Monetary Policy, Deposit Funding Shocks, and Bank Credit Supply: Bank-Level IV Evidence

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Abstract

This paper studies how monetary policy transmits to bank credit supply through deposit funding conditions during the 2022–2023 tightening cycle. Using a quarterly panel of 3,849 U.S. commercial banks, the analysis constructs predetermined exposure indices capturing depositor sophistication, branch intensity, and local deposit-market concentration, and interacts them with cumulative changes in the federal funds rate to generate bank-level shift–share instruments. These interactions are used in a two-stage least squares framework to instrument for cumulative effective deposit rates and, more weakly, deposit growth. The first-stage estimates reveal strong and economically meaningful heterogeneity in cumulative deposit-rate pass-through across banks, driven primarily by depositor sophistication and branch intensity, whereas the corresponding deposit-quantity responses are small, imprecise, and inconsistent with canonical quantity-based deposit-channel predictions. In the second stage, a larger policy-induced increase in a bank's effective deposit rate is associated with a statistically and economically significant slowdown in the growth of loans not held for sale, indicating a funding-cost channel linking monetary tightening to reduced credit supply. By contrast, quantity-based specifications using instrumented deposit growth yield coefficients of the wrong sign and only marginal significance, consistent with banks' ability to substitute across liability classes when faced with deposit outflows. Overall, the results support a bank-level deposit channel that operates primarily through funding costs and depositor-composition–driven pricing behavior rather than through a simple mechanical link between core-deposit volumes and balance-sheet capacity.

1 Introduction

Rapid monetary tightening since March 2022 has renewed interest in how deposit funding transmits policy to bank credit supply. A prominent recent account is the "deposits channel" of Drechsler et al. (2016). In their framework, households value bank deposits because they are safe and liquid, but banks possess pricing power in local deposit markets. When the Federal Reserve raises the policy rate, outside short rates jump, yet deposit rates adjust only partially. The spread between the federal funds rate and the deposit rate widens, so holding deposits becomes more expensive relative to money market instruments. Households respond by shifting out of checking and savings into higher-yield alternatives.

Drechsler et al. (2016) formalize this mechanism using branch–level data and county-level deposit concentration (HHI) as a proxy for local pricing power. The key empirical patterns are: (i) after a policy tightening, branches in more concentrated counties raise deposit rates less, so the deposit spread widens more there; and (ii) those same branches suffer larger net outflows of core deposits than branches in more competitive counties. Core deposits are assumed to be only imperfectly replaced by wholesale and large time deposits, so the net outflow of deposits forces banks to shrink their balance sheets. In the aggregate, deposits contract, banks cut lending, and the supply of safe and liquid claims to households falls, raising the liquidity premium. In this view, the deposit channel is fundamentally a quantity channel operating through local concentration, sluggish pass-through, and incomplete liability substitution.

Subsequent work has raised serious doubts about this particular implementation of the deposit channel. Begenau and Stafford (2023) document that U.S. banks, especially larger ones, predominantly use uniform deposit rate setting across their networks. Retail deposit rates are set centrally and vary little with county-level HHI, so branch-level heterogeneity in local concentration cannot, in practice, be a main driver of banks' pricing decisions. Begenau and Stafford (2023) further show that the original DSS first-stage result relies on dropping "follower" branches whose rates are set elsewhere; once those branches, representing the bulk of the branch universe, are included, the relationship between HHI interacted with policy changes and deposit-rate pass-through largely disappears. At the same time, deposit flows continue to comove with HHI even when local pricing cannot be the mechanism, suggesting that county concentration is picking up who banks serve rather than how they set rates.

BS also highlight an aggregation problem. For large, networked banks, deposit outflows in tightening cycles are often offset by increases in other funding sources, such as large time deposits or wholesale debt, so total liabilities and assets move much less than core deposits (Begenau and Stafford 2023). Narayanan and Ratnadiwakara (2024) complement this critique by shifting attention from geography to depositor characteristics. Using proprietary geolocation and customer-profile data, they show that cross-bank differences in depositor income, education, and financial engagement strongly predict both deposit-rate pass-through and deposit run-offs in the 2022–2023 hiking cycle. Banks funded by younger, wealthier, and more financially active depositors raise rates more and still lose more deposits, while banks with older, less sophisticated depositor bases adjust rates less and retain deposits more easily. Traditional concentration measures such as HHI largely proxy for this depositor mix rather than providing an independent handle on pricing power.

Taken together, this subsequent evidence substantially weakens the original DSS picture. If deposit rates are mostly set at the bank level rather than locally, if county-level HHI primarily captures depositor composition instead of genuine pricing power, and if large banks can substitute across liability classes when deposits run off, then a branch-level, HHI-driven quantity channel is an unsteady foundation for thinking about monetary transmission. Nevertheless, even if the original DSS identification strategy and local-market design are problematic, the broader hypothesis that monetary policy transmits to bank credit supply through deposit funding conditions remains appealing and warrants a bank-level formulation that is consistent with uniform pricing, depositor heterogeneity, and liability substitution.

The present study takes that step by reformulating and testing a different deposit channel: a funding-cost deposit channel operating at the bank level. Rather than treating county HHI as the sufficient statistic for pricing power, the analysis separates three distinct, predetermined dimensions of exposure: (i) a depositor sophistication index built from county-level education, financial participation, broadband access, and mortgage refinancing activity; (ii) a branch-intensity measure capturing how branch-heavy and relationship-based a bank's funding model is; and (iii) a deposit-weighted HHI exposure that retains the traditional notion of local concentration but does not give it pride of place. These pre-2021 indices are interacted with the cumulative change in the federal funds rate over the 2021Q4–2023Q4 hiking cycle to construct bank-level, shift–share instruments for deposit funding conditions. Banks serving sophisticated, metropolitan households with thin branch networks are, ex ante, expected to face more elastic deposit demand and thus higher pass-through; branch-intensive banks in concentrated markets are expected to have more scope to hold deposit rates down.

Working at the bank rather than branch level directly addresses the uniform-pricing critique in Begenau and Stafford (2023), and using depositor sophistication as a central exposure allows the design to speak to the depositor-composition view in Narayanan and Ratnadiwakara (2024). Within this framework, the first step of the analysis estimates how the exposure–shock interactions shift cumulative effective deposit rates and deposit quantities, and the second step uses these interactions as instruments in a two-stage least squares (2SLS) design to recover a bank-level local average treatment effect of policy-induced funding-cost shocks on credit supply. The main endogenous variable is the cumulative change in each bank's effective deposit rate, interpreted as a cycle-level shock to the cost of deposit funding; deposit-growth measures are used in parallel specifications to probe the quantity side of the channel. The primary outcome is the growth of loans not held for sale.

The empirical findings point to a deposit channel that is primarily cost-based rather than quantity-based. On the funding side, the exposure–shock interactions strongly predict cumulative deposit rates: banks whose deposits are more exposed to financially sophisticated households exhibit much higher pass-through, whereas branch-intensive and high-HHI banks raise deposit rates less. This pattern is consistent with banks that rely on branch-intensive funding models and less sophisticated depositor bases being able to keep effective deposit rates farther below the policy rate, while banks facing more sophisticated depositors cannot. By contrast, the same interactions are noticeably weaker and less stable in explaining deposit quantities, and the sign pattern does not line up cleanly with the canonical predictions.

