Hand-to-Mouth Banks: Deposit Inflows and the Marginal Propensity to Lend*

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Abstract

In modern macroeconomics, the *marginal propensity to consume* out of transitory income shocks is a central object of interest. This paper empirically explores a parallel concept in banking: the *marginal propensity to lend* out of unsolicited deposit inflows (MPLD). Using county-level dividend payouts as an instrument for deposit inflows, I estimate the MPLD for U.S. banks and show that before QE, the average bank operated "hand-to-mouth" — it transformed approximately every dollar of deposit inflow into new loans, consistent with tight liquidity constraints. However, since then, the MPLD has dropped to 0.35. Moreover, the MPLD decreases in banks' cash-to-asset ratio and deposit market power. The findings suggest that the QE-induced abundant reserves regime significantly relaxed liquidity constraints for the majority of banks, but did not eliminate them entirely.

Keywords: Banking, deposits, loans, money creation, reserves
JEL Classification: G21, E42, E51

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1 Introduction

The marginal propensity to consume (MPC) out of transitory income shocks is a key concept in modern macroeconomics. It plays a particularly important role in models with heterogeneous agents, where some agents face binding liquidity or borrowing constraints and thus cannot reach their desired consumption levels (Auclert *et al.*, 2024; Kaplan and Violante, 2014; Kaplan *et al.*, 2018). These "hand-to-mouth" agents exhibit large MPCs, as positive income shocks relax their constraints and allow them to spend more on consumption. In contrast, unconstrained "Ricardian" agents often have near-zero MPCs, as they spread any windfall income over their lifetimes. MPCs thus serve as an indicator of binding constraints and help policymakers identify the parts of the population where targeted policies (e.g., fiscal transfers) have maximum economic impact.

This paper explores a parallel concept for banks: the *marginal propensity to lend* out of unsolicited deposit inflows (MPLD). When choosing their portfolios, banks are subject to various constraints, including regulatory ones. Assuming that banks face loan opportunities with diminishing returns, an unconstrained bank should use any unexpected cash inflow to either optimize its liability structure (e.g., pay down expensive wholesale funding) or simply increase cash holdings (Stulz *et al.*, 2024). In other words, the MPLD for "Ricardian" banks should be close to zero. However, there is ample empirical evidence that unsolicited deposit inflows do affect bank outcomes, including credit supply (Cortés and Strahan, 2017; Darst *et al.*, 2025; Gilje *et al.*, 2016; Gilje, 2019). This suggests that some banks are, in fact, facing tight constraints. In this paper, I propose a novel instrumental variable (IV) approach based on county-level dividend payouts (Lin, 2022) to estimate the MPLD for U.S. banks and answer the question (paraphrasing Aguiar *et al.* (2025)) "Who are the hand-to-mouth *banks*?"

Understanding the distributional characteristics of the MPLD is beneficial for three key reasons: (a) policymakers can design more efficient credit easing policies that specifically target high-MPLD banks; (b) supervisors and regulators learn about which regulatory constraints are most binding; and (c) economists can target the MPLD distribution when calibrating quantitative models with heterogeneous banks.[1]

My analysis yields three key results: First, during the sample period of 1995–2021, the average MPLD is strictly positive, in line with previous local estimates. Moreover, before Quantitative Easing (QE) started in 2008, the MPLD was approximately one, i.e., the average bank transformed roughly every dollar of dividend-induced deposit inflows into new credit, espe-

[1]See, e.g., Bellifemine *et al.* (2025); Jamilov and Monacelli (2025); Abad *et al.* (2024). I will make bank-by-bank estimates of the MPLD available on my website for interested researchers.

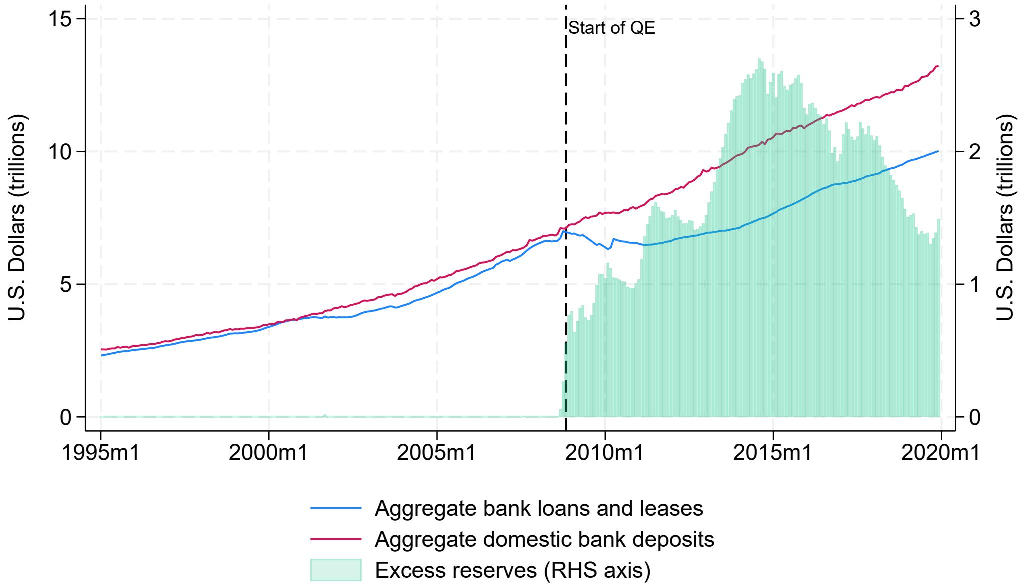


Figure 1: Aggregate loans, deposits, and excess reserves in U.S. banks

Source: FRED

cially real estate loans. However, during the QE era the average MPLD dropped to 0.35 (again driven by real estate lending), which mirrors the decoupling of aggregate loans from aggregate deposits depicted in Figure 1.

Second, the MPLD is decreasing in banks' cash-to-asset ratios and deposit market power, measured by a bank's average deposit Herfindahl index (HHI) across counties. Similarly, the MPLD is increasing in banks' deposit beta (Drechsler *et al.*, 2017), i.e., banks that need to raise their deposit rates more strongly in response to Fed funds rate hikes (a measure of deposit flightiness, as in Zhang *et al.* (2024)) exhibit higher MPLDs. These results jointly suggest that liquidity constraints (related to both asset liquidity and funding stability) are important determinants of "hand-to-mouth" lending behavior, and that the QE-induced abundant reserves regime relaxed these constraints for the U.S. banking sector.

Third, much of the banking literature has focused on *leverage* as the key source of constraints (e.g., in the form of regulatory minimum capital requirements). Indeed, I also find a generally positive relationship between leverage and the MPLD. However, as pointed out by Bolton *et al.* (2025), deposit inflows *tighten* leverage constraints on impact, which can lead to loan contractions for banks that are close to their minimum leverage ratios. Consistent with this argument, I show that the relationship between the MPLD and leverage is non-monotonic: banks at the upper end of the leverage distribution have small (and sometimes even negative) MPLDs.

The MPLD is defined as the amount of new lending that is triggered per dollar of unexpected, unsolicited deposit inflow. The big challenge in measuring MPLDs is that bank deposits are a highly endogenous object. Banks often solicit deposits (e.g., by raising deposit rates) specifically to fund asset expansions (Ben-David *et al.*, 2017), or to support their balance sheet in times of economic slowdowns (Iyer *et al.*, 2023). Therefore, a simple regression of loan growth on deposit growth would yield biased estimates of the MPLD — not just because of reverse causality (banks create new deposits mechanically when they make loans), but also because both bank deposits and loans are driven by common (often unobserved) macroeconomic fundamentals.

Therefore, based on recent research by Lin (2020, 2022), I use annual county-level *dividend income* to construct an instrument for deposit inflows. The argument is simple: When households receive dividends, at least part of this income translates into higher bank deposits. Using FDIC data on branch-level deposits, I can allocate local dividend income to all banks within a given county in proportion to their pre-existing deposit market shares. Then, aggregating these "predicted" local flows to the bank-level yields an instrument with strong first-stage explanatory power for *actual* bank-level deposit flows, consistent with the causal county-level findings in Lin (2022).[2]

The exogeneity assumption of the dividend instrument is violated only if two conditions hold simultaneously: (a) dividend income is correlated with unobserved local credit demand shocks at the county level; and (b) banks' lending opportunities are geographically aligned with their deposit distribution. I take measures to alleviate each concern individually. Specifically, I show that my results are robust to using a shift-share instrument in the Bartik (1991) tradition instead of actual dividend income to construct the instrument. The remaining variation in the instrument derives only from aggregate corporate payouts, which are orthogonal to county-level shocks. Moreover, I restrict the sample to banks that maintain deposits in at least a minimum number of counties. This filter removes precisely those banks that are most likely to focus their lending business on the same counties where they raise deposits (Aguirregabiria *et al.*, 2025). Moreover, I show that the results remain robust if I restrict the sample based on the geographical "imbalance index" (II) from Aguirregabiria *et al.* (2025) instead — a measure

[2] Lin (2022) uses a shift-share instrument to calculate that a $1 increase in dividend income is associated with a $0.53 increase in county deposits. Moreover, he shows that "within the same bank, deposits also grow faster at branches located in areas receiving larger dividend income."

of how strongly the geographical distribution of a bank's lending activity differs from that of its deposit-taking business.

