Depositor Characteristics and Deposit Stability

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Using cellphone geolocation data to identify the characteristics of bank depositors, we document considerable heterogeneity in terms of the age, income, education, and financial sophistication of depositors across banks and branches. We show that depositor characteristics influence a bank's rate-setting behavior and its deposit flows. Despite increasing deposit rates, banks with financially sophisticated depositors suffered greater deposit runoffs when market interest rates increased during 2022-2023, across bank sizes and more so for banks exposed to interest rate risk. These effects were not present during the 2015-2019 interest rate hiking cycle. Our findings suggest that assessments of bank stability could benefit from incorporating information on a bank's depositor base.

Keywords: Depositor base, Deposit Stability, Interest rate risk

JEL Classifications: E20, G21, G32

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1. Introduction

Banks rely on deposits for a majority of their funding because of their low cost and stability. But, as the banking turmoil of 2023 showed, they are vulnerable to episodes of deposit instability.[1] Deposit stability depends on the rate the bank offers and the withdrawal propensity of its depositors. When market rates increase relative to the rate it offers on its deposits, some depositors may leave the bank for other higher paying alternatives. Alternatively, other depositors who value the convenience of remaining with the same bank may choose to stay and accept the lower rate offered by the bank. In equilibrium, banks anticipate their depositors' behavior and set rates and depositors respond to these rates by either staying or withdrawing their funds from the bank. Our objective in this paper is to observe how a bank's depositor characteristics are related to these equilibrium outcomes.

To do so, we use cellphone geolocation data to map bank visitors to the census block groups from which they originate. This mapping allows us to observe their characteristics such as age, income, education, participation in financial markets etc., at the census tract level and construct a bank's depositor profile. We use these profiles to examine the relationship between a bank's depositors, its deposit flows and rate setting behavior during the 2022-2023 interest rate hiking cycle.

We first document the considerable heterogeneity that exists across bank depositors. Depositors at small banks (total 2019 assets below $1 billion) have a mean family income of $98,600, and about 27% of these customers are college-educated. In comparison, depositors at large banks (total 2019 assets above $250 billion) have a mean family income of 146,700, and 44% of them have a college degree. These numbers are 47% and 63% larger relative to

[1]The banking system as a whole lost about $900 billion in deposits when market interest rates increased from 0% to 5.25% between February 2022 and December 2023. Individual banks lost varying amounts of deposits, and some even gained deposits. The median large bank (2019 assets > $10 billion) lost about 5% of its core deposits during this time period, but roughly 10% of the large banks also gained over 28%, or lost over 19% of their core deposits.

the same numbers for banks with less than $1 billion in assets. Depositors at large banks are also more likely to participate in financial markets (have investment income), and be more financially aware or literate (refinance their homes in 2020-2021 when interest rates were near zero). They are also younger, more diverse ethnically/racially, and renters, while those at smaller banks tend to be older, white, and homeowners. These characteristics are stable over time across bank sizes.

We show that the characteristics of a bank's depositors are related to both its deposit rate response to changes in the market rate (deposit beta), and its deposit stability. Over the recent interest rate hiking cycle from 2022Q1 to 2023Q4, the average bank's response to the 5.25% increase in market rates was to increase its deposit rates by 1.43% – its *cumulative* deposit beta was 0.27, with the beta increasing in asset size, ranging from 0.25 for the smallest banks (less than $1 billion in assets) to 0.44 for the largest banks (assets greater than $250 billion). Banks serving the top quartile of depositors by income or education raised their deposit rates more than those with depositors in the bottom quartile. For small banks (less than $10 billion in assets) with high-income or educated depositors, this rate increase was about 0.20 percentage points higher, while for large banks (greater than $10 billion in assets), it was 0.80 percentage points higher. These differences, representing 14% and 34% higher interest expense adjustments for small and large banks respectively, are economically significant compared to the average interest expense changes during the rate hike cycle. In contrast, banks with older depositors did not increase their rates as much as those with younger depositors. Banks with financially sophisticated depositor bases – those with higher education, income, participation in financial markets, and financial literacy were more responsive to changes in market interest rates both in their timing and magnitude. However their responsiveness was not related to their interest rate exposure that imposed unrealized losses on their balance sheets.

During the rate hike cycle, banks with financially sophisticated depositors experienced a greater decline in deposits despite increasing their rates. Total deposits at banks with financially sophisticated depositors declined by about 2% more when compared to banks with less financially sophisticated depositors. These differences arise from declines in core and uninsured deposits and not from insured deposits. Financially sophisticated depositors respond almost immediately to increases in the fed funds rate. Higher income, college-educated depositors who are financially aware are associated with the more pronounced shifts in deposits across both small and large banks. These depositors also withdraw more from banks that are more exposed to interest rate risk. Within bank estimates that control for differences in banks' strategies or responses through bank fixed effects, and for local factors through county fixed effects, indicate that branches with financially sophisticated depositors within the same bank on average lost about 2% of their total deposits. This effect is highly economically significant given the 2% increase in aggregate deposits during the time period. This result suggests that our findings are unlikely to be due to unobserved bank-level or local economy-level confounding factors.

We also estimate the influence of financial sophisticated depositors on deposit franchise value. The deposit franchise value of a bank is a function of the spread it earns on the deposits it retains, net of the costs it incurs to operate and maintain the deposit franchise. We have established that a bank's depositor base affects its deposit beta (and hence its spread per dollar of deposits) and its deposit stability (the deposits it retains). It is possible that banks incurred additional costs to attract depositors or strengthen their existing relationships to retain existing ones in a rising rate environment. However, we do not find any evidence that they did – their operating costs were largely invariant during the hiking cycle. We therefore estimate the deposit franchise value of banks assuming a constant operating cost, and the differences we observe are driven by changes in the deposit beta and the deposit retention ratio. Our estimates indicate that the deposit franchise value, as a percentage of equity, is about 26% lower for small banks (assets < $ 1 billion) with a financially sophisticated depositor base when compared to their counterparts with a less sophisticated depositor base. For large banks (assets > $10 billion), this difference is about

39%.

Finally, we show that this recent interest rate hiking cycle elicited a different response from financial sophisticated depositors when compared to the previous rate hiking cycle of 2015-2019 where interest rates rose gradually from near zero to 2.5%. During the previous hike cycle, banks with sophisticated depositors were more responsive, increasing their interest rates as market rates rose more so than those with less sophisticated depositors. Financially sophisticated depositors remained and banks experienced an increase in deposits. In contrast, the rapid pace of interest rate increase during this recent cycle, where interest rates were raised by 5.25% in less than 2 years, made them "flighty."

A potential concern with constructing depositor profiles based on the physical visit data is that we are not capturing customers who access banking services digitally. Indeed Haendler (2022) and Koont, Santos, and Zingales (2023) provide evidence on the increased use by bank customers of the digital channel during this recent interest rate hiking cycle. However, data from the Survey of Consumer Finances show that 79% of the households that used internet banking still visited a physical branch during the year as of 2019 (Bhutta et al. 2020). Similarly, FDIC data shows that for 41% of individuals, visiting bank branches or ATMs was still the primary method of banking as of 2019, suggesting that depositor base profiles based on physical visits remain relevant (FDIC 2021). Moreover, online visitors to a bank are likely to reside near their bank, and hence our use of census tract-level demographics is most likely to capture their characteristics as well. Nevertheless, we supplement our physical visit data with mobile and web visit data and run our analysis. We find that our results are qualitatively unchanged, but stronger for banks with lower online visit intensity.

There is limited evidence in the literature on depositor characteristics and how they relate to deposit stability. What little is known primarily relies on data from an individual bank and during distress periods. For instance, Iyer and Puri (2012) and Iyer, Puri, and Ryan (2016) show using data from an Indian bank that older depositors with long-term relationships with the bank are less likely to run, while those that are more transactional, or have informational advantages from being employees of the bank, are more likely to run. Similarly, Chernykh and Mityakov (2022) show using a bank panic episode in Russia that corporate depositors are more likely to run. However, there is broader evidence from U.S. banks that suggests that depositor characteristics do matter. For instance, Drechsler, Savov, and Schnabl (2017) show that that bank deposit spreads and changes are more sensitive to Fed funds rate increases in counties that have lower levels of financial sophistication (an older population, lower median household income, and less college education). Our paper takes advantage of cellphone geolocation data to construct a granular view of depositor characteristics across and within banks, and provides evidence on their relationship with a bank's deposit flows, rate setting behavior and deposit franchise value.

Recent literature attributes advances in digital technology that have made it easier for more tech-savvy and financially sophisticated depositors to monitor and shift their deposits for better returns as contributing to deposit instability. For example, Koont, Santos, and Zingales (2023) provide evidence that depositors use online banking options to "digitally walk" to higher-yielding alternatives. Similarly, Benmelech, Yang, and Zator (2023) show that digital banking enabled banks to grow faster and attract uninsured deposits that flowed out the same way they came in when interest rates increased. Cookson et al. (2023) show how social media platforms allowed depositors to gather and disseminate information, and coordinate withdrawals. Traditionally, deposit modeling has relied on broad categories like product types or FDIC insurance limits. However, with the advances in digital technology, regulators and policymakers have begun to consider a more granular approach to deposit modeling (Kupiec 2023; Federal Reserve Bank of San Francisco 2021; Moody's Analytics 2023). Our paper which shows how differences among depositors, even within traditionally grouped deposit categories, can account for the varied stability of deposits when interest rates increase rapidly suggests that such a granular approach to deposit modeling is indeed warranted.

2. Theoretical Background: Deposit Franchise Value

Traditional banking literature suggests that a significant portion of a bank's value stems from its ability to process information and effectively screen and monitor borrowers using this information (e.g., Diamond (1984); Petersen and Rajan (2002)). However, in recent decades, information-sensitive lending has been gradually migrating out of the banking system, making the value derived from deposits an increasingly important component of a bank's overall value proposition (Buchak et al. (2024); Hanson et al. (2024)).

The value from deposits is derived due to banks' ability to attract and retain customer deposits below prevailing market rates. This advantage translates into a sustained stream of deposit spread, the difference between what the bank pays on deposits and the market interest rates. The present value of this spread represents the franchise value, capturing the economic worth of the bank's established customer base and its ability to secure low-cost funding. Egan, Lewellen, and Sunderam (2022) provide evidence that approximately two-thirds of the value of a median bank derives from its deposit franchise.

Drechsler et al. (2023) offers a framework for valuing the deposit franchise (DF) as a function of deposit beta (β), deposit withdrawal rate (w), change in the interest rate (to r' from r), and operating costs (c). Deposit beta (β) captures the responsiveness of the bank to changes in market interest rates. A higher β implies a lower deposit spread for the bank and hence a lower deposit franchise value. The deposit withdrawal rate (w) depends on both the deposit rate and the market rate, and increases as the difference in the rates increases. A higher w implies less deposits for the bank to earn a spread on, and hence a lower deposit franchise value. The operating costs associated with maintaining the deposit franchise (c) captures the expenses associated with catering to depositors such as maintaining branches, staff, marketing, IT infrastructure, and more. Higher operating costs (c) reduce the net deposit spread, and hence the franchise value.

Specifically, their valuation formula is as follows:

$$DF(r') = D(1 - w(s, r'))\left(1 - \beta - \frac{c}{r'}\right) \tag{1}$$

where DF represents the deposit franchise value, r' is the market interest rate, D stands for total deposits, s denotes the deposit spread, β captures the deposit beta, and c represents operating costs normalized by total deposits.

Our goal is to examine how a bank's depositor characteristics are related to the individual components – β, w, and c, of its deposit franchise value.

3. Data

We combine data from various sources to estimate demographic characteristics, including income, education, age, and race, of the average customer visiting each bank branch. We then aggregate these branch-level characteristics to the bank level by calculating a weighted average of branch-level attributes, considering the significance of each branch to the overall bank profile. We then merge these depositor characteristics data with bank financial data obtained from quarterly call report data to study the impact of depositor characteristics on the deposit rates and flows.

3.1. Data Sources

Advan Monthly Patterns: The Advan Monthly Patterns dataset provides aggregated raw counts of visits to points of interest (POIs) in the US, gathered from a panel of mobile devices. This anonymized and aggregated dataset provides details on monthly visitor frequency, duration, and the origin census block group, enabling an analysis of behavioral patterns at specific POIs. The dataset initiates from January 2019. We use this dataset to identify bank branches and census block groups from which the individuals are visiting a given bank branch.

FDIC Summary of Deposit (SOD) data: This data set provides information on deposit distribution across the U.S. bank branches. Specifically, for our purpose, this data set provides branch-level deposits for bank branches as of June 30th of each year, with bank and county identifiers and the branch address.

US Call Reports data: Federal Financial Institutions Examination Council (FFIEC) requires US banks to file information on the financial health and performance at the end of each quarter and these are made publicly available. These reports provide a breakdown of balance sheets and income statements for each bank-quarter. For our purpose, we obtain bank-quarter-level information such as assets, equity, interest expense, interest income, net profits, deposits, and operating expenses from these reports.