On the credit-supply side, the 2SLS estimates reveal a robust funding-cost channel: banks that experience larger instrumented increases in cumulative effective deposit rates see materially slower growth in loans not held for sale, both in the full sample and among small banks. The effect is statistically and economically meaningful, and it is stable across alternative rate measures. When instrumented deposit-growth measures are used instead, the coefficients are negative rather than positive and only marginally significant, a pattern that is difficult to reconcile with a simple "deposit-outflow tightens balance-sheet constraints" story. Interpreted in light of the first stage, these results suggest that deposit quantities are best viewed as an endogenous reflection of the same funding-cost shocks that move deposit rates, not as an independent transmission margin.

The paper makes three contributions. First, it recasts the deposit channel in terms of bank-level funding costs and depositor-based pricing power, exercised through particular clienteles and branch-intensive funding models rather than through counties with high HHI alone. Second, it provides, to the best of current knowledge, the first bank-level IV estimates of the causal effect of policy-induced deposit funding-cost shocks on lending under an identification strategy that is explicitly designed to be consistent with uniform pricing and depositor heterogeneity. Third, it clarifies how the traditional deposit-franchise mechanism and the depositor-composition evidence fit within a common deposit channel in which banks' ability to pay below-market rates to particular depositor bases remains central, but the best-identified transmission margin is the cost of deposit funding rather than the volume of core deposits.

The remainder of the paper reviews the relevant literature (Section 2), describes the data, exposure measures, and empirical strategy (Section 3), presents the first-stage and second-stage results (Section 4), discusses their implications for the deposit-channel and credit-channel literatures (Section 5), and concludes (Section 6).

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 may never have 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). Against this backdrop, the literature recast monetary transmission in terms of a broader "credit channel," comprising a balance-sheet channel—tightening weakens borrower cash flow and collateral, raising external-finance premia—and a bank-lending channel, in which reserve drains or funding-cost increases reduce core deposits and, when nondeposit liabilities are imperfect or costly substitutes, shift banks' loan-supply schedules inward (Bernanke and Gertler 1995; Kashyap and Stein, n.d.).

A complementary line of work emphasizes the bank-capital channel. Since Basel I, 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 new standards (Bernanke and Lown 1991; Hancock and Wilcox 1994). Quasi-experimental studies find that tighter, bank-specific capital requirements contract lending at affected institutions, 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), who formalize how banks use their deposit franchise to transmit monetary policy shocks when they possess local pricing power. Building on classic evidence that deposit rates are sluggish and adjust less where competition is weaker (Hannan and Berger 1997; Neumark and Sharpe 1992), DSS combine a branch-level within-bank design with bank-level balance-sheet regressions. In their framework, a policy-rate increase lifts outside short rates, but with search frictions and imperfect competition in deposit markets, branch-level deposit rates move by less than one-for-one. The spread between the federal funds rate and the deposit rate therefore widens, and households shift out of low-yield deposits into higher-yield alternatives. In the data, these price–quantity gradients are strongest where local competition is weak: following a Fed funds hike, branches in less competitive (high-HHI) counties raise their deposit spreads more and experience lower subsequent deposit growth—larger net outflows—than branches of the same bank in more competitive counties.

This is captured in regressions that interact changes in the target federal funds rate with lagged county Herfindahl indices under rich fixed effects. In the branch-level specifications, changes in deposit spreads and in core-deposit growth are regressed on $\Delta FFR_t \times HHI_c$ with bank–time, county, state–time, and branch fixed effects, so identification comes from comparing branches of the same bank facing different local concentration. Complementary bank-level Call Report regressions relate changes in core deposits, the aggregate deposit spread (Fed funds minus the average deposit rate), and deposit "revenue" (the spread times the deposit base) to $\Delta FFR_t \times HHI_b$, where HHI_b is constructed as the deposit-weighted average of county HHI_c. Aggregation in DSS is essentially mechanical: core deposits—roughly four-fifths of bank liabilities—fall on net when policy tightens; substitution into wholesale and large time deposits is incomplete; total liabilities track the decline in core deposits; and assets and loans contract. Because deposits are households' primary liquid claim, the system-wide shrinkage of deposits raises the liquidity premium relative to other safe but less liquid instruments, so monetary tightening operates through a quantity-based "deposit channel" in which local market structure shapes the joint response of deposit prices and quantities.

Subsequent work refines both the mechanism and its quantitative importance. 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 net interest margins and profitability relatively stable around rate moves, so tightening transmits mainly through funding-quantity pressure and the liquidity premium rather than large swings in bank net worth (Drechsler et al. 2021). On magnitudes, decompositions of bank valuations show that liability "productivity" explains a large share of cross-bank value: for the median bank, a substantial fraction of market-to-book is attributable to the deposit franchise, and stronger savings-deposit capability is especially valuable (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 also reshape the first stage: online and national banks pass through more and attract inflows, while smaller institutions face sharper outflows, reallocating credit supply across balance sheets rather than simply shrinking the aggregate (Erel et al. 2023; d'Avernas et al. 2023). Outside the United States, evidence from the 2022–2023 cycle shows that larger deposit outflows map into quantity rationing—especially for fixed-rate, longer-maturity loans—and that 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). Structural estimates link the deposits and capital channels, showing that 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).

A separate strand raises important critiques of the deposit channel as originally identified. One set concerns uniform pricing. Large "large-reach" banking networks post near-uniform retail deposit rates across broad geographies, so that most of the variation in offer rates is explained by bank–quarter rather than county–quarter fixed effects; branch-level dispersion within a given bank is minimal except for a small group of mid-sized regional institutions (Begenau and Stafford 2023). In this environment, county-level concentration (HHI) is at best a noisy proxy for deposit-market power, and within-bank cross-county designs risk attributing pass-through and outflows to "local competition" when they largely reflect centralized rate sheets and corporate pricing policies (Begenau and Stafford 2023; d'Avernas et al. 2023). BS show that the canonical first-stage relation between $\Delta\text{FFR}_t \times HHI_c$ and deposit-rate pass-through disappears once follower branches—over 90% of the branch universe—are reinstated, and that similar deposit-flow sensitivities to $\Delta\text{FFR}_t \times HHI_c$ arise even among follower branches that do not set rates locally. A related critique emphasizes depositor composition. Using geolocation data matched to census and tax records, Narayanan and Ratnadiwakara (2024) document large cross-bank differences in depositor income, education, age, and financial-market participation, and show that these characteristics strongly predict both deposit betas and deposit run-offs in the 2022–2023 hiking cycle: banks with younger, wealthier, and more financially sophisticated customers raise rates earlier and more aggressively, yet still experience larger core-deposit and uninsured outflows, and generate substantially lower deposit-franchise value per dollar of deposits than banks serving less sophisticated clients. On this view, county HHI largely proxies for differences in depositor types and digital engagement rather than independent pricing power, and the relevant heterogeneity is at the bank–depositor level rather than the branch–county level (Narayanan and Ratnadiwakara 2024; d'Avernas et al. 2023).