The findings presented in this paper have important policy implications. Obviously, knowing what effectively constrains bank lending is crucial to designing expansionary, but also contractionary policies. For example, to calibrate their quantitative tightening (QT) efforts, central banks could benefit from a better understanding of the link between the level of reserve supply and binding liquidity constraints in the banking system (Acharya *et al.*, 2023; Anbil *et al.*, 2023; Copeland *et al.*, 2025). For example, in a speech in 2023, ECB Director Isabel Schnabel emphasized that "the uneven distribution of reserves within the system, together with the large uncertainty about banks' underlying liquidity preferences, imply that central banks may have to keep a significant buffer of excess reserves in the financial system to avoid unwarranted interest rate volatility" (Schnabel, 2023). The uneven distribution of excess reserves is one way to reconcile theoretical predictions of an MPLD near zero for reserve-flush banks with a strictly positive MPLD for the average bank, even in the post-QE era (Copeland *et al.*, 2025).

Furthermore, in the current debate about central bank digital currencies (CBDC) some critics argue that retail CBDC might crowd out bank deposits and hence lead to a permanent reduction in bank lending. For instance, Greg Baer, president and CEO of the Bank Policy Institute, worries that *"given that the average loan-to-deposit ratio for banks is generally around 1:1, every dollar that migrates from commercial bank deposits to CBDC is one less dollar of lending."*[3] Recent academic work, both theoretically (e.g., by Keister and Sanches (2023)) and empirically (Whited *et al.* (2022)) confirmed that while concerns of "bank disintermediation" are warranted qualitatively, the quantitative significance might be small. My results will help understand which banks are the most deposit-sensitive, and hence most prone to losing market share to a hypothetical CBDC.

The remainder of this article proceeds as follows: The next section discusses related literature. Section 3 introduces a highly stylized model that highlights the relationship between liquidity constraints and the marginal propensity to lend. Section 4 then describes the dataset in detail. Section 5 explains the instrumental variable approach that produces the results presented in Section 6. Finally, Section 7 summarizes the results and briefly discusses implications.

[3]See "Confronting the hard truths and easy fictions of a CBDC", *Business Reporter*, September 23, 2021.

2 Related Literature

This paper is conceptually closely related (and complementary) to Stulz *et al.* (2024). However, while I focus on the MPLD, they are primarily interested in the determinants of banks' liquid asset holdings, i.e., the exact *complement* of the MPLD. Moreover, much of their analysis revolves around the relationship between the *stocks* of liquid assets and illiquid loans. In contrast, this paper studies the sensitivity of lending to deposit *flows*. Stulz *et al.* (2024) show that less advantageous lending opportunities caused a steep increase in liquid asset holdings after 2008, with post-GFC regulatory changes contributing as well. These findings are perfectly consistent with the decrease in the MPLD after 2008 documented in this paper.

The core theme of this paper — the excess deposit sensitivity of bank lending in times of abundant reserves — has a close counterpart in banks' intra-daily liquidity management, as documented by Afonso *et al.* (2022). They show that despite high excess reserves in the system, "the amount of payments that a bank makes in a given minute depends significantly on the amount of payments that it has received over preceding minutes." According to the authors, this behavior reveals "significant balance-sheet liquidity constraints". Although their analysis focuses on banks' incoming and outgoing payment behavior (and does not track the exact sources or targets, e.g., deposits or loans), their finding can be interpreted as a high-frequency version of the MPLD studied in this paper.

Several works have developed identification strategies to document a positive causal link between banks' deposit base and their loan portfolio. In particular, two other approaches to identifying quasi-exogenous variation in banks' deposit base have been prominent in the recent literature: On the one hand, some papers (e.g., Cortés and Strahan (2017); Kundu *et al.* (2021); Thakor and Yu (2022)) exploit local natural disaster damages (in conjunction with the geographical distribution of banks' deposit activities) to construct an instrument that has predictive power for banks' deposit growth.

On the other hand, Gilje *et al.* (2016), Gilje (2019), and Plosser (2014) exploit the exogenous nature of windfall incomes from oil and natural gas shale discoveries in the U.S. They demonstrate that banks with a strong presence in counties that experience shale booms enjoy deposit inflows, which increase their capacity to originate new mortgages in non-boom counties.

In more aggregated data, Drechsler *et al.* (2022) show that during the 1970s and 1980s, banks' average lending standards eased whenever aggregate deposit growth was high. As argued above, this is not surprising in periods of scarce reserves, i.e., when liquidity constraints are tight.

My approach is methodologically similar to many of these studies, but to the best of my knowledge, I am the first to explicitly estimate the per-dollar MPLD, analyze its distributional properties, and interpret it as an indicator of liquidity constraint tightness. The specific instrument I use in my analysis — local dividend income — is inspired by Lin (2022) who also used the geographical distribution of corporate equity payouts to construct bank-level deposit shocks. His results suggest that banks with a high deposit share in counties with high dividend income receive significant deposit inflows and increase lending. In fact, the bank-level estimation in Lin (2022) can be understood as a reduced-form version of the 2SLS approach in this paper. When comparing the three candidate local shocks, dividend income has the key advantage that it is available for every U.S. county, whereas natural disaster damage and, even more so, shale oil discoveries are much more geographically concentrated, which limits the sample of banks with usable variation and thus external validity.[4]

The identifying assumption of the instrumental variable approach detailed in Section 5 is strengthened by the presence of internal capital markets by which banks allocate deposits not only locally (where depositors live), but across multiple regions. In this regard, two recent articles are particularly insightful: First, Kundu *et al.* (2021) demonstrate how local natural disasters can result in large deposit outflows for multi-market banks, resulting in lending contractions that are amplified across counties through bank internal capital markets. Second, Aguirregabiria *et al.* (2025) quantify the level of geographical imbalance between banks' deposit-taking and mortgage-lending business. The "imbalance index" they propose to measure the extent of cross-county internal capital markets is a crucial input to my analysis, as it allows limiting the sample in a way that renders the IV exclusion restriction more plausible.

Finally, the term *marginal propensity to lend* is also used in Bellifemine *et al.* (2025), Jamilov and Monacelli (2025), and Abad *et al.* (2024) where the authors build macroeconomic models with heterogeneous banks, analogously to seminal heterogeneous household models à la Aiyagari (1994), Bewley (1986), Huggett (1993), and Imrohoroğlu (1989). In those heterogeneous-banks papers, the MPL measures the response of banks' loan supply to a change in their *net worth*, whereas in this paper the MPLD is defined in terms of shocks to the deposit base.

[4]For example, the analysis in Gilje *et al.* (2016) is limited to 7 U.S. states.

3 A Stylized Model

In this section, I introduce a highly stylized three-period bank portfolio choice problem in partial equilibrium to illustrate potential channels that can deliver a positive marginal propensity to lend.

At $t = 0$, a risk-neutral, profit-maximizing bank invests in illiquid loans ℓ and liquid cash c (including central bank reserves) with returns $r_\ell(\ell)$ and r_c, respectively. Funding comes from an initial equity endowment e, deposits d, and wholesale debt b. Payoffs happen at $t = 2$, and for the sake of simplicity, I ignore default risk.

In the middle period $t = 1$, a fraction of creditors $\omega_i \in [0, 1]$ with $i \in \{d, b\}$ withdraws their funding from the bank. Assuming that liquidating loans would be prohibitively costly, these withdrawals have to be satisfied in cash. Since failure to meet the withdrawal demands would be associated with an infinite utility cost for the bank, it will always hold enough cash to pay out withdrawing creditors at $t = 1$. For simplicity, I assume that ω is known to the bank. Alternatively, ω can also be interpreted as a regulatory minimum liquidity requirement, similar to the Liquidity Coverage Ratio (LCR), a cornerstone of the Basel III regulatory framework.

On the asset side, the bank faces a downward-sloping loan demand curve with $r'_\ell(\ell) < 0$ and $r''_\ell(\ell) \leq 0$.[5] Cash yields a constant return of r_c, the equivalent of the Fed's interest on reserve balances (IORB).

On the liability side, the bank faces an upward-sloping deposit supply curve. Hence, to expand its deposit base, it needs to increase the deposit rate $r_d(d)$, that is $r'_d(d) > 0$. The same holds for the interest rate on wholesale funding $r_b(b)$, with the additional assumption that $r_b(0) > r_d(0) > 0$. As shown below, this assumption implies a funding pecking order, where the bank prefers deposits and only starts borrowing wholesale once the marginal cost of deposit funding reaches $r_b(0)$. In a model with risky loans and hence risky bank debt, the assumption could be motivated by distinguishing between insured deposits and uninsured wholesale debt.

The bank's profit in the final period can thus be expressed as

$$\pi = r_\ell(\ell)\ell + r_c(c - \omega_d d - \omega_b b) - r_d(d)(1 - \omega_d)d - r_b(b)(1 - \omega_b)b \tag{1}$$

[5] This assumption can be justified by assuming either (a) market power over homogeneous loans, or (b) perfect screening of borrowers of heterogeneous credit quality. In the latter case, r_ℓ would be interpreted as the risk-adjusted return, and the bank would grant loans to borrowers in decreasing order of creditworthiness.

