Deposit Funding Shocks and Credit Supply: Bank-Level IV Estimates and Heterogeneous Responses

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1 Introduction

Rapid tightening since March 2022 has renewed interest in how monetary policy transmits through banks to the real economy. A rising strand emphasizes the deposit channel: when policy rates increase, deposit spreads widen, deposit growth slows, and banks partly replace core deposits with more expensive wholesale liabilities, which still leaves assets and loan supply lower (Drechsler et al. 2016). This perspective fits within the broader credit-channel research program that tighter policy raises banks' funding costs and tightens loan supply (Bernanke and Gertler 1995). Following Drechsler et al. (2016), a large body of recent work documents substantial cross-sectional variation in deposit rate pass-through and deposit outflows, shaped by factors such as bank size and depositor sophistication. The foundational branch-level evidence on the "deposit channel" showed that when policy rates rise, banks in less competitive deposit markets raise rates more slowly and lose fewer deposits, while others face larger outflows and higher funding costs. Later studies questioned how well such local designs capture bank-level behavior. Evidence that large institutions price deposits uniformly across geographies raises concerns about county-level identification and suggests strong liability substitution at the largest banks(Begenau and Stafford 2023; Begenau and Stafford 2024). Related work shows depositor composition matters for pass-through and outflows and concentration indexes largely proxy deposit composition rather than market power, shifting attention from local market structure to who the depositors are. Against this backdrop, much less is known about the subsequent impact of higher funding costs on how much credit banks supply (Narayanan and Ratnadiwakara 2024).

The deposit channel rests on three testable premises. First, deposits are imperfect substitutes for other liabilities at the margin, so policy rate hikes raise both marginal and average funding costs for a meaningful subset of banks (Bernanke and Gertler 1995; Drechsler et al. 2016). Second, higher marginal funding costs shift banks' loan-supply schedules inward rather than being fully offset by repricing, fees, or operating adjustments (Bernanke and Gertler 1995). Third, borrowers face frictions in replacing relationship lenders, so bank-level supply contractions translate into lower aggregate credit availability (Erel et al. 2023). Each premise is contestable. Large banks can reoptimize liability structures at relatively low cost, dampening the effective increase in funding costs (Begenau and Stafford 2023). On the second premise in particular, the mapping from funding-cost shocks to bank credit supply remains

underdeveloped in both theory and evidence; two canonical frameworks motivate quantity (and terms) tightening without one-for-one price pass-through: credit-rationing logic, where higher loan rates worsen selection and incentives, making nonprice and quantity restrictions optimal (Stiglitz and Weiss 1981), and bank-capital models, where lower net interest margins slow retained-earnings accumulation and raise the likelihood of binding capital constraints (Van den Heuvel 2002). This paper does not attempt to identify these microfoundations; it estimates the reduced-form, bank-level local average treatment effect of policy-induced increases in effective funding costs on credit supply.

The paper estimates the bank-level local average treatment effect of policy-induced changes in deposit funding conditions on credit supply for the set of banks whose funding is shifted by the instrument. Identification uses a bank-level 2SLS design with instruments that interact predetermined, pre-2021 exposures with quarterly changes in the federal funds rate. Working at the bank rather than branch level and instrumenting both funding costs and outflows—while absorbing local demand with deposit-weighted region-by-quarter fixed effects and controlling for time-invariant heterogeneity with bank fixed effects—directly addresses uniform-pricing and aggregability critiques. The analysis reports elasticities for total and portfolio-level lending and examines size heterogeneity to test whether small and community banks contract credit more for a comparable policy-driven shift in funding conditions. The contribution is direct, reduced-form causal evidence on the linkage from policy-induced bank-specific deposit funding conditions to bank credit supply, without committing to a specific micro-mechanism.

2   Literature Review

The "standard interest-rate channel" is the textbook mechanism in which a policy-induced increase in the federal funds rate passes through to borrowing rates, raising the user cost of credit and reducing interest-sensitive spending (Bernanke and Gertler 1995). An earlier alternative emphasized a "reserve channel," under which the central bank's control of bank reserves and a stable reserve multiplier constrained loan supply (Bernanke and Blinder 1988; Balbach 1981). In practice, that mechanism weakened or had never been effective as financial innovation, regulatory change, and modern operating procedures decoupled lending from contemporaneous reserve quantities: banks reconfigured liability mixes and reserve requirements became less binding, while central banks accommodated aggregate reserve demand in order to target the overnight policy rate (Minsky 1957; Moore 1991). In the early 1990s, the discussion was recast as a "credit channel" comprising a balance-sheet channel—tightening weakens borrower cash flow and collateral, raising external-finance premia—and a bank-lending channel—reserve drains or funding-cost increases reduce core deposits and, when nondeposit liabilities are imperfect or costly substitutes, shift banks' loan-supply schedules inward, tightening bank credit supply (Bernanke and Gertler 1995; Kashyap and Stein, n.d.).