A further challenge is aggregation. The deposit channel has macro bite only if substitution from "deposit-channel" balances (non-interest-bearing and low-rate liquid deposits) into time deposits and non-deposit debt is incomplete. Asset-weighted analyses suggest that at the largest institutions substitution is ample: when policy tightens, rate-sensitive deposits flow out, but are offset by inflows into time deposits and by higher wholesale and bond funding, so that total liabilities and loans at the top decile of banks move very little even though cross-sectional patterns in spreads, core-deposit growth, and loan growth are visible in the full sample (Begenau and Stafford 2023). In that sense, HHI-based cross-sectional gradients may mainly reallocate intermediation across balance sheets rather than contract it in the aggregate. Even so, distributional effects remain first order: if bank-dependent borrowers cannot easily substitute away from relationship lending—classic examples being small and opaque firms, local borrowers without direct access to capital markets, or households reliant on community banks—or if smaller banks face higher marginal costs of wholesale replacement, monetary tightening can still produce sizeable contractions in credit where those relationships bind, generating partial aggregation on the small-business margin even when large banks can absorb outflows with alternative funding (Erel et al. 2023; Kashyap and Stein, n.d.; d'Avernas et al. 2023).

The remaining gap in the literature concerns a clean mapping from policy-induced, bank-specific changes in deposit funding conditions to bank credit supply. A substantial literature offers cross-sectional explanations of deposit-rate pass-through and deposit outflows and documents how deposit betas and flows vary with market structure, technology, and depositor characteristics, but much less is known about how a given bank-level increase in funding costs or a standardized deposit outflow translates into lending. Even flagship contributions such as Drechsler et al. (2016) and Narayanan and Ratnadiwakara (2024) relate deposit movements to lending in reduced form, without using policy-driven instruments to recover a bank-level causal elasticity of credit supply with respect to deposit funding shocks. Existing identification strategies typically operate at the branch–county level and rely heavily on local concentration measures, which is problematic in light of the uniform-pricing and depositor-composition critiques in Begenau and Stafford (2023) and Narayanan and Ratnadiwakara (2024). The empirical design here addresses this gap with a bank-level 2SLS framework: predetermined, pre-2021 exposures to deposit-rate and deposit-flow sensitivity—capturing depositor sophistication, branch intensity, and local concentration—are interacted with cumulative changes in the federal funds rate to construct shift–share instruments for, respectively, each bank's cumulative change in its effective deposit rate and its cumulative deposit outflow. Deposit-weighted region-by-quarter fixed effects absorb local demand conditions and common shocks, and bank fixed effects absorb time-invariant heterogeneity, so that the second stage maps the instrumented funding-cost shock and the instrumented outflow into total and portfolio-level lending, yielding a bank-level local average treatment effect for the credit-supply response that speaks directly to the identification and aggregation concerns raised in the recent deposit-channel literature.

These 2SLS regressions remain reduced form in the sense that they do not pin down a specific microeconomic mechanism through which higher funding costs reduce lending. The only assumption needed for a deposit channel to operate is that at least some borrowers cannot costlessly substitute away from relationship-based lenders when their banks face adverse funding shocks (Erel et al. 2023). Within this reduced-form framework, classic mechanisms such as credit rationing under adverse selection and capital or earnings constraints that make loan growth sensitive to net interest margins are treated as candidate channels consistent with the estimated elasticity, rather than as objects that are separately identified (Stiglitz and Weiss 1981; Van den Heuvel 2002; Wang et al. 2020).

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, with particular attention to loans not held for sale as the main credit-supply outcome in the second stage.

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; instead, income is introduced separately as a control.

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. This construction yields a panel in which the key exposure indices and controls are predetermined with respect to the tightening cycle and can be interpreted as quasi-time-invariant bank characteristics that shape how each balance sheet responds to policy shocks. These characteristics underpin the first-stage and second-stage relationships summarized in the empirical predictions in Section 3.7.

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 described above. The indices are best viewed as reduced-form proxies for how a bank's funding base is exposed to monetary tightening: depositor sophistication captures who the customers are and how financially engaged they are; branch intensity summarizes the extent of relationship-based retail banking; and the HHI exposure measures the degree of local concentration in deposit markets. Together, they provide the cross-sectional heterogeneity exploited by the exposure–shock instruments in the first stage and are central to the hypotheses in Section 3.7.

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. In the context of the hypotheses in Section 3.7, higher S_i is interpreted primarily as a depositor-composition measure in the spirit of Narayanan and Ratnadiwakara (2024); banks serving more sophisticated households are expected to exhibit stronger deposit-rate pass-through and, under a simple deposit-channel view, more fragile deposit funding when policy tightens.

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.

A high value of R_i indicates a traditional, branch-heavy funding model with dense local presence and potentially strong relationship ties to retail depositors. Such banks may enjoy substantial franchise value and local market power, which can translate into sluggish deposit-rate adjustment when policy tightens, but they may also be more exposed to retail depositors who respond to perceived return shortfalls by reallocating balances. In the empirical predictions, this index is expected to be associated with lower pass-through in deposit rates (H1) and, under a simple quantity view, with more vulnerable deposit quantities (H2), although the latter is ex ante more fragile.

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

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

which lies in the interval $[0, 1]$ and measures the 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.

HHI exposure is the canonical proxy for deposit-market power in the original deposit-channel literature Drechsler et al. (2016) but has been criticized as a noisy measure in more recent work focusing on uniform pricing and depositor composition Begenau and Stafford (2023); Narayanan and Ratnadiwakara (2024). In this paper, H_i is retained as one component of the exposure vector, but ex ante it is expected to play a weaker role than depositor sophistication and branch intensity in explaining cross-bank differences in deposit-rate pass-through and deposit outflows. This expectation is reflected in the hypotheses H1 and H2 and in the interpretation of the first-stage results.

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. Given the short time dimension of the panel, no additional lagged bank-level controls are included in the baseline specifications; time-invariant bank characteristics are absorbed by bank fixed effects, and common or region-specific shocks are absorbed by quarter and region-by-quarter fixed effects. Together, M_i, Y_i, and the region-share interactions help control for systematic differences in depositor income, urbanization, and regional demand conditions that might otherwise confound the relationship between the main exposure indices and deposit funding conditions, while preserving a clean exclusion restriction for the core exposure–shock interactions used to test H1–H4.

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 $t_0 = \text{2021Q4}$ 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. For each bank i and quarter t, the cumulative exposure–shock interactions are defined as

$$z_{S,i,t}^{\text{cum}} = S_i R_t^{FF}, \qquad z_{R,i,t}^{\text{cum}} = R_i R_t^{FF}, \qquad z_{H,i,t}^{\text{cum}} = H_i R_t^{FF}.$$

Because (S_i, R_i, H_i) are constructed using only pre-period data, these interactions are predetermined 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 a standard shift–share design: for a given path of policy shocks, banks with different pre-2021 exposures experience different effective shifts in deposit funding conditions.

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 and the focus on the full 2022–2023 hiking cycle. 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. The core identifying assumption is that, conditional on bank fixed effects, time effects, and region-by-quarter controls, these predetermined exposure–shock interactions affect loan growth only through their impact on deposit funding conditions.