The bank chooses (ℓ, c, d, b) to maximize (1) given e and subject to a balance sheet and a cash constraint (with associated Lagrange multipliers in parentheses), as well as respective non-negativity constraints (not shown here):

$$\ell + c \leq d + w + e \qquad (\lambda) \tag{2}$$

$$\omega_d d + \omega_b b \leq c \qquad (\theta) \tag{3}$$

The first-order conditions with respect to loans and cash imply that

$$r'_\ell(\ell)\ell + r(\ell) = r_c + \theta \ , \tag{4}$$

so the bank will choose its asset portfolio such that the marginal return on loans equals that on cash. Due to the assumptions above on $r_\ell(\ell)$, the left-hand side is decreasing in ℓ.

Similarly, the first-order conditions with respect to deposits and wholesale debt imply that

$$(1-\omega_d)[r'_d(d)d + r(d)] + \omega_d(r_c + \theta) = (1-\omega_w)[r'_w(w)w + r(w)] + \omega_w(r_c + \theta) \ , \tag{5}$$

hence the marginal cost of the two funding sources will also equalize. In general, it is reasonable to assume that $\omega_d < \omega_b$, i.e., that deposits are a more "stable" source of funding than various forms of wholesale bank debt.[6] For the basic argument, however, let $\omega_d = \omega_b \equiv \omega$. Then, because of the previous assumptions on $r_d(d)$ and $r_b(b)$, the bank's funding choice will be dictated by a "pecking order": There exists a level of deposits $\tilde{d}$ such that the optimal wholesale debt $b^* = 0$ if and only if $d^* < \tilde{d}$.[7]

The first-order conditions of the problem further imply that there are two possible scenarios, depending on whether the cash constraint in (3) is binding at the optimum or not. If it is slack, i.e., if $c^* > \omega(d^* + b^*)$ (and hence $\theta = 0$), we have

$$r'_\ell(\ell)\ell + r(\ell) = r_c = r'_d(d)d + r(d) \ , \tag{6}$$

so the marginal returns on both assets equal the marginal funding cost. In this case, I call the bank lending decision *unconstrained*. The exogenous interest on reserves, r_c, pins down the optimal loan level ℓ^* and the optimal deposit (and potentially wholesale debt) levels d^* and b^*

[6]Moreover, as the events around the failure of *Silicon Valley Bank* in March 2023 showed, the composition of depositors (insured vs. uninsured) matters for the "flightiness" of deposits, too. For instance, Mitkov (2020) shows how deposit insurance is more credible for poorer depositors (because of the government's redistribution motive), and hence wealthier depositors have stronger incentives to panic.

[7]$\omega_d < \omega_b$ would make deposits even more preferable to wholesale debt, thus strengthening the pecking order.

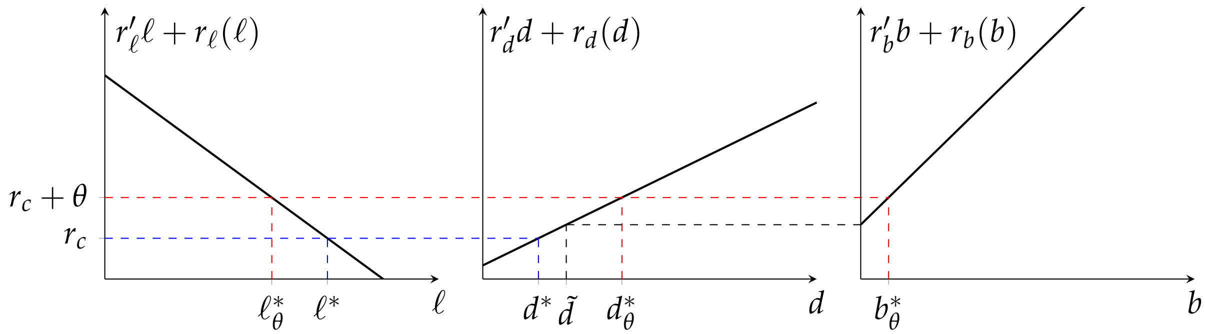


Figure 2: Graphical illustration of optimal portfolio choice

via the previous equations. The balance sheet constraint (2) then determines the optimal level of reserves c^* as a residual.

If, however, the cash constraint is binding at the optimum, (4) implies that there will be a wedge $\theta > 0$ between the marginal return on loans and that on cash, r_c. Compared to the unconstrained scenario, a *constrained* bank will choose a lower level of loans ℓ^*_θ, and a higher level of deposits d^*_θ (and potentially wholesale debt b^*_θ), even though this increases its marginal cost of funding. In other words, absent the constraint, the bank would prefer to invest more in loans and less in cash (see Figure 2).

To illustrate the effects of a positive deposit shock, suppose now that between $t = 0$ and $t = 1$, the bank receives an inflow of Δd deposits (and a corresponding increase in reserves Δc of the same amount), to be remunerated at the same deposit rate r_d.[8] In response, it can re-optimize the remaining balance sheet. Importantly, Δd is to be interpreted as an *inframarginal* funding shock, i.e., it does not change the bank's marginal funding cost.

Starting from the optimal balance sheet at $t = 0$, the increase in deposits $\Delta d = \Delta c$ relaxes the liquidity constraint in (3). If the bank was initially unconstrained ($\theta = 0$), the bank will keep the entire inflow Δc as reserves (as the marginal returns on reserves and loans were already equalized).[9] Only if the bank was initially constrained ($\theta > 0$), it would now increase its loan supply towards ℓ^*, implying a positive MPLD. Either way, the bank can now repay expensive wholesale funding and thus reduce interest expenses while maintaining a weakly higher revenue level than before the shock. This re-optimization echoes the observation in Plosser (2014) that a "positive lending sensitivity [to unsolicited deposit inflows] is considered a rejection of

[8]Since deposits are not only a financial asset, but also a widely used means of payment, it is reasonable to allow for these "quantity shocks" as in Bianchi and Bigio (2022).

[9]A similar argument can be found in Stulz *et al.* (2024). Their finding that "bank liquid asset holdings grew since the GFC because of weak lending opportunities" can be interpreted as a downward shift in the marginal revenue curve in Figure 2.

the Modigliani-Miller proposition, as unconstrained firms should invest inframarginal funding in lowering their marginal cost of capital."

4 Data

The main datasets used in this paper are publicly available and sourced from two U.S. institutions: the *Federal Deposit Insurance Corporation* (FDIC), and the *Internal Revenue Service* (IRS).

Bank balance sheet data

First, I retrieve quarterly balance sheet data for the universe of FDIC-insured institutions from the *Federal Financial Institutions Examination Council*'s (FFIEC) Call Reports. This includes data on each bank's total assets, loans (incl. a breakdown into real estate, commercial & industrial, consumer, and other loans), deposits, securities, cash holdings (incl. central bank reserves), and leverage (defined as total assets divided by total equity). Throughout the analysis, banks are identified by their unique FDIC Certification ID.

County-level bank deposit data

Second, I keep only end-of-year observations for the period 1994–2021 and merge them with annual information (always as of June 30) about each bank's distribution of deposits across branches, provided by the FDIC's *Summary of Deposits* (SOD).[10] This allows me to compute (a) deposit market shares for each bank in each county, and (b) Herfindahl indices (HHI) as the sum of squared market shares within each county. Moreover, bank-level HHIs — a measure of deposit market power — are computed as within-bank averages across county HHIs, weighted by banks' deposit share in each county (Drechsler *et al.*, 2017). For more details on the geographical distribution of bank deposits, see Appendix A.

I also use the SOD data to identify mergers and acquisitions. Specifically, I flag observations where a bank gains a new branch that previously belonged to another bank. I then remove each such bank-year observation because the implied jump in total loans and deposits is not exogenous to the bank and would introduce unwanted noise to the MPLD estimation.

[10] Deposits are usually assigned to branches based on the account holder's address, branch activity, or where the account was opened.

Dividend income data

Third, I add annual IRS data on county-level gross dividend income reported by residents in their tax returns, i.e., dividend income before subtracting any exclusions. In principle, this variable includes not just dividends distributed by publicly traded companies, but also by privately owned C-corporations. However, according to Chodorow-Reich *et al.* (2021), equity in privately owned C-corporations accounts for less than 7% of total C-corp equity. Therefore, the fraction of dividends from privately owned C-corporations in the IRS data is likely small.[11]

Figure 3 shows that (a) there is substantial heterogeneity in dividend income across counties, and (b) total dividend income in the U.S. has grown substantially since the mid-1990s, which motivated the research by Lin (2020, 2022). County-level dividend income will serve to construct a bank-level instrument for deposit inflows, as detailed in Section 5 below.

Deposit beta data

Fourth, I also add (time-invariant) bank-level estimates of deposit betas from Philipp Schnabl's website (Drechsler *et al.*, 2017, 2021). A bank's deposit beta measures the sensitivity of its deposit expenditures to changes in the Fed funds rate and is a common proxy for the "flightiness" of deposits, as low-beta banks tend to have "stickier" depositors by revealed preference (Zhang *et al.*, 2024).[12] The sample covers all commercial banks with at least 40 quarterly observations in the years 1984–2022, which explains why not all banks in my sample are matched to a deposit beta.