A complementary bank-capital channel traces how capital requirements and payout rules shape lending. Since Basel I (1988), risk-weighted capital standards have tied balance-sheet growth to capital; Basel II increased risk sensitivity, and Basel III added conservation and countercyclical buffers (Basel Committee on Banking Supervision 1988, 2011). Early credit-

crunch evidence showed that thinly capitalized banks slowed loan growth as they adjusted to standards (Bernanke and Lown 1991; Hancock and Wilcox 1994). Quasi-experimental work finds that tighter, bank-specific capital requirements contract lending at affected banks, with some migration to less-regulated lenders (Aiyar et al. 2014). Risk-sensitive rules can be procyclical: in downturns, higher measured default probabilities and losses given default raise required capital just as earnings weaken, amplifying credit retrenchment (Kashyap and Stein 2004; Gordy and Howells 2006; Heid 2007; Repullo and Suárez 2013). Importantly, banks need not be at regulatory minima to pull back: when margins compress, value-maximizing banks may conserve capital and smooth dividends, raising the shadow cost of capital and shifting loan supply inward even without a binding constraint (Van den Heuvel 2002).

The modern deposit channel begins with Drechsler et al. (2016), which builds on classic evidence that deposit pricing is sluggish and more so where banks face less competition (Hannan and Berger 1997; Neumark and Sharpe 1992). In DSS, a policy-rate increase lifts outside short rates; with search frictions and deposit-market power, deposit rates adjust only partially, widening the funds–deposit spread and inducing households to shift out of checking and savings. The gradients are strongest where competition is weak: spreads rise more and deposit growth falls more in high-HHI counties, a price–quantity pattern that identifies a supply shift rather than demand. They establish causality with a within-bank design that interacts policy moves with county HHI under bank-time fixed effects, relying on internal capital markets that equalize marginal lending returns across branches so branch lending is independent of local deposit taking. A weekly event study shows spreads step up at FOMC enactment with no pre-trends, and expected and unexpected rate changes have similar effects, ruling out Fed-information stories. Aggregation follows from funding arithmetic: core deposits, which are about four-fifths of bank liabilities, fall on net, banks only partly substitute into wholesale or large time deposits, total liabilities mirror the core-deposit decline, and assets and loans contract. Because deposits are households' primary liquid claim, the systemwide shrinkage raises the liquidity premium, a macro link they document via the tight comovement between the aggregate deposit spread and the T-bill liquidity premium.

A newer wave refines mechanism and magnitudes. On mechanics, retail deposits provide a built-in duration hedge: when deposit rates adjust only slowly to policy, the deposit franchise behaves like a negative-duration asset. Banks pair that hedge with long-duration, fixed-rate assets, keeping NIM and ROA relatively stable around rate moves; as a result, tightening transmits mainly through funding-quantity pressure and the liquidity premium rather than large net-worth swings (Drechsler et al. 2021). If imperfect passthrough causes core deposit outflow and banks could not substitute deposit with similar duration liabilties with low friction or cost, then this could cause banks to reduce duration risk taking. On magnitudes, a decomposition of bank valuations shows that liability "productivity" explains most cross-bank value; for the median bank roughly two-thirds of value is attributable to deposit productivity, and a one-standard-deviation increase in deposit productivity raises market-to-book by roughly 0.2–0.8 points; savings-deposit capability is the tightest link to value (Egan et al. 2021). Deposit betas are state-dependent, rising with the level of rates, which shortens effective deposit duration and amplifies balance-sheet sensitivity in hiking cycles (Greenwald et al. 2023). Market structure and technology shift the first stage: online/national banks pass through more and attract inflows, while smaller institutions face sharper outflows, real-

locating credit supply across balance sheets (Erel et al. 2023; d'Avernas et al. 2023). Outside the U.S., the 2022–23 cycle shows that larger deposit outflows map into quantity rationing—especially for fixed-rate, longer-maturity loans—and the effect is stronger at banks entering with larger duration gaps (Bank 2024). Dynamic models microfound deposit demand and market power through search frictions, implying that reductions in frictions or better outside options weaken transmission (Choi and Rocheteau 2021). Finally, structural estimates link the deposits and capital channels: deposit-market power shapes pass-through to lending and interacts with capital requirements, potentially delivering a low "reversal rate" when cuts erode equity (Wang et al. 2020).

