How Do Banks Attract Deposits From Households?*

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Abstract

Banks do not compete only with one another; they also compete with capital markets for household savings. Using granular data covering nearly half of U.S. household financial assets, we show that banks offer higher deposit rates in markets where households exhibit greater equity participation, reflecting stronger outside-option pressure. A Salop-style model with endogenous risk-taking explains this behavior: higher household elasticity raises deposit rates, compresses margins, and induces banks to take more risk. Exploiting the 2017 Tax Cuts and Jobs Act for identification, we find that increased equity participation causally elevates deposit rates, raises bank risk, and reduces credit supply.

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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 a higher elasticity of substitution between deposits and other asset classes pay higher deposit rates. Despite paying higher rates, banks are unable to completely undo household preferences for other asset classes, thus receiving lower depository capital at these higher rates. Ultimately, to provide higher returns for deposits while maintaining returns for their own equity holders, banks take on higher risks in hopes of earning higher returns from their assets.

In recent years, the 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 consumer reporting agency that captures almost half of the financial holdings in the U.S., we are able to document that banks are also responsive to depositors' portfolio decisions.[3]

The intuition behind this result is straightforward: from the perspective of depositor households, the bank deposit market exists alongside 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 also 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 ability to document an empirical relation between household portfolio allocation decisions and bank deposit rates is due to access to a novel dataset that represents roughly 45 percent of all

[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, February 2025.

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

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

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. For the first time, this level of granularity enables an analysis of how banks compete for deposits, conditional on household balance sheets.

We begin by developing a parsimonious Salop-style model that jointly endogenizes deposit rates, deposit-market size, and bank risk-taking. In the model, banks compete for deposits from households, who can alternatively invest in an outside equity market. Higher deposit rates attract households away from equities, expanding the deposit base, while banks can raise their rates further by taking on greater lending risks. Risk-taking, however, is costly and interacts with market structure and household sensitivity to rates. The equilibrium links competition, portfolio choice, and risk-taking: banks facing more rate-sensitive households or fewer competitors take on greater risk and offer higher deposit rates, while tighter monetary policy reduces both. The framework, therefore, highlights how household portfolio elasticity shapes deposit competition and why deposit-rate pass-through to policy rates is incomplete when bank risk adjusts endogenously.

Next, we empirically document that household portfolio composition—specifically, local equity participation—is a central determinant of deposit pricing and monetary transmission. In cross-sectional and within-bank analyzes, banks consistently offer higher deposit rates in ZIP codes where households hold more equities, reflecting stronger competition from capital markets for household savings (Figure 1). The magnitude is economically meaningful: even within the same institution, a one-standard-deviation increase in local equity exposure is associated with roughly 20 basis points higher deposit spreads. Moreover, when the Fed funds rate increases, banks in high-equity-exposure markets exhibit a stronger pass-through to deposit rates. At the same time, such banks experience slower deposit growth following increases in the Fed funds rate. This is consistent with households having a choice to allocate to higher-yielding assets. Thus, equity-market competition complements traditional interbank competition in shaping deposit pricing and monetary-policy transmission.

To establish that the relationship between household equity holdings and bank behavior is causal, we employ two quasi-experimental approaches. First, propensity-score matching between ZIP codes with similar characteristics but differing equity exposure shows that higher equity participation systematically leads to higher deposit spreads across the distribution. Second, an instrumental-variable design leverages exogenous variation from the 2017 Tax Cuts and Jobs Act (TCJA), which lowered taxes on capital income and disproportionately boosted equity investment among higher-income households. ZIP codes that benefited more from TCJA tax savings experienced larger increases in equity ownership, which, in turn, caused banks in those markets to raise deposit rates. The IV estimates confirm a strong first stage and support the causal interpretation that increased household equity participation exerts upward pressure on deposit pricing.

The higher deposit rates paid by banks to compete with equity markets have important real consequences for bank behavior and credit supply. As banks pay more to attract deposits, their funding costs increase, leading to tighter margins and greater incentives to take risk. Consistent with the model's predictions, we find that higher local equity exposure is associated with higher market-implied probabilities of default for banks operating in those areas. On the asset side, we document that banks facing greater equity-market competition reduce lending: mortgage and small-business originations fall significantly following increases in local equity participation. These findings indicate that asset-market competition not only influences deposit pricing but also affects bank risk-taking and the transmission of monetary policy to the real economy through credit supply.

With the empirical facts established, we structurally estimate our stylized model of deposit competition with household portfolio choice using a Generalized Method of Moments (GMM) framework. The model links bank behavior (rates and risk) and household behavior (deposit participation) through closed-form equilibrium relationships that correspond directly to observable data moments. These include the average deposit spread, deposit-rate pass-through to the policy rate, equity participation rates and elasticities, market concentration, and average bank risk. The estimated parameters jointly capture banks' risk-return tradeoff, the marginal cost of risk-taking, household responsiveness to deposit rates, and the degree of banking competition and depositor stickiness. Using RateWatch–Call Report–CRA data, we compute empirical moments across both time-series and cross-sectional dimensions and estimate the parameters via nonlinear optimization, ensuring that each parameter class is locally identified by distinct moments.

The estimated model successfully replicates key empirical patterns in the data. The implied deposit-rate pass-through of roughly 0.55, deposit-market concentration near 0.39, and household equity participation around 50% align with observed values. The participation elasticity indicates that households reallocate approximately 1.6 percentage points of assets from equities to deposits for each 1 percentage point rise in deposit rates—consistent with empirical estimates in the household portfolio literature. Estimated risk parameters imply a realistic equilibrium risk level that matches the data and confirm that banks raise rates and increase risk-taking when household rate sensitivity or concentration increases. The implied differentiation cost and effective number of competitors reflect moderate competition and depositor stickiness, consistent with U.S. retail deposit markets.

We conduct counterfactual experiments in which we vary three estimated parameters — concentration, household elasticity, and product differentiation — to understand their nuanced effects on the equilibrium outcomes of deposit markets. Increasing concentration from 0.20 HHI to 0.50 lowers equilibrium deposit rates by over 5 percentage points and nearly doubles bank risk-taking. As banks can borrow cheaply due to lower competition among them, the marginal benefits of bank risk taking increase. Raising household elasticity from 0.5 to 2.5 has a similar effect on pricing, but this is a household demand side channel: in response to rate-sensitive households, banks raise deposit rates but also take on more risk as deposit margins compress. Finally, reducing product differentiation from 0.20 to 0.05 intensifies head-to-head competition, pushing deposit rates up by more than 6 percentage points and cutting risk roughly in half. Together, these counterfactuals demonstrate that the structure and substitutability of deposits on both the bank side and the household side critically govern pricing, risk-taking, and the strength of monetary transmission.

We further document how household heterogeneity shapes deposit elasticity and bank pricing. Using IRS–SOI data, we show that banks offer higher deposit rates in areas with a greater share of middle-income households—those most likely to participate in equity markets and switch between assets. This pattern of geographic rate dispersion is consistent with third-degree price discrimination, where banks tailor rates to local sensitivity. A ZIP-level "deposit sensitivity" index confirms that areas with higher estimated elasticity receive higher rates and exhibit stronger deposit growth responses to rate increases.

In summary, our analysis shows that modern deposit competition is shaped as much by households' portfolio choices as by traditional market structure. Banks do not merely compete with one another—they compete with capital markets for households' savings. The intensity of this competition depends on how readily depositors substitute between deposits and other asset classes, which, in turn, influences deposit pricing, risk-taking, and the transmission of monetary policy. By linking household portfolio elasticity to bank behavior in both theory and data, this paper provides a unified framework to better understand the competitive forces at play in modern deposit markets.

Eminent researchers have investigated the competition for deposits among banks, the 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) show 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 the 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, the growth of deposits from households declines, suggesting a substitution between these two asset markets. Bisetti and Sarkar (2025) show that banks offer lower deposit rates to lower-income consumers. The authors also hypothesize that observed lower deposit spreads may be a byproduct of differential participation in non-deposit assets along the income distribution. Melcangi and Sterk (2024) shows that as stock market participation increases, monetary policy transmission strengthens. d'Avernas et al. (2023) on the other hand, show that a large portion of the variation in deposit-pricing behavior between large and small banks reflects differences in preferences and technologies. In our paper, we also find evidence that banks face competition from other asset classes. We further contribute by focusing on the response of banks to attract deposits from households and the real outcome of banks given such competition.

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 bonds, and private bond markets in Europe, the 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-sized borrowers, as well as increase risk-taking by banks.

1 Deposit Competition with Portfolio Choice

We develop a parsimonious Salop-style model that jointly determines deposit rates, deposit-market size, and bank risk-taking. The framework isolates four empirically relevant features: (i) banks compete for deposits, (ii) households may allocate funds to an equity outside option, endogenously shrinking the deposit-market size, (iii) banks can increase lending risk to offer higher deposit rates and expand their deposit base, and (iv) the pass-through of deposit rates to the policy (fed funds) rate is dampened when risk adjusts endogenously.

1.1 Environment

A continuum of households with a total measure of one is uniformly distributed along a unit Salop (1979) circle. There are $N \geq 2$ symmetric banks positioned evenly on the circle. Each household can place one unit of savings either in a bank deposit or in a generic equity market outside option. Moving deposits across banks entails a linear "transport" cost $\tau > 0$, which can be interpreted broadly as physical or behavioral switching frictions: branch distance, relationship inertia, search costs, or technological stickiness. Banks compete in deposit rates $\{d_i\}$, taking τ and the aggregate deposit market size as given in Section 1.2 that describes equilibrium with exogenous risk-taking by banks.

A fraction φ of households is *equity-active* and invests directly in the external equity market. The remaining fraction $(1-\varphi)$ participates in deposit competition among banks. We allow φ to depend endogenously on the attractiveness of the equity market relative to deposits. Specifically, the participation share depends linearly on the average deposit rate $\bar{d}$ relative to an exogenous equity appeal R_e:

$$\varphi(\bar{d}) = \varphi_0 + \eta\,(R_e - \bar{d}), \qquad \eta \geq 0,$$

so that the total deposit-market size is

$$M(\bar{d}) = 1 - \varphi(\bar{d}) = A + \eta\bar{d}, \qquad A := 1 - \varphi_0 - \eta R_e.$$

Hence, higher deposit rates reduce equity participation and increase the size of the deposit market. In equilibrium, both $\bar{d}$ and $M(\bar{d})$ are endogenously determined. We impose truncation of M to $[0,1]$ in numerical simulations.

