatch$ and $I_{PeerROA<Med}$, γ_1. A significantly negative γ_1 indicates that when *PeerROA* deteriorates from above to below-median

[10] Chen et al. (2024) show that a necessary condition for the sensitivity test is that the density distribution function of the performance signal (*PeerROA* in our case) is upward sloping in the region of performance where withdrawals may take place. As we show later in Figures 1 and 2, this condition is met in our sample.

regions, banks with high *Mismatch* experience lower levels of uninsured deposit flows, which is consistent with panic-based withdrawals.

Following Chen et al. (2024), we measure banks' mismatch by two features that lie at the root of panic-run incentives: (i) a bank's reliance on uninsured deposits *(%Uninsured*) and (ii) the degree of a bank's asset illiquidity (*Asset Illiquidity*). Intuitively, all else equal, an uninsured depositor has little or no incentive to withdraw early when she knows that most of her fellow depositors have little incentive to withdraw early because of deposit insurance. Thus, the fear of early withdrawals is expected to increase in *%Uninsured*.

We also expect an uninsured depositor to be more fearful of early withdrawals by fellow depositors when their banks' assets are more illiquid and likely to sell at a greater fire-sale discount in the event of liquidation. Our measure of asset illiquidity comes from Berger and Bouwman (2009), who 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). [11] 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 both *%Uninsured* and *Asset Illiquidity* using their average values from the previous three years instead of the value at end of quarter *t-1*, so that the variables do not simply capture the recent trends in deposit flows or bank asset choices at specific time points.

3. Data sources and sample selection

[11] Our measure of asset illiquidity is downloaded from Christa Bouwman's website at https://sites.google.com/a/tamu.edu/bouwman/data-forms-and-links-to-websites-for-u-s-banking-research?authuser=0 up to 2016Q4. We thank Zeqiong Huang for providing data on asset illiquidity after 2016.

We obtain most of our bank financial variables from U.S. Call Reports as disseminated by the Wharton Research Data Services (WRDS).[12] Call Reports contain quarterly data on all commercial banks' income statements and balance sheets. We identify banks' geographic operations using their branch office deposit information from the annual Summary of Deposit (SOD) survey data provided by the FDIC. Our sample period is from 1994Q1 to 2022Q4, and our bank-quarter observation is at the commercial bank level. To mitigate the impact of mergers and acquisitions, we exclude bank-quarter observations with quarterly asset growth greater than 10%. We also exclude bank-quarter observations with total bank assets smaller than 100 million and winsorize all continuous variables at 1% and 99% percentiles. These sample selection and cleaning procedures are commonly used in prior studies (Acharya and Mora, 2015; Chen et al., 2022, 2024). Appendix 2 provides all variable definitions and details about specific Call Report items used to measure these variables. Our final sample consists of 363,595 bank-quarter observations from 8,792 unique commercial banks.

Table 1 presents the summary statistics of variables in our sample. Panel A shows that the average annualized *ROA (PeerROA)* is 1.02% (0.91%) with a standard deviation of 0.84% (0.60%). Mean *PeerROA_Inform* is 0.20, suggesting peer banks' earnings information can explain 20% of the variation in the focal bank's future asset write-offs. With an interquartile range of 76%, *PeerROA_Inform* also exhibits substantial variation that we later use to test for the asset commonality mechanism. The average annualized growth in uninsured (insured) deposits is 2.40% (2.75%) of total assets.

[12] Since WRDS coverage of Call Reports is incomplete after 2011, we supplement the incomplete WRDS data using two other sources. First is the Central Data Repository's Public Data distribution of FFIEC (https://cdr.ffiec.gov/public/ManageFacsimiles.aspx). Second is S&P's SNL financial database.

Panel B of Table 1 reports the correlation among all key variables. The correlation between uninsured deposit flows and lagged *ROA* (at 0.13), much higher than the correlation between insured deposit flows and lagged *ROA* (at 0.02), confirming that uninsured deposit flows are more sensitive to their own bank performance. These statistics are comparable to those reported in Chen et al. (2022, 2024). We also find a positive correlation (0.11) between uninsured deposit flows and *PeerROA,* consistent with a positive spillover of peer banks' earnings shocks to the focal bank's uninsured depositors. Lastly, Panel B shows that the focal and peer banks not only have highly correlated performance (with a correlation coefficient of 0.36 between *PeerROA* and *ROA*), but also share similar business characteristics in terms of their measures of liquidity mismatch: the correlation coefficient between their *%Uninsured* (*Asset Illiquidity*) measures is 0.57 (0.48). We view these statistics as generally supportive of our definition of peer banks.

4. Evidence on earnings information spillovers

4.1 Semiparametric analyses

We begin with a diagnostic analysis of the relation between deposit flows and *PeerROA* using semi-parametric regressions so that we do not make functional form assumptions. The semi-parametric specification is estimated using the following form:

$$\Delta Dep_{i,t} = f\left(PeerROA_{i,t-1}\right) + ROA_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t} \quad (6)$$

where $\Delta Dep_{i,t}$ is the deposit flow and $PeerROA_{i,t-1}$ is measured at the end of quarter *t-1*. Following prior studies (e.g., Chevalier and Ellison, 1997; Chen et al., 2010; Chen et al., 2024), we use the Robinson (1988) estimator implemented using Gaussian local kernel regressions.

Figure 2 Panel A presents the flow-to-peer performance relation for uninsured and insured deposit flows. The figure reveals strikingly different patterns in the above- and below-median regions of *PeerROA*. When *PeerROA* is above the median, both uninsured and insured deposit

flows exhibit a relatively flat relation with *PeerROA* and are virtually indistinguishable. As *PeerROA* declines to below-median levels, uninsured deposit flows start to decline steeply, but insured deposit flows increase. These patterns reveal several useful insights. First, there is no evidence of positive externalities of peer earnings – the spillovers seem to occur only when peer banks are performing poorly. Second, the patterns justify our focus on the below-median region of *PeerROA* when trying to detect panic-based withdrawals. Finally, there is evidence of substitution between uninsured and insured deposits when peer performance is below median; this finding is consistent with several prior studies showing that banks attempt to make up for their loss of uninsured deposits by paying higher rates to attract insured deposits (e.g., Martin, Puri, and Ufier, 2023; Chen et al., 2022, 2024).

Next, we explore the mechanisms behind the relation between uninsured deposit flows and *PeerROA*. To examine whether the spillover reflects the information in *PeerROA* about the cash-generating potential of the focal bank's assets, we divide our sample into terciles based on *PeerROA_Inform* and estimate the uninsured deposit flow-to-peer performance relation for the bottom and top tercile groups. Panel B of Figure 2 presents the plot. Compared to the bottom-tercile, uninsured deposit flows exhibit a sharper decline in response to declining *PeerROA* in the top-tercile of *PeerROA_Inform.* This lends support to the idea that correlated asset payoffs are partly responsible for depositor contagion. Panels C and D explore the role of panic by providing similar plots for top- and bottom-terciles of the focal bank's *%Uninsured* and *Asset Illiquidity,* respectively. Consistent with the presence of panic, banks in the top-tercile of *%Uninsured* and *Asset Illiquidity* experience sharper drops in uninsured deposits as *PeerROA* declines compared to banks in the bottom-tercile.

While the semi-parametric plots provide informative exploration of the flow-to-peer performance relation without making functional form assumptions, we cannot include bank fixed effects and conduct formal tests for differences in depositors' behavior across banks with different *PeerROA_Inform* or *MisMatch*. We next employ parametric regressions to address these issues.

4.2 Parametric analyses

Table 2 presents the OLS estimates of various versions of equation (3). In all regressions, we obtain standard errors using two-way clustering at the bank and year-quarter level. Column (1) presents the results without fixed effects to allow both cross-sectional and time-series variations in *PeerROA*. The coefficient estimate on *PeerROA* is positive and statistically significant at 1% level, suggesting that uninsured deposit flows are positively associated with *PeerROA*. Note that our specification controls for the focal bank's *ROA*, meaning that *PeerROA* provides incremental information for uninsured depositors that is not subsumed by *ROA*.

In column (2), we explore whether uninsured depositors' response to *PeerROA* depends on whether it falls above- or below- the sample median. We do this using a piecewise linear regression that allows for the coefficient on *PeerROA* to vary depending on whether it is above or below the sample median. The results confirm the pattern shown in the semi-parametric plot: the coefficient estimate on below-median levels of *PeerROA* is statistically significant at 5% level (coeff=1.459) but is of much smaller magnitude (coeff=0.214) and not significant at conventional levels when *PeerROA* is above the sample median. Similar results are obtained in column (3) where we also allow the coefficient on the focal bank's *ROA* to vary depending on whether the focal bank *ROA* is above or below the sample median.

Column (4) presents the estimates after we include the bank fixed effects. The results remain robust. Both *ROA* and *PeerROA* are positively associated with uninsured deposit flows.

The economic magnitudes are meaningful. A one-standard-deviation increase in the focal bank's *ROA* is associated with a 0.92% (=0.84*1.089) increase in uninsured deposit flows, representing about 38% (=0.92/2.40) of the average uninsured deposit flows in the sample. Turning to *PeerROA*, a one-standard-deviation increase in *PeerROA* is associated with a 0.93% (=0.60*1.554) increase in uninsured deposit flows, representing about 39% (=0.93/2.40) of the average uninsured deposit flows.

The coefficient estimates indicate that a one-unit decline in *PeerROA* has an effect on uninsured deposit flows comparable to a one-unit decline in the bank's own *ROA*. Several mechanisms help explain this magnitude. First, *PeerROA* provides an informative signal about local shocks. Since bank performance is closely tied to local economic conditions, depositors rely more on signals that better capture these conditions. By averaging out the idiosyncratic components of peer performance, *PeerROA* can be more informative about common local shocks than the focal bank's own *ROA*, thus carrying more weight in depositors' assessment of bank default risk. Second, panic-based theories of contagion suggest that banks can face withdrawal pressures from both within- and cross-bank complementarities. Within-bank complementarities stem from liquidity mismatch on the bank's own balance sheet, whereas cross-bank complementarities arise when banks liquidate assets in shared markets at fire-sale discounts (Liu, 2023; Goldstein et al., 2024). This implies that deposit outflows may occur even if *PeerROA* reflects only idiosyncratic shocks, provided that these shocks trigger premature asset liquidation by peer banks and consequently generate fire-sale discounts that affect focal banks. Third, fire-sale discounts are likely high when the entire industry performs poorly (Shleifer and Vishny, 1992; Liu, 2016, 2023). In this case, declining *PeerROA* signals both higher likelihood of asset sales by peer banks and reduced local capital to absorb these sales (Granja et al., 2017), thereby amplifying

the fire-sale discounts. As we show in subsequent analyses, all these mechanisms are indeed at play, resulting in strong reaction by uninsured depositors to declines in *PeerROA*.

We conclude this section by exploring the robustness of our results to using time dummies instead of macroeconomic controls to account for fluctuations in aggregate demand for holding deposit claims. As discussed in Section 2.2, using time dummies is not our preferred specification because it does not allow us to examine depositors' responses to systematic declines in performance. This is problematic because many important performance swings in the cyclical banking industry tend to be systematic and depositor contagion is likely to manifest in periods of systematic performance declines. Estimates in column (5) show that the coefficient on *PeerROA* remains significant at 1% level but as expected, has a lower economic magnitude (coeff=0.329). In subsequent analyses, we present results using our preferred specification with macroeconomic controls. In Table A1 of the Appendix 1, we show that our main results exploring the underlying mechanisms for depositor contagion are also robust to using time-dummies instead of macro-controls.

5. Evidence on underlying mechanisms

Results in Table 2 reveal the presence of strong spillovers from peers' earnings information that are concentrated in periods when peer banks perform poorly. We next examine the underlying mechanisms as studied in the theory literature.

5.1 Evidence on asset commonality

To the extent that peer banks hold similar assets, earnings shocks at one bank can provide incremental information about the asset quality of others. Under this mechanism, we expect uninsured deposit flows to react more strongly to *PeerROA* when peer banks' financial disclosures are more informative about the cash-generating potential of the focal bank's assets. Following the

discussion in Section 2.3.1, we test this mechanism by estimating equation (4), which allows the coefficient on *PeerROA* to vary by *PeerROA_Inform*, our measure of the informativeness of peer earnings for the focal bank's fundamentals.

Table 3 presents the results from estimating equation (4). The coefficient estimate on *PeerROA* is significantly positive at 1% level (coeff=1.440), and the coefficient estimate on the interaction term between *PeerROA_Inform* and *PeerROA* is also significantly positive at 5% level (coeff=0.651). The results indicate that the average uninsured deposit flow-to-*PeerROA* sensitivity is higher when *PeerROA* contains more information relevant to understanding the focal bank's fundamentals. The magnitudes of the coefficient estimates are economically meaningful: a one-standard-deviation increase in *PeerROA_Inform* is associated with a 23% (=0.51*0.651/1.44) increase in the average flow-to-peer performance sensitivity. These results lend support to the idea that depositor contagion in peer banks, at least partly, stems from asset commonality.