3.4 Cumulative effective deposit rates and deposit quantities

Call Report effective deposit rates frequently reflect rate adjustments implemented in the previous quarter and smooth within-quarter changes in posted rates. To mitigate this timing misalignment and to capture the full effect of the 2022–2023 tightening cycle, the analysis focuses on cumulative changes over the entire hiking period. Let $r^{\text{dep}}_{i,t}$ denote the effective deposit rate at bank i in quarter t. The cumulative change in the effective deposit rate relative to 2021Q4 is

$$R^{\text{dep}}_{i,t} = r^{\text{dep}}_{i,t} - r^{\text{dep}}_{i,t_0} = \sum_{s=t_0+1}^{t} \left(r^{\text{dep}}_{i,s} - r^{\text{dep}}_{i,s-1} \right),$$

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

Deposit-quantity measures are constructed analogously. Let $\text{Dep}_{i,t}$ denote domestic deposits at bank i in quarter t, and define the quarter-on-quarter growth rate

$$g^{\text{Dep}}_{i,t} = \frac{\text{Dep}_{i,t} - \text{Dep}_{i,t-1}}{\text{Dep}_{i,t-1}}.$$

Cumulative deposit-quantity measures, such as the cumulative change in average deposits, are obtained by summing these growth rates over the cycle,

$$R^{\text{Dep}}_{i,t} = \sum_{s=t_0+1}^{t} g^{\text{Dep}}_{i,s},$$

and are used primarily in robustness exercises. In the baseline specifications, cumulative effective deposit rates $R^{\text{dep}}_{i,t}$ serve as the main endogenous funding-cost variable, while quarter-on-quarter deposit growth rates and cumulative deposit quantities enter as alternative endogenous variables that speak to the quantity side of the deposit channel.

3.5 First-stage specification

The first-stage regression for cumulative deposit rates is

$$R^{\text{dep}}_{i,t} = \alpha_i + \lambda_t + \beta_S z^{\text{cum}}_{S,i,t} + \beta_R z^{\text{cum}}_{R,i,t} + \beta_H z^{\text{cum}}_{H,i,t} + \phi_M M_i R^{FF}_t + \phi_Y Y_i R^{FF}_t + \sum_r \sum_\tau \gamma_{r,\tau} s_{i,r} 1\{t = \tau\} + \varepsilon_{i,t},$$

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, conditional on metropolitan and income interactions and on region-specific shocks captured by the region-by-quarter terms. Hypothesis H1 specifies the expected sign pattern for these coefficients.

For deposit quantities, an analogous first-stage specification is estimated with a deposit-quantity outcome $Q_{i,t}$ in place of $R^{\text{dep}}_{i,t}$:

$$Q_{i,t} = \alpha_i + \lambda_t + \beta^Q_S z^{\text{cum}}_{S,i,t} + \beta^Q_R z^{\text{cum}}_{R,i,t} + \beta^Q_H z^{\text{cum}}_{H,i,t} + \phi^Q_M M_i R^{FF}_t + \phi^Q_Y Y_i R^{FF}_t + \sum_r \sum_\tau \gamma^Q_{r,\tau} s_{i,r} 1\{t=\tau\} + \varepsilon^Q_{i,t},$$

where $Q_{i,t}$ denotes either the quarter-on-quarter growth rate of average deposits, the growth of interest-bearing deposits, the change in core-deposit share, or a cumulative deposit-growth measure, depending on the specification. Hypothesis H2 states the canonical expectation that the coefficients $(\beta^Q_S, \beta^Q_R, \beta^Q_H)$ should be negative if higher sophistication, higher branch intensity, and higher HHI each increase the fragility of deposit funding when policy tightens. As discussed in Section 3.7, this prediction is theoretically weaker than for rates, and the identifying variation for quantities is expected to overlap substantially with that for rates.

3.6 Second-stage specification

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

$$g^k_{i,t} = \alpha^k_i + \lambda^k_t + \theta^k \widehat{F}_{i,t} + \sum_{r,\tau} \eta^k_{r,\tau} s_{i,r} 1\{t=\tau\} + u^k_{i,t},$$

where $g^k_{i,t}$ denotes loan growth in category k, and $\widehat{F}_{i,t}$ is the fitted value of a bank-level funding variable from the corresponding first stage. In the baseline specifications, $F_{i,t} = R^{\text{dep}}_{i,t}$ is the cumulative effective deposit rate, so θ^k measures the effect of a policy-induced cumulative increase in the deposit funding cost on banks' loan growth during the tightening cycle. In alternative specifications, $F_{i,t}$ is replaced by a deposit-quantity measure (such as the growth of average deposits), and θ^k is then interpreted as the elasticity of loan growth with respect to an instrumented change in deposit quantities.

The endogenous variable $F_{i,t}$ is instrumented using the cumulative exposure interactions $(z^{\text{cum}}_{S,i,t}, z^{\text{cum}}_{R,i,t}, z^{\text{cum}}_{H,i,t})$, while the metropolitan and income interactions always enter as controls. Given the short time dimension of the panel and the inclusion of bank, time, and region-by-quarter fixed effects, no additional lagged bank-level controls are included in the baseline; time-invariant heterogeneity is absorbed by α^k_i, and common or region-specific shocks are absorbed by λ^k_t and the region-share interactions. The coefficient θ^k is interpreted as a reduced-form local average treatment effect of a policy-induced change in deposit funding conditions on bank i's loan growth in category k, for the set of banks whose funding reacts to the instruments. Hypothesis H3 concerns the sign and magnitude of θ^k when $F_{i,t}$ is a cost-based measure, while H4 concerns the case where $F_{i,t}$ is a quantity-based measure.

3.7 Empirical predictions

The empirical analysis focuses on two related margins of the deposit channel: the cost of deposit funding and the quantity of deposit funding. The first-stage specifications in Sections 3.5–3.6 are primarily diagnostic, but they imply a set of sign predictions that follow directly from existing work on deposit-rate pass-through and deposit outflows. On the pricing side, banks with more sophisticated deposit bases are expected to exhibit higher cumulative pass-through from the policy rate to effective deposit rates, while banks that rely more heavily on branch-based relationship models or operate in more concentrated local markets are expected to adjust deposit rates more sluggishly (Narayanan and Ratnadiwakara 2024; Drechsler et al. 2016). These cross-sectional patterns reflect the idea that depositor characteristics and local market structure shape the elasticity of deposit demand and hence banks' optimal pricing responses to monetary tightening. Banks whose deposits are concentrated in more sophisticated areas face more rate-sensitive customers and therefore pass through a larger share of policy tightening into effective deposit rates. By contrast, banks with dense branch networks and those operating in more concentrated local markets enjoy stronger deposit franchises and greater market power, and therefore adjust deposit rates less for a given cumulative increase in the federal funds rate.

> **H1 (First-stage: deposit rates).** In the cumulative deposit-rate first-stage regressions, the exposure–shock interactions should satisfy the following sign pattern: the coefficient on the sophistication interaction is positive, while the coefficients on the branch-intensity and HHI interactions are negative.

On the quantity side, a simple view of the deposit channel suggests that, holding everything else constant, the same exposures that make depositors more rate-sensitive or shape banks' deposit-pricing behavior could also make deposit funding more fragile when policy tightens. Interpreting the sophistication index primarily as a depositor-composition measure in the spirit of Narayanan and Ratnadiwakara (2024), banks serving more sophisticated households should face larger deposit outflows when rates rise, because these customers are better able to monitor relative returns and to reallocate into higher-yield alternatives. By contrast, the implications for branch intensity and HHI are less clear-cut. Branch-intensive banks may rely more on relationship-based, less digitally engaged customers, which can dampen outflows even when pass-through is limited, while HHI combines elements of both local structure and depositor mix and need not have a uniform sign once depositor characteristics are explicitly controlled for. In this formulation, the fragility of funding is governed first by who the depositors are and only secondarily by how local markets are structured, so the direction of the quantity response is unambiguous only along the sophistication dimension.

At the same time, because the exposure–shock interactions are designed to capture both deposit-rate sensitivity and deposit-flow sensitivity, and because deposit outflows in practice operate partly through the induced changes in deposit rates, the identifying variation for quantities is likely to overlap substantially with that for rates. Ex ante, it is therefore reasonable to expect that the first-stage relationships for deposit quantities will be weaker and noisier than for deposit rates.

