The Dynamics of Deposit Flightiness and its Impact on Financial Stability*

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Abstract

We document that deposit flightiness varies significantly over time. Elevated deposit flightiness coincides with large deposit inflows into the banking system. We rationalize these trends based on heterogeneity in investors' convenience value. Investors in the banking system value the convenience benefits of deposits more than outside investors. Following deposit inflows, e.g., due to QE's reserve expansions, the marginal depositor in the banking system becomes less convenience-seeking and the risk of panic runs increases. As a result, policy rate hikes are more destabilizing when preceded by QE. Our findings reveal a novel linkage between conventional and unconventional monetary policy.

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1 Introduction

Deposits are a fundamental building block of the banking system. While stable deposits allow banks to engage in liquidity transformation and invest in long-term assets, flighty deposits, i.e., deposits that are more likely to leave the bank, can be destabilizing. They can trigger the liquidation of illiquid assets and lower the franchise value of banks. Despite the importance of deposit flightiness for financial stability, there has been no systematic analysis of its variation over time. Existing work has mostly focused on cross-sectional differences in deposit flightiness, e.g., wholesale deposits are more flighty than retail deposits, uninsured deposits are more flighty than insured deposits, etc. Nevertheless, cross-sectional comparisons of deposit flightiness do not inform us about how flighty aggregate deposits in the banking system are at a given point in time, how aggregate deposit flightiness evolves over time, and what the drivers of the deposit flightiness dynamics are.

In this paper, we analyze the magnitude, determinants, and implications of variations in the aggregate deposit flightiness over time. First, we empirically document that the sensitivity of deposit flows to deposit rates displays pronounced fluctuations from 2000 to 2023. We find that large increases in deposit flow sensitivity coincide with large deposit inflows. Deposit inflows occurred during low-interest-rate environments and expansions in the Federal Reserve's balance sheet. In particular, deposit flow sensitivity reached unprecedentedly high levels after the large injection of bank reserves following the Covid-19 crisis.

We then develop a dynamic bank run model to rationalize the fluctuations in deposit flow sensitivity and to connect it to deposit flightiness. We build on He and Xiong (2012) and introduce heterogeneity in investors' convenience value for deposits. Our model shows that investors who value deposit convenience less are more sensitive to deposit rates. At the same time, investors who value deposit convenience less are also more likely to exit the banking system and switch to non-banks, i.e., they are flightier. This is why variations in the sensitivity of deposit flows to deposit rates capture variations in deposit flightiness.

Importantly, our model shows that heterogeneity in investors' convenience value, coupled with a fixed cost of moving funds between bank deposits and non-banks, causes the marginal depositor in the banking system to be time-varying and path-dependent. At any given point in time, those remaining in the banking system value the convenience of bank deposits more than those who invest in non-banks. Thus, following large deposit inflows from outside investors, the marginal depositor in the banking system values deposit convenience less, is more sensitive to deposit rates, and is flightier in leaving the banking system. This is why aggregate deposit flightiness increases following the influx of deposits. Finally, our model shows that a flightier deposit base increases the risk of panic runs unless all assets are costless to sell.

Our findings have important implications. For a given monetary policy rate hike, the expected deposit outflow is larger when it follows QE, as QE attracts inflows and introduces flightier deposits into the banking system. The increase in run risk is also larger unless banks can liquidate all reserves without incurring costs, including regulatory costs. We thereby pinpoint a novel linkage between conventional and unconventional monetary policy through the depositor base.

We begin our analysis by examining fluctuations in aggregate deposit flow sensitivity over time. Informed by the model, we use depositors' sensitivity to deposit rates as a proxy for their flightiness. To isolate the sensitivity of deposit flows to deposit rates, we instrument for deposit rates using per unit asset fixed costs and salary expense, following the industrial organization literature. We then estimate the sensitivity of bank-level deposit flows to instrumented deposit rates using rolling window regressions and analyze how the regression coefficients evolve over time.

Our estimated deposit flow sensitivities exhibit pronounced variation over time. As shown in Figure 1, they remained at low levels before 2008, became increasingly positive after the 2008 financial crisis, and then fell back again around 2015. In the more recent period, deposit flow sensitivities have become even larger in magnitude, with a sharp rise in early 2020, reaching historical highs before the rate hike cycle started in early 2022. We consider a number of alternative specifications to ensure this pattern of deposit flow sensitivities is robust.

We find that the evolution in deposit flow sensitivities closely tracks the movement of aggregate deposit flows. Aggregate deposit flows, in turn, comove with the amount of central bank reserves in the banking system, consistent with the finding by Acharya and Rajan (2022) that reserve injections expand bank deposits.[1] We argue that these observed patterns in flow sensitivities arise because investors who switch to bank deposits from other kinds of investments value the convenience of bank deposits less and are more sensitive to rates than those investors who have always been invested in bank deposits.

[1] Intuitively, when the Fed bought Treasuries and MBS in QE, not all of these securities were held on bank balance sheets. Some were sold by non-banks like hedge funds and asset management companies. These institutions do not have an account at the Fed. Instead, they receive a deposit at the bank that receives the reserves from the Fed. Note, however, that these institutions may not be the ultimate holders of deposits. They could use their deposit to buy other assets, and the deposits would be transferred to the sellers of those assets. This process goes on until the economy equilibrates.

Although our proposed channel applies generally to the aggregate deposit base, we further examine the characteristics of the deposits that comprise the aggregate deposit inflows during our sample period. Using regulatory data from the Federal Reserve, we find that relative to retail deposits, deposits by non-financial corporates experienced both a disproportionate growth following the Covid-19 reserve expansions as well as a disproportionate decline in the 2022 rate hike cycle. We also find that these fluctuations are especially pronounced for corporate deposits in non-operational accounts compared to operational accounts. The rise and fall in the proportion of corporate deposits is consistent with the observed variation in aggregate deposit flightiness, given that corporate depositors are more volatile than retail depositors.

We further corroborate the variation in deposit flightiness using novel transaction-level data covering bank accounts at more than 1400 U.S. depository institutions. One advantage of this data is that we observe, for each user, not only transactions between accounts at different banks but also transactions between bank and investment accounts. In other words, this dataset allows us to uncover the movement of funds between banks and between banks and non-bank investment options, which is not possible with bank-level call report data. In the cross-section of depositors, we find that the sensitivity of a depositor's flows between banks is positively correlated with the sensitivity of her flows between banks and investment options. This finding is consistent with the idea that depositors who are more sensitive to deposit rates in moving across banks, i.e., higher deposit flow sensitivity, are also more sensitive to moving from the banking system to outside investments, i.e., higher flightiness. Further, the time-series variation in bank-to-bank flow sensitivities estimated from depositor-level data closely aligns with the variation in deposit flow sensitivities estimated from bank-level data.

To rationalize the observed variation in deposit flightiness and to shed light on the implications for financial fragility, we develop a dynamic model in which banks fund illiquid long-term projects with one-period deposits. Investors derive utility from the convenience of deposits and perceive deposits across different banks as imperfect substitutes. Crucially, the relative importance of this convenience feature varies among investors, influencing their trade-off between convenience and returns. We demonstrate that investors who place a higher value on deposit convenience exhibit lower sensitivity to deposit rates. At the same time, an investor's valuation of deposit convenience determines the likelihood of the investor exiting the banking system for a given interest rate spread, i.e., flightiness. Therefore, investors who value the convenience benefit of deposits less are both more sensitive to deposit rates and more likely to leave the banking system, i.e., more flighty. Each period, investors choose whether to hold deposits or to invest in an outside option without convenience, such as MMFs or Treasuries. Investors bear switching costs for moving money in and out of banks, generating sluggishness in the adjustment of the depositor base.

On banks' asset side, in each period, projects mature with a certain probability and produce cash flows driven by that period's fundamentals. If there are deposit outflows at a bank, it has to sell a fraction of its asset. The asset is illiquid in the sense that aggressive fire sales are associated with significant liquidity discounts. Specifically, banks incur a discount when the fraction of assets sold in a given period exceeds a certain threshold. Such a liquidation schedule can be rationalized by a cash-in-the-market constraint or slow-moving capital. The costly liquidation region gives rise to strategic complementarity among investors that leads to potential bank runs. Each bank chooses its deposit rate to maximize equity value. To ensure tractability, we assume banks have common fundamentals and focus on symmetric equilibria.

We first show that our model rationalizes the empirical relationship between changes in rate sensitivity and deposit flows. In any given period, investors who value deposit convenience more stay in banks, while those who value deposit convenience less invest in the outside option. Furthermore, deposit rate sensitivity is determined by the average convenience value of depositors in the banking system. Hence, when the banking system experiences aggregate deposit inflows, the marginal depositor's convenience value declines, lowering the average convenience value of deposits. Consequently, deposits become more sensitive to interest rate differences.

In our model, banks can choose their deposit rates to influence deposit outflows. In equilibrium, banks offer higher deposit rates when the depositor base is flightier and when asset fundamentals are stronger. As fundamentals deteriorate, banks offer lower deposit rates, leading to deposit outflows and asset liquidation. Eventually, as fundamentals fall below an endogenous threshold, banks can no longer retain enough depositors. Run-driven outflows ensue, and banks fail.

One key prediction from our model is that the expected outflow and run probability in a given period decrease with the marginal depositor's convenience value for banking services. When the marginal depositor in the banking system values deposit convenience less, banks face greater failure risks. As a result, all other depositors are more likely to withdraw their money, and the probability of runs increases. Therefore, the influx of less convenience-seeking investors not only has an "averaging effect" on the depositor base but also an "interaction effect", where the same existing depositors become more incentivized to run. Furthermore, because of the switching cost of moving funds, the depositor base exhibits stickiness, and the marginal depositor type in a given period depends on the path of fundamentals.

We then calibrate the model to investigate the financial stability impact of conventional and unconventional monetary policy, highlighting their interdependency through the depositor base. We interpret conventional monetary policy rate hikes as the outside option relative to bank deposits becoming more attractive. In the baseline specification, we interpret unconventional policy as an inflow of deposits into the banking system, following Acharya and Rajan (2022), Acharya et al. (2023) and Lopez-Salido and Vissing-Jorgensen (2023). Based on the model, this inflow of deposits translates into a marginal depositor who values deposit convenience less.

We find that the influx of investors following QE amplifies deposit outflows and run risk as long as not all newly added reserves are costless to liquidate. Our baseline estimates show that the increase in bank default risk from a 2% rate hike in 2022Q1 would be halved absent the QE-induced deposit expansions following the Covid-19 crisis. Our estimates also show that the amplifying effect of deposit expansions on run risk could be alleviated if a larger share of reserves is costless to liquidate, which highlights that the ultimate financial stability impact of flightier deposits interacts with bank assets and regulatory requirements. Finally, we allow for monetary policy rate hikes to simultaneously worsen bank fundamentals, e.g., through reducing the value of banks' long-term fixed-income portfolio, and show that the impact on outflows and run risk would be further exacerbated.

Taken together, our model predictions can rationalize the variation in aggregate deposit flightiness we uncovered from the data. They also highlight the importance of understanding how various monetary policy measures influence deposit flightiness. In particular, we identify an important linkage between conventional and unconventional monetary policies through the depositor base. This linkage implies that rate hikes are more destabilizing when the central bank's balance sheet is large. Reducing the supply of reserves through QT ahead of rate hikes may help to alleviate the financial fragility concerns.

1.1 Literature Review

Our model on dynamic depositor composition and run risk contributes to the literature on bank fragility. Deposit-funded banks transforming illiquid assets are subject to coordination failure, e.g., Diamond and Dybvig (1983) and Goldstein and Pauzner (2005).[2] Most closely related to our model is He and Xiong (2012), who show that coordination failure also arises when deposi-

[2]More recently, Drechsler, Savov, Schnabl and Wang (2023), Granja, Jiang, Matvos, Piskorski and Seru (2024) and Haddad, Hartman-Glaser and Muir (2023) show that panic runs may also be driven by the "illiquidity" of banks' deposit franchise value.

tors make rollover decisions across periods. We build on He and Xiong (2012) and further show how depositors' value for payment convenience affects run risk and how the composition of the depositor base is determined. Consistent with these papers, run risk is also influenced by bank fundamentals in our model. Relatedly, Ordonez and Llambias (2024) develop a dynamic bank run model to analyze the effect of communication technology on financial stability. Few other papers have considered the effect of investor heterogeneity on the risk of panic runs. Begenau, Elenev and Landvoigt (2025b) develop a quantitative model of heterogeneous banks to analyze the financial stability risks of banks with different uninsured deposit funding shares and interest rate risk exposure. Egan, Hortaçsu and Matvos (2017) and Jiang, Matvos, Piskorski and Seru (2023) analyze the effect of uninsured versus insured depositors on run risk. Dávila and Goldstein (2023) and Mitkov (2020) allow for differences in endowments and focus on the determination of optimal deposit insurance and governments' policy responses in crisis times, respectively. We contribute to the literature by introducing a novel source of heterogeneity in terms of investors' value for deposit convenience.

Our findings also relate to the unintended consequences of QE. Diamond, Jiang and Ma (2023) show that reserve injections from QE may crowd out lending from bank balance sheets. Acharya and Rajan (2022) show that reserve injections expand bank deposits, but a subsequent shrinkage in reserves may not symmetrically reduce deposit claims, and banks may also hoard excess reserves during liquidity stress. Acharya, Chauhan, Rajan and Steffen (2023) empirically show that banks that took up more reserves during QE expanded their credit lines and demandable uninsured deposits by more but did not proportionally reduce these claims during QT, which renders them more vulnerable to liquidity shocks. Similarly, Darst et al. (2025) argue that banks adjust credit supply and manage liquidity risk following QE. Finally, Lopez-Salido and Vissing-Jorgensen (2023) develop a framework for understanding banks' demand for reserves to estimate when QT would lead to heightened interest rate volatility, while Afonso et al. (2022) also estimate banks' reserve demand and show when reserves are ample versus scarce. We highlight another important side effect of the deposit expansions from QE is that they add to and amplify the flightiness of the depositor base because of investor heterogeneity. Importantly, we show that run risk is heightened with respect to subsequent rate hikes, which uncovers an important linkage between conventional and unconventional monetary policy.

Further, our results relate to the literature on depositors' sensitivity to interest rates and the passthrough of monetary policy. Drechsler, Savov and Schnabl (2017) show that the response of deposit flows to monetary policy shocks depends on bank market power, which varies across regions with different degrees of deposit concentration. More recently, d'Avernas, Eisfeldt, Huang, Stanton and Wallace (2023) show that depositors at large banks are less sensitive to interest rates and more attracted to the better liquidity services that large banks offer. Erel, Liebersohn, Yannelis and Earnest (2023) and Koont, Santos and Zingales (2023) show that depositors at digital banks are more sensitive to interest rates. Lu, Song and Zeng (2024) show that depositors are more alert with better payment technology. Zhang, Muir and Kundu (2024) analyze the emergence of high-rate and low-rate banks, while Gelman and MacKinlay (2024) find that banks with unsought deposit inflows have higher losses during monetary tightening. While investors' sensitivity to deposit rates is also the key economic variable in our paper, we shed light on how it varies for investors inside the banking sector over time, rather than focusing on its cross-sectional variation across banks. Relatedly, Egan et al. (2025) shed light on the sleepiness of depositors who infrequently shop for deposits and examine their effect on the dynamics of bank deposit competition using a structural model. Also using structural models, Xiao (2020) and Wang, Whited, Wu and Xiao (2022) allow for heterogeneous investor preferences to rationalize the transmission of monetary policy to shadow banks and banks, respectively. We contribute by empirically estimating the aggregate variation in investors' rate sensitivity over time and analyzing its effect on banking sector fragility. Our results also have important implications for how the speed of rate hikes influences run risk and how conventional and unconventional monetary policy interact through the deposit base.

Finally, in analyzing the dynamics of depositor flows and bank liquidity management, our paper also relates to dynamic banking models. Jermann and Xiang (2023) study endogenous deposit maturity as depositors trade off liquidity needs and default risks, highlighting the risk of dilution. Bolton, Li, Wang and Yang (2023) investigate both the liability and asset side management in which banks have imperfect control over their deposits. Hugonnier and Morellec (2017) study the effects of liquidity and leverage requirements on banks' financing decisions and insolvency risk. Begenau et al. (2025a) study the interaction between regulation and delayed accounting in a dynamic banking model. Gertler and Kiyotaki (2015) focus on endogenous liquidation prices in a macro banking model with runs.[3] Furthermore, Kashyap et al. (2002) and Gatev and Strahan (2006) emphasize the correlation between deposit flows and loan demand. In our dynamic model, banks set deposit rates optimally, taking into account the switching cost that depositors face when

[3]More generally, several macro models with a banking sector focus on quantifying the effects of banking regulations in a dynamic general equilibrium model (e.g., Van den Heuvel 2008, De Nicolò et al. 2014, Begenau 2020). Jermann and Quadrini (2012) document the cyclicality of financial flows and develop a dynamic model to study the impacts of financial shocks. Finally, existing work highlights bank equity as an important state variable (e.g., Gertler and Kiyotaki 2010, He and Krishnamurthy 2013, Brunnermeier and Sannikov 2014, Rampini and Viswanathan 2018).

moving money in and out of the bank. We leverage the model to study the time variation of the aggregate depositor base.

2 Data

Our empirical findings are based on several sources of data.

Call Report Data We use Call Reports data to obtain quarterly bank-level characteristics including deposit volumes and deposit rates from 1998 to 2023. We calculate deposit rates by dividing deposit expense by the volume of deposits.

Deposit Data by Counterparty and Account Type We are the first to use regulatory data from the Complex Institution Liquidity Monitoring Report (FR2052) to shed light on the amount of deposits held by different counterparties using different types of deposit accounts. This data allows us to break down bank-level deposits by retail versus corporate depositors. Monthly data is reported by banks with more than $100 billion in assets, while the daily data is reported by 11 systemically important institutions. Deposits by counterparty type are available from 2018 through 2023. Deposits by account type are available from 2018 through 2021 because of a change in variable definitions in 2022.

Depositor-level Data We obtain transaction-level data of bank accounts for more than 1,400 U.S. depository institutions from a leading financial data processor from 2015 to 2022. This dataset provides, for each de-identified user, transactions between checking and savings accounts at different banks as well as transactions between bank accounts and investment accounts. In Appendix B, we provide further details on how we identify flows between banks and between banks and investment options from the data.

Aggregate Data We obtain aggregate data, including the Fed funds rate and the volume of outstanding reserves on bank balance sheets from FRED.

3 Stylized Facts

In this section, we document several novel facts about variations in the depositor base over time. Deposit flightiness, i.e., the tendency of depositors to leave the banking system, is difficult to observe in the aggregate data. That is why we first measure how responsive deposit flows are to deposit rates in Section 3.1. Our model will show that this deposit flow sensitivity is a proxy for deposit flightiness because both are determined by investors' convenience value for deposits.

In Section 3.2, we further examine how the composition of deposits is changing over time by investor and account type. Finally, in Sections 3.3 and 3.4, we use investor-level data to show that investors who are more active in transferring funds across banks are also more active in transferring funds between banks and non-banks, and to confirm our baseline result in Section 3.1.

3.1 Bank-level Deposit Flow Sensitivity over Time

We first measure how deposit flow sensitivity varies over time using bank-level data. To isolate the response of deposit flows to deposit rate shocks, we instrument deposit rates using supply-side instruments from the industrial organization literature. Specifically, we follow Xiao (2020) in using fixed costs and salary expenses over total assets as instruments. The assumption is that changes in a bank's per unit fixed costs and salary expenses affect its deposit rates through the cost of producing deposits rather than depositors' demand for deposits. Indeed, increases in fixed costs and salary expenses are associated with lower deposit rates (see Table C.1).

Formally, we first run a first-stage regression of deposit rates on the instruments using an 8-quarter rolling window. Figure C.1 shows the results. We then use the instrumented deposit rates for bank j in quarter t, $\widehat{DepRate}_{jt}$, to estimate the rolling window regression:

$$Flow_{jt} = \beta_y \widehat{DepRate}_{jt} + FE_t + \epsilon_{jt}, \tag{3.1}$$

where $Flow_{jt}$ is the deposit flow of bank j in quarter t. β_y indicates the sensitivity of bank-level deposit flows to bank-level deposit rates in rolling window y. A positive flow sensitivity β_y indicates that the deposit base has become more rate-sensitive than before, with deposits being more disproportionately attracted to banks offering higher deposit rates. The inclusion of time fixed effects implies that β_y captures the sensitivity of deposit flows between banks.[4] We estimate flow sensitivities using an 8-quarter rolling window for banks that existed over the sample period.[5] Standard errors are clustered at the bank level.

The estimated flow sensitivities in Figure 1a display significant fluctuations over time. They remained relatively close to zero before 2008, became increasingly positive after the 2008 financial crisis, and then fell back again around 2015. The fact that deposit flow sensitivities rise gradually

[4] For further details regarding this specification, please refer to Appendix A.

[5] In theory, the specification can also be run quarter by quarter, but the rolling window helps to reduce the effect of seasonal fluctuations in deposit flows and improve statistical power. We include banks that are present over the full sample period to ensure a stable sample of banks, but our results are qualitatively robust to relaxing this filter. For example, see Figure C.4, where we include banks present in at least half of the sample period.

after, rather than during, the peak of the 2008 financial crisis suggests that they are unlikely to be driven by spikes in risk aversion in bad times. This is also evident when comparing the evolution of flow sensitivities with the VIX index in Figure C.5. In the more recent period, fluctuations in deposit flow sensitivities have become even more pronounced with a sharp rise in early 2020 to reach historical highs in 2022Q, when a 1% higher deposit rates at a given bank induced a 10.1% larger deposit flow than other banks.