5.2 Evidence on panic-based withdrawals

5.2.1 Effects of focal banks' liquidity mismatch

As discussed in Section 2.3.2, we examine the effects of panic on focal banks' uninsured depositors' response to peer bank performance by adapting the sensitivity test[13] and the levels test developed in Chen et al. (2024). We first examine whether the impact of *PeerROA* is greater at focal banks with higher *Asset Illiquidity* or *%Uninsured.* The idea is that poor performance signals at peer banks revise downward depositors' belief about focal banks' fundamentals, triggering withdrawal. Panic-driven withdrawals manifest in the forms of stronger uninsured depositor flow-

[13] As shown in Chen et al. (2024), for the sensitivity test to detect panic-based withdrawals, the distribution of *PeerROA* need to be increasing in the region of performance where panic-withdrawal may occur. To verify that this is indeed the case, we present the histogram of *PeerROA* in Figure 1. It shows that the distribution of *PeerROA* follows a unimodal distribution largely symmetric around the median. In addition, Figure 2 shows that uninsured deposit flows only become sensitive to peer performance when peer banks exhibit below median performance. Together, they indicate that the condition for the sensitivity test is met in our sample.

to-peer performance sensitivity and lower levels of deposit flows in banks with more liquidity transformation.

Table 4 presents the results. Columns (1) and (2) present the estimates of equation (5a) that examines the differential impact of *%Uninsured* and *Asset Illiquidity* on the sensitivity of uninsured deposit flows to *PeerROA*. In column (1), the coefficient estimate on *PeerROA* is significantly positive at 1% level (coeff=1.198), and the coefficient estimate on the interaction term between *PeerROA* and *%Uninsured* is also significantly positive at 1% level (coeff=0.051). Similarly, column (2) shows that the coefficient estimates on *PeerROA* (coeff=1.441) and *Asset Illiquidity*PeerROA* (coeff=4.161) are positive and statistically significant at 1% levels. The results are consistent with predictions that the average flow-to-peer performance sensitivity is higher when the focal bank has more liquidity mismatch on its balance sheet, as measured by *%Uninsured* and *Asset Illiquidity*. The economic magnitudes are quite meaningful: a one-standard-deviation increase in *%Uninsured* and *Asset Illiquidity* is associated with a 60% (=14*0.051/1.198) and 40% (=0.14*4.161/1.441) increase in the average flow-to-peer performance sensitivity, respectively.

Columns (3) and (4) present estimates of equation (5b) that examines the differential impact of *%Uninsured* and *Asset Illiquidity* on the level of deposit flows as *PeerROA* deteriorates from above- to below-median. Column (3) shows that the coefficient estimate on *I(PeerROA<Med)* is significantly negative at 10% level (coeff=-0.339) and that on the interaction term between *%Uninsured* and *I(PeerROA<Med)* is significantly negative at 1% level (coeff=-0.048). These estimates are consistent with the prediction that banks with higher levels of *%Uninsured* experience additional uninsured deposit outflows as *PeerROA* declines from above- to below-median. Similar patterns are observed in column (4), which shows that the coefficient estimate on

*Asset Illiquidity*I(PeerROA<Med)* is significantly negative at 1% level (coeff=-3.843). In terms of the economic magnitude, the additional uninsured deposit outflows from a one-standard-deviation increase in *%Uninsured* and *Asset Illiquidity* are about 28% (=14*0.048/2.40) and 22% (=0.14*3.843/2.40) of the average uninsured deposit flows, respectively.[14]

5.2.2 Effects of peer banks' liquidity mismatch

The previous results indicate that *PeerROA* triggers negative deposit spillover by conveying adverse information about the focal bank's asset quality and the effect is amplified by the focal bank's liquidity mismatch, consistent with a role for panic in contagion. We next examine if the flow-to-peer performance relation is stronger when peer banks also have high liquidity mismatch. The idea is based on the insight from theory that the risk of panic withdrawals increases as the liquidation value of bank assets declines, even when these assets' value-in-use remains intact,[15] because depositors are more concerned about early withdrawals by other depositors. Recent theoretical studies (Liu, 2023; Goldstein et al., 2024) apply this insight to formally show that panic at one bank can spread to other banks via fire-sale spillovers: asset sales at one bank in response to panic-driven withdrawals by its depositors can depress the liquidation values of other banks' assets, prompting broader panic-withdrawals at other banks. This implies stronger response of focal banks' deposit flows to *PeerROA* when peer banks have greater liquidity mismatch, even if *PeerROA* contains little information about the values-in-use of the focal banks' assets. Thus,

[14] Chen et al. (2024) find that uninsured depositors at more mismatched banks respond more strongly to their own bank's *ROA*. To ensure that our results are not driven by the correlation between *ROA* and *PeerROA*, we re-estimate equations 5(a) and 5(b) by including the interactive terms between the mismatch measures (*%Uninsured* and *Asset Illiquidity*) and the focal bank's performance indicators (*ROA* and *I(ROA<Med)*) and find that our results (presented in Table A2 in the Appendix 1) are robust to including these controls.

[15] Consistent with this insight, Chen, Vashishtha, and Wang (2025) find evidence that uninsured depositors withdraw in response to declines in the liquidation (fair) values of bank loans, more so when banks have high liquidity mismatch, even when the fair value declines contain no information content about the quality (values-in-use) of bank loans.

both the focal and peer banks' liquidity mismatch can heighten depositor sensitivity to adverse peer performance and amplify contagion.

We measure the peer banks' mismatch by their *%Uninsured* and *Asset Illiquidity*, with the same weighting schemes as those used in constructing *PeerROA*. As a preliminary exploration, Panels E and F of Figure 2 present the semi-parametric plots of flow-to-peer performance relation for the subsample partitioned by the tercile ranks of *Peer %Uninsured* and *Peer Asset Illiquidity*, respectively. In both plots, the relation between focal banks' uninsured deposit flows and *PeerROA* is nearly flat when peer banks are in the bottom tercile of liquidity mismatch. However, it becomes noticeably positive when peer banks are in the top tercile of liquidity mismatch: focal banks experience lower levels of deposit growth as peer bank earnings fall below the median level.

We formally test the above predictions by estimating a modified version of equation (5a/b) where we interact *Peer %Uninsured* and *Peer Asset Illiquidity* with either *PeerROA* or *I(PeerROA < Med)*. Columns (1) and (2) of Table 5 present the estimation results from the sensitivity test. The coefficient estimates for the interactive terms between *PeerROA* and the two mismatch measures (*Peer%Uninsured* and *Peer Asset Illiquidity*) are both positive and significant at less than 1% level, indicating that depositors at the focal bank react more strongly to peer banks' performance when peer banks have more liquidity mismatch In terms of economic magnitude, the estimates indicate that one-standard deviation-increase in peer banks' *%Uninsured* and *Asset Illiquidity* raises the flow-to-peer performance sensitivity by 50% (= 12.31*0.058/1.439) and 51% (=0.09*7.088/1.249), respectively. These effects are comparable to the 60% and 40% increases in sensitivity from a one-standard deviation increase in the focal bank's *%Uninsured* and *Asset Illiquidity* that we document earlier in Table 4.

The results from the levels test, shown in columns (3) and (4) of Table 5, are qualitatively similar. The coefficient estimates on the interactive term between *I(PeerROA<Med)* and *Peer %Uninsured* and *Peer Asset Illiquidity* are both significantly negative at less than 1% level. In terms of economic magnitude, these estimates imply that when *PeerROA* drops from above- to below-median, a one-standard deviation-increase in peer banks' *%Uninsured* and *Asset Illiquidity* is associated with a 30% (= 12.31*0.058/2.4) and 28% (=0.09*7.352/2.4) reduction in uninsured deposit flows, respectively.

5.3 Additional evidence on panic-based contagion

An important insight of theories of panic-based contagion is that different mechanisms of contagion interact with each other to further amplify the spillover of negative shocks in the banking system. In this section, we take advantage of our cross-bank setting to explore two interactive effects: the interaction between the focal and peer banks' liquidity mismatch (in Section 5.3.1) and the interaction between asset return comovement and liquidity mismatch (in Section 5.3.2).

5.3.1 Interaction between focal and peer bank liquidity mismatch

We begin by examining the interaction between liquidity mismatch at focal and peer banks. Theory models (Liu, 2023; Goldstein et al., 2024) show that contagion is amplified when both banks have high liquidity mismatch, beyond the effects of each bank's mismatch alone, as shown in Tables 4 and 5. Table 6 tests this prediction. Specifically, we examine whether the effects of focal banks' mismatch measures (*Focal %Uninsured* and *Focal Asset Illiquidity*) on the flow-to-peer performance relation vary by the tercile ranks of the peer bank's mismatch (*Peer%Uninsured* and *PeerAsset Illiquidity)*.

We start with the sensitivity test, estimating equation 5(a) and allowing all coefficient estimates to vary by the tercile rank of peer mismatch. Table 6 Panel A presents the estimation

results. Results shown in columns (1) and (2), where we form the tercile rank by peer banks' *Asset Illiquidity*, indicate strong interactive effects of focal and peer banks' liquidity mismatch. Specifically, the coefficient estimate for *Focal %Uninsured*PeerROA* is more than doubled from 0.024 to 0.055, when peer banks' *Asset Illiquidity* moves from the bottom to the top tercile, with the difference significant at 10% level. The interactive effects are even stronger in column (2) where focal bank mismatch is measured with *Focal Asset Illiquidity*. The coefficient estimate for *Bottom*Focal Asset Illiquidity*PeerROA* is statistically insignificant, suggesting that panic plays little role in focal depositors' response to peer performance when peer banks have highly liquid assets. This is expected: peer banks with liquid assets are less susceptible to panic-driven withdrawal, require fewer forced asset sales, and thus generate smaller fire-sale discounts that might otherwise trigger panic withdrawals at the focal bank. In contrast, the coefficient estimate for *Focal Asset Illiquidity*PeerROA* becomes significantly positive (coeff = 2.379) when peer banks' *Asset Illiquidity* is in the middle tercile. It is more than doubled to 4.745 when *Peer Asset Illiquidity* is in the top tercile, significantly higher than the coefficient in the bottom tercile at less than 1% level.

Similar patterns are observed in columns (3) and (4) when we form terciles based on the *Peer %Uninsured.* When *Peer %Uninsured* moves from the bottom to the top tercile, the coefficient estimate for *Focal %Uninsured*PeerROA*, shown in column (3), increases from 0.033 to 0.049, although the difference is not significant at conventional levels. The coefficient estimate for *Focal Asset Illiquidity*PeerROA*, shown in column (4), increases from 1.876 to 4.485, with the difference significant at 5% level.

Panel B presents the results from the levels test where we estimate equation 5(b) by allowing the coefficients to vary by the tercile rankings of *Peer Asset Illiquidity* (columns (1) and

(2)) and *Peer %Uninsured* (columns (3) and (4)). The results are consistent with those from the sensitivity tests. When peer banks' mismatch is in the bottom tercile, except for *Bottom*Focal %Uninsured*I(PeerROA<Med)* in column (1), the coefficient estimates for *Bottom*Focal MisMatch*I(PeerROA<Med)* from columns (2) to (4) are all statistically insignificant, indicating no or little panic withdrawal by focal depositors when *PeerROA* falls from above- to below-median level. However, evidence of panic appears when peer banks are in the middle and top tercile of liquidity mismatch: the coefficient estimates for *Middle*Focal MisMatch*I(PeerROA<Med)* and *Top*Focal MisMatch*I(PeerROA<Med)* are significantly negative across all four columns, and the differences between the coefficient estimates for *Top*Focal MisMatch*I(PeerROA<Med)* and *Bottom*Focal MisMatch*I(PeerROA<Med)* are significant at 10% or better.

5.3.3. Interaction between liquidity mismatch and asset commonality

We next explore the interactive effect of liquidity mismatch and asset comovement. Specifically, we test whether the effects of liquidity mismatch on the flow-to-peer performance relations are stronger when there is more asset return comovement among banks in the local markets. Panic-based contagion models of Liu (2023) and Goldstein et al. (2024) predict that aggregate shocks to the banking system amplify panic-based withdrawals. This is because when the system is under distress, fire-sale discounts are higher (Shleifer and Vishny, 1992), as the interbank lending markets have limited ability to meet banks' liquidity needs (Liu, 2016) and the local capital markets have less money to absorb asset sales (Granja et al., 2017).[16] This in turn increases depositors' incentives to withdraw due to concerns of early withdrawals by other depositors. In markets with more comovement in banks' asset returns, a systematic distress is more

[16] Consistent with this prediction, Chen et al. (2024) find stronger evidence of panic-driven withdrawals when banks' performance decline is more systematic than when it's idiosyncratic.

likely to accompany declines in *PeerROA*. Consequently, we expect panic to play a more significant role in depositors' response to *PeerROA*.

