

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

Chenning Xu

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 liabilities with low friction or cost, then this could cause banks to reduce duration risk taking. On magnitudes, a decomposition of bank valuations shows that liability “productivity” explains most cross-bank value; for the median bank roughly two-thirds of value is attributable to deposit productivity, and a one-standard-deviation increase in deposit productivity raises market-to-book by roughly 0.2–0.8 points; savings-deposit capability is the tightest link to value (Egan et al. 2021). Deposit betas are state-dependent, rising with the level of rates, which shortens effective deposit duration and amplifies balance-sheet sensitivity in hiking cycles (Greenwald et al. 2023). Market structure and technology shift the first stage: online/national banks pass through more and attract inflows, while smaller institutions face sharper outflows, real-locating credit supply across balance sheets (Erel et al. 2023; d’Avernas et al. 2023). Outside the U.S., the 2022–23 cycle shows that larger deposit outflows map into quantity rationing—especially for fixed-rate, longer-maturity loans—and the effect is stronger at banks entering with larger duration gaps (Bank 2024). Dynamic models microfound deposit demand and market power through search frictions, implying that reductions in frictions or better outside options weaken transmission (Choi and Rocheteau 2021). Finally, structural estimates link the deposits and capital channels: deposit-market power shapes pass-through to lending and interacts with capital requirements, potentially delivering a low “reversal rate” when cuts erode equity (Wang et al. 2020).

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

smaller banks face higher marginal costs of wholesale replacement, policy can still tighten credit where those relationships bind, producing partial aggregation on the small-business margin (Erel et al. 2023; Kashyap and Stein, n.d.; d’Avernas et al. 2023).

The main gap is a clean mapping from policy-induced, bank-specific changes in funding conditions to lending. A substantial literature offers cross-sectional explanations of deposit-rate pass-through and deposit outflows, but far fewer papers quantify how a given bank-level increase in funding costs or a standardized deposit outflow translates into credit supply; even flagship contributions relate deposit movements to lending in reduced form rather than recovering a causal elasticity with instruments (Drechsler et al. 2016; Narayanan and Ratnadivakara 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 sensitiv-

ity and financial sophistication. All county-level variables used in the sophistication index are standardized prior to aggregation. No median household income measure enters the construction of the sophistication index.

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

3.2 Construction of cross-sectional exposure indices

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

3.2.1 Depositor sophistication index

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

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

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

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

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

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

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

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

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

3.2.2 Relationship-banking (branch-intensity) index

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

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

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

3.2.3 Local concentration index (HHI exposure)

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

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

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

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

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

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

3.2.4 Additional bank-level controls

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

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

3.3 Monetary policy shocks and instruments

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

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

and the cumulative change from the pre-tightening quarter $t_0 = 2021\text{Q4}$ 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:

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

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

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

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

3.4 Cumulative effective deposit rates and deposit quantities

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

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

and similarly for interest-bearing deposits $R_{i,t}^{IB}$. For a given R_t^{FF} , the cumulative change $R_{i,t}^{\text{dep}}$ 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

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

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.

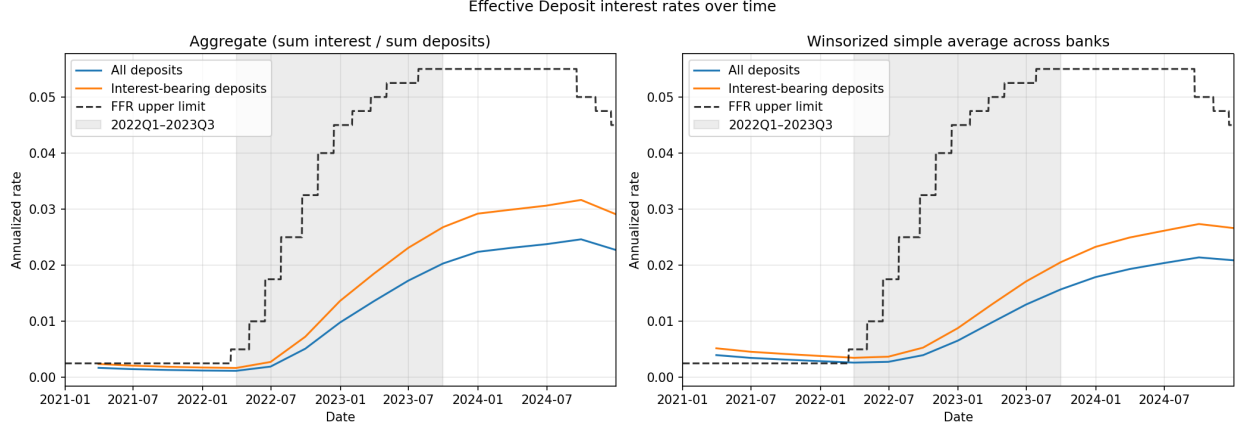
The coefficient θ^k is interpreted as the effect of a policy-induced cumulative increase in the deposit funding cost on banks' loan growth during the tightening cycle, identified through exogenous cross-sectional variation in depositor sophistication, branch intensity, and local concentration.

