How Do Banks Attract Deposits From Households?*

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Abstract

Banks face intense competition for deposits, especially in recent years. Using a novel dataset from the Equifax-IXI network that captures almost half of financial holdings in the U.S., we document that banks set interest rates to compete for deposits with other asset classes. Banks pay higher deposit rates to depositors with higher elasticity of substitution between deposits and other asset classes.

Using two empirical approaches—an instrumental variables strategy and a matching approach—we show that as equity holdings increase in a zip code, banks offer higher deposit rates to attract deposits. Thus, we document that banks engage in third-degree price discrimination across geographies to attract deposits. As already established in the literature, banks also compete for deposits with other banks.

Through higher rates, banks draw some deposits away from capital markets. Nevertheless, the equilibrium outcome is relatively lower deposit allocation at relatively higher deposit rates. Higher funding costs reduce bank lending and spur banks to increase risks. Overall, as capital markets become more accessible, banks face increasing competition for depository capital and take greater balance sheet risks.

An important implication of these results is that policymakers should not consider competition between banks as the only source of competition for deposits. Asset markets compete for potential bank deposits as well, and this competitive effect has a similar order of magnitude as the competitive effects among banks.

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Banks face intense competition for deposits, especially in recent years.[1] This paper shows that to attract deposits from households, banks respond to depositor portfolio allocation decisions through their deposit rate-setting strategy. Banks facing depositors with higher elasticity of substitution between deposits and other asset classes pay higher deposit rates. Despite paying higher rates, banks are unable to completely undo the household preferences for other asset classes, thus receiving lower depository capital at higher rates. Ultimately, to provide higher returns for deposits while maintaining returns for their own equity holders, banks take higher risks in hopes of earning higher returns from their assets.

In recent years, cost of funds has increased for banks as they compete to attract and retain household deposits. The importance of the market power of banks in setting deposit rates is well established (recent influential papers include Drechsler et al., 2017, 2021; Wang et al., 2022).[2] Using a novel dataset from the Equifax-IXI network that captures almost half of financial holdings in the U.S., we are able to document that banks are also responsive to depositors' portfolio decisions.[3] We document that banks engage in third-degree price discrimination across geographies to attract deposits (seminal work includes Schmalensee, 1981; Varian, 1985; Holmes, 1989).

The intuition of this result is straightforward: from the perspective of depositor households, the bank deposit market exists along with other capital markets. Households decide (i) how to allocate assets across equities, bonds, certificates of deposits (CDs), and cash, along with the decision of (ii) which bank to use to invest in CDs and cash. Thus, banks have to compete for deposits not only with other banks, but with other asset classes such as equities, bonds, and CDs. Hence, deposit rates are a function of this competition across asset classes.

Empirically, we find that the two most important asset classes for households are equity and bank deposits. Hence, we focus specifically on equity allocation. Our results show that indeed bank deposit rates are related to local household equity allocations (Figure 1). These preliminary

[1]As examples, see recent articles (hyperlinked) in professional outlets such as "The battle for deposits remains fierce" in the American Bankers Association Banking Journal, November 2024; and "Deposits: The top profitability lever for retail banks' CEOs" in McKinsey and Company Insights, Feb 2025.

[2]A recent survey paper on the role of market power in banking is Carletti et al. (2024).

[3]See brochure on attracting deposits "Make Deposits Happen" by Experian.

results suggest that banks are competing for deposits with other asset markets.

Conceptually, the portfolio allocation problem faced by households between equity and bank deposits is clear. At the same time, an empirical challenge is that households at different income and wealth levels differ in their equity market exposure because of additional factors. Further, wealth itself is a function of equity market exposure and returns. Hence, to address this empirical challenge of differential stock market exposure, we next focus on the primitive variable of household income.[4] We estimate the equilibrium response function of banks in terms of offered deposit rates in a location given the composition of households by income in that location. We use the resulting estimates to calculate the average zip-code level price response of banks to the representative households in each location.

First, we confirm that the zip-level sensitivity measure of banks to income groups is positively correlated with the zip-level bank spreads (Figure 2, top panel). Second, in the bottom panel, we find that as zip-level bank sensitivity increases, households allocate less to equity markets. Thus, banks are able to successfully draw away a portion of the capital from rate-sensitive households. The results obtain after addressing heterogeneity across banks based on the fraction of insured deposits, bank size, and other potential explanatory variables.

To provide intuition, the rate-responsive households are households with middle-income populations. Banks are responsive to these households in equilibrium and offer higher rates to areas with larger middle-income populations. Lower-income households cannot add a large amount in terms of additional deposits since their equity market participation is low to begin with. Higher-income households do not want to keep a very large portion of their assets in deposits given the decreasing returns to additional liquidity.

Third, using an instrumental variables approach and a difference-in-differences approach to establish a causal channel between equity holdings and deposit rates. The instrumental variables

[4]Banks can and do price discriminate or conduct marketing campaigns based on additional household characteristics. See, for example, a case study that recognizes the benefits of targeting consumers groups for marketing campaigns based on their assets for bank deposit growth. For example, see "Determining the Opportunity and Creating Client Treatment Groups." At the same time, the significant importance of income as a price discriminating household characteristic is self-evident.

approach utilizes the Tax Cuts and Jobs Act (TCJA) of 2017 as an exogenous shock to household equity holdings. The difference-in-differences approach utilizes local initial public offerings as exogenous shocks to the equity holding interest of local investors (Jiang et al., 2024). Both approaches confirm that banks offer higher deposit rates when households have an attractive outside option—in this case, equity.

Finally, to provide higher returns for deposits while maintaining returns for their own equity holders, banks must earn higher returns from their assets. This expected return cannot be generated without taking higher interest rate and credit risk. We also demonstrate that indeed banks take more risk to offer higher rates to depositors.

In sum, our paper shows that when household portfolio allocation is taken into account, competition between asset markets uniformly leads to higher returns and higher risks in the deposit market, similar to other asset markets.[5] In other words, this paper shows that given asset market competition between banks and other asset classes, bank deposit markets also face the same proportional risk-reward trade-off that is present in all capital markets.

An important implication of these results is that policymakers should not consider competition between banks as the only source of competition for deposits. Asset markets compete for potential bank deposits as well, and this competitive effect has a similar order of magnitude as the competitive effects among banks.

Our ability to document an empirical relation between household portfolio allocation decisions and bank deposit rates is due to access to a novel dataset from the Equifax-IXI network. Using the IXI network, Equifax directly measures approximately $30.6 trillion in anonymous U.S. consumer assets, representing approximately 45 percent of all U.S. consumer-invested assets. The dataset provides ZIP+4 level asset composition sourced from over 95 financial institutions, including retail banks, brokers, mutual funds, and insurance firms. This dataset for the first time provides sufficiently granular information to analyze how banks compete for deposits conditional

[5]Higher risk-taking behavior by banks can take place in the absence of the general asset market competition channel that we discuss in this paper. Our results are not due to banks facing moral hazard in the presence of federal deposit insurance.

on household balance sheets.

Our paper begins by noting that banks offer higher deposit rates in zip codes with higher equity allocation rates. These results are also present for the same bank across zip codes over time. Our data are for the period 2014Q2–2019Q2 which is a period of low deposit rates, with the median rate just 3.4 basis points over the federal funds rate. The average fed funds rate was 0.87% in this period. Nevertheless, after including bank semi-annual year fixed effects, we find that for one standard deviation increase in equity fraction (11.8%), a zip code level representative bank pays 0.31 basis points more for deposits. For comparison, one standard deviation (0.074) decrease in bank competition captured by Herfindahl–Hirschman index is associated with 0.5 basis points higher deposit rates in this period. Thus, the effect of asset market competition is more than half the magnitude of the effect of bank competition on deposit rates.

To validate the main results, we employ two different approaches. The first instrumental variable strategy utilizes the exogenous incentives provided by the Tax Cuts and Jobs Act (TCJA) of 2017 to households for holding equities. Chodorow-Reich et al. (2024) finds that the law spurred domestic investments of firms. As the relevance condition test, we find that areas that benefit more from the tax cuts experienced a larger increase in equity holdings. The second stage shows that deposit rates responded significantly to the increase in equity holdings instrumented by the tax policy shock.

We also conduct a second test where we employ exogenous geographical variation in equity holdings created by large initial public offerings (IPO). Jiang et al. (2024) shows that when a significant IPO takes place, local investors are more aware of equity investment opportunities and participate more in the equity markets. We find that as equity holdings grow as a percentage of household balance sheets around an IPO, deposit rates also increase.

The higher rates offered by banks induce banks to take additional risks. We find that banks in areas where households have more equity holdings have lower deposits. At the same time, such banks charge higher interest rates and face higher charge-off rates. In sum, our results suggest that competition for deposits with equity markets leads banks to pay higher deposit rates and take more risks in their lending activities.

Eminent researchers have investigated the competition for deposits among banks—and associated deposit market power—and its role in bank lending and interest rates. Drechsler et al. (2017) find that when the fed funds rate increases, banks with more deposit market power charge a wider spread on deposits, and deposits flow out of the banking system. Drechsler et al. (2021) shows that the deposit franchise of banks—the ability of banks to attract and retain deposits at below-market interest rates—acts as a negative duration asset and banks hedge this duration exposure through long-term loans and securities. Li et al. (2023) find that deposit market power increases the funding stability of banks and allows banks more flexibility to originate long-term loans. Our results complement these findings by showing that along with deposit competition, banks also face competition from other asset classes that affect their deposit rates. Thus, the value of the deposit franchise and associated lending behavior of banks may be additionally affected by the propensity of depositors to hold equity, bonds, and other non-bank assets.

Researchers have also investigated how households reallocate deposits in response to aggregate economic conditions. Drechsler et al. (2017) shows that as fed funds rates rise, deposits flow out of the banking system. Lin (2019) shows that when the stock market booms, growth of deposits from households declines. Melcangi and Sterk (2024) shows that as stock market participation increases, monetary policy transmission strengthens. In our paper, we focus on the response of banks to attract deposits from households.

Researchers have also investigated the role of deposit insurance in attracting deposits to the banking system. The theoretical literature on this topic includes seminal works of Diamond and Dybvig (1983); Bhattacharya et al. (1998); Goldstein and Pauzner (2005). In recent empirical work, Martin et al. (2018) find that at a distressed bank, uninsured deposits flow out while at the same time, there are large inflows into insured deposit accounts. Kim et al. (2024) investigate the implications of reciprocal deposits among banks on the financial stability of banks. Our focus is on deposit rates as a mechanism to attract deposits from households.

Our paper underscores the changing role of banks in the economy. Banks are the primary source of credit for most of the economy (e.g., Petersen and Rajan, 1994). They are also a key amplifier of business cycles (Bernanke and Gertler, 1989, 1995; Bernanke et al., 1999; Holmstrom and Tirole, 1997; Kiyotaki and Moore, 1997; Becker and Ivashina, 2014). The assets of the banking sector are still larger than the total capitalization of public equity, public bond, and private bond markets in Europe, UK, and Japan. However, in the U.S., the total depository capital of banks is smaller than the capitalization of just the equity market even without considering the bond market (Allen et al., 2008). Our paper shows that banks have to compete for deposits and pay higher rates to attract capital. We also show that this effective disintermediation of the U.S. economy through a smaller role of banks can reduce access to capital for small and mid-size borrowers, as well as increase risk-taking by banks.

1 Data and Summary Statistics

This section describes the sources of data used in this paper, provides summary statistics, and conducts some validation exercises on the new sources of data.