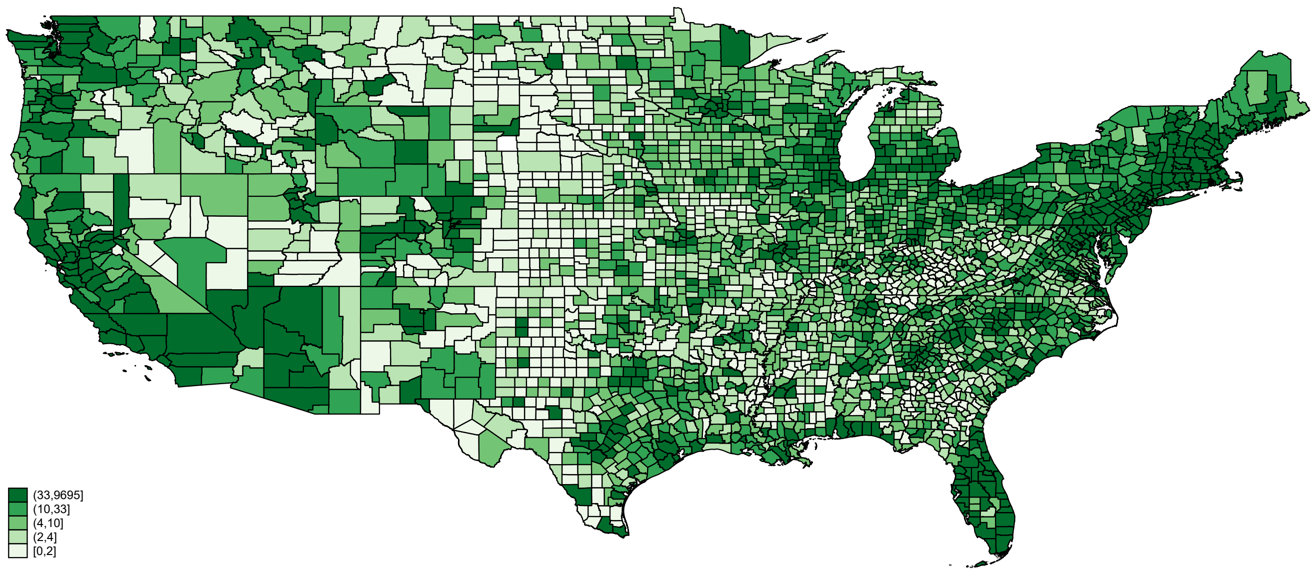
Imbalance index

Finally, I obtain a dataset constructed by Aguirregabiria *et al.* (2025) that contains their "imbalance index" (II) for 7,809 U.S. banks between 1998–2010.[13] The II is a measure of the joint geographical distributions of a bank's mortgage lending (based on HMDA data) and deposit activity (based on SOD data), and it ranges from 0 (extreme home bias; the lending distribution exactly mirrors the deposit distribution) to 1 (the bank gets all its deposits in counties where it does not provide loans and vice versa).

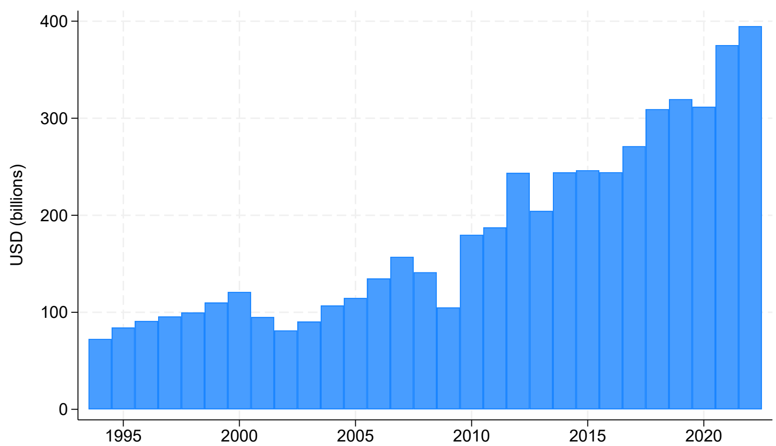
[11] This detail is important for my identification strategy, as private corporations are often headquartered in the same county as their owners. Hence, there may be a positive correlation between dividends of privately owned corporations and business loan demand within the same county.

[12] For a thorough discussion of the relationship between deposit flightiness and betas, see also Blickle *et al.* (2024).

[13] I am grateful to the authors for sharing their data.



(a) Annual dividend income (mln USD) across U.S. counties (2013)



(b) Total U.S. dividend income over time

Figure 3: U.S. gross dividend income (IRS Statistics of Income)

Table 1: Summary Statistics

Panel A: Bank level						
	N	Mean	SD	p5	p50	p95
Total assets (USD mln)	201,163	1362.44	30193.53	21.00	121.49	1405.68
Total loans (USD mln)	201,163	742.98	13606.61	10.16	74.91	938.25
Real estate loans (USD mln)	201,163	398.32	6253.51	4.01	52.06	678.64
Commercial & industrial loans (USD mln)	201,163	148.82	3203.76	0.05	7.82	128.19
Consumer loans (USD mln)	200,962	121.96	2807.27	0.27	3.79	50.69
Total cash and interbank balances (USD mln)	201,163	131.40	4311.15	0.89	6.12	82.38
Total domestic deposits (USD mln)	201,163	891.16	18715.18	17.67	101.68	1097.24
Dividend exposure (USD mln)	201,163	18.36	391.93	0.22	1.93	28.73
Total assets / Total equity	200,962	10.15	2.87	5.74	10.07	14.65
Cash / Total assets	201,163	0.10	0.08	0.02	0.08	0.26
Number of counties with deposits	201,163	2.85	13.93	1.00	1.00	7.00
Number of branches	201,163	9.22	93.68	1.00	3.00	19.00
Bank HHI	201,163	0.21	0.12	0.08	0.18	0.46
Deposit β	164,593	0.37	0.09	0.23	0.36	0.52
Average Imbalance Index (II)	122,894	0.30	0.18	0.05	0.28	0.62
Panel B: County level						
	N	Mean	SD	p5	p50	p95
Number of branches (per county)	90,216	27.40	68.34	2.00	10.00	110.00
Number of banks (per county)	90,216	8.37	9.20	2.00	6.00	23.00
HHI	90,216	0.32	0.21	0.11	0.26	0.87
Dividend income (USD mln)	90,216	57.83	314.11	0.51	5.70	213.93

Note: Sample period is 1994–2022.

The II allows me to restrict the sample to only banks with sufficiently strong internal capital markets that transfer deposits across county borders, which mitigates threats to the exclusion restriction of my IV approach. However, since the original authors used a shorter sample period and a smaller sample of banks, the II is only available for about 25% of bank-year observations. To increase coverage beyond 2010, I calculate within-bank average IIs, with the caveat that these are based only on pre-2010 information.

Final dataset and summary statistics

The final dataset is an annual unbalanced panel that covers 13,968 U.S. banks over the period 1994–2021. Please note that I trimmed the dataset at the 1st and 99th percentile in terms of asset, loan, and deposit growth rates within each year to remove outliers. Table 1 contains summary statistics on all variables used in the analysis.

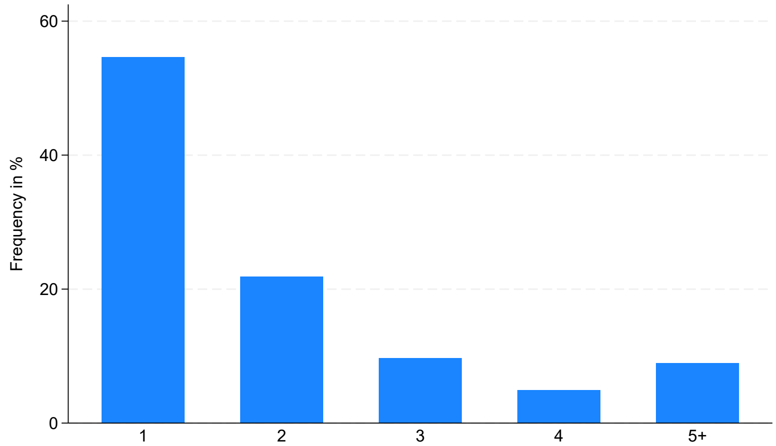


Figure 4: Number of counties in which banks raise deposits

Source: FDIC Summary of Deposits

Panel A of the table reveals, among other things, that the size distribution of U.S. banks (in terms of total assets) is heavily skewed; there are many relatively small banks (the median bank's balance sheet size is only $121 million), but also a few very big players with total assets of more than $2 trillion. Since these very large banks also have larger absolute loan and deposit growth (and larger variance thereof), observations will be weighted by inverse lagged total assets in all regression specifications, as detailed further below.

Furthermore, the table shows that for the median bank, domestic bank deposits constitute more than 80% of total balance sheet size, and thus an even larger share of total liabilities. This shows that despite a variety of other liabilities (e.g., repo borrowing), deposits are the single most important source of funding for U.S. banks.

Moreover, the table and Figure 4 illustrate that banks are, on average, geographically not very diversified in terms of their deposit-taking business. The majority of banks operates very locally, with more than half of all banks raising deposits in just one single county.[14] However, similar to bank size, this distribution has a very long right tail, with some banks operating in hundreds of counties across the U.S. In much of the following analysis, the focus will be on those geographically diversified banks.

Although this paper does not itself use any data about the geographical distribution of banks' *lending* activities, recent work by Aguirregabiria *et al.* (2025) shows that it is considerably more diversified than the deposit business. In their sample, the average and median number

[14]See also Kundu *et al.* (2021). This development is partly driven by the secular trend in bank branch closures documented by Keil and Ongena (2024) and Narayanan *et al.* (2025).

of counties per bank with mortgage lending activity are 30 and 8, respectively. Therefore, even the median bank that sources deposits from just one county faces potential loan demand from at least 8 counties. This observation mitigates the concern that the estimated MPLD might be driven by local loan demand instead of deposit inflows.