Banks invest deposits in risky loans that yield a gross return $R(q) = R_0 + bq$ and default with a probability of $\pi(q) = aq$, where $a, b > 0$ and $q \geq 0$ index the *risk intensity* of the portfolio. The parameter b measures the incremental return per unit of risk, and a scales the probability of default. The baseline safe return is $R_0 = r_f + \mu$, with r_f as the policy (fed funds) rate and μ as a constant loan spread.

Taking risks entail a convex cost $K(q) = \frac{\kappa}{2}q^2$ with $\kappa > 0$, representing capital requirements, monitoring costs, or regulatory constraints. We abstract from franchise-value losses in this simplified framework.

1.2 Deposit-rate competition given exogenous risk level

Consider the deposit-market subgame holding risk q fixed. A household located at an arc distance x from bank i obtains utility $u_i = d_i - \tau \times \text{distance}(x, i)$ if depositing with bank i. Standard Salop geometry implies that, in a symmetric equilibrium, each bank faces a linear demand schedule and sets its rate such that the per-unit funding margin equals the business-stealing wedge:

$$m \equiv (1-\pi)R(q) - d = \frac{2\tau}{N} \quad \Longrightarrow \quad d(q) = (1-aq)\big(R_0 + bq\big) - \frac{2\tau}{N}. \tag{1}$$

This condition states that banks pass part of their asset returns $(1-\pi)R(q)$ through to depositors, net of the competition-induced margin $\frac{2\tau}{N}$. The margin declines with more competitors (N) or lower switching costs (τ).

1.3 Equilibrium with endogenous risk

In Section 1.2, each bank chooses risk q, anticipating how it affects both deposit rates and the deposit-market size. Under symmetry, each bank serves a deposit mass of $D_i = M(d)/N$. The term $S := \frac{2\tau}{N^2}$ summarizes local market power, which is the effective franchise value per unit deposit.

Thus, the expected profits are:

$$\Pi(q) = \underbrace{\frac{M(d(q))}{N} \cdot \frac{2\tau}{N}}_{\text{deposit franchise from competition}} - \frac{\kappa}{2} q^2 = S\left[A + \eta d(q)\right] - \frac{\kappa}{2} q^2.$$

The first term represents the effective "franchise rent" from holding deposits, proportional to market size and local market power. Substituting (1),

$$d(q) = R_0 - \frac{2\tau}{N} + q(b - aR_0) - abq^2,$$

implies $\Pi(q)$ is a concave quadratic in q. The first-order condition gives a unique interior optimum:

$$q^* = \frac{\eta S\,(b - aR_0)}{2\eta S ab + \kappa}. \tag{2}$$

Intuitively, banks increase risk (q^*) when the marginal benefit of attracting more deposits (through a higher rate d) outweighs the marginal cost of risk.

Equilibrium deposit rates and aggregate deposits are then

$$d^* = R_0 - \frac{2\tau}{N} + q^*(b - aR_0) - ab(q^*)^2, \qquad D = A + \eta d^*. \tag{3}$$

Thus, both equilibrium rates and market size depend jointly on competition, stickiness, and the responsiveness of households to deposit yields.

Equation (2) shows that banks take more risk when households are more rate-sensitive (higher η), when competition is less intense (lower N increases S), or when the risk–return tradeoff b/a is favorable. In turn, (3) implies that equilibrium deposit rates increase with η and b but decline with greater competition (higher N) or stickiness (higher τ).

Proposition 1 (Comparative statics). *Assume $b > aR_0$ and an interior solution. Then:*

1. **Equity competition:** $\dfrac{\partial q^*}{\partial \eta} > 0$ and $\dfrac{\partial d^*}{\partial \eta} > 0$. Greater sensitivity of households to rates induces banks to take more risk and offer higher deposit rates.

2. **Bank competition:** $\dfrac{\partial q^*}{\partial N} < 0$, since more competitors reduce the effective franchise wedge $S = \frac{2\tau}{N^2}$.

3. **Technology and costs:** $\dfrac{\partial q^*}{\partial b} > 0$, $\dfrac{\partial q^*}{\partial a} < 0$, and $\dfrac{\partial q^*}{\partial \kappa} < 0$. A higher return-to-risk slope b raises incentives for risk taking, while greater default sensitivity a or risk cost κ dampens it.

4. **Stickiness:** $\dfrac{\partial d^*}{\partial \tau}$ combines a direct negative effect $(-2/N)$ and an indirect effect via q^*, yielding an ambiguous total sign a priori.

All proofs are by differentiating (2) and (3) (see Appendix).

1.4 Fed funds pass-through

The baseline loan return is $R_0 = r_f + \mu$, where r_f is the policy rate. Differentiating (2) yields

$$\frac{\partial q^*}{\partial r_f} = -\frac{\eta a S}{2\eta S a b + \kappa} < 0,$$

so a higher policy rate reduces banks' risk-taking incentives. The total pass-through of deposit rates to the policy rate is

$$\frac{\partial d^*}{\partial r_f} = 1 - a q^* + (b - a R_0 - 2ab q^*) \frac{\partial q^*}{\partial r_f},$$

which is strictly less than one. Thus, when risk adjusts endogenously, changes in the policy rate are only partially transmitted to deposit rates. Moreover, stronger competition from asset markets (higher η) amplifies this dampening effect because $\partial q^*/\partial r_f$ becomes more negative. Intuitively, when policy rates rise, banks' risk incentives fall, so the deposit rate responds less than one-for-one—mirroring the incomplete pass-through observed in the data.

Together, equations (2)–(3) generate the comparative statics that guide our empirical tests. A higher elasticity of household portfolio choice (η) amplifies deposit-rate competition and bank risk-taking, while stronger interbank competition (higher N) and tighter monetary policy (higher r_f) attenuate both.

2 Data and Empirical Strategy

This section describes the data sources, variable construction, and empirical design used to test the predictions of the model. The analysis combines household portfolio information with branch-level deposit rates, bank balance sheets, and lending outcomes to map the model's comparative statics onto observable behavior.

2.1 Data Sources

We assemble our panel dataset at the bank-ZIP-quarter level from four main sources. We obtain anonymized consumer data covering roughly 45% of U.S. household financial assets at the ZIP+4 level (2014–2024) from one of the three nationwide consumer reporting agencies. The data provide balances across checking, savings, brokerage, retirement, and investment accounts. Thus, the data allow us to compute each ZIP's *equity share*: the ratio of equity and mutual-fund holdings to total financial assets.

For deposit rates, RateWatch provides branch-level offered rates for standardized 12-month CDs ($10,000 minimum). We link each bank branch to its ZIP code through the FDIC Summary of Deposits (SOD), yielding quarterly measures of local deposit rates.

We obtain bank balance sheets and risk-taking data from Call Reports. Call Reports and Y-9C filings supply loan yields, risk-weighted assets, and market-implied default probabilities (PD) following Nagel and Purnanandam (2019). We merge these data with bank-level Summary of Deposits (SOD) shares to obtain ZIP-level exposure to higher-risk banks.

To obtain data on lending activity, we utilize data available through the Community Reinvestment Act (CRA) and the Home Mortgage Disclosure Act (HMDA). These laws require the Federal government to provide mortgage and small-business lending volumes at the ZIP-bank-year level, enabling the measurement of how funding competition affects credit supply.

All datasets are harmonized to a consistent panel structure at the bank-ZIP and ZIP levels. Variables originally reported at different frequencies (semi-annual or annual) are aligned to the appropriate time grid for analysis. Real-effects variables (mortgage and small-business lending) are maintained in a separate county-level dataset and analyzed independently. Additional details on data sources are provided in the appendix.

2.2 Summary Statistics

The asset composition data are only available at the ZIP code level, which does not allow for a direct link with bank-level data. To enable meaningful analysis, we transformed the bank-level data to the ZIP code level, allowing for geographic alignment. We use SOD to identify the zip code of each bank branch. For each zipcode, we calculated the weighted average of deposit rates and PD, using the deposit amounts for each bank branch as weights.

The descriptive statistics of the ZIP code-level panel are presented in Table 1. Panel A shows household asset allocation. On average, 47.7% of financial assets are allocated to equity, which includes retirement accounts, mutual funds, and direct investment in stocks. Households allocate approximately 30.3% to deposits and cash. Panel B reports deposit rate spreads relative to the federal funds rate for the two standardized products. The 12-month CD (12MCD10K) has an average spread of –0.909 percentage points, and the money market account (MM25K) has an average spread of –1.212 percentage points. Our definition of deposit rate spread is opposite to the spread in Drechsler et al. (2017), because we want to make an intuitive argument about 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.

In Panel C, we present statistics for control variables related to deposit insurance, bank size, and regional competition. These variables originate at the bank level and are allocated to ZIP codes by weighting each bank's characteristics by its local deposit share, producing ZIP-level measures consistent with the rest of the dataset. Panel D reports real-impact variables, including dollar amounts and counts for both mortgage and small-business origination, which are at the bank-county-year level. Lastly, the PD is measured at the bank level and similarly allocated to ZIP codes using deposit-share weights.

2.3 Empirical Design and Identification

We estimate a unified set of empirical models corresponding to the main comparative statics in the theoretical framework. The regressions exploit both cross-sectional and temporal variation in household portfolio composition, using within-bank, across-location comparisons and exogenous shocks to household equity participation as sources of identification.

Our first specification examines how deposit rates vary with the equity exposure of local households:

$$d_{b,z,t} = \alpha_{bz} + \beta_e \, e_{z,t} + \mathbf{X}'_{b,z,t}\beta_x + \lambda_t + \varepsilon_{b,z,t}. \tag{4}$$

where d_{bzt} is the deposit rate offered by bank b in ZIP z and quarter t, α_{bz} are bank–ZIP fixed effects, λ_t are time effects, and X_{bzt} includes controls for concentration, bank size, and funding mix. The coefficient β_e captures how deposit rates differ across locations with varying degrees of household equity participation, holding bank identity and national conditions constant. A positive value of β_e would indicate that banks offer higher rates in equity-heavy areas, consistent with stronger asset-market competition.

To study how household elasticity shapes the transmission of monetary policy, in addition to the interaction between bank concentration HHI and the fed funds rate ΔFF (Drechsler et al., 2017), we estimate a specification that interacts equity exposure with changes in the federal funds rate:

$$\Delta y_{b,z,t} = \beta_1 \cdot (\mathrm{HHI}_{z,t} \times \Delta \mathrm{FF}_t) + \beta_2 \cdot (e_{z,t} \times \Delta \mathrm{FF}_t) + \gamma_{b\times t} + \alpha_z + \lambda_t + \varepsilon_{b,z,t}, \tag{5}$$

where y represents deposit rates and deposits for bank b in ZIP z. A positive β_2 implies stronger policy-rate pass-through in more equity-exposed markets, consistent with banks responding more aggressively to retain rate-sensitive depositors when households have higher η in the model.