There are some important critiques for the deposit channel. A first set concerns uniform pricing: large networks often post near-uniform retail deposit rates across geographies, so pricing is effectively national rather than local. If so, county concentration (HHI) is a weak proxy for deposit-market power and within-bank cross-county designs risk attributing pass-through and outflows to "local competition" when they largely reflect head-office rate sheets (Begenau and Stafford 2023; d'Avernas et al. 2023). A related specification critique emphasizes depositor composition: who the customers are, not where they bank, predicts pass-through and run-off in 2022–23 (Narayanan and Ratnadiwakara 2024). The deeper challenge is aggregation: the mechanism has macro bite only if substitution from core deposits into time deposits and non-deposit debt is incomplete; asset-weighted analyses suggest that at the largest institutions substitution is ample, so cross-sectional gradients may reallocate intermediation across balance sheets rather than contract it in the aggregate (Begenau and Stafford 2023). Even so, distributional effects remain first order: if bank-dependent borrowers cannot easily substitute away from relationship lending, such as small businesses, or if smaller banks face higher marginal costs of wholesale replacement, policy can still tighten credit where those relationships bind, producing partial aggregation on the small-business margin (Erel et al. 2023; Kashyap and Stein, n.d.; d'Avernas et al. 2023).

The main gap is a clean mapping from policy-induced, bank-specific changes in funding conditions to lending. A substantial literature offers cross-sectional explanations of deposit-rate pass-through and deposit outflows, but far fewer papers quantify how a given bank-level increase in funding costs or a standardized deposit outflow translates into credit supply; even flagship contributions relate deposit movements to lending in reduced form rather than recovering a causal elasticity with instruments (Drechsler et al. 2016; Narayanan and Ratnadiwakara 2024). This paper addresses that gap with a bank-level 2SLS design: predetermined, pre-2021 exposures to deposit-rate sensitivity and to deposit-flow sensitivity are interacted with quarterly federal funds rate changes to instrument, respectively, each bank's change in its effective deposit rate and its deposit outflow; deposit-weighted region-by-quarter fixed effects absorb local demand and common shocks, and bank fixed effects absorb time-invariant heterogeneity. The second stage maps the instrumented funding-cost shock and the instrumented outflow into total and portfolio-level lending, delivering a bank-level LATE for the credit-supply response. By construction, the design speaks to uniform-pricing and aggregability critiques by shifting identification away from county concentration and by reporting size-split elasticities that test whether substitution at large institutions mutes macro transmission (Begenau and Stafford 2023).

3 Data and methodology

3.1 Data sources and sample construction

The empirical analysis uses a quarterly panel of U.S. commercial banks constructed from the FFIEC Call Reports merged with the FDIC Summary of Deposits (SOD) and county-level demographic, internet-access, financial participation, and mortgage-refinancing data. Call Reports provide, for each bank i and quarter t, information on asset composition, capital, domestic deposits, interest expenses on domestic deposits, and loan balances by category. Effective deposit rates are constructed as interest expense divided by the average stock of domestic deposits across the quarter. Loan growth is measured as the quarter-on-quarter change in outstanding loans relative to lagged balances.

SOD provides branch-level deposit balances and geographic identifiers. The pre-tightening SOD cross-section (2019–2021) is used to recover each bank's deposit distribution across counties, which serves as the basis for constructing deposit-weighted measures of depositor sophistication, branch intensity, and local market concentration. County-level data from ACS, IRS SOI, FCC broadband statistics, and HMDA refinancing data are merged by FIPS code and used to construct the depositor sophistication index. These raw variables include the share of adults holding a bachelor's degree, the share above age 65, the share of households with an internet subscription, the fraction of tax returns reporting dividend income, the fraction reporting interest income, and the mortgage-refinancing share in HMDA data. The refinancing share in particular is interpreted as a proxy for both interest-rate sensitivity and financial sophistication. All county-level variables used in the sophistication index are standardized prior to aggregation. No median household income measure enters the construction of the sophistication index.

Banks are included in the analysis if they are insured commercial banks, report positive domestic deposits, appear in both Call Reports and SOD in the pre-hike period, and have sufficient observations around the 2021Q4–2023Q4 tightening cycle to support fixed-effects estimation. Banks with implausible accounting values or inconsistent reporting are removed.

