Interdependence of Bank Run Risk and Interest Rate Risk

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Abstract

I study how strategising to mitigate liquidity risk in stress periods exposes banks to interest rate risk in normal times. Building on (Drechsler et al., 2021), I show that small banks in the bottom quintile are not able to perform interest sensitivity matching and hence, are exposed to interest rate risk. These banks are primarily funded by retail deposits which results in low interest expense beta. Despite being funded by retail deposits, I show that stress periods trigger a relative reallocation of deposits from small banks to large banks, exposing these banks to higher funding instability in stress periods. To mitigate the anticipated bank-run risk, small banks hold shorter-duration assets to maintain liquidity in stress periods. Holding shorter-duration assets results in increasing their interest income beta. As a consequence, they end up pairing low-interest expense beta with high-interest income beta leading to an interest sensitivity mismatch. I also conduct additional tests using the variation in banks' presence on the reciprocal deposit network to show that since small banks on the network experience lower bank-run risk in stress periods, they can perform interest sensitivity matching to mitigate interest rate risk. These results demonstrate the interdependence of liquidity risk and interest risk management and emphasise the importance of the stability of the deposits in a bank's ability to provide long-term credit.

JEL Classification: G21, E43, E52

Keywords: Interest rate risk, bank deposits, bank runs, flight to safety, liquidity risk.

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I. Introduction

A defining feature of banks is the coexistence of deposit-taking and long-term lending in the same institution. Kashyap et al. (2002) theorised that deposit-taking and lending coexist because there is an imperfect correlation between deposit withdrawals and commitment drawdowns. The deposit-lending synergy has contributed to the stability and resilience of the banking sector throughout the decades. Gatev and Strahan (2009); Li et al. (2020) expounded on it to show that since banks are liquidity providers, deposits flow into the banking sector during recessions when firms draw on their credit lines. However, there can be exceptions to this pattern especially if the banking sector itself is in distress. Ippolito et al. (2016) showed during the 2007 European interbank market freeze, banks experienced double runs on both sides of their balance sheets. Acharya and Mora (2015) showed that banks had to increase their interest rate to attract deposits at the onset of the Global Financial crisis. Such periods of severe stress can also trigger reallocation of deposits within the banking sector (Caglio et al., 2023). The distribution of deposit flows in the banking sector during the stress period is not uniform. Some banks experience deposit inflows while others experience outflows.

Understanding the distribution of deposit flows across bank groups during stress periods is paramount given financial stability concerns. Baron et al. (2022) documented that historically in most of the banking crises, large banks tend to survive and increase their market share following a bank crisis when small banks are more likely to fail or get absorbed. Caglio et al. (2023) showed that during the 2023 regional banking crisis deposit growth rates at large banks were higher compared to all the other banks after controlling for bank characteristics, uninsured deposit funding and unrealised mark-to-market losses. Similarly, Cipriani et al. (2024) add to this literature by using high-frequency interbank payments data to show that during the 2023 regional banking crisis deposits were reallocated from super-regional banks to large banks. In aggregate, the findings of the current literature suggest a significant heterogeneity in deposit flows across banks during stress periods and the deposit flows vary based on bank size resulting in large banks gaining more deposits while small banks experience a decline in deposits. This implies small banks experience a loss of retail deposits precisely when it is needed the most.

In this paper, we study the interdependence of interest rate risk and liquidity risk management. We document that small banks in the bottom quintile are not performing interest sensitivity matching and thus are exposed to higher interest rate risk. The interest sensitivity mismatch is primarily attributable to the fact that their interest expense beta is much lower than their interest income beta. These small banks are primarily funded with retail deposits and have relatively more rate-insensitive liabilities in their liability structure than other banks. Their funding structure results in a disproportionately lower interest expense beta relative to other bank groups. However, these small banks experience higher funding instability in stress periods. We show that stress periods trigger a relative reallocation of deposits from small banks to large banks exposing these small banks to higher funding instability in stress periods. To mitigate the anticipated bank-run risk, small banks hold shorter-duration assets to maintain liquidity in stress periods. As a consequence, their interest income beta increases leading to interest sensitivity mismatch. Thus, in an attempt to lower the anticipated bank-run risk in stress periods, small banks in the bottom quintile expose themselves to higher interest rate risk in normal times. We conduct additional tests using the variation in banks' presence on the reciprocal deposit network to show that since small banks on the network experience reduced bank-run risk in stress periods, they can implement interest sensitivity matching to mitigate interest rate risk. To test the validity of our results, we also conduct an alternative test to show that the low demand for long-term credit among small banks' borrowers, as an additional channel, is not driving the results.

Small banks play a vital role in promoting regional economic development and in preserving financial stability. A persistent economic problem in corporate finance is the size gap in credit markets (Maimbo et al., 2011). Small firms find it harder to access finance (Maimbo et al., 2011). This result holds for firms in developing as well as developed countries. Banks find it difficult to lend to small firms because they are informationally opaque, involve higher transaction costs and lack pledgeable assets. A close lender-borrower relationship is key to lending to these borrowers (Petersen and Rajan, 1994; Berger et al., 1998). Large firms have direct access to capital markets, but small firms are more reliant on banks for financing. Berger et al. (2005) showed that small banks have a comparative advantage in extending loans based on soft information (relationship lending). Due to their comparative advantage in relationship lending, small banks are instrumental in providing financing to small businesses (Langenfeld, 1994; Weston and Strahan, 1996; Peek and Rosengren, 1998). Small banks also specialise in agricultural lending, a segment that has been under-served by large banks. d'Avernas et al. (2023) showed that in the year 2019, small banks allocated 10% of their loan portfolios to agricultural lending, while large banks did not extend any loans to the agricultural sector. Hakenes et al. (2015) showed that small banks prevent capital flows from poor to rich regions and spur regional economic development. Deyoung et al. (2015) showed that a small group of community banks in the US that precommitted to making loans to their borrowers continued to extend credit during the global financial crisis. This finding has important financial stability implications – it shows that relationship lending by small community banks can have a stabilizing effect during the crisis by extending credit to firms during the crisis. Baron et al. (2022) showed that large banks tend to cut back their lending more than other groups of banks during the post-crisis period, prolonging the recession. Overall, the literature documents that small banks are crucial to the economy, driving local economic growth, accelerating recovery during post-crisis periods, and often outperforming large banks in lending during post-crisis periods, which enhances financial stability.

Our results are relevant for two reasons. First, we show the interdependence of liquidity risk and interest rate risk management. We highlight that since small banks are exposed to higher bank-run risk in stress periods, it limits their ability to perform interest sensitivity matching to hedge interest rate risk in normal times. Second, we emphasise the importance of the stability of the deposits in banks' ability to provide long-term credit. Specifically, we show that if a bank's deposits are flighty then it will shorten the duration of their assets to preserve liquidity and mitigate liquidity and solvency risk during stress periods.

We begin by documenting that unlike the aggregate banking sector, small banks in the bottom quintile do not perform interest sensitivity matching. An influential paper by Drechsler et al. (2021) (abbreviated as DSS) showed that banks closely match their interest expense sensitivity to fed funds rates (interest expense beta) with interest income sensitivity to fed funds rates (interest income beta) and as a result, their equity is isolated from interest rate movements. Thus, in the new DSS paradigm maturity transformation does not expose banks to interest rate risk but rather hedges it. We show that only banks in the bottom quintile do not perform interest sensitivity matching and as a result, they are exposed to interest rate risk. An alternative strategy for banks to manage interest rate risk is by using derivatives. However, the literature documents that banks rarely use derivatives to hedge interest rate risk, primarily because it is costly to use derivatives for hedging interest rate risk. The term premium earned from holding long-term assets and short-term liabilities is offset by hedging with derivatives (McPhail et al., 2023). McPhail et al. (2023) concluded that swap positions do not have an economically significant impact in mitigating interest rate risk. Granja et al. (2024) documented using data from call reports and SEC filings that only 6% of U.S. banks used derivatives to hedge interest rate risk, with even the most frequent users of derivatives leaving the majority of their assets unhedged. Hoffmann et al. (2019) showed that even banks in the Euro area use derivatives to only partially hedge interest rate risk. Table 1 shows that the swap ratio and interest rate derivatives ratio of small banks in our dataset is zero, implying that small banks do not use derivatives to hedge interest rate risk. Thus, small banks can hedge interest rate risk solely through interest sensitivity matching.

Second, we show that banks in the bottom quintile are more exposed to funding stress during stress periods than other bank groups. Prior literature has documented that even though deposits flow into the banking sector during stress periods, there is a significant reallocation of deposits within the banking sector. This reallocation is primarily attributable to the flight to safety mechanisms and implicit guarantees that large banks enjoy. Building on this literature, we show stress periods affect the funding position of these small banks differentially than other groups of banks exposing these small banks to higher funding instability during stress periods. We show that only the small banks in the bottom quintile experience an increase in their cost of financing in stress periods. The stress periods trigger a relative reallocation of deposits from small banks to large banks exposing these banks to higher bank-run risk. This relative reallocation is associated with increased relative deposit variability. The fact that small banks lose deposits during stress periods implies that these banks experience a loss of retail deposits precisely when it is needed the most. We also show that during stress periods the bank run is primarily in interest-bearing deposits which comprise 69% of the total funding for these banks. Thus, a relative reallocation of these deposits severely deteriorates their liquidity position and hence impacts their asset portfolio choices. Altogether, our results suggest that small banks experience heightened funding pressure relative to other bank groups during stress periods. To alleviate their funding stress during period stress periods, small banks liquidate their securities, leading to balance sheet contraction and increased exposure to solvency risk.

Third, we use an instrumental variable (IV) estimation to reduce endogeneity concerns in estimating the relationship between deposit variability in stress periods and asset duration. Deposit market power is used as an instrument to show that instrumented deposit variability in stress periods is negatively associated with asset duration which implies banks with higher deposit variability in stress periods will have shorter-duration assets. These small banks experience higher deposit variability in stress periods and hence, hold shorter-duration assets. These small banks are primarily funded with retail deposits and have relatively more rate-insensitive liabilities in their liability structure than other banks. Their funding structure results in a disproportionately lower interest expense beta relative to other bank groups. However, these small banks also experience higher bank-run risk in stress periods. To mitigate the anticipated bank-run risk, small banks hold shorter-duration assets to maintain liquidity in stress periods. As a consequence, their interest income beta increases leading to interest sensitivity mismatch.

Fourth, we further test our hypothesis using recent a financial innovation, reciprocal deposits. Kim et al. (2024) showed that during the 2023 regional bank crisis, banks on reciprocal deposit networks were able to attract and retain their deposit base more than the non-network banks. Thus, banks on the network were able to effectively reduce their bank run risk during the stress period. We use the variation in the presence of banks on the network to show that since small banks on the network experience lower bank-run risk in stress periods, these small banks on the network were able to perform interest sensitivity matching to hedge interest rate risk.

Fifth, we also perform an alternative test to account for the lower demand for long-term credit among small banks' borrowers as an additional channel influencing our findings. An alternative explanation for our results could be that lower demand for long-term credit among small banks' borrowers could lead to small banks reducing the supply of long-term assets. We show that comparable banks in quintile 2 that coexist in the same city as small banks are able to increase their holdings of long-term assets in their asset structure over the years. Our results show that in geographical areas where quintile 1 banks co-exist with higher quintile banks (2 to 4), those higher quintile banks have systematically higher maturity of assets. This provides some evidence for the existence of demand for long-term credit among borrowers of small banks. Our results hold even after the inclusion of various fixed effects.

To summarise, we present four main findings - (a) small banks in the bottom quintile do not perform interest sensitivity matching and this mismatch is primarily attributable to the fact that their interest expense beta is much lower than their interest income beta, (b) these small banks experience relative reallocation of deposits during stress periods which exposes them to higher bank run risk during crises, (c) to mitigate the anticipated bank-run risk, small banks hold shorter-duration assets. As a consequence, their interest income beta increases leading to interest sensitivity mismatch and exposing these banks to higher interest rate risk in normal times, (d) we also conduct additional tests to show that since small banks on the reciprocal deposit network experience lower bank-run risk in stress periods, this enables small banks on the network to implement interest sensitivity matching to hedge interest rate risk.

The remaining paper is structured as follows. Section II. discusses the related literature. Section III. describes the data and relevant definitions and presents the summary statistics. Section IV. presents and explains our results. Section V. concludes.

II. Related Literature

The literature on bank runs and interest risk management is vast considering the significance of bank runs and interest rate risk in banking literature. We contribute to this literature by documenting how attempting to mitigate bank run risk in crisis periods can inadvertently expose banks to higher interest risk in quiet times.

According to the conventional view, banks perform maturity transformation but maturity transformation also exposes banks to interest rate risk in normal times. However, there is little empirical evidence that banks' profit margins are exposed to interest rate shocks. Prior literature has documented that banks' net interest margin (NIM) is mostly insensitive to interest rate shocks. Flannery (1981) showed that for fifteen large banks, their profits are unaffected by the changes in interest rates. Flannery (1983) documents similar results hold for a sample of sixty small banks. English et al. (2002) reported inconsistent results when measuring interest rate risk linked with net interest income for a sample of ten countries. Purnanandam (2007) showed that banks that are more likely to fail are more hedged against interest rate risk by using either balance sheet or non-balance sheet financial instruments like derivatives. Hoffmann et al. (2019) studied interest rate risk in the European banking sector. They found that on aggregate banks have low exposure to interest rate risk and banks partially mitigate their interest risk exposures using derivatives. Recently, an influential paper by Drechsler et al. (2021) (abbreviated as DSS) showed that banks closely match their interest expense sensitivity with interest income sensitivity and as a result, their equity is isolated from interest rate fluctuations. Our paper documents that when the aggregate banking sector performs interest sensitivity matching, small banks in the bottom quintile do not perform interest sensitivity matching and are thus, exposed to interest rate risk.