Other Data Sources: American Community Survey (ACS) 5-Year Data provides demographic and socioeconomic information across various geographical levels in the United States. We use the census tract level information on income, education, age, and race to proxy for characteristics of visitors who are visiting a given bank branch in Advan Monthly Patterns data.

To proxy for depositors' financial sophistication and literacy, we utilize Home Mortgage Disclosure Act (HMDA) data to calculate the percentage of mortgages refinanced during the 2020-2021 period when interest rates were historically low. Specifically, we obtain the number of mortgages refinanced in each census tract from the HMDA data and the total number of homes in each tract using American Community Survey (ACS) data. We then calculate the refinance rate as the number of refinanced mortgages divided by the total number of homes for each census tract. A higher refinance rate is interpreted as indicating that individuals in that geographic area are more aware of the prevailing interest rate environment and financially sophisticated enough to understand the potential savings from refinancing their mortgages to take advantage of lower rates.

We further proxy for depositors' financial literacy and sophistication using zip code-level data from the IRS Statistics of Income (SOI) on Individual Income Tax Returns, specifically the fractions of tax returns reporting dividend income and capital gains.

3.2. Key Variables

3.2.1. Branch-Level Customer Characteristics

We integrate Advan Monthly Patterns and ACS 5-year estimates to compute weighted averages for income, the proportion of college-educated individuals, age, refinance rate, individuals with dividend income, and capital gains visiting each bank branch in 2019.

The initial step involves identifying all bank branches within the Advan Point of Interest (POI) table. To accomplish this, we filter POIs where 'TOP_CATEGORY' is categorized as 'Depository Credit Intermediation' or where the 'NAICS_CODE' equals 'Credit Intermediation and Related Activities (522)'. Each POI is uniquely identified by a 'PLACE_KEY' and includes a complete address. Subsequently, we merge this dataset with SOD data using the full address. Before the merging process, we standardize addresses in both datasets using the USPS API. This standardization ensures consistency, addressing potential variations in representation (e.g., 'st' vs. 'street') between the two datasets.[2]

Following this process, we successfully matched 74.99% (62,257) of US bank branches from SOD data with the POI data. Figure 1 visually illustrates the branches that were matched with the POI data, with green dots representing successfully matched branches and red dots indicating unmatched bank branches.

Table 1 presents a breakdown of match rates for banks across different size cohorts. The first column indicates the number of bank branches in each size cohort. Columns (2)

[2]see https://www.usps.com/business/web-tools-apis/address-information-api.pdf for details on the USPS API

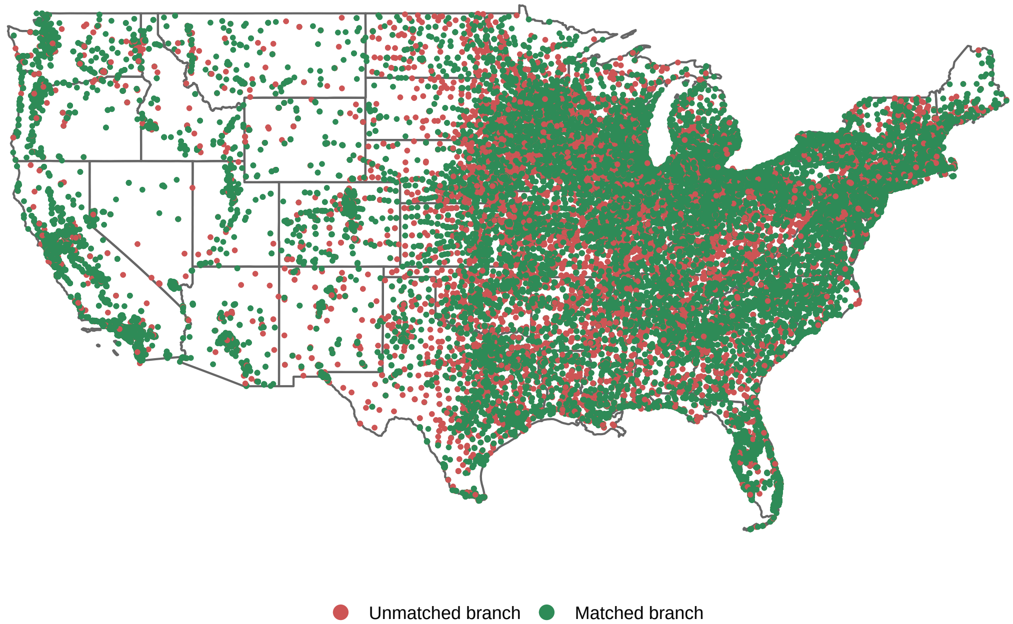


FIGURE 1. Bank Branches - SOD-POI Match

This figure plots all the bank branches in the SOD data set. Green branches are successfully matched with Advan POI data, while red branches remain unmatched.

and (3) highlight the percentage of branches and total deposits successfully matched with the Advan data, respectively. Although the match rate is slightly lower for the smallest bank category, we achieve over approximately 70% matching for all other categories the total deposit amount.

Subsequently, we proceed to identify visits for each matched bank branch in the monthly foot traffic (MFT) table. Consider a single matched bank branch, uniquely identified by a PLACE_KEY' in the POI data set. For each PLACE_KEY' in the POI data, the MFT table provides the total number of visits and the distribution of these visits across census tract blocks for each month. For instance, the Chase branch located at '9901 N LAMAR BLVD AUSTIN TX 78753' is identified by the PLACE_KEY '224-222@8t2-f57-zzz'. Using this information, we can determine the number of individuals visiting this branch from each census block group in a given month.

Once we extract the visit data for each bank branch, we aggregate this information

TABLE 1. Match Rate

Bank Size	No of Branches (1)	No match (%) (2)	Amount match (%) (3)
Less than 1b	16,084	58.9	68.2
1 to 10b	17,817	71.9	74.1
10 to 50b	10,543	83.1	79.1
50 to 250b	12,119	86.4	69.4
More than 250b	22,623	93.0	77.3

This table presents the percentage of bank branches in the FDIC's Summary of Deposits data for which customer geolocation data is available in the Dewey database, by bank size

at the census tract level. It's important to note that a block group comprises clusters of blocks within the same census tract, and the first 11 characters of the block group identifier represent the census tract in the ACS data. We use this census tract identifier to merge visit data with the ACS 5-year estimates.

Using the merged dataset, we compute branch-level estimates for visitor characteristics by calculating a weighted average of census tract characteristics. This involves assigning weights to each census tract based on the proportion of visits from each census tract. Consequently, for each bank branch, we can derive an estimate of the mean income, education, age, percentage of visitors with dividend income, and percentage of visitors who refinanced their mortgages based on the census tracts from which visitors originate.

Formally, the estimation of branch-month level customer characteristics is represented by the equation:

$$X_{bim} = \sum_t \left[\frac{v_{itm}}{V_{im}} \times X_t \right] \tag{2}$$

Here, b is the bank, i denotes the bank branch, m signifies the month, and t represents the census tract. X represents the demographic characteristic estimated, and v_{itm} is the number of visitors to bank branch i from census tract t in month m. V_{im} is the total number of visits to branch i in month m.

Finally, we calculate the branch-level measures X_i by taking the mean of estimated X_{bim} values, i.e.: $X_{bi} = \frac{\sum_m X_{im}}{\sum_m}$.

Our main measure of characteristics for the visitors to a given branch is based on measures calculated over the 12-month period of 2019.

A potential concern with our measures is that the characteristics of visitors to a bank branch could be influenced by seasonality or time variations, introducing potential noise. However, in unreported tests, we verify the robust persistence of these measures over time.

3.2.2. Bank-Level Customer Characteristics

After estimating the branch-level customer characteristics, the process of deriving bank-level customer characteristics is straightforward.

To obtain the bank-level measure, we assign weights to branch-level customer visits based on the total visits to each branch in a given month within each bank. Specifically, for bank b and month m, the calculation for characteristics $X_{b,m}$ is expressed as follows:

$$X_{bm} = \sum_i \left[\frac{v_{im}}{V_{bm}} \times X_{bim} \right] \tag{3}$$

Here, i represents the branch, X signifies the characteristic, v_{im} is the total number of visitors to branch i in month m, and V_{bm} is the total number of visitors to the bank in the month m (i.e.: $V_{bm} = \sum_i v_{im}$).

3.2.3. Banks with Sophisticated Customers

To capture the level of financial sophistication among a bank's customer base, we construct a key explanatory variable termed 'Sophisticated'. This binary variable takes a value of one for banks that serve customers exhibiting characteristics associated with higher financial literacy and engagement. Specifically, a bank is classified as 'Sophisticated' if it meets or exceeds the following median thresholds within its respective size category (small banks with total assets less than $10 billion, and large banks with total assets greater than $10 billion): customer income levels, percentage of customers with a college education, percentage of customers receiving dividend income, and percentage of customers who refinanced mortgages in 2020-2021.

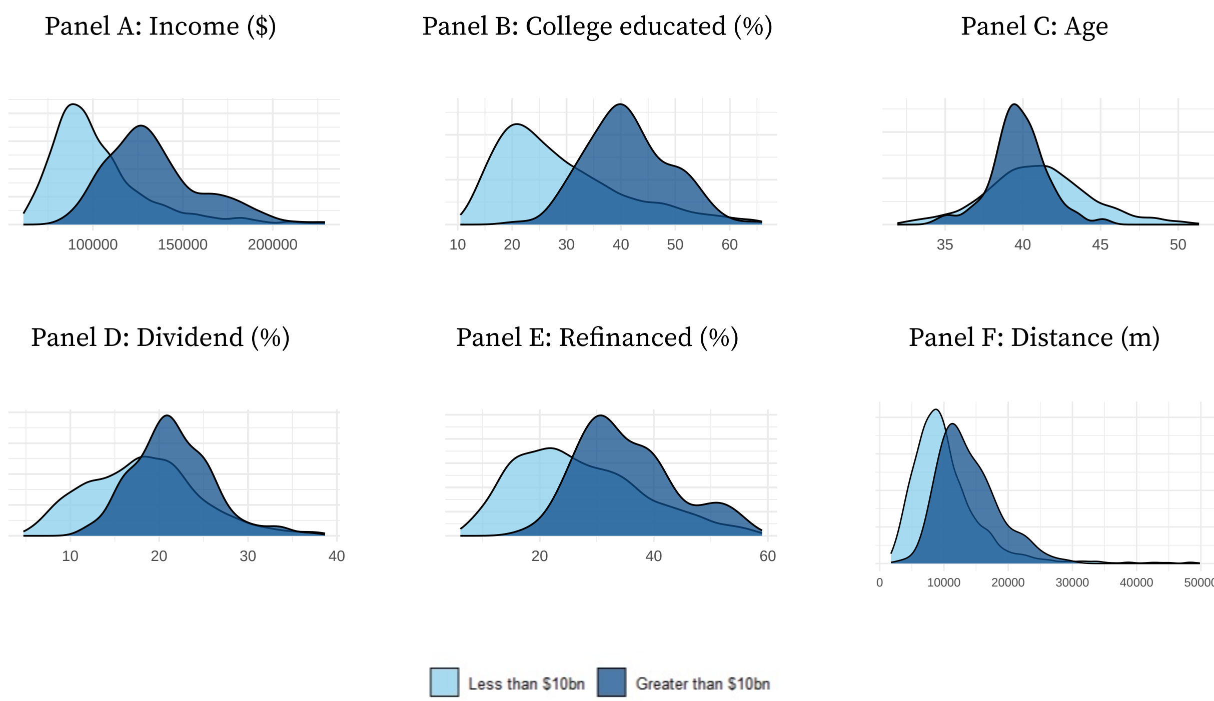
The 'Sophisticated' variable serves as our primary independent variable of interest across the empirical analyses. However, we supplement these findings with additional model specifications that employ the individual customer characteristics (income, education, dividend income, and refinancing activity) as separate explanatory variables.

4. Bank-Level Customer Characteristics

In this section, we provide a summary of customer characteristics estimated at the bank level. We begin by visually representing the distribution of key customer features in Figure 2. The density plot in Panel A illustrates the estimated income distribution across banks separately for small banks with less than $10 billion in assets (light blue) and large banks with assets greater than $10 billion (dark blue). This panel reveals that while small banks, on average, have customers with lower incomes, there is substantial variation in customer income across banks. Similarly, Panels B through F display the distributions of education, age, percentage of customers with dividend income, percentage of customers who refinanced their mortgages in 2020-2021, and the average distance customers travel to visit the bank. Across all panels, it is evident that there is considerable variation in customer characteristics among banks, and large banks have more educated and more financially sophisticated customers.