1.1 Data Sources

1.1.1 IXI asset composition data

We obtained ZIP+4 level asset composition (IXI) data from Equifax, which provides comprehensive, anonymized records of household financial asset composition. The IXI data is sourced from over 95 financial institutions, including retail banks, brokers, mutual funds, and insurance firms. While not fully comprehensive, it captures \$30.6 trillion in assets, representing 45% of U.S. consumer financial holdings. The dataset includes detailed categories such as bonds, deposits, cash, stocks, and equity investments.

The dataset spans from 2014 to 2024, with the reporting frequency being semi-annual until 2018 and quarterly starting from 2019. For our analysis, we utilize a 1% sample of the data and aggregate it to the ZIP code level by taking averages. To match ZIP codes to corresponding counties and states, we merge the aggregated IXI data with a crosswalk file developed by Wilson and Din (2018).

We define asset composition by dividing the average household asset components by total assets at the ZIP code level. We then filter out rows with negative asset values and ensuring that all asset percentages fall within the range of 0 to 1. After cleaning, the final dataset comprises 34,882 unique ZIP codes and 3,143 unique counties across all 50 states within the continental U.S., as well as Washington, D.C.

1.1.2 Probability of Default (PD)

We measure banks' risk using the Probability of Default (PD), following the modified Merton model from Nagel and Purnanandam (2019), which accounts for the unique asset and liability structures of financial institutions. Unlike the standard Merton (1974) model, which assumes log-normal asset distributions and constant volatility, the modified model shifts the lognormal assumptions to borrowers' assets as collateral and treats banks' equity as contingent claims on those assets.

The PD measure used in your study comes from the full replication package of Nagel and Purnanandam (2019), which is identified by PERMCO codes. To merge with other bank datasets (e.g. Ratewatch, SOD, Call Reports), we used the CRSP-FRB link table to map PERMCOs to RSSD IDs. The link table usually maps to the highest orgational parent, which is usually a Bank Holding Company (BHC). Thus, our final dataset ranges from 2001 to 2023, provides quarterly PD measure for up to 862 BHCs.

1.1.3 Small Business Lending Data (CRA)

Small business lending data is sourced from the Community Reinvestment Act (CRA). The CRA defines small business loans as those with an original amount of $1 million or less. Financial institutions under regulation by OCC, Federal Reserve, and FDIC must report small business lending data if they meet specific asset thresholds. Before 2005, banks with assets exceeding $250 million or those belonging to bank holding companies with over $1 billion in assets were required to report. After 2005, the reporting requirement was relaxed to apply only to banks with assets over \$1 billion, allowing smaller banks to report voluntarily. As of January 1, 2018, the asset threshold increased to \$1.252 billion.

The CRA data includes small business loans categorized by loan size, specifically those under \$100,000, between \$100,000 and \$250,000, and between \$250,000 and \$1 million. These loans encompass commercial and industrial loans secured by non-farm or non-residential real estate, business credit cards, and lines of credit. Since the data is collected at the county level, it provides a detailed breakdown of small business lending activity across geographic areas. Additionally, CRA reporting captures the lending activity of large banks but does not fully account for small financial institutions that fall below the mandatory reporting threshold.

1.1.4 Other data sources

Ratewatch: We obtain deposit interest rates from RateWatch. Our RateWatch data spans from 2001 to 2019:Q2 and includes weekly branch-level deposit rates for various financial products, such as Certificates of Deposit, savings accounts, and money market accounts. Consistent with Drechsler et al. (2017) and other studies, we focus on the \$10,000 12-month Certificate of Deposit (12MCD10K) and \$25,000 money-market account (MM25K) due to their broad coverage. To align with the frequency of other datasets, we aggregate the data from weekly to quarterly intervals and from the branch level to the bank holding company (BHC) level by averaging rates across quarters within the same BHC. To adjust for the interest rate environment set by the Federal Reserve, we subtract the deposit rates by the fed fund rate obtained from Federal Reserve Bank of St. Louis. also aggregated to quarterly frequency.

SOD: We obtain branch-level deposit data from the FDIC's Summary of Deposits (SOD) at annual frequency from 2001 to 2023. Along with deposit amounts, the SOD provides branch details, including affiliations with commercial banks and BHCs, and geographical information like ZIP codes. This data is crucial for merging datasets and conducting analyses at the ZIP code level.

Call Report: The bank financial statement data are from U.S. Call Reports provided by the

Federal Reserve Bank of Chicago. We use data from 2001:Q1 to 2023:Q4. In order to match the call report data with the PD measure at BHC level, we use the relationship file provided by Federal Financial Institutions Examination Council (FFIEC). The relationship file contains the organizational hierarchies of banks, including parent companies and subsidiary relationships, along with their respective start and end dates. We merge the call report data with the relationship link table to get the organizational parents, then sum all variables to parent level. Then, we merge with PD measure, which yields 862 BHCs.

1.2 Summary Statistics

1.2.1 Bank Level Panel

We merge BHC level call reports, RateWatch, SOD and PD together using BHC RSSD ID. After merging, we get 671 unique BHCs, with sample period from 2001:Q1 to 2019:Q2. Table 1 gives the descriptive statistics of the merged data. On average, a BHC has $ 16.35 Billion total assets, $14.74 Billion total liabilities, by which $10.32 Billion are from deposits. Panel B displays the deposit rates subtracted by federal funds rate, offered by the two deposit products. Our definition of rate is opposite from the spread in Drechsler et al. (2017), because we want to make intuitive argument the rate increase and decrease, while adjusting for the macro environment. As shown in Drechsler et al. (2017), banks offer deposit rates below the federal funds rate to maintain their deposit franchise. Similarly, we find that, on average, the adjusted deposit rates are negative, indicating that banks consistently offer rates lower than the federal funds rate.

1.2.2 ZIP Code Level Panel

The IXI data identifies asset composition only at the ZIP code level, which does not allow for a direct link with bank-level data. To enable meaningful analysis, we transformed bank-level data into ZIP code-level data, allowing for geographical analysis.

We use SOD to identify the zipcode of each bank branch. For each zipcode, we calculated the weighted average of deposit rates and PD, using the deposit amount for each bank branch as weights.

The descriptive statistics of the zipcode level panel is in Table 1. Panel A shows the household asset allocation. On average, U.S. households hold 125,006 financial assets, by which 48.5% are allocated to equity, which includes retirement accounts, mutual funds, as well as direct investment in stocks. On average, households allocate 27% into deposits and cash. Panel B shows the bank data, but broken down to the ZIP code level instead of the BHC level. On average, the PD at the ZIP code level is 17.7%, which is smaller than 28% in BHC level. This could potentially be because of zipcode level PD reflects the weighted average of risk, where safer banks attracts more deposits. For simplicity, we further simplify the adjusted deposit rates to one product (12MCD10K), which on average has an adjusted rate of -0.58%. In Panel C, we present statistics for control variables constructed to account for the impact of deposit insurance, the effect of bank size, and the regional bank competition.

1.3 Data Validation

To address concerns about the coverage and representativeness of the Equifax data, which should cover 40-60% of all financial assets of U.S. households, we compare it with publicly available aggregate datasets, including measures from the Federal Reserve and SOD.

To verify the deposit data, we aggregate the IXI deposit measures by summing the 1% sample data and multiplying by 100 to estimate the total amount. This measure is then compared with the SOD dataset, which provides branch-level deposit data aggregated nationally, and the H.8 dataset from the Federal Reserve, which reports weekly aggregate measures of U.S. commercial bank assets and liabilities.

We further validate the IXI data by comparing its estimates of total assets and equity holdings with the Federal Reserve's Z.1 Financial Accounts of the United States. The Z.1 dataset provides quarterly aggregate measures of financial balance sheets across various sectors, including households and nonprofits, financial institutions, businesses, and governments. Specifically, we sum both direct and indirect equity holdings from Z.1 to calculate total equity holdings, which we then compare to the equity holdings reported in the IXI dataset. Similarly, we use the total financial assets from Z.1 to compare with the total assets in the IXI data, acknowledging that the IXI dataset only includes financial assets.

One small caveat of this approach is that the Z.1 estimates combine households and nonprofits, potentially overstating household holdings. However, given that nonprofits account for a relatively small share of financial assets compared to households, especially in equity holdings, we believe this combined measure is still broadly representative for our purposes.

Figure A.1 demonstrates that the datasets follow similar trends, although there are some gaps. The gap is more pronounced in total financial assets, as shown in Panel (c), likely due to the inclusion of both households and nonprofits in the Z.1 data, as previously discussed. Despite these differences, the overall trends align well, supporting the reliability of the IXI dataset. The coverages are consistent with Equifax's claim of covering 40-60% of U.S. household financial assets.

2 Household Price Elasticity and Bank Rate Setting

Section 2.1 shows that banks pay a higher interest rate in locations where households hold more equity. Section 2.2 digs deeper to understand why equity holdings and interest rates have a positive relation. The section uncovers that banks are offering higher rates in areas where there are more rate-sensitive depositors. We also find that more rate-sensitive depositors are households in middle-income groups who have sufficient numbers and assets, as well as the willingness to switch to deposits or away from them based on rates (higher elasticity of substitution between asset classes). Section 2.4 brings the results together and shows that more rate-sensitive depositors receive higher rates and also, in equilibrium, hold more equities. This is the reason we observe the positive relation between equity holdings and bank deposit rates.

2.1 Household Equity Holdings and Bank Interest Rates

We start transparently by documenting the relation between household balance sheets and bank risk-taking. The paper shows that in addition to deposit market competition, banks also compete with other classes for deposits. Households allocate capital to banks as well as to other capital markets, such as equity and debt markets. While not all households participate in capital markets, a significant portion of wealth belongs to households that do. As Table 1 reports, households in IXI allocate almost half of their financial assets in equity.

If households in an area are willing to allocate more assets to equity markets, banks face relatively stiffer competition to attract capital.[6] Therefore, banks may offer higher deposit rates to attract capital in areas with higher equity ownership.

2.1.1 Relation at the geographical unit level

This section documents a relation between bank deposit rates and equity allocation at the zip code level. Before we provide multivariate estimates, we start with a figure that reports the relation between the average deposit rates in each zip code and household equity holdings as a fraction of total assets. We use the offered interest rate on twelve-month CDs for $10,000 deposits as the deposit rate. We calculate average equity assets by scaling the sum of total assets in the equity markets in a zip code by the total amount of household financial assets in the same area. We also include zip code and semi-annual fixed effects.[7]

Figure 1 Panel A shows that a higher equity percentage in the zip code is positively related to the average deposit rates in the same area. This aligns with our premise that banks offer higher deposit rates when they face more competition for deposits.

Next, we conduct regressions to better estimate the relation between equity ownership and bank deposit rates. We estimate the following relation between the characteristics of a representative

[6]It is possible that this stiffer competition does not translate into higher deposit rates. This is especially possible for larger banks, which can, in certain cases, draw capital from other geographies (Gilje et al., 2016). However, as Gilje et al. (2016) note, contracting frictions limit the ability of arm's length finance to integrate credit markets fully.

[7]For a portion of the sample period only, data are available at quarterly frequency.

bank b in a zip code z at time t:

$$d_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \varepsilon_{z,t}, \tag{1}$$

where $d_{z,t}$ is the deposit weighted average deposit rate of a zip-code-level representative bank. As before, average equity assets $e_{z,t}$ are calculated by scaling the sum of total assets in the equity markets in a zip code by the total amount of household financial assets in the same area. $\mathbb{X}$ includes additional characteristics that affect bank response to competition: Specifically, deposit concentration (Herfindahl–Hirschman index) in the zip code, fraction of deposits insured by FDIC, and the size of the representative bank in the zip code.