At the county level, there is also significant heterogeneity in terms of bank activity. As shown in panel B, the average county hosts 27 branches from 8 different banks, but the median is only 2 branches.[15] This heterogeneity translates into vastly different levels of deposit concentration between counties, as measured by the Herfindahl index (HHI). A county's HHI is computed as the sum of squared bank market shares in terms of deposits, and it theoretically ranges from $1/N_c$ (where N_c is the number of banks active in a county) to 1 (a local monopoly).

5 Empirical Strategy

A first naive approach to estimating the marginal propensity to lend out of deposit inflows (MPLD) would be to run the regression

$$\Delta Loans_{bt} = \alpha_b + \gamma_t + \beta \, \Delta Deposits_{bt} + \varepsilon_{bt}, \tag{7}$$

where $\Delta Loans_{bt}$ and $\Delta Deposits_{bt}$ are changes in total loans and total deposits of bank b in year t, α_b and γ_t are bank and time fixed effects, and β measures the MPLD.

Bank fixed effects help to account for time-invariant differences between banks, e.g., related to size. However, in the face of the above-described skewed bank size distribution, the very largest banks also have a higher absolute variance of loan and deposit growth. Therefore, deviations from their within-bank means remain much larger than for small and medium-sized banks, and noise among these banks might significantly affect the estimation.

A standard choice in many empirical banking papers to account for this scale dependence would be to normalize both loan and deposit growth by, e.g., lagged total assets or deposits. In my case, however, this normalization would change the interpretation of the β coefficient to something that no longer corresponds to the definition of the MPLD as the *per-dollar* lending response to a deposit inflow. Therefore, I instead weight all observations by lagged inverse total assets in all subsequent regressions. This choice allows me to correct for the inherent heteroskedasticity without dropping the largest banks from the estimation entirely.

[15] In fact, Aguirregabiria *et al.* (2025) even document the presence of U.S. counties without any bank branches. Of course, these do not appear in the SOD data (and thus in this paper).

Obviously, the regression in (7) would lead to a biased estimate for the MPLD, for at least two reasons: First, there is built-in reverse causality running from loan growth to deposit growth because every dollar of loans instantly creates a dollar of new deposits. Usually, these newly created deposits are quickly deployed to pay for goods or services, and hence transferred to the balance sheets of the recipient's bank. However, in areas with high deposit concentration, the likelihood that the recipient has his account at the same bank is non-negligible, which strengthens the reverse causality argument. Second, both loan and deposit growth are driven by macroeconomic fundamentals. In a boom, both the supply of deposits to banks and the demand for bank loans tend to increase, and vice versa in a recession. Similarly, when banks face increased loan demand, they may also try to actively attract deposits, e.g., by offering higher rates. Therefore, observed increases in bank lending cannot be causally attributed to deposit growth.

Fortunately, it is well-established that banks cannot perfectly control the size of their deposit stock, since deposits are constantly used for payment purposes and circulate within the banking system (Bianchi and Bigio, 2022; Bolton *et al.*, 2025; Li *et al.*, 2024; Parlour *et al.*, 2022). Of course, banks account for some of this churn in their daily liquidity management. However, certain unexpected events, such as natural disasters (Cortés and Strahan, 2017; Kundu *et al.*, 2021; Thakor and Yu, 2022) or the discovery of shale oil (Gilje *et al.*, 2016; Gilje, 2019), have been shown to significantly affect bank deposits. Although the random nature of these shocks allows clean identification of causal effects, they are also period-specific and limited in terms of geographic scope. Therefore, based on recent research by Lin (2020, 2022), I use annual county-level *dividend income* to construct an instrument for deposit inflows. More precisely, I define the instrument as

$$Dividends_{bt} = \sum_i Dividends_{it} \times \frac{Deposits_{bi,t-1}}{Deposits_{i,t-1}}, \tag{8}$$

where $Dividends_{it}$ represents dividend income in county i in year t, and $Deposits_{bi,t-1}$ is the amount of deposits of bank b held in branches in county i in the previous period. The denominator in the last term measures total bank deposits in a given county, so the fractions can be interpreted as (lagged) local deposit market shares. The instrument thus constructed has an intuitive economic interpretation: It is the amount of new deposits that the bank would receive if (a) all dividend income were to flow into deposit accounts, and (b) the dividend income was allocated to banks according to pre-existing market shares.

Of course, local market shares are not exogenous to banks. On the contrary, banks might specifically penetrate markets where they expect high deposit growth to fund asset expansions.

To address this concern (and thus strengthen the exogeneity of the dividend instrument), I use time-averaged market shares, $\frac{1}{T_b}\sum_{t=0}^{T_b}\frac{Deposits_{bi,t}}{Deposits_{i,t}}$, for each bank-county pair. However, results remain qualitatively unchanged if I use (time-varying) lagged market shares as in (8).

The first stage of the 2SLS approach can be represented as follows, where I regress bank-level deposit growth on the bank-specific instrument defined in the previous equation:

$$\Delta Deposits_{bt} = \alpha_b + \gamma_t + \theta\ Dividends_{bt} + \epsilon_{bt} \tag{9}$$

Of course, some counties systematically receive higher dividend income than others, e.g., because of larger populations or higher stock market participation. Consequently, banks with a strong presence in these counties will have systematically higher predicted deposit inflows than others. Bank fixed effects absorb these time-invariant differences between banks, so that most of the variation in the instrument comes from within-county fluctuations in dividend income over time. Similarly, year fixed effects account for the fact that corporate payout is cyclical and often coincides with strong deposit and loan growth across the U.S. economy.

The second stage, in turn, regresses $\Delta Loans_{bt}$ on the predicted values $\Delta\widehat{Deposits}_{bt}$ from the first-stage regression, so it exploits only the variation in deposit growth that is due to the instrument and thus arguably exogenous to loan growth. The exclusion restriction requires that the instrument is correlated with banks' loan growth *only* via deposit flows. In this specific case, threats to identification have two components:

First, it is possible that county-level dividend income is correlated with local loan demand. For example, one might worry about an increased demand for higher mortgages (or home equity loans) in counties that experience a particularly "good" year in terms of dividend income. Similarly, high dividend payouts might coincide with high local business loan demand, especially in counties where dividends originate from a large local firm.

Second, banks' lending business might be geographically very correlated with their deposit-taking activity (Aguirregabiria *et al.*, 2025). Only if both conditions are met — correlation between unobserved local credit demand shocks and dividend income, and lack of cross-county internal capital markets — will my bank-level instrument be contaminated by unwanted loan demand effects, and the resulting IV estimate will still be upward biased.

I address this two-stage threat to instrument exogeneity in two ways. First, I show that my results are robust to using a shift-share projection in the spirit of Bartik (1991): Instead of actual dividend income, the annual dividend income per county that is allocated to local banks is then calculated as total U.S. dividend income multiplied by each county's (constant) average share in total dividend income. As a result, the intertemporal variation in projected county-level dividend income is driven only by aggregate corporate equity payouts, which should be exogenous to a given county (Lin, 2022).[16]

Second, and more importantly, I restrict the sample to only banks that raise deposits in a minimum number of different counties. According to recent evidence in Aguirregabiria *et al.* (2025), this filters out the banks that are most prone to concentrating credit and deposit business in the same counties. Of course, this restriction comes at the cost of sample size and external validity, since it removes the vast majority of small, local U.S. banks. To navigate this tradeoff, I chose a threshold of 5 counties for the baseline results (which corresponds approximately to the 90^{th} percentile of the U.S. bank distribution). However, I also document how the OLS and IV estimates change and how potential bias is reduced when increasing the cutoff gradually from 0 to 10 counties.[17]

Moreover, for the subset of banks that overlaps with the sample in Aguirregabiria *et al.* (2025), I can restrict attention to only banks above a certain "Imbalance Index" threshold. These are the banks with the highest geographical imbalance between their deposit-taking and mortgage-lending activity. This filter is much more targeted and efficient and leaves my results qualitatively unchanged, as shown in Table A4.

6 Results

6.1 Estimating the average MPLD

Table 2 displays the results of the weighted OLS regression from Equation (7), but also the first and second stages of the 2SLS procedure. The sample is restricted to banks that maintain deposits in at least five counties on average. Column (1) confirms the positive association between deposit and loan growth documented in the aggregate, suggesting a bank-level MPLD of around 0.42. However, the estimate is likely biased, as discussed above. Column (2) demonstrates that the dividend instrument has high predictive power for the endogenous regressor — banks exposed to higher dividend income counties enjoy larger deposit inflows. Finally, column (3) contains the IV estimate of the average MPLD. Of every $1 a bank receives in deposits,

[16] The results of this robustness test are relegated to Appendix B.1.

[17] This robustness exercise is documented in Table A3 and shows that the difference between the OLS and IV estimates is gradually increasing as the minimum number of active counties per bank increases, suggesting that the instrument becomes more and more effective in removing the bias from the OLS estimate. From a cutoff of 5 onward, the increments in bias reduction become numerically negligible.