Finally, we assess how asset-market competition affects banks' risk-taking and lending. Bank default risk is at the ZIP z-time t level. Lending outcomes are at the bank b, county c, and time t level. The following equations relate bank default risk and credit supply to funding costs and local equity exposure:

$$PD_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \lambda_t + \varepsilon_{z,t}, \tag{6}$$

$$Lending_{b,c,t} = \beta_e \, e_{b,t-1} + \beta_h \, \text{Herfindahl Index}_{b,t-1} + \alpha_b + \gamma_c + \lambda_t + \alpha_{b\times c} + \gamma_{c\times t} + \varepsilon_{b,c,t}. \tag{7}$$

Higher equity exposure or higher funding costs are expected to increase risk-taking and reduce credit supply, in line with the model's prediction that $\partial q^*/\partial \eta > 0$.

Identification relies on both the within-bank research design and quasi-experimental variation in household equity participation. The within-bank specification absorbs time-invariant characteristics of each institution and common shocks to policy rates, isolating cross-sectional differences in local household portfolios. To address residual endogeneity, we use two complementary approaches. First, we use propensity score matching to compare ZIP codes that are similar across observable characteristics such as income, demographics, and banking environment but differ in equity exposure. This ensures the ZIP codes with different equity exposure are otherwise comparable, isolating the effect of equity holdings on deposit rates. Second, we exploit the 2017 Tax Cuts and Jobs Act (TCJA) as an instrumental variable. The reform lowered taxes on capital gains and dividends, creating differential incentives for equity investment across ZIP codes based on pre-existing income distributions. This provides an exogenous instrument for household equity participation that is independent of local banking conditions. ZIP codes that benefited more from TCJA tax savings experienced larger increases in equity ownership, which in turn caused banks to raise deposit rates.

Each regression maps directly to a prediction from the theoretical model. Equation (4) tests whether deposit rates rise with household elasticity, corresponding to $\partial d^*/\partial \eta > 0$. Equation (5) examines incomplete and heterogeneous policy-rate pass-through, $\partial d^*/\partial r_f < 1$, which should be amplified where η is larger. Equations (6)–(7) test whether stronger asset-market competition increases risk-taking and contracts lending. Together, these empirical designs form the core of the paper's evidence linking household portfolio elasticity to deposit pricing, monetary transmission, and bank risk-taking.

3 Empirical Results

This section shows that household portfolio composition is a first-order determinant of bank deposit pricing and that banks adjust both rates and behavior in response to asset-market competition. We move from cross-sectional evidence to policy-rate pass-through, then to income-based heterogeneity and a ZIP-level sensitivity index, and finally to causal designs and real effects.

3.1 Deposit Rates and Household Equity Share

Households allocate savings between deposits and capital markets. Where households hold a larger equity share, banks face stronger outside-option competition and offer higher deposit rates to defend balances.[4] In our data, households allocate nearly half of their financial assets to equities (Table 1).

Panel A of Figure 1 plots deposit rates (12-month \$10,000 CDs from RateWatch) against the ZIP-level equity share (equities and mutual funds over total financial assets), controlling for ZIP and semiannual fixed effects.[5] The slope is positive, aligning with our premise that banks offer higher deposit rates when they face more competition for deposits. Next, we estimate the ZIP–time regression

$$d_{z,t} = \beta_e e_{z,t} + \mathbf{X}'_{z,t}\beta_x + \alpha_z + \lambda_t + \varepsilon_{z,t}, \tag{8}$$

where $d_{z,t}$ is the deposit-weighted average CD rate, $e_{z,t}$ is the local equity share, and $\mathbf{X}_{z,t}$ includes the HHI, the insured-deposit share, and representative-bank size. In Table 2, a one standard deviation (11.8 pp) increase in $e_{z,t}$ is associated with 0.31 basis points (bps) higher deposit rates (col. 4).

[4] Large institutions can partially source funds from other geographies (Gilje et al., 2016), but contracting and information frictions limit full integration (Gilje et al., 2016).

[5] Deposit rates are quarterly for part of the sample; we aggregate to semiannual.

For comparison, a one standard deviation (SD) decrease in competition (HHI increasing by 0.074) corresponds to 0.50 basis points (bps) higher rates, implying that asset-market competition exceeds half the magnitude of interbank competition. Insured-deposit share and bank size are negatively related to the offered rates.

To rule out bank-level heterogeneity, we exploit within-bank geography and estimate the following bank geography-time level specification:

$$d_{b,z,t} = \beta_e e_{z,t} + \mathbf{X}'_{b,z,t}\boldsymbol{\beta}_x + \gamma_b + \alpha_z + \lambda_t + \varepsilon_{b,z,t} \tag{4}$$

Columns (5)–(8) of Table 2 show positive, significant coefficients: branches of the same institution pay more in more equity-exposed ZIPs. The most saturated model (col. 8) implies that a one standard deviation increase in the equity share (0.174) is associated with a 21 bps higher deposit spread.

Overall, the cross-sectional evidence in this section shows that even the same bank offers higher deposit rates in areas with greater household equity ownership.

3.2 Policy-Rate Pass-Through and Equity Exposure

In this section, we examine how competition from equity markets shapes the transmission of monetary policy through banks. When the federal funds rate rises, households with greater equity exposure have more attractive investment alternatives, increasing the pressure on banks to adjust deposit rates. We test whether this external competition leads to stronger deposit rate pass-through and whether it also translates into slower deposit growth as funds reallocate toward higher-yielding assets.

We test whether equity exposure amplifies monetary-policy transmission. Our most exhaustive within-bank specification is as follows:

$$\Delta y_{b,z,t} = \beta_1 \cdot (\mathrm{HHI}_{z,t} \times \Delta \mathrm{FF}_t) + \beta_2 \cdot (e_{z,t} \times \Delta \mathrm{FF}_t) + \gamma_{b\times t} + \alpha_z + \lambda_t + \varepsilon_{b,z,t}, \tag{5}$$

where ΔFF_t is the change in the effective federal funds rate. Bank $\times$ Time fixed effects are included so the identification comes from within-bank variation across ZIP code markets in the same period.

Columns (1)–(3) of Table 3 report estimates using the Δ deposit rate spread as the dependent variable, measured on a bank–ZIP–semiannual panel. Positive and significant coefficients β_2 show that pass through is larger in regions with higher equity market competition. Columns (4)–(6) of Table 3 repeat the analysis using the Δ log(Deposits$_{z,t}$) as the dependent variable on a bank–ZIP–annual panel. The negative and significant coefficients on β_2 indicate that banks in high equity exposure markets experience slower deposit growth following increases in the federal funds rate.

The term $HHI_{z,t} \times \Delta FFt$ is included following Drechsler et al. (2017), who argue that markets with greater banking competition (lower HHIz,t) exhibit stronger monetary-policy pass-through. Consistent with this, the negative β_1 coefficients in Columns (1)–(3) indicate that in regions with higher banking competition, deposit rates adjust more strongly to changes in the federal funds rate. Conversely, the positive β_1 coefficients in Columns (4)–(6) suggest that these competitive regions experience slower deposit growth, consistent with higher deposit outflows during periods of monetary tightening.

Overall, equity market competition significantly amplifies both deposit rate pass-through and deposit outflows at the ZIP-code level within the same bank when the federal funds rate changes. These effects complement the traditional channel identified by Drechsler et al. (2017), where local banking competition influences how banks adjust rates and manage funding in response to policy shifts.

3.3 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 three different approaches to establish that higher equity holdings cause banks to respond with higher interest rates to attract deposits.

3.3.1 Matching

A potential concern is that both deposit spreads and household equity holdings are jointly driven by common local factors. To address this concern, we implement a matching framework adapted from the treatment-effect methodology. The goal is to compare ZIP codes that are similar along observable dimensions but different in equity holding exposure, allowing us to isolate the effect of equity holdings on deposit spreads.

Because our data is a continuous ZIP code semi-annual panel rather than a discrete treatment setting, we impose a quasi-experimental structure by self-defining treated and control status within each semi-annual period. Specifically, for each semiannual period, we sort ZIP codes into quintiles by household equity share. The top quintile (with highest equity exposure) is defined as the treated group and the bottom quintile defined as control group. Propensity score matching is then performed between the treated and control groups to ensure that compared ZIP codes are otherwise similar along observable dimensions. The propensity score is estimated from a logistic regression of the treatment indicator on covariates, including: median household income, median age, unemployment rate, poverty rate, log total population, and income inequality (Gini index), as well as local banking environment controls including bank size (log assets), market concentration (Herfindahl Index), and insured-deposit share at ZIP code level measured as deposit weighted average. The resulting propensity score represents the predicted probability that a ZIP code belongs to the treated group given its observable characteristics. To improve match quality, we impose a caliper of 0.1, restricting matches to pairs whose estimated propensity scores differ by no more than 0.1.

We implement three K-nearest-neighbor (KNN) matching specifications based on propensity scores: (i) one-nearest-neighbor without replacement, (ii) one-nearest-neighbor with replacement, and (iii) three-nearest-neighbor with replacement.

Figure A.1 illustrates the propensity score distributions for treated and control ZIP codes before and after matching. The pre-matching differences between the top and bottom quintiles highlight the need of controlling for observable characteristics. After matching, the covariate distributions of treated and control ZIP codes become closely aligned, making sure the treated and control are otherwise similar other than equity share.

We then estimate a simple regression of deposit spread on the treatment indicator, including matching–pair fixed effects to compare outcomes within each matched pair. This specification isolates the average treatment effect on the treated while holding constant all characteristics used in matching. Table 4 column (1) shows the treatment effect between the top and bottom quintiles of equity exposure. The effect is positive and statistically significant across all matching specifications, indicating that ZIP codes with higher equity exposure experience higher deposit spreads after accounting for observable characteristics.

To examine the effect across the full distribution, we extend the design by conducting pairwise matching between adjacent quintiles (bin 2 vs. 1, 3 vs. 2, etc.), producing four matched contrasts. Each contrast compares ZIP codes that are nearly identical in observed characteristics but differ marginally in equity exposure. This stepwise approach tests whether incremental increases in equity participation are systematically associated with differences in deposit spreads after accounting for local heterogeneity. Columns (2) – (5) of Table 4 report these pairwise treatment effects. The estimated coefficients remain positive and statistically significant across all comparisons and matching specifications, confirming that higher equity exposure is consistently associated with higher deposit spreads throughout the distribution, not only between the extremes.