Table 2 reports the regression results. We progressively include deposit market competition, deposit insurance, and bank size into account as the controls for bank characteristics. Columns (1) to (4) have deposit rate as the dependent variable. Column (4) reports that one standard deviation (11.8%) increase in equity exposure for households increases interest rates by 0.31 basis points. For comparison, one standard deviation (0.074) decrease in bank competition captured by Herfindahl–Hirschman index is associated with 0.5 basis points higher deposit rates in this period. Thus, the effect of asset market competition is more than half the magnitude of the effect of bank competition on deposit rates. A larger fraction of insured deposits in an area is associated with lower deposit rates offered by banks. Larger banks offer lower deposit rates as well.

2.1.2 Within bank-level results across geography

To address concerns regarding the significant heterogeneity among banks driving our result in Panel A, we conduct a within-bank analysis. We construct a bank-ZIP-semiannual panel, where each bank is matched to the ZIP codes in which it has branches presence. Panel B of Figure 1 tests the same correlation but uses bank-ZIP-semiannual panel and includes bank fixed effects. Thus, the comparison is within banks across locations and time. Again, we find that the same bank offers higher rates in areas with more average equity holdings.

Correspondingly, we run the following regression:

$$d_{b,z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{b,z,t,i} + \gamma_b + \gamma_z + \eta_t + \varepsilon_{b,z,t}, \tag{2}$$

This specification is very similar to Equation 1, but instead, it allows the deposit rate spread d to vary within a ZIP code across different banks and includes bank fixed effect. Columns (5)–(8) of Table 2 report within-bank regression results. The positive and significant coefficients in columns (5)–(8) suggest that even within the same bank, branches located in areas with higher household equity holdings offer higher deposit rates. Column (8), which is the most exhaustive specification, suggests that a one standard deviation (0.174) increase in equity holdings is associated with 21 basis points (bps) higher deposit spread.

2.2 Bank Rate Response by Household Income

The previous section showed that banks offer higher rates for deposits when the area in which they operate has a higher equity exposure as a fraction of the household balance sheet. Banks are responding to the trade-off faced by households: Households recognize that more equity exposure increases long-run returns, in expectation; however, a higher deposit share allows households to enjoy liquidity at the expense of lower returns. Thus, if households have a higher propensity to allocate capital to equity, then banks must pay higher deposit rates to draw an optimal amount of deposits from households.

Therefore, a key dimension of heterogeneity that drives differential rates is the propensity of households to allocate capital to equity holdings. As we observe the equilibrium outcome in terms of equity allocation, we cannot use final equity holdings as the ex-ante differentiator across households. For that, we need to focus on household heterogeneity in terms of an economic primitive, such as income.

Hence, we next estimate bank deposit rate spread response function $d(.)$ to the income-level composition of households in a location z by income level g at time t:

$$d_{b,z,t} = \sum_g \beta_g \cdot w_{g,z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \nu_b + \varepsilon_{b,z,t}. \tag{3}$$

The estimated β_g for different income groups offers the response of banks to the fraction of the population w that is in group g in a location. A high value of β for a group suggests that banks offer higher rates if a larger fraction of the population is in an income group g.

The key explanatory variables, $w_{g,z,t}$, capture the fraction of the population in ZIP code z that belongs to each of the six income groups, as classified using IRS Summary of Income (SOI) data. Specifically, w_1 represents the share of the population earning less than \$25,000, while w_2 corresponds to those with earnings between \$25,000 and \$50,000. w_3 includes individuals with income between \$50,000 and \$75,000, and w_4 covers those earning between \$75,000 and \$100,000. The next group, w_5, accounts for individuals with income between \$100,000 and \$200,000, and finally, w_6 represents the share of the population earning more than \$200,000. The descriptive stats of w_1 to w_6 are in Panel D of Table 1. The sample spans the period from 2014 to 2019. In addition to the income group shares, we control for ZIP code-level log population and log wealth.

Figure A.3 shows that most of the deposits banks have are from middle-income depositors. Only 20% of the deposits are from households with less than \$50,000 income. Less than 15% of the deposits are from households above \$200,000. Thus, as is intuitive, banks are dependent on the middle-income households for most of their deposits.

Table 3 estimates the response function in Equation 3. Columns include zip code and time fixed effects. In the presence of a larger fraction of lower income households, banks offer a higher interest rate. As income increases, deposit rates offered plateau for \$25,000–\$200,000 income households. These rates are compared against the omitted group of households above \$200,000 income, which is approximately 15% of the deposit base in the IXI sample.

The bank response function suggests that the very high-income households with relatively higher equity market exposure are not expected to keep a significant portion of assets in deposits.

Further, this group is also small as a fraction of the population, reducing the total amount of deposits that can be obtained from them by banks. Thus, the lion's share of banks' deposits is from households in the middle-income population group, with a population share of about 65%. These households are sensitive to deposit spreads when making their portfolio allocation decisions.

Thus, to attract deposits at the optimal level, banks must conduct third-degree price discrimination (seminal work includes Schmalensee, 1981; Varian, 1985; Holmes, 1989). In other words, banks offer different prices in different locations with different population compositions. In the next section, we create a measure for bank response to depositor heterogeneity that captures the differential deposit rates offered by banks.

2.3 Third-degree Price Discrimination in Deposit Pricing across Locations

Our data are at the zip level. Hence, we create a zip-level measure of bank price response to households in a location:

$$\text{zipresponse}_{z,t} = \sum_{g} \hat{\beta}_g \cdot w_{g,z,t}, \tag{4}$$

where estimates of sensitivity from Eq. 3 are aggregated weighted by the mass of the population in zip code z in each income group t. Given the point estimates in Table 3, the zip-level measure is bounded between 1.819% interest rate, when the whole population earns below \$25,000, and 0 when the whole population earns above \$200,000.

The measure can be understood as the differential price s offered by banks in each location given the heterogeneous price elasticity of demand for deposits e_d. We consider the marginal revenue MR of a representative bank in a zip code for additional dollar attracted in deposits d:

$$MR = s + d\frac{\partial s}{\partial d}, \tag{5}$$

where marginal revenue is the additional spread s collected on the dollar and a reduction in spread collected on the remaining deposits d due to the downward sloping demand curve of deposits. The above relation can be reorganized in terms of elasticity of deposit demand $e_d = (s/d)(\frac{\partial s}{\partial d})$:

$$MR = s\left(1 + \frac{1}{e_d}\right), \tag{6}$$

If the representative bank attracts an optimal amount of deposits until marginal revenue and marginal cost (MC) are equal, we obtain the following relation between deposit spread and price elasticity of demand:

$$s = \frac{MC}{1 + (1/e_d)} \tag{7}$$

If different zip codes z have different prices, as we obtain from Eq. 4, then we have the following equation across zip codes z and z':

$$\frac{s_z}{s_{z'}} = \frac{1 + (1/e_{d,z'})}{1 + (1/e_{d,z})}. \tag{8}$$

Without perfect competition among banks, $e_d < -1$. For elasticities less than -1, bank response in terms of deposit spreads charged in any location decreases with increasing demand elasticity of deposits (see Figure A.4 where marginal cost is normalized to one). In the next section, we use our bank location-specific response measure to bring together the equilibrium response of banks in terms of deposit rates and households in terms of equity holdings.

2.4 Bank Rate Response, Equity Holdings, and Bank Interest Rates

Figure 2 brings together the various results. The top panel shows that the zip-level sensitivity measure of banks to income groups is positively correlated with the zip-level bank spreads. The figure thus validates the zip-level aggregate measure: the figure shows that the zip-level measure of bank response is related to the response of the average bank.

Using bank-geographical unit-time level data, Table 4 shows that the average zip-level sensitivity of banks has a statistically significant effect on deposit rates offered by each bank. One standard deviation increase in the zip-level sensitivity of banks (0.17) to households increases interest rates offered by banks by 5% of the standard deviation of rates. Note that these data are for the low interest period of 2014–2019.

The bottom panel of Figure 2 finds that as zip-level bank sensitivity increases, i.e., banks are willing to offer higher rates to attract deposits, households allocate relatively less to equity markets. We thus isolate the impact of bank response on equity holdings (partial effect) in Figure 2 from the equilibrium outcome observed in Figure 1. Banks are thus able to undo only a portion of household allocation decisions through their interest rate response.

To understand the heterogeneous response faced by banks to attract deposits for a given change in rates, we next estimate the following equation:

$$\Delta \log \text{deposits}_{b,z,t} = \underbrace{(\beta \cdot \text{zipresponse}_{z,t})}_{\text{Heterogeneous response}} \Delta\text{rates} + \beta_z \cdot \text{zipresponse}_{z,t} + \beta_r \cdot \Delta\text{rates} + \gamma_z + \eta_t + \nu_b + \varepsilon_{b,z,t}, \tag{9}$$

where the product of point estimate β and $\text{zipresponse}_{z,t}$ captures the heterogeneous response of depositors to changing deposit rates.

Table 5 reports the results. Column (1) reports that, as expected, a higher deposit rate spread allows banks to attract more deposits. A 1 pp. increase in spreads increases deposit growth by 2.5 pp. Column (2) shows that these results are also present within the same bank across locations. Columns (3) and (4) focus on the ability of banks to attract deposits across heterogeneous locations. The most exhaustive specification in column (4) shows that when banks raise rates by 1 pp., in areas with one standard deviation (0.17) higher zip sensitivity, banks experience 1.5 pp. lower deposit growth. The average effect of raising rates on deposits is 3.4 pp. Thus, the heterogeneous response is almost half of the average effect.

The table empirically demonstrates why banks have to raise rates more in areas with higher zip sensitivity that proxies for higher elasticity of demand for deposits. In the absence of heterogeneous rate responses by banks, deposit growth will suffer in such areas. In contrast, by offering one standard deviation (0.713) higher deposit rates—i.e., 1.713 pp.in place of 1 pp. rate increase—in areas with mean zip response (0.201), banks can maintain deposit growth at 2.86 pp. This estimated response through higher rates restores 84% of the 3.4 pp. average growth for 1 pp. rise in rates.

3 A Causal Link between Equity Holdings and Bank Response

The previous section documented a relation between bank deposit rates and household equity holdings. It then investigates the microeconomic underpinnings of bank response to household portfolio allocation choices. In this section, we provide two different approaches to establish that higher equity holdings cause banks to respond with higher interest rates to attract deposits.

3.1 Instrumental Variables Strategy

An important concern in interpreting the positive relation between household equity holdings and bank deposit rates is that latent factors are endogenously determining both outcomes. For example, in regions with higher economic growth, households may have higher equity investments. At the same time, banks in these areas may have better investment opportunities—increasing their demand for deposits as they seek to fund additional projects. To address this endogeneity concern, we use the Tax Cuts and Jobs Act (TCJA) of 2017 as an exogenous shock to household equity holdings.

The TCJA introduced significant changes to the U.S. tax code for firms and households. Households faced lower taxes on capital gains, dividends, and alternative minimum tax.[8] Chodorow-Reich et al. (2024) show that domestic investment of firms increases 20% due to the law. Higher investment opportunities for firms combined with lower taxes on long-term capital gains and dividends make equity investments more attractive for households.