To examine this empirically, we form tercile ranks based on the degree of earnings comovement between the focal and peer ROAs. We measure earnings comovement (*EarnComove*) as the (signed) correlation coefficient between the focal bank's *ROA* and *PeerROA* over the preceding 12 quarters. We then estimate equations (5a) and (5b) while allowing the coefficients to vary by the tercile ranking of *EarnComove*.

Table 7 Panel A presents the results from the sensitivity test. It shows that the coefficient estimates on *MisMatch*PeerROA* are monotonically increasing as *EarnComove* moves from the bottom to the top tercile, consistent with the positive interactive effect of liquidity mismatch and asset comovement. The economic magnitudes of the interactive effect, captured by the difference between the estimates for *MisMatch*PeerROA* in the top and bottom tercile, are large. Except for column (4) where the mismatch measure is *Peer Asset Illiquidity*, the coefficient estimates for *Top*MisMatch*PeerROA* are at least twice as large as those for *Bottom*MisMatch*PeerROA*, with the differences statistically significant at 5% level or better. Panel B presents the estimation results for the levels test and yields even stronger inferences. The coefficient estimates on *MisMatch*I(PeerROA<Med)* in the top tercile of *EarnComove* are often much larger (in absolute terms) than the estimates in the bottom tercile, with the difference statistically significant at less than 5% or better across all columns. Together, these results strongly support the theory prediction that liquidity mismatch and asset commonality interact to amplify the spillovers of negative shocks in the banking system.

6. Implications of earnings spillovers for insured deposits and deposit rates

In this section, we examine if banks respond to uninsured deposit outflows triggered by adverse peer performance by adjusting deposit rates to attract insured deposits. Prior studies show that poorly performing banks attempt to achieve such substitution by offering higher deposit rates (Martin et al., 2023; Chen et al., 2022, 2024). Table 8 examines whether focal banks raise rates when *PeerROA* is low, particularly when either focal or peer banks have high levels of *%Uninsured*, and *Asset Illiquidity*. We estimate similar specifications as before but use large time deposit rates and core deposit rates as the dependent variable. Since we focus on banks' choice of deposit rates in response to deposit flows, we exclude deposit rate controls in these regressions.

Panel A of Table 8 examines how focal banks' liquidity mismatch affects their rate responses to peer banks' performance. Columns (1) to (4) present the results from the sensitivity specification. Across all columns, we find that the coefficients on *PeerROA* are significantly negative, indicating that focal banks raise rates in response to poor earnings news from peer banks. The coefficient estimates for the interactive term between focal banks' liquidity mismatch and *PeerROA* are negative and significant at less than 5% level or better, indicating that banks with greater liquidity mismatch, and thus larger uninsured outflows, respond more aggressively to peer shocks. Importantly, these effects are obtained after controlling for the interaction between bank characteristics and their own *ROA*, suggesting that these banks use deposit rates to manage their deposit base even beyond their own performance changes. Columns (5) to (8) report the results from the level specification and yield similar inferences.

Our earlier findings indicate that focal banks experience lower levels of uninsured deposit flows in response to adverse peer banks' earnings news when peer banks have higher liquidity mismatch and are more prone to deposit outflows. If focal banks use deposit rates to attract and retain deposits, we expect that the rate responses will be stronger when peer banks have more

liquidity mismatch. This is exactly what we find in Panel B of Table 8. In both the sensitivity and level specifications, the coefficients on the interactive terms between peer banks' liquidity mismatch measures (either *Peer%Uninsured* or *PeerAstIlliq*) and earnings news measures (either *PeerROA* or *I(PeerROA< Med))* are consistently significant at less than 1% level with the expected signs.

The above results provide unique insights into how banks attempt to manage the spillovers of bad earnings news at peer banks. The results show that banks' attempts to substitute the loss of uninsured deposits with higher deposit rates, which further show the costs of negative externalities of adverse earnings shocks from peer banks.

7. Conclusion

Understanding the nature of interconnections between banks is crucial to the knowledge of financial contagions and the appropriate policy response. We explore the interconnections that stem from spillovers of earnings information. Using a broad sample of nearly 8,800 commercial banks spanning nearly three decades, we find that banks' uninsured deposit flows respond strongly to their peer banks' performance. We further find that these information spillovers manifest primarily when peer banks are performing poorly and not when they are doing well. Exploring the mechanisms, we find that the earnings information spillovers reflect asset commonalities as well as the spread of a form of panic wherein depositors rush to withdraw because of concerns about withdrawals by fellow depositors.

Our evidence informs theories of contagion that highlight the role of asset commonalities and coordination failures in the spread of contagion and thus lend support to policies designed to promote asset differentiation or mitigate coordination failures (e.g., deposit insurance). Our work also has implications for the design of accounting rules and disclosure regulations. Presence of

positive information externalities – through, for example, reduction in demand and cost uncertainty for the entire industry – is typically offered as a rationale for mandating accounting information disclosures. Our work suggests that the banking industry may be unique because of the potential for negative information externalities and may provide a rationale for why banks are more opaque compared to firms in other industries. Furthermore, given the importance of earnings information in shaping depositors' beliefs, our findings suggest that the design of earnings measurement rules may be a fruitful policy tool for influencing depositor contagion that is worth exploring in future research.

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Figure 1: Distribution of *PeerROA* for our sample of banks

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

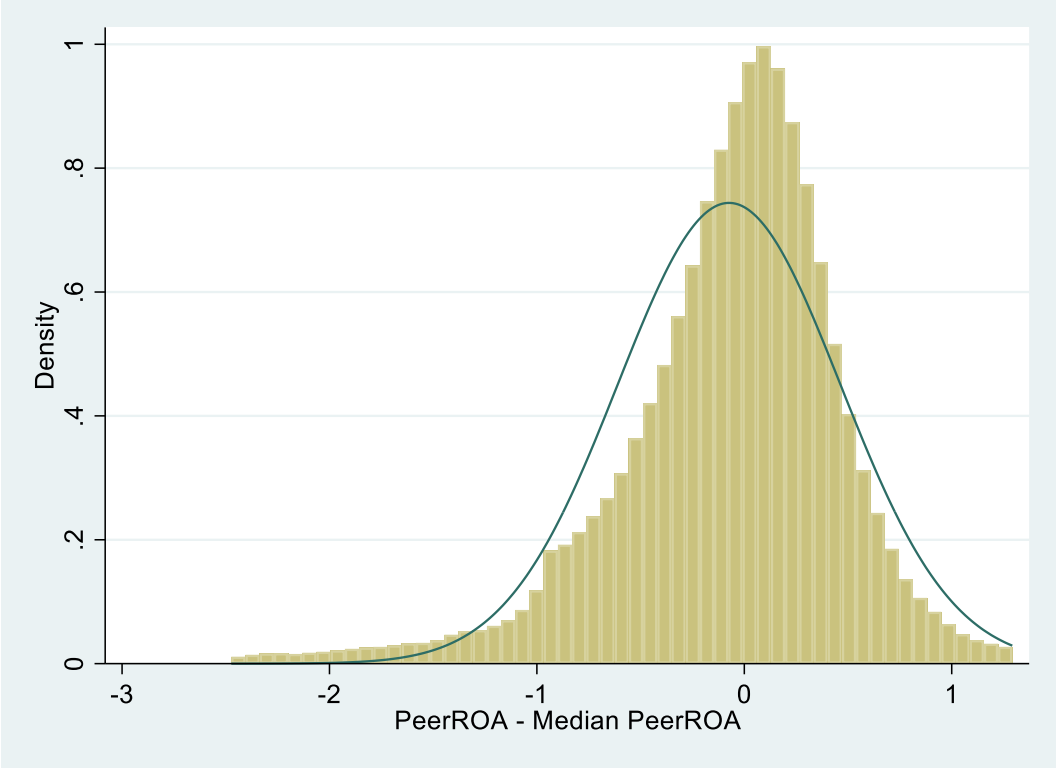
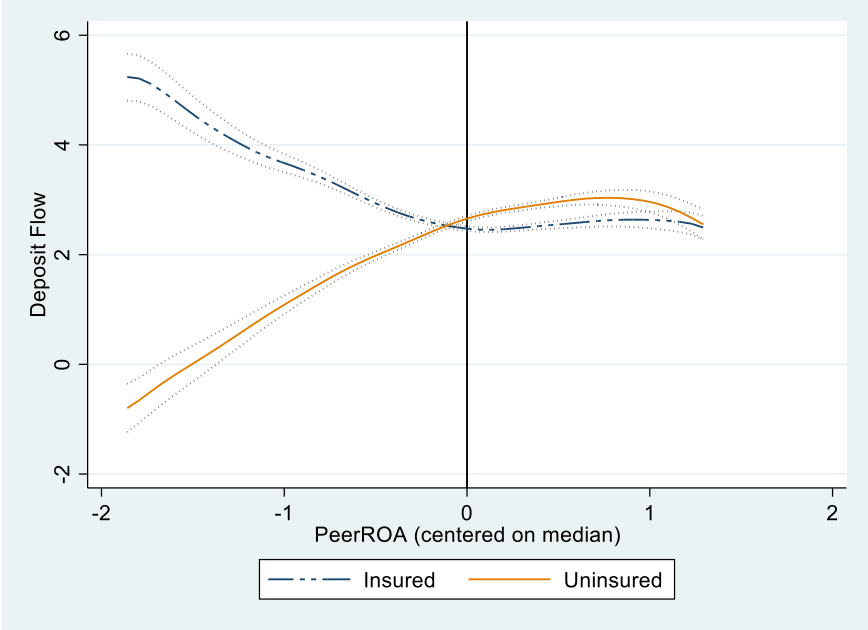


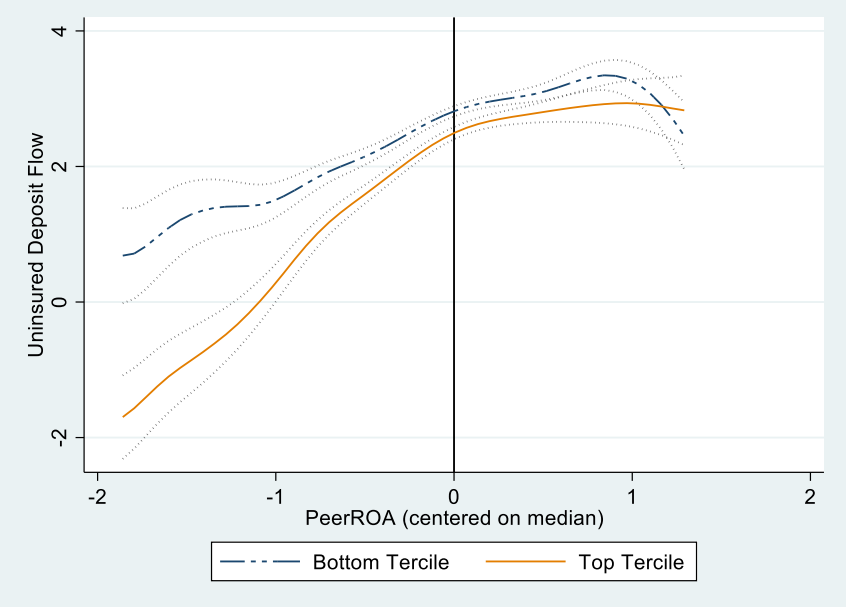
Figure 2: Semiparametric plots of the flow-to-peer performance relation

These figures plot semi-parametric estimates of the flow-to-peer performance relation using the Robinson's (1988) estimator implemented using Gaussian local kernel regressions. The 95% confidence intervals are shown in dotted lines. The Y-axis plots deposit flows and the X-axis plots *PeerROA* centered on median (i.e., *PeerROA* minus sample median *PeerROA*). The plots are for observations within three standard deviations of the mean *PeerROA*. Panel A plots the estimates for insured vs. uninsured deposit flows. Panels B, C, D, E, and F plot the estimates for uninsured deposit flows for banks in the top and bottom terciles of *PeerROA_Inform*, *%Uninsured*, *Asset Illiquidity*, *Peer%Uninsured*, and *Peer Asset Illiquidity* respectively.