Table 2: Estimating the Marginal Propensity to Lend (MPLD)

	OLS	First-stage	IV	
	(1)	(2)	(3)	(4)
	$\Delta Loans$	$\Delta Deposits$	$\Delta Loans$	$\Delta Loans$
$\Delta Deposits$	0.419***		0.306***	1.102***
	(0.0585)		(0.0571)	(0.120)
Dividend exposure		3.068***		
		(0.290)		
PostQE=1 $\times$ $\Delta Deposits$				-0.749***
				(0.0825)
Time FE	✓		✓	✓
Bank FE	✓		✓	✓
F	51	112	29	43
N(Banks)	1,089	1,089	1,089	1,089
N	15,111	15,111	15,111	15,111

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have deposits in at least 5 counties. *PostQE* is a binary indicator equal to 1 for all years from 2008 onward, and 0 otherwise. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

it lends out \$0.31 by the end of the same year. This number is considerably smaller than the OLS estimate (consistent with the expected upward bias of the latter), but still strictly positive.

Of course, the average MPLD does not need to be constant over time. In contrast, it should adjust in response to regulatory changes or monetary policy regimes. In this context, it is natural to hypothesize that the regime of abundant reserves that followed QE (see Figure 1) *relaxed* liquidity constraints in the banking system, leading to lower average MPLDs. On the other hand, the post-QE era also coincided with reforms that imposed *tighter* regulatory liquidity constraints, such as the Liquidity Coverage Ratio (LCR) in the context of Basel III that was adopted in 2014 and became binding in 2017. Moreover, as Blickle *et al.* (2024) point out, QE's reserve expansion coincided with the entry of more rate-sensitive depositors, which made the average depositor more flighty. As a consequence, liquidity constraints might effectively still be tight despite high excess liquidity.

It is therefore instructive to estimate the MPLD separately for the periods before and after the start of QE in 2008. Interestingly, the IV estimates in column (4) of Table 2 suggest that the MPLD has dropped considerably since the start of QE (from 1.102 to 0.35), consistent with the interpretation of relaxed liquidity constraints. In fact, the lower — but still positive — MPLD after 2008 can even be interpreted as a net effect of relaxed intrinsic and tighter extrinsic (i.e., regulatory) liquidity constraints.

6.2 Bank heterogeneity in MPLDs

To further investigate whether liquidity constraints are a determinant of the MPLD, I can now explore cross-sectional heterogeneity in MPLD estimates. Therefore, Table 3 documents the estimation results of an IV regression that also includes interaction terms with proxies for liquidity-related variables. In particular, deposit growth is interacted with a bank's lagged cash-to-asset ratio and the lagged bank-level HHI (as a proxy for market power).

If liquidity constraints are indeed relevant for banks' MPLD, I expect banks with higher cash-to-asset ratios to have a lower MPLD. Moreover, liquidity constraints also have a liability component that depends on the stability of a bank's funding mix.[18] The concentration of deposits in markets where a bank funds itself (measured by the bank's HHI) can serve as a proxy for this funding stability (Li *et al.*, 2023). Depositors in areas with limited bank competition are, ceteris paribus, more "sticky" than those in areas with high competition. Hence, banks with a

[18]The LCR is defined as high-quality liquid assets (HQLA) divided by the projected net cash outflow over 30 days. Note how the cash-to-asset ratio and the bank-HHI can be mapped to c, ω, and hence the liquidity constraint in the stylized model in Section 3.

Table 3: Heterogeneity in the Marginal Propensity to Lend (MPLD)

	Dependent variable: $\Delta Loans$			
	(1)	(2)	(3)	(4)
$\Delta Deposits$	0.415***	0.447***	0.738***	0.835***
	(0.0714)	(0.114)	(0.147)	(0.153)
$\Delta Deposits$ × Cash/Assets (lag)	-0.915**			-0.688**
	(0.418)			(0.305)
$\Delta Deposits$ × Leverage (lag)		-0.0160		-0.00404
		(0.0137)		(0.0120)
$\Delta Deposits$ × Bank-HHI (lag)			-1.904***	-1.811***
			(0.641)	(0.637)
Time FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
N(Banks)	1,089	1,089	1,089	1,089
N	15,111	15,111	15,111	15,111

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have deposits in at least 5 counties. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD). The interacted variables also enter the regression as independent regressors, but their estimates are not reported here. For definitions of the lagged interacted variables, see Section 4.

higher average HHI should be less liquidity-constrained for a given level of liquid assets, and thus exhibit lower MPLDs.

Table 3 confirms these conjectures, both in columns (1) and (3) and in the "horse race" specification shown in column (4). The latter implies that, in the subsample used for estimation, a one-standard deviation increase in banks' cash-to-asset ratio is associated with a drop in the MPLD of 0.04. Similarly, a one-standard deviation increase in Bank-HHI implies a decrease in the MPLD of 0.16. Relative to the average MPLD of 0.31, these are economically significant differences, which are further corroborated by the results of a bank-by-bank estimation in Section 6.4 below.

In contrast, the coefficient of the interaction term with leverage is statistically indistinguishable from zero, especially in specification (4). Indeed, leverage can have ambiguous effects on the MPLD: On the one hand, deposit inflows relax *future* leverage constraints through a funding cost channel, implying a higher MPLD for banks with higher leverage.[19] On the other hand, banks that are closer to their maximum regulatory leverage are expected to exhibit a smaller (or even negative) MPLD to meet their *contemporaneous* leverage constraints — in other words, "the marginal value of deposits turns negative" (Bolton *et al.*, 2025).

6.3 Breakdown by loan type

In the Call Reports balance sheet dataset, total loans can be broken down into real estate loans, commercial & industrial loans, consumer loans, and other loans. To better understand the marginal lending behavior of banks, Table 4 breaks down the MPLD analysis by loan category. This is not just a descriptive exercise, but it can help understand which category banks consider as the *marginal* lending opportunity that is just "waiting to be funded". Column (1) repeats the baseline coefficient for total loans from Table 2 for convenience, while columns (2)–(5) show the MPLDs for different loan categories, both before and after the introduction of QE.

The table suggests that in the pre-QE period, when liquidity constraints were tighter across the board and the average bank operated "hand-to-mouth", the MPLDs per category are approximately proportional to the composition of the total bank loan portfolio (see Table 1). For example, the average MPLD for C&I loans accounts for approximately 9% of the average total MPLD, while C&I loans also represent approximately 10% of the total loan stock for the median

[19] Using French administrative credit registry and regulatory bank data, Duquerroy *et al.* (2022) show that increases in bank funding costs reduce bank credit, especially for weakly capitalized banks and for banks with lower liquidity buffers.

Table 4: MPLD for different loan categories

	(1) $\Delta Loans$	(2) $\Delta C\&I Loans$	(3) $\Delta RE Loans$	(4) $\Delta Consumer Loans$	(5) $\Delta Other Loans$
$\Delta Deposits$	1.102***	0.101	0.841***	0.0937***	0.0696
	(0.120)	(0.0672)	(0.0692)	(0.0242)	(0.0448)
PostQE=1 × $\Delta Deposits$	-0.749***	-0.00399	-0.752***	-0.0227	0.0247
	(0.0825)	(0.0687)	(0.0685)	(0.0200)	(0.0382)
Time FE	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
N(Banks)	1,089	1,089	1,089	1,089	1,089
N	15,111	15,111	15,111	15,111	15,111

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel IV regressions at the bank-year level of the change in different subcategories of bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have deposits in at least 5 counties. $PostQE$ is a binary indicator equal to 1 for all years from 2008 onward, and 0 otherwise. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

bank. In other words, the dividend-induced cash inflow was transformed into different loan categories in proportion to the existing stock of loans.

However, in the post-QE period, the large drop in the MPLD is almost exclusively driven by the real estate lending component. In other words, real estate lending has become much less responsive to positive funding shocks at the bank level.

Although studying the reasons behind this finding is beyond the scope of this paper, it is related to the mechanism documented by Grosse-Rueschkamp *et al.* (2019) and Berg *et al.* (2024). These articles argue that in response to the European Central Bank's *Corporate Securities Purchasing Program* (CSPP) in 2016, European firms switched from bank funding to bond issuance, which freed up lending capacity in the banking sector and caused a reallocation of loans to previously underfunded firms (Grosse-Rueschkamp *et al.*, 2019), especially in the real estate sector (Berg *et al.*, 2024).

Of course, this "capital structure channel of monetary policy" (Grosse-Rueschkamp *et al.*, 2019) follows a different logic than this paper — the former essentially boils down to a reallocation of bank assets, whereas my analysis focuses on an expansion of deposits, and hence liabilities. However, the results reveal an interesting discrepancy: While risky real estate lending appears to be the key marginal loan category for German banks in Berg *et al.* (2024), the U.S. results point in the opposite direction, at least in the period after 2008.

One possible explanation for U.S. banks' relatively low post-QE real estate MPLD could be the institutional setup of the U.S. mortgage market. More precisely, the possibility for U.S. banks to securitize and/or sell certain mortgages to government-sponsored entities (GSEs) suggests that banks might treat mortgages akin to standardized commodities rather than a risky asset with diminishing marginal returns. Indeed, Gilje *et al.* (2016) find that banks exposed to deposit inflows related to the U.S. shale oil boom increase mortgage lending, "but only [...] for hard-to-securitize mortgages." I leave a more detailed reconciliation of these findings for future work.