> **H2 (First-stage: deposit quantities).** In the deposit-quantity first-stage regressions, the sophistication–shock interaction is expected to be negative, so that higher sophistication exposure is associated with lower cumulative deposit growth (larger deposit outflows) conditional on the common monetary shock. For the branch-intensity and HHI exposures, no sharp sign prediction is imposed ex ante, reflecting the competing mechanisms highlighted in the recent deposit-channel literature.

The main hypotheses for the second stage concern the mapping from policy-induced changes in deposit funding conditions to loan growth. The first is a cost-based funding channel:

> **H3 (Funding-cost channel).** For banks whose effective deposit rates are shifted upward by the exposure–shock instruments, higher cumulative deposit funding costs reduce the growth rate of loans not held for sale. In terms of equation (3.6), the coefficient on the instrumented cumulative deposit rate is expected to be negative for total loans not held for sale and, potentially, for interest-sensitive loan categories.

This hypothesis is directly implied by credit-channel and bank-capital frameworks in which higher marginal funding costs and thinner net interest margins shift loan-supply schedules inward, even when banks can partially adjust prices, fees, or expenses. It does not take a stand on whether the underlying mechanism is credit rationing, capital constraints, or balance-sheet management more broadly; the parameter of interest is a reduced-form local average treatment effect of a funding-cost shock on loan growth.

The second concerns the role of deposit quantities. A simple balance-sheet view of the deposit channel would suggest that larger deposit outflows tighten funding constraints and reduce lending, implying a positive association between deposit growth and loan growth:

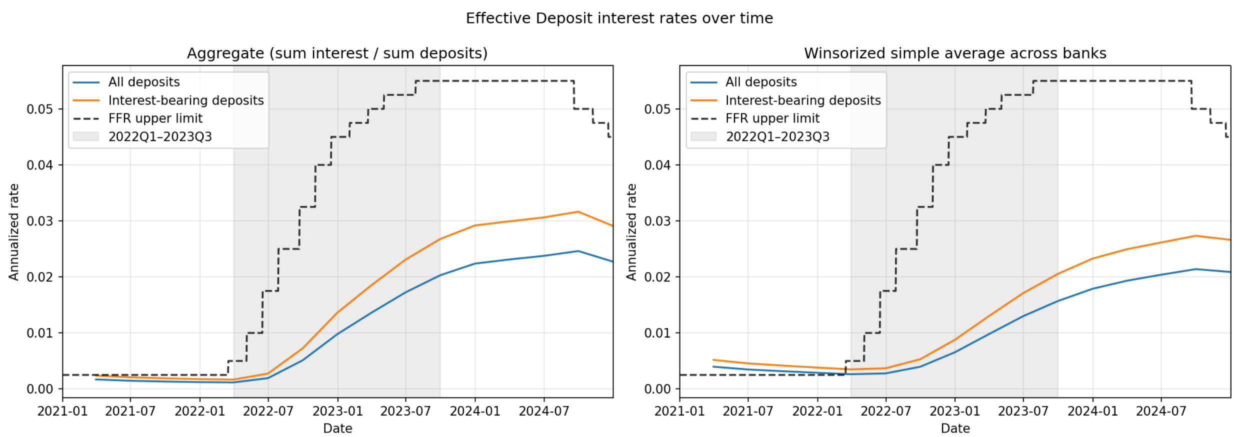
> **H4 (Quantity channel, canonical prediction).** If deposits are difficult or costly to replace with other liabilities at the margin, then, for banks whose deposit quantities are shifted by the exposure–shock instruments, higher deposit growth should be associated with higher loan growth. Equivalently, the coefficient on the instrumented deposit-growth measure in the second-stage regressions should be positive.

At the same time, the literature emphasizes banks' ability to substitute into wholesale and non-deposit liabilities, especially at larger institutions, and points to liability management, duration risk, and capital regulation as additional determinants of lending (Moore 1991; Minsky 1957; Begenau and Stafford 2023). These considerations make the quantity-based prediction theoretically weaker than the cost-based one. Moreover, if in practice the deposit-rate (funding-cost) channel dominates the pure quantity channel, then deposit growth is itself an endogenous response to the same underlying funding-cost shock: banks that face larger policy-induced increases in deposit rates may both reduce lending and experience weaker deposit growth, so an empirically negative coefficient on instrumented deposit growth is not inconsistent with a fundamentally cost-driven deposit channel. Accordingly, the quantity specifications are treated as exploratory tests of whether a separate "deposit-outflow" mechanism can be detected in the data, rather than as a sharp test of a tightly specified funding-quantity model. The interpretation of Section 4 therefore places more weight on the funding-cost hypothesis (H3), while viewing evidence on H4 as informative but inherently more ambiguous.

4 Results

4.1 Summary statistics

The empirical analysis draws on a cross-section of 3,849 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 \$304.9 million in assets, compared with a mean of \$3.83 billion. Asset size is highly skewed, with the largest decile of banks accounting for 90.26 percent of total system assets. Using the \$10 billion size threshold commonly employed in the literature, 115 banks qualify as large institutions, while 3,734 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	-0.075	0.967	-2.951	-0.723	0.564	3.032
zR	0.006	0.842	-7.489	-0.348	0.504	2.658
zH	0.034	0.992	-1.401	-0.644	0.432	5.997
Metropolitan dummy	0.521	0.442	0.000	0.000	1.000	1.000
zY	-0.068	0.961	-3.950	-0.642	0.459	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	0.031	0.050	-0.153	0.002	0.053	0.308
gIBDep	0.031	0.058	-0.241	0.001	0.057	0.498
gCoreDep	0.031	0.059	-0.228	-0.000	0.056	0.400
gTotalLoans	0.006	0.046	-0.141	-0.018	0.030	0.309
gLoansNotForSale	0.007	0.046	-0.140	-0.017	0.030	0.310
gSingleFamilyMortgages	0.013	0.081	-0.291	-0.022	0.037	0.801
gMultifamilyMortgages	0.035	0.251	-0.915	-0.018	0.038	2.580
gC&ILoans	-0.009	0.142	-0.471	-0.081	0.051	0.872

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 Baseline results

Table 3: Baseline first-stage results

	(1)	(2)	(3)	(4)
Dependent variable	cumΔ Deposit rate	cumΔ Deposit rate	Δ Deposit quantity	Δ Deposit quantity
Sample	All banks	Small banks	All banks	Small banks
zS $\times$ cum ΔFFR	0.000357***	0.000343***	0.001041***	0.000932**
	(0.000048)	(0.000048)	(0.000378)	(0.000382)
zR $\times$ cum ΔFFR	-0.000695***	-0.000716***	-0.001176***	-0.001387***
	(0.000038)	(0.000037)	(0.000242)	(0.000279)
zH $\times$ cum ΔFFR	-0.000062***	-0.000065***	0.000305*	0.000288
	(0.000022)	(0.000022)	(0.000176)	(0.000179)
Metro $\times$ cum ΔFFR	0.000236***	0.000226***	0.001434***	0.001302***
	(0.000056)	(0.000056)	(0.000450)	(0.000453)
zY $\times$ cum ΔFFR	-0.000151***	-0.000155***	-0.000812**	-0.000795**
	(0.000046)	(0.000047)	(0.000349)	(0.000355)
Observations	28,822	28,001	30,657	29,716
Clusters	3,820	3,707	4,143	4,010
Within R-sq.	0.822	0.820	0.069	0.071
Joint F	152.84	159.31	12.91	12.45
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: This table reports first-stage regressions for the IV specifications. The excluded instruments are interactions of cum ΔFFR with pre-determined bank characteristics. All models include bank and quarter fixed effects. Standard errors are clustered at the bank level, and the joint F-statistic tests the relevance of the excluded instruments.