3.2 Construction of cross-sectional exposure indices

The empirical design requires bank-level, time-invariant measures of depositor characteristics and local deposit-market structure. These indices are constructed using pre-period SOD deposit distributions and the county-level sophistication and concentration measures generated by the Python scripts.:contentReferenceoaicite:2 :contentReferenceoaicite:3

3.2.1 Depositor sophistication index

Let X_c denote the vector of standardized county-level variables:

$$X_c = \begin{pmatrix} \text{share of adults with a bachelor's degree or higher}_c \\ \text{share of population aged 65 or above}_c \\ \text{share of households with an internet subscription}_c \\ \text{fraction of tax returns reporting dividend income}_c \\ \text{fraction of tax returns reporting interest income}_c \\ \text{mortgage refinancing share (HMDA)}_c \end{pmatrix}.$$

all standardized across counties. Each variable is selected because it proxies for financial literacy, market participation, or sensitivity to interest rates. Refinancing intensity is particularly informative about rate sensitivity and financial sophistication.

The sophistication index at the county level is defined as the first principal component:

$$\text{DSI}_c = w'X_c,$$

where w is the eigenvector associated with the largest eigenvalue of the covariance matrix of X_c. The direction of w is chosen such that higher DSI_c corresponds to counties with more sophisticated and financially engaged households.

Because deposit markets are local, the relevant exposure for bank i aggregates county DSI values using the bank's SOD deposit distribution:

$$S_i = \frac{\sum_{b \in i} \text{DSI}_{c(b)} \, \text{Dep}_b}{\sum_{b \in i} \text{Dep}_b},$$

where Dep_b denotes deposits at branch b located in county $c(b)$. The index is then standardized across banks. This depositor sophistication measure is a central novelty of the paper: it combines multiple behavioral and demographic proxies into a single, data-driven index that captures meaningful cross-bank differences in deposit-base sensitivity to interest rates.

3.2.2 Relationship-banking (branch-intensity) index

Branch intensity captures the extent to which a bank maintains a branch-based retail relationship model. For each bank i, let branches_i denote its total number of domestic branches in the pre-period and let DEPDOM_i denote its total domestic deposits. The branch-intensity index is defined as

$$R_i = \frac{\text{branches}_i}{\text{DEPDOM}_i/10^9},$$

expressed as branches per billion dollars of domestic deposits. In practice, the logarithm of $R_i + 1$ is used for stability, and the variable is standardized across banks.

3.2.3 Local concentration index (HHI exposure)

County-level deposit concentration is measured via the Herfindahl–Hirschman Index. For county c in year t, let $d_{c,j}$ denote deposits of bank j in county c, and let $D_c = \sum_j d_{c,j}$ be total deposits in the county. The county-level HHI is

$$\text{HHI}_c = \sum_j \left(\frac{d_{c,j}}{D_c} \right)^2.$$

This index lies in the interval $[0, 1]$ and measures concentration of deposit-market shares.

Bank-level exposure to concentration aggregates county HHIs using deposit weights:

$$H_i = \frac{\sum_{b \in i} \text{HHI}_{c(b)} \, \text{Dep}_b}{\sum_{b \in i} \text{Dep}_b}.$$

This measure captures whether a bank primarily operates in more or less concentrated local deposit markets. The index is standardized across banks.

3.2.4 Additional bank-level controls

Because the panel is short and cannot support county-by-quarter fixed effects, two additional pre-period bank-level controls are constructed from SOD. Let M_i denote a metropolitan indicator equal to one if a majority of bank i's domestic deposits are located in metropolitan counties. Let Y_i denote the bank's deposit-weighted log median household income. Both variables are interacted with monetary policy shocks and enter regressions as controls; neither is used as an excluded instrument.

Each bank's pre-period regional deposit shares $s_{i,r}$ are also computed by mapping counties to one of nine Census regions. These region shares are interacted with quarter dummies to absorb region-specific shocks.