In Table 2, we present the mean values of various customer characteristics segmented by the size of banks. The table is organized into columns representing different bank

FIGURE 2. Bank-Level Customer Characteristics



This figure shows the distribution of various customer characteristics at the bank level.

size categories, ranging from less than 1 billion in assets (column (1)) to those exceeding 250 billion (column (5)). Each row corresponds to a specific characteristic, detailing the demographic composition of customers or the financial characteristics of banks based on the bank's size.

As we move across the columns toward larger banks, several interesting patterns emerge, reflecting changes in customer demographics and bank characteristics. For banks with assets exceeding $250 billion, represented in Column (5), the mean family income stands at $146,715, and 44.2% of the customers hold a college degree. These figures are substantially higher compared to those associated with the smallest banks and monotonically increasing with bank size, indicating that larger banks tend to serve customers with higher income levels and greater educational attainment.

Furthermore, larger banks also show a more diverse demographic profile in terms of race, with a lower percentage of white customers compared to smaller banks. The age of customers shows a decrease across bank sizes, suggesting that larger banks attract slightly younger customers.

The digital engagement, as indicated by internet access, increases with bank size, reflecting higher digital connectivity among customers of larger banks. This pattern also extends to measures of financial sophistication: customers of larger banks are more likely to have tax returns with dividends and capital gains, and more likely to refinance their mortgages when the interest rates drop.

Bank characteristics also reveal notable trends. Loans as a percentage of assets decrease with bank size, suggesting a shift in asset composition as banks grow. The proportion of core and time deposits to assets also decreases with size, indicating variations in funding structures across different-sized banks. Time deposits/assets ratio decreases with bank size, moving from 24.4% in banks with less than $1 billion in assets to 9.29% in banks with more than $250 billion. Larger banks attract customers with higher deposit balances, exceeding federal insurance limits, indicating a shift towards a more affluent customer base or those with more sophisticated financial needs. Notably, the net interest margin also decreases with bank size.

Starting with Column (1), which pertains to banks with total assets below $1 billion, we observe that the customers of these banks have a mean family income of $98,557. Additionally, approximately 26.9% of these customers hold a college degree.

As we move across the columns toward larger banks, several interesting patterns emerge, reflecting changes in customer demographics and bank characteristics. For banks with assets exceeding $250 billion, represented in Column (5), the mean family income stands at $146,715, and 44.2% of the customers hold a college degree. These figures are substantially higher compared to those associated with the smallest banks and monotonically increasing with bank size, indicating that larger banks tend to serve customers with higher income levels and greater educational attainment.

TABLE 2. Customer and Bank Characteristics by Bank Size

	Less than 1b (1)	1 to 10b (2)	10 to 50b (3)	50 to 250b (4)	More than 250b (5)
Number of banks	3,006	782	102	30	11
Customer characteristics					
Family income ($)	98, 557	120, 891	132, 158	152, 363	146, 715
College educated (%)	26.900	36.600	40.900	45.800	44.200
Age	41.200	40.300	39.800	39.700	39.100
Tax returns with dividend (%)	17.700	20.500	21.500	23.600	21.900
Tax returns with capital gains (%)	15.900	18.100	19.200	21.400	19.500
Homes refinanced in 2020-2021 (%)	25.600	33.100	36.500	37.600	34.700
White (%)	83.200	76.800	69.900	64.200	60.900
Internet access (%)	83.900	87.500	88.900	89.800	89.500
Owner occupied home (%)	72.300	67.000	62.500	57.600	55.800
Distance from home (m)	9, 972	11, 069	13, 995	15, 533	13, 345
Bank characteristics					
Loans/assets (%)	64.600	70.800	68.500	63.900	46.800
Core deposits/assets (%)	75.800	71.700	69.100	68.500	63.600
Time deposits/assets (%)	24.400	19.900	15.100	13.700	9.290
Uninsured deposits/assets (%)	30.500	36.600	38.800	40.400	38.800
Insured deposits/assets (%)	51.300	44.300	39	38.900	31.400
Deposits/loans (%)	140	120	119	126	166
Interest expense/assets (%)	1.600	1.970	2.180	2.400	2.370
Interest income/assets (%)	4.890	4.990	5.060	5.210	5.080
Non-interest expnese/assets (%)	2.420	2.290	1.920	1.910	2.110
Net interest margin (%)	3.270	2.990	2.790	2.740	2.640
Return-on-equity (%)	11.400	11.200	9.980	11.900	9.700

This table presents the estimated bank-level customer and bank characteristics by bank size groups.

Furthermore, larger banks also show a more diverse demographic profile in terms of race, with a lower percentage of white customers compared to smaller banks. The age of customers shows a decrease across bank sizes, suggesting that larger banks attract slightly younger customers.

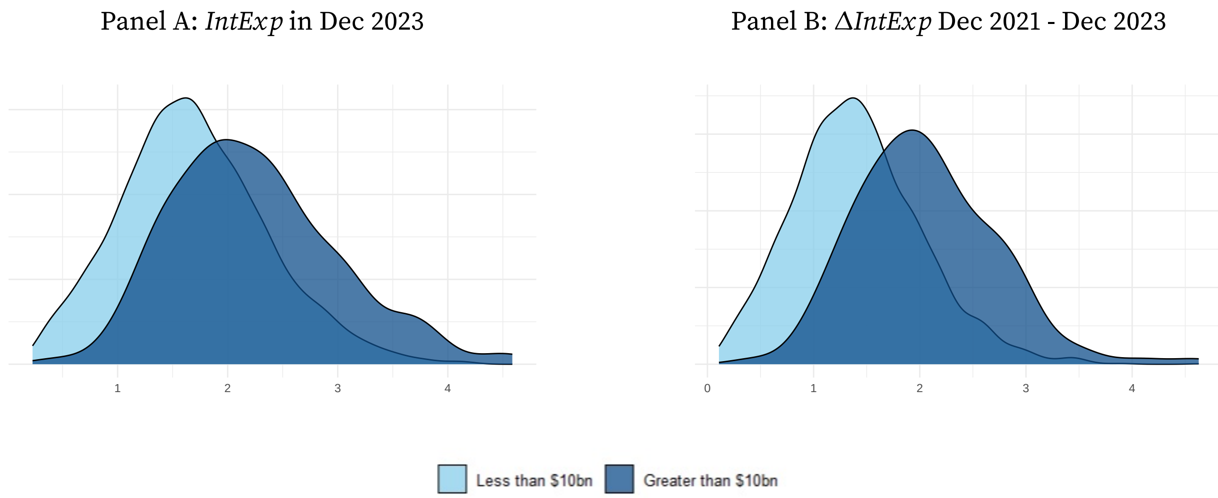
The digital engagement, as indicated by internet access, increases with bank size, reflecting higher digital connectivity among customers of larger banks. This pattern also extends to measures of financial sophistication: customers of larger banks are more likely to have tax returns with dividends and capital gains, and more likely to refinance their mortgages when the interest rates drop.

Bank characteristics also reveal notable trends. Loans as a percentage of assets decrease with bank size, suggesting a shift in asset composition as banks grow. The proportion of core and time deposits to assets also decreases with size, indicating variations in funding structures across different-sized banks. Time deposits/assets ratio decreases with bank size, moving from 24.4% in banks with less than $1 billion in assets to 9.29% in banks with more than $250 billion. Larger banks attract customers with higher deposit balances, exceeding federal insurance limits, indicating a shift towards a more affluent customer base or those with more sophisticated financial needs. Notably, the net interest margin also decreases with bank size.

5. Deposit Beta

The deposit beta, which measures the sensitivity of a bank's deposit interest expenses to changes in the Fed funds rate, is a crucial factor impacting the value of its deposit franchise (see Section 2). It is defined as the change in interest expenditure for a 1% change in the Fed funds rate. In this section, we investigate how the bank-level deposit beta varies by customer characteristics of each bank during the recent episode of Fed funds rate increases from 0% in December 2021 to 5.25% in Dec 2023 (see Figure A1).

FIGURE 3. $\Delta IntExp$ Dec 2021 - Dec 2023



This figure plots the interest rate expense/assets ($\Delta IntExp$) and its change from Dec 2021 to Dec 2023 for the banks in our sample.

We hypothesize that banks with more sophisticated depositors–those with higher education, higher income, higher percentage of customers with dividend income, and higher percentage of customers who refinanced their mortgages in 2020-2021–should exhibit greater sensitivity of their interest expenditure to changes in the Fed funds rate (higher beta). Specifically, these sophisticated depositors, when faced with high deposit spreads, would be more inclined to move deposits from lower-yielding accounts to potentially higher-yielding investments like money market funds in response to Fed funds rate increases, as suggested by Drechsler, Savov, and Schnabl (2017). Anticipating this behavior, banks would respond by offering higher interest rates on deposits, thereby reducing their deposit spread. Consequently, this effort to retain deposits can negatively impact the overall franchise value compared to banks with less sophisticated depositors, holding other factors constant.

In Figure 3 Panel A, we visually represent the distribution of the interest rate expenditure (defined as interest rate expense/total assets, and *IntExp* henceforth) for the quarter ended Dec 2023 separately for small banks (light blue) and large banks (dark blue). Large banks pay a slightly higher rate on deposits, and there is substantial variation in *IntExp*. Panel B shows the change in *IntExp* ($\Delta IntExp$) from Dec 2021 to Dec 2023 , responding to a 5.25% increase in the Fed funds rate. The graph illustrates a significant variation in the change of $\Delta IntExp$: on average, banks increased deposit expenditure by around 2% (corresponding to a beta of approximately 0.38, i.e. 2%/5.25%). However, certain banks had to increase their deposit expenditure by more than 3% (beta of 0.56), while 25% experienced an increase of less than 1% (beta of 0.20).

Figure 4 presents univariate evidence of the relationship between customer characteristics and $\Delta IntExp$. To construct Figure 4, banks are categorized into deciles based on their estimated customer characteristics, plotted on the x-axis. The y-axis displays the mean $\Delta IntExp$ for each decile, distinguishing between large and small banks.

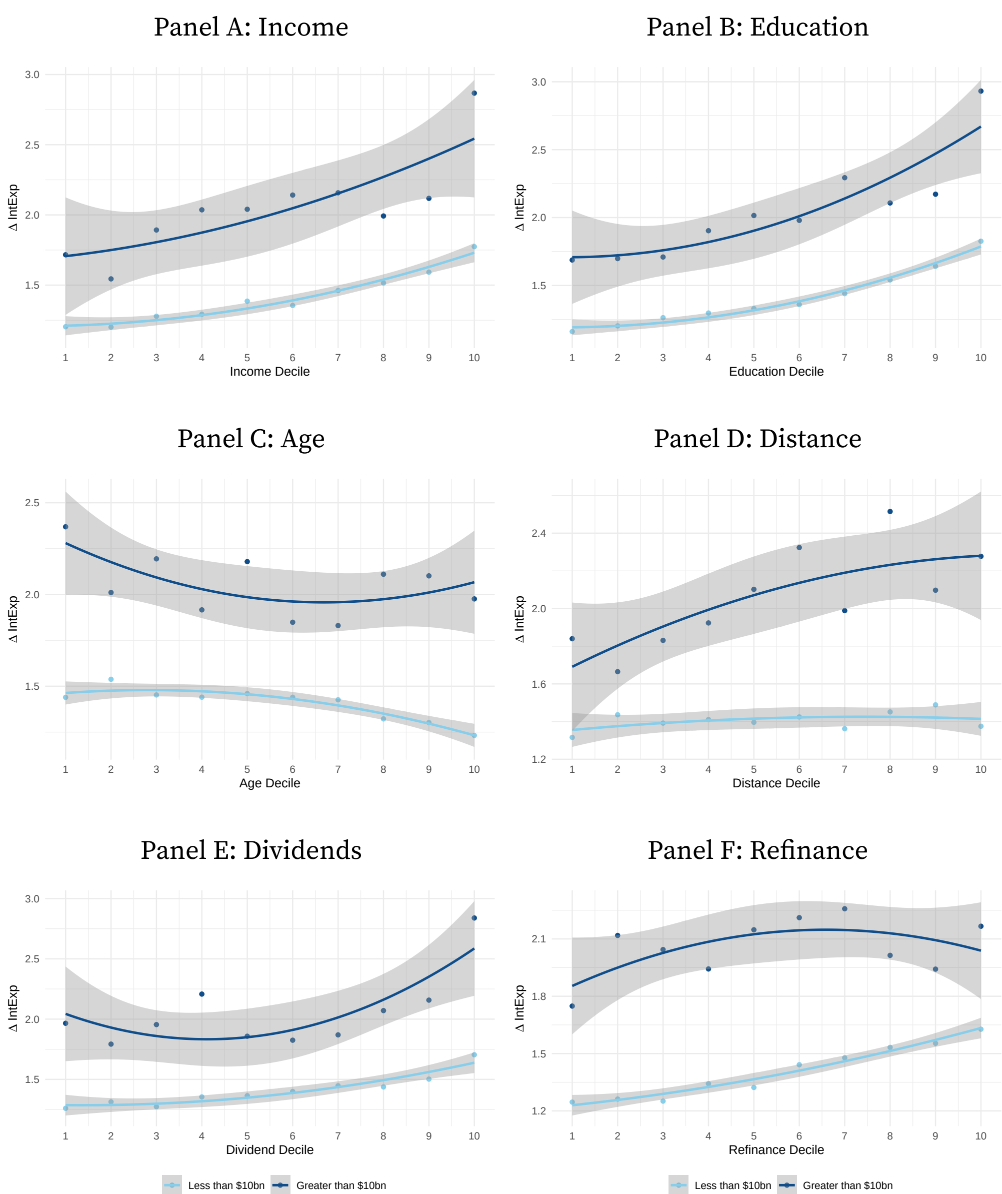
Panel A shows a positive correlation between customer income and deposit expense beta both for the large banks and small banks. Similarly, in Panel B, a positive correlation is observed between deposit expense beta and the education level of customers. These suggest that banks serving higher-income and higher-educated customers tend to experience more significant changes in interest expenditure in response to shifts in market rates.