In the new DSS paradigm, maturity transformation does not expose banks to interest rate risk but hedges it from interest shocks. However, financing long-term illiquid assets with liquid deposits also exposes banks to liquidity risk. Liquidity risk becomes more prominent during bank crisis periods. Liquidity risk induces the risk of a bank run during a crisis and threatens the solvency of a bank. There are two opposing views on what propels a bank run: The seminal paper by Diamond and Dybvig (1983) theorised that coordination failure among depositors can often trigger panic-based bank runs. This is the sunspot view of bank runs. Bernanke (2018) ascribe the exceptional severity of the Great Recession mainly to the panics in funding and securitisation markets leading to distortion in credit supply. In contrast, fundamental-based bank runs occur due to the worsening financial health of the bank or its poor fundamentals (Jacklin and Bhattacharya, 1988; Calomiris and Mason, 1994, and 2003; Baron et al., 2021; Correia et al., 2023).

The existing literature theorises that deposit financing and long-term lending coexist because there are synergies between deposit-taking and long-term lending. Kashyap et al. (2002) theorises that this synergy arises from the imperfect correlation between deposit-taking and commitment drawdowns. Generally, deposits fly to the safest institutions during crises (flight to safety). Since banks are liquidity providers, deposits flow into the banking sector during recessions when firms draw on their credit lines (Gatev and Strahan, 2009; Li et al., 2020). However, this pattern may not always hold. Ippolito et al. (2016) showed during the 2007 European interbank market freeze, banks experienced double runs on both sides of their balance sheets. Acharya and Mora (2015) showed that deposit inflows in the banking sector declined at the onset of the Global Financial crisis and as a result, banks had to increase their interest rate to attract deposits. The deposit flows into the banking sector during the stress period are not uniform. In episodes of severe stress, there can be significant reallocations within the banking sector from banks that are regarded as relatively risky to banks that are considered relatively safe (Caglio et al., 2023). Although the literature documents many instances of flight to safety in the banking sector, the perception of whether a bank is risky depends on the economic condition (Baubeau et al., 2021; Acharya et al., 2022; Caglio et al., 2023). During stress periods there can be significant reallocation within the banking sector (Caglio et al., 2023) because the market's perception of risk is also driven by bank size (Cornett et al., 2011). Baron et al. (2022) documented using an extensive novel dataset that covers 11,000 commercial banks across 17 different advanced economies spanning over 48 years that large banks are more likely to survive and increase their market share following a bank crisis when small banks are more likely to fail or get absorbed. This is in spite of the fact that large banks take on more risk in pre-crisis periods and reduce their lending more. The authors connect the resilience of the largest banks to government intervention and to the fact that large banks' deposit flows are unaffected by bank losses. Similarly, Caglio et al. (2023) showed that flight to safety mechanisms led to large banks experiencing higher deposit growth than small or regional banks during the regional banking crisis in 2023. Similarly, Luck et al. (2023) add to this literature by using confidential weekly H8 data to show during the 2023 regional banking crisis deposits were reallocated from super-regional banks to large banks. We find similar results as Caglio et al. (2023). We find that these reallocations of deposits during stress periods can inhibit small banks' ability to perform interest sensitivity matching.

Finally, the stability of the deposit has a substantial impact on banks' lending choices. Butt et al. (2015) showed that there was no substantial impact on the bank lending channel from the Bank of England's Quantitative Easing (QE) because QE gave rise to flighty deposits. Our paper shows that small banks, primarily funded by flighty deposits, shorten asset duration to maintain liquidity and alleviate liquidity and solvency risk in stress periods.

Our evidence on the flightiness of small banks' deposits contributes to three strands in the banking literature. Firstly, our paper contributes to the literature on interest risk management by documenting that unlike the aggregate banking sector, small banks in the bottom quintile do not perform interest sensitivity matching and thus, are exposed to interest rate risk. Secondly, we enrich the literature on bank runs by showing that higher bank run risk in stress periods limits small banks' ability to hedge interest risk, highlighting the interconnectedness of interest rate risk and liquidity risk. Thirdly, we add to the literature on banks' funding stability and lending choices by showing that banks predominantly funded by flighty deposits will shorten asset duration to preserve liquidity and mitigate liquidity and solvency risk during stress periods. Altogether, we highlight the interdependence of liquidity risk and interest risk management and its impact on a bank's asset-liability management (ALM).

III. Empirical Strategy

A. Data and Sample Construction

A.1. Bank Data

The bank data is originally from the US Call Reports. However, the data for this paper is from the NYU Stern website. The data covers the period from January 1976 to March 2020. The data is for 44 years. It is a quarterly dataset with bank-level identifiers, which is used to link other datasets. The bank data for the extended sample period April 2020 - December 2023 is from the FFEIC Call reports data.

A.2. Fed Funds Data

The Fed funds data is obtained from the H.15 release of the New York Federal Reserve Board. The data contains a monthly time series of Effective Fed funds rates from January 1976 to December 2023. This data is converted from a monthly time series into a quarterly time series and merged with the US Call reports data.

A.3. Bank Market Power Data

The data to construct bank market power is originally from the FDIC. However, for the replication study in this section, the database is obtained from the Journal of Finance website for publicly available databases for the replication studies. This database is then matched with the US call reports data using the RSSID (unique identifier for banks) and the FDIC certificate number, i.e. CERT.

A.4. CPI Index

The CPI index for tracking inflation has been originally sourced from the Bureau of Labour (BLS) database. The CPI had been used to calculate inflation-adjusted asset size. However, for the replication study in this section, the data for the period January 1976 to December 2023 is obtained from the Journal of Finance website for publicly available databases for the replication studies. The CPI Index data for the extended sample period April 2020 - December 2023 is from the Bureau of Labour (BLS) database.

B. Bank Size Groups

We divide the entire dataset of banks into 5 equal-sized buckets i.e., quintiles. Small banks are in the bottom quintile i.e., quintile 1. Table 1 shows that small banks in quintile 1 have an average log of real assets of 9.233 and around 50% of the banks have log-real assets of less than 9.33. Thus, quintile 1 is primarily composed of those banks that are below the 9.3 cutoff line shown in Figure 1 as banks that are not performing interest sensitivity matching. We choose quintile 2 as the reference category because these banks are much more similar to small banks in quintile 1 in terms of asset size, asset and liability characteristics and imposed regulations than large banks.

C. Defining Stress Periods

For this paper, we define "stress periods" as the bank-year observations that are in the year before to the year after the bank crisis. We identify bank crisis from Òscar Jordà et al. (2017) bank crisis chronology (abbreviated as JST crisis chronology). The Jordà, Schularick and Taylor (JST) Macrohistory database identifies an episode of bank distress as the first year of a bank crisis if there is a systemic bank crisis marked by failures of major banks, bank panics, significant losses or recapitalisation in the banking sector and/or substantial government intervention. This definition of bank crisis does not include failures of individual/small banks that did not have any systemic implications. We identify bank crises from JST crisis chronology because (a) we are primarily interested in systemic bank crises because these are the periods when banks need their deposits the most and (b) crises identified in this database are almost similar to other notable crisis chronology databases (as shown on Page 35 of JST crisis chronology). Given our dataset is from 1976 to 2020, there are two bank crisis years in this period identified in the JST crisis chronology - 1984 (Saving & Loan Associations' Crisis) and 2007 (Global Financial Crisis). We used an indicator variable to identify the stress periods. We define the stress period as one year before to one year after the bank crisis (from t=-1 to t=+1, where t=0 is the crisis year). The years 1984 and 2007 are identified as the bank crisis years in the JST crisis chronology. Thus, our stress period is defined as the bank-year observations for the period 1983 to 1985 and 2006 to 2008.

D. Summary Statistics

We begin our analysis by documenting summary statistics of small banks' asset and liability characteristics. Table 1 presents the summary statistics of small banks' assets and liabilities characteristics. It is for the period 1976Q1 to 2020Q4. The small banks in quintile 1 have a maximum asset size $ 44 million. They have an average deposits-to-assets ratio of 0.872. In other words, around 87% of their assets are financed by retail deposits. This implies that retail deposits are their primary source of funding. If we further look into the sub-categories of deposits, we find that around 69% of their assets are funded by interest-bearing deposits. Interest-bearing deposits are the total time deposits and certain forms of saving deposits. These deposits represent medium to long-term financing for banks. Around 26.4% of their assets are funded by transaction deposits. These deposits represent a cheap source of financing for the banks because the interest rates on transaction deposits are very low. Following deposits, equity is their second greatest source of financing. These banks are very well capitalised at 11% which is much higher than any other group of banks. They have a very low amount of wholesale financing at around 8% which is much lower than any other group of banks. Small banks also have relatively a higher share of securities and a lower share of loans in their asset structure compared to other groups of banks. Small banks hold relatively higher levels of securities to alleviate liquidity risk during stress periods since securities are more liquid than loans. The net income ratio of small banks is lower than that of the other groups of banks, suggesting that these banks are not earning excess profits due to interest sensitivity mismatch. The swap ratio and interest rate derivatives ratio of small banks is zero which implies that small banks do not use derivatives to hedge interest rate risk.

(Insert Table 1 about here)

We also perform paired t-tests to show that there is statistically significant difference in means of asset and liability characteristics between small banks in quintile 1 and comparable banks in quintile 2 as shown in Column (1) of Table 2 and small banks in quintile 1 and large banks in quintile 5 as shown in Column (2) of Table 2.

(Insert Table 2 about here)

The paired t-test result shows that the differences in means of all the asset and liability characteristics across the bank groups are highly statistically significant at the 1% level. This indicates that these bank groups have distinct asset and liability structures. The results indicate that banks in quintile 1 hold a statistically significant higher share of rate-insensitive deposits in the form of transaction deposits in their deposit structure compared to other banks. This would imply that their interest expense would be relatively less sensitive to interest rate shocks than other bank groups. In their asset structure, they hold a statistically significant higher share of securities and a lower share of loans relative to other groups. These banks also hold statistically significant shorter-duration assets than banks in quintile 1 and quintile 5.

E. Empirical Methodology

We estimate the following regression model to show the reallocation of deposits from small banks to large banks during stress periods. We then use IV estimation to establish the relationship between deposit variability and asset duration. Our basic regression model regresses the outcome variable on the bank size dummy. The specification also includes bank-fixed effects. The model can be written as follows :

$$y_{i,t} = \alpha + \Sigma_{j=1}^{5} \beta_j Size_j + \Sigma_{j=1}^{5} \beta_j Size_j \times Stress_t + Stress_t + \eta_i + \varepsilon_{i,t} \quad (1)$$

The regression is estimated for each bank i. In the above equation, $y_{i,t}$ represents the outcome variable. Depending on the specification, $y_{i,t}$ represents deposit growth rate, deposit variability and asset growth rates. $Size_j$ represents the size dummy equal to 1 if a bank is in size group j or 0 otherwise. $Stress_t$ indicates a dummy variable equal to 1 if it is a stress period or 0 otherwise. The event dummy i.e., stress period is included instead of quarterly time fixed effects because the inclusion of the event dummy will enable us to measure directly the overall effect of the stress period on deposit flows across banks. In contrast, if quarterly time-fixed effects are used then quarterly time-fixed effects will absorb the stress period along with other general time-varying factors which would make it complex to isolate and estimate the distinctive effect of the stress period on deposit flows across banks and we can only capture the relative effects of the stress period on the deposit flows across banks relative to the comparable group. Bank-fixed effects η_i are included to control for unobserved heterogeneity across banks.

IV. Empirical Results

A. Interest Sensitivity Matching across Bank Groups

We first show heterogeneity in the performance of interest sensitivity matching across banks. We document that small banks in the bottom quintile are not performing interest sensitivity matching. Figure 1 plots the interest betas of the banks against the logarithm-transformed inflation-adjusted assets. The plots in the figure suggest that when the aggregate banking sector performs interest sensitivity matching, small banks with logarithm-transformed real assets of less than 9.3 are not performing interest sensitivity matching. These small banks have a positive duration gap.