Table 3 reports the baseline first-stage regressions for cumulative effective deposit rates and deposit quantities and provides a direct test of H1 and H2. For the deposit-rate specifications, the exposure–shock interactions strongly support H1. The coefficient on the sophistication interaction is positive and highly significant, while the coefficients on the branch-intensity and HHI interactions are negative and highly significant, and the Joint F-statistics for the set of instruments are around 150. Banks whose deposits are concentrated in more sophisticated and metropolitan areas pass through a larger share of the cumulative policy tightening into effective deposit rates, whereas banks that rely more heavily on branch-based relationship models or operate in more concentrated local markets adjust deposit rates more slowly. This pattern is exactly what a deposit-market-power interpretation would predict: banks that face less sophisticated depositors or enjoy stronger local franchises are able to hold deposit rates further below the policy rate, while banks serving more sophisticated depositors must raise rates more aggressively. In this sense, the first-stage results are consistent with the view that depositor characteristics *mediate* market power rather than replacing it, and they place more weight on depositor sophistication and branch-based business models than on bare concentration indexes.

At the same time, the relative strength of the instruments is informative. The magnitude of the HHI coefficient in the rate regressions is much smaller than those on sophistication and branch intensity, so the predictive power of the rate first stage is driven primarily by depositor characteristics and branch-based business models, with HHI playing a secondary role. This is consistent with the critique in Begenau and Stafford (2023) and Narayanan and Ratnadiwakara (2024) that county-level HHI is a weak proxy for deposit-market power. However, the HHI interaction remains statistically significant and carries the theoretically expected sign for deposit rates, indicating that local market structure is not irrelevant; it is a weaker but still nontrivial component of the exposure vector once depositor characteristics are taken into account.

For deposit quantities, Table 3 offers a test of H2 along the sophistication dimension. Here the evidence is noticeably weaker than for rates, and the sign of the sophistication interaction runs counter to H2: the sophistication–shock coefficient is positive rather than negative, indicating that, conditional on the common monetary shock and controls, banks with more sophisticated depositor bases did not experience systematically larger deposit outflows; if anything, their average deposit growth is slightly higher. By contrast, the branch-intensity interaction is negative and statistically significant, indicating that more branch-intensive balance sheets tend to have somewhat weaker deposit growth when policy tightens, while the HHI interaction is small, often positive, and fragile across specifications. Joint F-statistics remain above conventional weak-instrument thresholds but are substantially smaller than for the rate regressions. This pattern is consistent with the ex ante expectation that the quantity channel would be harder to identify: the same exposure–shock interactions that generate strong variation in deposit rates also shape deposit outflows through those rate changes, so the quantity first stages necessarily overlap with, and are partly mediated by, the rate channel. Overall, H1 is strongly confirmed for deposit rates, whereas H2 is not supported: the instruments generate a powerful and theoretically coherent first stage on the pricing margin but only a noisy and internally inconsistent pattern on the quantity margin.

Table 4: Baseline second-stage results

	(1)	(2)	(3)	(4)
Dependent variable	Loans not for sale	Loans not for sale	Loans not for sale	Loans not for sale
Sample	All banks	Small banks	All banks	Small banks
cum ΔDeposit rate	-0.823610***	-0.760590**	-	-
	(0.276385)	(0.327778)	-	-
Δ Average deposit	-	-	-0.289041*	-0.281531*
	-	-	(0.154930)	(0.167968)
Observations	28,822	28,001	30,657	29,716
Clusters	3,820	3,707	4,143	4,010

Table 4: Baseline second-stage results

	(1)	(2)	(3)	(4)
KP rk Wald F	152.799	159.265	12.906	12.449
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: This table reports second-stage 2SLS estimates of the effect of deposit funding conditions on lending. The key regressors—cum ΔDeposit Rate and ΔDeposit Quantity—are instrumented using the same interactions from the first stage. All specifications include bank and quarter fixed effects. Standard errors are clustered at the bank level, and the Kleibergen–Paap F-statistic reports instrument strength.

Table 4 presents the baseline 2SLS estimates of the effect of deposit funding conditions on lending and provides tests of H3 and H4. The specifications that use cumulative effective deposit rates as the endogenous regressor directly test the funding-cost channel in H3. In both the full sample and the small-bank subsample, the coefficient on the instrumented cumulative deposit rate is negative, statistically significant, and economically meaningful: a one percentage point larger policy-induced cumulative increase in a bank's effective deposit rate reduces quarter-on-quarter growth in loans not held for sale by roughly 0.8 percentage points in the full sample and 0.76 percentage points for small banks, moving a typical bank from modest positive loan growth to around zero or slightly negative growth. These estimates, together with very high Kleibergen–Paap F-statistics, provide strong support for H3 and indicate that the cost of deposit funding is an active margin of monetary transmission at the bank level.

The quantity specifications use instrumented deposit growth as the endogenous variable and speak to H4. In the baseline, the coefficient on the instrumented deposit-growth measure is negative rather than positive and only marginally statistically significant, despite a reasonably strong first stage. A ten percentage point lower deposit growth rate is associated with a lower rate of loan growth, but the sign is opposite to the simple H4 prediction that faster deposit growth should relax funding constraints and support credit expansion. Interpreted literally, this would reject the canonical quantity channel. However, in light of the discussion in Section 3.7, a negative coefficient on deposit growth is also consistent with a setting in which the deposit-rate (funding-cost) channel dominates the pure quantity channel: banks that face larger policy-induced increases in deposit rates both cut lending and experience weaker deposit growth, so deposit growth is itself an endogenous response to the underlying funding-cost shock. In that case, instrumented deposit growth partly proxies for the cost shock and inherits its negative association with loan growth. Taken together with the weaker and less stable first-stage evidence for deposit quantities, these results suggest that H4 is not supported as a clean, stand-alone "deposit-outflow" mechanism: the best-identified relationship in this setting is the cost-based channel in H3, with quantity effects appearing as a noisy by-product of the same underlying funding-cost shocks rather than as an independent transmission margin.

4.3 Robustness checks

Table 5: Robustness checks - Rates

	(1)	(2)	(3)
Dependent variable	Deposit rate (cum)	Deposit rate (cum, int.-bearing)	Deposit rate (Δ)
Sample	All banks	All banks	All banks
zS $\times$ cum ΔFFR	0.000272***	0.000404***	0.000069***
	(0.000031)	(0.000058)	(0.000011)
zR $\times$ cum ΔFFR	-0.000704***	-0.000810***	-0.000078***
	(0.000038)	(0.000047)	(0.000009)
zH $\times$ cum ΔFFR	-0.000078***	-0.000079***	-0.000020***
	(0.000020)	(0.000026)	(0.000005)
Metro $\times$ cum ΔFFR	-	0.000381***	0.000029**
	(-)	(0.000068)	(0.000014)
zY $\times$ cum ΔFFR	-	-0.000142**	-0.000031**
	(-)	(0.000057)	(0.000011)
Observations	28,822	28,822	30,657
Clusters	3,820	3,820	4,143
Within R-sq.	0.822	0.844	0.499
Joint F	227.91	132.62	50.96
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Region $\times$ Quarter controls	Yes	Yes	Yes
SEs clustered by	Bank	Bank	Bank

Notes: This table reports robustness first-stage regressions for alternative deposit-rate measures. The excluded instruments remain interactions of cum ΔFFR and bank characteristics. All models include bank and quarter fixed effects. Standard errors are clustered at the bank level, and the Joint F-statistic is shown at the bottom of each column.