To interpret the economic magnitude, Panel A column (2) of Table 4 compares ZIP codes in the second and first quintiles of household equity exposure. The average equity share rises from 0.32 to 0.46, a difference of 0.14. With an estimated coefficient of 0.015, this contrast implies about 0.21 basis-point higher deposit rates. For comparison, the baseline regression finds that a one–standard–deviation (0.118) increase in equity exposure raises deposit rates by 0.31 basis points. The smaller magnitude reflects that the matching estimate captures a narrower, more local contrast between adjacent quintiles.

3.3.2 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.[6] 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 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

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

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 2021, the pre-treatment period (2014–2017) is assigned an IV value of zero. In the post-treatment period (2018–2021), 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 2021 has a mean of 1.2% and standard deviation of 0.3%

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 2 shows the binscatter plot of the first stage for 2018 to 2021, 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:

$$
\begin{aligned}
e_{z,t} &= \beta_\tau \,\text{Tax Savings}_{z,t} + \sum_i \beta_{x,i}\,\mathbb{X}_{z,t,i} + \gamma_z + \varepsilon_{z,t} \\
d_{z,t} &= \beta'_e \hat{e}_{z,t} + \sum_i \beta'_{x,i}\,\mathbb{X}_{z,t,i} + \gamma'_z + \eta_t + \varepsilon'_{z,t} \qquad (9)
\end{aligned}
$$

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 5 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. 9 is under-identified. The diagnostic statistics also satisfy the weak identification test.[7]

3.4 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.

3.4.1 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 (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

[7] 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.

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 B.

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:

$$PD_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \eta_t + \varepsilon_{z,t} \tag{6}$$

where $e_{z,t}$ denotes the average household equity holdings as a share 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 6. 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.

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.

3.4.2 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 of county-level equity holdings using the relative county-level deposit amounts as weights.

We estimate the following specification :

$$Lending_{b,c,t} = \beta_e \, e_{b,t-1} + \beta_h \, \text{Herfindahl Index}_{b,t-1} + \alpha_b + \gamma_c + \lambda_t + \alpha_{b\times c} + \gamma_{c\times t} + \varepsilon_{b,c,t} \quad (7)$$

where $Lending_{b,c,t}$ 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 share, and $\text{Herfindahl Index}_{b,t-1}$ 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 that banks face similar local lending opportunities.

The regression results are presented in Table 7. Columns (1) and (3) examine the log of new loan amounts originated for mortgage and small business lending, respectively. Columns (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), a one standard deviation increase in household equity holdings (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.

4 Estimation and Additional Discussion

4.1 Estimation Details

4.1.1 Mapping between data moments and model parameters.

The model provides closed-form expressions for equilibrium outcomes that map directly to observable quantities in the data. This mapping allows us to estimate the structural parameters

$$\theta = \{a, b, \kappa, \eta, \varphi_0, N, \tau\},$$

which respectively capture (i) the sensitivity of default probability and returns to risk-taking (a, b), (ii) the marginal cost of risk κ, (iii) the responsiveness of household equity participation (η, φ_0), and (iv) the structure of deposit-market competition (N, τ). The baseline loan spread μ is externally calibrated to -0.005. The small negative spread (μ) captures the cost of loan processing fees that banks must pay even for safe loans.

Each equilibrium condition in the model yields an analytical counterpart (Table 8) to an empirical moment, providing a direct bridge between theory and estimation. The key empirical moments are the average deposit spread $\mathbb{E}[d - r_f]$, policy-rate pass through $\frac{\partial d^*}{\partial r_f}$, equity participation, and elasticity of participation with respect to deposit rates, market concentration, and average bank risk-taking behavior. More details regarding the mapping between empirical moments and model parameters are in Appendix B.6.

Collectively, these moments form an exactly identified system that ties the theoretical structure to the data. In equilibrium, the moments link bank behavior (rates and risk) to household behavior (deposit participation), yielding a transparent structure for method-of-moments calibration. We estimate θ via a Generalized Method of Moments (GMM) procedure.

4.1.2 Identification and Empirical implementation

Each parameter class affects distinct moments, ensuring local identification: (i) (a, b, κ) affects risk and pass-through elasticities; (ii) (η, φ_0) affect equity participation levels and slopes; (iii) (N, τ) affects deposit spreads and market-structure variation; and (iv) μ shifts average levels of asset returns. Since the number of moments matches the number of parameters, the model is exactly-identified.

Empirical moments are computed from the merged RateWatch–Call Report–CRA dataset. For time-series moments (deposit rate pass-through), we estimate rolling regressions of bank-level deposit rates on the effective fed funds rate. For cross-sectional moments (equity participation, risk, and concentration), we take five-year averages to mitigate transitory variation. We evaluate the GMM objective on a discretized grid of starting values and refine it using nonlinear Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization with multiple random restarts to ensure convergence.

4.2 Estimation Results

Table 8 reports the parameters estimated from the GMM calibration of the Salop-style deposit competition model with equity-market interaction. The model is identified using seven moments: the mean deposit spread, the pass-through of deposit rates to the policy rate, the average household equity-participation rate, the Herfindahl index of deposit market concentration, the mean level of bank risk taking, and two additional higher-order moments capturing the covariance of deposit rates with the risk free rate and the variance of deposit rates (Panel B). The estimation converges with an objective value of 0.315, and all equilibrium conditions are satisfied.

The model reproduces the key empirical relationships well. The model-implied mean deposit spread (-0.0006) is modestly less negative than its empirical counterpart (-0.0075), while the equilibrium pass-through of deposit rates to the policy rate (0.55) exceeds but remains close to the empirical target (0.39). The predicted average household equity participation (0.500) and deposit-market concentration ($HHI = 0.395$) nearly match the data, and the implied average risk taking (0.342) lies within a realistic range around the empirical mean of 0.209. Variance and covariance moments of deposit rates are of the same order of magnitude as observed, confirming that the model generates the correct scale of rate volatility.

The estimated structural coefficients are economically intuitive. A participation elasticity of $\eta = 1.57$ indicates that households reallocate approximately 1.6 percentage points of portfolio share from equities to deposits when deposit rates rise by one percentage point. This confirms that portfolio rebalancing across asset classes is an active margin in equilibrium, though somewhat less pronounced than in the higher-elasticity baseline. The estimate falls well within the range of empirical elasticities reported in the literature. The household portfolio choice literature (e.g., Vissing-Jørgensen, 2002; Calvet et al., 2009; Egan et al., 2017) finds that the responsiveness of equity participation to expected returns is 2–4 pp. for every 1 pp. change in returns. In the deposit competition literature as well, Drechsler et al. (2021) finds that the deposit elasticity to policy rates or spreads typically lies within 1–3.

A household risk-sensitivity coefficient of $a = 1.81$ implies that depositors penalize banks for risk exposure. Together with a return-to-risk coefficient $b = 1.32$, banks face a meaningful but not excessive risk–return trade-off: increasing risk raises expected returns but also increases funding costs as households demand higher deposit rates. The estimated curvature parameter $\kappa = 0.21$ limits extreme risk taking and delivers an equilibrium risk level of $q^* = 0.189$, corresponding to a default-probability proxy level of roughly 0.34 in the data. The implied pass-through of 0.55 reflects the interplay between this risk-feedback channel and the moderating influence of household competition from equity markets.

The differentiation cost ($\tau = 0.20$) and implied effective number of competitors ($N \approx 2.53$) suggest moderate product differentiation among banks, consistent with a Herfindahl index of 0.39 in the data. The baseline depositor share ($\phi_0 = 0.286$) represents a sticky core of rate-insensitive depositors, implying that roughly 29% of deposits remain stable regardless of rate movements.

Overall, the estimated parameters capture the joint determination of deposit pricing, bank risk taking, and household portfolio reallocation. The model achieves partial pass-through, realistic risk levels, and market concentration patterns consistent with the data, validating its usefulness for studying how competition from equity markets shapes banks' pricing and risk behavior.

4.3 Counterfactual Experiments

Table 9 reports the results of some counterfactual experiments. It provides equilibrium outcomes for deposit rates d^*, bank risk-taking q^*, deposit shares D^*, and monetary pass-through across all scenarios. Panel A reports equilibrium outcomes as we change market concentration in the model. As bank concentration increases from 0.20 to 0.50, the equilibrium deposit rate (net of the fed funds rate) falls from $d^* = 3.2\%$ to $d^* = -2.36\%$. This nearly 5.6-percentage-point decline reflects the substantial increase in banks' marginal market power. The elasticity of the deposit rate with respect to HHI is roughly -0.27.[8] Risk-taking also increases as bank concentration increases. As bank deposits become cheaper, the marginal incentive for banks to take on more asset risk rises. Deposit shares exhibit a large response as well. D^* falls from 53.7pp. at HHI $= 0.20$ to 44.53 pp.

[8] We use HHI $= 0.30$ ($d^* = 0.030584$) and HHI $= 0.50$ ($d^* = -0.023651$). This yields $\frac{-0.023651-0.030584}{0.50-0.30} = -0.054235/0.20 \approx -0.27$.

at HHI = 0.50. As banks offer lower rates, the amount of deposits in the banking system declines. Using HHI at 0.3, as HHI increases by 20 pp. deposit share of household assets declines by 8.92 pp., yielding an elasticity of -0.45. Pass-through rates also decline significantly as concentration rises in Panel A. Overall, these patterns highlight how increases in concentration weaken deposit competition, encourage risk-taking as a substitute for rate competition, and reduce the sensitivity of deposit rates to policy.

As the elasticity of substitution η increases, households become more sensitive to the spread between equity returns and deposit rates. Banks respond by raising deposit rates but also by taking on more risk because stronger competition compresses deposit margins. In Panel B of Table 9, the equilibrium deposit rate d^* rises from -0.53 pp. at $\eta = 1$ to 1.77 pp. at $\eta = 2.5$. Risk-taking by banks increases by approximately 50% across the same range. As households exhibit higher willingness to substitute across asset classes, deposit shares fall from 63 pp. to 40 pp. and pass-through declines from 0.68 to 0.53, yielding an elasticity close to -0.040. These movements quantify the mechanism by which higher household elasticity intensifies rate competition, reduces deposit margins, and thereby increases banks' incentives to take risk.