To formally test the interest sensitivity matching for each size group of banks, we divide the entire dataset into 5 quintiles and check the interest sensitivity matching of each quintile. Table 3 replicates the interest sensitivity matching

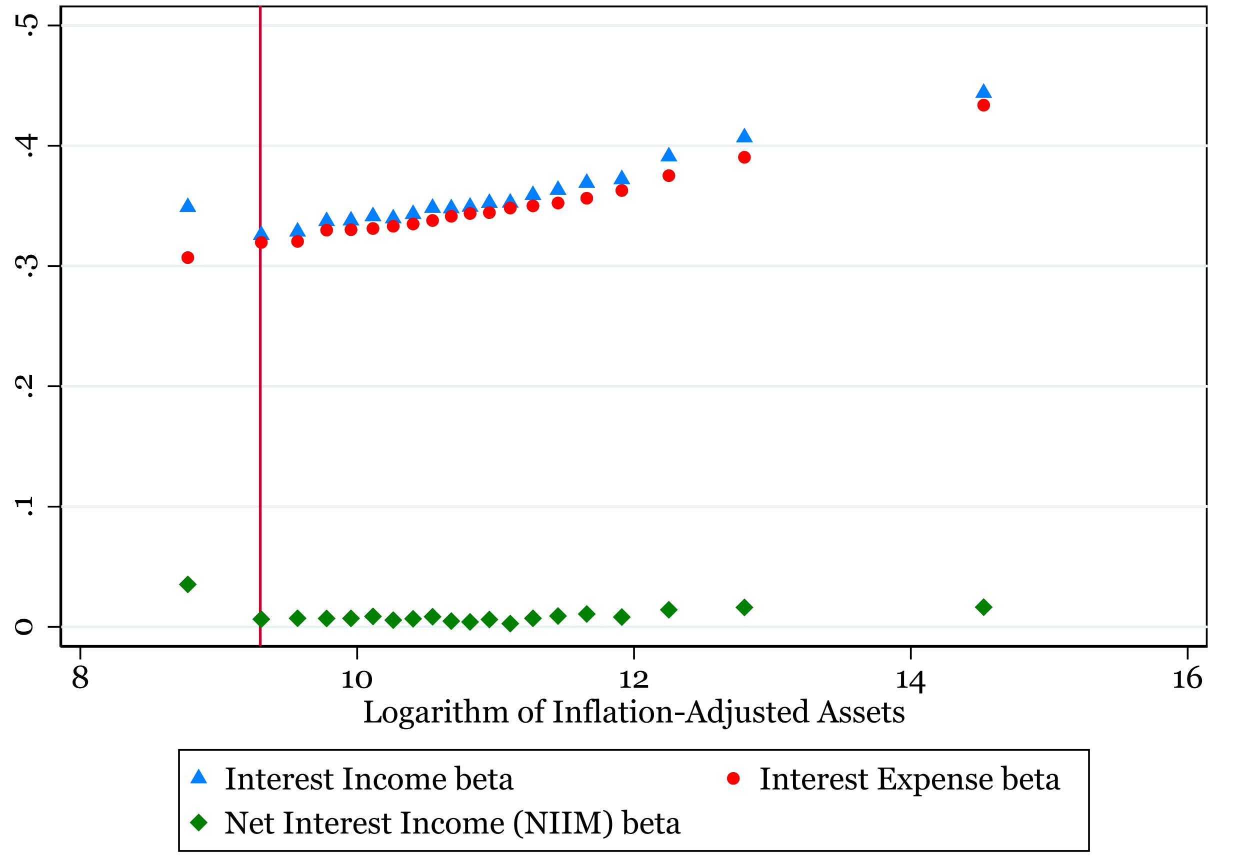

Figure 1: **Interest Betas by Logarithm of inflation-adjusted asset sizes** (Modified (Drechsler et al., 2021)). The figure shows the binned scatterplot of interest betas against the log of real assets. The line is at 9.3. Following Drechsler et al. (2021), The betas are determined by regressing the quarterly changes in each bank's interest expense rate or interest income rate against the three current and previous changes in the Fed funds rate. The interest betas are not winsorised. The sample period is 1984 to 2020.

results presented in Table 2 of Drechsler et al. (2021) for each quintile. The sample period is 1984Q1-2020Q4. Following Drechsler et al. (2021) the estimation only includes the US commercial banks with at least 60 observations in the sample period. The beta-on-beta regression is written as :

$$\beta_i^{Inc} = \alpha \ + \ \gamma\beta_i^{Exp} \ + \ \varepsilon_i \tag{2}$$

In the above equation, β_i^{Inc} and β_i^{Exp} represent the interest income beta and interest expense beta respectively of bank i. Equation 9 of Drechsler et al. (2021) is replicated to estimate the interest betas. Basically, the interest betas are estimated by regressing the interest expense rate or interest income rate on the federal funds rate with 3 lags. Columns

(1) and (2) of Table 3 show that for the aggregate banking sector, the interest sensitivity matching coefficient (γ) is around 0.796 and 0.949 (with Time FE). This implies that the aggregate banking sector performs interest sensitivity matching and their equity is insulated from interest rate shocks. Columns (6) and (7) of Table 3 report the matching coefficient (γ) is highest for large banks, represented by Quintile 5, at around 0.963 and 1.188 (with Time FE). However, Columns (3) and (4) show the matching coefficient (γ) is lowest for the small banks, represented by Quintile 1, at around 0.568 and 0.627 (with Time FE). This implies small banks in the bottom quintile are not performing interest sensitivity matching and are thus, exposed to interest rate risk. Table 3 shows that the matching coefficient sequentially increases from small banks to large banks. All results are highly statistically significant at the 1% level.

(Insert Table 3 about here)

Overall the results in Table 3 confirm that unlike the aggregate banking sector, small banks in the bottom quintile do not perform interest sensitivity matching. Figure 1 and Table 1 show that the interest sensitivity mismatch of small banks in the bottom quintile is primarily attributable to their interest expense beta being much lower than their interest income beta especially relative to the difference in interest betas for comparable banks. Small banks have a low-interest expense beta because of their funding structure. They have a very high average deposit ratio of 0.877 (as shown in Table 1) for the entire period. This implies that around 87% of their assets are funded by retail deposits. Drechsler et al. (2021) showed that the banks have a deposit franchise in the retail deposit market which enables banks to keep interest rates low and insensitive to market rates. Thus, being primarily funded by retail deposits enables small banks to keep a low-interest expense beta. Moreover, approximately on average 26.4% of their assets are funded by transaction deposits (as shown in Table 1) which is higher than any other groups of banks. Similarly, the paired t-test results in Table 2 show that these small banks have statistically significant higher transaction deposits than comparable banks and large banks. Transaction deposits are primarily demand deposits and some forms of savings deposits. Such transaction deposits are highly liquid and thus, banks charge higher deposit spreads[1] on these deposits. As a consequence, transaction deposit rates are very low and insensitive to the changes in the Fed funds rate. This results in lowering small banks' interest expense beta more than any other group of banks. The right panel in Figure 2 confirms a strong negative association between the transaction deposit ratio and interest expense beta. Overall, being primarily funded by retail deposits and having a relatively higher share of rate-insensitive liabilities in their liability structure than other groups of banks enables small banks to keep their interest expense beta lower than other groups.

Interest income beta is primarily influenced by the duration of assets or the proportion of securities and loans. Table 1 shows that small banks have a higher proportion of securities and a lower proportion of loans in their asset structure than other groups of banks. The left panel of Figure 3 shows that there is a negative relationship between the

[1]Deposit Spreads are calculated as the difference between the federal funds rate and deposit rates.

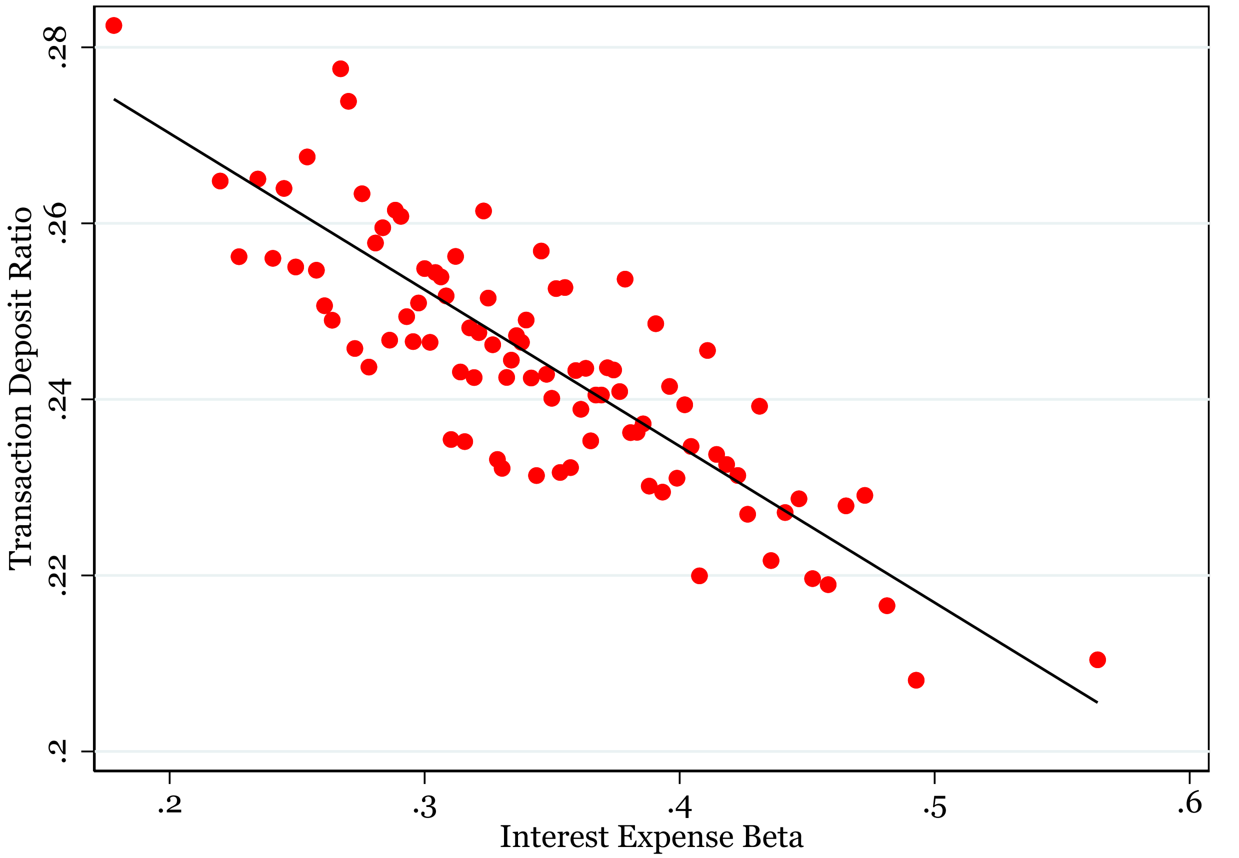

Figure 2: **Interest Expense Beta and Transaction Deposit Ratio**. Following Drechsler et al. (2021), The betas are determined by regressing the quarterly changes in each bank's interest expense rate or interest income rate against the three current and previous changes in the Fed funds rate. The transaction deposit ratio is calculated by dividing transaction deposits by assets. The interest expense beta is not winsorised. The sample period is 1984-2020.

proportion of securities and income beta. The right panel of Figure 3 shows that there is a positive association between the proportion of loans and income beta. This implies that banks with a higher proportion of securities and a lower proportion of loans in their asset structure would have lower income beta and vice-versa. However, small banks have a high income beta thus we can rule out the possibility that differences in the proportion of securities and loans are driving the high interest income beta.

Figure 4 and Table 1 show that small banks have the shortest maturity of assets relative to all other groups of banks. The average duration of assets for small banks is 2.883 years while for comparable banks it is 3.376 years and for large banks it is 4.062 years (as shown in Table 1). Similarly, the paired t-test results in Table 2 also show that compared to all other asset characteristics, the maturity of assets has the highest mean difference between small banks (Quintile

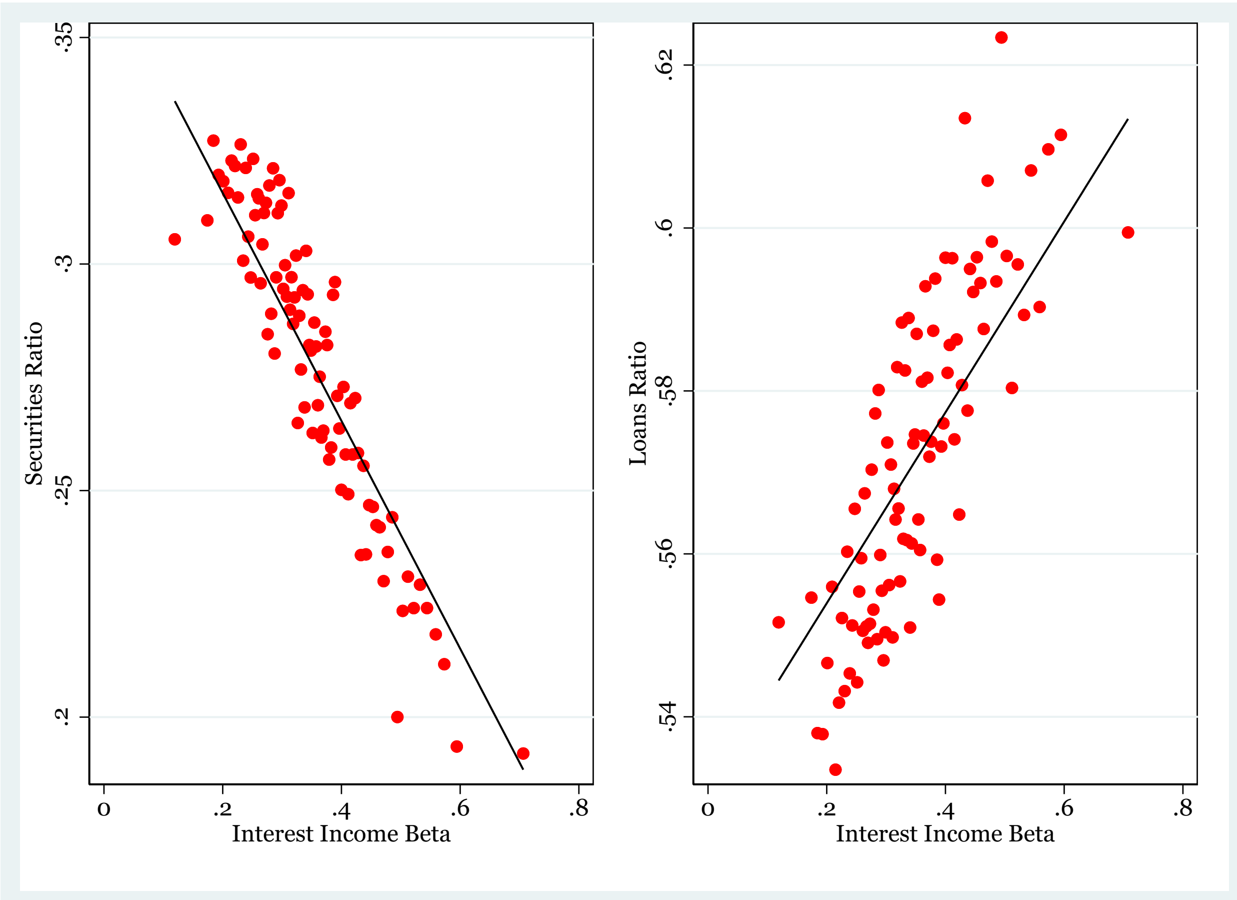

Figure 3: **Interest Income Beta and Securities Ratio (Left) and Interest Income Beta and Loans Ratio (Right)**. The figure shows a binned scatterplot of interest income beta, securities ratio and loan ratio. Following Drechsler et al. (2021), The betas are determined by regressing the quarterly changes in each bank's interest expense rate or interest income rate against the three current and previous changes in the Fed funds rate. The securities ratio and loan ratio are calculated by dividing securities by assets and loans by assets. The interest income beta is not winsorised. The sample period is 1984-2020.