Panel C reveals a negative correlation between the age of customers and deposit expense beta. This indicates that banks with older customer demographics tend to have lower sensitivity in deposit costs to changes in market rates, suggesting more stable deposit bases.

Panel D focuses on the distance between customers' homes and the banks, showing a generally positive correlation between customer-bank distance and deposit expense beta, especially for larger banks. This might imply that customers who are willing to bank farther from home are more rate-sensitive, possibly due to a higher likelihood of seeking out better rates online or being more financially sophisticated.

Together, Panels E and F suggest that banks with customer bases that exhibit higher financial sophistication—evidenced by receiving dividends and engaging in refinancing—are

FIGURE 4. Deposit Beta and Customer Characteristics



This figure shows the relationship between bank customer characteristics and expenditure beta associated with a higher deposit expense beta.

Overall, Figure 4 illustrates that banks catering to more financially sophisticated or affluent customers—evidenced by higher income, education levels, investment income from dividends, and mortgage refinancing activities—tend to exhibit a higher $\Delta IntExp$.

Next, we examine and quantify these observed relationships more rigorously in a regression framework. This analysis aims to explore the changes in bank-level interest expense to deposits ($\Delta IntExp$) from the period immediately preceding the Federal Reserve's initiation of interest rate increases in Dec 2021 to the most recent quarter (Dec 2023). Specifically, we focus on the impact of customer characteristics on the $\Delta IntExp$ throughout the entire interest rate hike cycle. Here, $\Delta IntExp$ can be interpreted as *cumulative* deposit beta. The regression specification is detailed below:

(4)

$$\Delta IntExp_b = IntExp_{b,Dec2023} - IntExp_{b,Dec2021} = \alpha + \sum_{q=1}^{4} \beta_q \times I(Type = q) + \mathbf{\Gamma X} + \text{Bank Size FE} + \epsilon_b$$

where b is the bank and q is quartile. X contains $log(assets)_b$, $equity_b/assets_b$, and HHI_b in 2021. The variable $Type$ indicates the quartile to which the bank b belongs based on a given customer characteristic. β_q coefficients capture the incremental sensitivity of $\Delta IntExp$ for the quartile indicated by q, relative to the omitted first quartile.

Drechsler, Savov, and Schnabl (2021) document a strong positive correlation between the asset size and the deposit beta (Figure 7 in their paper), and we showed in Table 2 that customer characteristics also vary by asset size. To address the potential confounding effects related to asset size, we control for $log(assets)$. We include additional controls non-parametrically by including dummy variables that represent each of the bank size categories: less than \$1 billion, \$1 to \$10 billion, \$10 to \$50 billion, and more than \$50 billion. These dummy variables capture the variations in depositor behavior across bank categories.

We follow the methodology outlined by Drechsler, Savov, and Schnabl (2021) for calculating the Herfindahl-Hirschman Index (HHI) at the bank level, denoted as HHI_b. This involves computing the county-level HHI using 2021-Summary of Deposits (SOD) deposit data and then averaging these county-level HHIs to obtain a bank-level measure. This captures the market power of each bank, which is shown to have a strong negative correlation with deposit beta, indicating that banks with greater market power tend to exhibit lower sensitivity of deposit rates to changes in the market interest rates.

The regression results are presented in Table 3. Panel A reports the analysis for small banks with total assets less than $10 billion, while Panel B focuses on large banks exceeding the $10 billion asset threshold. We delineate small and large banks at the $10 billion level as this asset size serves as a key regulatory threshold that subjects banks to enhanced prudential standards under the Dodd-Frank Act. Additionally, this threshold provides a sufficient sample of large banks to conduct meaningful regression analyses. In each panel, the last row specifies the $Type$ variable utilized in each regression.

The findings in column (1) of Panel A indicate that $\Delta IntExp$ was 0.154% higher for small banks serving sophisticated customers. A bank is considered to have sophisticated customers if it serves customers with above-median income, a higher-than-median percentage of college-educated individuals, an above-median percentage receiving dividend income, and an above-median percentage who refinanced in 2020-2021. Similarly, in Panel B, the $\Delta IntExp$ was 0.134% higher, although not statistically significant, for large banks serving sophisticated customers.

In Panel A, Column (2) suggests that $\Delta IntExp$ is 0.215% higher for banks within the top quartile of the income distribution compared to those in the bottom quartile, which represents approximately 11% of the average $\Delta IntExp$ in the sample. Similarly, Column (3) indicates that banks serving customers in the top education quartile had to increase their interest expenses by an additional 0.252% compared to banks with customers in the bottom education quartile. In Panel B, the corresponding figures are 0.792% and 0.666%,

TABLE 3. Sensitivity of Interest Expense to Customer Characteristics

Panel A: Small banks (<= 10bn in assets)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sophisticated	0.154***						
	(0.022)						
Type ∈ Q2		0.035	0.015	−0.014	−0.012	−0.034	−0.015
		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Type ∈ Q3		0.075***	0.058**	−0.044	0.054**	0.038	−0.020
		(0.027)	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)
Type ∈ Q4		0.215***	0.252***	−0.078***	0.160***	0.083***	0.004
		(0.029)	(0.029)	(0.028)	(0.027)	(0.029)	(0.027)
log(Assets)	0.184***	0.177***	0.173***	0.192***	0.192***	0.190***	0.198***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Equity/Assets	0.059	−0.030	−0.052	0.063	0.040	0.045	0.062
	(0.252)	(0.253)	(0.251)	(0.254)	(0.252)	(0.254)	(0.254)
Bank HHI	−0.277***	−0.273***	−0.269***	−0.296***	−0.289***	−0.286***	−0.303***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
N	3,404	3,404	3,404	3,404	3,404	3,404	3,404
Adjusted R^2	0.172	0.175	0.183	0.162	0.171	0.164	0.160
Type		Income	College educated	Age	Dividend	Refinance	Distance

Panel B: Large banks (> 10bn in assets)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sophisticated	0.134						
	(0.138)						
Q2		0.374***	0.095	0.063	0.012	−0.162	0.062
		(0.137)	(0.140)	(0.162)	(0.146)	(0.154)	(0.160)
Q3		0.359**	0.417***	−0.246	−0.011	0.089	0.153
		(0.138)	(0.145)	(0.159)	(0.144)	(0.159)	(0.168)
Q4		0.792***	0.666***	0.115	0.561***	−0.189	0.303*
		(0.155)	(0.159)	(0.154)	(0.158)	(0.164)	(0.165)
log(Assets)	0.118	0.217*	0.233**	0.108	0.236*	0.097	0.115
	(0.121)	(0.112)	(0.115)	(0.120)	(0.119)	(0.123)	(0.121)
Equity/Assets	−4.539**	−4.897**	−3.771*	−3.495	−3.003	−4.581**	−3.701
	(2.245)	(2.040)	(2.075)	(2.254)	(2.152)	(2.236)	(2.270)
Bank HHI	−0.595***	−0.658***	−0.578***	−0.652***	−0.564***	−0.659***	−0.560***
	(0.132)	(0.119)	(0.121)	(0.132)	(0.127)	(0.134)	(0.135)
N	111	111	111	111	111	111	111
Adjusted R^2	0.202	0.349	0.327	0.223	0.290	0.210	0.209
Type		Income	College educated	Age	Dividend	Refinance	Distance

Panel C: By interest rate risk exposures

	HTM/Assets			Maturity of Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
	HTM/Assets =0	0 < HTM/Assets <10	HTM/Assets>=10	WA(Maturity)<4	4<=WA(Maturity)<7	WA(Maturity)>=7
Sophisticated	0.145 * **	0.149 * **	0.153 * *	0.112 * **	0.170 * **	0.141 * **
	(0.029)	(0.040)	(0.062)	(0.038)	(0.033)	(0.043)
N	2,222	1,012	411	1,344	1,436	863

This table reports the results of regressions that study how the changes in deposit expenditure are related to depositor characteristics during the rate hike cycle from Dec 2021 to Dec 2023 using Equation 4. Panel A uses the sample of small banks (less than $10bn in assets) and Panel B uses the sample of large banks (greater than $10 bn in assets). In each panel, the last row indicates the $Type$ variable used in each regression. Standard errors are reported in parenthesis below the coefficients. Panel C reports the coefficient estimates of the 'Sophisticated' dummy variables in subsamples based on exposure to interest rate risk. Significance levels are indicated as follows: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

respectively, indicating that the effects are significantly more pronounced for large banks.

Column (5) in both panels indicates that $\Delta IntExp$ is significantly higher for banks whose customers are in the top quartile in terms of the percentage receiving dividend income. This result underscores that having dividend income serves as a marker of financial sophistication among customers, who are more likely to be attuned to prevailing market interest rates and possess the capability to invest in money market funds, which offer higher risk-free returns. Consequently, this customer demographic is likely to be less stable, as they may shift their deposits to higher-yielding alternatives in response to interest rate adjustments. This behavior leads banks to increase their interest expenses to retain these financially savvy customers.

The interest rate increase during our time period resulted in banks with longer duration assets and those held to maturity suffering (unrealized) losses, and many such banks experienced runs during the banking turmoil of 2023 that began with the run of Silicon Valley Bank. It is conceivable that for these banks, financially sophisticated depositors were the ones that were particularly prone to run, and such banks may have therefore increased their deposit rates to retain deposits. To examine if this is the case, in Panel C, we analyze sub-samples based on two key metrics of interest rate risk exposure: held-to-maturity securities as a percentage of assets (columns 1 through 3) and the weighted average maturity of bank assets (columns 4 through 6). The results show that interest expenses do not vary across banks with sophisticated depositors facing different levels of losses. This observation implies that the relationship between depositor sophistication and interest expense adjustments remains relatively consistent across different bank interest rate risk exposure levels.

Having shown that interest expenses of banks with more financially sophisticated or affluent customers are more sensitive to the changes in the Fed funds rate, we next turn to understanding the timing of the interest rate increase by the banks. In order to do this, we run the following dynamic difference-in-differences specification using a bank-quarter panel:

$$(5) \qquad IntExp_{b,q} = \alpha + \sum_{q=-6}^{8} \beta_q \times Sophisticated_b + \Gamma \boldsymbol{X} + \text{Bank FE} + \text{Quarter FE} + \epsilon_{bq}$$

where q indicates quarters since the Fed started raising interest rates, i.e., Q4 2021, and b represents the bank. *Sophisticated* is a dummy variable indicating whether bank b serves sophisticated customers. Control variables $\boldsymbol{X}$ include the interest rate paid in the last quarter and the log of total assets in the current quarter. We focus on the time period after COVID-19 until Q4 of 2023.

The coefficients of interest β_q capture the difference in interest rates paid by banks with sophisticated customers and those without sophisticated customers in quarter q relative to the same difference in quarter -6 (i.e., Q2 2020).

The estimates of β_q and their corresponding 95% confidence intervals are plotted in Figure 5. The results suggest that banks with sophisticated customers started increasing their deposit rates in line with the changes in the Fed Funds Rate.