To obtain the effect of the law at the zip code level, we take the following steps. First, we use Urban-Brookings Tax Policy Center (TPC)'s estimates to determine average tax savings for each income bracket. Specifically, households earning under \$25,000 receive no significant tax savings from preferential treatment on equity investment, while those earning between \$25,000 and \$50,000 benefit from an average of \$20 in tax savings. For households in the \$50,000 to \$75,000 bracket, the tax savings increase to \$60, and those in the \$75,000 to \$100,000 bracket

[8] See hyperlinked document "The Tax Policy Briefing Book" by the Tax Policy Center.

receive an average savings of $150. Higher-income households see even greater benefits, with those earning between $100,000 and $200,000 receiving an average of $310 in tax savings, while households with incomes over $200,000 receive an average of $1,140.

Second, we consolidate the tax savings to ZIP code level, taking into account the population in each of the six income brackets using Statistics of Income (SOI) data from the IRS. This consolidated tax saving reflects the TCJA's localized impact based on regional income distributions. To standardize this measure, we divide the tax savings in dollar terms by the total tax payment in each ZIP code, calculating a tax saving fraction. This fraction captures the relative benefit of the TCJA's preferential rates as a proportion of total tax liability, providing a more comparable metric across regions.

Third, given that the TCJA was signed into law at the end of 2017 and implemented in 2018, we construct an instrumental variable that captures both the treatment indicator and treatment intensity at ZIP code level. During our sample period from 2014 to 2019, the pre-treatment period (2014–2017) is assigned an IV value of zero. In the post-treatment period (2018–2019), the IV is set to the tax saving fraction, which serves as a continuous measure of treatment intensity based on the magnitude of tax savings realized in each ZIP code. The tax saving instrument in 2018 to 2019 has a mean of 1.21% and standard deviation of 0.29%

The tax saving instrument satisfies the relevance condition because the TCJA disproportionately benefits higher-income households, thereby incentivizing these households to increase their equity investments. Figure 3 shows the binscatter plot of the first stage for 2018 and 2019, showing a positive relation between the tax savings fraction and equity holdings across ZIP codes, supporting the validity of the instrument in explaining variations in equity holdings.

While local economic factors could influence both bank behavior and household financial decisions, the TCJA's tax savings are purely policy-driven and not tied to specific regional economic conditions. This independence ensures that any observed relationship between the tax saving measure and bank behavior arises solely from the TCJA's effect on household equity allocation, thus satisfying the exclusion restriction.

We estimate the following specification at the zip-code level:

$$
\begin{aligned}
e_{z,t} &= \beta_\tau \cdot \text{Tax Savings}_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \varepsilon_{z,t} \\
d_{z,t} &= \beta_e' \cdot \hat{e}_{z,t} + \sum_i \beta_{x,i}' \cdot \mathbb{X}_{z,t} + \gamma_z' + \eta_t + \varepsilon_{z,t}'.
\end{aligned} \tag{10}
$$

The first stage of the instrumental variables regression reports a statistically strong relevance of zip-code level tax savings on the equity ownership rate. Even after including bank concentration, average insured fraction of deposits, and average bank size, we find that a 1 pp. increase in tax savings as a percentage of total tax payment leads to a 0.995 bps increase in equity ownership. The coefficient estimate is statistically significant with a t-statistic of 4.74.

Table 6 reports the results of the second stage. The columns progressively include relevant controls. The point estimate remains stable across columns. The most exhaustive specification in column (4) suggests that a 0.1 pp. increase in equity ownership at the zip code level causes banks to raise interest rates by 0.9 pp. While the magnitude is large, the estimate at a minimum suggests a causal positive relation between equity holdings and bank response in terms of interest rates. We also note that instrumental variables diagnostic statistics reject the null that Eq. 10 is under-identified. The diagnostic statistics also satisfy the weak identification test.[9]

3.2 Local IPO shocks

To examine the causal relationship between stock market participation and bank deposit rate setting, we leverage local IPOs as exogenous shocks that generate geographical variation in equity holdings. If a local company went on IPO, it will significantly increase attention to the equity market in their headquarters' region through heightened media coverage, advertising, and social interaction. This mechanism, described as the attention channel by Jiang et al. (2024), demonstrates that the IPO-induced increase in stock market participation is not driven by localized wealth gains

[9] Regarding weak identification concerns, we report that for column (4), the Cragg-Donald Wald F statistic is 52.2 and Kleibergen-Paap rk Wald F statistic is 20.2. In reference to underidentification concerns, Kleibergen-Paap rk LM statistic is 19.2 with a χ^2 p-value < 0.000.

but by increased awareness of equity investment opportunities.

Using this attention channel, we treat local IPOs as shocks that shift household portfolio allocations, leveraging a dynamic difference-in-differences (DID) approach to capture their effects. To construct the treated and control groups, we first identify IPO events and headquarter locations. Using data from Compustat, we obtained the headquarters' zip codes of firms that underwent IPOs, while IPO dates were sourced from Jay Ritter's website. To ensure consistency with the semi-annual frequency of IXI data, each IPO is attributed to the end of the semi-annual period in which it occurred, either June 30 or December 31. Given the potentially far-reaching effects of IPOs, we aggregated data to the county level rather than limiting the analysis to zip codes.

The treated group includes counties that experienced a single IPO during the sample period. We excluded counties with multiple IPO events during the sample period to avoid confounding influences from overlapping treatments. Additionally, treated counties were never used as controls to avoid any contamination of the treatment effect. To allow for adequate pre- and post-treatment observations, we further restrict the sample period to 2016-2022, ensuring at least two years (four semi-annual periods) before and after the treatment.

Furthermore, we restrict the treated counties to those where the IPO had a negative 6-month cumulative return. While this does not fully control for all potential economic changes brought by an IPO in the local region, it helps mitigate concerns that the observed effects are primarily driven by local economic booms. Since these IPOs had negative post-listing returns, it is less likely that they generated substantial positive wealth effects, making it more plausible that any changes in household financial behavior and bank deposit rates stem from increased attention to the stock market rather than broader economic growth. After applying these restrictions, we find 96 treated counties, each of which experienced only one IPO during the sample period.

To construct the control group, we implemented a k-nearest neighbors (KNN) matching based on county-level demographic and economic characteristics, including: poverty rate, unemployment rate, Gini index, median age, and total population. For each treated county, three nearest neighbors were selected to serve as the control group. The treated and control groups of both methods are visualized in Figure 4 for demonstration purposes. The red counties are treated and the blue counties are controls.

To test the dynamic treatment effect, we run the following regression:

$$y_{ct} = \alpha + \sum_{k=-3}^{6} \beta_k \cdot \mathrm{IPO}_{c,t+k} + \delta_c + \lambda_t + \gamma_g + \varepsilon_{ct}$$

where y_{ct} is either the equity holding percentage or the deposit rate for county c at time t. The term $\mathrm{IPO}_{c,t+k}$ is an indicator variable that equals 1 if county c is treated k periods relative to the IPO event and 0 otherwise, and k ranges from three semi-annual periods before the IPO ($k = -3$) to six semi-annual periods after ($k = 6$). The coefficients β_k measure the dynamic treatment effects for each relative time period k. The model includes county fixed effects (δ_c), time fixed effects (λ_t), and treatment cohort fixed effects (γ_g).

The dynamic treatment effects are shown in Figure 5. The figure used the matching method and shows that as equity holdings increase by approximately 1 pp., banks offer 0.05 pp. to 0.1 pp. higher average deposit rates over time. The results are statistically significant at the 95% confidence level. Note that these results are for the 2014–2019 period when interest rates were lower.[10]

4 Real Effects of Bank Price Discrimination to Attract Deposits

As banks raise rates to attract deposits, cost of funds for banks also rises. If banks seek to protect net interest margins, then they take more risks and lend less overall. In the following subsections, we empirically investigate these real effects.

4.1 Bank Risk-Taking

In this section, we examine how household equity holdings influence bank-level outcomes. The bank-level data is sourced from the Call Report and aggregated to the Bank Holding Company

[10]We plan to obtain more recent data, where we expect a larger response.

(BHC) level.

A key concern with using accounting-based measures of bank risk is that they are lagged and subject to managerial discretion. Banks can delay loss recognition or adjust provisions to manage reported risk, making traditional metrics less reliable. To address this, we rely on a market-based measure of Probability of Default (PD) following the methodology of Nagel and Purnanandam (2019). This approach builds on the Merton model, which estimates bank risk using stock market returns and volatility, while also incorporating the unique asset and liability structure of financial institutions. The descriptive statistics for PD are documented in Table 1 Panel E. More details on the modified Merton model are documented in Appendix A.1.

To analyze the effect of equity holding on bank risk-taking at ZIP code level, we map bank-level PD to the ZIP code level based on branch presence. Specifically, a ZIP code's PD is calculated as a weighted average of the PDs of banks operating in that area, with weights based on the deposit amounts held in each branch. After obtaining $\text{PD}_{z,t}$, we estimate the following specification:

$$\text{PD}_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \varepsilon_{z,t} \tag{11}$$

where $e_{z,t}$ denotes the average household equity holdings as a percentage of total assets at the ZIP code level, while $\mathbb{X}_{z,t}$ includes additional control variables for Herfindahl index, insured fraction, and log bank size at ZIP code level. The regression results are presented in Table 7. The positive and significant relationship suggests that an increase in local equity holdings is associated with a higher probability of default for banks operating in the same zip code. The estimated coefficient of 0.015 in column (4) suggests that one standard deviation increase in equity holding (0.174) is associated with 0.261 percentage point increase in PD.

One potential explanation is that greater household equity holdings lead to deposit outflows, forcing banks to adjust their risk-taking strategy to attract deposits while remaining profitable. To further examine this relationship, we conduct a bank-level analysis by aggregating ZIP code-level equity holdings to the bank level. This aggregation is similarly based on the branch presence of each bank within a given ZIP code, using deposit amounts as weights. We refer to this bank-level measure as equity exposure, as it reflects the competitive pressure banks face from the equity market.

Next, we conduct a bank-level analysis to confirm whether banks adjust their risk-taking and pricing strategies in response to equity market competition. Specifically, we look at bank balance sheet variables including charge-off rates, log deposit, log loans, interest expense and interest income rates, as well as PD at bank level.

Charge-off rate is defined as net charge-off divided by total loans. Interest expense rate is defined as interest expense divided by total deposits, subtracting the fed funds rate. Similarly, interest income rate is defined as interest income divided by total loans, adjusted by the fed funds rate.

The bank-level equation is as follows:

$$y_{b,t} = \beta_e \cdot e_{b,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{b,t,i} + \gamma_b + \varepsilon_{b,t} \tag{12}$$

where $y_{b,t}$ are the bank-level dependent variables described above. $\mathbb{X}_{b,t}$ includes control variables including bank-level measures of Herfindahl index, insured fraction, log bank size. One challenge in this regression is the low variation in equity exposure over time, as each bank's exposure remains relatively stable throughout the sample period. Because of this, including time fixed effects would absorb much of the already limited variation in equity exposure, making it harder to estimate its effect on bank outcomes. To preserve as much variation as possible, we include only bank fixed effects in our regression specification.

The regression result is presented in Table 8. Both interest expense and interest income rates rise, indicating that banks offer higher deposit rates to retain funding while also raising loan rates to offset costs. Risk measures also increase, with a higher probability of default (PD) and charge-off rates, suggesting a shift toward riskier lending.

Overall, this section examines the impact of household equity holdings on bank risk-taking at both the ZIP code and bank levels. At the ZIP code level, higher equity holdings are associated with a higher probability of default in the local area. At the bank level, greater equity exposure leads to higher interest income and expense, alongside increased risk-taking in lending.

4.2 Effect on Lending

In this section, we analyze the effect of equity holdings on lending. We anticipate that changes in household equity holdings, which impact banks' deposit supply, should influence the amount and composition of new loan origination. Given that deposits are the cheapest source of funding for banks and are not perfectly substitutable with other funding sources, increased equity holdings should lead to a reduction in credit supply.