1) and comparable banks (Quintile 2) and small banks (Quintile 1) and large banks (Quintile 5). This suggests that having a substantially shorter duration of assets accounts for most of the variations in the asset characteristics across the groups. The right panel of Figure 4 shows a strong negative association between interest income beta and maturity of assets. This implies banks with shorter duration of assets will have higher income beta. Therefore, the high income beta for small banks is primarily attributable to the shorter maturity of their assets.

The fact that small banks hold shorter-duration assets despite being predominantly funded by retail deposits contradicts the extensive banking literature, which suggests that banks extend more long-term credit as retail deposits

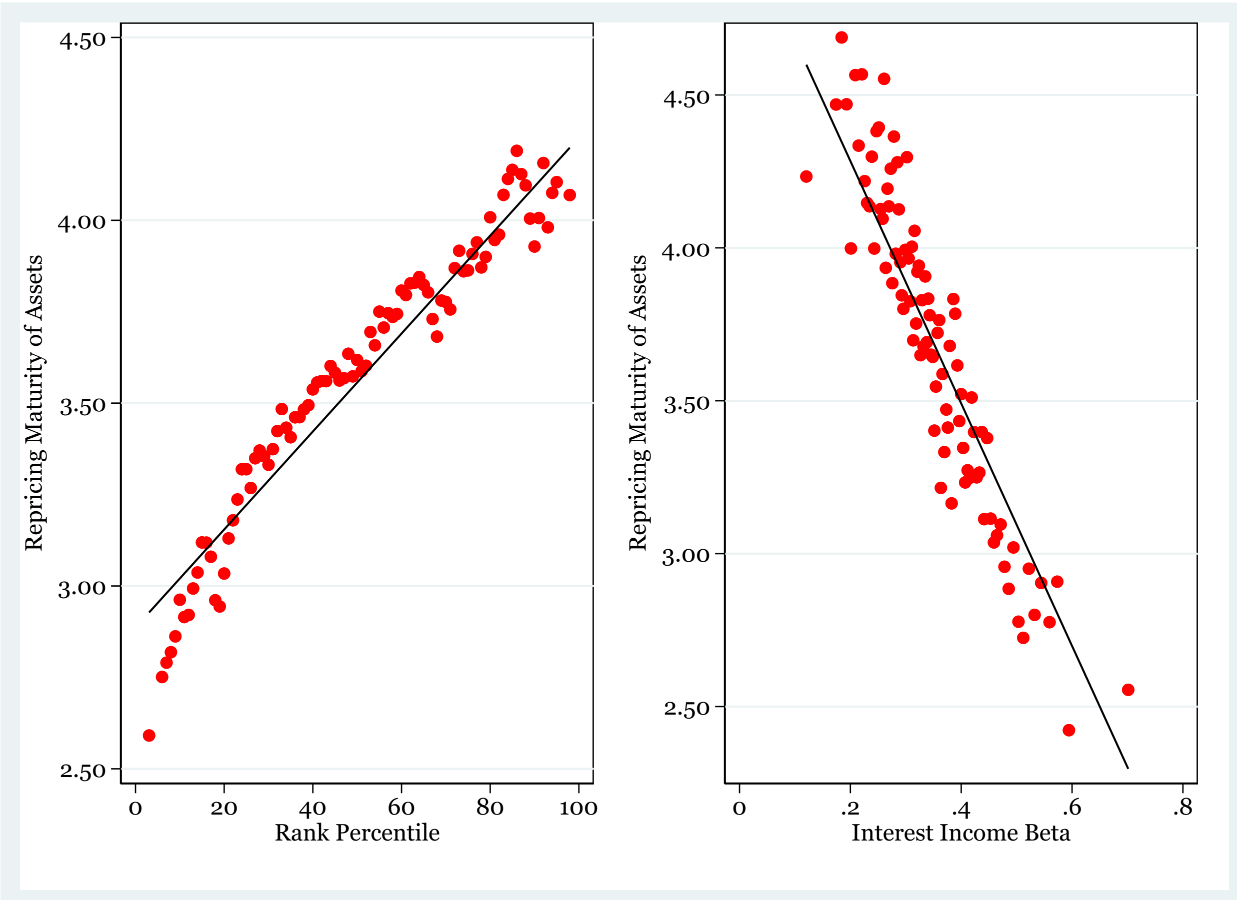

Figure 4: **Maturity of assets across banks (Left) and Interest Income beta and Maturity of assets (Right)**. The binned scatter plot shows the maturity of assets and interest income beta. Following Drechsler et al. (2021), The betas are determined by regressing the quarterly changes in each bank's interest expense rate or interest income rate against the three current and previous changes in the Fed funds rate. Following Drechsler et al. (2021), repricing maturity is calculated as the weighted average of bank loans, securities and short-term financial instruments. The interest income beta is not winsorised. The sample period is 1984-2020.

increase. For instance, Carletti et al. (2021) showed that an increase in deposit funding resulted in an increase in long-term credit extension by well-capitalised banks. These small banks have an average capital ratio of 0.111 for the entire period, which is much higher than any other group of banks (as shown in Table 1). Therefore, it is puzzling why small banks, despite being well-capitalised and primarily funded by retail deposits, are reluctant to hold longer-duration assets and thus expose themselves to interest rate risk. We show that this is due to small banks being primarily financed by runnable retail deposits and as a result, experiencing higher funding instability compared to other bank groups during stress periods. Thus, these small banks have relatively larger holdings of securities and have shorter duration assets in their asset structure to mitigate the liquidity risk exposure from runnable deposits during stress periods.

B. Funding Instability during Stress Periods

B.1. Cost of Financing during Stress Periods

We hypothesise that one of the possible channels through which the flightiness of deposits can affect banks' lending choices is by increasing their cost of financing during stress periods. In this section, we first document whether small banks' financing costs increase during stress periods.

(Insert Table 4 about here)

Table 4 shows the extent to which the percentage change in interest expense on deposits differs across bank groups during the stress periods. Bank FEs are included to control unobserved heterogeneity across banks. The results show that in quiet times there is a statistically insignificant difference in the cost of financing across different bank groups. However, during stress periods the interest expense for small banks in the bottom quintile (i.e., Quintile 1) is much higher compared to all the other groups. The interest expense for these small banks increases by an average rate of approximately 3.474 percentage points (1.227+2.247) during the stress periods. The result is statistically significant at the 10% level. The result is also economically significant because the average rate of increase in interest expense for small banks in normal times is only 1.58 pp. For all the other groups of banks, the change in the cost of financing is statistically insignificant during stress periods implying the stress period does not have a statistically significant effect on the cost of financing of these bank groups relative to the comparable group of banks i.e., quintile 2 banks. Thus, for the other groups of banks, the main effect is the coefficient of the stress period. All in all, our results show that the cost of financing for small banks increases disproportionately during the stress periods.

B.2. Deposit Growth Rates in Stress Periods

Table 5 shows the rate of change in deposit growth rates in quiet times and stress periods across different bank groups. Column (1) of Table 5 shows the log changes in deposits and Column (2) of Table 5 shows the percentage change in deposits. The results of log changes and level changes are very similar.

(Insert Table 5 about here)

Here, the stress period is defined as a year before to a year after the crisis (i.e., t = -1 to t= +1). The results show that during quiet times, small banks in the bottom quintile (i.e., Quintile 1) attract more deposits compared to the comparable group of banks. However, this result reverses during stress periods. The stress period has a differential effect on small banks' deposit growth rates. Specifically, the stress period has a detrimental effect on small banks' deposit growth rates while having a favourable impact on the other bank groups' deposit growth rates. During stress periods, only small banks experience a decline in their deposit growth rate relative to the omitted group i.e., the comparable banks while the average deposit growth rate increases for all the other groups of banks compared to the comparable group. The results show that during stress periods small banks experience an average rate of decline in their deposits of approximately 0.195% in log terms (as shown in Column (1)) and 0.13 pp in percentage terms (as shown in Column (2)) relative to the comparable banks in quintile 2. The result is highly statistically significant at the 1% level. The results also show that during stress periods when small banks experience a relative decline in their deposit growth rates, large banks in quintile 4 and quintile 5 experience a substantial increase in their relative deposit growth rates by approximately 0.139% and 0.166% in log terms (as shown in Column (1)) respectively and 0.143 pp and 0.192 pp in percentage terms (as shown in Column (2)) respectively. The log results are all highly statistically significant at the 5% level and the percentage change results are all highly statistically significant at the 1% level. Thus, the results show a sequential increase in the deposit growth rates during stress periods as we move from small banks to large banks.

Our results are consistent with the findings of Caglio et al. (2023). The authors showed that during the 2023 regional banking crisis deposit growth rates of large banks increased much faster compared to small and regional banks. Their results highlighted the flight to safety mechanisms during crisis periods. Overall, our results show that stress periods affect the deposit growth rates of these small banks differently than other groups of banks exposing these banks to funding instability in this period. Although the overall deposit growth rate results in Column (2) of Table 5 indicate a positive impact of the stress period on small banks, their overall deposit growth rate remains significantly lower compared to other bank groups. This suggests small banks' deposits grew at a much slower rate relative to other banks which implies small banks are facing funding constraints during stress periods. All in all, the results imply a relative reallocation of deposits from small banks to large banks during stress periods. Thus, small banks' deposits are relatively more runnable than other banks which exposes them to heightened liquidity risk during stress periods.

These results confirm our hypothesis and together with the previous result, the results suggest that in stress periods small banks experience a decline in their average deposit growth rates relative to the comparable group of banks exposing them to intense liquidity stress during the stress periods. These small banks also experience an increase in their cost of financing during the stress periods, possibly indicating that they are offering higher interest rates on deposits to attract or retain their depositors. Collectively, the results provide evidence that small banks in the bottom quintile experience funding instability during stress periods.

B.3. Deposit Variability in Stress Periods

Deposit variability is an important determinant of banks' lending choices, portfolio choices, asset mix and banks' holding of excess cash and reserves (Kane and Malkiel, 1965; Kaufman, 1972). Kaufman (1972) showed that bank size is one of the predominant factors that affect deposit variability. The literature is divided on whether small or large banks have higher deposit variability. Chairnoff (1967) showed that large banks have lower deposit variability than small banks. This could be because there is a higher probability for deposit flows to offset each other at large banks than at small banks. The author also showed that deposit variability is sensitive to the proportion of time deposits in banks' liability structure. A higher proportion of time deposits reduces deposit variability. This is important for small banks as the higher proportion of time deposits enables them to lower their deposit variability compared to a scenario if they did not have such a high proportion of time deposits. By contrast, Gramley (1962) cited in Kaufman (1972) reported evidence of large banks experiencing higher deposit variability while small banks experienced lower deposit variability. In an attempt to resolve the debate Kaufman (1972) showed empirically using a sample of 142 banks for the sample period 1967 to 1969 that large banks experience lower relative deposit variability than small banks if deposit variability is measured for a longer period i.e., weekly or monthly. However, large banks experience a higher relative deposit variability if daily deposit variability is considered. Dewald and Dreese (1970) took a different approach by focusing on random deposit variability rather than aggregate deposit variability as a predictor of the borrowings from the Federal Reserve. Their rationale was banks could hedge against expected deposit variability by adjusting their asset portfolios such as modifying the asset structure and maturities. However, unexpected or random deposit variability is harder for banks to hedge. As a result, it is the random deposit variability that predicts borrowings of a bank from the Fed and excess reserve and cash holdings.

The literature on deposit variability is dated and there have been few recent contributions to the literature. However, we use deposit variability as a relevant measure because deposit variability indicates the stability and predictability of the deposit flows of a bank. Building on previous literature on deposit variability, we present an alternative approach to conceptualising when deposit variability becomes relevant. We propose that deposit variability in stress periods is more important for a bank's asset portfolio decisions such as planning asset structure and tailoring asset maturities. This is because in normal times most of the deposit flows are offsetting in nature. It is much harder to offset deposit variability or attract deposits during stress periods, especially if the banking sector itself is in distress. For instance, Acharya and Mora (2015) showed that at the beginning of the 2007-09 global financial crisis, deposit inflows reduced in the banking sector. As a result, banks had to substantially increase their interest rates to attract deposits resulting in an increased cost of financing during the crisis period. Thus, we hypothesize that if a bank expects higher deposit fluctuations during stress periods when the cost of funding is already high, then the bank will take a more defensive stance by holding a higher proportion of cash, liquid securities and assets with shorter maturities.