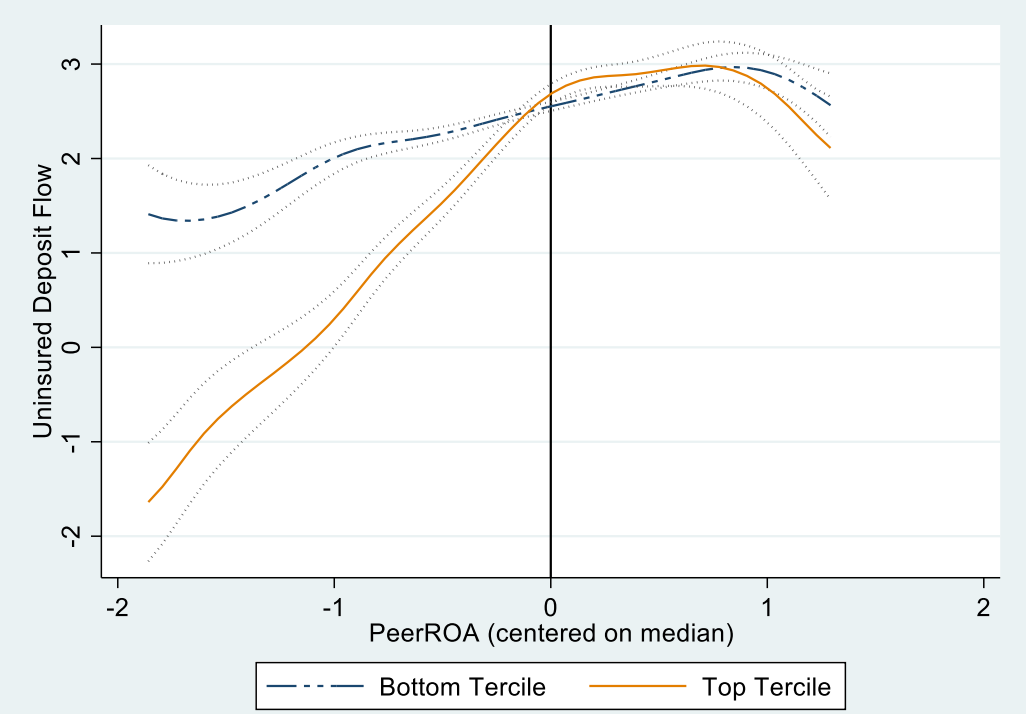
Panel A: Insured vs. uninsured deposit flows



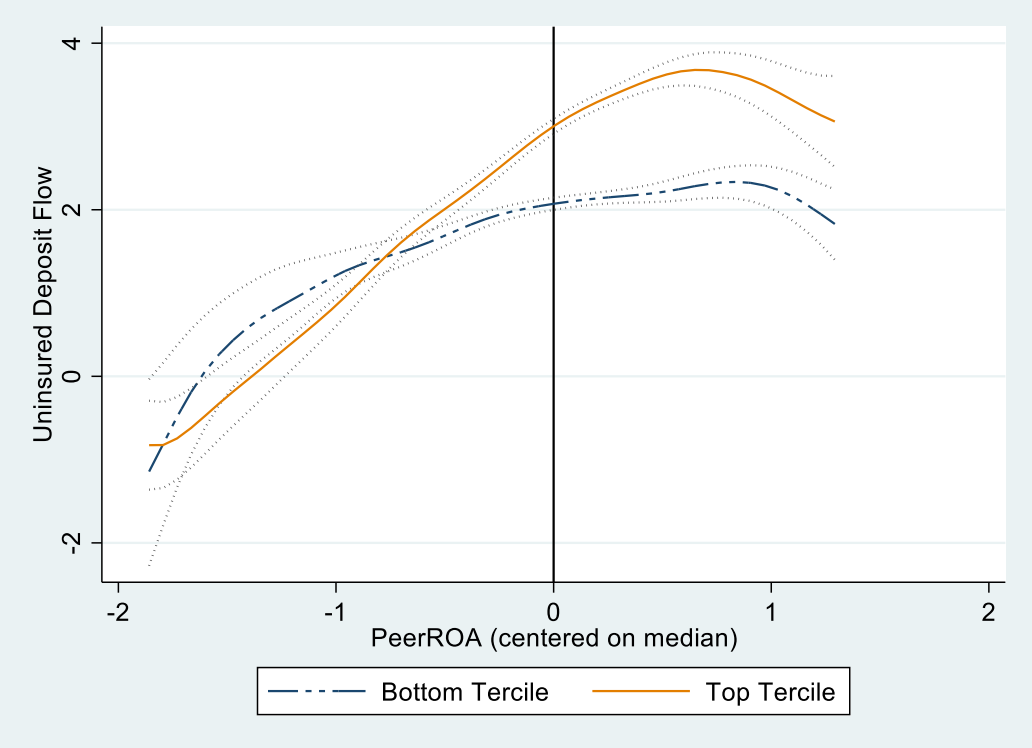
Panel B: Top and bottom terciles of PeerROA_Inform



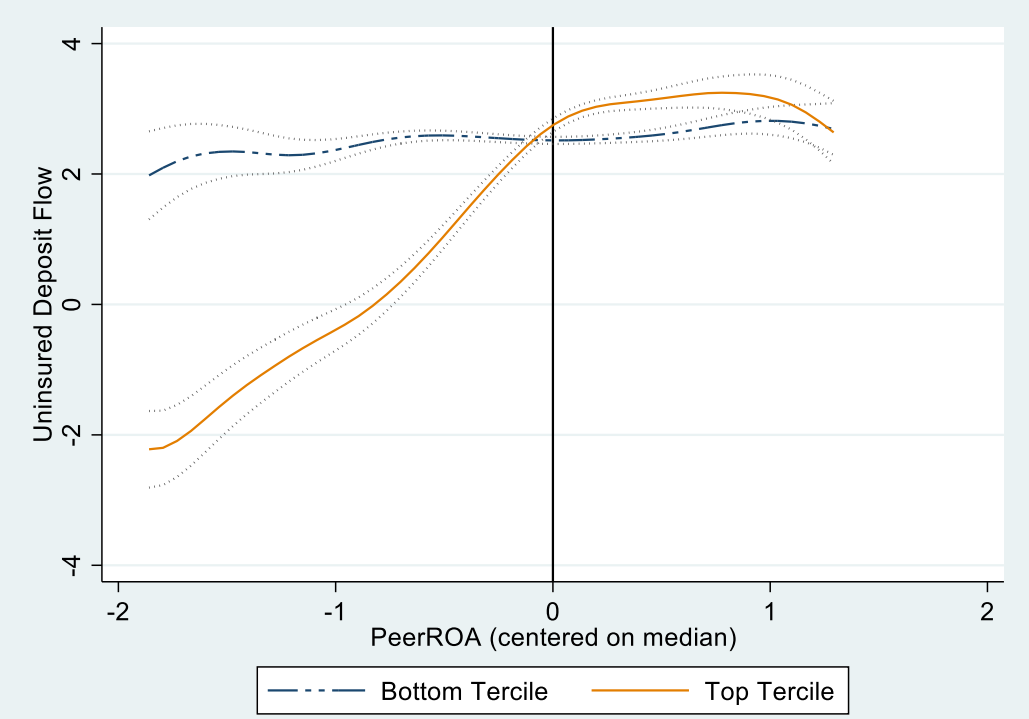
Panel C: Top and bottom terciles of focal bank %Uninsured



Panel D: Top and bottom terciles of focal bank asset illiquidity



Panel E: Top and bottom terciles of peer bank %Uninsured



Panel F: Top and bottom terciles of peer bank Asset Illiquidity

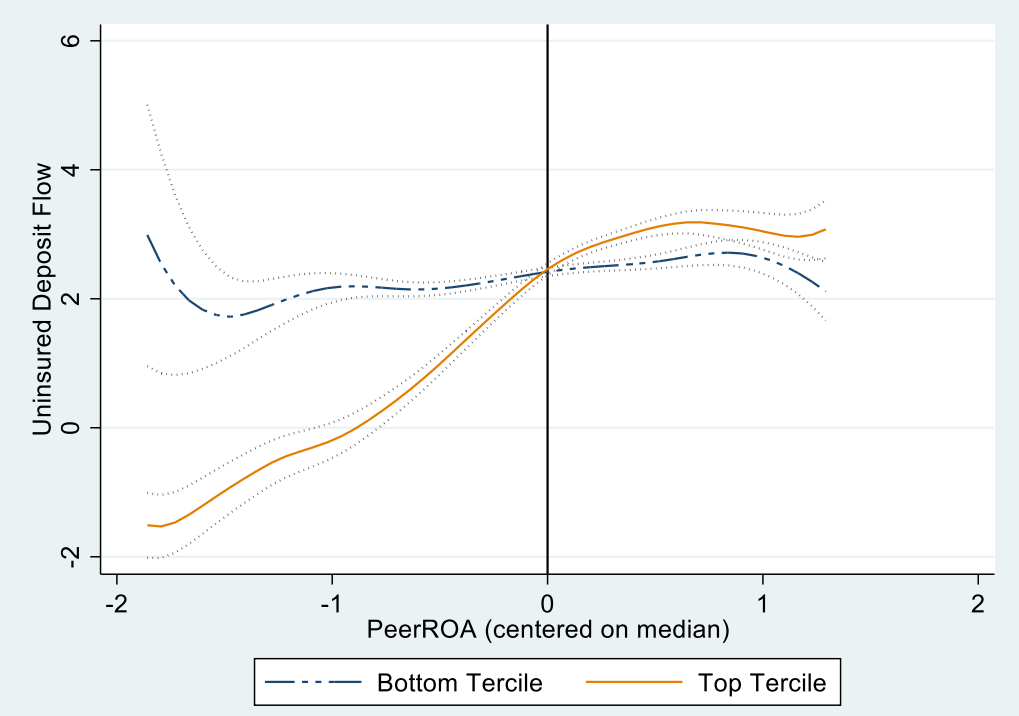


Table 1 Summary statistics

Panel A presents the descriptive statistics, and Panel B presents the correlation table for the main variables used in our bank-quarter level tests. These statistics are calculated over the whole sample. To avoid the impact of mergers and acquisitions, we exclude bank quarter observations with quarterly asset growth greater than 10%. We also exclude observations with total assets less than 100 million. There are 8,792 unique commercial banks in the period from 1994Q1 to 2022Q4. Appendix 2 provides detailed variable definitions.

Panel A: Descriptive statistics of main variables

	N	Mean	Std.Dev	p25	p50	p75
ΔDep_{it}^{U}	363,595	2.40	9.63	-1.87	2.32	7.07
ΔDep_{it}^{I}	363,595	2.75	8.70	-1.52	1.38	5.03
ΔDep_{it}^{T}	363,595	5.15	11.08	-1.23	4.17	10.27
$\Delta Dep_{it}^{U}_alt$	363,595	10.28	34.79	-7.41	9.34	27.27
ROA_{it-1}	363,595	1.02	0.84	0.70	1.07	1.44
$PeerROA_{it-1}$	363,595	0.91	0.60	0.65	0.99	1.26
$Ln(Assets)_{it-1}$	363,595	12.70	1.05	11.93	12.42	13.13
$Capital_Ratio_{it-1}$	363,595	0.10	0.03	0.08	0.10	0.11
$Wholesale_Funding_{it-1}$	363,595	0.20	0.10	0.12	0.18	0.25
$RealEstate_Loans_{it-1}$	363,595	0.71	0.17	0.61	0.73	0.83
$C\&I_Loans_{it-1}$	363,595	0.15	0.10	0.08	0.13	0.20
$\%\ Deposits_{it-1}$	363,595	0.83	0.07	0.80	0.85	0.88
Std_ROA_{it-1}	363,595	0.53	0.69	0.18	0.29	0.54
$Large\ Time\ Deposit\ Rate_{it}$	363,595	2.78	1.77	1.20	2.38	4.33
$Core\ Deposit\ Rate_{it}$	363,595	1.91	1.41	0.67	1.54	3.02
$ExpDepHHI_{it-1}$	363,595	0.21	0.11	0.13	0.18	0.26
$Focal\ \%\ Uninsured_{it-1}$	363,595	33.83	13.99	23.79	31.52	41.35
$Focal\ Asset\ Illiquidity_{it-1}$	363,595	0.08	0.14	-0.01	0.09	0.18
$Peer\%Uninsured_{it-1}$	363,595	31.57	12.31	23.15	30.33	39.04
$Peer\ Asset\ Illiquidity_{it-1}$	363,595	0.07	0.09	0.01	0.07	0.14
$PeerROA_Inform_{it-1}$	327,713	0.20	0.51	-0.14	0.29	0.62
$EarnComove_{it-1}$	357,959	0.15	0.37	-0.12	0.15	0.42