To test the effect of higher equity holdings on bank lending, we obtain lending data from CRA Analytics Data Tables offered by the Federal Reserve System (hereafter, CRA Analytics). This data merges the Community Reinvestment Act (CRA) data with the Home Mortgage Disclosure Act (HMDA) data. The data is reported at the bank-county-year level and documents the mortgage origination as well as small business loan origination for each bank at each county in a given year. The sample period covers 2014 to 2021. To merge our existing panel with the CRA Analytics data, we aggregate our original zipcode-bank-semi-annual data to the bank-county-year level.

Following Drechsler et al. (2017), given that banks can allocate funds across branches, and that lending decisions are made at the bank level, we can no longer rely on within-bank variation. Similar to the Bank-HHI measure constructed by Drechsler et al. (2017), we construct a bank-level measure of equity exposure, $e_{b,t}$, by taking the weighted average county-level equity holdings using the relative county-level deposit amount as weights.

We estimate the following specification:

$$y_{b,c,t} = \beta_e \cdot e_{b,t-1} + \beta_h \cdot \text{Herfindahl Index}_{b,t-1} + \gamma_b + \gamma_c + \gamma_t + \gamma_{b,c} + \gamma_{c,t} + \varepsilon_{b,c,t}, \tag{13}$$

where $y_{b,c,t}$ represents the loan origination outcomes by bank b in county c, from year t to t+1.

$e_{b,t-1}$ is the one-year lagged equity percentage, and Herfindahl Index$_{b,t-1}$ is the Herfindahl-Hirschman Index, measuring market concentration. Bank-county and county-year fixed effects are included. The standard errors are clustered at the bank and county level.

We include county-time fixed effects, which absorb changes in local lending opportunities. We also include county-bank fixed effects, which absorb time-invariant characteristics. This specification allows us to compare the lending behavior within the same county, based on bank-level equity exposure, ensuring banks face similar local lending opportunities.

The regression results are presented in Table 9. Column (1) and (3) examine the log of new loan amounts originated for mortgage and small business lending, respectively. Column (2) and (4) examine the number of new contracts originated for mortgage and small business lending, respectively.

The results indicate that an increase in household equity holdings faced by the bank is associated with a contraction in bank lending. From columns (1) and (3), one standard deviation increase in household equity holding (5.65 percentage points at the bank level) is associated with a 2.36% decline in mortgage origination and an 8.63% decline in small business origination. Similarly, looking at the number of loans originated, the same increase in household equity holdings results in a 4.55% decline in the number of new mortgages originated and a 6.68% decline in the number of small business loans originated.

Overall, our approach examines how households' equity holdings affect bank lending decisions by leveraging within-county variation. The findings suggest that banks adjust their lending activity in response to household balance sheet conditions.

5 Conclusion

Using a novel granular dataset on household financial positions, this paper shows that banks not only compete with other banks for deposits, but also compete with other asset classes for household investments. We document that banks engage in third degree price discrimination across geographies to attract deposits: Banks pay higher deposit rates to depositors with higher elasticity of substitution with other asset classes. Despite paying higher deposit rates, banks are unable to completely undo household preferences for equity markets, thus receiving lower depository capital at higher rates.

This competition for assets reduces the deposit market power and associated deposit franchise of banks. As a result, banks take more risks to compete for deposits by providing higher deposit interest rates and by taking more lending risks. As more households gain access to public debt and equity markets, the competition for deposits will only increase. Along with it, banking system fragility and credit rationing of less creditworthy entities will also increase.

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Table 1: Summary Statistics

Panel A presents the composition of household assets using Equifax data. The dataset is structured at the ZIP code level with semi-annual frequency, covering the period from June 2014 to June 2024. *Panel B* is based on RateWatch data, which provides semi-annual observations at the ZIP code level from June 2014 to June 2019. *Panel C* contains bank-level control variables at the Bank Holding Company level. These controls are disaggregated to the ZIP code level using deposit amounts as weights, covering the period from June 2014 to June 2023. *Panel D* reports mortgage and small business lending data at the bank-county-year level, covering 2014 to 2021.

	Count	Mean	Std. Dev.	Min.	p25	p50	p75	Max
Panel A: Household Asset Composition								
Equity pct	949,651	0.477	0.174	0	0.390	0.506	0.591	1
Equity Market Adjusted pct	949,651	0.406	0.172	0	0.304	0.426	0.521	1
Deposit and Cash pct	949,651	0.303	0.218	0	0.155	0.245	0.379	1
All Assets	949,651	106,850	654,010	0	16,652	45,824	101,540	138,023,609
Panel B: Deposit Rate Spread								
	Count	Mean	Std. Dev.	Min.	p25	p50	p75	Max
12MCD10K - FF rate (%)	200,575	-0.506	0.713	-2.390	-1.029	-0.238	0.052	1.118
MM25K - FF rate (%)	196,835	-0.700	0.777	-2.390	-1.344	-0.334	-0.043	1.077
Panel C: Bank Controls								
	Count	Mean	Std. Dev.	Min.	p25	p50	p75	Max
Insured Fraction	517,908	0.688	0.124	0.019	0.599	0.693	0.782	1
log(Bank Size)	517,908	16.188	3.123	8.928	13.378	16.058	18.846	21.955
Herfindahl Index	517,908	0.558	0.336	0.035	0.254	0.502	1	1
Panel D: Zip sensitivity								
	Count	Mean	SD	Min	P25	P50	P75	Max
% Pop. < $25,000	367,959	0.242	0.109	0	0.159	0.228	0.307	1
% Pop. >= $25,000 and <$50,000	367,959	0.223	0.068	0	0.176	0.231	0.271	0.6
% Pop. >= $50,000 and <$75,000	367,959	0.148	0.034	0	0.127	0.152	0.171	0.5
% Pop. >= $75,000 and <$100,000	367,959	0.111	0.032	0	0.091	0.113	0.133	0.516
% Pop. >= $100,000 and <$200,000	367,959	0.188	0.087	0	0.121	0.180	0.254	0.543
% Pop. >= $200,000	367,959	0.088	0.108	0	0.020	0.045	0.115	0.764
zipresponse	367,959	0.201	0.170	-0.541	0.110	0.221	0.309	1.052
Panel E: Real Effects								
	Count	Mean	Std. Dev.	Min.	p25	p50	p75	Max
Mortgage Amount ($K)	213,654	26,488	165,708	0	746	3,380	13,602	15,597,580
Mortgage Count	213,654	87	291	0	5	20	68	15,846
SB Loan Amount ($K)	213,654	7,302	28,830	0	0	515	4,660	2,396,586
SB Loan Count	213,654	111	757	0	0	7	50	82,077
Probability of Default (PD)	30,751	0.28	0.18	0.05	0.16	0.23	0.34	0.97

Table 2: Household Equity Holdings and Bank Deposit Rates

Columns (1)–(4) estimate the following regression: $d_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \varepsilon_{z,t}$ where $d_{z,t}$ is the ZIP code-level average deposit rate spread. $e_{z,t}$ represents the average household equity holdings as a percentage of total assets at the ZIP code level, while $\mathbb{X}_{z,t}$ includes additional ZIP code characteristics. The specification includes fixed effects for ZIP codes (γ_z) and time (η_t). Columns (5)–(8) estimate the following regression: $d_{b,z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{b,z,t,i} + \gamma_b + \gamma_z + \eta_t + \varepsilon_{b,z,t}$, where $d_{b,z,t}$ denotes the deposit rate spread for bank b at the ZIP code z. $e_{z,t}$ captures the average household equity holdings at the ZIP code level. This specification accounts for bank fixed effects (γ_b), ZIP code fixed effects (γ_z), and time fixed effects (η_t). The sample covers the period from June 2014 to June 2019. Standard errors are clustered at the county level.

	Deposit Rate Spread (Zip Code Level)				Deposit Rate Spread (BHC-Zip Code Level)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$e_{z,t}$	0.053***	0.037***	0.036**	0.027*	0.019***	0.017***	0.011*	0.012**
	(0.011)	(0.014)	(0.014)	(0.014)	(0.005)	(0.006)	(0.006)	(0.006)
Herfindahl Index$_{z,t}$		-0.046	-0.046	-0.068*		-0.002	-0.002	-0.002
		(0.038)	(0.038)	(0.038)		(0.002)	(0.002)	(0.002)
Insured Fraction$_{z,t}$			0.063	-0.132***			-1.003**	-0.898**
			(0.038)	(0.044)			(0.403)	(0.384)
log(Bank Size)$_{z,t}$				-0.028***				0.113
				(0.002)				(0.083)
Zipcode FE	Y	Y	Y	Y	Y	Y	Y	Y
BHC FE	N	N	N	N	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	218,228	135,690	135,690	135,690	799,146	770,962	501,571	501,571
R^2	0.94	0.97	0.97	0.97	0.91	0.91	0.91	0.91

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Deposit rate on income composition within a bank

This table estimates the following regression:

$$d_{b,z,t} = \sum_{g} \beta_g \cdot w_{g,z,t} + \sum_{i} \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \nu_b + \varepsilon_{b,z,t}.$$

where $d_{b,z,t}$ represents deposit rate at bank b located in zipcode z in year t. $w_{g,z,t}$ represents fraction of population located in zipcode z from income group g. The sample covers period from 2014 to 2019. Zipcode level log population and log wealth are included as control. Standard errors are clustered at county level.

	Deposit Rate Spread (12MCD10K)			
	(1)	(2)	(3)	(4)
% Pop. < \$25,000	1.833***	1.798***	1.824***	1.819***
	(0.23)	(0.22)	(0.22)	(0.22)
% Pop. >= \$25,000 and <\$50,000	0.651***	0.676***	0.707***	0.700***
	(0.18)	(0.17)	(0.17)	(0.17)
% Pop. >= \$50,000 and <\$75,000	0.752***	0.719***	0.773***	0.768***
	(0.16)	(0.15)	(0.16)	(0.16)
% Pop. >= \$75,000 and <\$100,000	0.927***	0.915***	0.959***	0.954***
	(0.17)	(0.16)	(0.17)	(0.17)
% Pop. >= \$100,000 and <\$200,000	0.772***	0.806***	0.820***	0.816***
	(0.21)	(0.20)	(0.20)	(0.20)
% Pop. >= \$200,000	baseline	baseline	baseline	baseline
$\log(\text{population})_{z,t}$			0.051	0.051
			(0.04)	(0.04)
$\log(\text{wealth})_{z,t}$				-0.003
				(0.00)
Zipcode FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
BHC FE	N	Y	Y	Y
Observations	367,502	367,380	367,380	367,380
R^2	0.84	0.92	0.92	0.92

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Deposit Rates and Bank Sensitivity

This table estimates the following regression:

$$d_{b,z,t} = \beta_{zipresponse} \cdot \text{zipresponse}_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{b,z,t,i} + \gamma_b + \gamma_z + \eta_t$$

where $d_{b,z,t}$ denotes the deposit rate spread for bank b at the ZIP code z. $\text{zipresponse}_{z,t}$ captures the bank's response to zipcode level income composition. This specification accounts for bank fixed effects (γ_b), ZIP code fixed effects (γ_z), and time fixed effects (η_t).