As more fintech institutions compete with banks and introduce more and more similar products, product differentiation in the banking sector will decline. Thus, product differentiation parameter τ produces patterns similar to those observed for HHI, as both change the effective substitutability across banks. Panel (C) shows that lowering τ from 0.20 to 0.05 increases the deposit rate from 0.98 pp. to 7.13 pp. and reduces risk-taking from 0.180 to 0.0927. Deposit shares fall from 0.60 pp. to 50 pp., reflecting heightened competition and the pass-through decline from 0.71 to 0.55. Together, these effects show how lower differentiation intensifies price competition and strengthens the transmission of monetary policy.

Taken together, the counterfactual experiments help us understand the economic mechanisms at play. The results show that market structure and household finance jointly determine the strength of deposit-market competition and the effectiveness of monetary-policy transmission.

5 Conclusion

This paper shows that modern deposit competition is shaped not only by market structure among banks but also by the portfolio choices of households. Using granular data on household financial positions, we document that banks systematically pay higher deposit rates in markets where households hold more equities, reflecting stronger competition from outside asset classes. Despite offering higher rates, banks are unable to offset households' preferences for equities, resulting in smaller deposit bases at higher funding costs. The Salop-style model with endogenous risk-taking provides a coherent interpretation of these patterns: greater household elasticity compresses deposit margins, induces banks to raise rates, and increases their incentives to take risk.

The empirical analysis further shows that this asset-market competition has meaningful implications for monetary transmission and real economic activity. Banks operating in high-equity-exposure markets exhibit stronger deposit-rate pass-through, greater balance-sheet risk, and reduced mortgage and small-business lending. A causal shock to equity participation from the 2017 TCJA confirms that increases in households' outside options lead banks to adjust both pricing and risk-taking. Together, these findings underscore that the interaction between household portfolio allocation and bank competition plays a central role in shaping deposit pricing, bank behavior, and the availability of credit in the economy.

References

Allen, F., Carletti, E., and Gu, X. (2008). The roles of banks in financial systems. *The Oxford handbook of banking*, 3:39–61.

Becker, B. and Ivashina, V. (2014). Cyclicality of credit supply: Firm level evidence. *Journal of Monetary Economics*, 62:76–93.

Bernanke, B. and Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. *American Economic Review*, 79(1):14–31.

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). Chapter 21 The financial accelerator in a quantitative business cycle framework. In *Handbook of Macroeconomics*, volume 1, pages 1341–1393. Elsevier.

Bisetti, E. and Sarkar, A. (2025). Poverty spreads in deposit markets. National University of Singapore and HKUST Working Paper.

Calvet, L. E., Campbell, J. Y., and Sodini, P. (2009). Measuring the financial sophistication of households. *American Economic Review*, 99(2):393–98.

Carletti, E., Leonello, A., and Marquez, R. (2024). Market power in banking. *Annual Review of Financial Economics*, 16(Volume 16, 2024):233–251.

Chodorow-Reich, G., Smith, M., Zidar, O. M., and Zwick, E. (2024). Tax policy and investment in a global economy. Working Paper 32180, National Bureau of Economic Research.

d'Avernas, A., Eisfeldt, A. L., Huang, C., Stanton, R., and Wallace, N. (2023). The deposit business at large vs. small banks. Working Paper 31865, National Bureau of Economic Research.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The Deposits Channel of Monetary Policy. *Quarterly Journal of Economics*, 132(4):1819–1876.

Drechsler, I., Savov, A., and Schnabl, P. (2021). Banking on deposits: Maturity transformation without interest rate risk. *Journal of Finance*, 76(3):1091–1143.

Egan, M., Hortaçsu, A., and Matvos, G. (2017). Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review*, 107(1):169–216.

Gilje, E. P., Loutskina, E., and Strahan, P. E. (2016). Exporting liquidity: Branch banking and financial integration. *Journal of Finance*, 71(3):1159–1184.

Holmstrom, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, 112(3):663–691.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2):211–248.

Li, L., Loutskina, E., and Strahan, P. E. (2023). Deposit market power, funding stability and long-term credit. *Journal of Monetary Economics*, 138(C):14–30.

Lin, L. (2019). Bank deposits and the stock market. *Review of Financial Studies*, 33(6):2622–2658.

Melcangi, D. and Sterk, V. (2024). Stock market participation, inequality, and monetary policy. *The Review of Economic Studies*, 92(4):2656–2690.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2):449–470.

Nagel, S. and Purnanandam, A. (2019). Banks' risk dynamics and distance to default. *Review of Financial Studies*, 33(6):2421–2467.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, 49(1):3–37.

Salop, S. C. (1979). Monopolistic competition with outside goods. *The Bell Journal of Economics*, 10(1):141–156.

Vissing-Jørgensen, A. (2002). Limited asset market participation and the elasticity of intertemporal substitution. *Journal of Political Economy*, 110(4):825–853.

Wang, Y., Whited, T. M., Wu, Y., and Xiao, K. (2022). Bank market power and monetary policy transmission: Evidence from a structural estimation. *Journal of Finance*, 77(4):2093–2141.

Wilson, R. and Din, A. (2018). Understanding and enhancing the US Department of housing and urban development's ZIP code crosswalk files. *Cityscape*, 20(2):277–294.

Table 1: Summary Statistics

Panel A presents the composition of household assets using consumer reporting agency 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 2024. *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 share	949,651	0.477	0.174	0	0.390	0.506	0.591	1
Deposit and Cash share	949,651	0.303	0.218	0	0.155	0.245	0.379	1
Panel B: Deposit Rate Spread								
12MCD10K - FF rate (%)	564,040	-0.909	1.365	-5.320	-1.492	-0.322	0.045	2.043
MM25K - FF rate (%)	550,447	-1.212	1.545	-5.325	-1.873	-0.436	-0.045	1.293
Panel C: Bank Controls								
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: Real Effects								
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:

$$d_{z,t} = \beta_e e_{z,t} + \mathbf{X}'_{z,t}\beta_x + \alpha_z + \lambda_t + \varepsilon_{z,t} \tag{8}$$

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 $\mathbf{X}'_{z,t}$ includes additional ZIP code characteristics. The specification includes fixed effects for ZIP codes (α_z) and time (λ_t).
Columns (5)–(8) estimate the following regression:

$$d_{b,z,t} = \beta_e e_{z,t} + \mathbf{X}'_{b,z,t}\beta_x + \gamma_b + \alpha_z + \lambda_t + \varepsilon_{b,z,t} \tag{4}$$

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 (α_z), and time fixed effects (λ_t). The sample covers the period from June 2014 to June 2024. 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)
$e_{z,t}$	0.036**	0.036***	0.036***	0.032**	0.019***	0.019***	0.010**	0.010**
	(0.020)	(0.010)	(0.010)	(0.010)	(0.004)	(0.003)	(0.004)	(0.004)
Herfindahl $\text{Index}_{z,t}$		-0.063**	-0.065**	-0.119***		-0.001	-0.003	-0.003
		(0.030)	(0.030)	(0.030)		(0.001)	(0.002)	(0.002)
Insured $\text{Fraction}_{z,t}$			0.056	-0.128**			-0.200***	-0.205***
			(0.050)	(0.050)			(0.011)	(0.011)
Log(Bank $\text{Size})_{b,t}$				-0.028***				-0.007**
				(0.000)				(0.003)
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	367,559	320,774	320,769	320,769	1,664,483	1,604,632	1,052,787	1,052,787
R^2	0.91	0.92	0.92	0.92	0.88	0.89	0.89	0.89

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

Table 3: Household Equity Holdings and Fed Funds Rate Pass Through

This table estimates how changes in the federal funds rate pass through to both deposit rate spreads and deposit growth as a function of local market concentration ($\text{HHI}_{z,t}$) and household equity exposure ($e_{z,t}$). The estimated specification is:

$$\Delta y_{b,z,t} = \beta_1 \cdot (\text{HHI}_{z,t} \times \Delta\text{FF}_t) + \beta_2 \cdot (e_{z,t} \times \Delta\text{FF}_t) + \gamma_{b\times t} + \alpha_z + \lambda_t + \varepsilon_{b,z,t}, \tag{5}$$

where $\gamma_{b\times t}$, α_z, and λ_t denote bank–by–time, ZIP, and time fixed effects, respectively. In Columns (1)–(3), the dependent variable is the change in the deposit rate spread, defined as the deposit rate minus the federal funds rate, measured on a semiannual bank–ZIP panel. In Columns (4)–(6), the dependent variable is the change in the log of deposits, capturing deposit growth. Because deposit data are observed at an annual frequency, this specification is estimated on a bank–ZIP–annual panel. $\text{HHI}_{z,t}$ measures local market concentration, and $e_{z,t}$ denotes the share of household assets held in equities within each ZIP code. All specifications include bank–by–time fixed effects and progressively add ZIP and time fixed effects. Standard errors are clustered at the ZIP code level.

	Δ(Deposit Rate Spread)			$\Delta\log$(Deposits)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{HHI}_{z,t} \times \Delta\text{FF}_t$	-0.0028*	-0.0030*	-0.0030*	0.0031***	0.0092***	0.0092***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$e_{z,t} \times \Delta\text{FF}_t$	0.0066*	0.0065*	0.0065*	-0.0112***	-0.0054*	-0.0054*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Bank $\times$ Time FE	Y	Y	Y	Y	Y	Y
Zipcode FE	N	Y	Y	N	Y	Y
Time FE	N	N	Y	N	N	Y
Observations	1,106,359	1,106,041	1,106,041	513,311	512,982	512,982
R^2	0.978	0.979	0.979	0.687	0.701	0.701

Standard errors in parentheses

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

Table 4: Treatment Effects from Propensity Score Matching

This table reports regressions of deposit spreads on the treatment indicator, comparing ZIP codes with higher versus lower residualized equity exposure. Each column corresponds to a different comparison between quintiles of equity exposure: column (1) contrasts the top and bottom quintiles, while columns (2)–(5) show adjacent-quintile contrasts. Panels A–C present results under alternative K-nearest-neighbor (KNN) matching specifications: (A) $k = 1$ without replacement, (B) $k = 1$ with replacement, and (C) $k = 3$ with replacement. For each matched pair, deposit spread is regressed on the treatment indicator with match-pair fixed effects. Standard errors are clustered at the ZIP-code level.