Construction of Deposit Variability measure

Extending on earlier literature by (Chairnoff, 1967; Murphy, 1968; Dewald and Dreese, 1970; Streit et al., 2016), we construct deposit variability as the coefficient of variation of bank i. Deposit variability is calculated as the standard deviation of the changes in the bank i's logarithm-transformed deposits scaled by the mean of the bank i's log changes in deposits. Deposit variability is a time-invariant measure. Thus, we use fixed window summaries to estimate deposit variability for bank i for window j. The deposit variability (DV) formula can be written as:

$$DV_{i,j} = \frac{\sigma\left(Log\left(\Delta Dep\right)\right)_{i,j}}{\mu\left(Log\left(\Delta Dep\right)\right)_{i,j}} \tag{3}$$

In the above equation, $DV_{i,j}$ indicates the deposit variability of a bank i for the window j. $\sigma\left(Log\left(\Delta Dep\right)\right)_{i,j}$ indicates the standard deviation of log changes in deposits of bank i for window j. $\mu\left(Log\left(\Delta Dep\right)\right)_{i,j}$ indicates the mean of log changes in deposits of bank i for window j. We select the window size as 11 quarters. Although the results are almost similar across different window sizes, including short-range windows (i.e., 7, 8), medium-range windows (i.e., 10, 15), and long-range windows (i.e., 24, 25, 30, 32).

Deposit Variability in Stress Periods

We expect the deposit variability of small banks in stress periods to be higher than that of other groups of banks. In this section, first, we show graphically that deposit variability differs across banks of different sizes and then present the regression results for deposit variability in quiet times and stress periods across banks in different groups.

Figure 5 plots the deposit variability index across banks' rank percentiles for quiet times (right) and stress periods (left). For this graph, bins are constructed by grouping banks into 100 bins by rank percentile. The right panel of the graph shows the graphical representation of the distribution of the deposit variability index across banks during quiet times. The left panel of the graph shows the graphical representation of the distribution of deposit variability across banks during stress periods. We find that small banks have the lowest deposit variability during quiet times relative to all the other banks. This implies that small banks have lower fluctuations in their deposit base and thus have a stable funding base during quiet times. By contrast, large banks experience higher deposit variability during quiet times which could be driven by higher reliance on short-term wholesale financing. However, the scenario reverses during stress periods. Despite being primarily funded by retail deposits, small banks experience the highest deposit variability

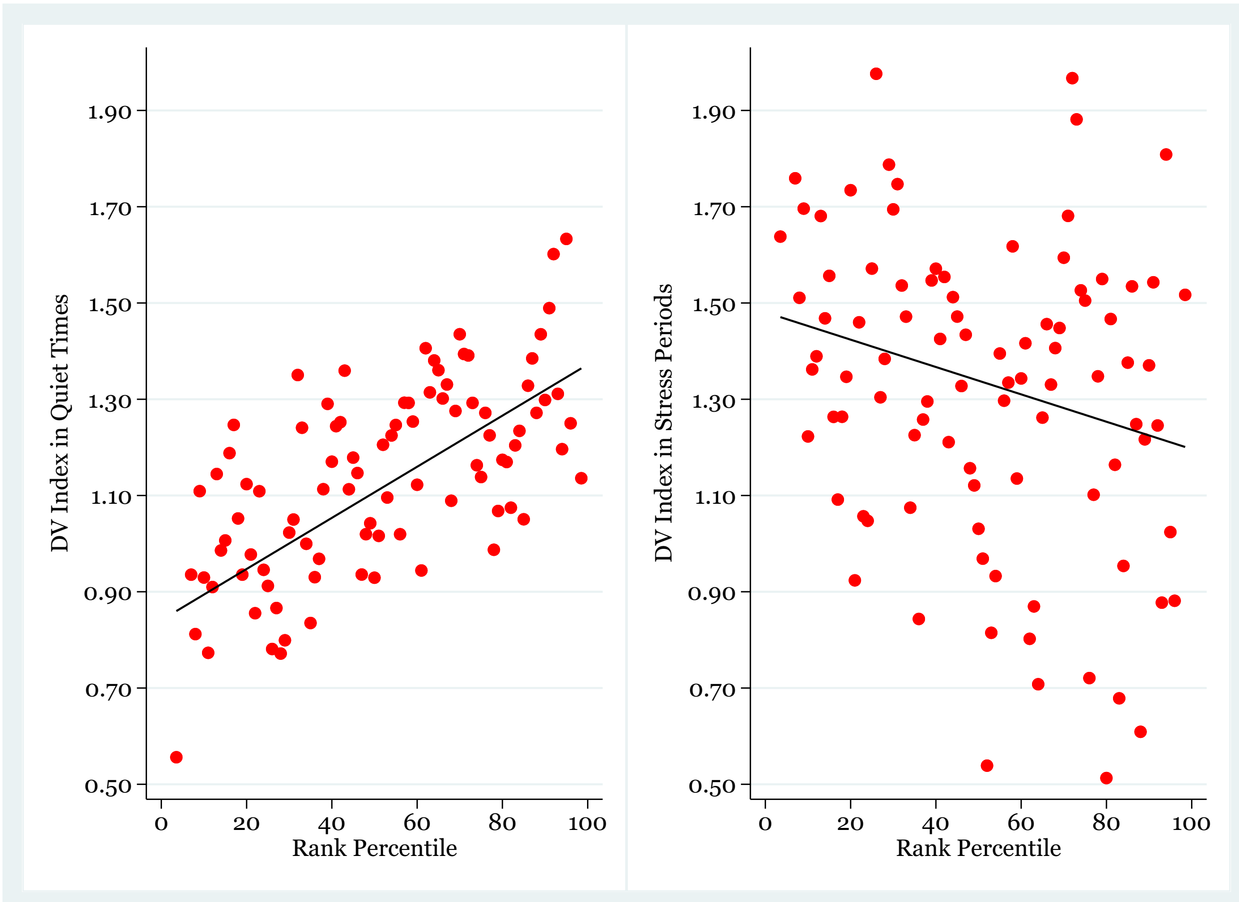

Figure 5: **Deposit Variability (DV) Index across Banks in Quiet Times (left) and Stress Periods (right)**. For this graph, bins are constructed by grouping banks into 100 bins by rank percentile. The deposit variability index for only this graph is winsorised at 1st and 95th percentiles to mitigate the impact of outliers.

in stress periods. This suggests small banks experience higher fluctuations in their deposits during stress periods. This increased funding instability exposes these small banks to heightened liquidity risk during stress periods when market liquidity is already low. Generally, this result also shows that even though retail deposits are sticky, the stickiness of retail deposits varies based on bank size.

Equation 1 is estimated again with the deposit variability index as the outcome variable. The focus of this section is to investigate the impact of the stress periods on the deposit variability index across bank groups. Since deposit variability is inherently a time-invariant measure, we have used the fixed window summaries to examine the impact of the stress periods on deposit variability across bank groups. The window size used here is 11 quarters. Table 6 shows the deposit variability index across banks during quiet times and stress periods. Here, the stress period is defined as a year before to a year after the crisis (i.e., t = -1 to t= +1). The outcome variable is the deposit variability index constructed based on the formula specified in Equation 3. The results indicate that during quiet times, the deposit variability index of small banks is statistically insignificant. Only large banks in quintiles 4 and 5 face a higher deposit variability during quiet times. This could be because large banks have a substantial portion of short-term wholesale financing in their liability structure. The results reverse during stress periods. The results show that small banks have positive deposit variability during stress periods when all the other banks have negative deposit variability relative to the comparable group. The coefficient for deposit variability during stress periods for small banks is statistically significant at the 10% level and the coefficient is 0.161. The overall effect of the stress period is insignificant which implies the deposit variability of the comparable banks in quintile 2 is statistically insignificant during stress periods. The coefficient for all the other groups of banks is either statistically significant and negative or statistically insignificant. This implies during stress periods when all banks lower their deposit variability index relative to the comparable banks, small banks experience an increase in their relative deposit variability to the comparable banks. This suggests the stress period differentially impacts these small banks compared to the rest of the bank groups. The results show a sequential decline in the deposit variability index as we move from small banks to large banks.

(Insert Table 6 about here)

Collectively, the results suggest that small banks experience the highest increase in their relative deposit variability during stress periods when all banks lower their deposit variability index relative to comparable banks. The results also complement our previous findings in Table 5 that showed relative reallocation of deposits from small banks to large banks during stress periods. All in all, the results in Tables 4 - 6 suggest that small banks experience higher funding stress than any other bank groups during stress periods.

B.4. Deposit Flows for different deposit products in stress periods

In this section, we look into the bank run effects in different sub-categories of deposits. The rationale is twofold : (a) if the bank run is on a deposit product that is the primary source of funding for a bank, it would have a more significant impact on the bank's lending choices than if the run were to be on a minor funding source. (b) Recently, Supera (2021) established that long-term low interest rates led to a decline in banks' supply of time deposits, which in turn resulted in an equivalent reduction in banks' provision of business loans. This occurred because banks endogenously match assets and deposits based on similar liquidity exposures and interest sensitivity to the Fed funds rate to mitigate interest rate risk and liquidity risk. Therefore, a run on interest-bearing deposits, which is more illiquid and rate-sensitive, will have a more pronounced impact on banks' ability to hold longer-duration assets. We analyse two subcategories of deposits, namely interest-bearing deposits and non-interest-bearing deposits, as proxied by demand deposits. Interest-bearing deposits represent the major source of funding for all bank groups. It comprises of at least 60% of the total funding for all bank groups (as shown in Table 1). Interest-bearing deposits are the sum of time deposits and some forms of saving deposits. They are reported in Call Reports as RCON2350 up until 1995 and from 2004 onwards. The gaps are calculated as the sum of transaction deposits and non-transaction deposits excluding the demand deposits [2]. These interest-bearing deposits are much less liquid than demand deposits. Demand deposits are reported in RCON2210 in the Call Reports.

Table 7 shows the bank run effects across various deposit products. The results in Table 7 suggest that the bank run is primarily on interest-bearing deposits. Columns (1) and (2) of Table 7 show that during quiet times small banks attract more interest-bearing deposits relative to the comparable group of banks. However, this result reverses during stress periods. In stress periods, when the average interest-bearing deposit growth rate increases for all the other groups of banks relative to the comparable group, only small banks' deposit growth rate declines relative to the comparable group. The results show that in stress periods small banks experience an average rate of decline in their interest-bearing deposits of approximately 0.141 pp in percentage terms and 0.128% in log terms relative to the comparable banks in quintile 2 in stress periods. The result is highly statistically significant at the 1% level. The results also show that during stress periods when small banks experience a relative decline in their interest-bearing deposit growth rates, large banks in quintile 4 and quintile 5 experience an increase in their relative deposit growth rates. The results indicate a progressive increase in the interest-bearing deposit growth rates as we move from small banks to large banks. The estimates indicate that during stress periods large banks in quintile 4 and quintile 5 experienced an increase in their deposit growth rates by approximately 0.291 pp and 0.303 pp in percentage terms respectively and 0.283% and 0.298% in log terms. The results are all highly statistically significant at the 1% level. The results suggest a relative reallocation of interest-bearing deposits from small banks to large banks during stress periods. The run on interest-bearing deposits is not surprising. Martin et al. (2018) showed that interest-bearing deposits in the form of time deposits are more prone to bank runs.

These interest-bearing deposits comprise 69% of the total funding of small banks in the bottom quintile (as shown in Table 1). Thus, a bank run on interest-bearing deposits will substantially deteriorate small banks' liquidity position during stress periods exposing these banks to liquidity risk and solvency risk. Columns (3) and (4) show that during stress periods the demand deposits growth rates of these small banks are insignificant in percentage terms but statistically significant in log terms. The results show that in stress periods all bank groups experience a decline in their demand deposit growth rate. Thus, stress periods uniformly impact the demand deposit growth rates of all bank groups leading to a decline in their demand deposit growth rate relative to the comparable group of banks.

(Insert Table 7 about here)

[2]More details in DSS Data Dictionary on NYU Stern Website

Overall, our results show that stress periods affect the interest-bearing deposit growth rates of these small banks differently than other groups of banks exposing these banks to higher funding instability in this period. Since the interest-bearing deposits are the primary funding source of these banks, a relative reallocation of these deposits severely deteriorates their liquidity position and hence their lending capacity.

B.5. Asset Side Drawdowns

So far, we have shown that small banks face a drawdown of their retail deposits during bank runs. How do small banks respond to these deposit outflows? One possible scenario is that they replace retail deposits with other funding sources. In such a case the asset size of these banks should remain unchanged during the stress periods. In this scenario, these banks would have then essentially solved their funding instability and hence the deposit withdrawals in the stress periods should not impact their asset structure choices. However, if small banks are unable to attract other funding sources and have to liquidate their securities to preserve liquidity then their assets are being depleted at the same time when their deposits are being withdrawn resulting in balance sheet contraction. In such a case, bank runs in stress periods would have a more significant impact on their asset structure choices.

To formally examine the asset growth rates of banks during the stress periods we estimate Equation 1 using asset growth rate as an outcome variable. The results include bank FE. The results for percentage and log changes are very similar. The results show that during quiet times, small banks in the bottom quintile (i.e., quintile 1) increase their asset base more than the comparable group of banks. Similar to the deposit growth rates results in Table 5, the asset growth rates across bank groups change during stress periods. In stress periods, only small banks have a lower asset growth rate relative to the comparable banks. In stress periods, when the average asset growth rate increases for all the other groups of banks compared to the comparable group, only small banks' asset growth rate declines relative to the comparable group. Thus, stress periods affect the asset growth rates of these small banks differently than other groups of banks. The results in columns (1) and (2) of Table 8 show that in stress periods small banks experience an average rate of decline in their assets by approximately 0.08 pp and 0.07 % relative to the comparable banks in the stress periods. The result is statistically significant at the 10% level. The results also show that during stress periods when small banks experience a relative decline in their asset growth rates, large banks in quintile 4 and quintile 5 experience an increase in their relative asset growth rates. The estimates indicate that during stress periods large banks in quintile 4 and quintile 5 experienced an increase in their asset growth rates by approximately 0.16 pp and 0.24 pp in percentage terms and 0.159% and 0.241% in log terms respectively. The results are all highly statistically significant at the 1% level. Thus, during stress periods large banks expand both their asset base and deposit base (as shown in Table 5). Essentially, during stress periods large banks expand their balance sheets when small banks contract their balance sheets.