	Deposit Rate Spread (12MCD10K)			
	(1)	(2)	(3)	(4)
$\text{zipresponse}_{z,t}$	0.213***	0.208***	0.208***	0.215***
	(0.03)	(0.04)	(0.04)	(0.04)
Insured $\text{Fraction}_{z,t}$		-0.195***	-0.195***	-0.177***
		(0.01)	(0.01)	(0.01)
Herfindahl $\text{Index}_{z,t}$			-0.016**	-0.017**
			(0.01)	(0.01)
Log(Bank $\text{Size})_{b,t}$				0.355***
				(0.06)
Zipcode FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
BHC FE	Y	Y	Y	Y
Observations	367,384	230,308	230,308	230,308
R^2	0.92	0.92	0.92	0.92

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of Deposit Rate Changes and Income Sensitivity on Log Deposits

This table estimates the following regression:

$$\Delta \log \text{deposits}_{b,z,t} = (\beta \cdot \text{zipresponse}_{z,t})\, \Delta\text{rates} + \beta_z \cdot \text{zipresponse}_{z,t} + \beta_r \cdot \Delta\text{rates} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} \gamma_z + \eta_t + \nu_b + \varepsilon_{b,z,t},$$

where $\Delta \log \text{deposits}_{b,z,t}$ is change in log deposit amount at bank b in ZIP code z from year t-1 to year t. $\text{zipresponse}_{z,t}$ captures the bank's response to Zipcode level income composition. Δrates represents change in deposit rate spread. This specification accounts for bank fixed effects γ_b, ZIP code fixed effects γ_z, and time fixed effects η_t.

	$\Delta\log(\text{Deposits})_{b,z,t}$			
	(1)	(2)	(3)	(4)
$\text{zipresponse}_{z,t} \times \Delta\text{rates}_{b,z,t}$			-0.076***	-0.086***
			(0.02)	(0.02)
$\text{zipresponse}_{z,t}$			0.008	-0.001
			(0.07)	(0.07)
$\Delta\text{rates}_{b,z,t}$	0.025***	0.020***	0.037***	0.034***
	(0.01)	(0.01)	(0.01)	(0.01)
Herfindahl $\text{Index}_{z,t}$	0.012	0.020	0.010	0.018
	(0.02)	(0.02)	(0.02)	(0.02)
Insured $\text{Fraction}_{z,t}$	-0.031*	-0.134***	-0.030*	-0.128***
	(0.02)	(0.04)	(0.02)	(0.04)
log(Bank $\text{Size})_{z,t}$	-0.005***	0.050***	-0.005***	0.051***
	(0.00)	(0.01)	(0.00)	(0.01)
Zipcode FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
BHC FE	N	Y	N	Y
Observations	179,592	179,510	177,851	177,769
R^2	0.10	0.14	0.09	0.14

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Tax savings as IV for Equity Holding

This table presents regression results using the TCJA's tax savings fraction as an instrumental variable (IV) for equity holdings at the ZIP code level. The analysis spans the period from 2014 to 2019, comparing pre-TCJA and post-TCJA effects. All regressions are estimated using Two-Stage Least Squares (2SLS). The instrumental variable takes a value of zero from 2014 to 2017 and transitions to a continuous measure of tax savings intensity starting in 2018. The dependent variable in all columns is the ZIP code-level average deposit spread $d_{z,t}$. Standard errors are clustered at the county level.

	Deposit Rate Spread (12MCD10K)			
	(1)	(2)	(3)	(4)
$e_{z,t}$ (Tax Savings)	8.219***	9.123***	9.123***	9.098***
	(1.967)	(2.274)	(2.273)	(2.246)
Insured Fraction$_{z,t}$		-0.089	-0.090	-0.006
		(0.091)	(0.091)	(0.115)
Herfindahl Index$_{z,t}$			0.012	0.031
			(0.058)	(0.067)
Log(Bank Size)$_{z,t}$				0.011
				(0.011)
Zipcode FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	106,181	96,514	96,514	96,514

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of Equity Holding on Bank Risk Taking

This table estimates the following regression:

$$\text{PD}_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \varepsilon_{z,t}$$

where $\text{PD}_{z,t}$ represents the Probability of Default for the average bank in ZIP code z at time t. This measure is constructed as a weighted average of individual bank default probabilities within a given ZIP code, where the weights correspond to the deposit amounts at the branch level. $e_{z,t}$ denotes the average household equity holdings as a percentage of total assets at the ZIP code level, while $\mathbb{X}_{z,t}$ includes additional control variables.

	Probability of Default$_{z,t}$			
	(1)	(2)	(3)	(4)
$e_{z,t}$	0.015***	0.015***	0.016***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)
Herfindahl Index$_{z,t}$		-0.005**	-0.005**	-0.009***
		(0.00)	(0.00)	(0.00)
Insured Fraction$_{z,t}$			-0.024***	-0.033***
			(0.01)	(0.01)
log(Bank Size)$_{z,t}$				-0.002***
				(0.00)
Zipcode FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	338,578	338,166	338,159	338,159
R^2	0.78	0.78	0.78	0.78

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Bank Level Regression on Equity Holdings

This table presents regression results estimating the relationship between equity market adjusted percentages and various bank-level outcomes. The regression follows the specification:

$$y_{b,t} = \beta_e \cdot e_{b,t} + \sum_i \beta_{x,i} \mathbb{X}_{b,t,i} + \gamma_b$$

where $y_{b,t}$ represents the dependent variables sourced from Call Report and aggregated to BHC level. $e_{b,t}$ is the equity market adjusted percentage, aggregated from zip code level to bank level using branch location and weighted by deposit amounts. $\mathbb{X}_{b,t}$ includes control variables: insured fraction, bank HHI, and log bank size, and γ_b captures bank fixed effects. Standard errors are clustered at the bank holding company (BHC) level.

	(1) Charge-off pct	(2) Log Deposits	(3) Log Loans	(4) Interest Expense Rate	(5) Interest Income Rate	(6) PD
$e_{b,t}$	0.034***	-0.018***	0.010	3.155***	3.353***	0.132***
	(0.013)	(0.005)	(0.015)	(0.150)	(0.156)	(0.036)
Constant	0.397***	-0.193***	-0.454***	26.975***	32.119***	-0.853***
	(0.068)	(0.046)	(0.103)	(0.745)	(0.799)	(0.071)
Controls	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Observations	58935	58,951	58,935	58,951	58,935	5,599
R^2	0.31	1.00	0.99	0.24	0.28	0.619

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect of Equity holding on new lending

This table presents the regression results on new loan origination. The regression specification is as follows:

$$y_{b,c,t} = \beta_e \cdot e_{b,t-1} + \beta_h \cdot \text{Herfindahl Index}_{b,t-1} + \gamma_b + \gamma_c + \gamma_t + \gamma_{b,c} + \gamma_{c,t} + \varepsilon_{b,c,t}$$

where $y_{b,c,t}$ represents the loan origination outcomes by bank b in county c, from year t to t+1. $e_{b,t-1}$ is the one-year lagged equity percentage, and Herfindahl Index$_{b,t-1}$ is the Herfindahl-Hirschman Index, measuring market concentration. Standard errors are clustered at the bank and county levels. Columns (1) and (3) examine the log of loan origination amount for mortgage and small business lending, respectively. Columns (2) and (4) use the logged number of new contracts originated for mortgage and small business lending, respectively.

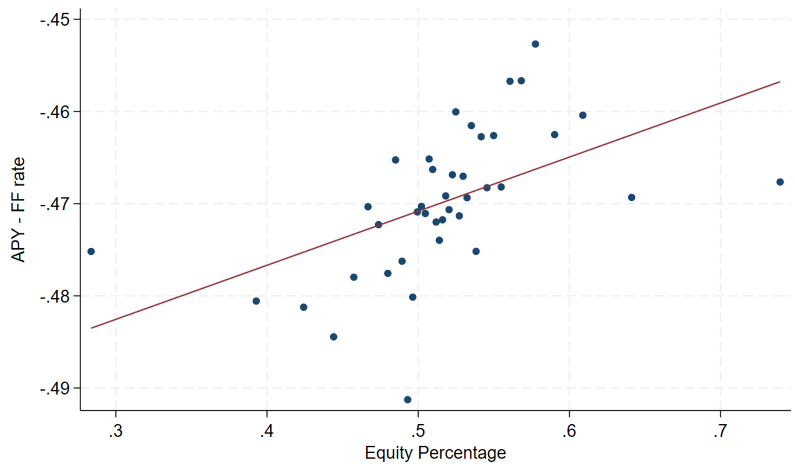
	(1) log(Mortgage Amount)	(2) log(Mortgage Count)	(3) log(Small Biz Amount)	(4) log(Small Biz Count)
$e_{b,t-1}$	-0.423***	-0.823***	-1.597***	-1.223***
	(0.10)	(0.11)	(0.23)	(0.19)
Herfindahl Index$_{b,t-1}$	-0.061	-0.342***	0.187	0.359***
	(0.07)	(0.08)	(0.12)	(0.11)
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
County-Bank FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Observations	158,752	158,757	109,907	109,908
R^2	0.92	0.93	0.93	0.93

Standard errors in parentheses

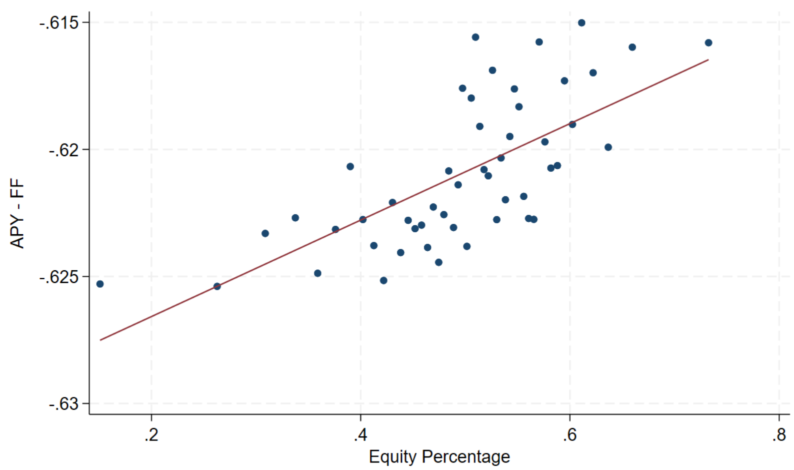
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Relationship Between Equity Percentage and Interest Rates

The plots illustrate the relation between the Deposit Rate Spread and equity percentage at the ZIP code level. Panel A shows the relation between equity percentage and adjusted APY after controlling for ZIP code and time fixed effects. The APY, representing deposit rates from a 12-month certificate of deposit with a $10,000 minimum requirement (12MCD10K), is sourced from RateWatch and adjusted by subtracting the Fed Funds Rate. The adjusted APY is aggregated to the ZIP code level by taking deposit amount-weighted averages within each ZIP code. The equity percentage, sourced from IXI, is calculated as the equity holdings divided by total assets. ZIP code and date fixed effects are included. Panel B shows the relationship between equity percentage and bank interest rates after controlling for bank-specific fixed effects. The sample period for both panels is 2014Q2–2019Q2.