	(1) 5 vs 1	(2) 2 vs 1	(3) 3 vs 2	(4) 4 vs 3	(5) 5 vs 4
(A) k=1, no replacement					
treat	0.029***	0.015***	0.016***	0.016***	0.005
	(0.006)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	34,098	96,466	114,760	116,172	98,028
(B) k=1, with replacement					
treat	0.026***	0.014***	0.012***	0.009***	0.019***
	(0.008)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	62,360	124,702	124,706	124,702	124,722
(C) k=3, with replacement					
treat	0.031***	0.014***	0.009***	0.008**	0.018***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Observations	62,356	249,383	249,396	249,404	249,444

Standard errors in parentheses

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

Table 5: Tax savings as IV for Equity Holding

This table presents regression results using the TCJA's tax-savings fraction as an instrumental variable for ZIP-code equity holdings. The two-stage least squares specification is:

$$
\begin{aligned}
e_{z,t} &= \beta_\tau \, \text{Tax Savings}_{z,t} + \sum_i \beta_{x,i} \mathbb{X}_{z,t,i} + \gamma_z + \varepsilon_{z,t} \\
d_{z,t} &= \beta'_e \hat{e}_{z,t} + \sum_i \beta'_{x,i} \mathbb{X}_{z,t,i} + \gamma'_z + \eta_t + \varepsilon'_{z,t}
\end{aligned} \tag{9}
$$

The analysis spans the period from 2014 to 2021, comparing pre-TCJA and post-TCJA effects. 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)	4.044***	4.714***	4.711***	4.702***
	(0.938)	(1.208)	(1.208)	(1.227)
Insured Fraction$_{z,t}$		0.014	0.012	0.000
		(0.042)	(0.042)	(0.050)
Herfindahl Index$_{z,t}$			0.020	0.017
			(0.025)	(0.027)
Log(Bank Size)$_{z,t}$				-0.002
				(0.005)
Zipcode FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	140,195	128,049	128,049	128,049

Standard errors in parentheses

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

Table 6: Effect of Equity Holding on Bank Risk Taking

This table estimates the following regression:

$$PD_{z,t} = \beta_e \cdot e_{z,t} + \sum_i \beta_{x,i} \cdot \mathbb{X}_{z,t,i} + \gamma_z + \lambda_t + \varepsilon_{z,t} \tag{6}$$

where $\mathrm{PD}_{z,t}$ 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)
$e_{z,t}$	0.016***	0.012***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Herfindahl Index$_{z,t}$		-0.007**	-0.007**	-0.012***
		(0.003)	(0.003)	(0.003)
Insured Fraction$_{z,t}$			-0.000	-0.031***
			(0.004)	(0.004)
Log(Bank Size)$_{z,t}$				-0.004***
				(0.0004)
Zipcode FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	237,094	223,699	223,694	223,694
R^2	0.78	0.79	0.79	0.79

Standard errors in parentheses

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

Table 7: Effect of Equity holding on new lending

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

$$Lending_{b,c,t} = \beta_e\, e_{b,t-1} + \beta_h \,\text{Herfindahl Index}_{b,t-1} + \alpha_b + \gamma_c + \lambda_t + \alpha_{b\times c} + \gamma_{c\times t} + \varepsilon_{b,c,t} \tag{7}$$

where $Lending_{b,c,t}$ 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 $\text{Herfindahl Index}_{b,t-1}$ is the Herfindahl-Hirschman Index, measuring market concentration. Standard errors are clustered at the 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***
	(0.103)	(0.106)	(0.229)	(0.189)
$\text{Herfindahl Index}_{b,t-1}$	-0.061	-0.342***	0.187	0.359***
	(0.069)	(0.082)	(0.123)	(0.107)
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

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

Table 8: GMM Estimates: Salop Deposit Competition Model with Extra Moments

Notes: Estimation uses seven moments including the mean spread, pass-through, participation rate, HHI, risk, and two auxiliary moments (covariance of deposit rates with r_f and variance of deposit rates). Rates and shares are in decimals. Objective value refers to the minimized GMM criterion. All equilibrium conditions satisfied; model converged with L-BFGS-B.

(A) Estimated Parameters		
Parameter		Estimate
a (household risk sensitivity)		1.809
b (return-to-risk coefficient)		1.319
κ (risk curvature)		0.209
τ (differentiation cost)		0.200
η (equity competition elasticity)		1.568
N (number of competitors)		2.534
ϕ_0 (baseline depositor share)		0.286
(B) Moments: Model vs. Target		
Moment	Model	Target
Mean spread $\mathbb{E}[d - r_f]$	-0.0006	-0.0075
Pass-through $\partial d / \partial r_f$	0.551	0.390
Equity participation $\mathbb{E}[\varphi]$	0.4995	0.4995
Market concentration HHI	0.395	0.395
Bank risk (proxy)	0.342	0.209
$\mathrm{Cov}(d, r_f)$	8.0×10^{-5}	2.3×10^{-5}
$\mathrm{Var}(d)$	4.4×10^{-5}	1.3×10^{-5}
(C) Auxiliary Levels and Diagnostics		
d^* (equilibrium deposit rate level)		0.0098
q^* (equilibrium risk level)		0.189
D^* (deposit share)		0.500
$\bar{r}_f$ (mean policy rate)		0.0104
$\bar{R}_e$ (mean equity return)		0.1462
Objective value		0.315

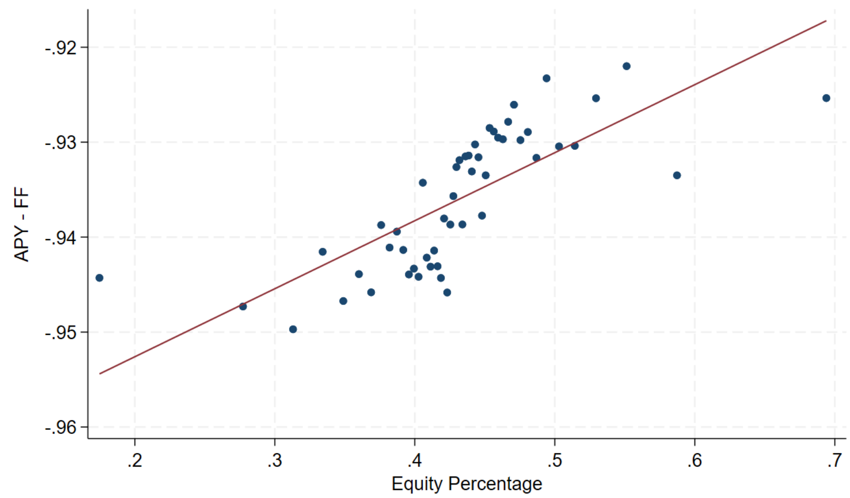
Table 9: Counterfactual Experiments

This table reports outcomes from counterfactual experiments in which one structural parameter is varied at a time, including (A) market concentration HHI, (B) household elasticity η, and (C) product differentiation τ, while all other parameters remain fixed at their estimated values. For each scenario the table lists the resulting equilibrium deposit rate d^*, bank risk q^*, deposit share D^*, and monetary pass-through.

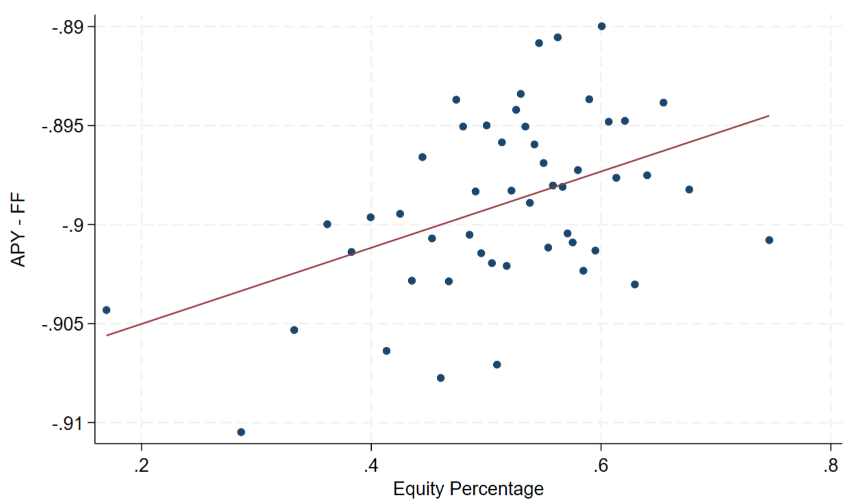
Scenario	**Value**	d^*	q^*	D^*	Pass
(A) Concentration: vary HHI					
HHI	0.20	0.03225	0.09434	0.53734	0.70466
HHI	0.30	0.03058	0.14593	0.53459	0.59868
HHI	0.39	0.01111	0.17766	0.50254	0.55300
HHI	0.50	-0.02365	0.20267	0.44531	0.52746
(B) Household Elasticity η					
η	1.00	-0.00536	0.14908	0.57334	0.59348
η	1.50	0.00752	0.17370	0.51689	0.55788
η	2.50	0.01774	0.20015	0.40381	0.52961
(C) Differentiation τ					
τ	0.05	0.07135	0.09270	0.60170	0.70866
τ	0.10	0.06579	0.13659	0.59254	0.61495
τ	0.20	0.00984	0.17896	0.50045	0.55145

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 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 2014Q2–2024Q2.



(a) Zip-level Equity Holdings and Deposit Rates



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

Figure 2: 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 after 2018. The tax savings is calculated from TPC's saving estimate for each income bracket, weighted by the population of each income bracket within each ZIP code.