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
$zS \times \text{cum } \Delta FFR$	0.000357*** (0.000048)	0.000343*** (0.000048)	0.001041*** (0.000378)	0.000932** (0.000382)
$zR \times \text{cum } \Delta FFR$	-0.000695*** (0.000038)	-0.000716*** (0.000037)	-0.001176*** (0.000242)	-0.001387*** (0.000279)
$zH \times \text{cum } \Delta FFR$	-0.000062*** (0.000022)	-0.000065*** (0.000022)	0.000305* (0.000176)	0.000288 (0.000179)
$\text{Metro} \times \text{cum } \Delta FFR$	0.000236*** (0.000056)	0.000226*** (0.000056)	0.001434*** (0.000450)	0.001302*** (0.000453)
$zY \times \text{cum } \Delta FFR$	-0.000151*** (0.000046)	-0.000155*** (0.000047)	-0.000812** (0.000349)	-0.000795** (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 Δ FFR 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 deposit rates and deposit quantities. The exposure–shock interactions are jointly strong predictors of both outcomes, with Joint F-statistics around 150 for cumulative deposit rates and above 12 for deposit quantities, and within R-squared around 0.82 for the rate specifications. Banks with more sophisticated depositor bases and metropolitan footprints exhibit higher cumulative pass-through to effective deposit rates, whereas branch-intensive and high-HHI banks raise deposit rates less in response to a given cumulative increase in the federal funds rate. On the quantity side, branch-intensive banks experience weaker deposit growth when policy tightens, while banks that operate in more concentrated deposit markets see more stable deposit quantities. The patterns are similar when the sample is restricted to small banks, which indicates that the instruments generate economically meaningful and robust bank-level variation in deposit funding conditions over the 2022–2023 tightening cycle.

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 Δ Deposit rate	-0.823610*** (0.276385)	-0.760590** (0.327778)	- -	- -
Δ Average deposit	- -	- -	-0.289041* (0.154930)	-0.281531* (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 \times 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 Δ Deposit Rate and Δ Deposit 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 reports the baseline 2SLS estimates of the effect of deposit funding conditions on lending, using the exposure–shock interactions as instruments for cumulative deposit-rate changes and deposit growth. A one percentage point larger policy-induced cumulative in-

crease 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, shifting a typical bank from modest positive loan growth to roughly zero or slightly negative growth over the tightening period. Instrumented deposit growth has a similar sign and economically meaningful magnitude: a ten percentage point lower deposit growth rate is associated with around a three percentage point reduction in loan growth. The coefficients are statistically significant and comparable across the full and small-bank samples, which implies that for the set of banks whose funding conditions are shifted by the instrument, tighter policy-induced deposit funding conditions translate into materially lower loan supply.

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
$zS \times \text{cum } \Delta\text{FFR}$	0.000272*** (0.000031)	0.000404*** (0.000058)	0.000069*** (0.000011)
$zR \times \text{cum } \Delta\text{FFR}$	-0.000704*** (0.000038)	-0.000810*** (0.000047)	-0.000078*** (0.000009)
$zH \times \text{cum } \Delta\text{FFR}$	-0.000078*** (0.000020)	-0.000079*** (0.000026)	-0.000020*** (0.000005)
$\text{Metro} \times \text{cum } \Delta\text{FFR}$	- (-)	0.000381*** (0.000068)	0.000029** (0.000014)
$zY \times \text{cum } \Delta\text{FFR}$	- (-)	-0.000142** (0.000057)	-0.000031** (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
$zS \times \text{cum } \Delta\text{FFR}$	0.000622** (0.000240)	0.001238** (0.000478)	0.001004** (0.000438)	0.000782 (0.000943)
$zR \times \text{cum } \Delta\text{FFR}$	-0.001235*** (0.000241)	-0.001362*** (0.000304)	-0.000923*** (0.000274)	-0.004121*** (0.000632)
$zH \times \text{cum } \Delta\text{FFR}$	0.000201 (0.000167)	0.000373* (0.000211)	0.000358* (0.000211)	-0.000171 (0.000410)
$\text{Metro} \times \text{cum } \Delta\text{FFR}$	- (-)	0.003185*** (0.000557)	0.000326 (0.000524)	0.003185*** (0.001085)
$zY \times \text{cum } \Delta\text{FFR}$	- (-)	-0.000477 (0.000452)	-0.000595 (0.000404)	-0.001026 (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 \times 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 show that the first-stage relationships are robust to alternative definitions of deposit-rate and deposit-quantity outcomes. When cumulative rates on interest-bearing deposits, quarterly changes in deposit rates, and various deposit-quantity measures are used as dependent variables, the signs and relative magnitudes of the exposure coefficients remain close to the baseline. Joint F-statistics stay comfortably above standard weak-instrument thresholds for all preferred specifications, and the within R-squared for cumulative-rate specifications remains high. These results confirm that the exposure–shock interactions continue to deliver coherent and powerful bank-level variation in deposit funding conditions across a range of measurement choices.