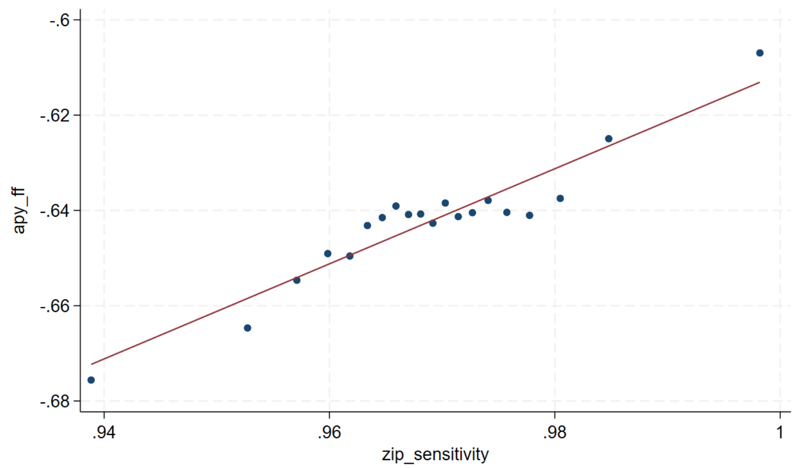
(a) Zip-level Equity Holdings and Deposit Rates



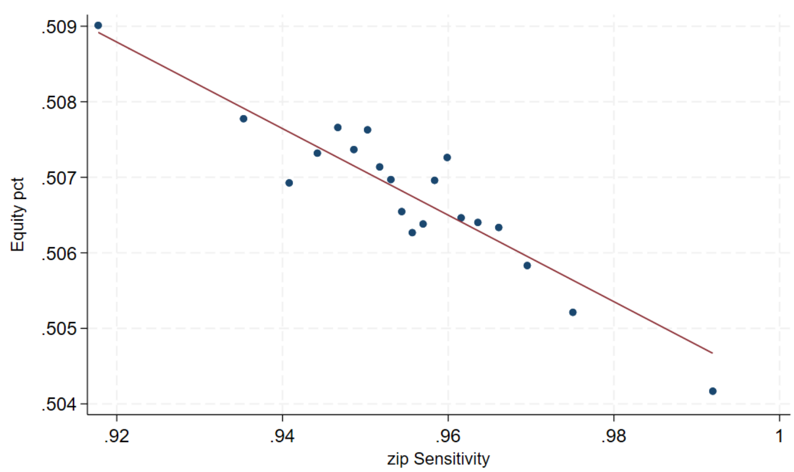
(b) Within Bank Deposit Rates and Zip-level Equity Holdings

Figure 2: Relation Between Zip-level rate response by banks, Deposit rates, and Equity Holdings

Panel A reports the relation between bank response at the aggregate level by ZIP code and the rates offered by individual banks. ZIP code, bank and date fixed effects are included. Panel B shows a relation between zip-level household equity holdings and average bank response to attract higher deposits. The equity percentage, sourced from IXI, is calculated as the equity holdings divided by total assets. The sample period for both panels is 2014Q2–2019Q2. ZIP code and date fixed effects are included.



(a) Zip-level rate response by banks and Deposit Rates



(b) Zip-level rate response by banks and Equity Holdings

Figure 3: Relationship Between Tax Savings and Equity Holdings (First Stage)

The binscatter plot illustrates the positive relationship between tax savings and equity holdings across ZIP codes in 2019. The tax savings is calculated from TPC's saving estimate for each income bracket, weighted by population of each income bracket within each zipcode.

Figure 4: Treated and Control Counties Visualization (Matching Method)

The figure visualizes the treated (red) and control (blue) counties on the U.S. map using the k-nearest neighbors (KNN) matching method. Control counties are selected based on demographic and economic variables, including poverty rate, unemployment rate, Gini index, median age, and total population, with three controls per treated county across all periods.

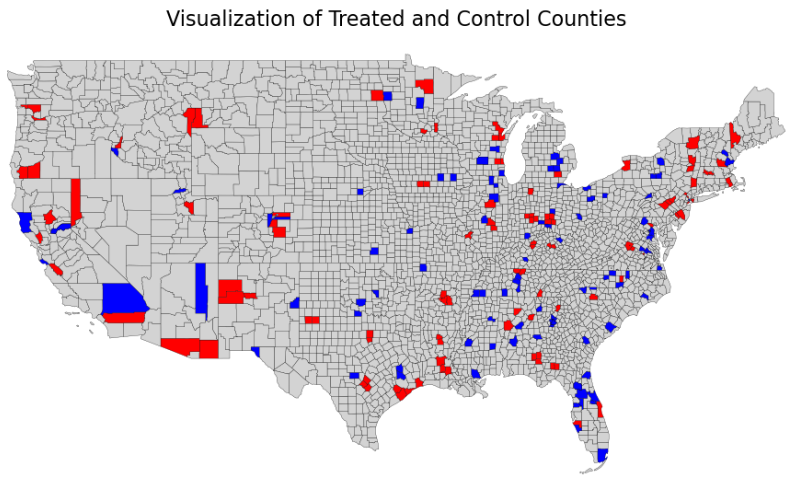
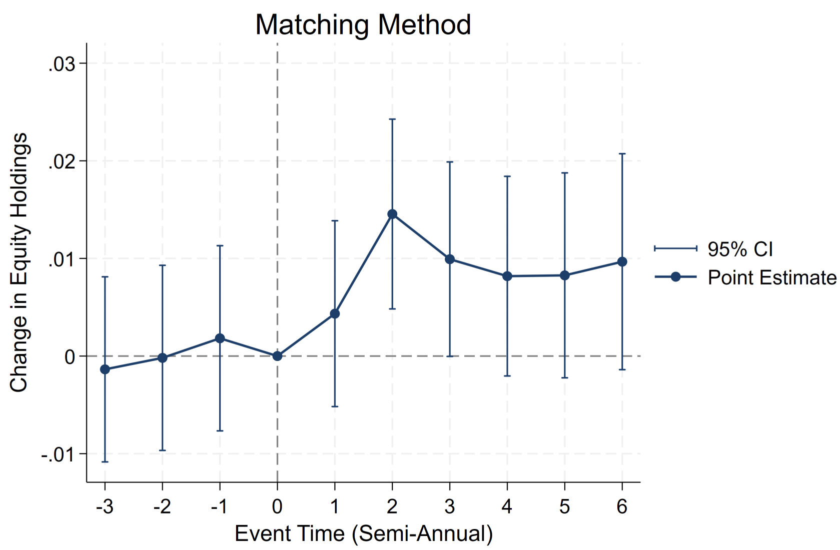
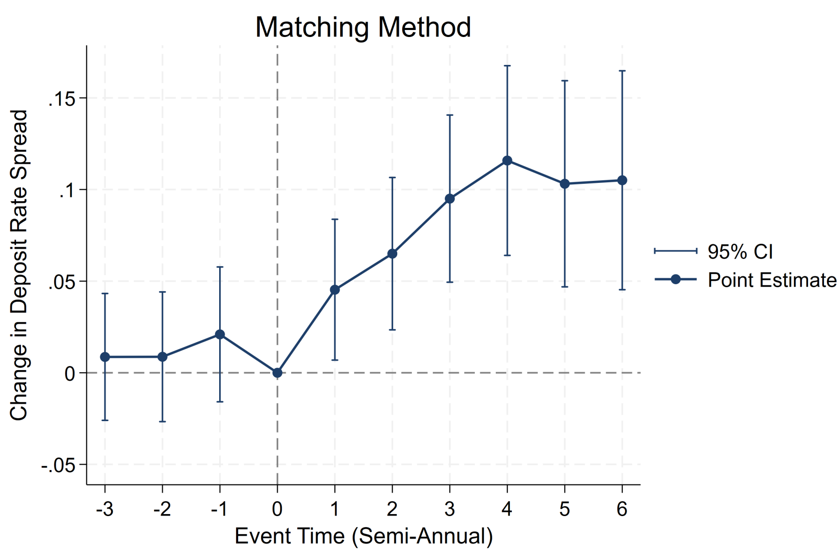


Figure 5: Dynamic Treatment Effects: Matching Method (KNN)

This figure presents the dynamic treatment effects using the k-nearest neighbors (KNN) matching method, restricting the sample to IPOs with negative 6-month cumulative returns. Control counties are selected based on demographic and economic variables, including poverty rate, unemployment rate, Gini index, median age, and total population, with three controls per treated county across all periods. Panel A shows the impact of IPOs on equity holding percentage, while Panel B shows the impact on deposit spreads (deposit rate minus the federal funds rate).



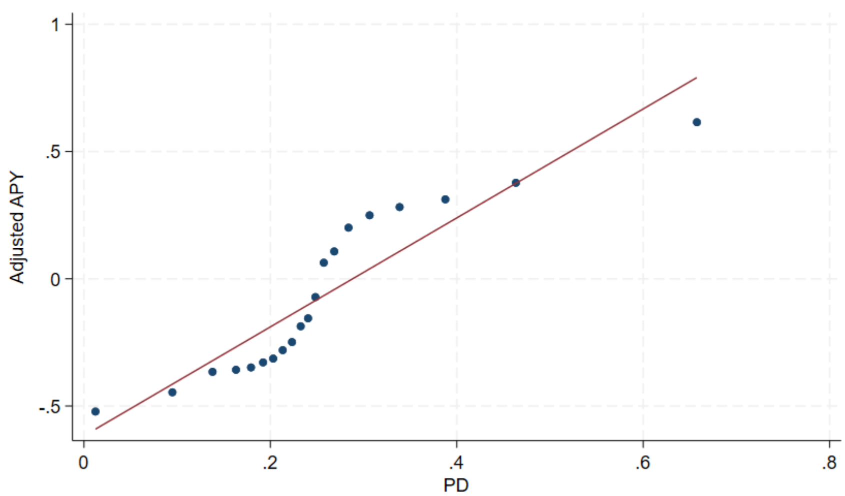
(a) Panel A: Equity Holding Percentage



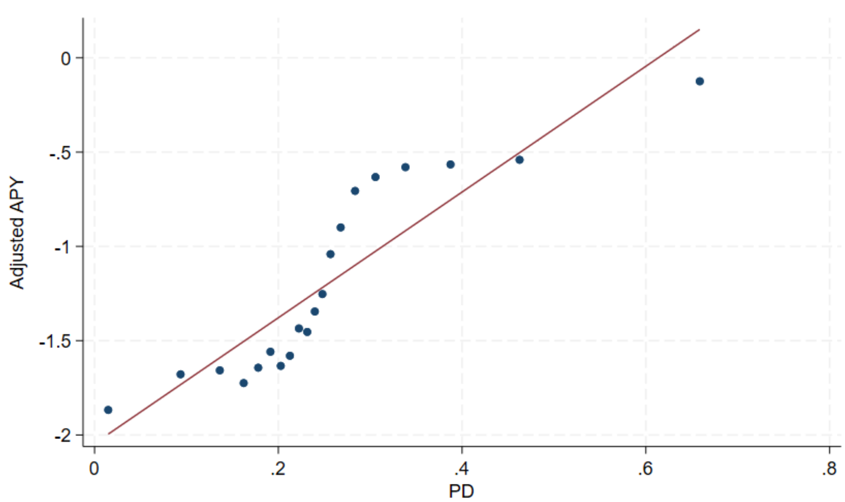
(b) Panel B: Deposit Spread (Deposit Rate - Fed Funds Rate)

Figure 6: Relation Between Deposit Rate and PD

The binscatter plots illustrate the relationship between BHC's PD and the adjusted APY for two deposit products. The sample frequency is quarterly, and the sample period spans from 2001Q1 to 2019Q2. Panel A shows 12 month certificate of deposit with $10,000 minimum requirement (12MCD10K), while Panel B shows money market fund with $25,000 minimum requirement (MM25K). The APY, representing deposit rates quoted in annual percentage yield, is sourced from RateWatch and aggregated to the BHC level at a quarterly frequency. APY is adjusted by subtracting the Fed Funds Rate. PD, also at the BHC level and quarterly frequency, is derived from Nagel and Purnanandam (2019), which employs an adjusted Merton model to estimate the probability of default for banks. BHC fixed effect is included in both panels.