We find that our estimated flow sensitivities are positively correlated with aggregate inflows to the banking system, as shown in Figure 1b. That is, flow sensitivities become more positive when aggregate deposit inflows are larger, and become less positive when aggregate deposit inflows are smaller. To show this relationship more formally, we estimate

$$Flow_{jt} = \beta_1 \widehat{DepRate}_{jt} + \beta_2 DepRate\widehat{_{jt} \cdot A}ggFlow_t + FE_t + FE_j + Controls + \epsilon_{jt}, \quad (3.2)$$

where $AggFlow_t$ is the one-year cumulative deposit flow in quarter t. The independent variable $\widehat{DepRate}_{jt}$ is instrumented with the same fixed cost and salary expenses as in Equation 3.1, and $DepRate\widehat{_{jt} \cdot A}ggFlow_t$ is instrumented with the cost instruments multiplied by $AggFlow_t$. In addition to time fixed effects, we further control for the ratio of insured deposits, bank equity, and non-deposit liabilities in select specifications. From the estimation results in Table 1, we see that deposit flows indeed become more sensitive to deposit rates when there have been large aggregate inflows into the banking system.

We argue that the investors drawn into banks as part of deposit inflows value the convenience of deposits, e.g., from the payment function of deposits, less than the existing depositors in the banking system. Our model shows that this is because investors outside the banking system are less convenience-seeking than those who chose to be in the banking system in the first place, where the convenience value makes depositors less sensitive to the deposit rate. As a result, the influx of deposits makes the depositor base in the banking system more sensitive to deposit rates.

Although our proposed channel holds more generally, we find that a key driver of deposit inflows in our sample period is unconventional monetary policy. Hence, flow sensitivities become more positive when reserves held on bank balance sheets increase following QE, and become less positive when reserves held on bank balance sheets decrease following QT (Figure 2). As Acharya and Rajan (2022) and Acharya et al. (2023) point out, increases in reserves on the asset side of bank balance sheets are accompanied by increases in deposits on the liability side. This is because most of the Treasuries sold to the Fed in QE were not held on banks' balance sheets. Many were sold by non-banks like hedge funds and asset management companies, which do not have an account at the Fed.[6] Instead, they received deposits at the bank that received the reserves from the Fed. Note, however, that these hedge funds and asset managers may not be the ultimate holders of deposits. They could use their deposits to buy other assets, and the deposits would be transferred to the sellers of those assets. This process goes on until the economy equilibrates. Therefore, the rise in deposit flow sensitivity following deposit inflows from QE is not mechanical because hedge funds and asset managers are holding deposits. Even if the ultimate holders of the new deposits are not hedge funds and asset managers, their convenience value for deposits should still be smaller than that of depositors who were in the banking system in the first place, which leads to elevated deposit flightiness post QE.

Another important driver of deposit flows is conventional monetary policy. As the deposits channel of monetary policy (Drechsler et al., 2017) shows, rate cuts lower the opportunity cost of holding deposits relative to outside investment options, which is why rate cuts draw deposits into the banking sector. Indeed, we observe that deposit flow sensitivities are more positive following rate cuts and in low-interest-rate environments. This pattern is evident from Figure 3a for the full sample period. It is also evident from Figure 3b, which zooms in on the pre-2010 period without QE. Consistent with our model, investors who switch from outside options to bank deposits have a lower convenience value for deposits and are more rate-sensitive than those who were already in the banking system, which is why deposit flow sensitivity becomes more positive following rate cuts.

One concern is that our results may be mechanically driven by changes in the ratio of demandable deposits. As Supera (2021) points out, there has been a secular decline in the fraction of time deposits over time. This trend may have contributed to the rise in overall deposit flightiness because there are more restrictions on withdrawing time deposits compared to demandable deposits. Nevertheless, when we estimate flow sensitivities within savings deposits, the same trends remain (Figure 4), suggesting that our findings are not mechanically driven by the shift from time to savings deposits.

Another possibility may be that the variation in flow sensitivities is driven by the fraction of uninsured deposits. Uninsured depositors are more flighty than insured depositors, and banks with more uninsured deposits are more prone to runs (Egan et al., 2017). The time-series variation of flow sensitivities for the aggregate banking sector, however, does not match the cyclical variation in aggregate uninsured deposits over time (Figure 5a). Controlling for the fraction of uninsured

[6] One exception is money market funds that have access to the Fed's overnight Reverse Repo (RRP) Facility. The outstanding volume in the RRP Facility indeed comoves positively with bank reserves, but they remain at much lower levels, and they cannot be used to settle payments like bank reserves.

deposits at the bank level also has a limited impact on the overall trends in flow sensitivities (Figure 5b).

Further, one may worry whether other bank characteristics could be confounding our estimation despite the use of instruments. To this end, we control for banks' fundamentals using return on assets as a proxy following Chen et al. (2022) and Chen et al. (2024).[7] We further control for indicators of banks' branch density and service quality using assets per branch, number of employees per branch, and salary per employee. The results in Figure 6 closely resemble the benchmark result in Figure 1a.

More generally, one may also ask how our results on flow sensitivity relate to investors' sensitivity to bank fundamentals and run risk. Note that we do not claim that deposit flow sensitivity is equal to run risk. Rather, we will derive in Section 4 that a more rate-sensitive depositor base reflects that the marginal depositor derives less convenience value from holding deposits. A lower convenience value, in turn, makes them flightier in leaving the banking system and eventually amplifies the run risk. In our model, bank fundamentals are also an important but separate driver of run risk, consistent with Goldstein and Pauzner (2005). To better understand this important channel, we examine how deposits respond to bank fundamentals over time following the work of Chen et al. (2022) and Chen et al. (2024). We use the specification in Equation 3.1, but replace deposit rates with banks' return on assets as a proxy for bank fundamentals. We also split up the response for insured and uninsured deposits. Figure C.6 shows that uninsured depositors become more sensitive to bank fundamentals after the 2008 crisis and again after the Covid-19 crisis, similar to the results with respect to deposit rates. In relative terms, depositors' sensitivity to fundamentals is more elevated following the 2008 crisis, while depositors' sensitivity to deposit rates is more elevated following the Covid-19 crisis. One reason may be that the 2008 crisis was a deeper recession with more concerns about credit risk in the financial system. As expected, the variation for insured deposits to bank fundamentals is much more muted than that for uninsured deposits. One exception is the brief period right after the 2008 crisis, when the cap for deposit insurance was lifted.

Finally, to ensure that our results are not driven by a particular subset of banks, we repeat the estimation by dividing banks into size-based quartiles. That is, we first sort banks into quartiles by asset size and then estimate Equation 3.1, replacing $\widehat{DepRate}_{jt}$ with $\widehat{DepRate}_{jt}$ interacted with dummy variables for each asset quartile. The coefficients for these interaction terms represent

[7] A more direct proxy for banks' fundamental risk would be banks' CDS spreads. However, CDS spreads are only available for a very small number of bank holding companies.

the deposit flow sensitivity for each quartile and are plotted in Figure C.7.[8] Figure C.7 confirms that the fluctuations in deposit flow sensitivities for all four quartiles follow the aggregate trend in Figure 1a, albeit larger banks display more pronounced fluctuations. An important but separate question is what drives individual banks' exposure to the variation in flow sensitivities over time. Blickle et al. (2025) shed light on this cross-sectional heterogeneity and its determinants.

3.2 Deposit Flows by Counterparty and Account Type

Our proposed mechanism is general and not limited to any particular type of deposits. That is, investors that remain in banks should always value bank convenience by more and be less rate-sensitive than investors outside of the banking system, both in aggregate and for any given deposit type. Nevertheless, it is valuable to understand how different types of deposits fluctuates over time and how they contribute to the variation in aggregate deposit flow sensitivities.

We provide the first evidence on which types of depositors hold what kind of accounts for large U.S. banks. This information is required to be reported monthly for banks with assets above $100 billion and daily for 11 of the largest banks as part of the Federal Reserve's Complex Institution Liquidity Monitoring Report. These banks make up the bulk of total bank assets in the U.S. at 74% and 55% in 2023Q4, respectively.

In Figure 7a, we first plot the total monthly deposits by counterparty type from 2018 through 2023. We observe that the three largest counterparty types are retail, non-financial corporate, and non-bank financial institutions, and that they all experienced a significant uptick in deposits in early 2020. For easier comparison, we normalize the level of deposits for each counterparty type by their values in January 2020 and plot the normalized graph in Figure 7b. Figure 7b shows that corporate deposits grew by more than 60% from the beginning of 2020 to the end of 2021 before contracting by 20% relative to the baseline in the 2022 rate hike cycle. The initial growth and subsequent decline in corporate deposits was much more pronounced than for retail and small business deposits, which provides the first evidence that corporate deposits have higher volatility.[9]

[8] Note that deposit flow sensitivities for each quartile should be estimated jointly in one specification by interacting $\widehat{DepRate}_{jt}$ with dummy variables for each asset quartile. Estimating deposit flow sensitivities using individual specifications of Equation 3.1 would allow different time fixed effects for each quartile. In that case, the estimates would only capture flows within each bank quartile without flows across quartiles, which are likely an important component of deposit flows in practice.

[9] We also observe that deposits at non-bank financial institutions experienced a sharp and short-lived rise in March 2020 before falling back to relatively stable values. This pattern may be explained by liquidity-providing non-banks, like MMFs and mutual funds, setting aside cash reserves in anticipation of redemption during the dash-for-cash episode in March 2020.

In Table 2, we examine the volatility of deposits held by different counterparties more closely.[10] Panel A shows bank-level deposit volatility calculated as the standard deviation of each bank's monthly deposits by counterparty type over the sample period, divided by their corresponding mean. We observe that at the 25^{th}, 50^{th}, and 75^{th} percentile, retail and small business deposits are less volatile than deposits by non-financial corporates, non-bank financial institutions, and other banks. This pattern is mirrored in the aggregate volatility shown in Panel B, which is calculated as the rolling standard deviation of the aggregate monthly deposits by counterparty type over 4-month windows, divided by the corresponding rolling mean. Similar trends are also evident from deposit volatility at a daily frequency (Panel C and D). This higher volatility of corporate deposits suggests that the disproportionate growth of corporate deposits starting in March 2020 (Figure 7b) increased the flightiness of the aggregate depositor base over the same period.

Similarly, we examine the volatility of deposits by account type in Table 3 and observe that deposits in non-operational accounts are more volatile than deposits in operational accounts. This pattern may arise because firms' operations involve more regular cash transfers, while investment decisions using excess cash in non-operational accounts fluctuates by more. Further, deposits in transactional accounts are more volatile than deposits in non-transactional accounts, which is consistent with retail depositors using transactional deposits to meet liquidity shocks and non-transactional deposits as a stable store of value.[11] At the same time, Figures 8a and 8b show that deposits in non-operational accounts grew by more than deposits in operational accounts from the start of 2020 to the end of 2021, while deposits in transactional accounts grew by more than deposits in non-transactional accounts in the same period.[12] This disproportionate growth in the more volatile non-operational deposits for firms and transactional deposits for retail may have also contributed to the rise of deposit flow sensitivity leading up to the 2022 rate hike cycle.

3.3 Depositor-level Flow Sensitivities in the Cross-section

In Section 3.1, our bank-level estimates of deposit flow sensitivities have been based on deposit flows between banks. Our model will show that these deposit flow sensitivities can capture the convenience value of depositors in the banking system and thereby their flightiness in leaving

[10]We calculate deposit volatility instead of deposit flow sensitivity because we do not have information on deposit rates in this data.

[11]The split between operational and non-operational accounts applies only to corporate deposits. The split between transactional and non-transactional accounts only apply to retail and small businesses accounts.

[12]Note that the sample of the account type data ends at the end of 2021 rather than 2023 because of a change in variable definition in 2022.

the banking system. In this section, we verify that bank-to-bank flow sensitivity is indeed informative about investors' tendency to switch between banks and non-banks. To this end, we use transaction-level data to uncover the movement of funds between banks and between banks and outside investment options at the depositor level. We provide further details about the data in Appendix B.

First, we show that there exists significant heterogeneity in both bank-to-bank and bank-to-non-bank deposit sensitivity across depositors. We evaluate deposit sensitivity using three measures: (1) the proportion of months in which a depositor had flows; (2) the standard deviation of flows scaled by total payment flows; (3) the sensitivity of deposit flows to rates. We construct each of these three measures separately for flows between banks and flows between banks and non-banks.

To compute the sensitivity of deposit flows to rates, we first sort depositors into 100 bins based on their standard deviation of deposit flows between banks. We then estimate bank-to-bank flow sensitivity for each bin b. For each bank account j of depositor i in month m, we calculate $BankFlow_{ijm}$ as the net volume of deposits transferred from other bank accounts of depositor i in the same month normalized by the total account balance of depositor i. We calculate deposit rate $DepRate_{ijm}$ by dividing interest income by account balance. Then, we estimate how deposit flows between banks respond to deposit rates:

$$BankFlow_{ijbm} = \gamma_b DepRate_{ijbm} + FE_{ib} + FE_m + Controls_{jbm} + \epsilon_{ijbm}, \tag{3.3}$$

where control variables include indicator variables for various time-varying account-level characteristics, including the presence of overdraft fees, ATMs, and fast payment services like Zelle. The assumption is that after controlling for these characteristics, we can interpret γ_b as the sensitivity of bank-to-bank deposit flows to deposit rates for bin b.

To capture the sensitivity of deposit flows between banks, we then re-estimate Equation 3.3 replacing bank-to-bank flows $BankFlow_{ijbm}$ with bank-to-non-banks flows $NonBankFlow_{ijbm}$ and deposit rates $DepRate_{ijbm}$ with deposit spreads $DepSpread_{ijbm}$, where deposit spreads are defined relative to the Fed funds rate.

From the summary statistics in Table 4, we observe significant heterogeneity in depositors' sensitivity to move funds between banks and between banks and non-banks across all three measures. The median depositor transfers funds between banks in 1.06% of months, while the 75^{th} percentile depositor transfers funds between banks in 5.32% of months. Similarly, the median depositor transfers funds in and out of the banking sector in 2.13% of months, while the 75^{th} percentile depositor does so in 14.89% of months. Further, some depositors display much more variation in their deposit flows between banks and between banks and non-banks as a proportion of total deposit flows. Finally, deposit flow sensitivity between banks and that between banks and non-banks vary in the cross section as well.

Most importantly, we find that depositors who switch funds more readily between banks are also more active in moving deposits between banks and non-banks. In Figure 9, we show binned scatter plots of depositor-level sensitivity in flows between banks versus flows between banks and non-banks. Across all three measures, Figure 9 displays a clear positive relationship between the two dimensions of deposit sensitivity. These results imply that depositors that are more sensitive in substituting between banks are also more sensitive in substituting between banks and non-banks.

3.4 Depositor-Level Flow Sensitivities over Time

Having examined the cross-sectional heterogeneity in depositors' sensitivity, we proceed to examine how the sensitivity of bank-to-bank deposit flows evolves over time in the depositor-level data, as a verification of our baseline estimates using bank-level data in Section 3.1.

We estimate how deposit flows between banks respond to deposit rates for a given depositor similar as in Equation 3.3 and repeat the estimation for each month m:

$$BankFlow_{ijm} = \gamma_m DepRate_{ijm} + FE_i + FE_m + Controls_{jkm} + \epsilon_{jkm}. \tag{3.4}$$

where the fixed effects and control variables are the same as before. γ_m is then the depositor-level sensitivity of bank-to-bank deposit flows to deposit rates in month m.

We plot the 12-month moving average of γ_m in Figure 10. Observe that depositor-level deposit flow sensitivity falls from 2016 to early 2020, rises from early 2020 onward before declining again in early 2022. Note that this pattern closely resembles of the bank-level deposit flow sensitivity in Section 3.1, which corroborates the dynamics of aggregate depositor sensitivity over time. It is also aligned with the pattern of aggregate deposit inflows bringing in more rate-sensitive depositors into the banking system. One relative difference is that the rise in deposit flow sensitivity in early 2020 is not as drastic in the depositor-level data. This could be because this dataset has a smaller share of corporate depositors, which may have contributed to the large increase in deposit flightiness in the bank-level data.

4 Model

Our empirical facts provide strong support that investors indeed have heterogeneous flow sensitivity. To rationalize the time-varying depositor flow-sensitivity and investigate its financial stability implications, we build a dynamic banking model with run risks by incorporating a heterogeneous investor base into the framework of (He and Xiong, 2012). The key novelty of our model is to endogenize the investor base in the banking system over time and show how it drives bank vulnerability. A dynamic model allows us to capture the path dependency of the depositor base over time, which is essential for tracking how past monetary policy decisions interact with future ones in Section 5. Nevertheless, the core intuition of run risk remains the same as in static models like Diamond and Dybvig (1983) and Goldstein and Pauzner (2005). We start by presenting the model setup in Section 4.1 and the value functions in Section 4.2. We then derive the equilibrium run conditions and agents' optimal strategies in Section 4.3.

4.1 Setup

Investors There is measure one of continuum of investors who are infinitely lived. Each investor has one dollar available for investment, and can choose to either deposit the money with banks or invest in an outside option, such as MMFs and Treasuries. The outside option has value R but does not provide convenience value. Importantly, investors are heterogeneous in how much they value the convenience feature of deposits. Such convenience benefits can be motivated by the payment function that is unique to deposits and can vary across investors depending on their payment needs. For investor i, the convenience value she derives from holding deposits is

$$\theta_i \left(\sum_{j=1}^{N} d_{i,j,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{4.1}$$

where $d_{i,j,t}$ is the amount of deposit that investor i holds at bank j at time t. Deposits at different banks are imperfect substitutes because of the differentiated services offered by banks. The coefficient σ is the elasticity of substitution, capturing the degree of deposit differentiation across banks. The coefficient θ_i controls how much the investor values the convenience benefit of deposits relative to financial returns. For a given investor i, θ_i is known and fixed over time. The value of θ_i varies across investors — capturing the heterogeneity in how much weight investors place on the convenience benefit of deposits. We denote the cumulative density function (CDF) of θ_i as $H(\cdot)$, and $G(\theta) \equiv 1 - H(\theta)$. We can also interpret θ_i as the convenience value that an investor attaches to each dollar, and such value varies as the investor puts more money in deposits. We will later show how θ_i determines investor i's sensitivity to rates as well as how likely investor i leaves the banking system, i.e., flightiness.

Investors face switching cost $f > 0$ whenever they move money in and out of the banking system, similar to the marginal withdrawal cost in Jermann and Xiang (2023) and switching cost in Haddad et al. (2023). Such cost is homogeneous across investors and generates sluggishness in the depositor base. Finally, we assume all investors are risk neutral with discount rate β, and no shorting is allowed. This implies that each investor either invests everything in bank deposits or the outside option.

Banks There are $N \geq 1$ banks in the economy. Banks offer one-period deposits to investors in order to fund long-term illiquid projects. The equity holders of banks are long-lived with discount rate $\beta \in (0, 1)$. To study the liquidity problem faced by banks, we assume that equity holders have no endowment and cannot issue equity at any point in time.

On the asset side, banks invest in projects that mature with probability λ each period. The project generates no cash-flow before maturity. If the project matures at the end of period t, it produces cash-flow $y_t \geq 0$ per unit of asset and the game ends. y_t is i.i.d. across periods and is drawn from the CDF $F(\cdot)$. Even though the event of maturity is realized at the end of period t, all agents observe a signal about the value of y_t at the beginning of period t. The signal of y_t serves as a coordinating signal among investors. This asset could be interpreted as long-term loans made by banks, whose cash flow is mostly generated upon maturity and the fundamentals of the loan varies overtime.[13]

Modeling bank-run problems with bank competition is notoriously difficult. In order to simplify the problem of bank competition, we assume that banks are symmetric, i.e. their asset side returns are homogeneous. This allows us to characterize the dynamic investor base in a tractable way.

Next, we describe how banks adjust their balance sheet with deposit flows. When there are deposit inflows, banks use the influx of money to scale up their projects at per-unit cost 1. When there are deposit outflows, banks need to liquidate their assets to meet the outflows. Banks assets are illiquid in the sense that aggressive fire sales in a given period are associated with heavy dis-

[13] We can relax the i.i.d. assumption of y_t and also allow intermediate cash flows being generated before the project matures. Since they do not change the key mechanisms, we present the simplest case. In the calibration, we extend the model to the case when y_t follows an AR(1) process.

counts. Specifically, in a given period, if the asset sold is more than a fraction ϕ of the total asset, each unit is sold at $L(y) < 1$. Otherwise, each unit of asset can be sold frictionlessly at price 1. This liquidation schedule can be motivated by cash-in-the-market constraints or slow moving capital (Mitchell et al., 2007, Duffie, 2010). We assume the liquidation value is piece-wise linear in y,

$$L(y) = \min(\alpha_0 + \alpha_1 y, 1). \tag{4.2}$$

This liquidity discount will eventually give rise to strategic complementarity among investors.

For each dollar of deposit, bank j promises deposit rate $r_{j,t}$ if the asset side matures in period t; otherwise investors get face value 1 at the end of the period. Since investors are risk-neutral, this is equivalent to an expected interest rate payment of $\lambda(r_{j,t} - 1)$. Because projects generate no intermediate cash flows before maturity, banks can only pay interests when the projects mature. As the equity holders of the banks have no endowment, the promised deposit rate to the investors $r_{j,t}$ has to be weakly smaller than the cash flow generated from the asset side y_t, i.e.,

$$r_t \leq y_t. \tag{4.3}$$

This is effectively a liquidity constraint, limiting how much interest payment can be promised to retain depositors. When bank fundamentals deteriorate—that is, when y_t is low—banks are unable to offer sufficiently attractive rates to retain depositors, leading to outflows and potentially triggering runs. This constraint is crucial for generating runs in equilibrium.

Banks profit from the spread between the asset side returns and the deposit rates paid to investors. Bank equity holders are risk-neutral and choose the deposit rate optimally each period to maximize their expected equity value.