6. Deposit Change

The previous section shows that banks catering to financially sophisticated depositor bases raised their deposit rates more aggressively in response to increases in the Fed funds rate. The next logical question, given these increases in interest expenditure, is whether this upward adjustment in deposit rates is effective in preventing the outflow of deposits from these banks. As discussed in Section 2, the deposit franchise value is derived from the ability of banks to maintain a stable and sticky deposit base, even in the face of rising market rates. If the increase in the deposit rate offered by a bank is not sufficient to prevent deposit withdrawals by its sophisticated customers, then that would have a negative impact on the franchise value, all else equal. Sophisticated depositors, being more sensitive to interest rate changes and actively seeking higher-yielding alternatives, may be more prone

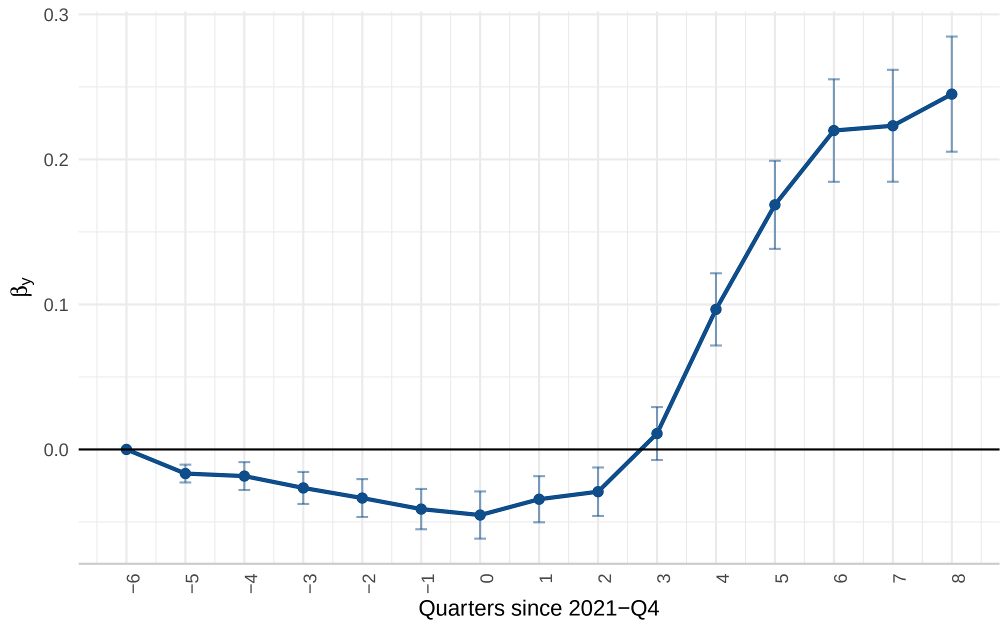


FIGURE 5. Beta - Time - Q

Note: This figure plots the estimation of β_q and the corresponding 95% confidence intervals based on Equation 5. It compares the change in interest rate expenditure between banks with more sophisticated customers and those with less sophisticated customers during the 2022-2023 rate hike cycle.

to reallocating their funds away from banks that fail to match competitive rates, thereby eroding the stability of those banks' deposit bases.

Table 4 illustrates the distributions of bank-level changes in core deposits (Panel A), uninsured deposits (Panel B), insured deposits (Panel C), and time deposits (Panel D) from Dec 2021 to Dec 2023 .[3] During the rate hike cycle, core deposits dropped by an average of 1.16% for small banks and 6.04% for large banks, indicating a general decline in these stable funding sources. Similarly, uninsured deposits dropped by an average of 1% for small banks and 9% for large banks. In contrast, both small and large banks gained insured and time deposits.

The table also highlights substantial cross-sectional variations in these changes, with some banks experiencing over a 25% growth in core deposits during this time period, while over 5% of banks witnessed a decline of more than 17%. Additionally, more than

[3]Core deposits, as defined by the FDIC, encompass the sum of transaction accounts, MMDAs, non-transaction savings (excluding MMDAs), and smaller time deposits, excluding fully insured brokered deposits under $250,000, representing a stable source of funding for banks.

TABLE 4. Change in Deposits from Dec 2021 to Dec 2023

Variable	Bank size	p10	p25	p50	p75	p90
Core deposits	Less than 10b	–13.560	–7.760	–1.170	6.240	17.920
	More than 10b	–19.020	–13.360	–5.280	4.920	28.860
Uninsured deposits	Less than 10b	–24.250	–13.660	–0.820	14.170	35.120
	More than 10b	–27.450	–21.500	–8.710	2.710	30.470
Insured deposits	Less than 10b	–5.960	–0.810	6.490	19.070	44.230
	More than 10b	0.790	6.650	20.770	56.080	89.200
Time deposits	Less than 10b	–4.370	15.070	43.150	85.720	148.560
	More than 10b	29.250	61.220	138.060	305.160	472.120

This table shows the distribution of percentage changes in different types of deposits from Dec 2021 to Dec 2023

10% of banks observed uninsured deposit withdrawals exceeding 25%, underscoring the vulnerability of these deposits to market rate fluctuations. This section investigates whether the characteristics of a bank's depositor base, such as their demographic profiles and financial sophistication can account for the observed variation in deposit movements during the rate hike cycle.

6.1. Bank-Level Evidence

We commence our analysis by investigating how changes in deposits at the bank level are associated with depositor characteristics. We implement a regression framework where we regress the changes in the levels of different types of deposits from just prior to the Federal Reserve initiating interest rate hikes (Dec 2021) to the most recent quarter (Dec 2023) on depositor characteristics. Specifically, the specification is similar to Equation 4, and is given by the following formula:

(6) $$\Delta Y_b = \frac{Y_{b,Dec2023} - Y_{b,Dec2021}}{Y_{b,Dec2021}} = \alpha + \beta \times Characteristic_b + \Gamma \boldsymbol{X} + \epsilon_b$$

where b is the bank and q is quartile. Y is the measure of deposits. X contains $log(Assets)_b$, $Equity_b/Assets_b$, and HHI_b in 2021. The variable $Characteristic$ indicates the depositor characteristic estimate.

Table 5 presents the regression results. Panel A focuses on the indicator variable 'sophisticated' as the key explanatory variable of interest. This binary variable captures whether a bank's customer base is characterized as financially sophisticated, and a bank is considered to have sophisticated customers if it serves customers with above-median income, a higher-than-median percentage of college-educated individuals, an above-median percentage receiving dividend income, and an above-median percentage who refinanced in 2020-2021.

Panel B summarizes the results of six separate regression analyses, each utilizing a different customer characteristic as the main variable of interest. These characteristics are listed in the first column. To conserve space, Panel B omits the coefficients and regression statistics associated with the bank-level control variables included in the model. Only the key coefficients of interest, along with their standard errors and corresponding significance levels, are reported.

The results presented in Panel A show the differential impacts of customer sophistication on the deposit flows at banks segmented by asset size. In Panel A, focusing on small banks, Column (1) highlights a significant decrease in core deposits – 3.26% more pronounced – for banks with sophisticated customers compared to their counterparts with less sophisticated depositors. Column (5) shows that large banks with sophisticated customers experienced a drop in core deposits of 1.17%, albeit without statistical significance.

Columns (2) and (6) reveal a consistent pattern across both small and large banks,

TABLE 5. Deposit Change

Panel A

	Assets <= 10bn				Assets > 10bn			
	ΔCore	ΔUninsued	ΔInsured	ΔTime	ΔCore	ΔUninsued	ΔInsured	ΔTime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sophisticated	−3.263***	−5.100***	0.524	−0.174	−1.167	−4.188	0.827	−36.574***
	(0.495)	(0.769)	(0.551)	(1.191)	(3.578)	(3.409)	(4.662)	(12.163)
log(Assets)	0.542***	−0.633**	2.983***	2.456***	−0.024	0.027	−2.112	10.739*
	(0.191)	(0.302)	(0.213)	(0.442)	(1.223)	(1.150)	(1.390)	(5.806)
Equity/assets	−14.976***	10.383	−35.226***	−24.757**	132.115**	88.602	101.420	180.238
	(5.604)	(8.748)	(6.428)	(10.839)	(57.700)	(56.275)	(81.837)	(187.252)
Bank HHI	−1.051*	−2.104**	−2.464***	−2.035	−1.614	0.154	−2.265	25.207***
	(0.583)	(0.946)	(0.637)	(1.413)	(3.315)	(3.151)	(3.804)	(8.452)
Constant	−4.135	8.951**	−25.576***	−10.548*	−16.690	−18.808	40.906	−161.964
	(2.526)	(3.992)	(2.804)	(5.692)	(23.368)	(22.230)	(27.424)	(104.764)
N	3,524	3,389	3,288	1,987	121	116	93	50
Adjusted R^2	0.014	0.019	0.077	0.019	0.017	0.002	0.027	0.254

Panel B

	Assets <= 10bn				Assets > 10bn			
	ΔCore	ΔUninsued	ΔInsured	ΔTime	ΔCore	ΔUninsued	ΔInsured	ΔTime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Family income/1000	−0.571***	−0.687***	−0.121	−0.332**	−1.157**	−0.734	−0.491	−2.305
	(0.070)	(0.109)	(0.085)	(0.168)	(0.537)	(0.524)	(0.675)	(1.637)
College educated (%)	−0.149***	−0.216***	0.001	−0.065	−0.440**	−0.343*	0.029	−0.953
	(0.019)	(0.029)	(0.021)	(0.043)	(0.190)	(0.184)	(0.247)	(0.604)
Age	−0.194***	−0.367***	0.001	0.417***	−0.854	1.540*	−0.637	1.554
	(0.060)	(0.094)	(0.065)	(0.129)	(0.831)	(0.802)	(0.988)	(2.218)
Dividend income (%)	−0.240***	−0.404***	0.023	0.105	−0.544	−0.299	0.064	−0.880
	(0.031)	(0.048)	(0.035)	(0.069)	(0.344)	(0.346)	(0.447)	(1.148)
Refinanced (%)	−0.140***	−0.232***	0.011	−0.082*	−0.069	−0.279*	−0.180	−0.870**
	(0.020)	(0.031)	(0.022)	(0.046)	(0.156)	(0.152)	(0.182)	(0.400)
Distance (km)	−0.008	−0.004	−0.0004	−0.055	−0.003	0.021	−0.044	0.012
	(0.010)	(0.015)	(0.010)	(0.038)	(0.047)	(0.045)	(0.051)	(0.096)

Panel C: By exposure to interest rate risk

	HTM/Assets			Maturity of Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
	HTM/Assets =0	0 < HTM/Assets <10	HTM/Assets>=10	WA(Maturity)<4	4<=WA(Maturity)<7	WA(Maturity)>=7
Sophisticated	−2.390 * **	−3.491 * **	−4.447 * **	−3.138 * **	−2.880 * **	−3.708 * **
	(0.640)	(0.891)	(1.289)	(0.903)	(0.749)	(0.809)
N	2,222	1,012	411	1,344	1,436	863

This table reports the results of regressions that model the change in different types of deposits as a function of customer characteristics, based on Equation 6, separately for small (columns (1) through (4)) and large banks (columns (5) through (8)). Panel A uses the indicator variable 'sophisticated' as the main variable of interest. In Panel B, we summarize the results of six regression outputs, where the variable indicated in the first column is the variable of interest–each row corresponds to one set of regressions similar to those in Panel A. We have suppressed other control variables and regression statistics to conserve space. Column headings indicate the dependent variables used in each regression. Standard errors are provided in parentheses below the coefficients. Panel C reports the coefficient estimates of the 'Sophisticated' dummy variable in sub-samples based on exposure to interest rate risk where the dependent variable is ΔCore. Significance levels are indicated as follows: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

with uninsured deposits declining by approximately 5% more among institutions serving more sophisticated depositors. This finding suggests that sophisticated depositors are more likely to reallocate their uninsured funds in response to changes in market rates, contributing to the instability of this deposit category. Columns (3) and (7) indicate muted impacts of customer sophistication on insured deposits, both for small and large banks.

In Panel B, we find that family income and the percentage of college-educated customers exhibit a significant negative impact on both core and uninsured deposits for smaller banks. Particularly striking is the effect of the percentage of depositors with dividend income and the percentage who refinanced their homes in 2020-2021, which serves as a proxy for financial market engagement and awareness, suggesting that higher engagement correlates with more pronounced shifts in deposit behavior. For larger banks, the impacts of these customer characteristics are larger, especially for income and education.

Interestingly, in column (4) we find that banks with older customers attracted more time deposits. This could be due to, as Kang-Landsberg, Luck, and Plosser (2023) point out, banks employing strategic measures to increase interest rates selectively on certain deposit categories, rather than adjusting rates across all deposits, as a retention strategy, and these types of customers being more likely to transfer checking deposits and savings accounts to time deposits. Kang-Landsberg, Luck, and Plosser (2023) document that banks provided higher interest rates for domestic time deposits in comparison to other deposit types in response to increase in the Fed Funds rate.

Building on our previous analysis, we focus on examining how changes in core deposits relate to depositor characteristics and banks' interest rate risk exposure. Panel C presents the results of this investigation, where the dependent variable is the change in core deposits. Columns 1 through 3 split the sample based on held-to-maturity (HTM) securities as a percentage of assets, while columns 4 through 6 segment the data according to the weighted average maturity of bank assets. Notably, and in contrast to our earlier findings on interest expenses, the results reveal a more pronounced effect when banks have a higher proportion of HTM securities relative to their assets. This suggests that the relationship between depositor sophistication and core deposit changes is influenced by a bank's interest rate risk exposure, as measured by its HTM holdings. Such a finding implies that sophisticated depositors may be more sensitive to the interest rate risk exposure of banks when making decisions about their core deposit allocations.