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 Δ Deposit 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 Δ FFR 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 reports 2SLS robustness specifications that use alternative deposit measures as the endogenous funding variable while keeping the outcome as growth in loans not held for sale. Whether the funding shock is measured by cumulative interest-bearing deposit rates, the growth of interest-bearing deposits, or cumulative average deposits, the estimated effects on loan growth are negative, statistically significant, and similar in magnitude to the baseline results in Table 4. Kleibergen–Paap F-statistics remain well above conventional cutoffs, indicating that the instruments remain strong in each specification. Overall, the credit-supply response to policy-induced changes in deposit funding conditions is robust to how the funding margin is defined and measured.

5 Discussion

The estimates in Sections 4.2 and 4.3 provide direct reduced-form evidence that policy-induced increases in banks’ effective deposit rates are associated with materially weaker loan growth, but they offer a more ambiguous picture for the quantity side of the deposit channel. On the cost margin, the cumulative deposit-rate specifications deliver strong first stages and stable second-stage estimates: banks whose effective deposit rates rise more

over the 2022–2023 tightening cycle experience significantly lower growth in loans not held for sale, with magnitudes large enough to move a typical bank from modest expansion to near-zero or slightly negative loan growth over the period. These results are robust across alternative rate measures and sample splits and are supported by very high Kleibergen–Paap F-statistics, which suggests that the “funding-cost” component of the deposit channel is empirically relevant at the bank level. :contentReferenceoaicite:0

By contrast, the evidence on a separate “deposit quantity” channel is weaker and less consistent with the canonical deposit-channel narrative. When loan growth is instrumented with policy-induced variation in deposit growth, the 2SLS coefficients are negative rather than positive: in the baseline specification, lower deposit growth is associated with lower loan growth, but the sign is opposite to the simple expectation that faster deposit growth should relax funding constraints and support credit expansion. Moreover, these quantity coefficients are only marginally statistically significant, and the corresponding first-stage F-statistics are much smaller than for effective deposit rates, with Kleibergen–Paap values near conventional weak-instrument thresholds rather than far above them. Robustness checks that use alternative quantity measures yield qualitatively similar signs but remain statistically fragile. Taken together, these features suggest that the quantity specifications should be interpreted cautiously and not as a precise estimate of a separate, well-identified deposit-outflow channel.

From the perspective of the broader literature, a natural interpretation is that the credit-supply effects uncovered here are primarily tied to the cost of deposit funding rather than to mechanical constraints on the level of core deposits. This reading is consistent with work emphasizing banks’ ability to substitute into wholesale and non-deposit liabilities, especially at larger institutions, which weakens any tight link between core-deposit stocks and balance-sheet size but leaves funding costs and duration risk as key transmission margins. It also aligns with credit-channel and bank-capital mechanisms in which higher marginal funding costs and thinner net interest margins lead banks to contract lending—even when deposits can be partly replaced—because the shadow cost of capital rises or higher loan rates exacerbate selection and incentive problems. In this framework, deposit outflows still matter to the extent that they are costly to offset, but the mapping from deposit quantities to lending is mediated by liability substitution, pricing, and balance-sheet management rather than by a simple one-for-one funding constraint.

Accordingly, the main contribution of the paper is to provide a bank-level local average treatment effect that links policy-induced shifts in effective deposit funding costs to loan growth, under an identification strategy that directly addresses uniform-pricing and aggregability critiques. The quantity results are better viewed as indicating that the deposit channel does not operate through a clean, stand-alone “outflow” mechanism in this sample, rather than as overturning deposit-channel logic. Future work can build on this distinction by modeling how banks jointly choose deposit pricing, liability mix, and lending when policy shocks hit, and by using richer data on wholesale funding and off-balance-sheet liquidity to separate funding-cost effects from pure balance-sheet quantity constraints.

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.

