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 U.S. commercial banks, I construct predetermined exposure indices capturing depositor sophistication, branch intensity, and local deposit-market concentration, and interact them with cumulative changes in the federal funds rate to instrument for bank-level variation in effective deposit rates and deposit growth. The first-stage estimates reveal strong and economically meaningful heterogeneity in cumulative deposit-rate pass-through across banks, whereas the corresponding deposit-quantity responses are weaker and less aligned with canonical 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, the quantity channel is imprecisely estimated and theoretically more ambiguous in this setting, consistent with banks' ability to substitute across liability classes when faced with deposit outflows. The results support a view of the deposit channel as operating primarily through funding costs rather than through a simple mechanical link between core-deposit volumes and balance-sheet capacity.

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, reallocating 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:

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

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:

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

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 $t_0 = 2021\text{Q4}$ 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:

$$zS_{i,t}^{\text{cum}} = S_i\, R_t^{FF}, \qquad zR_{i,t}^{\text{cum}} = R_i\, R_t^{FF}, \qquad zH_{i,t}^{\text{cum}} = H_i\, R_t^{FF}.$$

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 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

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

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.

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 should 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 reallocate into higher-yield alternatives. Branch-intensive banks may be more exposed to retail depositors who respond to perceived return shortfalls, and high-HHI banks may choose to accommodate outflows by limiting pass-through rather than fully matching outside options. This formulation is closer to the depositor-characteristics view in Narayanan and Ratnadiwakara (2024) than to the Drechsler et al. (2016) emphasis on local concentration as the primary proxy for market power: the prediction is that who the depositors are, and how they are served, governs the fragility of funding, even if concentration still plays a secondary role. 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 exposure–shock interactions are expected to be negative for all three main instruments. Conditional on the common monetary shock, higher sophistication, higher branch intensity, and higher HHI should each be associated with lower cumulative deposit growth or larger deposit outflows.

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.

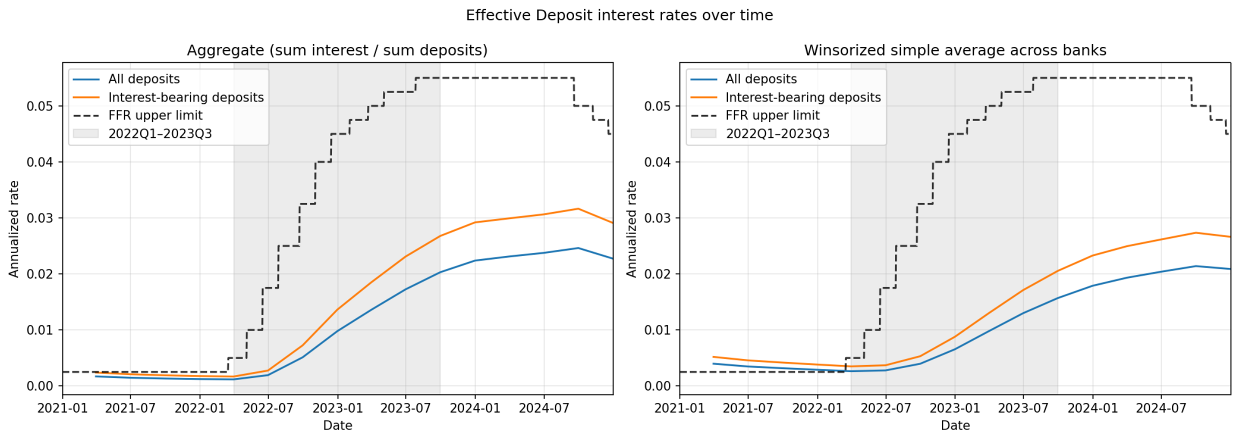
At the same time, the literature emphasizes banks' ability to substitute into wholesale and non-deposit liabilities, especially at larger institutions, and points to liability management, duration risk, and capital regulation as additional determinants of lending (Moore 1991; Minsky 1957). These considerations 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.

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.



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

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

Table 2: Summary Statistics - Deposit and Loan Growth

Variable	mean	std	min	25%	75%	max
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	Deposit rate	Deposit rate	Deposit quantity	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. Here the evidence is noticeably weaker and less aligned with the canonical quantity prediction that higher sophistication, higher branch intensity, and higher HHI should all be associated with lower deposit growth. The branch-intensity interaction is negative, as H2 would suggest, but the sophistication and HHI interactions are positive and either only marginally significant or 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, while H2 receives at best limited support; the instruments are powerful and theoretically coherent on the pricing margin but yield a noisier and less stable 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
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 share	cum Δ Average deposit
Sample	All banks	All banks	All banks	All banks
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 confirm that H2 is at best weakly supported. Across alternative outcomes—average deposit growth, interest-bearing deposit growth, core-deposit share, 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, and in some specifications they come close to standard weak-instrument thresholds. These results underscore that deposit quantities are much harder to explain with the exposure–shock interactions than deposit rates and that the role of HHI is particularly weak on this margin. In line with recent critiques, simple concentration measures appear to carry limited independent identifying power for deposit quantities once depositor characteristics and branch-based business models are controlled for. They also illustrate the ex ante concern that quantities are partly an endogenous reflection of the same funding-cost shocks captured in the rate equations, which makes a clean, separate quantity first stage difficult to achieve.

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 receives limited support: branch intensity behaves as expected, but the sophistication and HHI interactions do not, and the overall first-stage fit 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 market power. On the other hand, the positive sophistication coefficient and negative branch-intensity and HHI coefficients in the deposit-rate regressions are exactly what a market-power interpretation would predict: banks that face less sophisticated depositors or enjoy strong local 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 mechanism that is still about market power, but the relevant market power is exercised over particular types of depositors and is better proxied by depositor characteristics and branch-based business models than by HHI alone.

Finally, the contrast between the strong, coherent funding-cost channel (H3) and the weak, ambiguous quantity channel (H4) suggests that deposit outflows in this cycle do not map into lending through a simple balance-sheet constraint. Instead, banks appear able to substitute across liability classes and to adjust pricing, duration, and risk exposures in ways that weaken any tight link between core-deposit volumes and loan supply. The main contribution of the paper is therefore to provide a bank-level, reduced-form estimate of the funding-cost component of the deposit channel under an identification strategy that speaks directly to uniform-pricing and aggregability critiques. Future work can build on these results by modeling how depositor characteristics, branch networks, and liability choices jointly determine banks' effective market power over deposit funding, and by incorporating richer information on wholesale funding and capital to disentangle more sharply the roles of funding costs and funding quantities in monetary transmission.

6 Conclusion

This paper investigates how policy-induced shifts in deposit funding conditions affect bank credit supply over the 2022–2023 monetary tightening cycle. Using predetermined exposure indices interacted with cumulative federal funds rate changes, the design delivers exogenous bank-level variation in cumulative deposit-rate adjustments and weaker, less stable variation in deposit quantities. The second-stage estimates show that 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. In contrast, the estimated deposit-quantity effects are only marginally significant and exhibit signs inconsistent with a simple quantity-based deposit channel, reflecting both weaker first-stage strength and the likelihood that banks substitute toward alternative liabilities when deposits decline. 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 absent strong mechanical constraints on core-deposit levels. The paper contributes evidence on this funding-cost mechanism under an identification approach that directly addresses uniform-pricing and aggregability critiques in the deposit-channel literature, and suggests that future work integrate wholesale funding, liability substitution, and dynamic bank balance-sheet management to further disentangle the cost and quantity margins of monetary transmission.

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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