Table 6: Robustness checks - Quantities

	(1)	(2)	(3)	(4)
Dependent variable	Δ Average deposit	Δ Interest-bearing deposits	Δ Core deposit	cum Δ Average deposit
Sample	All banks	All banks	All banks	All banks

Table 6: Robustness checks - Quantities

	(1)	(2)	(3)	(4)
zS × cum ΔFFR	0.000622**	0.001238**	0.001004**	0.000782
	(0.000240)	(0.000478)	(0.000438)	(0.000943)
zR × cum ΔFFR	-0.001235***	-0.001362***	-0.000923***	-0.004121***
	(0.000241)	(0.000304)	(0.000274)	(0.000632)
zH × cum ΔFFR	0.000201	0.000373*	0.000358*	-0.000171
	(0.000167)	(0.000211)	(0.000211)	(0.000410)
Metro × cum ΔFFR	-	0.003185***	0.000326	0.003185***
	(-)	(0.000557)	(0.000524)	(0.001085)
zY × cum ΔFFR	-	-0.000477	-0.000595	-0.001026
	(-)	(0.000452)	(0.000404)	(0.000905)
Observations	30,657	30,657	30,657	28,822
Clusters	4,143	4,143	4,143	3,820
Within R-sq.	0.069	0.046	0.057	0.049
Joint F	15.98	10.77	7.24	15.13
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: This table reports first-stage robustness regressions for alternative deposit-quantity outcomes. The excluded instruments are the same interactions of cum ΔFFR and bank characteristics. All models include bank and quarter fixed effects. Standard errors are clustered at the bank level, and the Joint F-statistic reports instrument relevance.

Table 5 and Table 6 examine the robustness of the first-stage relationships for a variety of alternative deposit-rate and deposit-quantity measures and provide additional evidence on H1 and H2. For deposit rates, the results are highly stable across specifications. Whether the dependent variable is the cumulative rate on all deposits, the cumulative rate on interest-bearing deposits, or the quarterly change in the effective deposit rate, the sophistication interaction remains positive and precisely estimated, and the branch-intensity and HHI interactions remain negative and precisely estimated. Joint F-statistics range from about 50 to more than 200, and within R-squared for the cumulative-rate specifications remain very high. These robustness checks reinforce the conclusion that H1 is strongly supported: the exposure–shock interactions consistently generate a powerful and theoretically coherent first stage for deposit pricing, with sophistication and branch intensity playing the dominant roles and HHI contributing more modest but still significant variation.

For deposit quantities, the robustness patterns reinforce the conclusion that H2 is not supported. Across alternative outcomes—average deposit growth, interest-bearing deposit growth, changes in core deposits (demand, savings, and small time deposits under 250K USD), and cumulative average deposit growth—the branch-intensity interaction is consistently negative, but the sophistication interaction is typically positive and significant, and the HHI interaction is small, often positive, and only sporadically significant. Joint F-statistics for the quantity regressions are lower than for the rate regressions, and in some specifications they come close to standard weak-instrument thresholds. These results underscore that, while the exposure–shock interactions reliably describe heterogeneity in deposit pricing, they generate much weaker and less interpretable variation in deposit quantities. In particular, the data contradict the hypothesis in H2 that banks with more sophisticated depositor bases experienced systematically larger deposit outflows during this tightening cycle.

Table 7: Robustness checks - 2SLS

	(1)	(2)	(3)
Dependent variable	Loans not for sale	Loans not for sale	Loans not for sale
Sample	All banks	All banks	All banks
cum ΔDeposit rate (int.-bearing)	-0.712136***	-	-
	(0.237866)	-	-
Δ Interest-bearing deposits	-	-0.243202*	-
	-	(0.131824)	-
cum Δ Average deposit	-	-	-0.143536***
	-	-	(0.053143)
Observations	28,822	30,657	28,822
Clusters	3,820	4,143	3,820
KP rk Wald F	132.585	10.768	15.125
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Region $\times$ Quarter controls	Yes	Yes	Yes
SEs clustered by	Bank	Bank	Bank

Notes: This table reports robustness 2SLS estimates using alternative deposit measures as the endogenous variable. All specifications instrument the deposit variable with interactions of cum ΔFFR and pre-determined bank characteristics. Bank and quarter fixed effects are included. Standard errors are clustered at the bank level, and the Kleibergen–Paap F-statistic is reported for instrument strength.

Table 7 presents robustness 2SLS specifications that use alternative deposit measures as the endogenous funding variable while keeping the outcome as growth in loans not held for sale. When cumulative interest-bearing deposit rates are used, the estimated effect on loan growth remains negative, statistically significant, and close in magnitude to the baseline, and the Kleibergen–Paap F-statistic remains comfortably above conventional cutoffs. This reinforces the evidence for H3: the funding-cost channel is robust to reasonable alternative definitions of the effective deposit rate. When instrumented deposit-quantity measures are used, the coefficients continue to be negative and statistically significant in some specifications, but their signs and magnitudes remain inconsistent with the simple H4 prediction, and the associated first-stage diagnostics are weaker. In light of the discussion above, this pattern is again consistent with a dominant cost channel: variation in deposit quantities that is induced by the exposure–shock instruments appears to operate largely through the same underlying funding-cost shocks rather than through a separate balance-sheet-constraint mechanism. Furthermore, Appendix 2 shows that the 2SLS estimates for loan subcategories—including single-family mortgages, multifamily mortgages, and C&I loans—are statistically insignificant across the board, indicating that the transmission through deposit funding costs does not generate precisely estimated category-level responses in this sample. Taken together, these robustness checks suggest that the best-identified aspect of the deposit channel in this episode is the cost side; the quantity side is informative but noisy, and any category-specific loan effects are too diffuse to be estimated precisely with the available data.

5 Discussion

The results can be summarized in terms of the four hypotheses set out in Section 3.7. On the pricing margin, the data strongly confirm H1: banks with more sophisticated depositor bases and fewer branches per dollar of deposits pass through more of the cumulative policy tightening into effective deposit rates, while banks with dense branch networks and those operating in more concentrated local markets raise deposit rates less. Instrument strength is very high in these specifications, and the signs are stable across a range of deposit-rate measures. On the quantity margin, H2 is rejected: the sophistication interaction has the opposite sign to the prediction, the HHI interaction is weak and unstable, and only branch intensity generates consistently negative quantity effects, with an overall first-stage fit that is modest. In the second stage, H3 is clearly supported—policy-induced increases in effective deposit rates have a statistically and economically significant negative effect on loan growth, whereas H4 is not: the quantity-based specifications yield coefficients of the wrong sign and only marginal significance. For the local average treatment group identified by the instruments, the deposit channel in this episode operates primarily through the cost of deposit funding, not through a simple mechanical link between deposit quantities and lending.