3.3 Monetary policy shocks and instruments

Monetary policy is measured by the target federal funds rate r_t^{FF}. The quarterly change is

$$\Delta r_t^{FF} = r_t^{FF} - r_{t-1}^{FF},$$

and the cumulative change from the pre-tightening quarter $t_0 = 2021\text{Q}4$ is

$$R_t^{FF} = r_t^{FF} - r_{t_0}^{FF} = \sum_{s=t_0+1}^{t} \Delta r_s^{FF}.$$

The main instruments exploit cross-sectional heterogeneity in (S_i, R_i, H_i) and the common cumulative monetary shock:

$$z S_{i,t}^{\text{cum}} = S_i \, R_t^{FF}, \qquad z R_{i,t}^{\text{cum}} = R_i \, R_t^{FF}, \qquad z H_{i,t}^{\text{cum}} = H_i \, R_t^{FF}.$$

Because (S_i, R_i, H_i) are constructed using only pre-period data, these interactions are pre-determined with respect to post-2021 outcomes. They vary over time exclusively through R_t^{FF} and across banks exclusively through the cross-sectional indices, and thus constitute valid excluded instruments.

Flow instruments $S_i \Delta r_t^{FF}$, $R_i \Delta r_t^{FF}$, and $H_i \Delta r_t^{FF}$ are constructed for robustness exercises, but cumulative instruments constitute the preferred specification given the timing mismatch inherent in Call Report accruals.

Metropolitan and income controls enter as their own interactions with the cumulative shock, $M_i R_t^{FF}$ and $Y_i R_t^{FF}$, but are always included as controls rather than excluded instruments.

3.4 Cumulative effective deposit rates and deposit quantities

Call Report effective deposit rates frequently reflect rate adjustments implemented in the previous quarter. To mitigate this timing misalignment, the analysis focuses on cumulative changes over the entire hiking cycle. Let $r_{i,t}^{dep}$ denote the effective deposit rate. The cumulative change is

$$R_{i,t}^{dep} = r_{i,t}^{dep} - r_{i,t_0}^{dep} = \sum_{s=t_0+1}^{t} \left(r_{i,s}^{dep} - r_{i,s-1}^{dep} \right),$$

and similarly for interest-bearing deposits $R_{i,t}^{IB}$. For a given R_t^{FF}, the cumulative change $R_{i,t}^{dep}$ can be interpreted as the bank's cycle-level deposit beta multiplied by R_t^{FF}, plus noise. Aggregating over the full tightening cycle reduces the effect of quarter-level timing slippage.

Cumulative deposit-quantity measures are also constructed by summing quarter-on-quarter growth rates, though these serve primarily as descriptive auxiliary outcomes.

3.5 First-stage specification

The first-stage regression for cumulative deposit rates is

$$\begin{aligned}
R_{i,t}^{dep} = {} & \alpha_i + \lambda_t + \beta_S z S_{i,t}^{\text{cum}} + \beta_R z R_{i,t}^{\text{cum}} + \beta_H z H_{i,t}^{\text{cum}} \\
& + \phi_M M_i R_t^{FF} + \phi_Y Y_i R_t^{FF} + \sum_r \sum_\tau \gamma_{r,\tau} \, s_{i,r} \mathbf{1}\{t = \tau\} + \varepsilon_{i,t},
\end{aligned}$$

with bank fixed effects α_i and quarter fixed effects λ_t. The coefficients $(\beta_S, \beta_R, \beta_H)$ identify heterogeneity in cumulative deposit-rate pass-through as a function of depositor sophistication, branch intensity, and local concentration.

3.6 Second-stage specification

To quantify the effect of deposit funding costs on lending, the following IV specification is estimated:

$$g_{i,t}^k = \alpha_i^k + \lambda_t^k + \theta^k \widehat{R_{i,t}^{dep}} + X_{i,t-1}' \delta^k + \sum_{r,\tau} \eta_{r,\tau}^k \, s_{i,r} \mathbf{1}\{t = \tau\} + u_{i,t}^k,$$
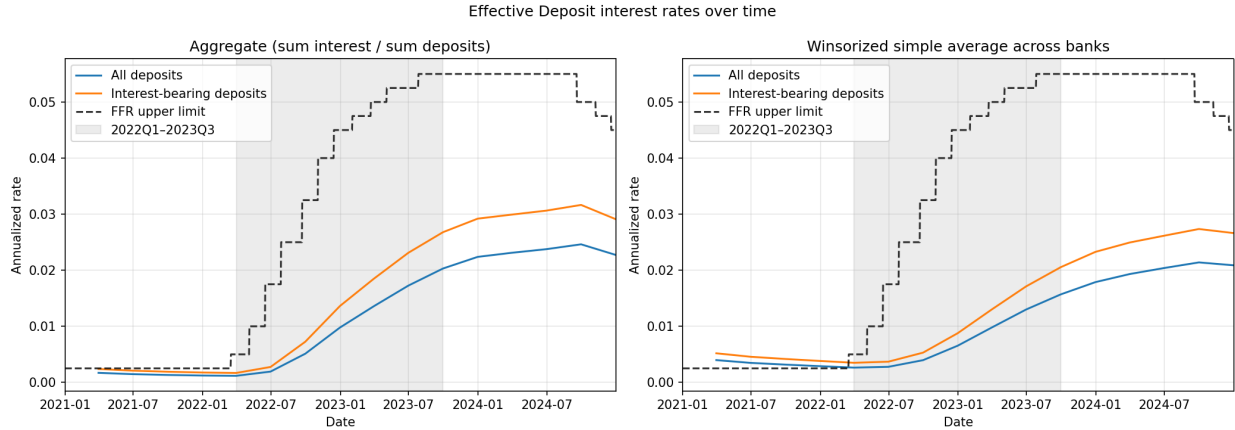
where $g_{i,t}^k$ denotes loan growth in category k, $\widehat{R_{i,t}^{dep}}$ is the fitted value of cumulative effective deposit rates from the first stage, and $X_{i,t-1}$ contains lagged balance-sheet controls. The endogenous variable $R_{i,t}^{dep}$ is instrumented using the cumulative exposure interactions $(zS_{i,t}^{\text{cum}}, zR_{i,t}^{\text{cum}}, zH_{i,t}^{\text{cum}})$, while the metropolitan and income interactions are included as controls.

The coefficient θ^k is interpreted as the effect of a policy-induced cumulative increase in the deposit funding cost on banks' loan growth during the tightening cycle, identified through exogenous cross-sectional variation in depositor sophistication, branch intensity, and local concentration.

4 Results

4.1 Summary statistics

The empirical analysis draws on a cross-section of 4,075 commercial banks observed in 2022Q1, the quarter immediately preceding the onset of the tightening cycle. Banks in the sample are predominantly small and community institutions: the median bank reports $288 million in assets, compared with a mean of $3.31 billion. Asset size is highly skewed, with the largest decile of banks accounting for 89.40 percent of total system assets. Using the $10 billion size threshold commonly employed in the literature, only 106 banks qualify as large institutions, while 3,969 banks fall below this cutoff. This size distribution ensures that the cross-section captures the segment of the banking sector most exposed to deposit-franchise considerations and most relevant for heterogeneity in deposit-rate passthrough.

Notes: The left panel shows aggregate deposit-weighted effective rates; the right panel shows winsorized simple averages across banks (0.5–99.5%). The shaded region marks 2022Q1–2023Q3.

Figure 1: Deposit Rates and Policy Shocks

Figure 1 reports summary statistics for effective deposit rates and the associated monetary-policy shock over the 2022–2023 tightening cycle. The federal funds rate rose by roughly 525

basis points between 2022Q1 and 2023Q3, while the effective deposit rate on all domestic deposits increased much more gradually, from near-zero levels to approximately 2.3 percent by late 2023. Interest-bearing deposits adjusted more quickly, rising to about 3.0 percent over the same period, but still remained well below the policy rate. The cumulative changes reported in Figure 1 highlight both the magnitude of the common policy shock and the substantial sluggishness and incompleteness of deposit-rate pass-through. These patterns motivate the use of cumulative deposit-rate changes as the key endogenous funding-cost variable in the empirical analysis.

Table 1: Summary Statistics - Instruments and Selected Controls

Variable	mean	std	min	25%	75%	max
zS	-0.074	0.973	-2.951	-0.722	0.571	3.032
zR	0.014	0.869	-7.489	-0.348	0.513	4.856
zH	0.044	1.015	-1.401	-0.644	0.441	5.997
Metropolitan dummy	0.519	0.443	0.000	0.000	1.000	1.000
zY	-0.069	0.968	-3.950	-0.642	0.466	3.430

Table 1 reports summary statistics for the cross-sectional exposure indices and selected controls for the 2022Q1 cross-section. zS is the depositor sophistication index, zR is the branch intensity index, zH is the local concentration index, Metropolitan dummy is a dummy variable for whether a bank is located in a metropolitan area, and zY is the deposit-weighted log median household income. Z scores are clipped at +/- 10.