(a) Panel A: 12MCD10K



(b) Panel B: MM25K

Appendix: For Online Publication Only

A Appendix

A.1 Bank probability of default

We measure the bank's risk by the probability of default (PD), following the Nagel and Purnanandam (2019) method of the modified Merton model, specifically tailored for the special asset and liability structure of financial institutions.

The standard Merton (1974) model provides a framework for estimating a firm's credit risk. The Distance to Default (DD) is calculated as the number of standard deviations between the firm's current asset value and its default point, where assets equal liabilities. The Probability of Default (PD) is then derived from the DD, representing the likelihood that the firm's asset value will fall below the default point by the debt's maturity date.

The Merton model makes two assumptions that limit its effectiveness for assessing credit risk for financial institutions. First, Merton model assumes firms' assets follow a lognormal distribution. This is unrealistic for banks because banks' assets are mostly claims like loans and mortgages. These assets usually have capped upside payoffs, which is not consistent with the unlimited upside implied by a lognormal distribution. Second, the Merton model assumes a constant asset volatility, which may be reasonable for non-financial institutions, but not for banks. In reality, banks' asset volatility could substantially rise following a bad asset value shock.

Nagel and Purnanandam (2019) modified the Merton model by shifting the log-normal distribution assumption from the bank's own assets to the assets of the bank's borrowers, which serve as collateral for loans. In this revised framework, the borrowers' assets are assumed to follow a log-normal distribution, while the bank's assets are modeled as contingent claims on borrower assets. Consequently, the bank's equity is treated as a contingent claim on the bank's own assets.

We obtained the Probability of Default (PD) measure from the full replication package provided by Nagel and Purnanandam (2019). This PD data is identified by the PERMCO identifiers for each bank. However, in order to merge this PD measure with other bank datasets, such as RateWatch, SOD, and Call Reports, we needed to map the PERMCO identifiers to bank identifiers (RSSD ID). To achieve this, we used the CRSP-FRB link table published by the Federal Reserve Bank of New York. The link table maps the PERMCO to the RSSD ID of the highest organizational parent, which is usually a Bank Holding Company (BHC). Our final dataset ranges from 2001 to 2023, providing quarterly PD for up to 862 BHCs.

Table 1 presents the summary statistics of the PD measure from this study, alongside those reported in Nagel and Purnanandam (2019), Table 4. Since Nagel and Purnanandam (2019) covers a sample period from 1987 to 2016, their PD statistics are based on a larger number of observations. The other descriptive statistics, while varying slightly, are very similar to those found in our data.

Table A.1: Linear Regression of BHC level data on Lagged PD

This table estimates the effect of lagged probability of default (PD) on BHC-level outcomes. The dependent variable is BHC-level deposit amounts, sourced from Call Report data and aggregated to the BHC level. The PD is derived from Nagel and Purnanandam (2019), which employs an adjusted Merton Model to estimate the probability of default for banks. Standard errors are clustered at the BHC level.

	Insured Deposit	Uninsured Deposit	Insured Fraction	Total Deposit
L.PD	-0.001	-0.441***	0.063***	-0.085
	(0.99)	(0.00)	(0.00)	(0.13)
Year-Quarter FE	Y	Y	Y	Y
BHC FE	Y	Y	Y	Y
Observations	27250	27250	27250	27250
R^2	0.95	0.95	0.86	0.96

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Bank Deposit Rate and Bank Risk-Taking

This table estimates the relationship between bank's deposit rate and bank's risk. The regression is specified as follows:

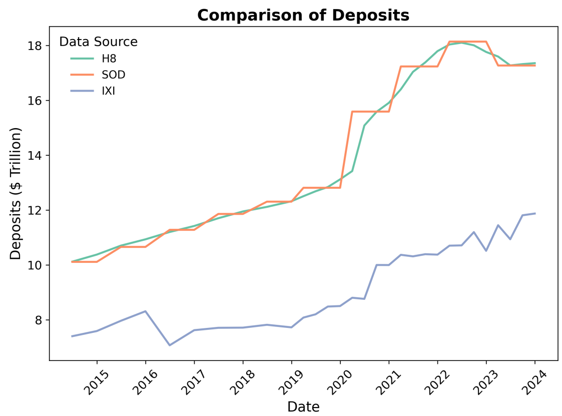
$$\text{Deposit Rate Spread}_{b,t} = \beta_0 + \beta_1 \cdot \text{PD}_{b,t} + \alpha_i + \varepsilon_{b,t}$$

The Deposit Rate Spread is the deposit rates sourced from RateWatch, adjusted by subtracting the Fed Funds Rate. The PD is derived from Nagel and Purnanandam (2019), which employs an adjusted Merton Model to estimate the probability of default for banks. Column 1 reports rates for 12MCD10K, while Column 2 reports rates for MM25K. The regression includes BHC fixed effects, and standard errors are clustered at the BHC level. The data spans from 2001Q1 to 2019Q2 at BHC level at a quarterly frequency.

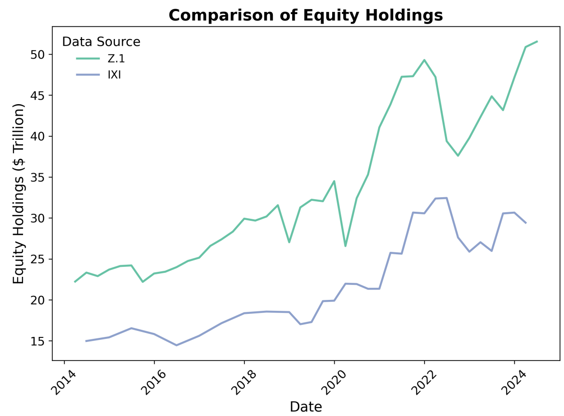
	12MCD10K	12MCD10K	MM25K	MM25K
PD	1.517***	2.127***	2.300***	3.318***
	(0.00)	(0.00)	(0.00)	(0.00)
BHC FE	N	Y	N	Y
Observations	31076	31057	31862	31844
R^2	0.09	0.21	0.08	0.22

p-values in parentheses

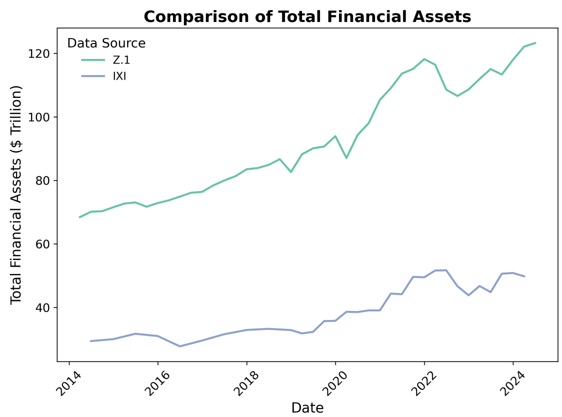
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



(a) Deposit Comparison



(b) Equity Comparison



(c) Total Financial Assets Comparison

Figure A.1: Validation of IXI data

This figure validates the representativeness of IXI data by comparing it with other aggregated public datasets. Panel (a) shows time trends in deposits over time, comparing IXI's aggregated deposit with the SOD data and H.8 report from the Federal Reserve. Panel (b) compares equity holdings, with IXI's household-level equity holdings and Z.1 data from Federal Reserve. Panel (c) examines total financial assets, comparing IXI's household-level total assets with Z.1's total financial assets for households and nonprofits.

Figure A.2: Time Trend of 12-Month CD Products with Varying Minimum Deposit Requirements

This figure visualizes the aggregated quarterly rates across five different 12-month Certificate of Deposits products with varying minimum deposit requirements ($10K, $25K, $100K, $250K, $1M). The deposit rate are sourced from Ratewatch, and aggregated to quarterly frequency for each product. The sample period spans 2001Q1 to 2019Q2. The figure plots the raw rate quoted in annual percentage yield (APY).

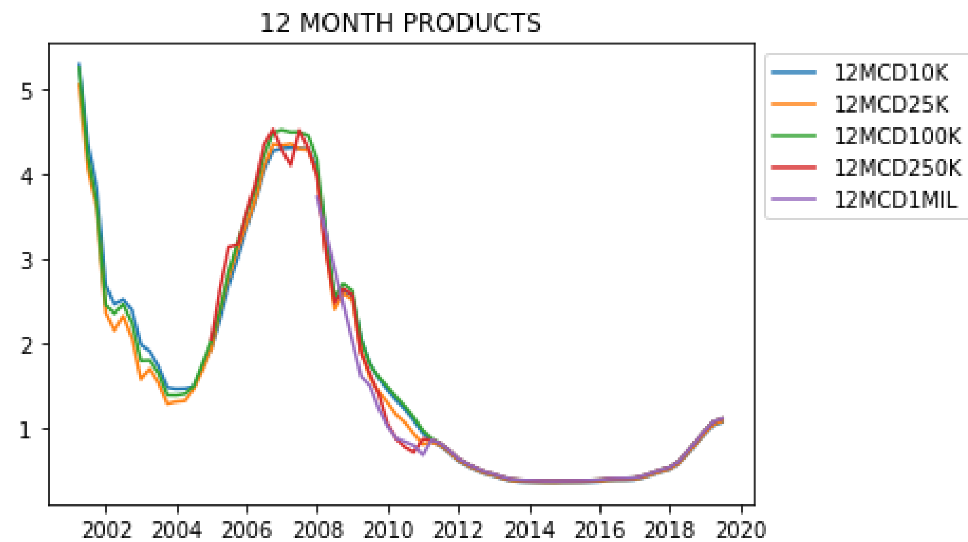
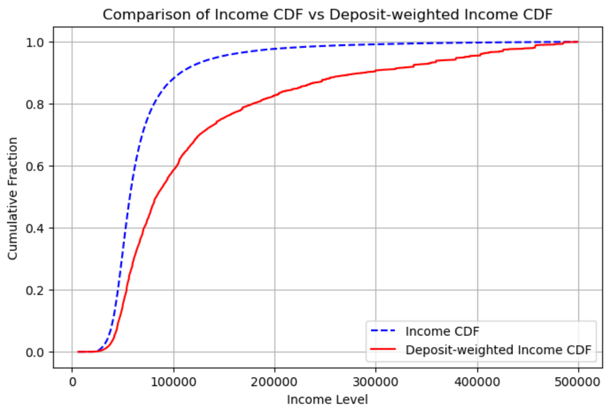
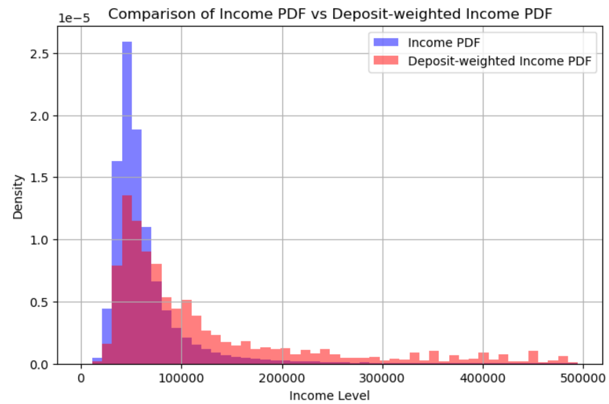


Figure A.3: Contribution of income groups to bank deposits

The figure reports the distribution of deposit-weighted household income for bank depositors. Data source is IXI.



Cumulative Distribution Function



Probability Density Function

Figure A.4: Relation between spread charged and elasticity of demand for deposits

The figure provides an illustration of the relation between price elasticity of demand for deposits and deposit spread.