Timing At the beginning of each period, all agents observe the same signal about the value of y_t, which is the fundamental cash flow *if* the banks' projects mature this period. This serves as a coordination signal for the investors. Banks then choose deposit rates $r_{j,t}$, and investors decide whether and where to hold deposits. Banks scale up or sell their assets depending on the deposit flows. Finally, whether the projects mature or not is realized at the end of the period. If the projects mature, cash is paid out and the economy ends; otherwise, the economy continues to the next period.

4.2 Value Functions

Investors For investor i, her value from holding bank deposits in period t is denoted as $D(\{r_{j,t}\}, \theta_i, \Theta_t)$, where Θ_t is the set of investors in the banking system in period t. As we will see later in Section 4.3, banks' default probabilities depend on the set of existing depositors.

$$D(\{r_{j,t}\}, \theta_i, \Theta_t) = \max_{\{d_{i,j,t} \geq 0\}} \underbrace{\theta_i \left(\sum_{j=1}^{N} d_{i,j,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}}_{\text{convenience benefit}} + \underbrace{\lambda \sum_j r_{j,t} d_{i,j,t}}_{\text{expected (gross) interest payment}} \tag{4.4}$$

$$+ (1-\lambda)\beta \mathbb{E}[(1 - \mathbf{1}_{def,t+1}) \underbrace{\max\{D(\{r_{j,t+1}\}, \theta_i, \Theta_{t+1}), R - f\}}_{\text{Continuation value if no bank default}} + \mathbf{1}_{def,t+1} L(y_{t+1})] \tag{4.5}$$

$$s.t. \quad \sum_j d_{i,j,t} = 1, \tag{4.6}$$

where $d_{i,j,t}$ is the amount of deposits that investor i holds at bank j in period t. The first term in Equation 4.4 is the convenience value that investor i derives from holding deposits, and the second term is the gross interest payment that the investor expects to receive. Investors with higher θ_i derive higher value from holding deposits. Equation 4.5 is the continuation value if the projects do not mature in this period. The indicator function $\mathbf{1}_{def,t+1}$ equals 1 if and only if the banks experience a run and default in period $t+1$. It is a function of the fundamental realization y_{t+1} as well as the set of existing depositors Θ_t. If the banks default in the next period, then the investor gets the liquidation value $L(y_{t+1})$. Otherwise, the investor reallocates her money between deposits and the outside option. Because of symmetry, in equilibrium, the default risks of the banks are perfectly correlated.

Equation 4.4 implies that, investors with higher θ_i derive greater benefit from holding deposits and are therefore more inclined to remain in the banking system, all else equal. In contrast, those with lower θ_i are more likely to withdraw deposits from the banking system, so that an individual investor's convenience value naturally captures her flightiness. In Section 4.3.2, we will show formally that the marginal depositor's value of θ determines the probability of a panic-driven bank run.

Investors take the deposit rates offered and the default probability as given and allocate money across banks to maximize their value, subject to the constraint that the total deposits sum to one. To gain insights into how θ_i is directly related to deposit rate sensitivity, let us consider depositor's optimization problem, which yields the following relationship between the deposit demand at bank j_1 and bank j_2,

$$\lambda(r_{j_1,t} - r_{j_2,t}) = -\theta_i \left(\sum_{j=1}^{N} d_{i,j,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} \left(d_{j_1}^{-\frac{1}{\sigma}} - d_{j_2}^{-\frac{1}{\sigma}} \right) \tag{4.7}$$

Equation 4.7 shows that $1/\theta_i$ controls investor i's sensitivity to deposit rates when allocating deposits across banks. Investors with smaller θ_i value convenience benefit less, and hence are more sensitive to deposit rates. As we will show in Section 4.3.1, this then implies that from banks' perspective, deposit rate sensitivity is determined by the set of investors who are in the banking system. As the depositor base endogenously changes overtime, the rate sensitivity of deposits in the banking system evolves as well.

Because our focus is on investor heterogeneity, our model features both coordination frictions among investors within periods as well as inter-temporally, which differs from the typical dynamic bank run models in the literature (He and Xiong, 2012, He and Li, 2024). This structure also enables us to capture situations where banks experience moderate deposit outflows without triggering full-fledged runs. However, as a result, we do not necessarily have equilibrium uniqueness.[14] In the rest of the paper, we focus on the threshold equilibrium, where banks survive if the fundamental cash flow is above an endogenous threshold.

Banks We denote bank j's value function as $V(y_t, r_{j,t}, \theta_t)$. Conditional on not experiencing a run, the banker's equity value is

$$V(y_t, r_{j,t}, \theta_t) = \lambda(y_t - r_{j,t})D_{j,t} + (1-\lambda)\beta\mathbb{E}[(1 - \mathbf{1}_{def,t+1})V^*(y_{t+1}, \theta_t)], \tag{4.8}$$

where $D_{j,t} \equiv \int_{\theta_i \geq \theta_t} d_{i,j,t}$ is the total amount of deposits in the bank. If the project matures, the banker earns $y_t - r_{j,t}$ per unit of deposit. If the project does not mature and the bank does not experience a run, the banker gets the continuation value $V^*(y_{t+1}, \theta_t)$.

When the bank does not face a run, it chooses a deposit rate to maximize its value, subject to the liquidity constraint in Equation 4.3. However, if outflows become too large, the bank may be forced to liquidate a substantial portion of its assets at steep discounts, potentially triggering a depositor run. In that case, the bank fails and its value drops to zero. Under symmetric equilibrium, we can collapse the equilibrium deposit rates offered $\{r^*_{j,t}\}$ to simply r^*_t.

[14] In particular, a bad equilibrium always exists in which all investors leave the banks.

4.3 Equilibrium Analysis

In this section, we first describe the equilibrium depositor base and how it affects deposit rate sensitivity within the banking sector. This rationalizes the time-series variation in deposit flow sensitivity that we document empirically. We then characterize when banks experience runs and defaults. We find that the risk of panic run increases when the previous period's marginal depositor is flightier. Finally, we proceed to solve for banks' optimal strategy and the equilibrium flows.

4.3.1 Depositor Composition and Rate Sensitivity

Given the value of holding deposits, we can characterize which investors endogenously sort into bank deposits.

Lemma 1. *For a given period t, there exists an endogenous cutoff θ_t, such that investors with $\theta_i \geq \theta_t$ hold deposits, and investors with $\theta_i < \theta_t$ invest in the outside option. In other words,*

$$\Theta_t = \{\theta_i : \theta_i \geq \theta_t\}. \tag{4.9}$$

Lemma 1 highlights an important intuition: investors who are more convenience-seeking sort into banks, while those who are less convenience-seeking invest in the outside option. The marginal depositor θ_t is indifferent between the two and her θ_t is a sufficient statistic for the depositor base. A smaller θ_t implies there are more deposits in banks and the marginal depositor has a smaller convenience value. From now on, we denote the deposit value of investor i as $D(\{r_{j,t}\}, \theta_i, \theta_t)$.

Another implication of Lemma 1 is that when the bank receives deposit inflows, the incoming depositors necessarily have lower convenience values than the incumbents. As deposit inflows increases, the convenience value of the marginal depositor declines, making that depositor more prone to exit the banking system, i.e., flightier. Another interpretation is that as inflows increase, the convenience value of the marginal dollar of deposits declines, making that dollar more prone to existing the banking system. Hence, our model establishes a tight link between deposit-flow dynamics and shifts in the characteristics of the depositor base.

Evolution of Depositor Base Each period, investors compare their values from holding deposits with their outside option. If investor i already holds deposits in period $t-1$, then she will continue to hold deposits if and only if the value of holding deposits exceeds the value of the outside option less the switching cost, i.e., $D(\{r_{j,t}\}, \theta_i, \Theta_t) \geq R - f$. Otherwise, she will switch to holding deposits in period t if and only if the value of holding deposits minus the switching cost exceeds the outside option value, i.e., $D(\{r_{j,t}\}, \theta_i, \Theta_t) - f \geq R$.

Given that θ_t captures the depositor base, we can summarize the evolution of depositor base in the following equation,

$$\begin{cases} D(\{r_{j,t}\}, \theta_t, \theta_t) = R - f & \text{if} \quad \theta_t > \theta_{t-1} \\ D(\{r_{j,t}\}, \theta_t, \theta_t) \in (R - f, R + f) & \text{if} \quad \theta_t = \theta_{t-1} \\ D(\{r_{j,t}\}, \theta_t, \theta_t) = R + f & \text{if} \quad \theta_t < \theta_{t-1} \end{cases} . \tag{4.10}$$

If there is inflow into the banking system, it must mean that the marginal depositor is willing to pay the fixed cost f to move money into the banks; alternatively, if there is outflow, it must mean the marginal depositor is indifferent between staying in the banking system and receiving the outside option minus the fixed cost. When there is no flow, the deposit value must be in between. As the above equation shows, the marginal depositor θ_{t-1} becomes an important state variable for the dynamics of deposit rates, flows and default risks. Any shocks affecting the depositor base can have long-lasting impact.

Rate Sensitivity and Aggregate Flows To connect our model to the empirical facts documented in Section 3, we analyze how the marginal depositor θ_t affects the rate sensitivity of deposits within the banking system. The semi-elasticity of bank deposits with respect to deposit rates is given by

$$\frac{\partial ln D_{j,t}}{\partial r_{j,t}} = \sigma\lambda \frac{1 - 1/N}{N^{1/(\sigma-1)}} \frac{\int_{\theta_i \geq \theta_t} \frac{1}{\theta} dH(\theta)}{G(\theta_t)} = \sigma\lambda \frac{1 - 1/N}{N^{1/(\sigma-1)}} \mathbb{E}\left[\frac{1}{\theta} \middle| \theta \geq \theta_t\right]. \tag{4.11}$$

The expression shows that the rate sensitivity of deposits within the banking system is inversely proportional to the average convenience value of depositors in the banking system, i.e., $\mathbb{E}\left[\frac{1}{\theta} \middle| \theta \geq \theta_t\right]$. Therefore, when there is an aggregate deposit inflow, the marginal depositor θ_t decreases, leading to a decrease in the average convenience value of depositors in the banking system. As a result, the rate sensitivity of deposits increases. The relationship between aggregate flows and changes in rate sensitivity is consistent with our empirical findings in Figure 1b and Table 1.

Furthermore, our model connects changes in the marginal depositor's convenience value, θ_t, to shifts in the aggregate deposit flightiness and bank run risks (as we will show in the next subsection). Empirically observing the marginal depositor's convenience value is inherently difficult. However, given the relationship in Equation 4.11, we can use changes in the sensitivity of deposits to rate differentials in the cross-section as in Figure 1a to proxy for changes in the convenience value and flightiness of the depositor base.[15]

4.3.2 Bank Runs

Whether higher rate sensitivity and large outflows lead to panic runs further depends on the banks' assets. When a bank sells less than ϕ fraction of its assets, there is no liquidation discount. Hence, a bank can always sell the necessary amount of assets to meet outflows. However, when outflows exceed ϕ, the bank needs to sell more assets per unit deposit outflow due to fire-sale discounts. This incurred discount, in turn, makes remaining investors more likely to leave as well. We show that when the liquidity discount is large, i.e., α_0 and α_1 are small, the bank experiences a run if it cannot retain more than $(1-\phi)$ fraction of its investors.

We note that bank runs in our model are closely tied to deteriorating bank fundamentals, as they occur only when fundamentals fall below an endogenous threshold. This is consistent with the findings by Goldstein and Pauzner (2005) that fundamentals coordinate panic runs and by Baron et al. (2020), Correia et al. (2025) that fundamentals play an important role in explaining bank runs empirically. In our model, the incentive to run is further amplified by strategic complementarity among investors when they value the convenience of bank deposits less.

Under symmetric equilibrium, each bank's deposit flow is perfectly correlated with the aggregate flow. To characterize the aggregate flow, we define $\bar{\theta}_t$ as the "critical" depositor in period t, in the sense that if the depositor with convenience benefit $\bar{\theta}_t$ leaves, then the banking sector experiences more than ϕ fraction of outflows and the banks need to liquidate more than ϕ fraction of assets, incurring high liquidation losses, i.e.,

$$\underbrace{G(\theta_{t-1}) - G(\bar{\theta}_t)}_{\text{flow}} = \phi G(\theta_{t-1}). \tag{4.12}$$

Banks can potentially reduce outflows by increasing the deposit rate paid to investors. However, when y_t is low, banks may not be able to pay the deposit rate necessary to retain a critical mass of investors. As we show in Lemma 2, when y_t falls below an endogenous threshold, all depositors choose to leave, triggering a bank run.

[15] Recall that the deposit flow sensitivities in Figure 1a reflect changes in the sensitivity of deposits to rate differentials in the cross-section. A positive deposit flow-sensitivity estimates imply that this underlying average rate sensitivity has increased. Since our model is stationary, these predicted changes should be interpreted relative to a long-run trend, which may itself reflect digitization or other structural shifts in the economy.

Lemma 2. *When α_0 and α_1 are small, a bank experiences a run in period t when $y_t < y^*(\theta_{t-1})$, where θ_{t-1} is the previous period's marginal depositor in the banking sector. The run threshold $y^*(\theta_{t-1})$ is defined implicitly by,*

$$D(y^*(\theta_{t-1}), \bar{\theta}_t(\theta_{t-1}), \bar{\theta}_t(\theta_{t-1})) = R - f, \tag{4.13}$$

where $\bar{\theta}_t$ is defined in Equation 4.12.

Lemma 2 shows that when the liquidation discount is large, all investors choose to leave the bank if the critical depositor $\bar{\theta}_t$ chooses to leave, due to the strategic complementarity from the liquidation costs. Hence, whether banks can survive depends on whether they can offer a high enough deposit rate to convince the critical depositor to stay. When y_t is smaller than the threshold $y^*(\theta_{t-1})$, the critical investor $\bar{\theta}_t$ leaves even when banks set the highest deposit rate possible $r_{j,t} = y_t$. In this case, all investors leave, triggering a bank run. When y_t is above this threshold, then banks can set a high enough deposit rate to retain enough investors.

The run threshold y^* is endogenously pinned down by the strategic complementarity among investors making rollover decisions: if future investors are more likely to run, current investors require a higher deposit rate, raising the run threshold and the run probability. Building on He and Xiong (2012) and He and Li (2024), our model introduces the novel dimension of investor heterogeneity. Specifically, we show that the probability of a run is closely linked to the composition of the existing depositor base, which is both endogenous and time-varying. Proposition 1 formally characterizes how the depositor base shapes the equilibrium run probability.

Proposition 1. *The critical depositor $\bar{\theta}_t$ in period t is increasing in the previous period's marginal depositor's θ_{t-1}. The run threshold $y^*(\theta_{t-1})$ and a bank's run probability is decreasing in θ_{t-1}.*

Proposition 1 formally shows that the convenience value of the marginal depositor θ_{t-1} determines the risk of panic runs. When the previous period's marginal depositor is less convenience-seeking (with lower θ_{t-1}), then the critical depositor in the current period is also less convenience-seeking. This implies that, all else equal, a bank needs to pay higher interest rates in order to convince depositors to stay. Consequently, there is a higher run threshold and larger run probability in equilibrium.

Furthermore, Proposition 1 also highlights how a given investors' value of deposits depends on other types of investors in the banking system. If the marginal depositor is less convenience-seeking, this increases future run probability and lowers the value of bank deposits for *all* investors in the current period.

We note that while the precise threshold for a run depends on the liquidity frictions, bank runs occur only when fundamentals deteriorate sufficiently. Hence, any factor that weakens bank fundamentals further amplifies the risk of a run. For instance, if the value of bank assets depreciates due to rising Fed Funds rates (Haddad et al., 2023, Drechsler et al., 2023, Jiang et al., 2023) or downturns in commercial loans (Chang et al., 2025), as in the 2023 Regional Banking Crisis, the likelihood of a run increases.

Having characterized the run condition, we can rewrite bank j's problem as the following,

$$V^*(y_t, \theta_t) = \max_{r_{j,t}} \quad V(y_t, r_{j,t}, \theta_t) \tag{4.14}$$

$$s.t. \quad r_{j,t} \leq y_t \tag{4.15}$$

$$D_{j,t} \geq (1-\phi) D_{j,t-1}, \tag{4.16}$$

When constraint (4.15) and (4.16) cannot be both satisfied, the bank fails.

Bank's Liquidity Management So far, we have abstracted away from banks' asset side adjustment for tractability reasons, in line with the broad bank run literature. Nevertheless, to address the concern that banks may want to disproportionately purchase liquid assets over illiquid assets to offset the run risk of deposit inflows, we extend the model and discuss the conditions under which our results in Proposition 1 go through. Specifically, we allow the fraction of liquid assets $\phi(\theta_t)$ to be a function of the marginal depositor flightiness θ_t. One could think of this function as the outcome of banks' optimal portfolio choice problem given the banking sector's depositor base. Here we model it in a reduced form way, where we assume that the chosen fraction of liquid assets is higher when the marginal depositor becomes flightier, i.e., $\phi'(\theta_t) < 0$. We then have the following corollary.

Corollary 1. *When α_0 and α_1 are small, the run threshold $y^*(\theta_{t-1})$ and the bank's run probability decreases with θ_{t-1} if*

$$\frac{G'(\theta_{t-1})}{G(\theta_{t-1})} < \frac{\phi'(\theta_{t-1})}{1-\phi(\theta_{t-1})}. \tag{4.17}$$

To understand Corollary 1, consider the relationship between the critical depositor $\bar{\theta}_t$ and the previous period marginal depositor θ_{t-1}. As before, the critical depositor is defined as the depositor whose departure would force banks into selling illiquid assets and incur liquidation discounts. The marginal depositor influences banks' default probabilities by affecting who the critical depositor is.

Different from before, ϕ now varies with θ_{t-1}, which changes the relationship between the critical depositor and the marginal depositor. Specifically, $\bar{\theta}_t$ is now defined by

$$G(\theta_{t-1}) - G(\bar{\theta}_t) = \phi(\theta_{t-1})G(\theta_{t-1}). \tag{4.18}$$

When ϕ is fixed, $\bar{\theta}_t$ is always increasing in θ_{t-1} — as the marginal depositor becomes flightier, the critical depositor also becomes flightier, which means banks need to promise higher deposit rates to convince investors to stay in the banking system. However, if banks can increase the fraction of liquid assets ϕ as the marginal depositor becomes flightier, i.e., $\phi' < 0$, the relationship between the flightiness of the critical depositor and that of the marginal depositor is weakened. Condition (4.17) compares the adjustment in liquid assets scaled by the existing fraction of illiquid assets $|\frac{\phi'(\theta_{t-1})}{1-\phi(\theta_{t-1})}|$ and the amount of deposit flow $|\frac{G'(\theta_{t-1})}{G(\theta_{t-1})}|$ scaled by existing depositor base.[16] When the two terms are exactly equal, all deposit inflows are invested in the liquid assets. As a result, the adjustment in asset composition fully offsets the change in the depositor base, and the critical depositor flightiness does not vary with the marginal depositor flightiness at all. Outside of this extreme case, Corollary 1 states that our results go through. In practice, an incremental inflow of deposits tends to be allocated partly to liquid assets and partly to illiquid assets in order to earn the associated risk and liquidity premia, and the allocation towards illiquid assets may be further amplified by bank agency frictions. Hence, even though the bank may tilt its portfolio more towards liquid assets when incoming investors are flightier, our main results hold as long as inflows are not 100% invested in fully liquid assets.

4.3.3 Deposit Rates and Flows

To determine the endogenous depositor base in the banking system, we solve for banks' optimal policy function and the equilibrium deposit flows. In general, banks trade-off higher interest rate expenses with the benefit of more deposits. Denote the Lagrangian Multiplier in front of the flow constraint Equation 4.16 as ι. Bank j's first order condition with respect to its deposit rate $r_{j,t}$ is

$$-\lambda D_{j,t} + \left[\lambda(y_t - r_{j,t}) + \iota + (1-\lambda)\beta\frac{\partial \mathbb{E}[(1-\mathbf{1}_{def})V^*]}{\partial D_{j,t}}\right]\int_{\theta_t}\frac{\partial d_{i,j,t}}{\partial r_{j,t}}dH(\theta) = 0. \tag{4.19}$$

The first term captures the additional interest expense if the deposit rate is higher, while the second term captures the benefit of the additional deposits that a higher rate would attract. Finally, if

[16] Note that $\phi' < 0$ and $G' < 0$.

the flow constraint is binding, the bank needs to set a higher rate than otherwise to avoid large-scale asset sales and bank runs. Note that an individual bank takes the aggregate depositor base, characterized by θ_t, as given, but internalizes the effect of deposit rates on flows between banks. Given the deposit rates, the deposit flow is pinned down by the conditions in Equation 4.10 and is characterized by different regions in Proposition 2.

Proposition 2. *For a given θ_{t-1}, there exists an outflow threshold $y_{out}(\theta_{t-1})$, defined by Equation D.19, and an inflow threshold $y_{in}(\theta_{t-1})$, defined by Equation D.20, such that*

1. *For $y_t \in [y^*(\theta_{t-1}), y_{out}(\theta_{t-1}))$, $\theta_t^* = \min\{\theta_1(y_t), \bar{\theta}_t\}$, where $\theta_1(y_t)$ is defined by Equation D.21. In this case, $\theta_t^* > \theta_{t-1}$ and the bank has deposit outflows.*

2. *For $y_t \in [y_{out}(\theta_{t-1}), y_{in}(\theta_{t-1})]$, $\theta_t^* = \theta_{t-1}$. There is no deposit flow.*

3. *For $y_t > y_{in}(\theta_{t-1})$, $\theta_t^* = \theta_2(y_t)$, where $\theta_2(y_t)$ is defined in Equation D.22. In this case, $\theta_t^* < \theta_{t-1}$ and the bank has deposit inflows.*

Proposition 2 provides a complete characterization of the banking sector's marginal depositor under different scenarios. In the first case when fundamentals are weak, banks do not want to invest much. Hence banks set low deposit rates, which lead to a moderate degree of deposit outflows. However, the outflows cannot be too large or else banks risk selling large amounts of assets that incur liquidation discounts. When y_t is very low, the flow constraint starts to bind, in which case banks are forced to set a higher deposit rate than the unconstrained level to reduce the outflows. When y_t is below y^*, banks cannot keep the critical depositor and experience runs, as explained in Section 4.3.2. In the second case, y_t is in an intermediate region with no flows at all, due to the switching cost. Finally, in the third case, y_t is so high that banks want to make more investments by attracting more deposits. Competition among banks leads to high deposit rates, which convince outside investors to pay the switching cost and move money into banks. This only occurs when the fundamentals are above the inflow threshold $y_{in}(\theta_{t-1})$.