To elaborate further we find small banks liquidate their securities to improve their liquidity position in stress periods. Columns (3) and (4) of Table 8 show that in quiet times small banks acquire more securities relative to the comparable banks. However, in stress periods when small banks are exposed to heightened funding pressures, they sell securities to preserve liquidity. The overall effect of the stress periods on the growth rates of securities is approximately -2.395 pp (-1.021-1.374) in percentage terms and -1.57% (-0.626-0.9435) in log terms. The result is highly statistically significant at the 1% level. For all the other groups of banks, the growth rates of securities are statistically insignificant during stress periods. Thus, for the other groups of banks, the main effect is captured by the coefficient of the stress period. Overall, the results indicate that small banks liquidate securities to meet their liquidity needs when experiencing heightened funding pressure during stress periods.

(Insert Table 8 about here)

Overall, the results indicate that small banks find it difficult to replace retail deposits with other funding sources during stress periods. This reinforces that small banks have runnable deposits and face higher funding instability in stress periods. The results indicate that during the stress period when small banks' deposits are being withdrawn, their assets also deplete, while all the other groups of banks simultaneously expand their balance sheets. In an attempt to ease their funding stress, small banks liquidate their securities resulting in balance sheet contraction during stress periods which exposes them to higher solvency risk. Stress periods disproportionately affect both sides of these small banks' balance sheets leading to balance sheet contraction. Thus, heightened funding stress during stress periods exposes these small banks simultaneously to liquidity and solvency risk. Possibly, this is one of the reasons why small banks fail more often during bank crises.

C. Deposit Variability and Repricing Maturity of Assets

In this section, we establish the relationship between deposit variability in stress periods and asset duration. Figure 6 shows the binned scatter plots of logarithm-transformed deposit variability in stress periods and logarithm-transformed maturity of assets. The binned scatterplot classifies banks into 100 bins by the explanatory variable i.e. log of maturity of assets and then plots the log deposit variability (DV) in stress periods for each bin. Figure 6 shows a negative relationship between the maturity of assets and deposit variability in stress periods. This suggests that banks that experience higher deposit variability in stress periods will have shorter-duration assets than other groups of banks and vice-versa.

Bank's funding choices and lending choices are endogenous. To overcome these endogeneity concerns, we use an instrumental variables (IV) estimation to establish the relationship between deposit variability in stress periods and asset duration. We use deposit market power (HHI) as an instrument for estimating the impact of deposit variability

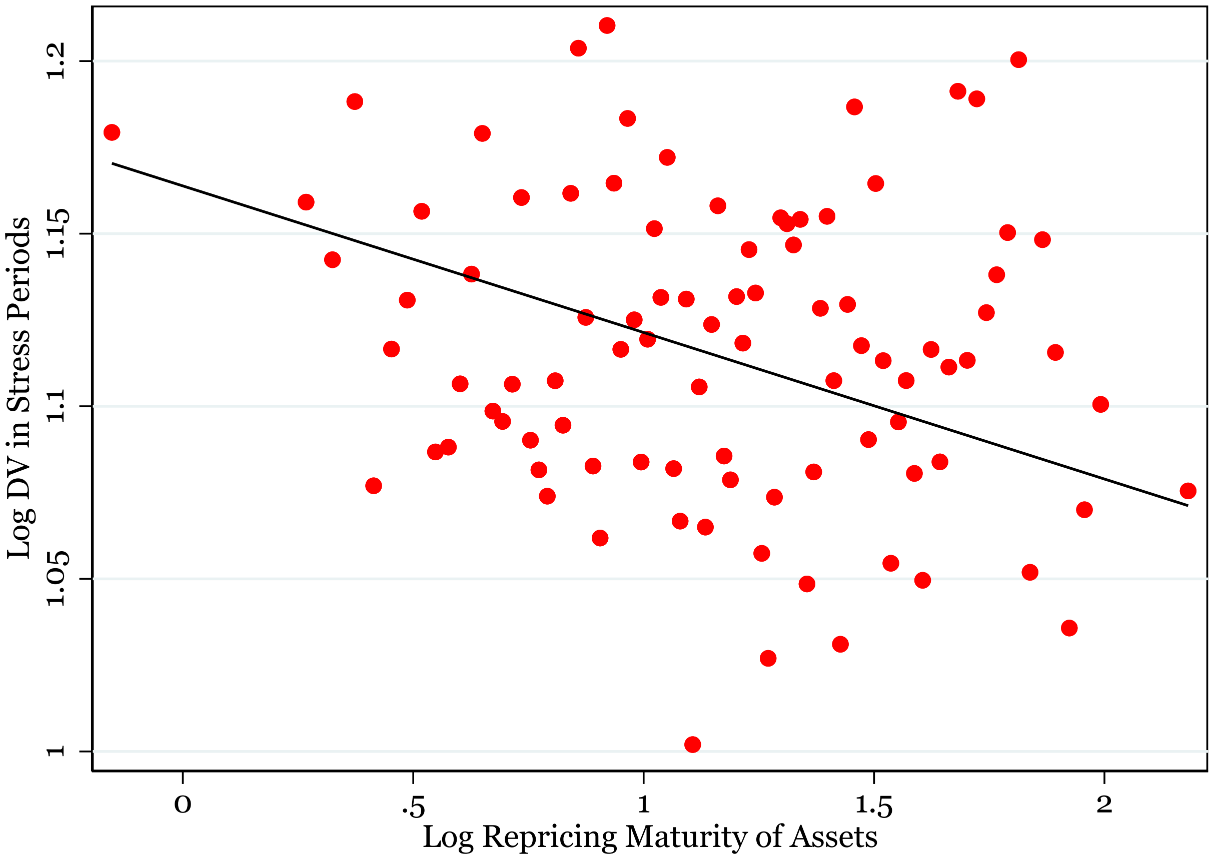

Figure 6: **Log Deposit Variability (DV) in Stress Periods and Log Repricing Maturity of Assets.** The binned scatterplot classifies banks into 100 bins by the log of maturity of assets and then plots the log deposit variability (DV) in stress periods for each bin. Following Drechsler et al. (2021), repricing maturity is calculated as the weighted average of bank loans, securities and short-term financial instruments. Log Deposit Variability (DV) in Stress Periods is calculated by taking the log of deposit variability in stress periods.

in stress periods on the repricing maturity of assets. Similar to Drechsler et al. (2021), repricing maturity is used as a proxy for asset duration. Following Drechsler et al. (2021), repricing maturity is calculated as the weighted average of bank loans, securities and other short-term financial instruments such as cash, Fed funds sold, and securities under repurchase agreements. We exploit the geographic variation in banks' market power as a source of variation in deposit variability. Following Drechsler et al. (2021), we construct HHI at the bank level as an average of the market power of a bank branch in each county. The rationale here is that if a bank has a high deposit market power then it will have higher funding stability and hence lower deposit variability in stress periods (relevance assumption). However, individual banks cannot directly influence their deposit market power (exclusion restriction). Even though IV estimation is a robust method to mitigate endogeneity concerns, we do acknowledge the limitations of our instrument to satisfy exclusion restriction in certain scenarios. We use two-stage least squares regression to estimate the impact of deposit variability in stress periods on the maturity of assets. In the first stage, we regress deposit variability in stress periods on deposit market power. In the second stage, we regress the repricing maturity of assets on the instrumented deposit variability in stress periods. The two-stage regression for repricing maturity of assets can be written as follows :

$$DV_{Stress} = \gamma HHI_i + u_i \tag{4}$$

$$D_N^A = \hat{DV_{Stress}} + u_i \tag{5}$$

In the above equation, i denotes each bank. DV_{Stress} indicates deposit variability in stress periods. The deposit variability in stress periods is calculated as deposit variability in Equation 3 in stress periods. HHI_i indicates deposit market power. D_N^A indicates the repricing maturity of assets. $\hat{DV_{Stress}}$ represents the predicted value of deposit variability in stress periods from the first stage regression.

The results in Table 9 are consistent with our hypotheses. The first-stage estimates show that the market power is negatively associated with the deposit variability in stress periods. The result is highly statistically significant at the 1% level. This is intuitive because banks with low deposit market power have lower funding stability (Li et al., 2023). The lower funding stability suggests higher deposit variability in stress periods. The second stage shows the regression results of the repricing maturity of assets on instrumented deposit variability in stress periods. The instrumented deposit variability in stress periods is negative and highly statistically significant at the 1% level. This implies an increase in deposit variability in stress periods results in lowering the duration of banks' assets.

(Insert Table 9 about here)

Collectively, our results suggest that small banks experience relative reallocation of deposits during stress periods. We also show that only for small banks deposit variability increases in stress periods. These results suggest that stress periods have a differential effect on these small banks compared to other groups of banks. In an attempt to retain their depositors and lower deposit volatility, small banks respond by increasing their interest rates on deposits. As a consequence, their cost of financing increases during the stress periods. All in all, these results show that small banks' deposits are runnable and thus it exposes them to heightened liquidity risk during stress periods. We also show that small banks liquidate their securities to improve their liquidity position in stress periods. As a result, their asset side depletes when their deposits are being withdrawn leading to a balance sheet contraction during stress periods. To mitigate the anticipated bank-run risk and solvency risk during stress periods, small banks shorten the duration of their assets and increase their short-term asset holdings to preserve liquidity. This, in turn, causes interest income beta to rise, resulting in interest sensitivity mismatch.

D. Additional Tests - Reciprocal Deposits

We further test our hypothesis using a recent financial innovation i.e., reciprocal deposits. In the Code of Federal Regulations, reciprocal deposits is defined as "deposits received by an agent institution through a deposit placement network with the same maturity (if any) and in the same aggregate amount as covered deposits placed by the agent institution in other network member banks." (Electronic Code of Federal Regulations, 2024). Banks on the network split large deposits into smaller amounts within the deposit insurance limit of $250,000 and place them with participating banks on the network. In this way, the banks in the network insure a part of each other's large deposits and remain within the deposit insurance limit (Kim et al., 2024). Thus, the depositors of the banks on the network are able to obtain explicit deposit insurance for their entire deposit (Kim et al., 2024).

The reciprocal deposits became popular following the FDIC ruling in 2018 (Kim et al., 2024). In 2018, under Section 202 of the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA), the FDIC exempted certain reciprocal deposits within a general cap [3] from being classified as brokered deposits. Before this FDIC ruling, reciprocal deposits were classified as brokered deposits which are subjected to higher deposit insurance premiums and thus were not a popular source of financing for banks. This rule made reciprocal deposits a cheaper and more attractive source of financing for banks (Kim et al., 2024). Kim et al. (2024) is one of the first papers to document the increased usage and significance of reciprocal deposits following the 2018 FDIC ruling. The authors showed that following the FDIC 2018 ruling, the annual growth rate of the reciprocal deposits increased from 9% during 2011-2017 to approximately 20% during 2018-2022. During the period 2011-2018, only 20% of the banks were on the deposit placement network, following the FDIC ruling it increased to 32% by the end of 2022. The authors also documented that reciprocal deposits are mainly used by small and medium-sized banks rather than large banks with mid-sized banks being the largest users of the reciprocal deposit network. The authors showed that during the 2023 Silicon Valley Bank (SVB) crisis, banks on the network were able to attract more insured deposits and also retain their deposit base more than the non-network banks throughout 2023. Thus, banks on the network were able to effectively reduce their bank-run risk during the regional bank crisis in 2023. Drawing on the insights from Kim et al. (2024), I hypothesise that since banks on the network can mitigate bank run risk during a crisis then small banks on the reciprocal deposit network should be able to perform interest sensitivity matching.

The FDIC Ruling came into effect in July 2018, so we focus on the period 2019Q1 to 2023Q4 for identifying the banks on the reciprocal deposit network and their interest risk exposures. I use Call Reports data to identify whether the

[3] More details on the FDIC Ruling in this FDIC Report - Federal Deposit Insurance Corporation (2019)

banks are participating in the reciprocal deposit network. Following Kim et al. (2024), I construct reciprocal deposit series at the bank-quarter level as a total of RCONJH83 (Total Reciprocal Deposits) and RCONG803 (Reciprocal Brokered Deposits). I use an indicator variable to identify if the bank is on the reciprocal deposit network. Following Kim et al. (2024), I codify the indicator variable as 1 implying the bank is on the network if it has a positive reciprocal deposit balance and 0 implying the bank is not on the network if the balance of the reciprocal deposit is 0 in any quarter.