Table 2: Summary Statistics - Deposit and Loan Growth

Variable	mean	std	min	25%	75%	max
gDep	0.034	0.059	-0.161	0.002	0.055	0.314
gIBDep	0.035	0.077	-0.246	0.001	0.059	0.504
gCoreDep	0.037	0.126	-0.857	-0.001	0.059	5.186
gTotalLoans	0.007	0.058	-0.148	-0.020	0.030	0.323
gLoansNotForSale	0.807	0.056	-0.140	-0.018	0.031	0.310
gSingleFamilyMortgages	0.033	0.796	-1.000	-0.024	0.037	49.000
gC&ILoans	-0.001	0.260	-1.000	-0.083	0.053	6.876

Table 2 reports summary statistics for the deposit and loan growth rates from 2022Q1 to 2023Q3. All growth rates are expressed as quarter-on-quarter changes, and winsorized at the 0.5th and 99.5th percentiles. gDep is the growth rate of all deposits, gIBDep is the growth rate of interest-bearing deposits, gCoreDep is the growth rate of core deposits which includes demand deposits, saving deposits MMDAs, and small time deposits under 250K USD, gTotalLoans is the growth rate of total loans, gLoansNotForSale is the growth rate of loans not for sale, gSingleFamilyMortgages is the growth rate of 1-4 family mortgages, and gC&ILoans is the growth rate of commercial and industrial loans.

4.2 First-stage regressions

Table 3: First-stage regressions for cumulative deposit rates

	(1)	(2)	(3)	(4)
Dependent variable	All deposits	All deposits	IB deposits	IB deposits
Sample	All banks	Small banks	All banks	Small banks
zS × cum ΔFFR	0.000389***	0.000378***	0.000444***	0.000425***
	(0.000047)	(0.000047)	(0.000057)	(0.000057)
zR × cum ΔFFR	-0.000650***	-0.000661***	-0.000769***	-0.000813***
	(0.000034)	(0.000037)	(0.000043)	(0.000043)
zH × cum ΔFFR	-0.000060***	-0.000061***	-0.000073***	-0.000072***
	(0.000021)	(0.000021)	(0.000026)	(0.000026)
Metro × cum ΔFFR	0.000232***	0.000223***	0.000363***	0.000347***
	(0.000057)	(0.000057)	(0.000068)	(0.000068)
zY × cum ΔFFR	-0.000131***	-0.000134***	-0.000111**	-0.000117**
	(0.000045)	(0.000046)	(0.000055)	(0.000056)
Observations	32,057	31,167	32,057	31,167
Clusters	4,119	4,000	4,119	4,000
Within R-sq.	0.818	0.815	0.844	0.841
Joint F (zS = zR = zH = 0)	162.92	144.50	144.31	153.51
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Region × Quarter controls	Yes	Yes	Yes	Yes
SEs clustered by	Bank	Bank	Bank	Bank

Notes: Coefficients shown with clustered standard errors in parentheses. *, **, *** denote p < 0.10, 0.05, 0.01 respectively. "cum ΔFFR" is the cumulative change in the federal funds rate since 2021Q4. Columns (2) and (4) restrict the sample to small banks. All specifications absorb bank fixed effects and quarter fixed effects, and include deposit-weighted Census region × quarter interactions. Dependent variables are cumulative changes in effective deposit rates: all deposits in columns (1)–(2); interest-bearing deposits in columns (3)–(4).

Table 3 reports the first-stage panel regressions of cumulative effective deposit rates on the exposure–policy interactions and shows that deposit-rate pass-through varies systematically across banks. In columns (1)–(2), the coefficient on `zS × cum_d_ffr` is positive, while the coefficients on `zR × cum_d_ffr` and `zH × cum_d_ffr` are negative, with very similar patterns for interest-bearing deposits in columns (3)–(4). Using the column (1) estimates and the standard deviations in Table 1, and interpreting `cum_d_ffr` in 100-basis-point units, a one–standard deviation higher depositor-sophistication index `zS` raises the cumulative all-deposit rate by about **3.5 basis points** more in response to a 100 bps tightening than at the sample mean, whereas a one–standard deviation higher branch-intensity index `zR` lowers pass-through by roughly **5.6 bps** and a one–standard deviation higher local concentration

index zH reduces pass-through by about **0.5 bps**. These signs are in line with the deposit-franchise logic in Drechsler et al. (2016): banks with more market power (branch-intensive models in concentrated markets) keep deposit rates lower and preserve the franchise, while those facing more sophisticated depositors are forced to pass through more of the policy shock. At the same time, the fact that these bank-level betas load primarily on depositor sophistication and branch intensity, rather than strongly on HHI, echoes the more recent emphasis in Narayanan and Ratnadiwakara (2024) on depositor characteristics as key drivers of deposit betas and outflows during the 2022–23 tightening. However, the very existence of this cross-sectional heterogeneity in bank-level pass-through sits uneasily with the uniform-pricing view in Begenau and Begenau and Stafford (2023), which is derived from branch-level RateWatch data for large banks and implies that concentration-driven dispersion in deposit betas should be weak; for the mostly small and community banks in my sample, Table 3 instead suggests that cumulative funding costs do move differentially with policy along the exposure dimensions captured by zS, zR, and zH.