Panel B: Pairwise correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) ΔDep_{it}^{U}	1.00																				
(2) ΔDep_{it}^{I}	-0.27	1.00																			
(3) ΔDep_{it}^{T}	0.65	0.55	1.00																		
(4) $\Delta Dep_{it}^{U}_alt$	0.92	-0.23	0.61	1.00																	
(5) ROA_{it-1}	0.13	0.02	0.13	0.12	1.00																
(6) $PeerROA_{it-1}$	0.11	-0.05	0.05	0.10	0.36	1.00															
(7) $Ln(Assets)_{it-1}$	0.03	-0.01	0.02	-0.01	0.01	0.00	1.00														
(8) $Capital_Ratio_{it-1}$	0.02	-0.02	0.00	0.03	0.15	0.02	-0.02	1.00													
(9) $Wholesale_Funding_{it-1}$	-0.02	0.06	0.03	-0.02	-0.14	-0.13	0.13	-0.09	1.00												
(10) $RealEstate_Loans_{it-1}$	-0.03	0.01	-0.02	-0.03	-0.16	-0.20	-0.02	0.01	0.02	1.00											
(11) $C\&I_Loans_{it-1}$	0.07	0.01	0.07	0.03	0.03	0.09	0.11	-0.08	0.04	-0.60	1.00										
(12) $\%\ Deposits_{it-1}$	-0.02	-0.03	-0.04	-0.04	-0.02	0.02	-0.32	-0.26	-0.54	0.03	0.01	1.00									
(13) Std_ROA_{it-1}	-0.08	-0.05	-0.10	-0.07	-0.33	-0.20	0.03	0.02	0.12	0.03	0.03	-0.03	1.00								
(14) *Large Time Deposit* $Rate_{it}$	0.00	0.08	0.06	0.01	0.10	0.13	-0.11	-0.20	0.06	-0.20	0.10	-0.08	-0.09	1.00							
(15) *Core Deposit* $Rate_{it}$	0.00	0.08	0.07	0.02	0.09	0.14	-0.14	-0.19	0.08	-0.21	0.10	-0.06	-0.07	0.90	1.00						
(16) $ExpDepHHI_{it-1}$	-0.02	-0.02	-0.03	0.00	0.10	0.04	-0.10	0.09	-0.02	-0.16	-0.08	0.04	-0.06	-0.08	-0.06	1.00					
(17) *Focal %* $Uninsured_{it-1}$	0.01	0.09	0.08	-0.09	-0.04	-0.08	0.33	-0.03	0.29	-0.05	0.29	-0.13	0.05	-0.04	-0.07	-0.12	1.00				
(18) *Focal Asset* $Illiquidity_{it-1}$	0.03	0.07	0.08	0.00	-0.08	-0.11	0.14	-0.07	0.20	0.10	0.16	0.01	0.16	-0.19	-0.15	-0.09	0.20	1.00			
(19) $Peer\%Uninsured_{it-1}$	-0.01	0.06	0.04	-0.06	-0.09	0.02	0.33	0.00	0.25	0.05	0.15	-0.15	0.11	-0.03	-0.05	-0.25	0.57	0.20	1.00		
(20) $PeerAssetIlliq_{it-1}$	-0.02	0.04	0.02	-0.03	-0.11	-0.10	0.09	0.04	0.12	0.13	0.02	-0.03	0.13	-0.26	-0.25	-0.09	0.21	0.48	0.32	1.00	
(21) $Peer_Inform_{it-1}$	-0.04	0.03	-0.01	-0.04	-0.08	-0.08	0.09	-0.01	0.03	0.03	-0.01	-0.03	0.06	-0.02	-0.02	-0.03	0.05	0.04	0.06	0.04	1.00
(22) $EarnComove_{it-1}$	-0.04	0.03	-0.01	-0.04	-0.08	-0.08	0.04	0.00	0.02	0.04	-0.01	0.02	0.07	-0.05	-0.04	-0.03	0.05	0.09	0.08	0.09	0.05

Table 2 Relations between uninsured deposit flows and peer performance

This table examines the relation between uninsured deposit flows and peer performance. *PeerROA1(<Med)* and *PeerROA2(>Med)* equal to *PeerROA* when *PeerROA* is respectively below and above the sample median and zero otherwise. *I(ROA<Med)* is an indicator variable that equals 1 when ROA is below the sample median. See Appendix 2 for all variable definitions and constructions. Macro controls include current and two lagged federal fund rates and stock market returns. T-statistics, reported in parentheses, are based on two-way clustered standard errors at the bank and year-quarter level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable			ΔDep_{it}^{U}		
PeerROA	1.090***			1.554***	0.329***
	(2.94)			(3.63)	(4.26)
PeerROA1(<Med)		1.459**	1.353**		
		(2.28)	(2.19)		
PeerROA2(>Med)		0.214	0.346**		
		(1.37)	(2.34)		
I(ROA<Med)			-1.703***		
			(-6.86)		
*ROA*I(ROA<Med)*			1.346***		
			(5.55)		
ROA	1.104***	1.096***	0.167*	1.089***	0.778***
	(9.93)	(10.18)	(1.96)	(7.50)	(14.34)
ExpDepHHI	-1.349***	-1.214**	-1.305***	5.474***	1.547*
	(-2.81)	(-2.45)	(-2.64)	(4.27)	(1.86)
Ln(Assets)	0.033	0.029	0.019	-1.884***	-3.331***
	(0.45)	(0.40)	(0.25)	(-4.02)	(-16.21)
Capital_Ratio	-4.169*	-4.139	-3.338	9.091	7.939***
	(-1.66)	(-1.65)	(-1.34)	(1.53)	(2.73)
Wholesale_Funding	-0.173	-0.080	0.132	-7.203**	-0.906
	(-0.17)	(-0.08)	(0.13)	(-2.55)	(-0.65)
% Deposits	-4.033***	-3.988***	-3.899***	-22.188***	-23.115***
	(-3.80)	(-3.75)	(-3.64)	(-9.83)	(-14.15)
RealEstate_Loans	2.791***	2.791***	2.790***	-0.520	-0.493
	(5.06)	(5.07)	(5.09)	(-0.36)	(-0.75)
C&I_Loans	8.182***	8.186***	8.137***	6.709***	3.475***
	(10.73)	(10.75)	(10.75)	(3.59)	(4.33)
Std_ROA	-0.394***	-0.362***	-0.166	-0.386***	-0.329***
	(-3.93)	(-3.41)	(-1.33)	(-3.33)	(-5.71)
Large Time Deposit Rate	-0.635	-0.623	-0.619	-0.784*	0.334***
	(-1.51)	(-1.50)	(-1.49)	(-1.76)	(4.92)
Core Deposit Rate	-0.277	-0.272	-0.268	-0.722	0.917***
	(-0.79)	(-0.78)	(-0.78)	(-1.09)	(7.80)
Observations	363,595	363,595	363,595	363,595	363,595
Adjusted R-squared	0.082	0.082	0.084	0.122	0.278
Bank FE	No	No	No	Yes	Yes
MacroControl	Yes	Yes	Yes	Yes	No
Year-Quarter FE	No	No	No	No	Yes

Table 3 Exploring the role of asset commonality

This table presents the OLS estimation of equation (4) focusing on how uninsured deposit flow-to-peer performance sensitivity varies with *PeerROA_Inform*. Interactive controls include the interaction terms between *PeerROA* and demeaned values of time-varying bank characteristics (*ExpDepHHI*, *Ln(Assets)*, *%Deposits*, *RealEstate_Loans*, *C&I_Loans*, *Capital_Ratio*, *Wholesale_Funding*, and *Std(ROA)*). Macro controls include current and two lagged federal fund rates and stock market returns. T-statistics, reported in parentheses, are based on two-way clustered standard errors at the bank and year-quarter level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1)
Dependent variable	ΔDep_{it}^{U}
PeerROA	1.440***
	(3.80)
*PeerROA*PeerROA_Inform*	0.651**
	(2.40)
PeerROA_Inform	-1.019***
	(-2.97)
ROA	1.021***
	(7.95)
ExpDepHHI	8.984***
	(4.18)
Ln(Assets)	-2.376***
	(-4.45)
Capital_Ratio	11.829
	(1.65)
Wholesale_Funding	-12.632***
	(-3.62)
% Deposits	-25.264***
	(-6.55)
RealEstate_Loans	-2.679
	(-1.28)
C&I_Loans	3.576
	(1.43)
Std_ROA	-0.161
	(-0.92)
Large Time Deposit Rate	-0.947*
	(-1.96)
Core Deposit Rate	-0.661
	(-0.98)
Observations	327,316
Adjusted R-squared	0.133
Interactive controls	Yes
Bank FE	Yes
MacroControl	Yes

Table 4 Exploring the effect of focal bank's liquidity mismatch on the deposit flow-to-peer performance relations

This table presents the results from estimating equations (5a) and (5b), focusing on how uninsured deposit flow-to-peer performance sensitivity (columns (1) and (2)) and flow levels (columns (3) and (4)) vary with focal banks' measures of *MisMatch*. The *MisMatch* measure is the focal bank's *%Uninsured* in columns (1) and (3) and is the focal bank's *Asset Illiquidity* in columns (2) and (4). *I(PeerROA<Med)* is an indicator variable that equals 1 if *PeerROA* is below the sample median and equals 0 otherwise. Controls include the demeaned values of time-varying bank characteristics (*ExpDepHHI*, *Ln(Assets)*, *RealEstate_Loans*, *%Deposits*, *C&I_Loans*, *Capital_Ratio*, *Wholesale_Funding*, and *Std(ROA)*) and their interactive terms with *PeerROA* for columns (1) and (2) (or *I(PeerROA<Med)* for columns (3) and (4)). Macro controls include current and two lagged federal fund rates and stock market returns. T-statistics, reported in parentheses, are based on two-way clustered standard errors at the bank and year-quarter level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	ΔDep_{it}^{U}			
	Sensitivity test		**Levels test**	
Measure of MisMatch	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Focal %Uninsured*	*Focal Asset Illiquidity*
	(1)	(2)	(3)	(4)
PeerROA	1.198***	1.441***	1.200***	1.470***
	(3.77)	(3.90)	(2.82)	(3.11)
*PeerROA*MisMatch*	0.051***	4.161***		
	(2.98)	(4.57)		
*I(PeerROA<Med)*MisMatch*			-0.048***	-3.843***
			(-3.38)	(-4.26)
I(PeerROA<Med)			-0.339*	-0.200
			(-1.80)	(-1.04)
MisMatch	-0.200***	2.744	-0.133***	8.426***
	(-3.68)	(1.26)	(-3.50)	(5.53)
ROA	1.032***	1.013***	1.049***	1.044***
	(8.12)	(8.10)	(7.49)	(7.50)
Observations	363,595	363,595	363,595	363,595
Adjusted R-squared	0.135	0.134	0.126	0.125
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
MacroControl	Yes	Yes	Yes	Yes

Table 5 Exploring the effect of peer bank's liquidity mismatch on the deposit flow-to-peer performance relations

This table presents the results from estimating a modified version of equations (5a) and (5b), focusing on how uninsured deposit flow-to-peer performance sensitivity (columns (1) and (2)) and flow levels (columns (3) and (4)) vary with measures of peer banks' *MisMatch*. The *MisMatch* measure is the peer bank's %Uninsured (*Peer %Uninsured)* in columns (1) and (3) and is the peer bank's asset illiquidity (*Peer Asset Illiquidity)* in columns (2) and (4). *I(PeerROA<Med)* is an indicator variable that equals 1 if *PeerROA* is below the sample median and equals 0 otherwise. Controls include the demeaned values of time-varying bank characteristics (*ExpDepHHI*, *Ln(Assets)*, *RealEstate_Loans*, *%Deposits*, *C&I_Loans*, *Capital_Ratio*, *Wholesale_Funding*, and *Std(ROA)*) and their interactive terms with *PeerROA* for columns (1) and (2) (or *I(PeerROA<Med)* for columns (3) and (4)). Macro controls include current and two lagged federal fund rates and stock market returns. T-statistics, reported in parentheses, are based on two-way clustered standard errors at the bank and year-quarter level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	ΔDep_{it}^{U}			
	Sensitivity Test		**Levels test**	
Measure of MisMatch	*Peer %Uninsured*	*Peer Asset Illiquidity*	*Peer %Uninsured*	*Peer Asset Illiquidity*
	(1)	(2)	(3)	(4)
PeerROA	1.439***	1.249***	1.441***	1.349***
	(3.78)	(3.64)	(2.99)	(2.95)
*MisMatch*PeerROA*	0.058***	7.088***		
	(2.70)	(4.38)		
*MisMatch*I(PeerROA<Med)*			-0.058***	-7.352***
			(-3.85)	(-4.06)
I(PeerROA<Med)			-0.312	-0.234
			(-1.66)	(-1.23)
MisMatch	-0.120**	-7.500**	-0.044	2.347
	(-2.46)	(-2.09)	(-1.37)	(1.07)
ROA	0.990***	1.026***	1.011***	1.046***
	(8.71)	(8.31)	(7.88)	(7.71)
Observations	363,595	363,595	363,595	363,595
Adjusted R-squared	0.128	0.125	0.127	0.124
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
MacroControl	Yes	Yes	Yes	Yes