Table 10 shows the interest sensitivity matching results for the network and non-network banks for the period 2019Q1 to 2023Q4. The even number of columns represents the banks on the reciprocal deposit network for that bank group. The small banks are banks in Quintile 1 and large banks are banks in Quintile 5. The results in Table 10 report the interest risk exposures of non-network banks and network banks in each sub-sample. All the results are highly statistically significant at the 1% level. The results are also reported with interest betas adjusted with time-fixed effects (FE). Columns (1) and (2) of Table 10 report that for the aggregate banking sector, banks on the network have a higher matching coefficient than banks not on the network. This implies banks on the network are exposed to lower interest rate risk than banks not on the network. This result is contradictory to the findings of Kim et al. (2024). The difference in results arises because of the difference in interest rate risk measures used. Kim et al. (2024) used maturity gap as a measure of interest rate risk. We follow the new DSS Paradigm and use interest sensitivity matching as a measure of interest risk exposure. In the new DSS paradigm, the duration gap does not expose banks to interest rate risk, in fact, it hedges it. Columns (3) and (4) show the regression results for interest betas adjusted with time FE. The matching coefficient decreases to 0.513 after the inclusion of time FE for the full sample of banks that are not on the network. However, Column (4) shows that the matching coefficient for the full sample of banks that are on the network increases to 0.691 even after the inclusion of time FE. This implies network banks in general have lower interest rate risk exposure than non-network banks. Column (5) indicates that non-network small banks do not perform interest sensitivity matching since they have a very low matching coefficient at 0.605 which is much lower than the aggregate banking sector (as shown in Column 1). However, Column (6) shows that small banks on the reciprocal deposit network perform interest sensitivity matching and have a very high matching coefficient of 0.957. Columns (7) and (8) show the results with interest betas that are adjusted with time FE. Even after the inclusion of the time FE, small banks on the network have a higher matching coefficient than small banks that are not on the network. This confirms our hypothesis that small banks on the network face lower bank-run risk and hence, can perform interest sensitivity matching. Columns (9) and (10) show that large banks have a very high matching coefficient. The matching coefficient for large banks on the network increases to 1.00. Column (11) and (12) shows the results with interest betas that are adjusted with time FE. After the inclusion of time FE, the matching coefficient for large banks on the network is lower than non-network large banks. However, even after the inclusion of time FE both non-network and network large banks have a high matching coefficient of 0.844 and 0.788 implying that both these groups perform interest sensitivity matching. For large banks, the difference in the matching coefficient for network and non-network banks is relatively small and after the inclusion of Time FE the network banks have a lower matching coefficient than non-network banks. This further shows that since large banks do not face the friction of higher bank run risk during stress periods, being on the reciprocal deposit network does not affect their ability to perform interest sensitivity matching.

(Insert Table 10 about here)

I also perform a placebo test to check the robustness of the above result. I check whether there is any difference in interest sensitivity matching between the network and non-network banks before the FDIC 2018 ruling. The rationale here is to show that banks identified as network banks in the post-FDIC 2018 ruling period did not have much difference in their interest sensitivity matching before joining the network. Since interest betas are time-invariant, we re-estimate the interest betas for the period 1984-2017Q4. We select the period 2012-2017 as the pre-FDIC 2018 ruling period. In this period, reciprocal deposits had to be classified as brokered deposits which attracted higher insurance premiums and hence were not much used by banks (Kim et al., 2024). We expect the difference in the matching coefficient between network and non-network banks to be negligible in the period 2012-2017.

(Insert Table 11 about here)

Post 2019, network and non-network banks are defined as banks with a reciprocal deposit for any given quarter. To identify these network banks in the 2012-2017 period, we consider only those network banks that were on the network 90% of the time in the period 2019-2023Q4. The results are similar when 80% and 70% thresholds are used. The results in Table 11 show that consistent with our expectation the difference between the matching coefficients of network and non-network banks is very small during the pre-FDIC 2018 ruling period. Columns (1) and (2) of Table 11 show that for the full sample of banks, the matching coefficient of the full sample of banks on the network is 0.745 and for non-network banks is 0.785. Thus, there is only a marginal difference between the interest sensitivity matching coefficient of network banks and non-network banks. Results are similar even after the inclusion of quarterly time FE. Interestingly, column (6) shows that small banks on the network have a marginally lower matching coefficient than small banks not on the network. The matching coefficient of small banks on the network is 0.553 while small banks not on the network have a matching coefficient of 0.561 (as shown in Column (5)). The result is similar even after the inclusion of quarterly time FE. This result shows that small banks on the network did not perform interest sensitivity matching before the FDIC 2018 ruling. This further supports our hypothesis that being on the reciprocal deposit network reduces their bank-run risk during period stress periods, thereby facilitating their ability to perform interest sensitivity matching. Columns (9) and (10) show that large banks on the network have a lower matching coefficient than non-network large banks. The results are similar even after the inclusion of quarterly time-fixed effects.

Columns (9) to (12) in Table 10 showed that in the post-FDIC 2018 ruling period, large banks on the network had marginally higher matching coefficients than non-network banks and after the inclusion of quarterly time fixed effects large banks on the network had lower matching coefficient than non-network large banks. Thus, the interest sensitivity matching results for network and non-network large banks in the pre-2018 FDIC ruling period (as shown in Table 11) is very similar to the post-2018 FDIC ruling period (as shown in Table 10) for large banks. This further supports our hypothesis that network and non-network small banks are broadly comparable, without substantial differences in their observable characteristics.

V. Conclusion

We build upon the foundational work of Drechsler et al. (2021) to study the cross-sectional heterogeneity among bank groups in the performance of interest sensitivity matching to hedge interest rate risk. We find that when the aggregate banking sector performs interest sensitivity matching, small banks in the bottom quintile do not perform interest sensitivity matching and are thus, exposed to interest rate risk. We present evidence of the relative reallocation of deposits from small banks to large banks during stress periods. Prior literature shows that depositors might perceive large banks to be safer during crises possibly because (a) large banks enjoy implicit Government guarantees, (b) large banks are subjected to more rigorous supervision and oversight, (c) large banks can have strong fundamentals, and (d) the high persistence and resilience of large banks over decades [4]. This flight to safety mechanism exposes small banks in the bottom quintile to higher bank-run risk in stress periods than all the other bank groups. This implies small banks experience a loss of retail deposits precisely when it is needed the most.

Funding instability during stress periods can impact small banks' asset choices because it increases their preference for preserving liquidity. Using IV estimation with deposit market power as an instrument, we show that instrumented deposit variability in stress periods is negatively associated with asset duration which implies banks with higher deposit variability in stress periods will have shorter-duration assets. Thus, the higher deposit variability in stress periods impedes small banks' ability to offer long-term credit.

Our results highlight three main insights. First, the stickiness of deposits is one of the key factors contributing to the stability and resilience of the banking sector over the centuries. Bank for International Settlements (BIS) defines the stickiness of deposits as "the tendency of the liabilities not to run off quickly under stress" (Bank for International Settlements, 2024). Our results show that the stickiness of retail deposits varies based on bank size. Specifically, small banks in the bottom quintile have runnable retail deposits exposing them to higher funding instability in stress periods. Second, to mitigate the anticipated bank-run risk in stress periods, small banks hold shorter-duration assets to preserve

[4]See Baron et al. (2021, and 2022); Acharya et al. (2022); Caglio et al. (2023)

liquidity. As a consequence, these small banks are pairing their low interest expense beta with high interest income beta, leading to interest sensitivity mismatch and thus, higher exposure to interest rate risk in normal times. Therefore, attempting to mitigate bank run risk in stress periods exposes these banks to higher interest rate risk in normal times. Thus, there is a strong interdependence between interest rate risk and liquidity risk management. Third, our results underscore the importance of the stability of the deposits in a bank's ability to hold longer-duration assets. Specifically, we show that if a bank's deposits are flighty, it will reduce the maturity of its assets to preserve liquidity and mitigate bank run risk and solvency risk during stress periods.

From the policy perspective, the results suggest that it is important to be cognisant of the fact that small banks, on average, have higher exposure to interest rate risk than large banks do. With respect to the financial stability implications, since the root cause of interest sensitivity mismatch is deposit reallocation during stress periods, then policies targeted to: (1) enhance deposit stability at small banks or (2) encourage interbank deposit transfers from large banks to small banks during stress periods. Anderson et al. (2021) showed that forced reallocation of deposits across banks obviates the need for intervention from central banks and improves welfare, or (3) providing small banks with additional liquidity will enable these small banks to perform interest sensitivity matching. Importantly, policies promoting market-based solutions like reciprocal deposit can help small banks to perform interest sensitivity matching. Overall, the results emphasise that small banks in the bottom quintile strategise to mitigate bank run risk during stress periods; however, this choice also exposes them to higher interest rate risk in normal times.

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Appendix: Tables

Table 1: **Summary Statistics for small banks (Quintile 1), comparable banks (Quintile 2) and large banks (Quintile 5).** The sample period is 1976Q1-2020Q1.

Small Banks (Quintile 1)

	Mean	SD	p25	p50	p75	p90	Max
Assets	14125.840	7664.529	8286.500	12868.500	18522.000	24812.000	44465.000
Log Inflation-adjusted Assets	9.233	0.421	9.013	9.333	9.559	9.676	9.751
Repricing Maturity of Assets	2.883	1.650	1.740	2.518	3.635	5.062	18.536
Repricing Maturity of Liabilities	0.404	0.226	0.256	0.370	0.507	0.669	5.000
Deposits Ratio	0.872	0.073	0.859	0.889	0.909	0.921	1.412
Interest-bearing Deposits Ratio	0.691	0.133	0.637	0.723	0.781	0.814	6.430
Transaction Deposit Ratio	0.264	0.098	0.198	0.250	0.315	0.389	0.931
Wholesale Ratio	0.084	0.077	0.028	0.065	0.119	0.184	0.886
Equity Ratio	0.111	0.066	0.081	0.096	0.121	0.159	1.000
Loan Ratio	0.517	0.153	0.419	0.531	0.627	0.702	1.091
Securities Ratio	0.303	0.159	0.188	0.290	0.406	0.515	1.000
Interest Income Beta	0.335	0.143	0.243	0.320	0.409	0.515	0.809
Interest Expense Beta	0.317	0.089	0.260	0.314	0.368	0.426	0.635
NIM Beta	0.015	0.117	-0.061	0.005	0.086	0.168	0.391
Net Income to Quarterly Average Assets Ratio (annualised)	0.0071	0.0431	0.0040	0.0096	0.0146	0.0201	3.8538
Total Swap Ratio	0.0000	0.0015	0.0000	0.0000	0.0000	0.0000	0.1924
Interest rate Derivatives Ratio	0.0000	0.0020	0.0000	0.0000	0.0000	0.0000	0.2742

Comparable Banks (Quintile 2)

	Mean	SD	p25	p50	p75	p90	Max
Assets	32951.637	13801.833	22425.000	30796.000	41590.000	52420.000	80903.000
Log Inflation-adjusted Assets	10.065	0.172	9.918	10.071	10.213	10.298	10.353
Repricing Maturity of Assets	3.376	1.825	2.098	2.972	4.253	5.797	17.174
Repricing Maturity of Liabilities	0.431	0.234	0.271	0.394	0.542	0.718	3.053
Deposits Ratio	0.877	0.051	0.859	0.889	0.907	0.920	1.260
Interest-bearing Deposits Ratio	0.713	0.098	0.666	0.732	0.782	0.814	1.038
Transaction Deposit Ratio	0.257	0.092	0.193	0.242	0.306	0.377	0.920
Wholesale Ratio	0.103	0.078	0.046	0.086	0.141	0.206	2.654
Equity Ratio	0.099	0.036	0.078	0.092	0.112	0.140	0.992
Loan Ratio	0.547	0.142	0.454	0.559	0.649	0.719	1.003
Securities Ratio	0.301	0.148	0.196	0.290	0.397	0.501	0.991
Interest Income Beta	0.339	0.123	0.261	0.327	0.403	0.494	0.809
Interest Expense Beta	0.332	0.079	0.281	0.327	0.379	0.428	0.635
NIM Beta	0.007	0.102	-0.059	0.000	0.070	0.137	0.391
Net Income to Quarterly Average Assets Ratio (annualised)	0.0094	0.0212	0.0062	0.0107	0.0148	0.0194	5.9828
Total Swap Ratio	0.0001	0.0035	0.0000	0.0000	0.0000	0.0000	0.4082
Interest rate Derivatives Ratio	0.0001	0.0069	0.0000	0.0000	0.0000	0.0000	0.9004

Large Banks (Quintile 5)

	Mean	SD	p25	p50	p75	p90	Max
Assets	3758741.794	46614418.474	247990.000	394255.000	840595.000	2588485.000	2.691e+09
Log Inflation-adjusted Assets	12.731	1.170	11.931	12.336	13.098	14.291	20.762
Repricing Maturity of Assets	4.062	2.115	2.550	3.673	5.194	6.882	18.372
Repricing Maturity of Liabilities	0.403	0.265	0.229	0.360	0.519	0.705	5.000
Deposits Ratio	0.819	0.114	0.791	0.848	0.886	0.907	1.061
Interest-bearing Deposits Ratio	0.681	0.132	0.629	0.709	0.767	0.809	0.985
Transaction Deposit Ratio	0.195	0.108	0.103	0.193	0.265	0.332	0.918
Wholesale Ratio	0.161	0.100	0.092	0.142	0.207	0.286	0.932
Equity Ratio	0.091	0.035	0.072	0.086	0.103	0.123	0.965
Loans Ratio	0.617	0.146	0.535	0.631	0.716	0.788	1.174
Securities Ratio	0.236	0.134	0.142	0.220	0.310	0.411	0.995
Interest Income Beta	0.400	0.141	0.308	0.384	0.473	0.586	0.809
Interest Expense Beta	0.387	0.093	0.325	0.375	0.438	0.509	0.635
NIM Beta	0.014	0.094	-0.047	0.007	0.077	0.127	0.391
Net Income to Quarterly Average Assets Ratio (annualised)	0.0102	0.0153	0.0076	0.0110	0.0143	0.0182	1.2085
Total Swap Ratio	0.0533	0.7563	0.0000	0.0000	0.0000	0.0377	48.3444
Interest rate Derivatives Ratio	0.0320	0.1531	0.0000	0.0000	0.0000	0.0658	5.0278

Table 2: **Paired T-Test Results for Groups.** The t-statistics are reported below in parentheses. The significance levels are for two-tailed tests. Small banks are in Quintile 1, comparable banks in Quintile 2 and large banks in Quintile 5. The sample period is 1976Q1-2020Q1.