These findings have direct implications for the ongoing debate over whether the deposit channel is fundamentally about bank market power or about depositor characteristics. A strict reading of Narayanan and Ratnadiwakara (2024) would suggest that once depositor composition is accounted for, market power in the sense of local concentration plays little role in shaping deposit responses to policy. The evidence here is more nuanced. On the one hand, the HHI interaction is indeed much weaker than the sophistication and branch-intensity interactions, especially for deposit quantities, and this is consistent with the critique that county-level concentration is a noisy stand-in for pricing power (Begenau and Stafford 2023). On the other hand, the positive sophistication coefficient and negative branch-intensity and HHI coefficients in the deposit-rate regressions are exactly what a deposit-franchise interpretation would predict: banks that face less sophisticated depositors or enjoy strong branch-based franchises are able to hold deposit rates further below the policy rate, while banks whose depositors are more sophisticated must raise rates more. In this sense, the results support a deposit channel that is still about banks' ability to pay below-market rates to certain depositor bases, but in which depositor characteristics and branch-intensive funding models are better empirical proxies than HHI alone.

The weakness of the quantity side is, to some extent, consistent with a horizontalist view of banking and monetary transmission. In a horizontalist framework, reserves are supplied elastically at the policy rate, banks adjust liability mixes endogenously, and loan supply is not tightly constrained by contemporaneous reserve or deposit quantities (Moore 1991). The finding that policy-induced heterogeneity in deposit funding costs has clear effects on loan growth, while corresponding heterogeneity in deposit quantities is harder to detect and sometimes points in the "wrong" direction, fits a picture in which banks actively substitute across liabilities and manage balance sheets so that core-deposit volumes are not the primary binding constraint. In such an environment, the deposit channel operates mainly through the pricing of funding rather than through a hard funding-quantity constraint, and the empirical importance of the "deposit price channel" warrants more theoretical work that explicitly links deposit-franchise value, depositor characteristics, and loan-supply decisions.

At the same time, the estimates here remain reduced form. The 2SLS coefficients do not separately identify the micro mechanisms through which higher funding costs reduce lending. The interpretation of the results rests on the assumption that at least some borrowers cannot costlessly substitute away from relationship-based lenders when their banks face adverse funding shocks (Erel et al. 2023). Within this reduced-form framework, classic channels such as credit rationing under adverse selection (Stiglitz and Weiss 1981), bank-capital and earnings constraints that tie loan growth to net interest margins (Van den Heuvel 2002), and the interaction of deposit-market power with regulatory capital requirements (Wang et al. 2020) are all consistent with the estimated elasticity. Future work could push beyond this reduced form by modeling explicitly how depositor sophistication, branch networks, and liability choices interact with these mechanisms, and by using richer balance-sheet and income data to distinguish funding-cost effects from capital and risk-management effects.

Several limitations suggest directions for future research. First, the sample window covers only the 2022–2023 tightening cycle. A longer panel spanning multiple cycles would allow the stability of the funding-cost elasticity to be tested across different rate environments, regulatory regimes, and competitive structures. Second, the key assumption that some borrowers cannot easily replace relationship lenders could be examined more directly with borrower-level data. Existing evidence from emerging markets suggests that deposit funding shocks can sharply contract credit to small firms with limited outside options, including in settings such as Pakistan, but comparable micro data for the United States are scarce (Khwaja and Mian 2008). Third, although the identification strategy is designed to absorb local demand conditions using region-by-quarter effects, a metropolitan dummy, and deposit-weighted median income, there remains a risk that the three exposure indices capture residual variation in loan demand or local economic prospects. As emphasized by Begenau and Stafford (2023), this concern is difficult to avoid in any design that relies on cross-sectional heterogeneity in funding structures or geography; it is a general feature of the deposit-channel literature rather than a limitation unique to this paper. Nevertheless, future work could combine bank-level instruments with borrower-level outcomes or with more granular local controls to further mitigate such concerns.

Overall, the evidence supports a cost-based formulation of the deposit channel in which tighter policy raises effective deposit funding costs and banks respond by slowing balance-sheet expansion, while the pure quantity channel appears weak and empirically fragile. The contribution of this paper is to provide a bank-level, policy-driven estimate of that funding-cost effect under an identification strategy that explicitly addresses uniform-pricing and aggregability critiques. Theoretical and empirical work that builds micro foundations for the deposit price channel, explores its interaction with capital regulation and competition, and tests its implications in longer and richer datasets remains an important agenda for future research.

6 Conclusion

This paper investigates how policy-induced shifts in deposit funding conditions affect bank credit supply over the 2022–2023 monetary tightening cycle. Predetermined exposure indices capturing depositor sophistication, branch intensity, and local concentration are interacted with cumulative changes in the federal funds rate to generate bank-level shift–share instruments that move cumulative effective deposit rates strongly and deposit quantities more weakly. The first-stage evidence confirms a pricing-based deposit channel: banks with more sophisticated depositor bases and less branch-intensive, less concentrated footprints exhibit higher cumulative deposit-rate pass-through, whereas branch-intensive and high-HHI banks adjust deposit rates more sluggishly, with HHI playing a secondary role. In the second stage, higher instrumented effective deposit rates lead to materially slower growth in loans not held for sale, providing a robust bank-level local average treatment effect that links monetary tightening to credit supply through the cost of deposit funding. By contrast, instrumented deposit-growth measures yield coefficients that are only marginally significant and of the opposite sign to a simple quantity-based deposit channel, reflecting both weaker instrument strength and the fact that banks facing larger funding-cost shocks both cut lending and experience weaker deposit growth. Overall, the findings support a cost-based formulation of the deposit channel in which tighter policy raises effective funding costs and banks respond by contracting balance-sheet expansion even in the presence of active liability substitution, while the pure quantity channel appears weak and empirically fragile.

These results highlight the importance of deposit pricing and depositor composition for monetary transmission and suggest that the deposit price channel deserves further theoretical and empirical attention. Because the 2SLS estimates are reduced form, they do not separately identify the micro mechanisms through which higher funding costs reduce lending; classic channels such as credit rationing under adverse selection, capital and earnings constraints, and the presence of borrowers that cannot easily replace relationship lenders remain alternative interpretations of the estimated elasticity. The analysis is limited to a single tightening cycle and relies on cross-sectional exposure indices that may still capture residual local demand conditions, despite controls for metropolitan status, income, and region-by-quarter shocks, a concern that is common to identification strategies in this literature. Future work could build on the framework developed here by microfounding the deposit price channel in models that jointly treat depositor sophistication, branch networks, and liability management; extending the empirical analysis to longer panels spanning multiple cycles; and combining bank-level instruments with borrower-level or regional outcomes to test more directly whether some borrowers are unable to substitute away from relationship lenders when banks are hit by deposit funding shocks.

7 References

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8 Appendix

8.1 Appendix 1: Principal Component Analysis

Table 8: 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 8 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.

8.2 Appendix 2: 2SLS results for loan sub-categories

Table 9: 2SLS results for loan sub-categories

	(1)	(2)	(3)
Dependent variable	Single-family loans	Multifamily loans	C&I loans
Sample	All banks	All banks	All banks
cum ΔDeposit rate	-0.270780	1.194144	-0.942587
	(0.538551)	(1.360042)	(0.809926)
Observations	28,822	28,822	28,822
Clusters	3,820	3,820	3,820
KP rk Wald F	152.799	152.799	152.799
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Region $\times$ Quarter controls	Yes	Yes	Yes
SEs clustered by	Bank	Bank	Bank