Table 6 Interaction between Peer and Focal Bank Liquidity MisMatch

This table explores deposit contagion from peer banks' earnings information via the interactive effects of liquidity mismatch between the focal and peer banks. Panel A (B) presents the results from estimating equation 5(a) (5(b)) by allowing the coefficient estimates to vary by the tercile ranking of peer banks' liquidity mismatch measures. In both panels, *Bottom, Middle*, and *Top* are indicator variables that equal to 1 when the peer banks' liquidity mismatch measure (*Peer Asset Illiquidity* in columns (1) and (2) and *Peer %Uninsured* in columns (3) and (4)) falls in the bottom, middle, and top tercile of the sample. Controls include time-varying bank characteristics and the interaction terms between their demeaned values and *PeerROA* (or *I(PeerROA<Med)*), current deposit rates, and macro controls. T-statistics, reported in parentheses, are based on two-way clustered standard errors 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: The sensitivity test

Dependent variable	ΔDep_{it}^{U}			
Tercile indicator based on	*Peer Asset Illiquidity*		*Peer %Uninsured*	
Measure of MisMatch	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Focal %Uninsured*	*Focal Asset Illiquidity*
	(1)	(2)	(3)	(4)
*Bottom*PeerROA*	0.603**	0.632**	0.620***	0.609***
	(2.45)	(2.46)	(3.15)	(4.33)
*Middle*PeerROA*	0.983***	1.161***	1.128***	1.202***
	(3.24)	(3.45)	(4.03)	(4.34)
*Top*PeerROA*	1.563***	1.746***	1.397***	2.013***
	(4.04)	(4.12)	(3.27)	(4.17)
*(a) Bottom*Focal MisMatch*PeerROA*	**0.024****	**-0.473**	**0.033***	**1.876****
	(2.01)	**(-0.62)**	**(1.77)**	**(2.52)**
*(b) Middle*Focal MisMatch*PeerROA*	**0.046*****	**2.379*****	**0.020**	**4.538*****
	(2.68)	**(2.86)**	**(1.35)**	**(4.82)**
*(c) Top*Focal MisMatch*PeerROA*	**0.055*****	**4.745*****	**0.049*****	**4.485*****
	(2.74)	**(3.96)**	**(3.89)**	**(4.05)**
(c) – (a)	**0.032***	**5.217*****	**0.016**	**2.609****
	(1.69)	**(3.91)**	**(0.88)**	**(2.09)**
Observations	362,962	362,962	362,861	362,861
Adjusted R-squared	0.157	0.146	0.163	0.155
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Panel B: The levels test

Dependent variable	ΔDep_{it}^{U}			
Tercile indicator based on	*Peer Asset Illiquidity*		*Peer %Uninsured*	
Measure of MisMatch	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Focal %Uninsured*	*Focal Asset Illiquidity*
	(1)	(2)	(3)	(4)
*Bottom*I(PeerROA<Med)*	-0.286**	-0.228*	-0.311*	-0.166
	(-2.44)	(-1.85)	(-1.76)	(-1.49)
*Middle*I(PeerROA<Med)*	-0.132	-0.033	-0.577***	-0.460***
	(-0.76)	(-0.18)	(-3.36)	(-3.07)
*Top*I(PeerROA<Med)*	-0.903***	-0.463	-0.163	-0.348
	(-2.91)	(-1.58)	(-0.50)	(-1.09)
*(a) Bottom*Focal MisMatch*I(PeerROA<Med)*	**-0.020***	**-0.239**	**-0.019**	**-0.606**
	(-1.84)	**(-0.32)**	**(-1.19)**	**(-0.90)**
*(b) Middle*Focal Mismatch*I(PeerROA<Med)*	**-0.037*****	**-1.675****	**-0.028****	**-3.815*****
	(-2.73)	**(-2.05)**	**(-2.32)**	**(-3.83)**
*(c) Top*Focal MisMatch*I(PeerROA<Med)*	**-0.061*****	**-5.670*****	**-0.047*****	**-5.747*****
	(-3.17)	**(-4.68)**	**(-3.67)**	**(-5.34)**
(c) – (a)	**-0.041***	**-5.431*****	**-0.028***	**-5.142*****
	(-1.91)	**(-4.05)**	**(-1.64)**	**(-4.65)**
Observations	362,962	362,962	362,861	362,861
Adjusted R-squared	0.156	0.146	0.162	0.155
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Table 7 Interaction between liquidity mismatch and asset commonality

This table explores the interactive effects of liquidity mismatch and asset commonality in the banking system as the mechanism of deposit contagion from peer earnings information spillovers. Panel A (B) presents the results from estimating equation 5(a) (5(b)) by allowing the coefficient estimates to vary by the tercile rank of asset commonality (measured with *EarnComove*) between banks. In both panels, *Bottom*, *Middle*, and *Top* are indicator variables that equal 1 when *EarnComove* is in the bottom, middle, and top tercile, respectively, and equal 0 otherwise. Controls include time-varying bank characteristics and the interaction terms between their demeaned values and *PeerROA* in panel A (or *I(PeerROA<Med)* in panel B), current deposit rates, and macro controls. T-statistics, reported in parentheses, are based on two-way clustered standard errors 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 The sensitivity test

Dependent variable	ΔDep_{it}^{U}			
Tercile indicator based on	***EarnComove***			
Measure of MisMatch	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer %Uninsured*	*Peer Asset Illiquidity*
	(1)	(2)	(3)	(4)
*Bottom*PeerROA*	0.843***	0.918***	1.013***	0.820***
	(3.56)	(3.61)	(3.32)	(3.24)
*Middle*PeerROA*	1.144***	1.268***	1.349***	1.116***
	(4.64)	(4.74)	(4.38)	(4.40)
*Top*PeerROA*	1.237***	1.658***	1.521***	1.426***
	(3.47)	(4.01)	(4.07)	(3.72)
*(a) Bottom*Mismatch*PeerROA*	**0.015**	**1.375***	**0.035*****	**4.689*****
	(1.12)	**(1.86)**	**(2.70)**	**(4.39)**
*(b) Middle*Mismatch*PeerROA*	**0.043*****	**3.179*****	**0.037*****	**5.632*****
	(3.03)	**(4.09)**	**(2.75)**	**(4.01)**
*(c) Top*Mismatch*PeerROA*	**0.071*****	**4.959*****	**0.073*****	**7.159*****
	(3.67)	**(3.75)**	**(2.67)**	**(3.94)**
(c) – (a)	**0.056*****	**3.584****	**0.038****	**2.469**
	(4.98)	**(2.30)**	**(2.14)**	**(1.48)**
Observations	356,542	356,542	356,542	356,542
Adjusted R-squared	0.158	0.149	0.150	0.147
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Panel B The levels test

Dependent variable	ΔDep_{it}^{U}			
Tercile indicator based on	***EarnComove***			
Measure of MisMatch	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer %Uninsured*	*Peer Asset Illiquidity*
	(1)	(2)	(3)	(4)
*Bottom*I(PeerROA<Med)*	-0.378***	-0.332**	-0.388***	-0.350***
	(-2.87)	(-2.59)	(-2.81)	(-2.70)
*Middle*I(PeerROA<Med)*	-0.443***	-0.345**	-0.428***	-0.352**
	(-3.11)	(-2.47)	(-2.89)	(-2.53)
*Top*I(PeerROA<Med)*	-0.555*	-0.299	-0.488	-0.345
	(-1.79)	(-0.94)	(-1.58)	(-1.09)
*(a) Bottom*MisMatch*I(PeerROA<Med)*	**-0.011**	**-1.251***	**-0.028*****	**-4.875*****
	(-1.02)	**(-1.87)**	**(-2.70)**	**(-3.34)**
*(b) Middle*MisMatch*I(PeerROA<Med)*	**-0.040*****	**-2.754*****	**-0.037*****	**-6.297*****
	(-3.64)	**(-3.37)**	**(-3.51)**	**(-3.95)**
*(c) Top*MisMatch*I(PeerROA<Med)*	**-0.083*****	**-5.979*****	**-0.096*****	**-8.623*****
	(-4.41)	**(-4.88)**	**(-4.55)**	**(-4.35)**
(c) – (a)	**-0.071*****	**-4.728*****	**-0.068*****	**-3.748****
	(-5.48)	**(-3.93)**	**(-3.95)**	**(-2.58)**
Observations	356,542	356,542	356,542	356,542
Adjusted R-squared	0.157	0.148	0.150	0.147
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Table 8 Deposit rate responses to peer performance

This table explores how deposit rates relate to peer performance, focusing on how such relations vary with both focal (Panel A) and peer bank (Panel B) liquidity mismatch as measured by *%Uninsured* and *Asset Illiquidity*. In both panels, columns (1)-(4) present the sensitivity specification, and columns (5)-(8) present the level specification. Controls include time-varying bank characteristics and the interaction terms between their demeaned values and *PeerROA* and *ROA* (*I(PeerROA<Med)* and *I(ROA<Med)*), and macro controls. T-statistics, reported in parentheses, are based on two-way clustered standard errors 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 Effect of focal bank liquidity mismatch on focal bank's deposit rates response to peer performance

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Dependent Variable	Large Time Rate	Core Rate	Large Time Rate	Core Rate		Large Time Rate	Core Rate	Large Time Rate	Core Rate
MisMatch measure	Focal % Uninsured	Focal % Uninsured	Focal Asset Illiquidity	Focal Asset Illiquidity		Focal % Uninsured	Focal % Uninsured	Focal Asset Illiquidity	Focal Asset Illiquidity
PeerROA	-0.079***	-0.054***	-0.085***	-0.058***	*I(PeerROA<Med)*	0.026	0.003	0.023	0.001
	(-3.48)	(-2.74)	(-3.37)	(-2.81)		(1.30)	(0.18)	(1.09)	(0.04)
ROA	-0.026*	-0.036***	-0.019	-0.033***	*I(ROA<Med)*	0.007	0.022*	0.007	0.022*
	(-1.89)	(-3.19)	(-1.34)	(-2.88)		(0.52)	(1.77)	(0.48)	(1.84)
*MisMatch*PeerROA*	-0.002**	-0.003***	-0.361***	-0.285***	*MisMatch*I(PeerROA<Med)*	0.003***	0.004***	0.331***	0.245***
	(-2.42)	(-3.80)	(-6.19)	(-4.99)		(3.68)	(5.39)	(4.25)	(3.57)
*MisMatch*ROA*	-0.002***	-0.003***	-0.310***	-0.236***	*MisMatch*I(ROA<Med)*	0.003***	0.006***	0.459***	0.380***
	(-5.75)	(-8.18)	(-7.79)	(-6.74)		(4.73)	(8.40)	(5.47)	(5.26)
MisMatch	0.018***	0.011***	1.413***	1.095***	*MisMatch*	0.012***	0.001	0.435***	0.340**
	(6.24)	(4.41)	(7.02)	(6.49)		(4.69)	(0.57)	(3.02)	(2.59)
Observations	363,595	363,595	363,595	363,595		363,595	363,595	363,595	363,595
Adj R-squared	0.881	0.891	0.879	0.891		0.880	0.890	0.877	0.889
Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes

Panel B: Effect of peer bank liquidity mismatch on focal bank's deposit rates response to peer performance

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Dependent Variable	Large Time Rate	Core Rate	Large Time Rate	Core Rate		Large Time Rate	Core Rate	Large Time Rate	Core Rate
MisMatch measure	Peer % Uninsured	Peer % Uninsured	Peer Asset Illiquidity	Peer Asset Illiquidity		Peer % Uninsured	Peer % Uninsured	Peer Asset Illiquidity	Peer Asset Illiquidity
PeerROA	-0.109***	-0.062***	-0.069***	-0.044**	*I(PeerROA<Med)*	0.050**	0.010	0.026	0.002
	(-4.42)	(-2.90)	(-2.94)	(-2.17)		(2.18)	(0.47)	(1.20)	(0.09)
ROA	-0.018	-0.031***	-0.020	-0.035***	*I(ROA<Med)*	0.002	0.019	0.002	0.019
	(-1.35)	(-2.80)	(-1.39)	(-2.96)		(0.18)	(1.63)	(0.11)	(1.61)
*MisMatch*PeerROA*	-0.003***	-0.005***	-0.927***	-0.836***	*MisMatch*I(PeerROA<Med)*	0.004***	0.007***	0.983***	0.924***
	(-3.75)	(-7.22)	(-10.03)	(-10.25)		(4.08)	(7.99)	(5.86)	(6.75)
*MisMatch*ROA*	-0.002***	-0.002***	-0.233***	-0.166***	*MisMatch*I(ROA<Med)*	0.003***	0.006***	0.449***	0.376***
	(-3.98)	(-5.89)	(-4.79)	(-4.02)		(3.62)	(7.24)	(4.34)	(4.38)
MisMatch	0.018***	0.012***	1.519***	0.907***	*MisMatch*	0.010***	-0.002	-0.213	-0.607***
	(6.64)	(5.24)	(5.81)	(4.05)		(4.64)	(-0.73)	(-1.37)	(-3.64)
Observations	363,595	363,595	363,595	363,595		363,595	363,595	363,595	363,595
Adjusted R-squared	0.881	0.892	0.878	0.891		0.879	0.890	0.877	0.889
Control	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes

Appendix 1: Robustness results

Table A1 Robustness to using year-quarter fixed effects instead of macroeconomic controls

This table examines the main results using year-quarter fixed effects instead of macro controls. Columns (2) to (5) present the sensitivity specification, and columns (6) to (9) present the level specification. Controls include time-varying bank characteristics and the interaction terms between their demeaned values and *PeerROA* (or *I(PeerROA<Med)*), current deposit rates, and macro controls. T-statistics, reported in parentheses, are based on two-way clustered standard errors 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 Baseline Results

Dependent variable	ΔDep_{it}^{U}								
		Sensitivity Test				**Levels Test**			
MisMatch Measure	n/a	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer%Uninsured*	*PeerAsset Illiquidity*	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer%Uninsured*	*Peer Asset Illiquidity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PeerROA	0.246***	0.207***	0.266***	0.220***	0.215***	0.308***	0.372***	0.345***	0.343***
	(3.30)	(3.30)	(3.81)	(3.32)	(3.12)	(3.61)	(4.17)	(3.82)	(3.91)
ROA	0.734***	0.763***	0.729***	0.742***	0.745***	0.778***	0.752***	0.760***	0.761***
	(13.53)	(14.12)	(13.92)	(14.29)	(14.09)	(14.24)	(14.31)	(14.49)	(14.40)
I(PeerROA<Med)						0.002	0.044	0.054	0.039
						(0.03)	(0.66)	(0.82)	(0.58)
PeerROA_Inform	-0.248***								
	(-3.21)								
*PeerROA_Inform*PeerROA*	0.150**								
	(2.31)								
MisMatch		-0.150***	3.721***	-0.014*	-3.072***	-0.125***	5.859***	0.011*	-0.895
		(-10.13)	(5.00)	(-1.70)	(-3.82)	(-9.97)	(8.79)	(1.75)	(-1.35)
*MisMatch*PeerROA*		0.019***	1.793***	0.020**	1.980***				
		(2.70)	(4.23)	(2.62)	(4.03)				
*MisMatch*I(PeerROA<Med)*						-0.018**	-1.073***	-0.018**	-0.938
						(-2.45)	(-2.66)	(-2.51)	(-1.58)
Observations	327,316	363,595	363,595	363,595	363,595	363,595	363,595	363,595	363,595
Adjusted R-squared	0.291	0.284	0.280	0.279	0.279	0.283	0.279	0.279	0.279
Interactive controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Interactive Effects of Focal and Peer Bank Liquidity MisMatch

Dependent variable	ΔDep_{it}^{U}			
Tercile indicator based on	Peer Asset Illiquidity		Peer %Uninsured	
MisMatch measures	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Focal %Uninsured*	*Focal Asset Illiquidity*
	Sensitivity Test			
*Bottom*PeerROA*	0.118	0.056	0.034	0.073
	(1.28)	(0.56)	(0.34)	(0.94)
*Middle*PeerROA*	0.195*	0.224**	0.169*	0.158*
	(1.91)	(2.15)	(1.92)	(1.78)
*Top*PeerROA*	0.105	0.114	0.023	0.287**
	(1.30)	(1.23)	(0.24)	(2.46)
*(a) Bottom*MisMatch* PeerROA*	0.011	-0.603	0.002	0.321
	(1.18)	(-0.87)	(0.21)	(0.59)
*(b) Middle*MisMatch*PeerROA*	0.013	1.662***	-0.001	1.777***
	(1.52)	(2.66)	(-0.07)	(3.55)
*(c) Top*MisMatch*PeerROA*	0.024**	2.147***	0.029***	2.897***
	(2.53)	(3.24)	(3.03)	(4.23)
(c) – (a)	0.013	2.750***	0.027**	2.576***
	(1.12)	(3.21)	(2.16)	(3.15)
Observations	362,962	362,962	362,861	362,861
Adjusted R-squared	0.298	0.293	0.296	0.292
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
	Levels Test			
*Bottom*I(PeerROA<Med)*	-0.166*	-0.103	0.065	0.058
	(-1.69)	(-1.04)	(0.49)	(0.57)
*Middle*I(PeerROA<Med)*	0.000	0.027	-0.077	-0.017
	(0.00)	(0.29)	(-0.78)	(-0.19)
*Top*I(PeerROA<Med)*	0.092	0.247**	0.310**	0.131
	(0.74)	(2.01)	(2.34)	(1.13)
*(a) Bottom*MisMatch*I(PeerROA<Med)*	-0.013	0.398	0.005	0.531
	(-1.38)	(0.61)	(0.57)	(0.98)
*(b) Middle*MisMatch*I(PeerROA<Med)*	-0.011	-0.721	-0.011	-1.114*
	(-1.42)	(-1.23)	(-1.34)	(-1.98)
*(c) Top*MisMatch*I(PeerROA<Med)*	-0.025**	-2.293***	-0.027**	-2.810***
	(-2.14)	(-2.98)	(-2.44)	(-3.81)
(c) – (a)	-0.012	-2.691**	-0.032**	-3.341***
	(-0.76)	(-2.61)	(-2.29)	(-3.98)
Observations	362,962	362,962	362,861	362,861
Adjusted R-squared	0.298	0.293	0.295	0.291
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes

Panel C: Interaction between bank liquidity mismatch and asset commonality

Dependent variable	ΔDep_{it}^{U}			
Tercile indicator based on	*EarnComove*			
MisMatch measures	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer %Uninsured*	*Peer Asset Illiquidity*
	Sensitivity Test			
*Bottom*PeerROA*	0.095	0.098	0.083	0.077
	(1.24)	(1.19)	(0.98)	(0.94)
*Middle*PeerROA*	0.221***	0.247***	0.227***	0.215***
	(2.94)	(3.25)	(3.00)	(2.69)
*Top*PeerROA*	0.240***	0.343***	0.265***	0.297***
	(2.86)	(3.53)	(2.85)	(3.10)
*(a) Bottom*MisMatch*PeerROA*	-0.004	0.725	0.012*	1.118
	(-0.44)	(1.25)	(1.71)	(1.59)
*(b) Middle*MisMatch*PeerROA*	0.019***	1.258**	0.013**	1.208
	(2.79)	(2.29)	(2.01)	(1.65)
*(c) Top*MisMatch*PeerROA*	0.032***	2.342***	0.027**	1.948***
	(3.23)	(3.38)	(2.55)	(2.76)
(c) – (a)	0.035***	1.617*	0.015*	0.829
	(4.24)	(1.90)	(1.70)	(0.81)
Observations	356,542	356,542	356,542	356,542
Adjusted R-squared	0.300	0.296	0.296	0.295
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
	Levels Test			
*Bottom*I(PeerROA<Med)*	-0.046	-0.043	-0.034	-0.038
	(-0.49)	(-0.45)	(-0.36)	(-0.40)
*Middle*I(PeerROA<Med)*	-0.081	-0.054	-0.049	-0.056
	(-0.96)	(-0.65)	(-0.60)	(-0.68)
*Top*I(PeerROA<Med)*	-0.033	0.064	0.071	0.046
	(-0.34)	(0.65)	(0.73)	(0.47)
*(a) Bottom*MisMatch*I(PeerROA<Med)*	0.003	0.179	-0.009	0.116
	(0.38)	(0.30)	(-1.19)	(0.13)
*(b) Middle*MisMatch*I(PeerROA<Med)*	-0.019**	-0.584	-0.014*	-1.035
	(-2.45)	(-1.07)	(-1.82)	(-1.39)
*(c) Top*MisMatch*I(PeerROA<Med)*	-0.034***	-2.316***	-0.033***	-0.797
	(-3.24)	(-3.33)	(-2.90)	(-0.86)
(c) – (a)	-0.037***	-2.496***	-0.024**	-0.912
	(-3.98)	(-2.96)	(-2.17)	(-0.76)
Observations	356,542	356,542	356,542	356,542
Adjusted R-squared	0.300	0.296	0.295	0.295
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes

Table A2 Robustness to including interactions between focal *ROA* (*I(ROA<Med)*) and focal *MisMatch*

This table examines the main results, adding interactions between the main variables of interest and *ROA* (*I(ROA<Med)*). Columns (1) to (2) present the sensitivity specification, and columns (3) to (4) present the level specification. Controls include time-varying bank characteristics and the interaction terms between their demeaned values and *PeerROA* (or *I(PeerROA<Med)*), current deposit rates, and macro controls. T-statistics, reported in parentheses, are based on two-way clustered standard errors at the bank and year-quarter level. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Dependent variable	ΔDep_{it}^{U}			
	Sensitivity Test		**Levels test**	
MisMatch Measure	Focal *%Unins ured*	Focal *Asset Illiquidity*	Focal *%Unins ured*	Focal *Asset Illiquidity*
	(1)	(2)	(3)	(4)
PeerROA	1.164***	1.402***	1.155***	1.430***
	(3.73)	(3.87)	(2.76)	(3.06)
*MisMatch*PeerROA*	0.037**	3.252***		
	(2.54)	(4.11)		
ROA	1.160***	1.097***	0.906***	0.921***
	(8.11)	(7.66)	(5.81)	(5.92)
*MisMatch*ROA*	0.030***	2.178***		
	(5.03)	(4.93)		
*MisMatch*I(PeerROA<Med)*			-0.041***	-3.136***
			(-3.30)	(-3.96)
I(PeerROA<Med)			-0.329*	-0.190
			(-1.80)	(-1.02)
*MisMatch*I(ROA<Med)*			-0.035***	-3.909***
			(-3.62)	(-5.02)
I(ROA<Med)			-0.438***	-0.342**
			(-3.29)	(-2.59)
MisMatch	-0.218***	1.315	-0.119***	9.994***
	(-3.91)	(0.56)	(-3.35)	(6.94)
Observations	363,595	363,595	363,595	363,595
Adjusted R-squared	0.137	0.127	0.136	0.126
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
MacroControl	Yes	Yes	Yes	Yes

Table A3 Robustness using uninsured deposit changes scaled by uninsured deposit base

This table examines the robustness of the main results from using an alternative measure of uninsured deposit flows (i.e., $\Delta Dep^{U}_{it}_Alt$) as the dependent variable where the changes in uninsured deposits are scaled by the lagged value of uninsured deposits (instead of the lagged value of assets). Controls include time-varying bank characteristics and the interaction terms between their demeaned values and *PeerROA* (or *I(PeerROA<Med)*), current deposit rates, and macro controls. T-statistics, reported in parentheses, are based on two-way clustered standard errors 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 Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\Delta Dep^{U}_{it}_Alt$					
PeerROA	3.237***			4.437***	0.950***	4.221***
	(2.88)			(3.42)	(3.33)	(3.54)
PeerROA1(<Med)		4.642**	4.212**			
		(2.48)	(2.33)			
PeerROA2(>Med)		0.212	0.735			
		(0.39)	(1.41)			
I(ROA<Med)			-6.111***			
			(-7.67)			
*I(ROA<Med)*ROA*			5.157***			
			(6.82)			
*PeerROA_Inform*PeerROA*						2.047***
						(2.67)
PeerROA_Inform						-3.201***
						(-3.26)
ROA	3.602***	3.575***	0.176	3.510***	2.659***	3.346***
	(10.46)	(10.70)	(0.61)	(8.16)	(12.65)	(8.61)
Observations	363,595	363,595	363,595	363,595	363,595	327,316
Adjusted R-squared	0.063	0.064	0.065	0.093	0.221	0.102
Bank FE	No	No	No	Yes	Yes	Yes
Year-Quarter FE	No	No	No	No	Yes	No
Controls	NA	NA	NA	NA	NA	Yes