7 References

- Aiyar, Shekhar, Charles W. Calomiris, and Tomasz Wieladek. 2014. “Does Macro-Prudential Regulation Leak? Evidence from a UK Policy Experiment.” *Journal of Money, Credit and Banking* 46 (S1): 181–214.
- Balbach, James H. 1981. “How Controllable Is Money Growth?” *Federal Reserve Bank of St. Louis Review*.
- Bank, European Central. 2024. “Flighty Deposits: The Impact of Deposit Outflows on Credit Supply.” *European Central Bank Working Paper*.
- Basel Committee on Banking Supervision. 1988. *International Convergence of Capital Measurement and Capital Standards*. Bank for International Settlements.
- Basel Committee on Banking Supervision. 2011. *Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems*. BCBS 189. Bank for International Settlements.
- Begenau, J., and E. Stafford. 2023. *Uniform Rate Setting and the Deposit Channel*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4839754.
- Begenau, Juliane, and Erik Stafford. 2024. *BANK CONSOLIDATION AND UNIFORM*

PRICING. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3488035.

Bernanke, B. S., and A. S. Blinder. 1988. *Credit, Money, and Aggregate Demand*.

Bernanke, B. S., and M. Gertler. 1995. “Inside the Black Box: The Credit Channel of Monetary Policy Transmission.” *Journal of Economic Perspectives* 9 (4): 27–48.

Bernanke, Ben S., and Cara S. Lown. 1991. “The Credit Crunch.” *Brookings Papers on Economic Activity* 1991 (2): 205–48.

Choi, M., and G. Rocheteau. 2021. *A Model of Retail Banking and the Deposits Channel of Monetary Policy*.

d’Avernas, A., A. L. Eisfeldt, C. Huang, R. Stanton, and N. Wallace. 2023. *The Deposit Business at Large Vs. Small Banks*. NBER Working Paper. no. 31865.

Drechsler, I., A. Savov, and P. Schnabl. 2016. *The Deposits Channel of Monetary Policy*. NBER Working Paper. no. 22152.

Drechsler, I., A. Savov, and P. Schnabl. 2021. “Banking on Deposits: Maturity Transformation Without Interest Rate Risk.” *The Journal of Finance* 76 (3): 1091–143.

Egan, M., S. Lewellen, and A. Sunderam. 2021. *The Cross Section of Bank Value*. <https://ssrn.com/abstract=2938065>.

Erel, I., J. Liebersohn, C. Yannelis, and S. Earnest. 2023. *Monetary Policy Transmission Through Online Banks*. NBER Working Paper. no. 31380.

Gordy, Michael B., and Bradley Howells. 2006. “Procyclicality in Basel II: Can We Treat the Disease Without Killing the Patient?” *Journal of Financial Intermediation* 15 (3): 395–417.

Greenwald, E., S. Schulhofer-Wohl, and J. Younger. 2023. *Deposit Convexity, Monetary Policy, and Financial Stability*. Working Paper. no. 2315. <https://doi.org/10.24149/wp2315>.

Hancock, Diana, and James A. Wilcox. 1994. “Bank Capital and the Credit Crunch: The Roles of Risk-Weighted and Unweighted Capital Regulations.” *Real Estate Economics* 22 (1): 59–94.

Hannan, T. H., and A. N. Berger. 1997. “The Rigidity of Prices: Evidence from the Banking Industry.” *Journal of Reprints for Antitrust Law and Economics* 27 (1): 245–54.

Heid, Frank. 2007. “The Cyclical Effects of the Basel II Capital Requirements.” *Journal of Banking & Finance* 31 (12): 3885–900.

- Kashyap, Anil K., and Jeremy C. Stein. 2004. “Cyclical Implications of the Basel II Capital Standards.” *Economic Perspectives* 28 (1): 18–31.
- Kashyap, Anil K., and Jeremy C. Stein. n.d. “What Do a Million Banks Have to Say about the Transmission of Monetary Policy?” *NBER Working Paper*.
- Minsky, H. P. 1957.
- Moore, B. J. 1991.
- Narayanan, R. P., and D. Ratnadiwakara. 2024. *Depositor Characteristics and Deposit Stability*.
- Neumark, D., and S. A. Sharpe. 1992. “Market Structure and the Nature of Price Rigidity: Evidence from the Market for Consumer Deposits.” *Quarterly Journal of Economics* 107 (2): 657–80.
- Repullo, Rafael, and Javier Suárez. 2013. “The Procyclical Effects of Bank Capital Regulation.” *Review of Financial Studies* 26 (2): 452–90.
- Stiglitz, J. E., and A. Weiss. 1981. “Credit Rationing in Markets with Imperfect Information.” *American Economic Review* 71 (3): 393–410. <https://doi.org/10.2307/1802787>.
- Van den Heuvel, Skander J. 2002. “Does Bank Capital Matter for Monetary Transmission?” *Economic Policy Review* 8 (1): 259–65.
- Wang, Y., T. M. Whited, Y. Wu, and K. Xiao. 2020. *Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation*. NBER Working Paper. no. 27258.

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 Δ Deposit rate	-0.270780 (0.538551)	1.194144 (1.360042)	-0.942587 (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