6.4 Bank-by-bank estimation

This final part is dedicated to estimating the MPLD separately for each bank, using only within-bank variation over time. Of course, with an annual dataset that spans 27 years, the statistical power of each regression is limited. Moreover, separate time-series regressions prohibit the use of year fixed effects to account for bank-invariant trends. Despite this limitation, the exercise is useful for three reasons: (a) Bank-by-bank estimates enable policymakers to precisely identify which banks exhibit the highest average MPLD; (b) they allow to corroborate the cross-sectional results from the previous section; and (c) interested researchers can use the distribution of estimates as a calibration target for models with heterogeneous banks and deposit withdrawal/inflow shocks as in Bianchi and Bigio (2022).

To be precise, I estimate the 2SLS regression

$$\Delta Loans_t = \alpha + \beta \, \Delta \widehat{Deposits}_t + \varepsilon_t \tag{10}$$

separately for each bank and collect the corresponding $\hat{\beta}$ estimates. To ensure a minimum number of observations per bank, I drop all banks with fewer than $T_b = 5$ annual observations (which corresponds to the 5$^{\text{th}}$ percentile of the T_b distribution). Moreover, I eliminate the bottom and top 10% of the resulting MPLD estimates to remove outliers. The resulting MPLD distribution is shown in Figure 5.

Three observations stand out: First, the majority of MPLDs lie between zero and one, consistent with the average results in Table 2. Second, a non-negligible amount of banks exhibit MPLDs above one. This suggests that deposit inflows may crowd in other forms of funding or trigger a reallocation of the existing asset portfolio towards loans. Third, there are banks with

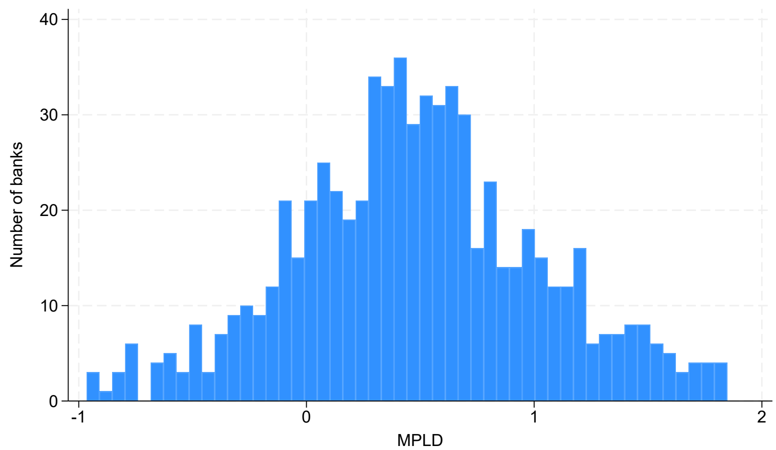


Figure 5: Distribution of MPLDs

Notes: This table contains the distribution of the marginal propensity to lend out of unsolicited deposit inflows (MPLD), obtained as the regression coefficients of separate bank-by-bank IV regressions of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. The sample period is 1994–2021, and the estimation sample includes only banks that have deposits in at least 5 counties and that have at least 5 annual observations. To remove outliers, the top and bottom 10 percent of the MPLD distribution have been discarded.

negative estimated MPLDs, suggesting that deposit inflows may also crowd out loans. Following the logic in Bolton *et al.* (2025), this could be explained by capital constraints that force banks to deleverage in response to an unsolicited expansion of liabilities.

To further corroborate the main results from the previous section, I can now regress the estimated MPLDs on within-bank averages of the same proxies for liquidity and leverage constraints. Table 5 presents the results of this cross-sectional regression. Similarly to the results obtained from the panel regressions in Section 6.2 above, the MPLD is negatively correlated with a bank's cash-to-asset ratio (column (1)) and its Bank-HHI (column (3)) which proxies for deposit market power. The numerical interpretation of the coefficients is similar as in Table 3: a one-standard deviation increase in a banks' average cash-to-asset ratio is associated with a 0.05 decrease in the MPLD.

Moreover, here I also add the (time-invariant) deposit beta of Drechsler *et al.* (2017, 2021) as a regressor in column (4), which is positively correlated with the MPLD and implies an increase of 0.09 in the MPLD for an increase of one standard deviation in beta. Hence, banks with a stronger passthrough of Fed funds rate hikes to their deposit rates (in order to prevent deposit outflows) exhibit higher MPLDs. In the final specification in column (5) that includes all regressors simultaneously, the HHI estimate is no longer statistically significant. This outcome

Table 5: Cross-sectional heterogeneity in MPLDs

	Dependent variable: MPLD				
	(1)	(2)	(3)	(4)	(5)
Cash/Assets	-1.225**				-1.380***
	(0.495)				(0.472)
Leverage		0.0274**			0.0232*
		(0.0137)			(0.0134)
Bank-HHI			-0.500*		-0.349
			(0.269)		(0.267)
Deposit β				1.176***	1.108***
				(0.265)	(0.267)
R^2	0.01	0.01	0.01	0.03	0.06
N	539	539	539	539	539

Heteroskedasticity-robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of OLS regressions at the bank level of the estimated MPLD on the within-bank average cash-to-asset ratio, leverage, bank-HHI, and deposit beta. For variable definitions, see Section 4. The sample period to compute the within-bank averages is 1994–2021 and the sample includes only banks that have deposits in at least 5 counties and that have at least 5 annual observations. To remove outliers, the top and bottom 10 percent of the MPLD distribution have been discarded.

is consistent with Drechsler *et al.* (2021) who show that deposit betas are negatively related to the Bank-HHI, which explains why they do not have independent explanatory power when both are included.

Finally, the estimated coefficient on leverage is positive, though only marginally significant in column (5). This might, of course, be due in part to the relatively small sample size and estimation noise. However, Figure 6 also suggests that the generally positive relationship is weakened by the fact that banks at the top of the leverage distribution have small (and sometimes negative) MPLDs. This observation is consistent with the argument in Bolton *et al.* (2025) that unsolicited deposit inflows force banks in the vicinity of their minimum leverage ratio to deleverage, for example, by reducing lending. In the binned scatterplot, the rightmost leverage values of approximately 16 imply a leverage ratio of around 6.25%, whereas the minimum leverage ratio for U.S. banks introduced under Basel III can reach up to 6% for some banks.

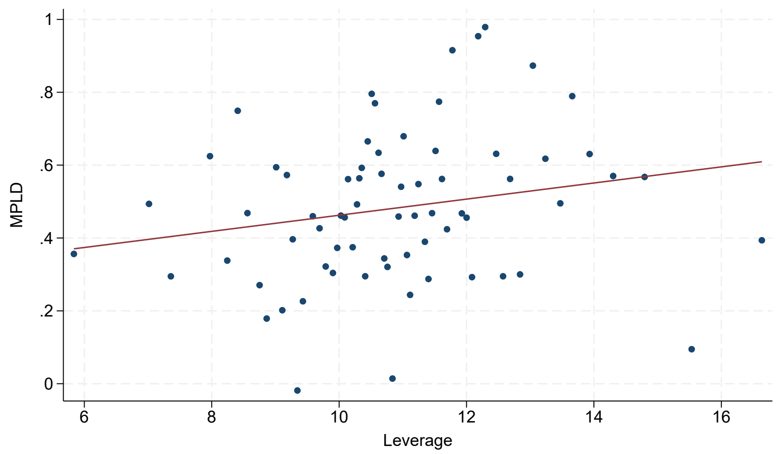


Figure 6: MPLD vs. leverage

Note: This figure shows estimated bank-level marginal propensities to lend out of unsolicited deposit inflows (MPLDs), plotted against banks' average leverage between 1994–2021. Each bin contains approximately 10 banks. The red line represents a fitted regression line, the slope of which corresponds to the estimated coefficient in column (2) of Table 5.

7 Conclusion

This paper contributes to the understanding of banks' marginal propensity to lend out of unsolicited deposit inflows (MPLD) by applying a novel identification strategy based on county-level dividend payouts. The analysis uncovers three main findings. First, the MPLD is on average positive, but time-varying: before the onset of Quantitative Easing (QE), the average U.S. bank operated effectively "hand-to-mouth", with approximately every dollar of exogenous deposit inflows converted into loans — especially in real estate. Since the start of QE, however, the MPLD has declined to approximately 0.35, indicating that liquidity constraints have loosened, though not disappeared. Second, the MPLD is strongly shaped by liquidity conditions and funding structure: it declines with higher cash-to-asset ratios and deposit market power (as proxied by the deposit Herfindahl index), and increases with deposit beta — a proxy for the "flightiness" of deposit funding. Third, the MPLD displays non-monotonic patterns with respect to leverage, suggesting a nuanced interaction between liquidity inflows and regulatory capital constraints.

These findings have several policy implications. The presence of "hand-to-mouth" banks implies that even in a system awash with reserves, marginal adjustments in reserve distribution could meaningfully impact credit supply. Conversely, in the context of QT, reserve withdrawals could inadvertently tighten credit for precisely those banks that are still liquidity-constrained.

Moreover, concerns about CBDC-induced deposit flight need to be calibrated against banks' MPLD and funding sensitivity — banks with small liquidity buffers and low deposit market power may be especially vulnerable.

Future research could explore several promising directions. First, it would be valuable to examine how the MPLD interacts with other forms of constraints, such as risk-based capital requirements, especially during periods of financial stress. Second, more granular data on the geographical and sectoral allocation of bank lending (e.g., HMDA data for mortgages or NCRC for small business loans) could allow for an investigation into the differential impact of deposit inflows across loan categories or regions. Third, it would be beneficial to account for changes in the maturity structure (e.g., savings vs. time deposits) in response to deposit inflows (Supera, 2022). Lastly, integrating the MPLD into macro-financial models with heterogeneous banks could improve our understanding of monetary transmission and help design more targeted policy interventions.