Therefore, our model endogenously links the flightiness of the current depositor base with the fundamentals on the asset side and the previous period depositor base. Intuitively, the marginal benefit of deposits is larger when the fundamentals are stronger. Hence, when y_t is larger, banks set higher rates, which attract flightier depositors. Furthermore, the depositor base is sticky due to the switching cost, which is why the marginal depositor's flightiness tends to be positively correlated across periods. Figure 11a provides a numerical illustration of the equilibrium strategy for two different levels of θ_{t-1}.

Having characterized the bank's optimal policy function, we next discuss how the magnitude of deposit flows depends on the fundamentals and the previous period's marginal depositor. The details are presented in Corollary 2.

Corollary 2. *For a given θ_{t-1}, θ^* is decreasing in y_t. The net deposit flow in period t, $G(\theta^*(y_t, \theta_{t-1})) - G(\theta_{t-1})$, is weakly increasing in y_t and θ_{t-1}.*

Figure 11b provides a numerical illustration of the equilibrium deposit flows. The banking sector's net inflow increases with y_t because banks set higher deposit rates when the fundamentals are stronger. Furthermore, banks are more likely to attract inflows when the previous period's depositor base is smaller and less flighty. As a result, the net inflow is increasing in θ_{t-1}.

Our model highlights that the deposit flow is an important object to keep track of for banking sector fragility. Given Lemma 1, whenever we see deposit inflows from the outside, the marginal depositor in the banking system becomes flightier, and whenever we see outflows, the marginal depositor becomes less flighty. Furthermore, the marginal depositor type affects the run probability directly, as shown in Proposition 1. Hence, the endogenous determination of flows characterized in Corollary 2 governs the evolution of financial fragility risks over time.

5 Implications for Monetary Policy and Financial Stability

In this section, we study the joint effect of conventional and unconventional monetary policy on financial stability considering a heterogeneous and path-dependent depositor base.

We first extend and calibrate the model in Section 5.1. In Section 5.2, we demonstrate a novel interaction effect between conventional and unconventional monetary policy. We show how the impact of rate hikes on financial fragility varies with the amount of QE, banks' liquid asset holdings, and shocks to bank fundamentals.

5.1 Model Calibration

We calibrate the model to match the size-weighted average of all U.S. banks. Unless otherwise mentioned, we use the call report data in Section 2 and average over the sample period from 2000Q1 to 2019Q4, before the latest round of QE. We take each period in the model to be one year and use annualized returns and interest rates. We summarize the empirical targets and moments in Table 5a and Table 5b . The calibrated parameter values are shown in Table 5c. In the remainder of this subsection, we discuss our calibration approach and intuition.

First, on the asset aside, we relax the model assumption that y_t is i.i.d. across periods. Instead, we extend the model to let y_t follow an AR(1) process, with mean μ and auto-correlation coefficient $\rho < 1$.

$$y_t - \mu = \rho(y_{t-1} - \mu) + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_y^2), \tag{5.1}$$

where ϵ_t is the shock in period t and is i.i.d. across periods. We run an AR(1) regression using the gross return on assets from the interest income, and we set ρ to the AR(1) coefficient from the regression. Furthermore, we set the expected project maturity $1/\lambda$ to the average bank asset maturity in the data.

For the liquidation value function, $L(y) = \min(\alpha_0 + \alpha_1 y, 1)$, we set $\alpha_0 = 0$ and match $1 - \alpha_1$ to the weighted average discount of bank assets. We follow Bai et al. (2018) to use the New York Fed's repo haircut data as liquidation discounts for Treasuries, agency securities, corporate bonds, municipal bonds, asset-backed securities, and mortgage-backed securities. For the cost of liquidating loans, we apply the estimate in Chernenko and Sunderam (2020) that loans are 4.8 times as illiquid as corporate bonds. For the liquid asset fraction, ϕ, we match the amount of "ample" reserves that can be liquidated without costs (Afonso et al., 2022).

We follow the literature (e.g., He and Krishnamurthy 2019 among others) and set the time discount rate to 2%, i.e. $\beta = 0.98$. We set the outside option value R to $1 + \overline{FFR}$ where $\overline{FFR}$ is the average Fed funds rate in our sample period.

To calibrate the remaining parameters, we simulate model moments to match their empirical counterparts. We assume the convenience value of investors θ_i follows an exponential distribution, i.e., $H(\theta) = 1 - e^{-\gamma\theta}$. We jointly estimate the rate parameter γ, switching cost f, the elasticity of substitution σ, the average asset return μ and the volatility of the shock process in Equation 5.1 to match the correlation between aggregate deposit flow and deposit spreads, the aggregate deposit flow volatility, the median deposit rate, the average asset return conditional on survival, and the median default probability in the data. We use the correlation between the aggregate deposit flow and the average deposit spread to infer the parameter γ.[17] The default probabilities are obtained from the average bank CDS spreads. We simulate the model for 10,000 periods, discard the first

[17]While bank-to-bank rate sensitivity depends solely on the level of the marginal depositor's θ_t at each date, the sensitivity of flows between the banking sector and outside investments is governed by the full distribution of θ.

500 periods to reduce the impact of the initial starting point, and calculate the same moments using model-simulated data.[18]

5.2 Counterfactual: Interaction Effect between QE and Rate Hikes

In this exercise, we would like to understand how the effect of policy rate hikes on run risk and deposit outflows interact with QE's deposit expansions. In the baseline estimates, we interpret conventional monetary policy as changing the value of the outside option R, since the returns on liquid assets are mostly determined by the policy rate. When the monetary policy rate is increased, the return that investors can earn from switching to the outside options, R, increases, leading to deposit outflows and raising the probability of bank runs as long as bank assets are not fully liquid. In an extension exercise, we further consider the effect of rate hikes that also influence the value of bank fundamentals.

In the baseline specification, we interpret unconventional monetary policy as an inflow of investors into the banking system. This mapping follows Acharya and Rajan (2022), Acharya et al. (2023), Lopez-Salido and Vissing-Jorgensen (2023) , who show that reserve injections from QE expand the depositor base. What happens in the background is that when the Fed buys Treasuries in QE, most of the Treasuries sold were not held on banks' balance sheets. Many were sold by non-banks like hedge funds and asset management companies, which do not have an account at the Fed. Instead, they received deposits at the bank that received the reserves from the Fed.[19] In this new equilibrium, more investors choose to hold deposits over Treasury securities than before QE because QE lowered the return on holding Treasuries. Modeling the general equilibrium adjustments in different asset markets are beyond the scope of our paper. Instead, in the baseline estimates, we use the volume of deposit expansions as a sufficient statistic that affects the composition and flightiness of the depositor base in equilibrium. By revealed preferences, as long as the total deposit volume increases, incoming investors value the convenience benefit of deposits less than existing depositors (Lemma 1), so the marginal depositor becomes flightier after QE, i.e., θ_{t-1} decreases. Therefore, we expect the same rate hike to cause larger deposit outflows and a larger jump in run risk following QE. Nevertheless, the effect on run risk is mitigated if banks invest a

[18]If the simulated fundamental value in a given period is below the run threshold in that period, we replace it with the value at the run threshold.

[19]Note, however, that these hedge funds and asset managers may not be the ultimate holders of deposits. They could use their deposits to buy other assets, and the deposits would be transferred to the sellers of those assets. This process goes on until the economy equilibrates.

larger share of their incoming funds into fully liquid assets such as reserves that are not required for meeting regulatory requirements. We further consider this scenario in an extension exercise.

First, we show that run risk is more sensitive to rate hikes when the marginal depositor has a lower convenience value, i.e., when θ_{t-1} is lower. We demonstrate this result by analyzing the impact of an unexpected 2% rate hike at the end of 2022Q1, which marks the start of the Federal Reserve's most recent rate hike cycle. In other words, the value of the outside option is increased by 2%. We set the starting point of the fundamental value y to match the asset return in 2022Q1 and estimate the increase in run risk with different convenience values of the existing marginal depositor currently in the banking system. Figure 12 shows that the increase in bank default probability for this 2% rate hike is increasing in the flightiness of the marginal depositor. When the marginal depositor in the banking sector values convenience by less, all investors expect banks to fail with higher probability in the future. Hence, investors are more likely to withdraw their deposits in the current period when the outside option becomes more attractive, leading to a larger jump in default risk.

We then ask how much QE's deposit expansions in the aftermath of the Covid-19 crisis raised the risk from subsequent rate hikes by drawing in less convenience-seeking investors into the banking system. Specifically, we compare the effect of a 2% rate hike with and without QE's deposit expansions. The reserves injected in QE attract new deposits (Acharya et al., 2023), which increases the average deposit rate sensitivity. Hence, to go from the case of "No QE" to "QE", we adjust the marginal depositor in the model such that the change in the deposit rate sensitivity relative to the simulation results matches with the cumulative flow sensitivity estimated between 2020Q1 to 2022Q1 in Figure 1a.

Figures 13a and 13b show our baseline estimates. We see that when the 2% rate hike follows QE's deposit expansions, there is a 185 bps increase in bank default probability. In comparison, if the same 2% rate hike were implemented absent of QE's deposit expansions, the increase in bank default probability would be reduced by almost 50% to 96 bps. We also calculated the expected outflows from the banking sector due to the same monetary policy tightening. A 2% rate hike would cause a 7% deposit outflow following QE's deposit expansions, compared to a 2.5% outflow absent QE's deposit expansions.

We note that QE also injects reserves into the banking system, thereby increasing the share of liquid assets on bank balance sheets. At the aggregate level, if QE's deposit expansions are fully invested in reserves and if reserves were fully liquid for banks to sell, then the increase in deposit flightiness and outflows in the banking sector would not increase financial stability risk. In practice, however, not all reserves are costless to sell, as banks have substantial demand for reserves to meet a range of regulatory constraints. In particular, banks are required to hold larger intraday reserve buffers following QE, but these requirements are not adjusted downwards in the presence of liquidity shocks or QT. These regulatory constraints and the anticipation of potential future constraints render it costly for banks to reduce their reserve holdings beyond a certain level. They may also cause banks to delay outgoing payments to other banks in an attempt to preserve their own reserves (Copeland et al., 2021, Acharya et al., 2023). Such strategic behavior encumbers the efficient reallocation of reserves across banks and further increases the overall demand for retaining reserves on bank balance sheets (Afonso et al., 2022).

At the individual bank level, the equilibrium distribution of reserves and deposits also varies. Some banks, for example, those with better loan demand, may absorb a disproportionate amount of deposits and invest them in loans rather than holding them as reserves. The increase in run risk from the same increase in deposit flightiness would be larger at these banks.

Our model shows that unless the entire increase in reserves is costless to sell, the amplification effect of a flightier deposit base on run risk persists (Corollary 1). To further explore the magnitude of the offsetting effect of reserves, we consider a variation of the counterfactual in which the QE scenario includes a higher level of liquid-asset holdings and an increase in deposit flightiness. Specifically, we set ϕ to 4.17% to match the median bank's ample-reserve position following QE in 2022Q1, following the estimates in Afonso et al. (2022). With a larger liquidity buffer, the increase in default probability associated with a 2% rate hike under QE declines to 105 basis points (Figure 14b), and the expected outflows fall to 3.3% (Figure 14a). These results show that the adverse effect of a flightier deposit base on run risk can be mitigated by reducing banks' demand for holding reserves to satisfy regulatory requirements. That would increase the proportion of reserves that can serve as truly liquid assets in the case of depositor withdrawals, which would, in expectation, reduce run risk.

Finally, monetary policy rate changes may directly affect bank asset fundamentals. For example, higher interest rates can reduce the value of banks' long-term fixed-income portfolios (Jiang et al., 2023). To capture this channel, we consider an additional counterfactual in which the fundamental value y declines by one-half of a standard deviation — 1.55% in the data — following the rate hike. This deterioration in fundamentals amplifies the effects of monetary tightening overall, but they remain more pronounced in the case with than without QE. Under QE, the increase in default probability associated with a 2% rate hike rises to 314 basis points, compared with 157 basis points in the absence of QE (Figure 15b). Expected outflows also increase, reaching 8% under QE and 2.9% without QE (Figure 15a). Therefore, the effect of rate hikes on bank asset values should be jointly considered in determining the impact on bank run risk and deposit outflows.

6 Conclusion

In this paper, we analyzed the magnitude, determinants, and implications of variations in the aggregate deposit flightiness over time. We show that the deposit flow sensitivity, which is a proxy for deposit flightiness, displays pronounced fluctuations over time. Large increases in deposit flightiness coincide with expansions in the Federal Reserve's balance sheet size and low interest rate environments. In particular, deposit flightiness reached unprecedentedly high levels following the large injection of central bank reserves in the aftermath of the Covid-19 crisis.

We rationalize the variation in deposit flightiness based on heterogeneity in investors' convenience value for deposits. With a fixed cost of moving deposits, the marginal depositor in the banking system is time-varying and path-dependent. At any given point in time, those remaining in the banking system value the convenience of bank deposits by more than those that invest in outside options. Following large deposit inflows from outside investors, the marginal depositor in the banking system values convenience less, and the aggregate depositor base becomes flightier. This is why aggregate deposit flightiness increases following an influx of deposits. Higher deposit flightiness eventually leads to higher run risk if incoming funds are partially invested in illiquid assets.

Our findings have far-reaching policy implications. For a given monetary policy rate hike, the expected deposit outflows are larger following large-scale QE programs, which introduce flightier deposits into the banking system. Run risk may also be heightened at banks that do not fully back their deposit inflows with reserves. Going forward, this linkage between the financial fragility risk of monetary policy and the size of the central bank's balance sheet is especially relevant as central banks navigate monetary policy in ample reserve environments.

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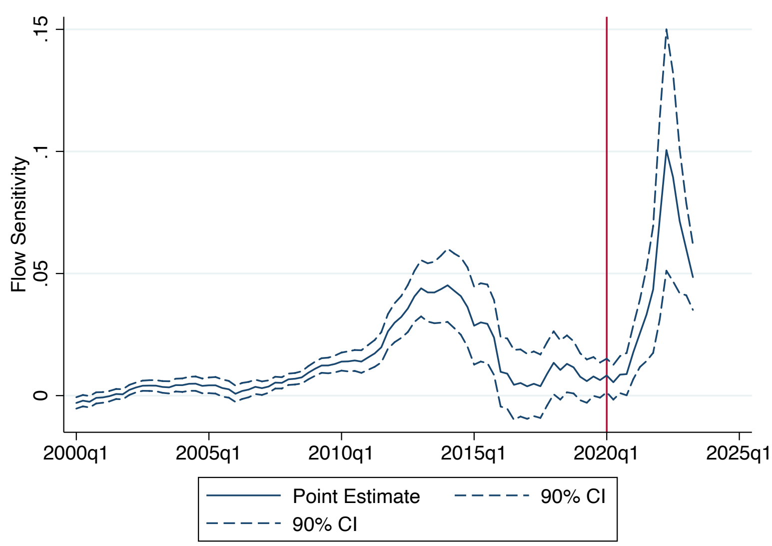
Figures and Tables

Figure 1: Deposit Flow Sensitivity

Panel (a) shows deposit flow sensitivities over time. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1. Panel (b) shows deposit flow sensitivities and aggregate deposit flows over time. Aggregate deposit flows are calculated as 8-quarter cumulative flows. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

(a) Deposit Flow Sensitivity



(b) Deposit Flow Sensitivity and Aggregate Deposit Flow

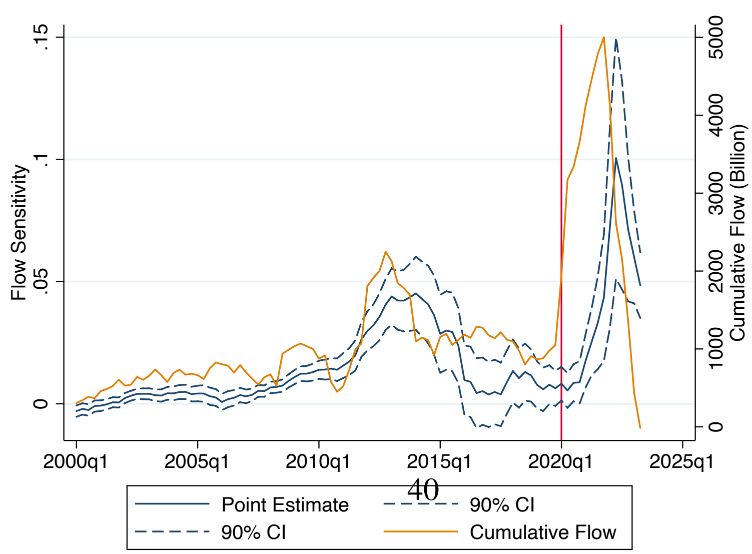


Figure 2: Deposit Flow Sensitivity and Reserve Supply

This graph shows deposit flow sensitivities and the supply of reserves over time. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation (3.1). Reserve supply is the total volume of outstanding reserves on bank balance sheets. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

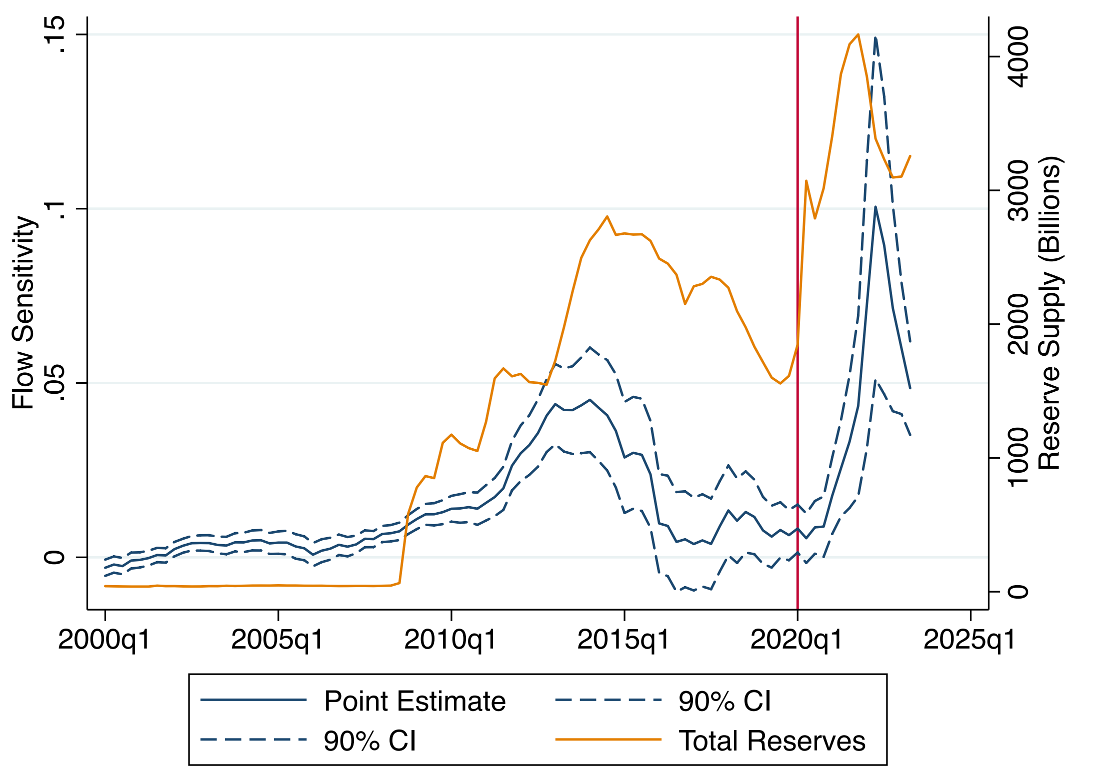
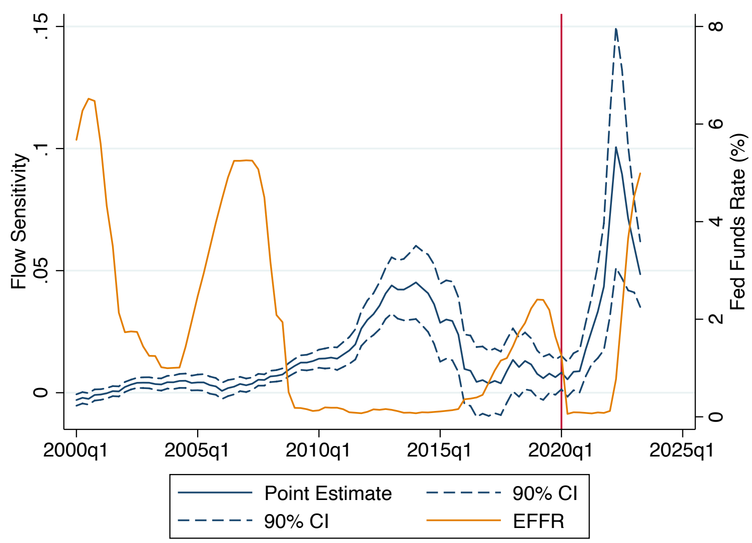


Figure 3: Deposit Flow Sensitivity and Monetary Policy

Panel (a) shows deposit flow sensitivities and the Fed funds rate over time for the full sample. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1. The vertical red line corresponds to 2020Q1. Panel (b) shows deposit flow sensitivities and the Fed funds rate from 2001 to 2009. Standard errors are clustered at the bank level.