Panel B: Effects of Liquidity MisMatch at Focal and Peer Banks

Dependent variable	$\Delta Dep_{it}^{U}_Alt$			
MisMatch Measure	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer %Uninsured*	*Peer Asset Illiquidity*
	(1)	(2)	(3)	(4)
	Sensitivity Test			
PeerROA	3.447***	4.201***	4.445***	3.631***
	(3.26)	(3.66)	(3.66)	(3.36)
*MisMatch*PeerROA*	0.075**	12.351***	0.117**	20.649***
	(2.31)	(4.13)	(2.08)	(4.37)
MisMatch	-0.823***	9.163	-0.411***	-24.715**
	(-6.10)	(1.28)	(-2.92)	(-2.17)
ROA	3.382***	3.297***	3.224***	3.331***
	(8.60)	(8.62)	(9.22)	(8.81)
Observations	363,595	363,595	363,595	363,595
Adjusted R-squared	0.113	0.095	0.098	0.094
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
	Levels Test			
*MisMatch*I(PeerROA<Med)*	-0.083***	-11.283***	-0.127***	-20.820***
	(-3.27)	(-3.59)	(-3.12)	(-3.60)
I(PeerROA<Med)	-1.075*	-0.522	-1.004	-0.637
	(-1.79)	(-0.87)	(-1.61)	(-1.06)
MisMatch	-0.720***	26.020***	-0.253**	3.835
	(-6.17)	(5.30)	(-2.40)	(0.52)
ROA	3.408***	3.389***	3.265***	3.391***
	(8.06)	(8.10)	(8.47)	(8.33)
PeerROA	3.212**	4.265***	4.244***	3.890***
	(2.52)	(3.05)	(2.98)	(2.87)
Observations	363,595	363,595	363,595	363,595
Adjusted R-squared	0.112	0.095	0.097	0.094
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Panel C: Interactive Effects of Focal and Peer Bank Liquidity MisMatch

Dependent variable	$\Delta Dep_{it}^{U}_Alt$			
Tercile indicator based on	Peer Asset Illiquidity		Peer %Uninsured	
MisMatch measures	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Focal %Uninsured*	*Focal Asset Illiquidity*
	Sensitivity Test			
*Bottom*PeerROA*	1.750**	1.844**	1.379**	2.141***
	(2.13)	(2.18)	(2.06)	(3.84)
*Middle*PeerROA*	2.835***	3.449***	3.183***	3.612***
	(2.84)	(3.19)	(3.35)	(3.85)
*Top*PeerROA*	4.757***	5.141***	4.154**	5.379***
	(3.44)	(3.77)	(2.46)	(3.51)
*(a) Bottom*MisMatch* PeerROA*	0.037	-2.408	0.014	7.593***
	(1.08)	(-0.93)	(0.27)	(2.69)
*(b) Middle*MisMatch*PeerROA*	0.079**	8.384***	-0.003	14.944***
	(2.33)	(3.08)	(-0.10)	(4.11)
*(c) Top*MisMatch*PeerROA*	0.069	13.094***	0.055	11.612***
	(1.60)	(3.16)	(1.33)	(3.58)
(c) – (a)	0.032	15.50***	0.04	4.019
	(0.68)	(3.12)	(0.49)	(1.03)
Observations	362,962	362,962	362,861	362,861
Adjusted R-squared	0.128	0.111	0.132	0.119
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
	Levels Test			
*Bottom*I(PeerROA<Med)*	-0.584	-0.360	-0.082	-0.090
	(-1.39)	(-0.79)	(-0.14)	(-0.20)
*Middle*I(PeerROA<Med)*	-0.245	0.149	-1.683***	-1.341**
	(-0.43)	(0.26)	(-2.74)	(-2.37)
*Top*I(PeerROA<Med)*	-3.165***	-1.563*	-1.213	-1.186
	(-3.03)	(-1.68)	(-1.13)	(-1.19)
*(a) Bottom*MisMatch*I(PeerROA<Med)*	-0.016	-0.024	0.019	-2.326
	(-0.48)	(-0.01)	(0.38)	(-0.80)
*(b) Middle*MisMatch*I(PeerROA<Med)*	-0.083***	-5.833**	-0.031	-12.611***
	(-2.73)	(-2.02)	(-1.06)	(-3.36)
*(c) Top*MisMatch*I(PeerROA<Med)*	-0.085**	-15.933***	-0.053	-14.883***
	(-2.30)	(-3.76)	(-1.46)	(-4.56)
(c) – (a)	-0.069	-15.91***	-0.072	-12.56***
	(-1.40)	(-3.35)	(-0.99)	(-3.34)
Observations	362,962	362,962	362,861	362,861
Adjusted R-squared	0.128	0.111	0.132	0.119
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Panel D: Interaction between bank liquidity mismatch and asset commonality

Dependent variable	$\Delta Dep_{it}^{U}_Alt$			
Tercile indicator based on	*EarnComove*			
MisMatch measures	*Focal %Uninsured*	*Focal Asset Illiquidity*	*Peer %Uninsured*	*Peer Asset Illiquidity*
	Sensitivity Test			
*Bottom*PeerROA*	2.356***	2.565***	3.089***	2.324***
	(2.89)	(3.06)	(3.07)	(2.76)
*Middle*PeerROA*	3.373***	3.789***	4.241***	3.298***
	(4.17)	(4.43)	(4.28)	(4.04)
*Top*PeerROA*	3.672***	4.840***	4.728***	4.124***
	(2.95)	(3.70)	(3.79)	(3.37)
*(a) Bottom*MisMatch*PeerROA*	0.022	2.875	0.056	11.047***
	(0.79)	(1.12)	(1.55)	(3.20)
*(b) Middle*MisMatch*PeerROA*	0.080**	10.011***	0.075**	18.399***
	(2.47)	(3.67)	(2.01)	(4.07)
*(c) Top*MisMatch*PeerROA*	0.099**	14.919***	0.150**	21.184***
	(2.53)	(3.48)	(2.08)	(3.87)
(c) – (a)	0.076**	12.04**	0.094*	10.14*
	(2.11)	(2.37)	(1.87)	(1.97)
Observations	356,542	356,542	356,542	356,542
Adjusted R-squared	0.130	0.113	0.116	0.112
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
	Levels Test			
*Bottom*I(PeerROA<Med)*	-1.314***	-1.087**	-1.366***	-1.132**
	(-2.81)	(-2.37)	(-2.73)	(-2.42)
*Middle*I(PeerROA<Med)*	-1.151**	-0.759	-1.109**	-0.794*
	(-2.44)	(-1.61)	(-2.18)	(-1.67)
*Top*I(PeerROA<Med)*	-1.806*	-0.879	-1.644*	-1.041
	(-1.90)	(-0.91)	(-1.68)	(-1.08)
*(a) Bottom*MisMatch*I(PeerROA<Med)*	0.004	-3.473	-0.034	-11.653**
	(0.15)	(-1.42)	(-1.05)	(-2.54)
*(b) Middle*MisMatch*I(PeerROA<Med)*	-0.094***	-7.788**	-0.093***	-18.569***
	(-3.38)	(-2.55)	(-2.84)	(-3.53)
*(c) Top*MisMatch*I(PeerROA<Med)*	-0.146***	-18.076***	-0.226***	-25.061***
	(-4.81)	(-4.41)	(-4.20)	(-3.84)
(c) – (a)	-0.150***	-14.60***	-0.191***	-13.41***
	(-4.74)	(-3.72)	(-3.96)	(-2.76)
Observations	356,542	356,542	356,542	356,542
Adjusted R-squared	0.130	0.113	0.116	0.112
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Appendix 2: Variable Definitions

Variables	Definitions
ΔDep_{it}^{I}	Annualized growth rate in insured deposits as a percentage of lagged assets in quarter t and t+1 (in %): *(Insured Deposits$_{it+1}$ - Insured Deposits$_{it-1}$)/Assets$_{it-1}$*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 $250,000. Insured deposits: RCON2702 (before 2006Q2); RCONF049 + RCONF045 (from 2006Q2).
ΔDep_{it}^{T}	Annualized growth rate in total deposits (RCFD2200) as a percentage of lagged assets in quarter t and t+1 (in %): *(Total Deposits$_{it+1}$ - Total Deposits$_{it-1}$)/Assets$_{it-1}$*200%.*
ΔDep_{it}^{U}	Annualized growth rate in uninsured deposits as a percentage of lagged assets (in %) in quarter t and $t + 1$. Uninsured deposit is calculated as deposits (RCFD2200) – insured deposits.
Ln(Assets)$_{it-1}$	The logarithm of total assets (RCFD2170) at the end of quarter t-1.
ROA$_{it-1}$	Annualized ROA (in %) in quarter t-1, calculated as net income (RIAD4300, adjusted year-to-date reporting to within quarter) divided by beginning assets (RCFD2170).
Capital_Ratio$_{it-1}$	Total equity (RCFD3210) divided by assets (RCFD2170) in quarter t-1.
RealEstate_Loans$_{it-1}$	Loans secured by real estate (RCFD1410), scaled by total loans in quarter t-1.
C&I_Loans$_{it-1}$	Commercial and industrial loans (RCFD1766), scaled by total loans in quarter t-1.
Wholesale_Funding$_{it-1}$	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.
Std_ROA$_{it-1}$	Standard deviation of ROA measured over 12 rolling quarters (from quarter t − 12 to t − 1).
% Deposits$_{it-1}$	Ratio of total deposits to total assets in quarter t-1.
Core Deposit Rate$_{it}$	Annualized average interest rate (in %) over the quarters t and t+1 on core deposits. Core deposits are the sum of transaction deposits, saving deposits, and small time deposits. The average balance items: transaction deposits: RCON3485; savings deposits: RCONB563 + (RCON3486 + RCON3487 before 2001Q1); small time deposits: RCONA529 (RCON3469 before 1997Q1). The interest expense items: transaction deposits: RIAD4508; saving deposits: RIAD0093 (RIAD4509 + RIAD4511 before 2001Q1); small time deposits: RIADA518 (RIAD4512 before 1997Q1), adjusted year-to-date reporting to within quarter.
Large Time Deposit Rate$_{it}$	Annualized average interest rate (in %) over the quarters t and t +1 on large time deposits. Calculated as quarterly interest expense

	(RIADA517 (RIAD4174 before 1997Q1), adjusted year-to-date reporting to within quarter) divided by the average balance of large time deposits (RCONA514 (RCON3345 before 1997Q1)).
% Uninsured$_{it-1}$	The fraction of deposits at focal bank that are uninsured (in %), averaged over the prior 12 quarters ending in t-1 (with a minimum of six observations available to calculate the average).
Asset Illiquidity$_{it-1}$	The measure of liquidity creation per unit of gross total assets at focal bank, in Berger and Bouwman (2009). Step 1: Classify all bank activities on a bank's asset side as liquid, semi-liquid, or illiquid based on product category. Step 2: Assign weights to the activities classified in Step 1. Illiquid assets, get 1/2, 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, and then scaled by gross total assets. The asset illiquidity measure is averaged over the prior 12 quarters ending in t-1 (with a minimum of six observations available to calculate the average).
PeerROA$_{it-1}$	The weighted average annualized *ROA* of peer banks (defined as banks in the same size group and operating in same counties with the focal bank) in quarter t-1 calculated in the following two steps: Step 1: calculate county weighted average *ROA* of peer banks operating in each county, using peer banks' local deposit share as the weight. $countyPeerROA_c = \sum_j w_j\, ROA_j\,, where\ w_j = \frac{Deposits_{j,c}}{\sum_j Deposits_{j,c}}$ (1) Step 2: calculate the bank-level weighted average *PeerROA* from all counties the bank operates, using the share of the bank's deposits in these counties as the weight. $PeerROA_i = \sum_c w_c\, countyROA_c\,, where\ w_c = \frac{Deposits_{i,c}}{\sum_c Deposits_{i,c}}$ (2)
Peer%Uninsured$_{it-1}$	The weighted average *%Uninsured* of peer banks in quarter t-1, calculated in a similar way as *PeerROA*.
Peer Asset Illiquidity$_{it-1}$	The weighted average *Asset Illiquidity* of peer banks in quarter t-1, calculated in a similar way as *PeerROA*.
ExpDepHHI$_{it-1}$	The weighted average exposure to local deposit competition, calculated in a similar way as *PeerROA*. For each county, the deposit concentration is measured as the Herfindahl–Hirschman index (HHI) of deposit shares. Then, the bank's exposure to deposit competition is calculated as the bank-level weighted average HHI from all counties in which the bank operates, using the share of the bank's deposits in these counties as the weight.
PeerROA_Inform$_{it-1}$	The adjusted R-squared from the following regression $Writeoff_{i,t} = \alpha_0 + \sum_{k=1}^{2} (\delta_k PeerEBLLP_{i,t-k} + \beta_k PeerLLP_{i,t-k} + \gamma_k \Delta PeerNPL_{t-k}) + \rho PeerCapRatio_{i,t-1} + \varepsilon_{i,t}$

	estimated for each bank-quarter using the bank's observations in prior 12 quarters ending in quarter t-1.
$EarnComove_{it-1}$	The correlation coefficient between $ROA_{i,t}$ and $PeerROA_{i,t}$ over the 12 quarters ending in quarter t-1.