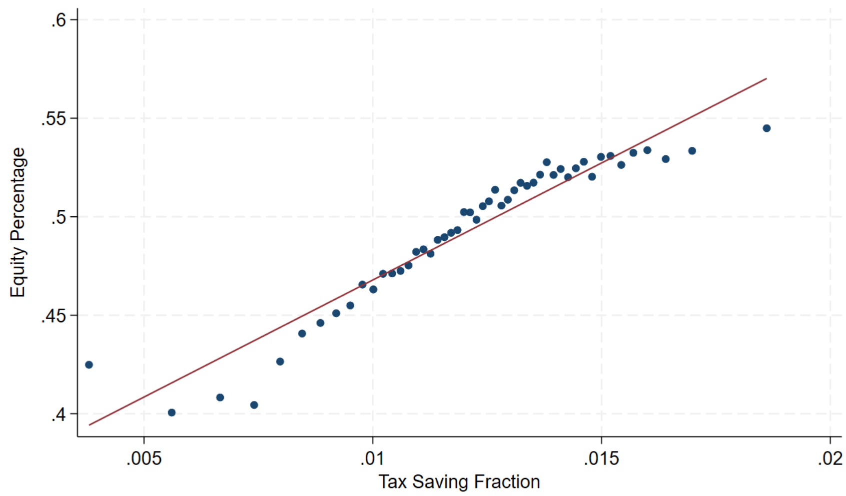
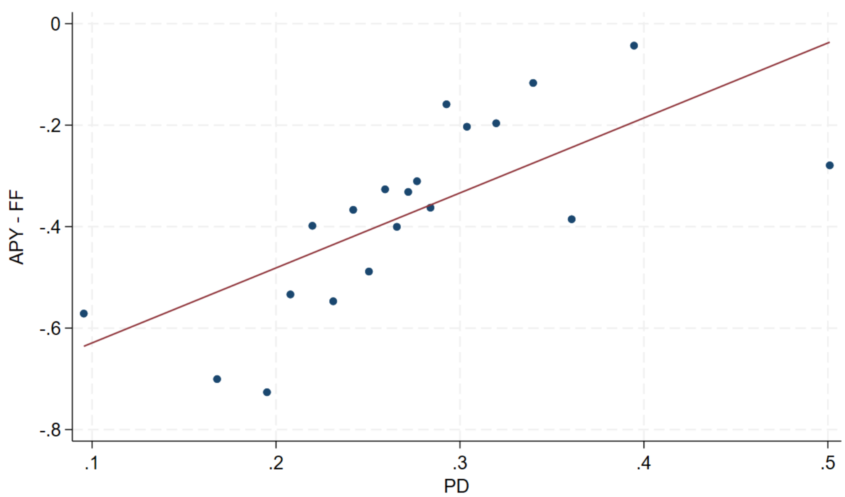
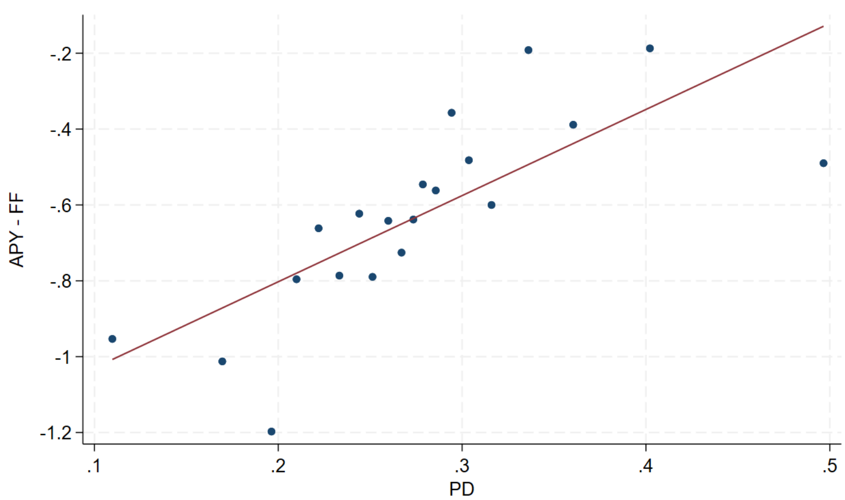


Figure 3: Relation Between Deposit Rate and PD

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 2024Q2. 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 Data Sources: Additional Discussion

A.1 Asset Composition Data

We obtained ZIP+4 level asset composition data from one of the three nationwide consumer reporting agencies. This data covers about half of US households and provides an aggregated estimate of anonymized household financial assets. The data is sourced from over 95 financial institutions, including retail banks, brokers, mutual funds, and insurance firms. 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 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.

A.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 lognormal 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.

A.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.

A.4 Other data sources

Ratewatch: We obtain deposit interest rates from RateWatch. Our RateWatch data spans from 2001 to 2024 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 2024. 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 2024: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.

B 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.

C Proofs and Additional Discussion

This appendix provides formal derivations for the model in Section 1, including (i) the Salop pricing ("margin pin") result, (ii) the existence and uniqueness of the risk choice, (iii) comparative statics, and (iv) policy pass-through.

B.1 Preliminaries and Notation

There are $N \geq 2$ symmetric banks on a unit Salop circle. Households (unit mass) are uniformly distributed and face transport costs $\tau > 0$. A fraction φ invests in the equity outside option; the remaining $M(\bar{d}) = A + \eta \bar{d}$ participates in deposit competition, with $A = 1 - \varphi_0 - \eta R_e$ and $\eta \geq 0$.

Banks invest deposits in loans that, given a *risk intensity* $q \geq 0$, produce

$$R(q) = R_0 + bq, \quad \pi(q) = aq, \qquad a, b > 0, \qquad R_0 = r_f + \mu.$$

Risk bears convex costs $K(q) = \frac{\kappa}{2} q^2$, $\kappa > 0$. Define the *per-bank competition wedge*

$$S := \frac{2\tau}{N^2}.$$

Under symmetry, all banks set the same rate d and choose the same risk q.

B.2 Lemma A.1 (Salop pricing with an outside option)

Fix q. In any symmetric price equilibrium of the Salop subgame, the per-unit funding margin equals the business-stealing wedge:

$$m \;\equiv\; (1-\pi)R(q)-d \;=\; \frac{2\tau}{N} \quad\Longrightarrow\quad d(q) \;=\; (1-aq)\big(R_0+bq\big) \;-\; \frac{2\tau}{N}. \tag{10}$$

Proof. Consider two adjacent banks i and j, charging d_i and d_j. A depositor at location x is indifferent when $d_i-\tau x = d_j-\tau(s-x)$ with $s=1/N$, yielding boundary $x=\frac{s}{2}+\frac{d_i-d_j}{2\tau}$. Bank i's within-deposit market length is the sum of the two boundaries with its neighbors,

$$q_i^D \;=\; s+\frac{d_i-d_{i+1}}{2\tau}+\frac{d_i-d_{i-1}}{2\tau}.$$

In a symmetric equilibrium ($d_i=d$ for all i), $q_i^D=s$ and $\frac{\partial q_i^D}{\partial d_i}=\frac{1}{\tau}$ (the standard business-stealing slope). With outside option captured by $(1-\pi)$, per-unit gross *asset* revenue is $(1-\pi)R(q)$; the funding cost is d. The bank's price problem is

$$\max_{d}\;\Big[(1-\pi)R(q)-d\Big]\cdot\frac{M(\bar d)}{N}\cdot q_i^D(d) \quad\Rightarrow\quad \text{FOC: } -\frac{M(\bar d)}{N}\,q_i^D(d) \;+\; \Big[(1-\pi)R(q)-d\Big]\frac{M(\bar d)}{N}\cdot\frac{1}{\tau} \;=\; 0.$$

Under symmetry $q_i^D=s=1/N$, the FOC reduces to

$$-(1/N) \;+\; \frac{(1-\pi)R(q)-d}{\tau} \;=\; 0 \quad\Rightarrow\quad (1-\pi)R(q)-d=\frac{2\tau}{N}.$$

This is the usual Salop "margin pin" with linear transport costs. Rearranging yields (10). □

Competition and switching frictions jointly determine a wedge between asset returns and deposit rates. More competition (higher N) or lower frictions (lower τ) compress the wedge and raise d for a given q.

B.3 Proposition 1 (Risk choice, existence, and uniqueness)

Let $d(q)$ be given by (10) *and $S = 2\tau/N^2$. Under symmetry, expected profits per bank are*

$$\Pi(q) \;=\; S\,[A+\eta\, d(q)] \;-\; \frac{\kappa}{2}q^2,$$

which are strictly concave in q for interior parameters. The unique interior maximizer is

$$q^* = \frac{\eta S\,(b-aR_0)}{2\eta S\,ab+\kappa}. \tag{11}$$

The associated deposit rate and market size are

$$d^* = R_0 - \frac{2\tau}{N} + q^*(b-aR_0) - ab(q^*)^2, \qquad D = A+\eta d^*.$$

Proof. From Lemma B.2, $d(q) = (1-aq)(R_0+bq) - \frac{2\tau}{N}$. Expand:

$$d(q) = R_0 - \frac{2\tau}{N} + q(b-aR_0) - abq^2, \quad \Rightarrow \quad d'(q) = (b-aR_0) - 2abq,\; d''(q) = -2ab < 0.$$

Profit is $\Pi(q) = S[A+\eta d(q)] - \frac{\kappa}{2}q^2$. Then

$$\Pi'(q) = S\eta\, d'(q) - \kappa q = S\eta\left[(b-aR_0) - 2abq\right] - \kappa q,$$

$$\Pi''(q) = S\eta\, d''(q) - \kappa = -2abS\eta - \kappa < 0,$$

so Π is strictly concave and has a unique maximizer. Setting $\Pi'(q) = 0$:

$$S\eta\,(b-aR_0) - \big(2abS\eta+\kappa\big)q = 0 \quad \Rightarrow \quad q^* = \frac{\eta S\,(b-aR_0)}{2\eta S\,ab+\kappa}.$$

Plug q^* into $d(q)$ and $D = A+\eta d$ to obtain the stated expressions. □

The benefit of risk is to raise d via $d'(q) > 0$ when $b > aR_0$; the cost is convex κq^2 and the induced default effect through $-2abq$ in $d'(q)$. The competition wedge S scales the value of attracting marginal deposits.

B.4 Proposition 2 (Comparative statics)

Assume $b > aR_0$ and an interior solution. Then:

1. **Equity competition:** $\dfrac{\partial q^*}{\partial \eta} > 0$ and $\dfrac{\partial d^*}{\partial \eta} > 0$.
2. **Bank competition:** $\dfrac{\partial q^*}{\partial N} < 0$ (since $S = 2\tau/N^2$ falls with N).
3. **Technology and costs:** $\dfrac{\partial q^*}{\partial b} > 0$, $\dfrac{\partial q^*}{\partial a} < 0$, and $\dfrac{\partial q^*}{\partial \kappa} < 0$.
4. **Stickiness:** $\dfrac{\partial d^*}{\partial \tau}$ combines a direct $(-2/N)$ and an indirect effect via q^*, so the total sign is ambiguous a priori.

Proof. Write $q^* = \frac{\eta S \Delta}{2\eta Sab+\kappa}$ with $\Delta := b - aR_0 > 0$, and $S = 2\tau/N^2$.

(1) Changes in η. Using quotient rule,

$$\frac{\partial q^*}{\partial \eta} = \frac{S\Delta(2\eta Sab+\kappa) - \eta S\Delta(2Sab)}{(2\eta Sab+\kappa)^2} = \frac{S\Delta\,\kappa}{(2\eta Sab+\kappa)^2} > 0.$$

Since $d^* = d(q^*)$ and $d'(q^*) = (b - aR_0) - 2abq^* > 0$ for interior q^*, we also have $\partial d^*/\partial \eta = d'(q^*)\,\partial q^*/\partial \eta > 0$.