(a) Deposit Flow Sensitivity and Monetary Policy



(b) Deposit Flow Sensitivity and Monetary Policy (2000 to 2009)

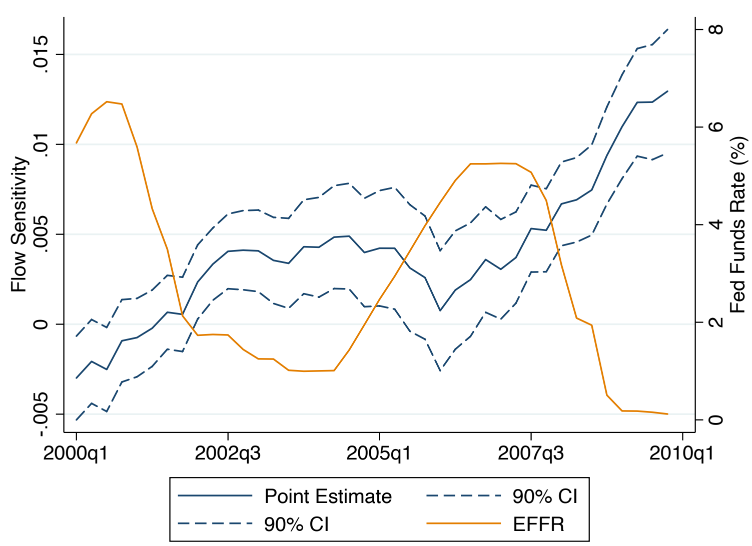


Figure 4: Savings Deposit Flow Sensitivity

This figure shows savings deposit flow sensitivities. Savings deposit flow sensitivities are obtained from regressing bank-level savings deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

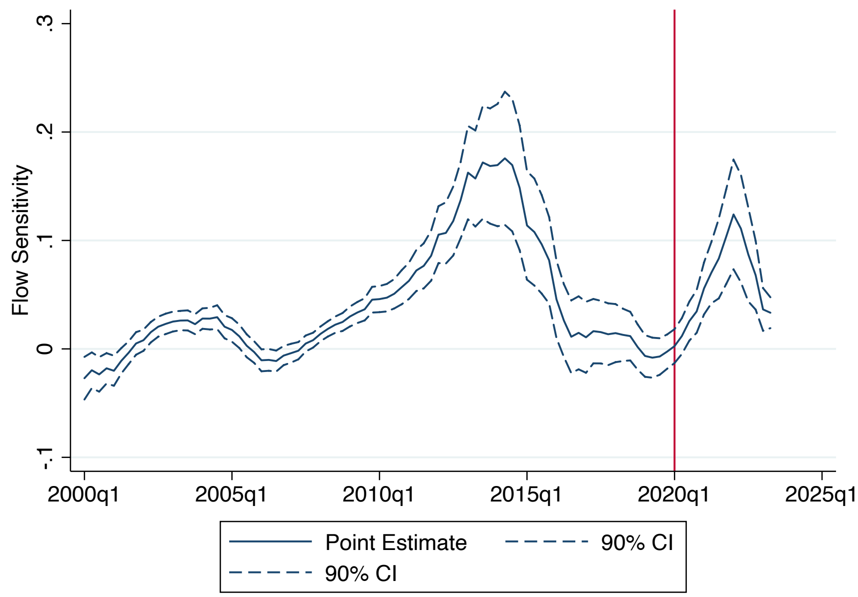
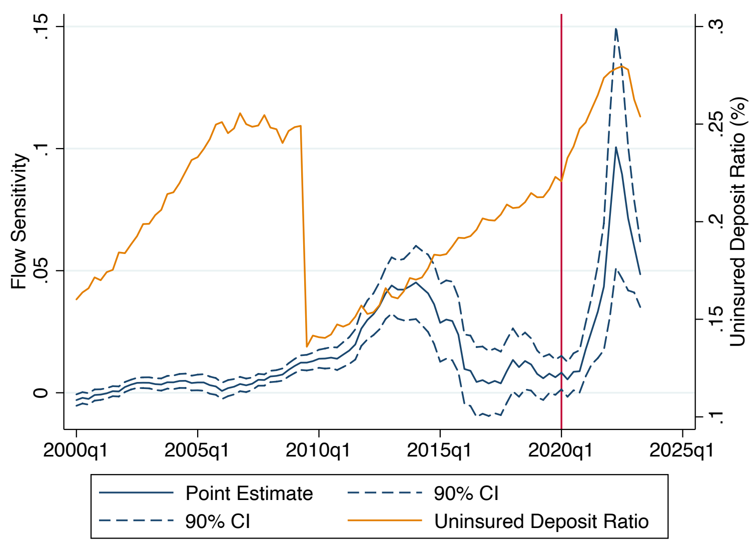


Figure 5: Deposit Flow Sensitivity and the Ratio of Uninsured Deposits

Panel (a) shows deposit flow sensitivities and the aggregate ratio of uninsured deposits over time. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1. Panel (b) shows deposit flow sensitivities controlling for the ratio of uninsured deposits at the bank level. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1 and controlling for the level of uninsured deposits. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

(a) Deposit Flow Sensitivity and the Aggregate Ratio of Uninsured Deposits



(b) Deposit Flow Sensitivity controlling for Uninsured Deposits

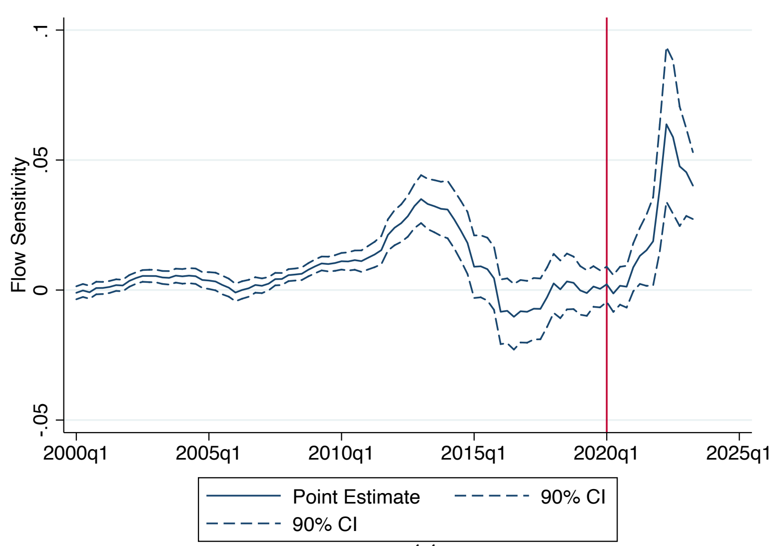


Figure 6: Deposit Flow Sensitivity (Additional Controls)

This figure shows deposit flow sensitivities over time controlling for additional bank characteristics. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1 with additional controls. Additional controls include banks' return on assets, assets per branch, number of employees per branch, and salaries per employee. The vertical red line corresponds to 2020Q1. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

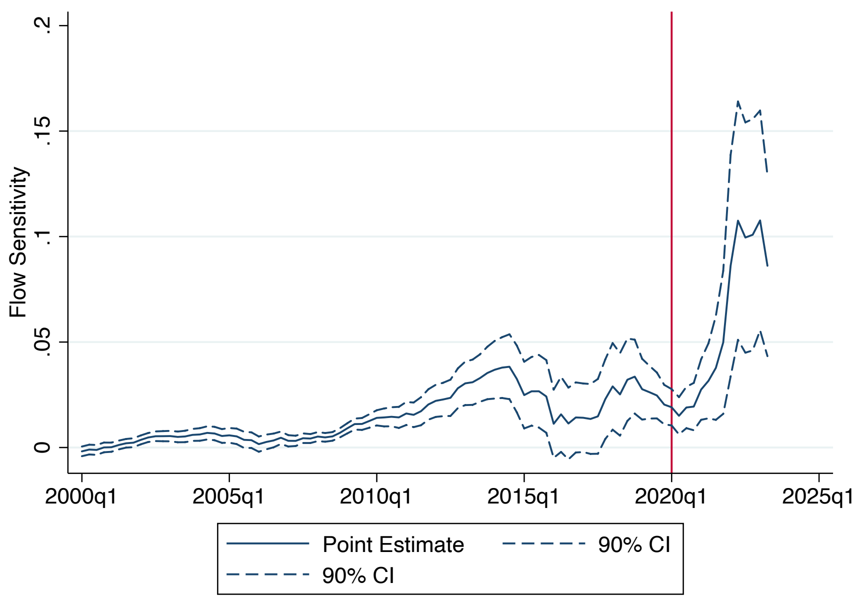
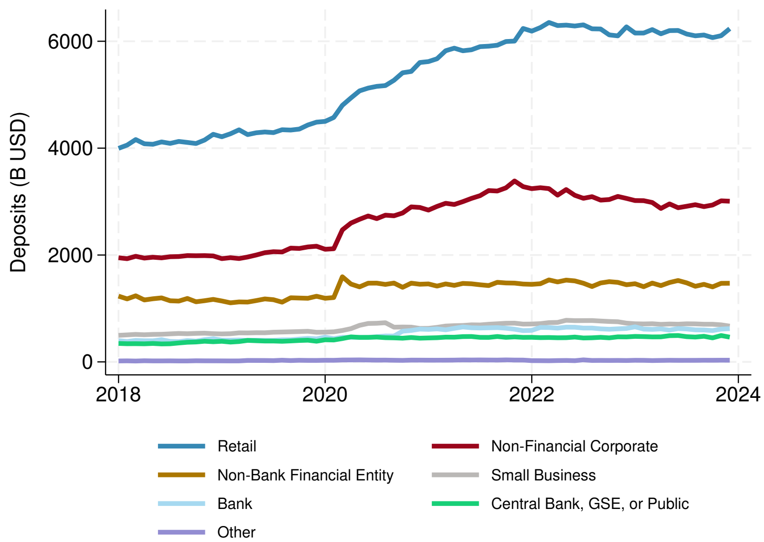


Figure 7: Deposits by Counterparty Type

Panel (a) shows the total volume of deposits by counterparty type. Panel (b) shows the volume of deposits by counterparty type as an index relative to their January 2020 levels. The sample includes banks with assets above $100 billion that filed the corresponding variables in the FR2052 form from 2018 through 2023.

(a) Volume of Deposits ($1 Billion)



(b) Volume of Deposits (Indexed to January 2020)

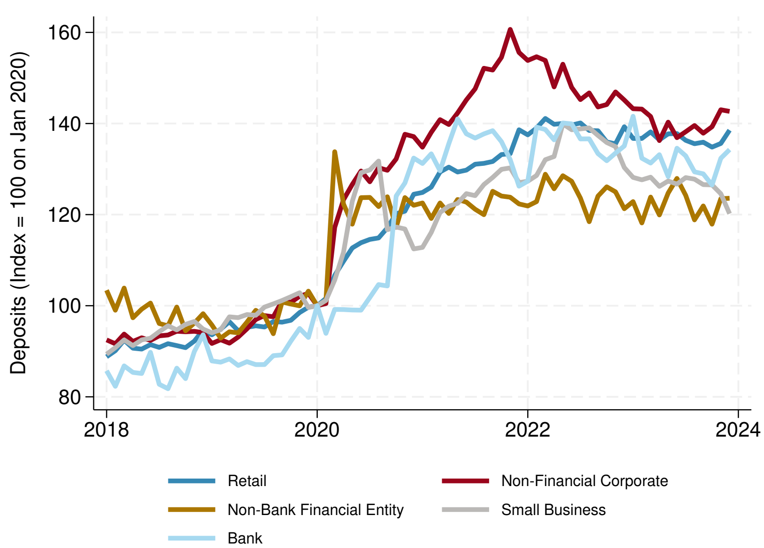
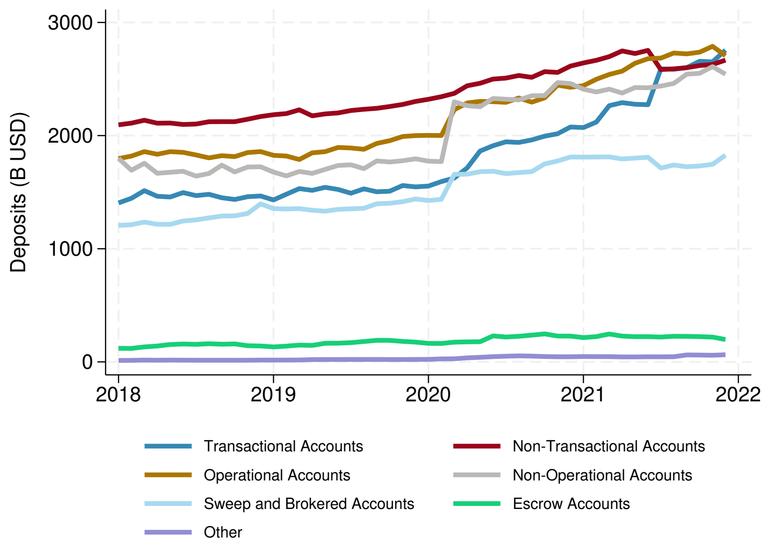


Figure 8: Deposits by Account Type

Panel (a) shows the total volume of deposits by account type. Panel (b) shows the volume of deposits by account type as an index relative to their January 2020 levels. The sample includes banks with assets above $100 billion that filed the corresponding variables in the FR2052 form from 2018 through 2021.

(a) Volume of Deposits ($1 Billion)



(b) Volume of Deposits (Indexed to January 2020)

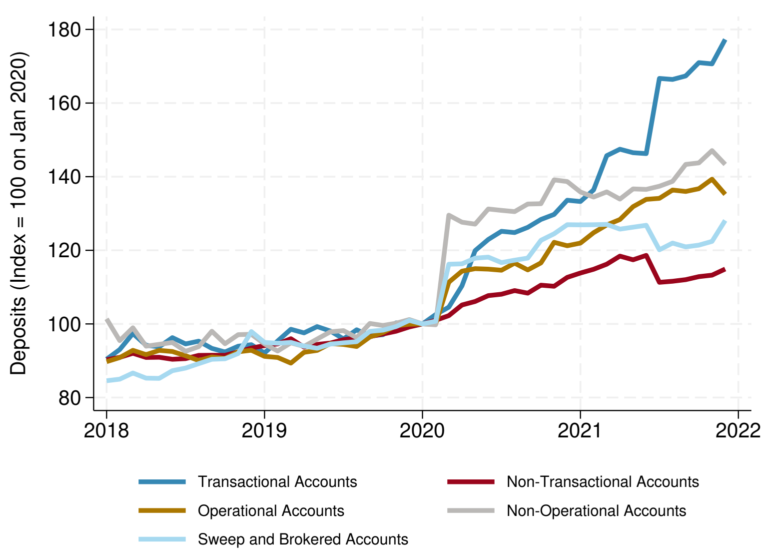
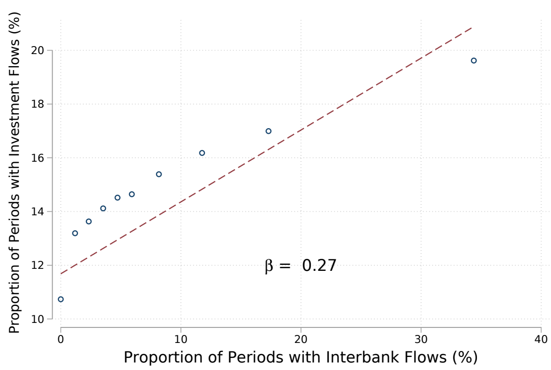


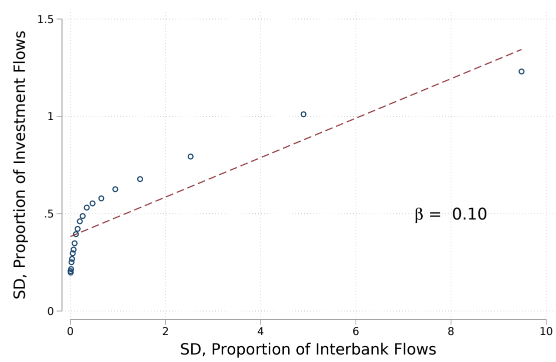
Figure 9: Depositor Flightiness in the Cross-Section

This figure shows binned scatter plots of depositor-level flightiness in moving funds between banks versus in moving funds between banks and outside investments during our sample period from Jan 2015 to Sep 2022. Panel (a) measures flightiness in terms of the proportion of months in which a depositor has flows between banks and between banks and non-banks. Panel (b) measures flightiness as the standard deviation in flows between banks and between banks and non-banks scaled by total payment flows. Panels (c) measures flightiness as the rate sensitivity of deposit flows between banks and between banks and non-banks.

(a) Prop of Months with Flows



(b) Scaled SD of Flows



(c) Flow Sensitivity

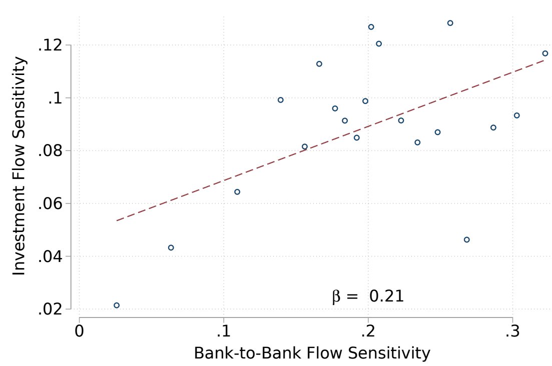


Figure 10: Depositor-Level Deposit Flow Sensitivity

This figure plots the depositor-level flow sensitivities between banks. It shows the sensitivity of net deposit flows to a depositor's bank account from her other bank accounts with respect to the deposit rate offered by that bank account. We run monthly regressions and plot 12-month moving averages of the coefficient on account-level interest rates. In each regression, we include depositor fixed effects and indicator variables for various account characteristics.

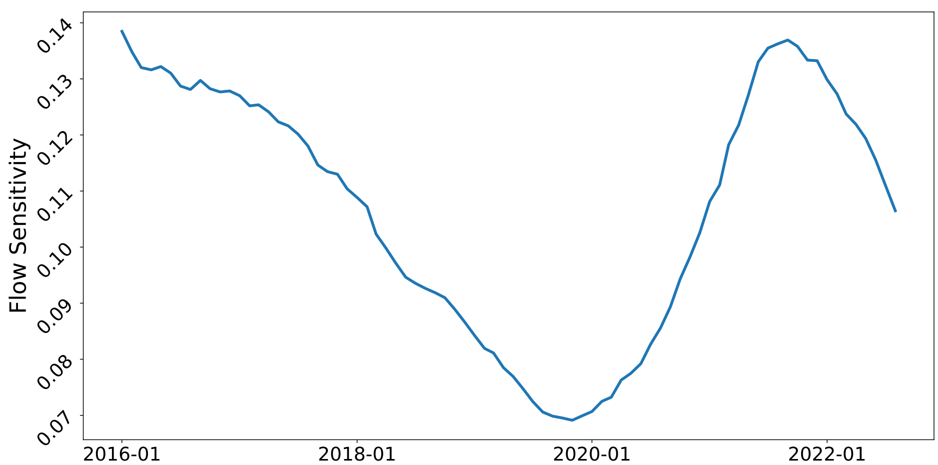


Figure 11: Numerical Illustration of the Equilibrium

Panel (a) plots the equilibrium marginal depositor type $\theta^*(y_t, \theta_{t-1})$ against the realized fundamental cash flow y_t. Panel (b) shows the net deposit flow under the bank's optimal rate setting policy against realizations of y_t. The black line shows the equilibrium solution for a high $\theta_{t-1} = 0.06$, and the blue line shows the solution for a low $\theta_{t-1} = 0.024$. The vertical line shows the run threshold in the two cases. We assume y is normally distributed with mean 1.02 and volatility 0.15, and θ_i is uniformly distributed in $[0, 0.6]$. For the other parameters, we set $R = 1$, $\lambda = 0.5$, $f = 0.05$, $\phi = 0.1$, $\beta = 0.9$, $\alpha_0 = 0$ and $\alpha_1 = 0.3$.

(a) Equilibrium θ_t^* **(b)** Net Deposit Flows

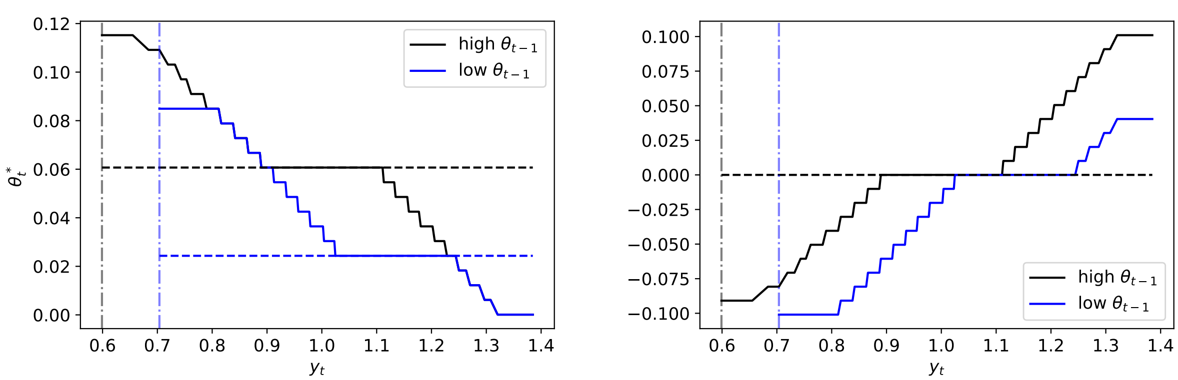


Figure 12: Change in Default Probability from a 2% Rate Hike by Marginal Investor Type

This figure plots the change in bank default probability $F(y^*)$ when the Fed Fund rate increases unexpectedly by 2% in one period, against the marginal depositor type θ_{t-1} at the beginning of the period. We use calibrated parameter values in Table 5c. The fundamental value y before the rate hike is set to match the asset return in 2022Q1.