6.2. Branch-Level Evidence with Bank and County Fixed-Effects

In this section, we provide evidence that the observed patterns above cannot be explained by bank-level unobserved factors, such as bank strategy or an increase in run probability, by focusing on the within-bank variation of deposit changes between June 2021 and June 2023. We also implement a variation with county-fixed effects to rule out the impact of local economic shocks that may differentially affect banks with different customer profiles. For example d'Avernas et al. (2023) show banks of various sizes function in different markets, catering to customer bases with differing attributes. For this analysis, we utilize branch-level deposit data from the FDIC Summary of Deposits (SOD). The SOD data is based on an annual survey of branch office deposits as of June 30th and provides total deposits at each bank branch surveyed.

We commence by presenting univariate evidence on the impact of branch-level depositor characteristics on changes in deposit balances in Figure 6. This figure plots the branch-level change in deposits from 2021 to 2023 against the estimated customer characteristics. In each panel, bank branches are grouped into deciles based on the estimated customer characteristics, represented on the x-axis. On the y-axis, we plot the mean deposit change from June 2021 to June 2023 for the corresponding decile, separately for each bank size category.

As can be observed in Panels A and B, we observe a negative monotonic relationship between the income and education levels of the customer base and the deposit change, and this pattern is robust across different bank size categories. Conversely, there is a slight positive relationship between the age of the customer base and deposit changes. Panels E and F, which use the percent of customers with dividend income and refinanced mortgages in 2020-2021 as measures of financial sophistication, show that branches with more sophisticated depositors experienced a larger drop in their deposit balances.

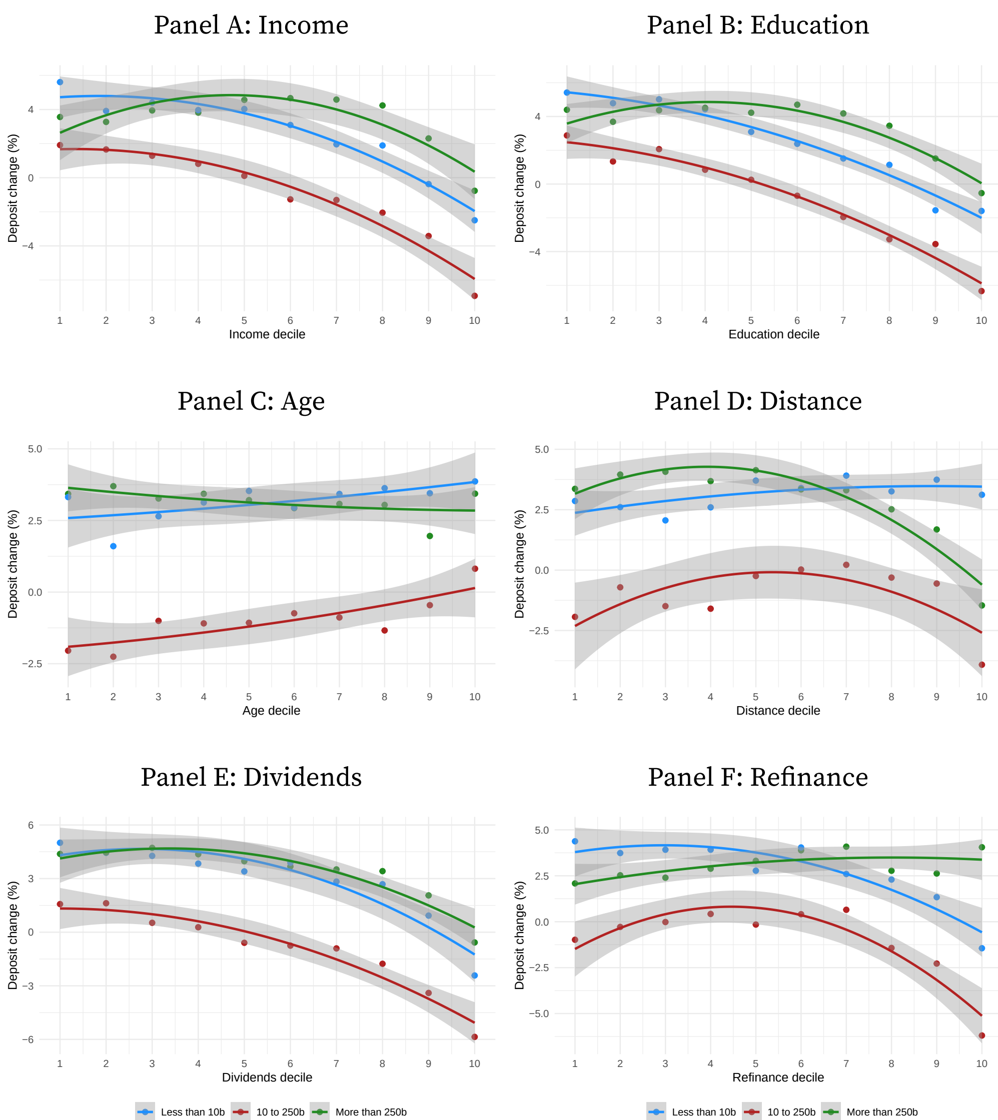
Next, we present formal regression evidence corroborating the robustness of these univariate findings. Specifically, we estimate the following cross-sectional regression at the bank-branch level:

$$\Delta deposits_{bi} = \frac{deposits_{bi,Jun2023} - deposits_{bi,Jun2021}}{deposits_{bi,Jun2021}} = \alpha + \beta \times X_{bi} + \gamma_b + \epsilon_{bi} \tag{7}$$

where b denotes the bank and i represents the branch. The dependent variable, $\Delta deposits_{bi}$, captures the percentage change in deposits at branch i of bank b between June 2021 and June 2023. The variable X_{bi} represents the branch-level customer characteristic of interest, such as income, education, age, or percentage with dividend income.

γ_b represents bank-fixed effects. By including bank-fixed effects in the regression specification, we effectively control for bank-level unobserved factors, such as bank strategy, risk profile, or run probability, that could potentially influence deposit dynamics. The inclusion of bank-fixed effects is particularly important in this context as banks typically implement uniform deposit pricing strategies across their branch networks, largely insensitive to local market (Begenau and Stafford 2022; Granja and Paixao 2021). By absorbing bank-level variation, the fixed effects isolate the impact of branch-level customer characteristics on deposit dynamics, effectively holding deposit rates constant. This approach mitigates concerns that differential deposit pricing across banks could confound the observed relationships between customer attributes and deposit flows. Consequently, this allows us to isolate the impact of branch-level customer characteristics on deposit changes, providing a more granular analysis of the relationship between depositor profiles and deposit flow patterns while accounting for confounding bank-level influences.

FIGURE 6. Branch-Level Deposit Change by Customer Characteristics



This figure shows the relationship between branch-level changes to total deposits and the customer profile of each branch separately for bank size categories. In each panel, the X-axis represents the decile based on the variable indicated in the panel title, and the y-axis shows the mean change in total deposits for each decile from Jun 2021 to Dec 2023 .

Based on the previous univariate evidence in Figure 6, we expect the coefficient β to be negative when X_{bi} is income, education, percent with dividend, and percent refinanced, indicating that branches with more affluent and financially sophisticated customer bases experienced larger deposit outflows. Conversely, we anticipate a positive coefficient when X_{bi} is age, suggesting that branches with older customer bases exhibited relatively stable or increasing deposit levels.

Table 6 presents the results of the branch-level regression analysis, estimated using Equation 7, where the change in branch-level deposits from June 2021 to June 2023 is modeled as a function of customer base characteristics. The analysis is conducted separately for small banks (assets less than $10 billion), medium banks (assets between $10 billion and $250 billion), large banks (assets greater than $250 billion), and the constituents of the SPDR S&P Regional Banking ETF (KRE), allowing for potential heterogeneity in the relationships across different bank size categories.

Panel A focuses on the indicator variable 'sophisticated' as the main explanatory variable of interest, capturing the impact of catering to financially sophisticated depositors on branch-level deposit changes. Odd numbered columns include bank fixed effects and even-numbered columns include both bank and county fixed effects. The county fixed effects control for factors–such as local unemployment–that impact changes in deposits at local economy levels.

In Panel B, we summarize the results of six separate regression outputs, each utilizing a different customer characteristic variable as the primary variable of interest. These characteristics, listed in the first column, include factors such as customer income, education level, and age, as well as proxies for financial sophistication, such as the percentage of customers with dividend income and those who refinanced their mortgages in 2020-2021. To conserve space, the table omits the coefficients and regression statistics associated with other control variables included in the model. However, the key coefficients of interest, along with their standard errors clustered at the bank level, are reported.

The coefficient of -2.659 in Panel A, Column (1) of Table 6 suggests that, within the sample of banks with less than $10 billion in assets, branches catering to more sophisticated customers experienced a 2.66% larger drop in deposit balances during the recent rate hike cycle, compared to branches with less sophisticated customers within the same bank. This finding highlights the impact of customer sophistication on deposit flow dynamics, even after accounting for bank-level factors through the inclusion of bank-fixed effects.

Notably, the estimate of -1.883 in Panel A, Column (2) indicates that the effect of customer sophistication on deposit changes persists, even after controlling for county-level unobservable factors that could potentially impact deposit balances. Specifically, branches with more sophisticated customers within the same bank experienced an approximately 1.88% larger decline in deposits, compared to their counterparts with less sophisticated customers, after accounting for local economic shocks through the inclusion of county-fixed effects.

We observe similar magnitudes of the customer sophistication effect on deposit changes for branches belonging to banks with assets between $10 billion and $250 billion, for those with assets exceeding $250 billion, and the KRE constituents, as evidenced by the coefficients in Panel A, Columns (3) through (8). These consistent patterns across different bank size categories underscore the robustness of the relationship between customer sophistication and deposit flow dynamics, suggesting that the observed effects are not driven by bank-specific factors or localized economic conditions.

Panel B of Table 6 shows the relationship between various customer characteristics and the change in branch-level deposits from June 2021 to June 2023, as estimated by Equation 7. For banks with assets less than $10 billion, a $10,000 increase in family income is associated with a decrease in deposits by about 0.5%, and the coefficients in columns (3) through (6) indicate a stronger negative correlation in smaller banks. The education level, represented as the percentage of college-educated customers, shows a consistent negative impact across all bank sizes, suggesting that branches serving a more educated customer

TABLE 6. Branch-Level Deposit Change by Customer Characteristics

Panel A

	Assets < 10 bn		Assets 10-250 bn		Assets > 250 bn		KRE Constituents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sophisticated	−2.659***	−1.883***	−3.106***	−1.517***	−2.040*	−2.005*	−2.973***	−1.393***
	(0.413)	(0.487)	(0.413)	(0.413)	(1.050)	(0.916)	(0.413)	(0.467)
N	16,541	16,541	15,193	15,193	16,741	16,741	12,433	12,433
Bank FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*N*	*Y*	*N*	*Y*	*N*	*Y*	*N*	*Y*
Adjusted R^2	0.129	0.144	0.223	0.243	0.090	0.139	0.095	0.119

Panel B

	Assets < 10 bn		Assets 10-250 bn		Assets > 250 bn		KRE Constituents	
Family income/10000	−0.500***	−0.367***	−0.396***	−0.261***	−0.323***	−0.284**	−0.468***	−0.309***
	(0.058)	(0.058)	(0.051)	(0.043)	(0.082)	(0.088)	(0.044)	(0.047)
College educated (%)	−0.156***	−0.136***	−0.146***	−0.104***	−0.105***	−0.095**	−0.155***	−0.111***
	(0.015)	(0.017)	(0.012)	(0.013)	(0.026)	(0.032)	(0.011)	(0.015)
Age	0.097**	0.061	0.146***	0.051	−0.015	−0.193*	0.167***	0.053
	(0.046)	(0.051)	(0.049)	(0.048)	(0.078)	(0.101)	(0.051)	(0.059)
Dividend income (%)	−0.200***	−0.168***	−0.159***	−0.116***	−0.159***	−0.147**	−0.180***	−0.133***
	(0.026)	(0.024)	(0.019)	(0.020)	(0.042)	(0.049)	(0.019)	(0.027)
Refinanced (%)	−0.084***	−0.016	−0.065**	−0.016	0.008	−0.016	−0.067***	0.005
	(0.022)	(0.030)	(0.026)	(0.020)	(0.049)	(0.060)	(0.023)	(0.027)
Distance (km)	0.002	−0.025	−0.005	−0.005	−0.089***	−0.142**	−0.005	−0.003
	(0.008)	(0.016)	(0.004)	(0.005)	(0.021)	(0.045)	(0.004)	(0.005)

This table presents the results of branch-level regression estimated using the Equation 7 where changes in branch-level deposits from Jun 2021 to Jun 2023 is regressed on customer base characteristics separately for small banks (assets less than 10b), medium banks (assets between 10 to 250b), large banks (assets greater than 250b), and the constituents of SPDR S&P Regional Banking ETF (KRE). Panel A uses the indicator variable 'sophisticated' as the main variable of interest. In Panel B, we summarize the results of six regression outputs, where the variable indicated in the first column is the variable of interest–each row corresponds to one set of regressions similar to those in Panel A. We have suppressed the other control variables and regression statistics to conserve space. The standard errors, clustered at bank level, are reported below the coefficient estimates. Significance levels are indicated as follows: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

base see a reduced growth in deposits.