(2) Changes in N. Because $S = 2\tau/N^2$, $\partial S/\partial N = -4\tau/N^3 < 0$. Treating $\eta, \Delta, a, b, \kappa$ as constants,

$$\frac{\partial q^*}{\partial S} = \frac{\eta\Delta(2\eta Sab+\kappa) - \eta S\Delta(2\eta ab)}{(2\eta Sab+\kappa)^2} = \frac{\eta\Delta\,\kappa}{(2\eta Sab+\kappa)^2} > 0.$$

Hence $\frac{\partial q^*}{\partial N} = \frac{\partial q^*}{\partial S}\cdot\frac{\partial S}{\partial N} < 0$.

(3) Changes in b, a, κ.

$$\frac{\partial q^*}{\partial b} = \frac{\eta S(2\eta Sab+\kappa)\cdot 1 - \eta S\Delta(2\eta Sa)}{(2\eta Sab+\kappa)^2} = \frac{\eta S\big(\kappa + \eta Sa(b+aR_0)\big)}{(2\eta Sab+\kappa)^2} > 0,$$

$$\frac{\partial q^*}{\partial a} = \frac{\eta S\big(-(R_0)(2\eta Sab+\kappa)\big) - \eta S\Delta(2\eta Sb)}{(2\eta Sab+\kappa)^2} < 0, \qquad \frac{\partial q^*}{\partial \kappa} = \frac{-\eta S\Delta}{(2\eta Sab+\kappa)^2} < 0.$$

(4) Changes in τ. The direct effect on d^* is $-2/N$ from (10); the indirect effect is $d'(q^*)\cdot \partial q^*/\partial\tau$, where $\partial q^*/\partial\tau = (\partial q^*/\partial S)\cdot(\partial S/\partial\tau)$ with $\partial S/\partial\tau = 2/N^2 > 0$. Since $d'(q^*)$ can be positive or small depending on the parameters and $\partial q^*/\partial\tau > 0$, the overall sign of $\partial d^*/\partial\tau$ is ambiguous a priori. □

Greater household rate sensitivity (η) raises the value of supply expansion, so banks take more risk and pay higher rates. More bank competition (N) lowers the per-bank franchise wedge S, weakening the incentive to raise q.

B.5 Proposition 3 (Policy pass-through)

Let $R_0 = r_f + \mu$. Then

$$\frac{\partial q^*}{\partial r_f} = -\frac{\eta a S}{2\eta Sab+\kappa} < 0,$$

and the deposit-rate pass-through satisfies

$$\frac{\partial d^*}{\partial r_f} = \underbrace{(1-aq^*)}_{\text{direct}} + \underbrace{\big(b - aR_0 - 2abq^*\big)}_{\text{risk-to-rate}} \underbrace{\frac{\partial q^*}{\partial r_f}}_{<0} < 1.$$

Moreover, the dampening $1 - \partial d^*/\partial r_f$ is increasing in η.

Proof. From (11), $q^* = \frac{\eta S(b-aR_0)}{2\eta Sab+\kappa}$, so

$$\frac{\partial q^*}{\partial r_f} = \frac{\eta S(-a)}{2\eta Sab+\kappa} < 0.$$

Since $d(q) = (1-aq)(R_0+bq) - \frac{2\tau}{N}$,

$$\frac{\partial d^*}{\partial r_f} = \frac{\partial}{\partial r_f}\big[(1-aq^*)R_0 + (1-aq^*)bq^*\big] = (1-aq^*) + \big(-aR_0 + b - 2abq^*\big)\frac{\partial q^*}{\partial r_f}.$$

Because $\partial q^*/\partial r_f < 0$, the second term is negative whenever $b - aR_0 - 2abq^* > 0$ (the empirically relevant interior region), implying $\partial d^*/\partial r_f < 1$. Finally, $\partial q^*/\partial r_f$ is proportional to $-\eta$, so the magnitude of dampening $1 - \partial d^*/\partial r_f$ increases with η. $\square$

A higher policy rate reduces banks' incentives to take risks (tightening q^*). Because d^* co-moves with q^* through $d'(q^*) > 0$ in the interior region, the endogenous fall in q^* partially offsets the direct effect of r_f on d^*, producing pass-through strictly below one. This dampening is stronger when households are more rate sensitive (larger η).

B.6 Estimation Details

The key empirical moments are:

1. **Average deposit spread.** The model implies

$$\mathbb{E}[d - r_f] = \mathbb{E}\left[(1 - \pi(q^*))R(q^*) - r_f - \frac{2\tau}{N}\right],$$

   which corresponds to the average excess deposit rate observed in the data. This moment identifies the effective competition wedge $(2\tau/N)$ and the baseline asset spread μ.

2. **Policy-rate pass-through.** Empirically, we estimate how deposit rates respond to changes in the fed funds rate, $\partial d/\partial r_f$. In the model,

$$\frac{\partial d^*}{\partial r_f} = (1 - aq^*) + \left(b - aR_0 - 2abq^*\right)\frac{\partial q^*}{\partial r_f},$$

   so the observed pass-through elasticity identifies the extent of endogenous risk adjustment and thus the parameters (a, b, κ).

3. **Equity participation and elasticity.** The average household equity share is $\mathbb{E}[\varphi] = \varphi_0 + \eta(R_e - \mathbb{E}[\bar{d}])$, and the slope of equity participation with respect to deposit rates identifies (η, φ_0). These parameters capture the strength of household substitution between deposits and capital-market assets.

4. **Market concentration.** The Herfindahl–Hirschman Index observed in local deposit markets proxies for $1/N$ in the model. Cross-sectional variation in HHI identifies the degree of bank competition and the implied Salop wedge $S = 2\tau/N^2$.

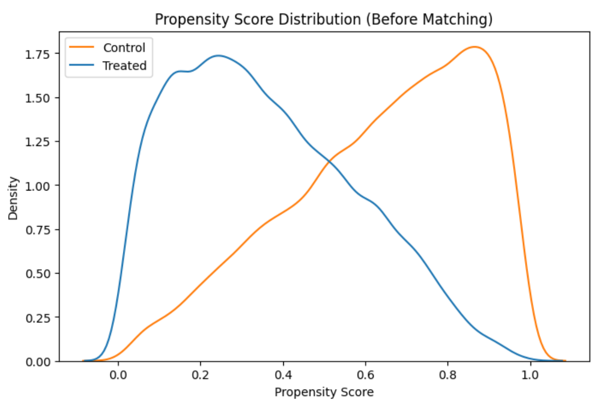
5. **Average bank risk.** Empirical measures such as probability of default, chargeoffs, or loan-loss provisions correspond to aq^*. Matching the mean and dispersion of these risk measures identifies the curvature parameters (a, κ) that govern the cost of risk-taking.

6. **Covariance of deposit rates with the risk-free rate.** The moment $\text{Cov}(d^*, r_f)$ captures how deposit rates co-move with policy shocks through banks' endogenous adjustments in q^*, and helps identify the parameters (a, b, κ) that govern the sensitivity of risk-taking to changes in the policy rate.

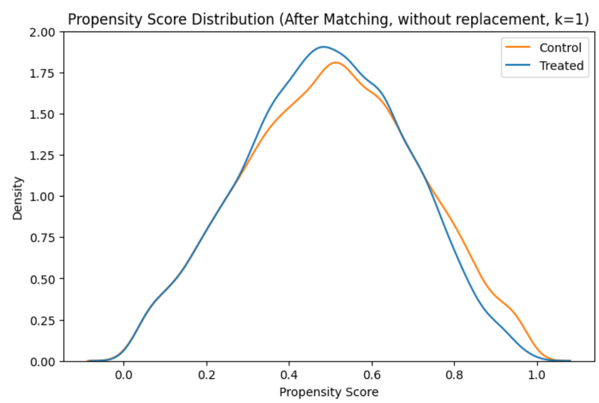
7. **Variance of deposit rates.** The dispersion of observed deposit rates, summarized by $\text{Var}(d^*)$, reflects cross-sectional heterogeneity in competitive wedges and equilibrium risk-taking, and helps identify (τ, N, κ) by disciplining how much variation the model must generate across banks.

Figure A.1: Propensity score distributions across matching specifications

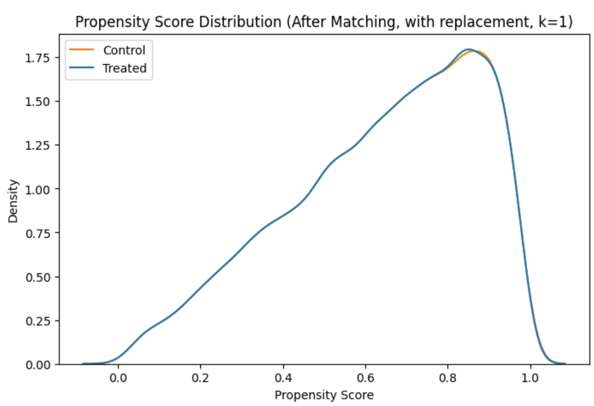
This figure shows propensity score distributions for treated and control ZIP codes under different matching specifications. Treated ZIP codes are in the top quintile of residualized household equity-holding share, and controls are in the bottom quintile. Propensity scores are estimated using demographic and banking covariates: income, age, unemployment, poverty, log population, inequality (Gini), log bank asset, market concentration (HHI), and insured-deposit share. Panel (a) shows the pre-matching distribution; panels (b)–(d) show results for KNN matching with (b) (k=1) without replacement, (c) (k=1) with replacement, and (d) (k=3) with replacement. Improved overlap indicates better covariate balance between treated and control groups.



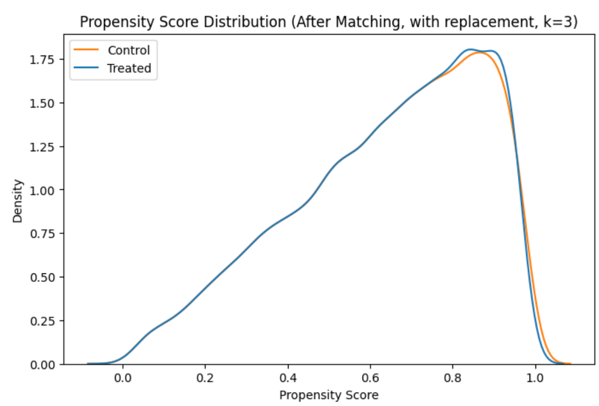
(a) Before matching



(b) KNN ($k = 1$) without replacement



(c) KNN ($k = 1$) with replacement



(d) KNN ($k = 3$) with replacement