	Quintile 1 and Quintile 2 (1)	Quintile 1 and Quintile 5 (2)
Deposits ratio	-0.0044295***	0.0534695***
	(-26.41)	(210.0289)
Interest bearing deposit ratio	-0.0226064***	0.0098074***
	(-72.9724)	(27.9159)
Wholesale ratio	-0.0188212***	-0.0773663***
	(-91.3524)	(-3.3e+02)
Transaction deposit ratio	0.0073793***	0.0689132***
	(24.3164)	(215.3863)
Loan ratio	-0.0295986***	-0.1001543***
	(-72.6908)	(-2.3e+02)
Securities ratio	0.0010772***	0.0665689***
	(2.6406)	(170.4680)
Repricing Maturity of assets	-0.4937448***	-1.179518***
	(-55.0609)	(-1.3e+02)

Table 3: **Interest Sensitivity Matching across Banks.** Following Drechsler et al. (2021), The betas are determined by regressing the quarterly changes in each bank's interest expense rate or interest income rate against the three current and previous changes in the Fed funds rate. The sample period is 1984-2020. Standard Errors are bootstrapped up to 1000 iterations.

	Interest Income Beta											
	Full Sample		Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Int. exp. beta	0.796***		0.568***		0.655***		0.768***		0.841***		0.963***	
	(0.00161)		(0.00433)		(0.00386)		(0.00391)		(0.00346)		(0.00300)	
Int. exp. beta with Time FE		0.949***		0.627***		0.737***		0.994***		1.037***		1.188***
		(0.0145)		(0.0227)		(0.0281)		(0.0401)		(0.0376)		(0.0316)
Constant	0.0816***	0.0280***	0.155***	0.133***	0.122***	0.0920***	0.0866***	0.00968	0.0639***	-0.00509	0.0273***	-0.0586***
	(0.000561)	(0.00484)	(0.00139)	(0.00684)	(0.00126)	(0.00894)	(0.00131)	(0.0131)	(0.00121)	(0.0127)	(0.00116)	(0.0118)
Observations	1,078,275	1,078,275	180,398	180,398	204,891	204,891	215,156	215,156	233,024	233,024	244,806	244,806
R-squared	0.271	0.262	0.123	0.134	0.179	0.179	0.240	0.254	0.282	0.269	0.403	0.351

Bootstrapped Standard Errors up to 1000 iterations in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: **Cost of Financing in Stress Periods.** Quintile 2 is the omitted group. The cost of financing is calculated as the percentage change in the total interest expense. The sample period is 1976-2020. Robust standard errors are reported in parentheses.

	Rate of Change in Interest Expense
Quintile 1	-0.670
	(3.412)
Quintile 3	-0.492
	(1.156)
Quintile 4	0.531
	(2.320)
Quintile 5	-0.0384
	(2.201)
Stress Period	1.227***
	(0.464)
Quintile 1 x Stress Period	2.247*
	(1.223)
Quintile 3 x Stress Period	0.182
	(0.566)
Quintile 4 x Stress Period	-0.756
	(0.715)
Quintile 5 x Stress Period	20.00
	(20.58)
Constant	1.799***
	(0.688)
Bank FE	Yes
Observations	1,078,281
R-squared	0.014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: **Deposit Growth Rates during Quiet Times and Stress Periods.** Quintile 2 is the omitted group. Deposit Growth rate in Column (2) is winsorised at the 1% level. Similar results with deposit growth rate winsorised at the 5% level. The sample period is 1976-2020. Robust standard errors are reported in paratheses.

	Log Change in Deposits (1)	Deposit Growth Rate (2)
Quintile 1	0.0158***	0.836***
	(0.000590)	(0.0292)
Quintile 3	-0.00812***	-0.584***
	(0.000342)	(0.0221)
Quintile 4	-0.0143***	-1.169***
	(0.000482)	(0.0265)
Quintile 5	-0.0199***	-1.820***
	(0.000686)	(0.0326)
Stress Period	0.00195***	0.224***
	(0.000407)	(0.0314)
Quintile 1 x Stress Period	-0.00196***	-0.130***
	(0.000725)	(0.0478)
Quintile 3 x Stress Period	0.000570	0.0529
	(0.000550)	(0.0434)
Quintile 4 x Stress Period	0.00139**	0.143***
	(0.000586)	(0.0432)
Quintile 5 x Stress Period	0.00166**	0.192***
	(0.000811)	(0.0464)
Constant	0.0257***	2.586***
	(0.000287)	(0.0171)
Bank FE	Yes	Yes
Observations	1,401,512	1,401,539
R-squared	0.029	0.042

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Deposit Variability Index across banks in quiet times and stress periods.** Quintile 2 is the omitted group. The window size is 11. The outcome variables are winsorised at the 5% level. Almost similar results for window sizes 7,8,10,15,24,25,30,32. Similar results with deposit growth rate winsorised at the 5% level. Robust standard errors are reported in parentheses.

	Deposit Variability Index (1)
Quintile 1	-0.0221
	(0.0467)
Quintile 3	-0.0215
	(0.0398)
Quintile 4	0.155***
	(0.0428)
Quintile 5	0.121**
	(0.0474)
Stress Period	0.0155
	(0.0635)
Quintile 1 x Stress Period	0.161*
	(0.0929)
Quintile 3 x Stress Period	-0.224**
	(0.0878)
Quintile 4 x Stress Period	-0.157*
	(0.0865)
Quintile 5 x Stress Period	-0.0963
	(0.0847)
Constant	2.141***
	(0.0294)
Bank FE	Yes
Observations	1,402,030
R-squared	0.089

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: **Deposit Flows for different deposit categories during Stress Periods and Quiet times.** Quintile 2 is the omitted group. The outcome variables are winsorised at the 1% level. Similar results when the outcome variables are winsorised at the 5% level. Robust standard errors are reported in parentheses.

	Int-Bearing Dep Growth Rate (1)	Log(Int-Bearing Dep Δ) (2)	Demand Dep Growth Rate (3)	Log(Demand Dep Δ) (4)
Quintile 1	1.367***	0.0120***	0.141*	-0.00221***
	(0.0312)	(0.000286)	(0.0757)	(0.000702)
Quintile 3	-0.868***	-0.00784***	-0.113*	0.00179***
	(0.0236)	(0.000219)	(0.0591)	(0.000555)
Quintile 4	-1.689***	-0.0155***	-0.117*	0.00387***
	(0.0284)	(0.000262)	(0.0678)	(0.000630)
Quintile 5	-2.411***	-0.0224***	-0.335***	0.000195
	(0.0353)	(0.000323)	(0.0831)	(0.000768)
Stress Period	0.372***	0.00347***	-0.654***	-0.00818***
	(0.0336)	(0.000317)	(0.0961)	(0.000919)
Quintile 1 x Stress Period	-0.141***	-0.00128***	-0.234	-0.00311**
	(0.0513)	(0.000480)	(0.145)	(0.00139)
Quintile 3 x Stress Period	0.146***	0.00142***	-0.229*	-0.00203
	(0.0468)	(0.000440)	(0.130)	(0.00125)
Quintile 4 x Stress Period	0.291***	0.00283***	-0.264**	-0.00249**
	(0.0469)	(0.000441)	(0.127)	(0.00122)
Quintile 5 x Stress Period	0.303***	0.00298***	-0.239*	-0.00398***
	(0.0501)	(0.000468)	(0.139)	(0.00133)
Constant	2.947***	0.0270***	2.914***	0.0151***
	(0.0182)	(0.000169)	(0.0457)	(0.000428)
Bank FE	Yes	Yes	Yes	Yes
Observations	1,400,273	1,400,185	1,399,680	1,399,589
R-squared	0.047	0.043	0.010	0.007

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: **Asset Growth and securities available for sale across banks.** All variables are winsorised at the 1% level. Quintile 2 which are the comparable banks is the omitted group. The sample period is 1976-2020. Robust standard errors are reported in paratheses.

	Asset Growth rate	Log (Asset Growth)	Growth rate for Securities available for sale	Log (Securities available for sale Growth)
	(1)	(2)	(3)	(4)
Quintile 1	0.595***	0.00508***	0.975***	0.00384**
	(0.0248)	(0.000233)	(0.238)	(0.00180)
Quintile 3	-0.490***	-0.00439***	-1.541***	-0.00841***
	(0.0192)	(0.000182)	(0.162)	(0.00124)
Quintile 4	-1.020***	-0.00930***	-2.636***	-0.0145***
	(0.0228)	(0.000215)	(0.196)	(0.00149)
Quintile 5	-1.632***	-0.0150***	-4.145***	-0.0235***
	(0.0280)	(0.000262)	(0.233)	(0.00175)
Stress Period	0.134***	0.00127***	-1.021***	-0.00628***
	(0.0272)	(0.000260)	(0.217)	(0.00177)
Quintile 1 x Stress Period	-0.0801*	-0.000721*	-1.374***	-0.00948***
	(0.0411)	(0.000392)	(0.348)	(0.00288)
Quintile 3 x Stress Period	0.0568	0.000560	-0.0501	-0.000979
	(0.0378)	(0.000362)	(0.289)	(0.00235)
Quintile 4 x Stress Period	0.160***	0.00159***	-0.143	-0.00196
	(0.0375)	(0.000358)	(0.273)	(0.00223)
Quintile 5 x Stress Period	0.241***	0.00241***	-0.0824	-0.00269
	(0.0399)	(0.000379)	(0.269)	(0.00217)
Constant	2.519***	0.0234***	5.584***	0.0294***
	(0.0148)	(0.000140)	(0.143)	(0.00108)
Bank FE	Yes	Yes	Yes	Yes
Observations	1,401,652	1,401,651	621,120	619,705
R-squared	0.045	0.043	0.025	0.021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: **IV Estimation for Logarithm of Deposit Variability Index (DV) for stress periods and Maturity of Assets.** The deposit variability in stress periods is calculated as deposit variability in Equation 3 in stress periods. The sample period is 1976-2020. None of the variables are winsorised. Standard Errors are bootstrapped up to 1000 iterations.

	DV_{Stress}	Repricing Maturity of Assets
	(1)	(2)
HHI Score	-33.6035***	
	(8.9952)	
$\widehat{DV_{Stress}}$		-0.0299***
		(0.0008)
Constant	11.0375***	3.8260***
	(2.5025)	(0.0047)
Observations	74,488	553,230
R-squared	0.0001	0.0023

Bootstrapped Standard Errors up to 1000 iterations in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: **Interest Sensitivity Matching for Network Banks and Non-Network Banks.** Sample Period 2019Q1-2024Q1. All interest betas are winsorised at the 5% level. The even number of columns represents the banks on the reciprocal deposit network for that bank group. Small banks are banks in Quintile 1 and large banks are banks in Quintile 5. Standard Errors are bootstrapped up to 1000 iterations.

	Interest Income Beta											
	Full Sample				Small Banks				Large Banks			
	Non-Network	Network	Non-Network	Network	Non-Network	Network	Non-Network	Network	Non-Network	Network	Non-Network	Network
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Int. exp. beta	0.698***	0.933***			0.605***	0.957***			0.898***	1.000***		
	(0.00702)	(0.00919)			(0.0149)	(0.0393)			(0.0222)	(0.0169)		
Int. exp. beta with Time FE			0.513***	0.691***			0.456***	0.614***			0.844***	0.788***
			(0.00633)	(0.00837)			(0.0143)	(0.0398)			(0.0186)	(0.0148)
Constant	0.357***	0.249***	0.292***	0.216***	0.392***	0.264***	0.320***	0.275***	0.277***	0.215***	0.169***	0.179***
	(0.00286)	(0.00445)	(0.00229)	(0.00363)	(0.00555)	(0.0165)	(0.00476)	(0.0153)	(0.0106)	(0.00883)	(0.00793)	(0.00690)
Observations	51,106	24,449	51,106	24,449	14,461	862	14,461	862	4,623	9,675	4,623	9,675
R-squared	0.185	0.310	0.127	0.237	0.110	0.368	0.075	0.177	0.279	0.300	0.307	0.256

Bootstrapped Standard Errors up to 1000 iterations in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: **Placebo Test: Interest Sensitivity Matching for Network Banks and Non-Network Banks pre 2018 FDIC Ruling.** Sample Period 2012Q1-2017Q4. All interest betas are winsorised at the 5% level. The even number of columns represents the banks on the reciprocal deposit network for that bank group. Small banks are banks in Quintile 1 and large banks are banks in Quintile 5. Standard Errors are bootstrapped up to 1000 iterations.

	Interest Income Beta											
	Full Sample				Small Banks				Large Banks			
	Non-Network	Network	Non-Network	Network	Non-Network	Network	Non-Network	Network	Non-Network	Network	Non-Network	Network
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Int. exp. beta	0.745***	0.785***			0.561***	0.553***			0.972***	0.869***		
	(0.00546)	(0.00681)			(0.0209)	(0.0289)			(0.00957)	(0.00991)		
Int. exp. beta with Time FE			0.747***	0.802***			0.567***	0.550***			0.981***	0.896***
			(0.00540)	(0.00670)			(0.0207)	(0.0290)			(0.00950)	(0.00983)
Constant	0.0872***	0.0816***	0.0805***	0.0699***	0.158***	0.151***	0.150***	0.146***	0.0139***	0.0570***	0.00524	0.0414***
	(0.00181)	(0.00241)	(0.00177)	(0.00235)	(0.00643)	(0.00897)	(0.00627)	(0.00887)	(0.00341)	(0.00369)	(0.00335)	(0.00364)
Observations	71,268	43,864	71,268	43,864	6,473	2,633	6,473	2,633	18,462	21,785	18,462	21,785
R-squared	0.234	0.260	0.239	0.273	0.106	0.124	0.111	0.123	0.372	0.311	0.374	0.325

Bootstrapped Standard Errors up to 1000 iterations in parentheses
*** p<0.01, ** p<0.05, * p<0.1