Table 4: First-stage regressions for deposit growth rates

	(1)	(2)	(3)	(4)
Dependent variable	All deposits	All deposits	IB deposits	IB deposits
Sample	All banks	Small banks	All banks	Small banks
zS $\times$ cum ΔFFR	0.000486	0.000443	0.000362	0.000254
	(0.000416)	(0.000420)	(0.000556)	(0.000561)
zR $\times$ cum ΔFFR	-0.001541***	-0.001865***	-0.001440***	-0.002008***
	(0.000305)	(0.000329)	(0.000418)	(0.000461)
zH $\times$ cum ΔFFR	0.000169	0.000203	0.000038	0.000104
	(0.000198)	(0.000198)	(0.000261)	(0.000263)
Metro $\times$ cum ΔFFR	0.000985*	0.000889*	0.002453***	0.002400***
	(0.000518)	(0.000520)	(0.000706)	(0.000708)
zY $\times$ cum ΔFFR	-0.000493	-0.000492	-0.000031	-0.000084
	(0.000394)	(0.000399)	(0.000530)	(0.000539)
Observations	31,935	31,003	32,346	31,365
Clusters	4,169	4,035	4,174	4,040
Within R-sq.	0.0607	0.0624	0.0314	0.0331
Joint F (zS = zR = zH = 0)	9.76	12.09	4.44	6.71
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Region $\times$ Quarter controls	Yes	Yes	Yes	Yes
SEs clustered by	Bank	Bank	Bank	Bank

Notes: Coefficients shown with clustered standard errors in parentheses. *, **, *** denote $p < 0.10, 0.05, 0.01$ respectively. "cum ΔFFR" is the cumulative change in the federal funds rate since 2021Q4. Columns (2) and (4) restrict the sample to small banks. All specifications absorb bank fixed effects and quarter fixed effects, and include deposit-weighted Census

region $\times$ quarter interactions. Dependent variables are quarter-on-quarter deposit growth rates (all deposits in columns (1)–(2); interest-bearing deposits in columns (3)–(4)).

Table 4 shows that the deposit-quantity channel does not receive empirical support in this sample. Neither the depositor-sophistation interaction (`zS × cum ΔFFR`) nor the concentration interaction (`zH × cum ΔFFR`) is statistically distinguishable from zero across all specifications, indicating no systematic relationship between these exposures and deposit outflows during the tightening cycle. More importantly, the coefficient on the relationship-banking interaction (`zR × cum ΔFFR`) is negative and significant, implying that banks with more branch-intensive, relationship-based models experience larger deposit outflows when cumulative policy tightening rises—opposite to the core prediction of the deposit-franchise view, where stronger relationship banking should moderate outflows. The within-R^2 values remain below 6 percent, and the joint F-statistics are far smaller than in the deposit-rate first-stage regressions. Taken together, these results indicate that the bank-level cross-sectional exposures used in Table 3 do not generate a strong or theoretically consistent first stage for deposit quantities. Consequently, the empirical strategy instruments only cumulative effective deposit rates in the second stage. The stock–stock specification using cumulative deposit changes produces even weaker and noisier results and is included solely as a robustness check.

4.3 Second-stage regressions

5 Robustness checks

6 Appendix

6.1 Appendix 1: Principal Component Analysis

Table 5: Principal Component Analysis Loadings

Variable	PC1	PC2	PC3	PC4	PC5	PC6
share_ba_plus_z	-0.828	-0.273	0.238	-0.294	0.259	-0.173
share_age_65plus_z	-0.064	0.926	-0.049	0.144	0.339	-0.027
share_internet_sub_z	-0.761	-0.366	0.224	0.482	0.057	0.022
share_dividend_z	-0.896	0.252	0.111	-0.181	-0.047	0.294
share_interest_z	-0.752	0.508	0.008	0.025	-0.381	-0.175
refi_share_z	-0.688	-0.235	-0.683	0.016	0.072	-0.005

Table 5 reports the loadings of the principal component analysis. The first principal component is considered as the depositor sophistication index, which explains 51.8% of the variance in the county-level data.

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