Age presents a mixed influence; in medium-sized banks, an increase in customer age correlates positively with deposit growth, particularly when bank fixed effects are included. However, this relationship becomes negative or insignificant in larger banks and when county fixed effects are considered. The percentage of customers with dividend income negatively affects deposit changes across all bank sizes, underscoring the influence of financial sophistication proxies on deposit dynamics. The refinancing variable indicates a generally negative but less consistent effect.

Next, we try to understand the timing of the deposit flows. Ex-ante, it is not obvious when the more sophisticated depositors start withdrawing money from low interest-paying deposits. On one hand, since it is not costless to transfer money from the bank account to a higher paying alternative like a money market fund, the deposit spread (market rate - deposit rate) would have to be sufficiently large for this to happen. On the other hand, given the recent development of mobile banking and fintechs, the cost of transferring money from the bank may not be that high. This is ultimately an empirical question.

To answer this question, we replicate the same analysis as Equation 5. Specifically, we regress the level of core deposits at the bank-level on the *sophisticated* dummy interacted with the quarter dummy. The specification is as follows:

$$\text{Core deposits}_{b,q} = \alpha + \sum_{q=-6}^{8} \beta_q \times \textit{Sophisticated}_b + \Gamma \boldsymbol{X} + \text{Bank FE} + \text{Quarter FE} + \epsilon_{bq} \tag{8}$$

where q indicates quarters since the Fed started raising interest rates, i.e., Q4 2021, and b represents the bank. *Sophisticated* is a dummy variable indicating whether bank b serves sophisticated customers. Control variables $\boldsymbol{X}$ include the interest rate paid in the last quarter and the log of total assets in the current quarter.

The results of this estimation are graphically presented in Figure 7. The results here

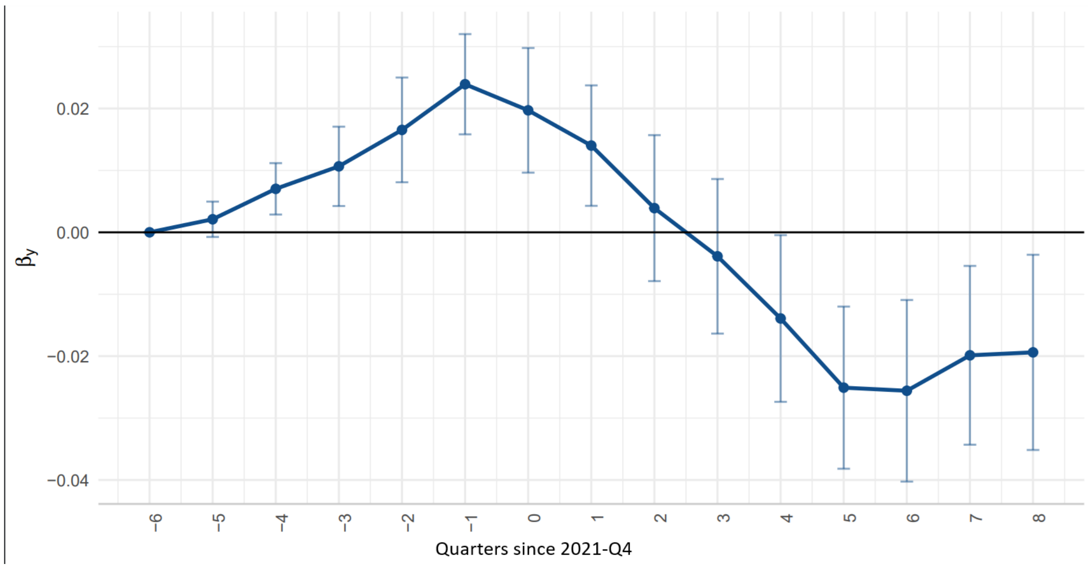


FIGURE 7. Beta - Time - Q

Note: This figure plots the estimates of β_q and the corresponding 95% confidence intervals based on Equation 8. It compares the change in core deposits between banks with more sophisticated customers and those with less sophisticated customers during the 2022-2023 rate hike cycle.

suggest that the sophisticated depositors responded almost immediately to changes in the Fed funds rates.

In sum, the results in this section confirm that customer characteristics are an important determinant of deposit flow in response to interest rate changes, and these results are unlikely to be due to unobserved bank-level or local economy-level confounding factors.

7. Cost of operations

The stickiness of deposits can exert a significant influence on the cost of operations for banks. When confronted with less sticky deposits, banks may need to allocate substantial resources to marketing and advertising efforts aimed at retaining depositors and bolstering their market position. These endeavors can consequently lead to increased operating costs. Conversely, the necessity to raise interest rates to retain less sticky depositors can impinge on profitability, compelling banks to contemplate cost-cutting measures as a countervailing strategy. The dominance of either effect – increased costs due to retention efforts or cost reductions driven by profitability pressures – is ultimately an empirical question. An increase in operating costs would have a negative impact on the deposit franchise value, while a decrease in costs would have a positive impact.

In this section, we investigate how the operating costs of banks evolved during the rate hiking cycle of 2021-2023 and how the change in operating costs from the beginning to the end of the cycle was impacted by the customer base characteristics. Our primary measure of operational costs is the noninterest expense of the bank as a percentage of total assets, which captures the recurring expenses associated with running the bank's operations, excluding interest expenses on borrowed funds and deposits. As reported in Table 2, the average noninterest expense to assets ratio is 2.1%, and it exhibits a decreasing trend with respect to bank size, suggesting potential economies of scale in operational costs for larger banks.

To test whether the cost of operations is impacted by customer base characteristics, we estimate a variant of Equation 4, where we use the change in noninterest expenses scaled by total assets (Δ Noninterest Expenses/Assets) as the dependent variable. This specification allows us to examine the relationship between changes in operational costs during the rate hike cycle and the demographic and financial profiles of a bank's customer base.

The results of this estimation are reported in Table 7. Across all specifications, we do not find meaningfully significant relationships between customer characteristics and changes in noninterest expenses. The coefficients on variables such as the sophistication indicator, income, education, and age of the customer base are consistently insignificant, suggesting that operating costs remained relatively stable over the rate hike period and did not vary systematically with customer base characteristics.

TABLE 7. Impact of Customer Characteristics on Non-interest Expense/Assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sophisticated	−0.106						
	(0.069)						
Family income/10000		−0.011					
		(0.010)					
College educated (%)			−0.003				
			(0.003)				
Age				−0.003			
				(0.009)			
Dividend income (%)					−0.012***		
					(0.004)		
Refinanced (%)						0.001	
						(0.003)	
Distance (km)							0.001
							(0.001)
log(Assets)	−0.029	−0.027	−0.027	−0.038*	−0.024	−0.039*	−0.037*
	(0.022)	(0.023)	(0.023)	(0.022)	(0.022)	(0.023)	(0.021)
Equity/assets	0.960	1.009	0.997	0.927	0.995	0.932	0.941
	(0.745)	(0.748)	(0.748)	(0.746)	(0.745)	(0.746)	(0.745)
Bank HHI	0.012	0.015	0.016	0.032	0.003	0.034	0.026
	(0.082)	(0.082)	(0.083)	(0.082)	(0.082)	(0.083)	(0.081)
Constant	1.244***	1.297***	1.260***	1.465***	1.375***	1.317***	1.305***
	(0.295)	(0.292)	(0.296)	(0.494)	(0.292)	(0.293)	(0.292)
N	3,734	3,734	3,734	3,734	3,734	3,734	3,734
Adjusted R^2	0.001	0.001	0.001	0.0003	0.002	0.0003	0.001

This table presents the results of regressions that estimate the effect of depositor characteristics on changes to the cost of operations in banks. The dependent variable is the change in non-operating expenses/assets from Dec 2021 to Dec 2023 . Significance levels are indicated as follows: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

8. Impact on Deposit Franchise Value

Having independently examined how customer base characteristics influence individual components impacting deposit franchise value—namely deposit beta, deposit outflows, and operational costs—in this section, we focus on the collective impact of customer base differences on banks' franchise value.

To assess the deposit franchise value ($DF(r')$) across various bank types, we use the Equation 1 explained in Section 2, reiterated below:

$$DF(f) = D(1 - w(s, r'))\left(1 - \beta - \frac{c}{r'}\right)$$

Here, $DF(r')$ represents the deposit franchise value, r' denotes the Fed funds rate, β signifies the deposit beta, and $w(s, r')$ represents the outflow rate, which increases with the deposit spread s.

Our analysis categorizes banks into small (assets < \$10 billion) and large (assets > \$10 billion). Within each size category, banks are further classified as having sophisticated customers or non-sophisticated customers based on customer income, education, dividend income percentage, and the percentage who refinanced in 2020-2021.

For each bank category, we estimate the components of the equation –$w(s, r')$, β, and c – using data from the 2021-2023 rate hike cycle, during which the Fed funds rate increased by 5.25% ($r' = 0.0525$). The deposit beta (β) is derived as the mean of $(IntExp_{b,Dec2023} - IntExp_{b,Dec2021})/r'$ for each bank (b), capturing the average sensitivity of deposit rates to changes in the Fed funds rate. Operational costs (c) are estimated as the mean of operating costs scaled by total assets for each category. Following Koont, Santos, and Zingales (2023), we estimate $w(s, r')$ as the mean change in core deposits for each category, which reflects the outflow rate of deposits in response to changes in deposit spreads.

The results of this estimation exercise are presented in Table 8. Rows (2) through (4) present the *aggregate* assets, deposits, and equity in each category. Rows (5), (6), and (7) present the estimates of β, w, and c, respectively, for each category.

In Row (8), we estimate the implied loss on the asset side of the balance sheet due to interest rate increases. During this period, the long-term rates increased by about 350 basis points, and the average maturity of assets is about 4 years. We obtain the drop in asset value by multiplying total assets (Row (2)) by the change in longer-term rates (0.035) and the average maturity (4 years). In Row (9), we estimate the annual deposit spread assuming r' stays constant by multiplying deposits by the deposit spread (1-β) and the market rate (0.0525). In Row (10), we estimate the number of years it would take for the annual deposit spread to offset the drop in asset value due to an increase in interest rates, assuming $w = 0$ and $c = 0$. In Row (11), we use Equation 1 to estimate the total franchise value for each category, and in Row (12), we use the franchise value as the present value of the deposit

TABLE 8. Deposit Franchise Value

		Small Sophisticated	Small Not-sophisticated	Large Sophisticated	Large Not-sophisticated
(1)	Number of banks	1,082	2,367	31	72
(2)	Total assets ($ bn)	1,416	1,373	1,640	2,668
(3)	Total deposits ($bn)	1,204	1,181	1,275	2,226
(4)	Total equity ($bn)	148	146	176	279
(5)	Expense beta (β)	0.300	0.240	0.430	0.350
(6)	Δ Deposits (%) (w)	−2.110	0.510	−6.970	−3.680
(7)	Cost of operations (c)	2.690	2.700	2.220	2.420
(8)	Implied loss on asset side ($bn) Assets $\times$ 0.035 $\times$ 4	170	165	197	320
(9)	Annual deposit spread ($bn) Deposits $\times$ (1 - β) $\times$ 0.0533	45	47.700	38.500	76.800
(10)	Time to offset asset losses (years)	3.770	3.460	5.110	4.170
(11)	Franchise value ($bn) $D \times (1 - w)\left(1 - \beta - \frac{c}{r}\right)$	242	295	204	447
(12)	Time to offset asset losses (years)	13.200	10.500	18.100	13.400

This table reports the estimates of deposit franchises for different bank-type categories.

franchise and estimate the number of years it takes to offset the drop in assets.

Results suggest that it takes longer for banks with sophisticated customers to offset the drop in asset value due to lower franchise value stemming from higher β and w.

The combination of higher β and w for banks with sophisticated customers results in a lower franchise value, as calculated in Row (11) using Equation 1. For large banks with sophisticated depositors, the franchise value loss is almost twice that of their counterparts with less-sophisticated depositors. A lower franchise value implies that the present value of future profits from the deposit franchise is diminished. Consequently, as shown in Row (12), it takes a longer period for the annual deposit spread to offset the initial drop in asset value caused by rising interest rates.

In summary, the results highlight the potential challenges faced by banks with more sophisticated customer bases during periods of rising interest rates.

9. 2015-2019 Interest Rate Hike Cycle

To provide a more comprehensive understanding of the relationship between depositor characteristics and bank behavior during periods of rising interest rates, we extend our analysis to the previous interest rate hike cycle that occurred from 2015 to 2019. This additional examination allows us to compare and contrast bank responses and depositor behavior across two distinct periods of monetary tightening.