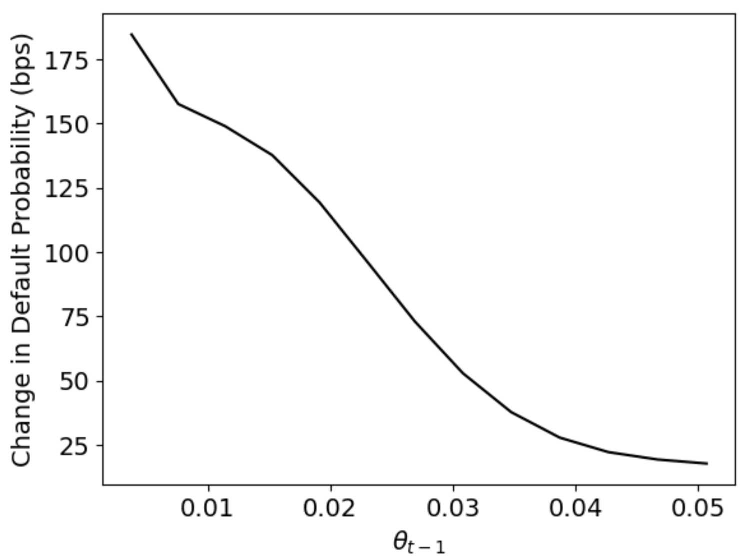
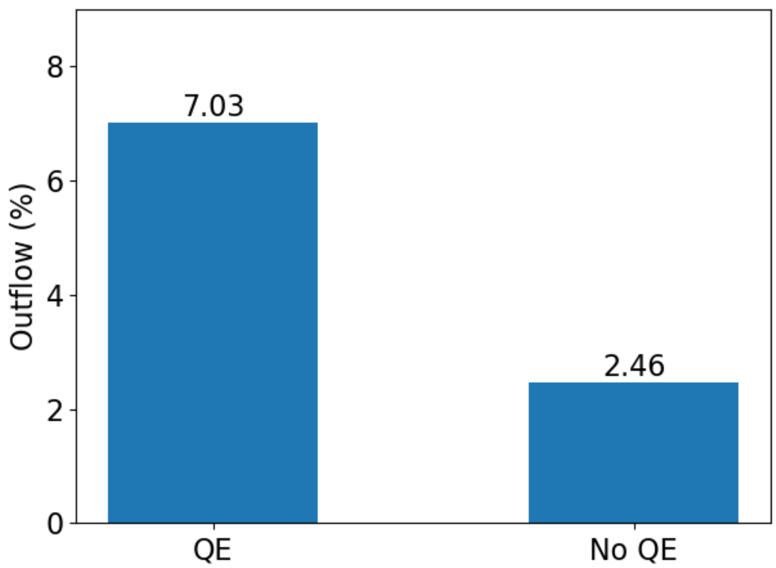


Figure 13: Effect of Rate Hikes (Baseline)

This figure plots the expected deposit outflows (Panel (a)) and change in default risk (Panel (b))from a 2% rate hike with and without QE. In the "No QE" case, the starting point of the marginal depositor is equal to the average marginal depositor in the simulation. In the "QE" case, we adjust the starting point of the marginal depositor such that the change in depositor rate sensitivity matches with the cumulative flow sensitivity estimates between 2020Q1 to 2022Q1 in Figure 1a. We use calibrated parameter values in Table 5c. The fundamental value y before the rate hike is set to match the asset return in 2022Q1.

(a) Expected Deposit Outflows with and without QE



(b) Change in Default Probability with and without QE

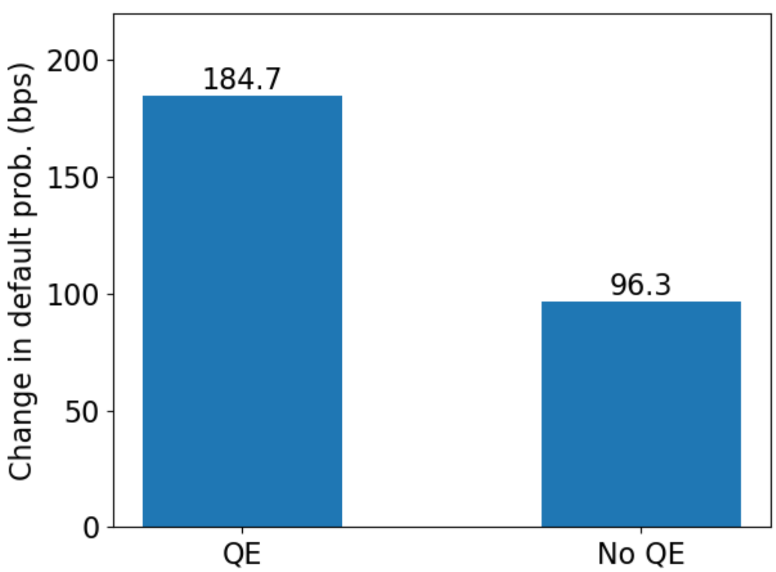
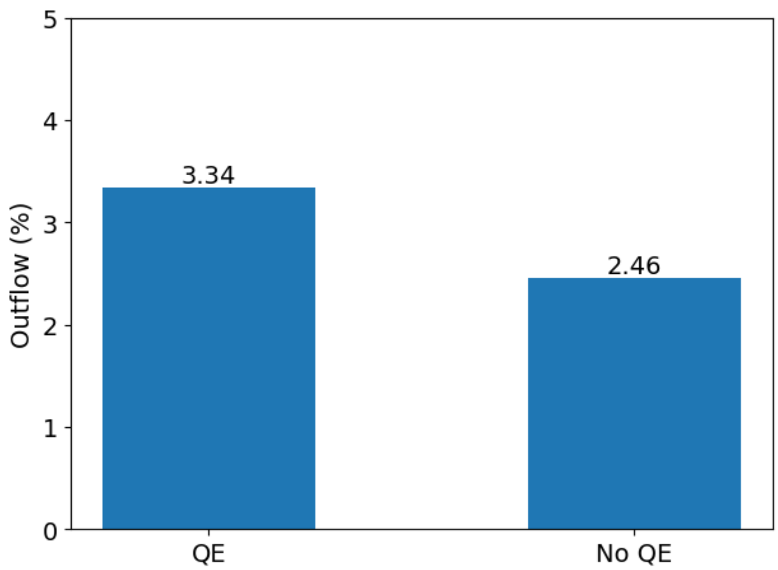


Figure 14: Effect of Rate Hikes (with Reserve Adjustment)

This figure plots the expected deposit outflows (Panel (a)) and change in default risk (Panel (b))from a 2% rate hike with and without QE. In the "No QE" case, the starting point of the marginal depositor is equal to the average marginal depositor in the simulation. In the "QE" case, we adjust the starting point of the marginal depositor such that the change in depositor rate sensitivity matches with the cumulative flow sensitivity estimates between 2020Q1 to 2022Q1 in Figure 1a. In addition, we increase ϕ to the median percentage of ample reserves that banks have after QE in 2022Q1. We use calibrated parameter values in Table 5c. The fundamental value y before the rate hike is set to match the asset return in 2022Q1.

(a) Expected Deposit Outflows with and without QE



(b) Change in Default Probability with and without QE

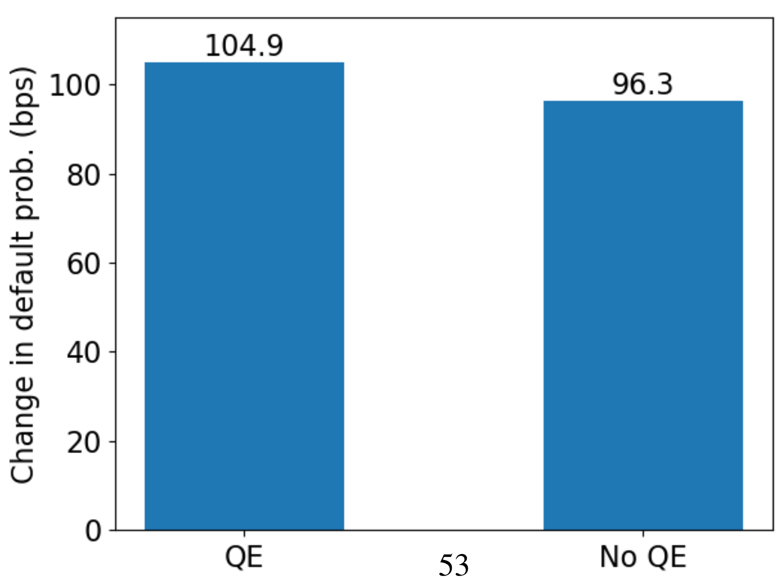
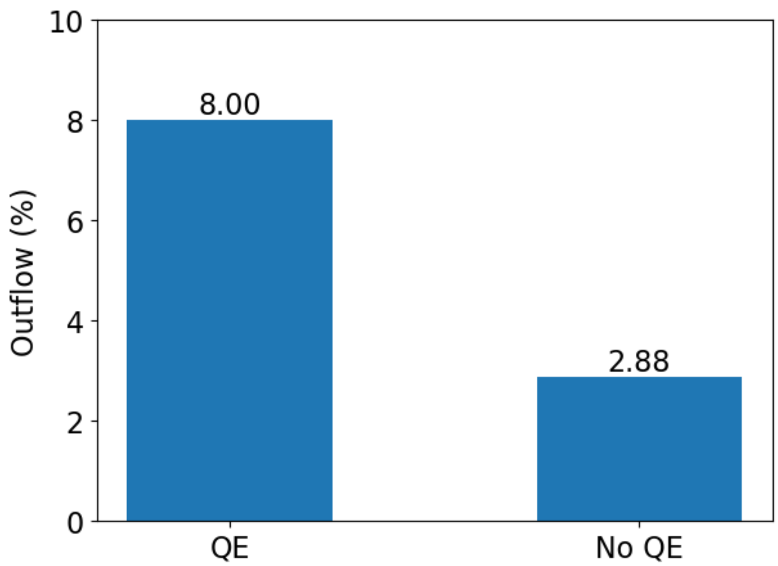


Figure 15: Effect of Rate Hikes (with Bank Fundamentals Adjustment)

This figure plots the expected deposit outflows (Panel (a)) and change in default risk (Panel (b))from a 2% rate hike with and without QE. In the "No QE" case, the starting point of the marginal depositor is equal to the average marginal depositor in the simulation. In the "QE" case, we adjust the starting point of the marginal depositor such that the change in depositor rate sensitivity matches with the cumulative flow sensitivity estimates between 2020Q1 to 2022Q1 in Figure 1a. We use calibrated parameter values in Table 5c. The fundamental value y before the rate hike is set to match the asset return in 2022Q1. In addition to the increase in R, we assume the rate hike also reduces bank fundamentals by half of its standard deviation.

(a) Expected Deposit Outflows with and without QE



(b) Change in Default Probability with and without QE

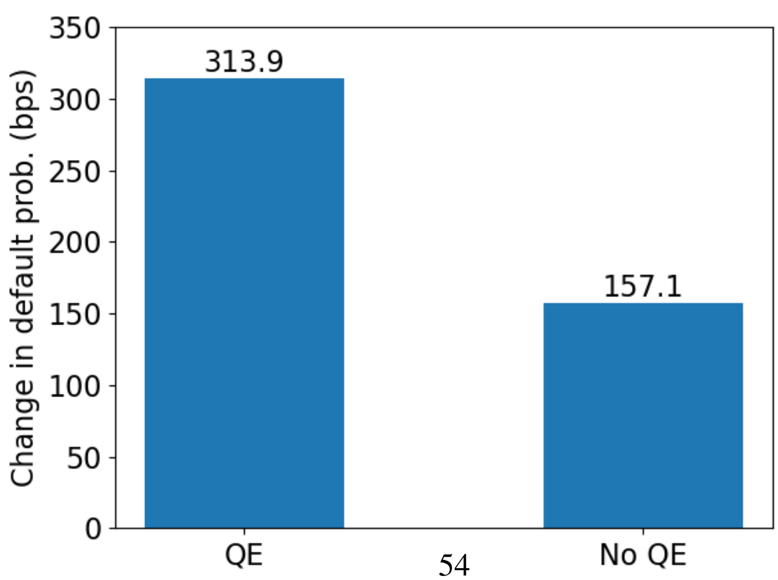


Table 1: Total Deposit Flow Sensitivity

This table shows how deposit flow sensitivity varies with aggregate flows to the banking system, estimated using Equation 3.2. The dependent variable, deposit flows, is the bank-level growth in deposits. The key dependent variables are the bank-level deposit rates and the interaction between bank-level deposit rates and the aggregate deposit flows to the banking sector. These variables are instrumented using fixed costs and salary expenses, and the results correspond to the IV estimates. Other control variables include the ratio of insured deposits, the equity ratio, and the non-deposit ratio. Standard errors are clustered at the bank level.

	Total Deposit Flow			
	(1)	(2)	(3)	(4)
Deposit Rate	-0.005**	0.013***	0.002	0.009**
	(0.002)	(0.003)	(0.003)	(0.004)
Deposit Rate × Cum Flow	0.182***	0.239***	0.127***	0.139***
	(0.035)	(0.038)	(0.034)	(0.036)
Insured Ratio			-0.057***	-0.109***
			(0.002)	(0.003)
Equity Ratio			-0.096***	-0.178***
			(0.004)	(0.011)
Non-Deposit Ratio			-0.034***	-0.070***
			(0.002)	(0.003)
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
Observations	365380	365380	325594	325594
Adjusted R2	-0.02	-0.10	0.01	0.00

Table 2: Deposit Volatility by Depositor Type

This table shows the volatility of deposits by counterparty type. In Panel A (C), deposit volatility is calculated as the standard deviation of each bank's monthly (daily) deposits by counterparty type over the entire sample period, divided by the mean of the bank's monthly (daily) deposits by that counterparty type over the same period. In Panel B (D), deposit volatility is calculated as the rolling standard deviation of monthly (daily) aggregate deposits by counterparty type over windows of 4 months (60 days), divided by the rolling mean of aggregate monthly (daily) deposits by that counterparty type over the same window. All deposit volatilities are scaled by 100. The sample for Panels A and B includes banks with assets above $100 billion that filed the corresponding monthly variables in the FR2052 form from 2018 through 2023. The sample for Panels C and D includes banks with assets above $100 billion that filed the corresponding daily variables in the FR2052 form 2018-2023.

Counterparty	25 Pctl	Median	75 Pctl
Panel A: Monthly Bank-Level SD			
Retail	14.10	20.07	29.21
Non-Financial Corporate	22.18	27.57	41.17
Non-Bank Financial Entity	18.79	38.00	56.06
Small Business	14.81	19.87	46.84
Bank	25.33	69.82	121.34
Panel B: Monthly Rolling Aggregate SD			
Retail	0.62	1.08	1.72
Non-Financial Corporate	1.04	1.41	2.08
Non-Bank Financial Entity	1.64	2.33	2.65
Small Business	1.03	1.40	2.37
Bank	1.55	2.49	3.44
Panel C: Daily Bank-Level SD			
Retail	17.92	25.44	29.66
Non-Financial Corporate	18.72	31.06	50.46
Non-Bank Financial Entity	17.08	21.79	66.82
Small Business	18.00	23.56	40.26
Bank	19.56	26.63	123.67
Panel D: Daily Rolling Aggregate SD			
Retail	0.50	0.63	0.97
Non-Financial Corporate	0.95	1.20	1.58
Non-Bank Financial Entity	1.77	2.00	2.32
Small Business	0.56	0.78	1.25
Bank	2.27	2.68	3.09

Table 3: Deposit Volatility by Account Type

This table shows the volatility of deposits by account type. In Panel A (C), deposit volatility is calculated as the standard deviation of each bank's monthly (daily) deposits by account type over the entire sample period, divided by the mean of the bank's monthly (daily) deposits in that account type over the same period. In Panel B (D), deposit volatility is calculated as the rolling standard deviation of aggregate monthly (daily) deposits by account type over windows of 4 months (60 days), divided by the rolling mean of aggregate monthly (daily) deposits in that account type over the same window. All deposit volatilities are scaled by 100. The sample for Panels A and B includes banks with assets above $100 billion that filed the corresponding monthly variables in the FR2052 form from 2018 through 2021. The sample for Panels C and D includes banks with assets above $100 billion that filed the corresponding daily variables in the FR2052 form from 2018 through 2021.

Account Type	25 Pctl	Median	75 Pctl
Panel A: Monthly Bank-Level SD			
Transactional Accounts	14.78	19.76	51.00
Non-Transactional Accounts	9.81	12.66	23.98
Operational Accounts	18.27	24.43	38.60
Non-Operational Accounts	19.40	25.07	41.69
Sweep and Brokered Accounts	19.75	28.79	55.44
Panel B: Monthly Rolling Aggregate SD			
Transactional Accounts	1.27	1.57	2.40
Non-Transactional Accounts	0.59	1.00	1.27
Operational Accounts	1.09	1.35	2.20
Non-Operational Accounts	1.17	1.76	2.43
Sweep and Brokered Accounts	0.85	1.61	2.46
Panel C: Daily Bank-Level SD			
Transactional Accounts	22.05	46.59	91.56
Non-Transactional Accounts	14.30	21.28	77.41
Operational Accounts	14.32	21.32	35.51
Non-Operational Accounts	15.16	31.60	69.91
Sweep and Brokered Accounts	14.58	29.48	48.68
Panel D: Daily Rolling Aggregate SD			
Transactional Accounts	0.92	1.13	1.64
Non-Transactional Accounts	0.32	0.58	0.84
Operational Accounts	0.94	1.16	1.52
Non-Operational Accounts	1.35	1.79	2.38
Sweep and Brokered Accounts	0.54	0.78	1.25

Table 4: Statistics on Depositor Flightiness

This table reports summary statistics of different measures of depositor flightiness in moving funds between banks versus in moving funds between banks and outside investments during our sample period from Jan 2015 to Sep 2022. We capture flightiness in terms of the proportion of months in which a depositor had flows between banks and between banks and outside investment options, the standard deviation in flows between banks and between banks and outside investment options scaled by total payment flows, and the rate sensitivity of bank to bank and bank to outside investment option deposit flows.

	Mean	SD	Median	25^{th} Pct	75^{th} Pct
Proportion of Months with Bank to Investment Flows (%)	4.50	8.79	1.06	0.00	5.32
Proportion of Months with Bank to Bank Flows (%)	13.34	23.35	2.13	0.00	14.89
SD (Proportion of Bank to Investment Flows)	0.50	0.84	0.14	0.03	0.59
SD (Proportion of Bank to Bank Flows)	1.12	2.42	0.17	0.04	0.78
Sensitivity of Bank to Investment Flows	0.09	0.05	0.09	0.05	0.12
Sensitivity of Bank to Bank Flows	0.20	0.07	0.20	0.16	0.26

Table 5: Calibration Moments and Estimates

Panel (a) summarizes the empirical moments we target directly. Panel (b) summarizes the empirical moments we target jointly. The moments are size-weighted averages of banks in the U.S. Our sample period is from 2000Q1 to 2019Q4. Panel (c) shows the calibrated parameter values.

(a) Empirical Moments

Parameter	Empirical target	Empirical moments
ρ	Persistence of asset returns	0.806
λ	Average asset maturity	2.845
α_1	Average asset discount	0.204
ϕ	Ample reserve proportion	0.031
R	Average Fed Fund Rate	1.784%
β	Discount rate	0.98

(b) Empirical Moments

Parameter	Empirical target	Empirical moments	Model moments
μ	Average asset return (%)	4.348	4.770
σ	Median deposit rate (bps)	95.410	99.984
σ_y	Median default prob. (bps)	72.302	76.041
γ	Flow-spread correlation	0.258	0.340
f	Flow volatility	1.628	1.487

(c) Parameter Estimates

Parameter	Description	Value
N	Number of banks	25
ρ	Persistence of y_t	0.806
λ	Maturity rate	0.352
α	Liquidity discount	0.796
ϕ	Ample reserve proportion	0.031
R	Value of outside option	1.018
β	Discount rate	0.98
γ	Rate parameter of θ distribution	1.122
μ	Mean of y_t	1.122
σ	Elasticity of substitution	9.637
σ_y	Sd of shock in asset return	0.186
f	Switching cost	0.141

Internet Appendix

A Estimation of Deposit Flow Sensitivity

In this appendix, we further discuss our estimation of deposit flow sensitivities in Equation 3.1. We first note that the standard specification for estimating deposit rate sensitivity at time t can be written as

$$Log(D_{jt}) = b_t DepRate_{jt} + TimeFE_t + \epsilon_{jt}, \tag{A.1}$$

where $Log(D_{jt})$ is the logged volume of deposits of bank j, $DepRate_{jt}$ is the deposit rate of bank j and b_t captures the sensitivity of bank-level deposits to bank-level deposit rates , i.e., the deposit rate sensitivitity.