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Appendix

A Additional material about bank deposits

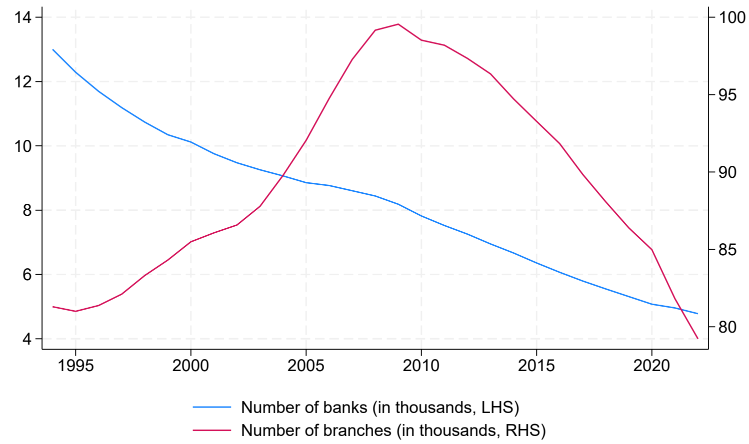

Figure A1: Number of U.S. banks and branches (1994–2022)

Source: FDIC Summary of Deposits

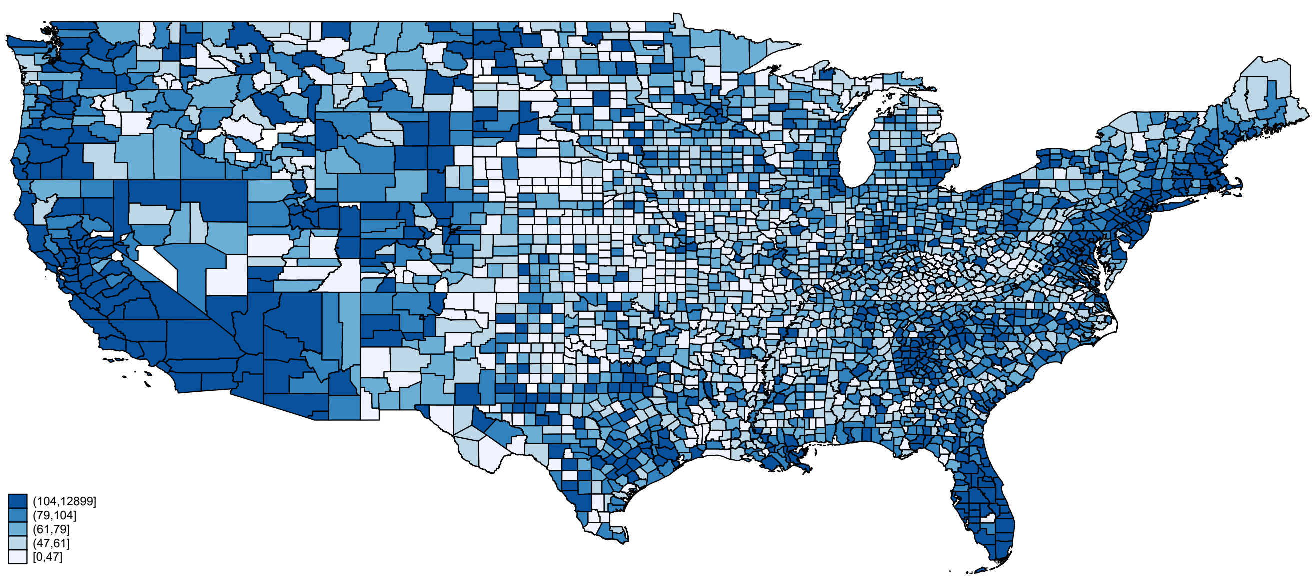

Figure A2: Bank deposits (mln USD) across U.S. counties (2022)

Source: FDIC Summary of Deposits

B Robustness Checks

B.1 Bartik instrument for county-level dividend income

The following two tables contain robustness checks for the main results presented in Tables 2 and 3. In the baseline analysis, the instrument for bank-level deposit growth is county-level dividend income, allocated to banks in proportion to their average deposit market share within counties, and aggregated to the bank-level across all counties where the bank is active.

The exogeneity of this instrument might be threatened if dividend income is correlated with loan demand at the county level. To mitigate this concern, a modification in the spirit of Bartik (1991) is proposed: Instead of actual dividend income of county i and time t, the variable $Dividends_{it}$ in equation (8) is replaced by the shift-share term

$$\widehat{Dividends}_{it} = Dividends_t \times \frac{1}{T} \sum_{t}^{T} \left(\frac{Dividends_{it}}{Dividends_t} \right) \tag{11}$$

where the last term is the share of county i's dividend income in total U.S. dividend income, averaged over time.

All intertemporal variation in the dividend income allocated to banks now comes from variation in *aggregate* dividend income, since both the allocation to individual counties and the aggregation to banks now happens according to static (time-averaged) shares. As a consequence, it is now harder to claim that counties with large dividend income in a given year have systematically higher unobserved loan demand than counties with low dividend income.

As Tables A1 and A2 demonstrate, the MPLD estimates obtained with this alternative IV procedure differ only marginally from the baseline results.

Table A1: Estimating the Marginal Propensity to Lend (MPLD)

	OLS	First-stage	IV	
	(1)	(2)	(3)	(4)
	$\Delta Loans$	$\Delta Deposits$	$\Delta Loans$	$\Delta Loans$
$\Delta Deposits$	0.419***		0.317***	1.106***
	(0.0585)		(0.0561)	(0.119)
Dividend exposure		3.199***		
		(0.289)		
PostQE=1 $\times$ $\Delta Deposits$				-0.747***
				(0.0819)
Time FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
F	51	123	32	44
N(Banks)	1,089	1,089	1,089	1,089
N	15,111	15,111	15,111	15,111

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have deposits in at least 5 counties. *PostQE* is a binary indicator equal to 1 for all years from 2008 onward, and 0 otherwise. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

Table A2: Heterogeneity in the Marginal Propensity to Lend (MPLD)

	IV (1) $\Delta Loans$	(2) $\Delta Loans$	(3) $\Delta Loans$	(4) $\Delta Loans$
$\Delta Deposits$	0.422***	0.446***	0.758***	0.844***
	(0.0684)	(0.113)	(0.146)	(0.154)
$\Delta Deposits$ × Cash/Assets (lag)	-0.897**			-0.672**
	(0.405)			(0.298)
$\Delta Deposits$ × Leverage (lag)		-0.0146		-0.00341
		(0.0136)		(0.0118)
$\Delta Deposits$ × Bank-HHI (lag)			-1.949***	-1.852***
			(0.639)	(0.636)
Time FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
N(Banks)	1,089	1,089	1,089	1,089
N	15,111	15,111	15,111	15,111

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have deposits in at least 5 counties. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD). The interacted variables also enter the regression as independent regressors, but their estimates are not reported here. For definitions of the lagged interacted variables, see Section 4.

B.2 Sensitivity of OLS vs. IV estimates to bank sample selection

Table A3: OLS vs. IV estimates for different geographic activity thresholds

	All banks		$\geq$ 3 counties		$\geq$ 5 counties		$\geq$ 7 counties		$\geq$ 10 counties	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
$\Delta Deposits$	0.416***	0.364***	0.425***	0.332***	0.419***	0.306***	0.411***	0.295***	0.396***	0.277***
	(0.0409)	(0.0576)	(0.0514)	(0.0580)	(0.0585)	(0.0571)	(0.0608)	(0.0570)	(0.0651)	(0.0563)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F	103	40	68	33	51	29	46	27	37	24
N(Banks)	13,088	13,088	2,445	2,445	1,089	1,089	641	641	386	386
N	200,283	200,283	37,214	37,214	15,111	15,111	8,544	8,544	4,833	4,833

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel OLS and IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks that have deposits in at least c counties, where c is gradually increased from 0 to 10 from column to column. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).

Table A4: OLS vs. IV estimates for different imbalance index thresholds

	All banks		II $\geq$ p50		II $\geq$ p75		II $\geq$ p90	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
$\Delta Deposits$	0.416***	0.364***	0.410***	0.319***	0.433***	0.342***	0.398***	0.339***
	(0.0409)	(0.0576)	(0.0535)	(0.0598)	(0.0557)	(0.0864)	(0.0798)	(0.105)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
F	103	40	59	29	60	16	25	10
N(Banks)	13,088	13,088	3,876	3,876	2,041	2,041	888	888
N	200,283	200,283	61,418	61,418	30,707	30,707	12,295	12,295

Standard errors (clustered at the bank-level) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table contains the results of panel OLS and IV regressions at the bank-year level of the change in bank loans on the change in bank deposits, where the latter is instrumented by a bank's exposure to dividend income in the counties where it has deposits. Observations are weighted by the inverse of lagged total assets. The sample period is 1995–2021 and the sample includes only banks with an "imbalance index" (Aguirregabiria *et al.*, 2025) above a certain percentile, where this cutoff is gradually increased from column to column. The estimated coefficient for $\Delta Deposits$ is the average marginal propensity to lend out of deposit inflows (MPLD).