The 2015-2019 cycle differs from the more recent 2022-2023 cycle in several important aspects. First, it was characterized by a more gradual and prolonged increase in interest rates. The Federal Reserve raised the federal funds rate from near-zero levels in December 2015 to a peak of 2.25-2.50% in December 2018, over a span of three years. This stands in contrast to the rapid and steep rate hikes observed in 2022-2023, where rates increased by 5.25 percentage points in less than two years.

Second, the economic and financial market conditions during these two periods were markedly different. The 2015-2019 cycle occurred against a backdrop of steady economic growth and low inflation, while the 2022-2023 cycle was implemented in response to high inflation following the economic disruptions caused by the COVID-19 pandemic.

It is also important to note a key limitation in our analysis of the 2015-2019 cycle. Our depositor characteristics data is derived from 2019 and 2020 observations, which postdate the period under examination. We believe this is unlikely to introduce significant measurement errors since we observe that depositor characteristics are very persistent over time during our original sample period.

The results of our analysis for the 2015-2019 rate hike cycle are presented in Table 9. Column (1) of the table presents the results of a regression analysis where the dependent variable is the change in interest rate expenditure as a percentage of assets from the beginning to the end of the 2015-2019 rate hike cycle. The key independent variable is a ’Sophisticated’ dummy, which identifies banks with more financially sophisticated depositors based on our earlier defined criteria.[4] We also include other relevant control variables to account for bank-specific characteristics that might influence interest rate decisions.

In Column (2), we employ a similar regression model, but with the change in core deposits as the dependent variable. This analysis aims to capture how deposit stability varied between banks with more sophisticated depositors and those with less sophisticated depositors during the rate hike cycle. The results of this exercise are presented in Table 9.

TABLE 9. 2015-2019 Interest Rate Hike Cycle

	Δ Interest Rate Expenses		Δ Core Deposits	
	<10bn	>=10bn	<10bn	>=10bn
	(1)	(2)	(3)	(4)
Sophisticated	0.049***	0.134**	2.556***	–0.082
	(0.009)	(0.062)	(0.617)	(4.014)
log(Assets)	0.008**	–0.007	3.500***	–2.406*
	(0.004)	(0.022)	(0.251)	(1.405)
Equity/assets	0.048	0.096	–39.917***	–109.116
	(0.100)	(1.103)	(6.654)	(71.070)
N	3,104	52	3,104	52
R^2	0.013	0.093	0.094	0.105
Adjusted R^2	0.012	0.037	0.093	0.049

This table reports the results that examine the change in interest rate expenditure and changes in core deposits during the 2015-2019 rate hike cycle. Robust standard errors are reported below the coefficient estimates. Significance levels are indicated as follows: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The findings in columns (1) and (2) are consistent with our previous results from the 2022-2023 cycle. In response to the 2.5% point increase in the federal funds rate during the 2015-2019 period, small banks with sophisticated customers increased their interest rates by 5 basis points more compared to other banks, and the large banks with sophisticated customers increased rates by 134 basis points. This aligns with our earlier observation that

[4]Higher income, higher education, more dividends, and more likely to refinance

banks serving more financially savvy depositors tend to be more responsive to market rate changes.

The result in columns (3) and (4) indicates that deposit stability varies across interest rate hiking cycles. During the 2015-2019 period, core deposits increased by 2% more in smaller banks with sophisticated customers, insignificant for large banks. This divergence could be attributed to the differences in the rate of increase across the two interest rate hike cycles mentioned earlier. The more gradual and prolonged nature of the 2015-2019 cycle, coupled with the different economic backdrop, may have influenced depositor behavior differently. Sophisticated depositors may have valued the convenience of staying with their bank and might have been less inclined to seek alternatives during this period of slower rate increases. In contrast, the sharp rise in interest rates may have made them more "flighty."

10. Robustness

10.1. Physical vs. Online Banking

One potential concern with our results is that we characterize banks' customer bases based on the demographic profiles of individuals visiting their physical branch locations. However, recent technological advances have enabled bank customers to conduct most of their banking activities without the need for physical branch visits. This raises the question of whether our branch-based characterization accurately captures the true demographic and financial profiles of a bank's depositors, given the increasing prevalence of digital banking. For example, Haendler (2022) shows that large banks have gained deposits and small business loans by substituting smaller banks' traditional branch- and relationship-based model with financial technology solutions. Koont (2023) further demonstrates that digitalization decreases market concentration, and average markups fall in deposit and loan markets as a result of increased competition facilitated by digital banking channels.

While the concern regarding the increasing prevalence of digital banking channels is valid, we argue that physical and virtual visits to banks are not mutually exclusive, and the customer characteristics of physical and virtual visitors are likely to be correlated. The FDIC (2021) shows that 41% of the individuals visited bank branches or ATMs in 2019 to conduct various banking activities, even as digital channels gain popularity. This suggests that the demographic and financial profiles of individuals visiting physical branches remain relevant and informative in characterizing a bank's overall customer base. Furthermore, it is reasonable to expect that individuals who prefer to visit physical branches share certain characteristics with those who primarily engage through digital channels.

Consequently, while our branch-based characterization of customer bases may suffer from measurement errors, as the customer characteristics are measured with error, these errors are likely to be correlated with the true characteristics of a bank's overall customer base, including those who engage through digital channels. As a result, our estimates might suffer from attenuation bias, meaning that they would represent a lower bound for the true effect of customer characteristics on deposit dynamics and franchise values.

In this section, we provide evidence consistent with the idea that our estimates are lower bounds of the true estimates by constructing an online banking intensity measure. To construct this measure, we utilize Advan Monthly Website Traffic (Mobile + Web) data and identify all the bank URLs using the information provided in the call reports. Then, we capture the total virtual visits in the year 2019 (the same year as the physical visits data) and normalize this by the total physical visits to the bank. When this ratio is higher, it suggests that the customers of a particular bank are more likely to use digital platforms for their banking activities, and vice versa. Consequently, the measurement error in characterizing the customer base should be most acute for banks with the highest online banking intensity.

In Table 10, we replicate the analysis from Table 3 separately for banks with higher and lower online banking intensity. Recall that in Table 3, we showed that banks with more sophisticated customers had to increase interest expenses more aggressively in response to market interest rate increases. In this table, we split the large banks into two categories (below median online banking intensity and above median) and small banks into three categories (bottom third, middle third, and top third online banking intensity).

Panel A uses a dummy variable indicating that a bank's customer base is in the top quartile in terms of income. For large banks, we observe no significant difference in the estimates between those with higher and lower online banking intensity. This could be attributed to the fact that large banks have a vast network of branches, and measurement errors in characterizing customers at individual branches are likely to have a less pronounced impact when aggregated at the bank level.

In the case of small banks, we observe that the effect is strongest for the least online-intensive banks and monotonically decreases with increasing online banking intensity. This pattern is consistent with the notion that measurement errors in customer characterization are more severe for small banks with higher digital connectedness, leading to an attenuation of the estimated effects.

In Panel B, we replicate the analysis from Panel A but report only the variable of interest in each row to conserve space. Each row in Panel B corresponds to a regression similar to those in Panel A but with a different customer characteristic as the main explanatory variable. Consistent with the findings in Panel A, we observe a similar pattern where the effects are strongest for small banks with lower online banking intensity, and the estimated coefficients decrease as online intensity increases.

These results provide evidence supporting our hypothesis that measurement errors in characterizing customer bases, particularly for banks with higher digital connectivity, lead to an attenuation of the estimated effects. Consequently, our main analysis, which relies on physical branch visits to characterize customer bases, likely yields conservative estimates, representing lower bounds of the true impact of customer characteristics on deposit dynamics and bank behavior.

11. Conclusion

This study shows deposit stability depends on depositor characteristics. By leveraging novel cell-phone geolocation data, we document considerable heterogeneity across banks in terms of the demographic and financial profiles of their depositor bases. We show that banks with financially sophisticated depositors, characterized by higher income, education levels, and participation in financial markets, respond to interest rate increases more aggressively in setting their deposit rates, but still experience greater deposit outflows, resulting in a loss in deposit franchise value.

Our findings suggest that evaluations of financial stability that advocate for a granular approach to deposit modeling that goes beyond traditional categorizations by product type or insured status may indeed be warranted.

TABLE 10. Impact of Online Banking

Panel A

	Assets <= 10bn		Assets > 10bn		
	< median	> median	Bottom third	Middle third	Top third
	(1)	(2)	(3)	(4)	(5)
Family income =Q4	0.433**	0.637***	0.240***	0.150***	0.127***
	(0.185)	(0.198)	(0.042)	(0.040)	(0.039)
log(Assets)	0.018	0.292**	0.208***	0.171***	0.187***
	(0.197)	(0.123)	(0.022)	(0.023)	(0.022)
Equity/Assets	−10.402***	1.079	−0.063	0.456	−0.623
	(3.123)	(2.712)	(0.367)	(0.559)	(0.448)
Bank HHI	−0.588***	−0.882***	−0.322***	−0.193***	−0.329***
	(0.159)	(0.167)	(0.048)	(0.043)	(0.045)
N	44	77	1,155	1,116	1,133
Adjusted R^2	0.325	0.410	0.222	0.149	0.162

Panel B

College educated (%)=Q4	0.539***	0.412**	0.275***	0.229***	0.166***
	(0.180)	(0.184)	(0.043)	(0.039)	(0.039)
Age =Q4	0.241	0.252	−0.097**	−0.041	−0.022
	(0.191)	(0.156)	(0.040)	(0.041)	(0.037)
Dividend income (%) =Q4	0.604***	0.329*	0.166***	0.157***	0.125***
	(0.172)	(0.196)	(0.041)	(0.039)	(0.037)
Refinanced (%) =Q4	−0.227	−0.192	0.132***	0.063*	0.078**
	(0.194)	(0.165)	(0.044)	(0.038)	(0.038)
Distance (km) =Q4	0.003	0.265*	0.006	0.038	−0.026
	(0.183)	(0.158)	(0.036)	(0.041)	(0.041)

This table replicates the analysis from Table 3, separately for banks with higher and lower online banking intensity. Large banks are split into two categories: below median online banking intensity and above median. Small banks are divided into three categories: bottom third, middle third, and top third online banking intensity. Panel A uses a dummy variable indicating that a bank's customer base is in the top quartile in terms of income. Panel B reports the variable of interest in each row, with each row corresponding to a regression similar to those in Panel A but with a different customer characteristic as the main explanatory variable. We suppress other control variables and regression statistics to conserve space. Standard errors are reported in parentheses below the coefficient estimates. Significance levels are indicated as follows: *, *, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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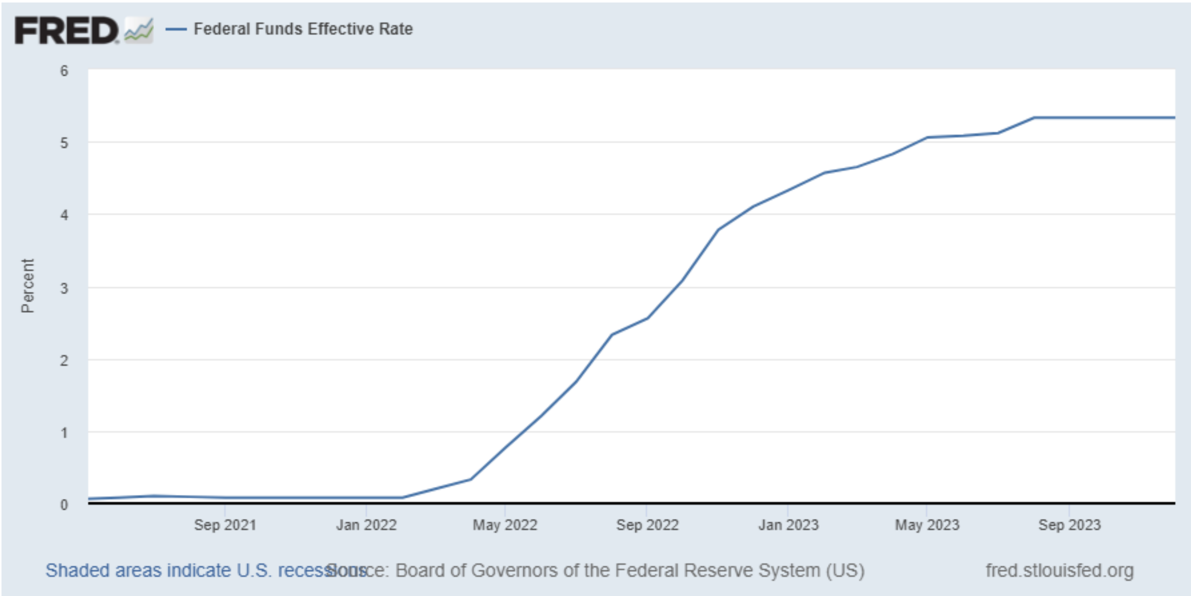
Appendix

FIGURE A1. Fed Funds Rate



Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate [FEDFUNDS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS, January 10, 2024.