To understand changes in deposit rate sensitivity over time, we take the first difference of Equation A.1:

$$Log(D_{jt}) - Log(D_{jt}) = b_t DepRate_{jt} - b_{t-1} DepRate_{jt-t} + TimeFE_t - TimeFE_{t-1} + \epsilon_{jt} - \epsilon_{jt-1}, \tag{A.2}$$

which translates into

$$Flow_{jt} = \Delta b_t DepRate_{jt} + b_{t-1}\Delta r_t + \Delta TimeFE_t + \Delta\epsilon_{jt}. \tag{A.3}$$

We note that Equation A.3 resembles Equation 3.1 with the addition of $b_{t-1}\Delta r_t$. Including or excluding this term should not make a material difference to our estimation if the sticky nature of deposit rate adjustments implies that Δr_t are very small. Indeed, repeating our baseline specification including $b_{t-1}\Delta r_t$, we obtain Figure C.2 below, which closely resembles the benchmark result in Figure 1a.

The sensitivity of bank-level deposit flows to bank-level deposit rates estimated from Equation 3.1 can thus be interpreted as the change in deposit rate sensitivity relative to the previous period. A positive sensitivity of bank-level deposit flows to bank-level deposit rates indicates that the deposit base has become more rate-sensitive than before, whereby deposits are more disproportionately attracted to banks offering higher deposit rates. Indeed, directly estimating Eqution A.1 would produce Figure C.3. Figure C.3 is consistent with the interpretation that rate sensitivity increases by more when flow sensitivities are more positive.

We refer to the sensitivity of bank-level deposit flows to bank-level deposit rates as flow sensitivity.

B Data Appendix

We use de-identified transaction-level bank account data provided by a prominent financial data processor. This data encompasses records from over 1,400 U.S. banks and credit unions. We observe an identifier for each depositor, which is linked across accounts belonging to the same depositor. Accounts include checking and savings accounts but exclude brokerage and investment accounts. For each withdrawal and deposit transaction, the date, amount, and category of transactions are given. The merchant name and descriptions are also provided with redaction of bank names.

B.1 Sample Selection

Our sample is from January 2015 to September 2022. We start our sample in 2015, when data quality becomes sufficiently reliable. Following Buda et al. (2023), our analysis concentrates on a panel of active users, which have at least ten transactions related to spending, income, or transfers in 32 of the 36 quarters in our sample. This selection criterion helps to ensure that account closures, which go unrecorded, do not skew the data.

Among depositors, we manually identify corporate depositors. First, we include accounts that have outgoing payments labeled as payroll or salary every quarter. Additionally, we include entities that have more than 50 bank accounts and those that include corporate-specific transactions every quarter. We obtain a panel of 5,294 unique corporate depositors and 1.26 million unique household depositors. The larger number of household depositors over corporate depositors is consistent with our conversations with the data provider.

Although our data does not cover the universe of household and corporate depositors, we find that the trend in deposit flows from our data is highly representative of the trends in aggregate deposit flows from public data sources. Figure C.9a plots the 12-month moving average of monthly deposit flows for household depositors in our data and the household and non-profit sector from FRED. Figure C.9b plots the 12-month moving average of monthly deposit flows for corporate depositors in our data and the non-financial corporate sector from FRED. While the aggregate volumes from our data are smaller than those from FRED, the variations in deposit flows closely track each other for both household and corporate depositors. These results provide suggestive evidence that the depositors in our sample are representative of the population of depositors.

B.2 Classification of Flows between Banks and Investments

We use a multi-step process to identify deposit flows to and from investment options. First, we examine all transactions from bank accounts to brokerages that are classified as securities trading, investments, or retirement-related transactions. We then review thousands of merchant names that represent more than 95% of these transaction volumes to confirm that they are investment-related. This step helps to filter out misclassified investment transactions. Once we have a verified list of brokerages, we manually check the corresponding transaction descriptions to extract relevant keywords. These keywords are in turn used to search through other transaction categories, including bank transfers, check payments, and direct deposits. This method ensures that we capture a comprehensive and accurate list of investment flows across all depositors.

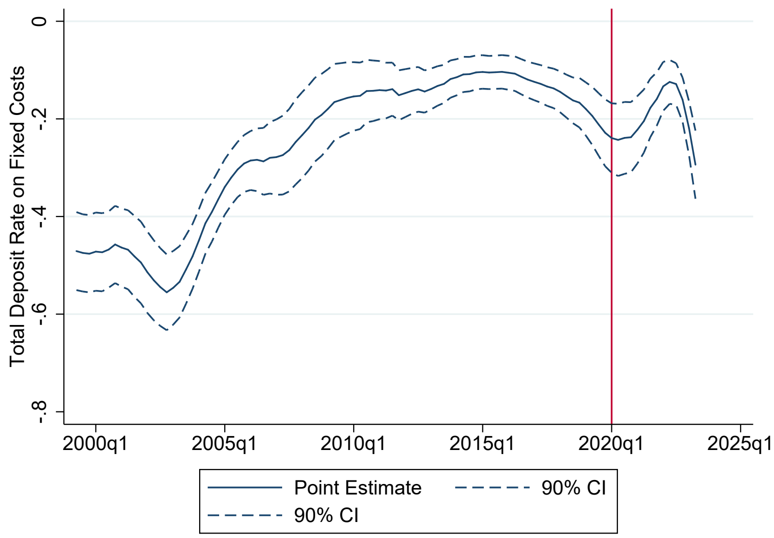
B.3 Classification of Flows between Banks

While we can link accounts belonging to the same depositor, the specific banks where these accounts are held remain unknown because bank identifiers for each account and bank names in transfer descriptions are redacted. To identify deposit flows between accounts of the same depositor at different banks, we adopt the methodology in Lu et al. (2024). We track the dollar value of each credit transaction C and each debit transaction D, and designate a transaction as an interbank deposit transfer if it meets the following criteria: first, C and D must originate from different accounts of the same depositor. Second, both C and D must exceed \$50, ensuring we do not capture minor fees or refunds. Third, the absolute difference between D and C, $|D - C|$, must be less than \$50 if D occurs on the next business day after C, and less than \$10 if the time between D and C exceeds one business day. Fourth, the temporal difference between the transactions must not exceed five business days. Additionally, transactions that are initiated and received on the same business day are excluded unless they include a fast payment technology marker including Venmo, PayPal, Cash App, or Zelle. This is because same-day transactions without a fee that are not through fast payment services are mostly across accounts at the same bank.

Figure C.1: Deposit Flow Sensitivity (First Stage)

This figure shows how deposit rates are affected by fixed costs and salary expenses. Panel (a) plots the coefficients from regressing deposit rates against fixed costs per unit bank assets in 8-quarter rolling windows. Panel (b) plots the coefficients from regressing deposit rates against salary expenses per unit bank assets in 8-quarter rolling windows. Standard errors are clustered at the bank level.

(a) Deposit Rate on Fixed Cost Ratio



(b) Deposit Rate on Salary Expense Ratio

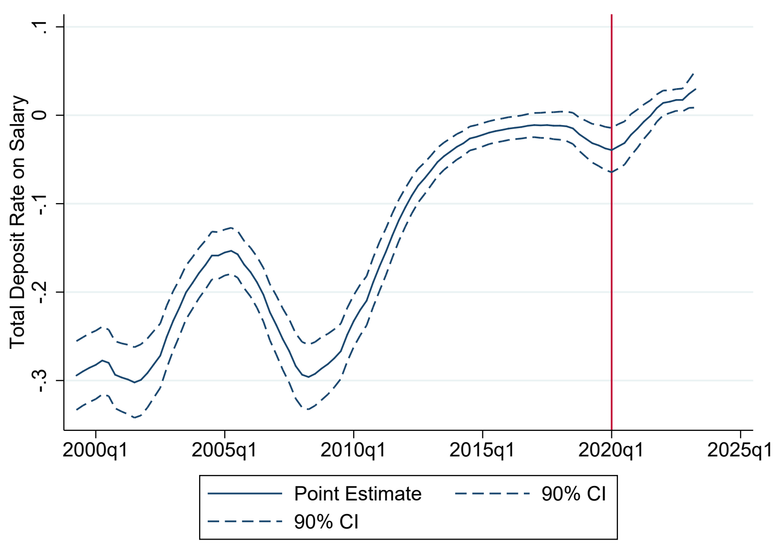


Figure C.2: Deposit Flow Sensitivity (with Deposit Rate Change Control)

This figure shows deposit flow sensitivities controlling for deposit rate changes. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation A.3. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

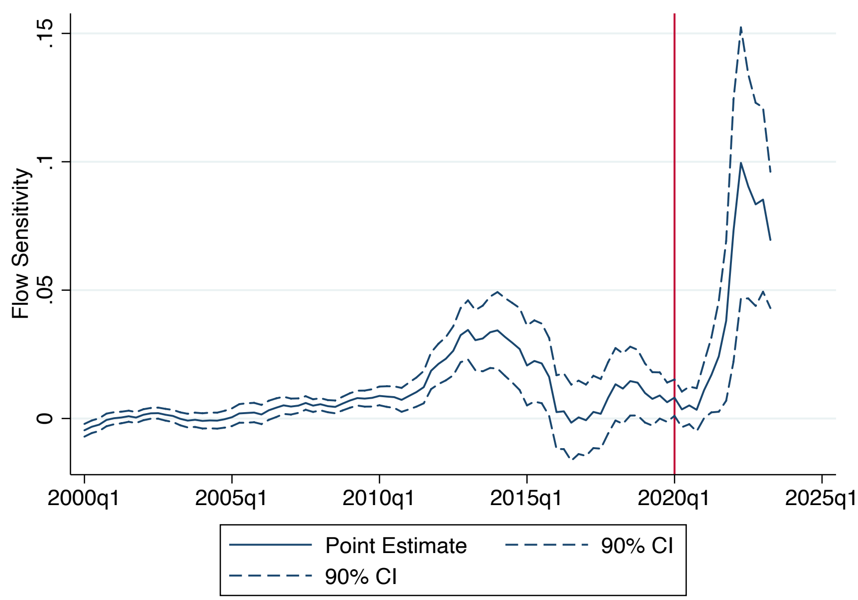


Figure C.3: Deposit Rate Sensitivity

This figure shows deposit rate sensitivities, which are obtained from regressing bank-level log deposits on instrumented bank-level interest rates (%) as described in Equation A.1. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

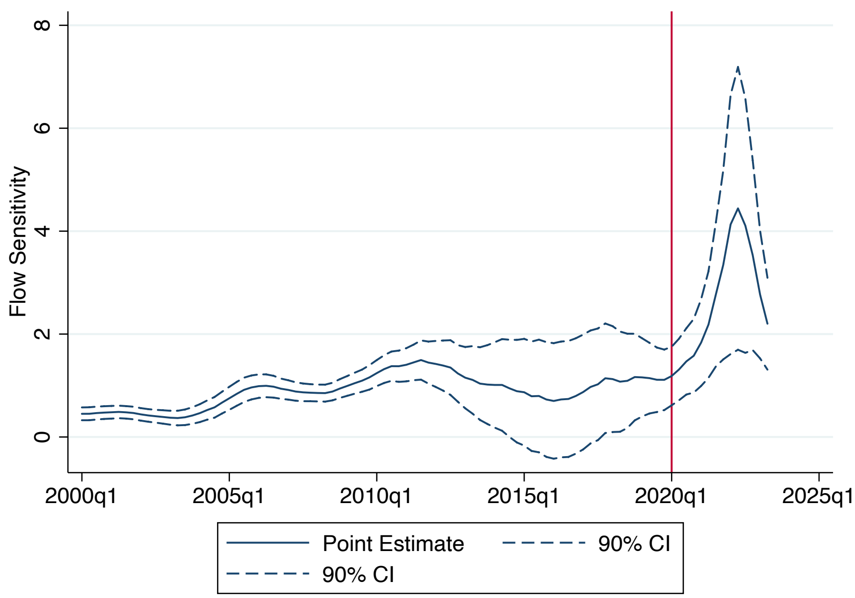


Figure C.4: Deposit Flow Sensitivity (50% Balancing)

This figure shows deposit flow sensitivities over time for banks that are present in at least half of the sample period. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

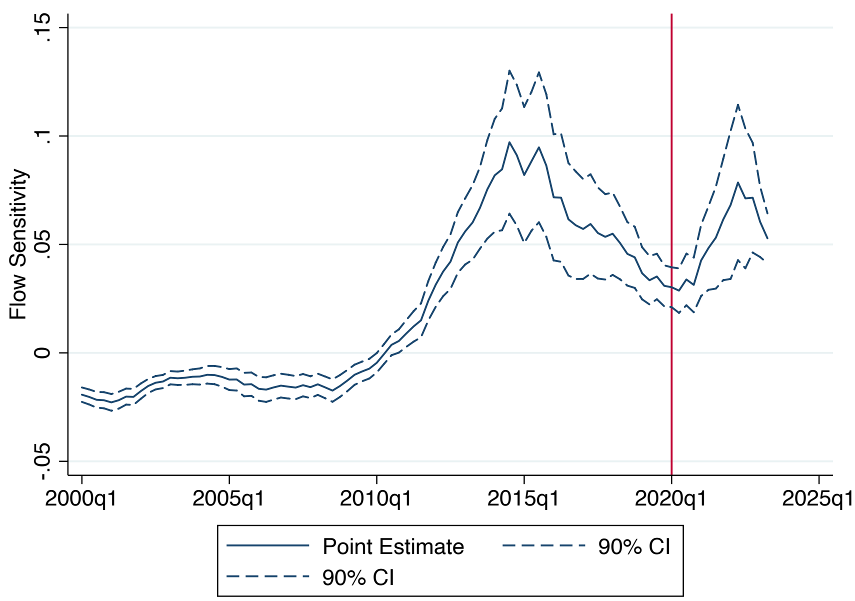


Figure C.5: Deposit Flow Sensitivity and VIX

This Figure shows deposit flow sensitivities and the VIX Index over time. Deposit flow sensitivities are obtained from regressing bank-level deposit flows on instrumented bank-level interest rates (%) as described in Equation 3.1. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

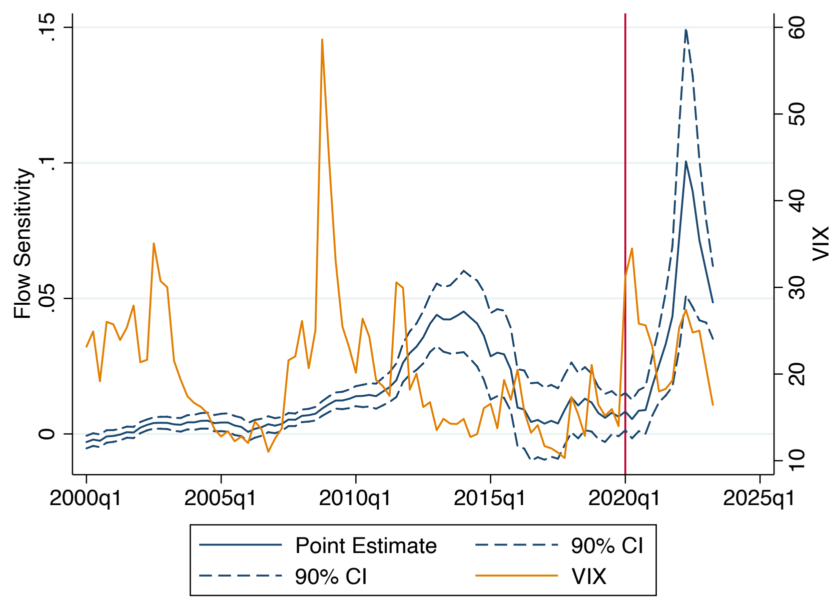


Figure C.6: Deposit Flow Sensitivity with respect to Bank Fundamentals

This figure shows insured and uninsured deposit flow sensitivities with respect to banks' return on assets over time. Deposit flow sensitivities are obtained by estimating Equation 3.1 with $\widehat{DepRate}_{jt}$ replaced by bank i's return on assets and interacted with dummy variables for insured and uninsured deposit flows. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

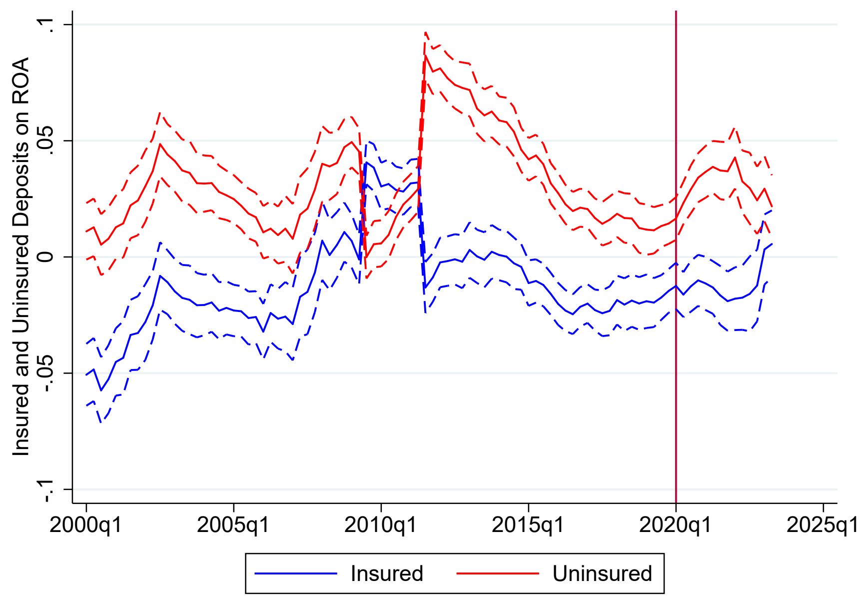


Figure C.7: Deposit Flow Sensitivity by Bank Asset Size

This figure shows deposit flow sensitivities over time by asset-based quartiles. Banks are first sorted into quartiles by asset size. Then, deposit flow sensitivities for each quartile are obtained by estimating Equation 3.1 with $\widehat{DepRate}_{jt}$ interacted with dummy variables for each asset quartile. The vertical red line corresponds to 2020Q1. Standard errors are clustered at the bank level.

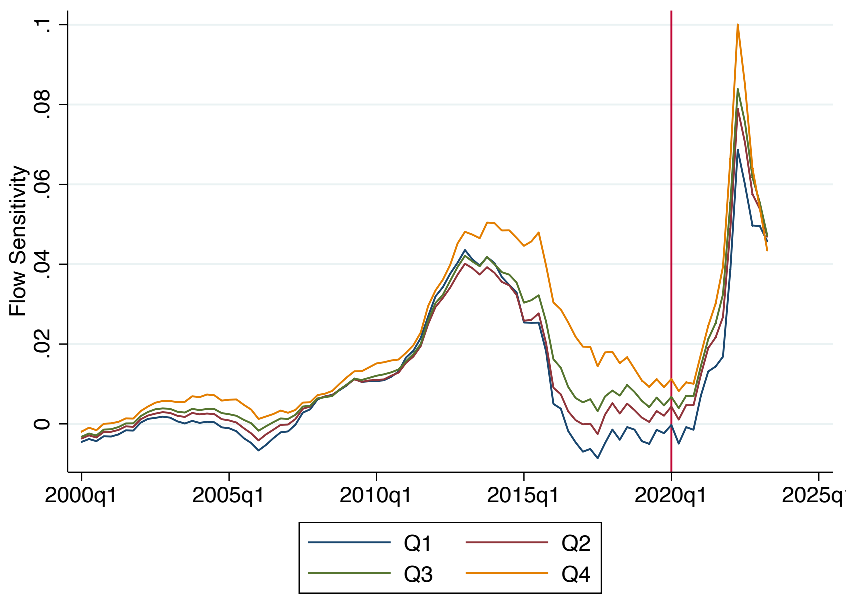
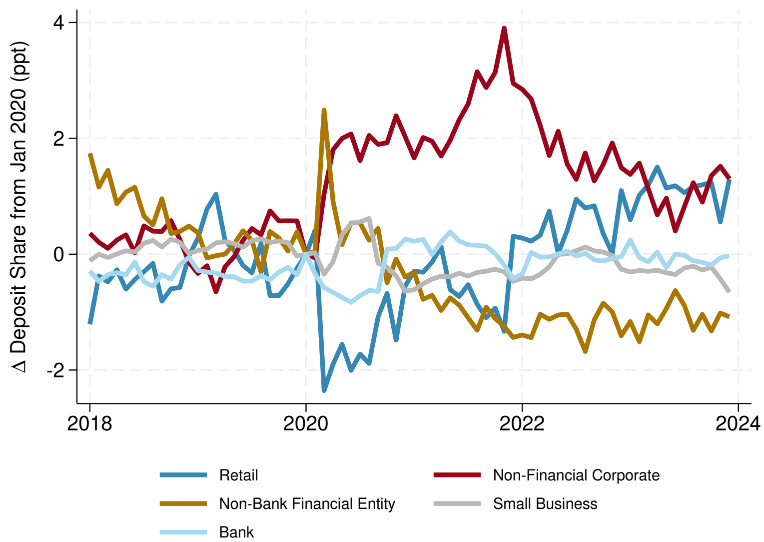


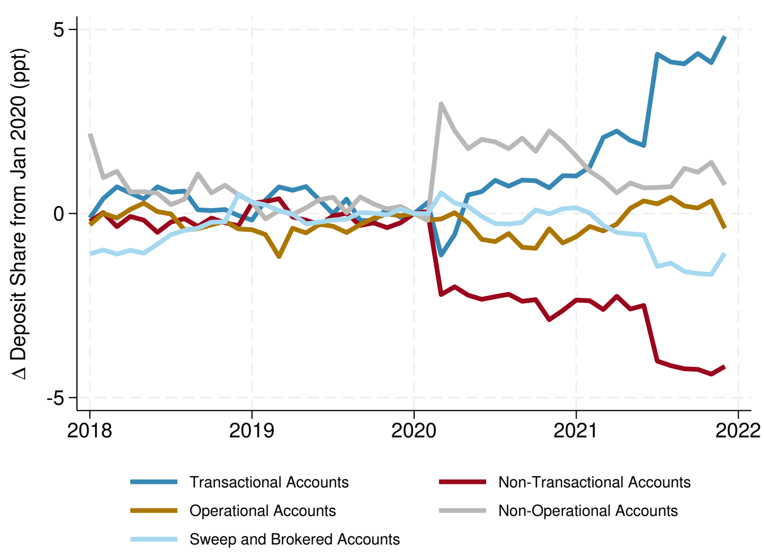
Figure C.8: Deposit Composition by Counterparty and Account Type

Panel (a) shows changes in the proportion of deposits by counterparty type relative to January 2020. The sample includes banks with assets above $100 billion that filed the corresponding variables in the FR2052 form from 2018 through 2023. Panel (b) shows changes in the proportion of deposits by account type relative to January 2020. The sample includes banks with assets above $100 billion that filed the corresponding variables in the FR2052 form from 2018 through 2021.

(a) Deposit Composition by Counterparty Type



(b) Deposit Composition by Account Type

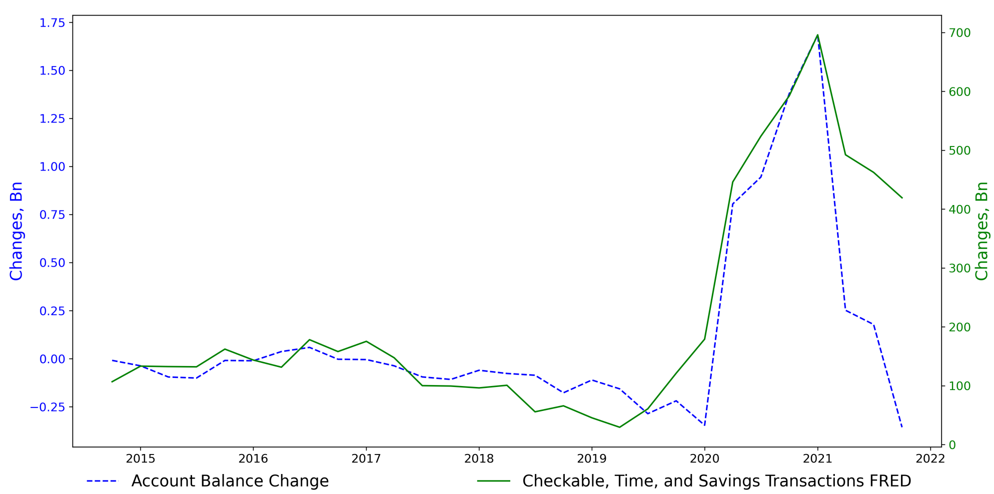


C Additional Figures and Tables

Figure C.9: Account-level Data versus Aggregate Data

This figure compares total deposit flows from our account-level data with aggregate data on deposit flows from FRED. The left-hand axis plots deposit flows from our data, which considers the sum of all incoming and outgoing deposit flows for our sample of account holders. The right-hand axis plots aggregate deposit flows from FRED. Both series are displayed as a 12-month moving average. Panel (a) shows the results for household depositors; panel (b) shows the results for corporate depositors.

(a) Household Depositors



(b) Corporate Depositors

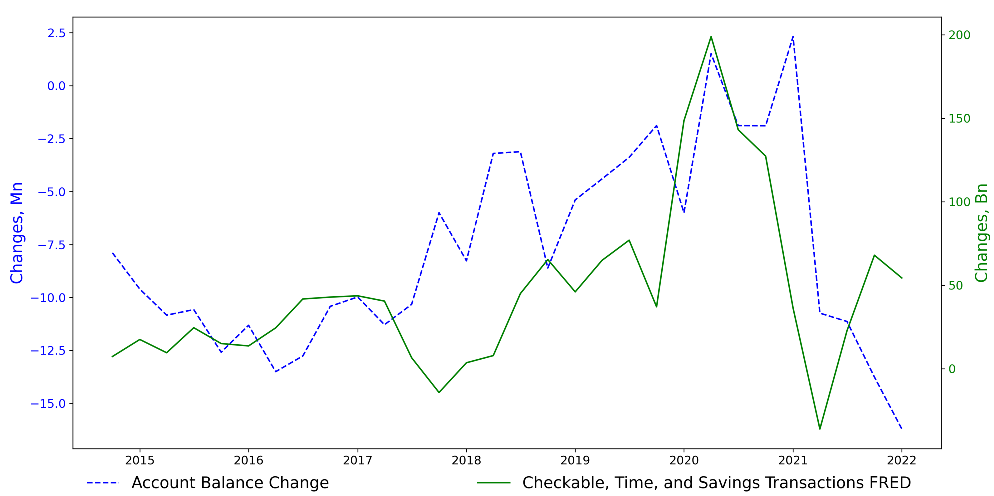


Table C.1: First Stage: Effect of Fixed Cost and Salary Expense on Deposit Rates

This table shows how deposit rates are affected fixed costs and salary expenses. Deposit rates are expressed in %. Fixed costs and salary expenses are measured per unit bank asset. Columns (1) and (2) show the results for all deposits; columns (3) and (4) show the results for savings deposits. Standard errors are clustered at the bank level.

	Deposit Rate		Savings Dep Rate	
	(1)	(2)	(3)	(4)
Fixed Cost	-0.325***	-0.180***	-0.157***	-0.060***
	(0.033)	(0.024)	(0.026)	(0.021)
Salary Expense	-0.137***	-0.155***	-0.048***	-0.048***
	(0.014)	(0.011)	(0.009)	(0.008)
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
Observations	368998	368998	367260	367260
Adjusted R2	0.87	0.94	0.64	0.78

D Derivation and Proofs

D.1 Proof of Lemma 1

Let T^θ be the Bellman operator

$$T^\theta V = \theta \left(\sum_{j=1}^{N} d_{i,j,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} + \lambda \sum_j r_{j,t} d_{i,j} + (1-\lambda)\beta \mathbb{E}[(1-\mathbf{1}_{def,t+1}) \max\{V, R-f\} + \mathbf{1}_{def,t+1} L(y_{t+1})]$$

Because $(1-\lambda)\beta < 1$, the operator T^θ is β-contraction. So the value iteration converges to a fixed point $D(\theta)$. Furthermore, T^θ is increasing in V, i.e. if $V_1 \geq V_2$, $T^\theta V_1 \geq T^\theta V_2$, and when $d_{i,j,t} \geq 0$, T^θ is increasing in θ, i.e., if $\theta_1 \geq \theta_2$, then $T^{\theta_1} V \geq T^{\theta_2} V$. As a result, the fixed point $D(\theta)$ is non-decreasing in θ. Hence, there exists an equilibrium where the set of investors in the banking system is characterized by a time-varying cutoff θ_t.

D.2 Proof of Lemma 2

To investigate the run condition, we look at the deposit value when the bank is liquidating more than one unit of asset to meet outflows. Denote the asset backing per unit of deposits as a_t. Given the deposits remaining in the bank, $D_{j,t}$, $a_{j,t}$ is determined by the following equation

$$a_{j,t}(D_{j,t}) = \begin{cases} 1 & \text{if} \quad D_{j,t} \geq (1-\phi)D_{j,t-1} \\ \frac{(1-\phi)D_{j,t-1} - \frac{(1-\phi)D_{j,t-1} - D_{j,t}}{L(y_t)}}{D_{j,t}} & \text{otherwise} \end{cases} \tag{D.1}$$

On the other hand, denote the demand for bank j's deposit as $\tilde{D}_{j,t}$, given the maximum deposit rate that the bank can offer y_t and the amount of asset backing each unit of deposit $a_{j,t}$. Because $a_{j,t}$ depends on $D_{j,t}$, the demand for deposit $\tilde{D}_{j,t}$ can also be written as a function of $D_{j,t}$. A stable equilibrium is where $\tilde{D}_{j,t}(D_{j,t})$ crosses the 45 degree line from above, i.e. the slope of the deposit demand $\tilde{D}_{j,t}$ as a function of the deposit volume $D_{j,t}$ is smaller than one. Next we show that when $D_{j,t} < (1-\phi)D_{j,t-1}$, the slope of $\tilde{D}_{j,t}$ as a function of $D_{j,t}$ is larger than 1 when $D_{j,t} > 0$, which then implies that the only equilibrium in that region is one in which the deposit volume is 0.

From Equation D.1, when $D_{j,t} < (1-\phi)D_{j,t-1}$

$$\frac{\partial a_{j,t}}{\partial D_{j,t}} = \left(\frac{1}{L(y_t)} - 1 \right) \frac{(1-\phi)D_{j,t-1}}{D_{j,t}^2} \tag{D.2}$$

We can write the depositor value as

$$D = \theta_i \left(\sum_{j=1}^{N} d_{i,j,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} + \lambda \sum_{j' \neq j} r_{j',t} d_{i,j',t} + y_t a_{j,t} d_{i,j,t} + (1-\lambda)\beta \mathbb{E}[D_{cont}] \tag{D.3}$$

where D_{cont} denotes the continuation value in the next period.

For a given investor, demand elasticity for investor i with respect to $a_{j,t}$ is

$$\frac{\partial d_{i,j,t}}{\partial a_{j,t}} = \sigma\lambda \frac{d_{i,j,t}(1-d_{i,j,t})}{\gamma_i - \lambda y_t} y_t > 0 \tag{D.4}$$

where γ_i is the Lagrangian multiplier in front of the budget constraint $\sum d_{i,j,t} = 1$. Under symmetric equilibrium, it is determined by

$$1 = \left(\sum_k \left(\frac{\theta_i}{\gamma_i - \lambda y_t} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{D.5}$$

Hence the effect of deposit volume on deposit demand is

$$\frac{\partial \tilde{D}_{j,t}}{\partial D_{j,t}} = \int_i \frac{\partial d_{i,j,t}}{\partial a_{j,t}} \left(\frac{1}{L(y_t)} - 1 \right) \frac{(1-\phi)D_{j,t-1}}{D_{j,t}^2} + \frac{\partial d_{i,j,t}}{\partial D_{j,t}} \tag{D.6}$$

where the second component captures any direct effect of deposit volume on deposit demand through future default probabilities. Notice that when $\alpha_0 \to 0$ and $\alpha_1 \to 0$, we have $\frac{1}{L(y_t)} \to \infty$. Since $\frac{\partial d_{i,j,t}}{\partial a_{j,t}}$ is positive, the slope of $\tilde{D}_{j,t}$ as a function of $D_{j,t}$ is above one when α_0 and α_1 are small enough. In other words, there is no stable equilibrium in the region where $D_{j,t} < (1-\phi)D_{j,t-1}$, except the one in which the deposit volume is zero. Hence, for a bank to avoid a run, it needs to retain at least $(1-\phi)$ fraction of its depositors.

In equilibrium, banks are symmetric and experience the same flows. For banks to retain at least $(1-\phi)$ fraction of its depositors, we must have $\theta_t \leq \bar{\theta}_t$. In other words, we need $D(y_t, \bar{\theta}_t, \bar{\theta}_t) \geq R - f$. Hence, the run threshold is determined by Equation 4.13.

D.3 Proof of Proposition 1

Given that the definition of critical investor in Equation 4.12,

$$G'(\bar{\theta}_t)d\bar{\theta}_t = (1-\phi)G'(\theta_{t-1})d\theta_{t-1}$$
$$\frac{d\bar{\theta}_t}{d\theta_{t-1}} = (1-\phi)\frac{G'(\theta_{t-1})}{G'(\bar{\theta}_1)} > 0$$

Hence, the critical investor's convenience benefit $\bar{\theta}_t$ is increasing in the previous period marginal depositor's θ_{t-1}.

Furthermore, $D(y, \bar{\theta}_t, \bar{\theta}_t)$ is increasing in y and $\bar{\theta}_t$. Given $D(y^*, \bar{\theta}_t, \bar{\theta}_t) = R - f$, by the implicit function theorem,

$$\frac{\partial y^*}{\partial \bar{\theta}_t} = -\frac{\partial D}{\partial \bar{\theta}_t} \Big/ \frac{\partial D}{\partial y} < 0.$$

D.4 Proof of Corollary 1

Taking into account that $\bar{\theta}_t$ is a function of θ_{t-1}, as defined in Equation 4.12, the effect of θ_{t-1} on the run threshold is

$$\frac{\partial y^*}{\partial \theta_{t-1}} = -\frac{\partial D}{\partial \bar{\theta}_t(\theta_{t-1})} \Big/ \frac{\partial D}{\partial y} \times \frac{\partial \bar{\theta}}{\partial \theta_{t-1}} \tag{D.7}$$

As we have shown above, $-\frac{\partial D}{\partial \bar{\theta}_t(\theta_{t-1})} \big/ \frac{\partial D}{\partial y} < 0$. As long as $\frac{\partial \bar{\theta}}{\partial \theta_{t-1}} > 0$, we have $\frac{\partial y^*}{\partial \theta_{t-1}} < 0$.

From Equation 4.18, we have

$$\frac{\partial \bar{\theta}}{\partial \theta_{t-1}} = \frac{(1-\phi(\theta_{t-1}))G'(\theta_{t-1}) - \phi'(\theta_{t-1})G(\theta_{t-1})}{G'(\bar{\theta})} \tag{D.8}$$

Under condition (4.17), $\frac{\partial \bar{\theta}}{\partial \theta_{t-1}} > 0$. In other words, the indirect effect from the adjustment in ϕ does not offset the direct effect. Consider an extreme case, suppose for all θ_{t-1}, the following condition holds,

$$(1-\phi(\theta_{t-1}))G'(\theta_{t-1}) - \phi'(\theta_{t-1})G(\theta_{t-1}) = 0 \tag{D.9}$$

This implies

$$\frac{G'(\theta_{t-1})}{G(\theta_{t-1})} = \frac{\phi'(\theta_{t-1})}{1-\phi(\theta_{t-1})} \tag{D.10}$$

which means that outside of default, all inflows and outflows only involve adjustment in the liquid assets and the amount of illiquid asset is fixed over time. Under most reasonable liquidity management problems, when there are inflows, banks will invest a smaller but non-zero fraction in illiquid assets, satisfying condition (4.17).

D.5 Proof of Proposition 2

Consider the first order condition of an individual bank

$$-\lambda D_{j,t} + \left[\lambda(y_t - r_{j,t}) + \iota + (1-\lambda)\beta \frac{\partial \mathbb{E}[(1-\mathbf{1}_{def})V^*]}{\partial D_{j,t}}\right] \frac{\partial D_{j,t}}{\partial r_{j,t}} = 0 \tag{D.11}$$

where

$$\frac{\partial D_{j,t}}{\partial r_{j,t}} = \int_{\theta_t} \frac{\partial d_{i,j,t}}{\partial r_{j,t}} dH(\theta) \tag{D.12}$$

The demand elasticity for investor i is

$$\frac{\partial d_{i,j,t}}{\partial r_{j,t}} = \sigma\lambda \frac{d_{i,j,t}(1-d_{i,j,t})}{\gamma - \lambda r_{j,t}} \tag{D.13}$$

where γ is the Lagrangian multiplier in front of the budget constraint $\sum d_{i,j,t} = 1$. In equilibrium we have

$$1 = \left(\sum_k \left(\frac{\theta_i}{\gamma - \lambda r_j}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{D.14}$$

In equilibrium $r_{j,t} = r_t^*$ and $d_{i,j,t} = \frac{1}{N}$. Substituting in $\gamma - \lambda r_j$ into (D.13) we get

$$\frac{\partial d_{i,j,t}}{\partial r_{j,t}} = \sigma\lambda \frac{1/N(1-1/N)}{N^{1/(\sigma-1)}} \frac{1}{\theta_i} \tag{D.15}$$

Hence from bank j's perspective, the deposit rate sensitivity is

$$\frac{\partial D_{j,t}}{\partial r_{j,t}} = \sigma\lambda \frac{1/N(1-1/N)}{N^{1/(\sigma-1)}} \int_{\theta \geq \theta_t} \frac{1}{\theta} dH(\theta) \tag{D.16}$$

The deposit semi-elasticity is hence (note that $D_{j,t} = \frac{G(\theta_t)}{N}$)

$$\frac{\partial lnD_{j,t}}{\partial r_{j,t}} = \sigma\lambda \frac{1-1/N}{N^{1/(\sigma-1)}} \frac{\int_{\theta_i \geq \theta_t} \frac{1}{\theta} dH(\theta)}{G(\theta_t)} \tag{D.17}$$

Hence Eq. (D.11) can be simplified to

$$-\lambda \frac{G(\theta_t)}{N} + [\lambda(y_t - r_t^*) + \iota_t + (1-\lambda)\beta \frac{\partial \mathbb{E}[(1-\mathbf{1}_{def})V^*]}{\partial D_{j,t}}]\sigma\lambda \frac{1/N(1-1/N)}{N^{1/(\sigma-1)}} \int_{\theta_t} \frac{1}{\theta} dH(\theta) = 0 \tag{D.18}$$

Furthermore

$$\mathbb{E}[(1-\mathbf{1}_{def})V^*] = \int_{y^*(\theta_t, D_{j,t})} V^*(y_{t+1}, \theta_t, D_{j,t}) dF(y_{t+1})$$
$$\frac{\partial \mathbb{E}[(1-\mathbf{1}_{def})V^*]}{\partial D_{j,t}} = -(1-\phi) \int_{y^*(\theta_t, D_{j,t})} \iota_{t+1} dF(y_{t+1}) - \frac{(1-\phi)}{\sigma\lambda_y \frac{1/N(1-1/N)}{N^{1/(\sigma-1)}} \int_{\bar{\theta}(\theta_t)} \frac{1}{\theta} dH(\theta)} f(y^*) V^*(y^*, \theta_t, D_{j,t})$$

We define the unconstrained optimal deposit rate as $\tilde{r}(y_t, \theta_t)$, which solves Equation D.18 when $\iota_t = 0$.

When $D(r_t^*, \theta_{t-1}, \theta_{t-1}) < R - f$, there is outflow and when $D(r_t^*, \theta_{t-1}, \theta_{t-1}) > R + f$, there is inflow. Hence $y_{in}(\theta_{t-1})$ and $y_{out}(\theta_{t-1})$ are implicitly defined recursively by

$$D(\tilde{r}(y_{out}, \theta_{t-1}), \theta_{t-1}, \theta_{t-1}) = R - f \tag{D.19}$$
$$D(\tilde{r}(y_{in}, \theta_{t-1}), \theta_{t-1}, \theta_{t-1}) = R + f \tag{D.20}$$

When there is unconstrained outflow, the new marginal depositor $\theta_1(y_t)$ is pinned down by

$$D(\tilde{r}(y_t, \theta_1), \theta_1, \theta_1) = R - f \tag{D.21}$$

When there is inflow, the new marginal depositor $\theta_2(y_t)$ is pinned down by

$$D(\tilde{r}(y_t, \theta_2), \theta_2, \theta_2) = R + f \tag{D.22}$$

D.6 Proof of Corollary 2

The equilibrium $\theta^*(y_t, \theta_{t-1})$ is decreasing in y_t follows from the partition across cases and the fact that $\theta_1(y_t)$ and $\theta_2(y_t)$ are decreasing in y_t. Fixing θ_{t-1}, the net deposit flow is decreasing in θ^*. Hence, it is increasing in y_t.

To investigate the relationship between the net flow and the previous period marginal depositor type, consider $\theta_{t-1,1} < \theta_{t-1,2}$. We have

$$y^*(\theta_{t-1,1}) > y^*(\theta_{t-1,2}) \tag{D.23}$$

$$y_{out}(\theta_{t-1,1}) > y_{out}(\theta_{t-1,2}) \tag{D.24}$$

$$y_{in}(\theta_{t-1,1}) > y_{in}(\theta_{t-1,2}) \tag{D.25}$$

We next show that for any y, we have $G(\theta^*(y, \theta_{t-1,1})) - G(\theta_{t-1,1}) \leq G(\theta^*(y, \theta_{t-1,2})) - G(\theta_{t-1,2})$.

When $y \leq y_{out}(\theta_{t-1,2})$, $\theta^*(y, \theta_{t-1,1}) = \min\{\theta_1(y), \bar{\theta}(\theta_{t-1,1})\}$ and $\theta^*(y, \theta_{t-1,2}) = \min\{\theta_1(y), \bar{\theta}(\theta_{t-1,2})\}$. Hence,

$$G(\theta^*(y, \theta_{t-1,1})) - G(\theta_{t-1,1}) \leq G(\theta^*(y, \theta_{t-1,2})) - G(\theta_{t-1,2}) \tag{D.26}$$

When $y \in (y_{out}(\theta_{t-1,2}), y_{out}(\theta_{t-1,1})]$,

$$G(\theta^*(y, \theta_{t-1,1})) - G(\theta_{t-1,1}) < 0 \tag{D.27}$$

$$G(\theta^*(y, \theta_{t-1,2})) - G(\theta_{t-1,2}) = 0 \tag{D.28}$$

When $y \in (y_{out}(\theta_{t-1,1}), y_{in}(\theta_{t-1,2})]$, there is no flow in either case, i.e., $G(\theta^*(y, \theta_{t-1,1})) - G(\theta_{t-1,1}) = G(\theta^*(y, \theta_{t-1,2})) - G(\theta_{t-1,2}) = 0$.

When $y \in (y_{in}(\theta_{t-1,2}), y_{in}(\theta_{t-1,1}),$

$$G(\theta^*(y, \theta_{t-1,1})) - G(\theta_{t-1,1}) = 0 \tag{D.29}$$

$$G(\theta^*(y, \theta_{t-1,2})) - G(\theta_{t-1,2}) > 0 \tag{D.30}$$

Finally, when $y > y_{in}(\theta_{t-1,1})$, $\theta^*(y, \theta_{t-1,1}) = \theta^*(y, \theta_{t-1,2})$. Hence we have $G(\theta^*(y, \theta_{t-1,1})) - G(\theta_{t-1,1}) \leq G(\theta^*(y, \theta_{t-1,2})) - G(\theta_{t-1,2})$ for $\forall y$.