Banking on Inattention*

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Abstract

We show that banks' deposit market power rests on *depositor inattention*. Using transaction-level bank data on millions of U.S. depositors, we document that income with unexpected timing stays in bank accounts about twice as long as expected income, signaling inattention. We measure inattention as the gap in estimated half-lives between unexpected and expected income, and show that more inattentive depositors respond less to rate changes around FOMC announcements. We scale this measure population-wide by training a statistical model that predicts inattention from demographic and socioeconomic data. Guided by these findings, we develop a model where banks price deposits trading higher spreads against spread-sensitive outflows from inattentive depositors. The model implies that banks with more inattentive depositors set lower deposit rates, have lower monetary policy pass-through, and adjust deposit rates more sluggishly after rate changes. We confirm these predictions empirically and, using geographic variation in inattention across a bank's branch network as an instrument, estimate deposit flow sensitivity. The calibrated franchise value of savings deposits is 18 cents per dollar, and a 10% drop in inattention lowers that value by 6.6%. We suggest that depositor inattention weakens monetary policy pass-through and underpins the deposit franchise value, which may be eroded as digital banking increases attention.

JEL Codes: E5, G2, G4.

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1. Introduction

Central banks rely on policy rates as their primary tool to influence economic activity. Yet banks typically offer deposit rates that are below policy rates, and often delay the pass-through of rate hikes. While prior work attributes this to banks' local monopoly power over depositors, the underlying economic drivers of that monopoly power remain elusive. This paper fills the gap by providing a systematic analysis of depositor inattention as the source of banks' monopoly power (Duffie and Krishnamurthy 2016, Drechsler, Savov, and Schnabl 2017, Yankov 2024, Egan et al. 2025).

We make three contributions. First, we present new evidence consistent with depositor inattention, construct a scalable, population-wide inattention measure, and show that it correlates with depositors' rate sensitivity. Second, we empirically and theoretically highlight that banks have *temporal monopoly* over inattentive depositors: banks extract surplus from depositors who manage their accounts sporadically, generating incomplete monetary policy pass-through to deposit rates. Finally, we estimate the franchise value of deposits and its comparative statics with respect to inattention and the policy rate.

We start with a new measure of depositor inattention. Using transaction-level data from checking and savings accounts of 26 million U.S. depositors, we find that many depositors, relative to a full-attention, frictionless benchmark, do not manage their account balances as actively. Specifically, we document that unexpected payment inflows, such as tax refunds, remain in bank accounts twice as long as scheduled paychecks. With full attention, depositors would have allocated dollars from every inflow identically, withdrawing similar shares of idle funds into higher-yield money market funds or other investments. Based on the difference in reaction times to expected and unexpected payment inflows, we build an in-sample inattention measure, which varies across individuals. We then train a predictive statistical model to project depositor inattention out of sample using socioeconomic and demographic variables, yielding a scalable, nationwide measure of inattention.

We document that depositor inattention closely correlates with how depositors react to policy rate changes around FOMC announcements, which causes changes in deposit spreads.[1] Tracking deposit balances from one week before to one week after each FOMC meeting, we find that inattentive depositors withdraw less than attentive depositors after rate hikes. Yet for the subset of inattentive depositors who withdraw, they move much larger sums, making inattentive depositors' outflows both more volatile and right-skewed after rate hikes.

To analyze the implications of depositor inattention on banks' rate setting, we develop a dynamic model where a bank prices deposits facing depositors who only check sporadically. The model aligns with existing findings that deposit rates sit persistently below the policy rate, and that the pass-through is strictly less than one. Further, it makes unique predictions on deposit rates and pass-through across banks with different depositor inattention. In setting the deposit rate, the bank faces a tradeoff: a lower deposit rate raises the profit margin but leads to larger outflows. With more inattentive depositors, outflows are less responsive to the deposit spread, and thus the bank sets a lower deposit rate. If depositors are very inattentive, the bank posts a zero deposit rate, which is the lowest possible.[2] For each bank, as the policy rate goes up, it discounts future profits more and thus the outflow consideration becomes less important. As a result, the bank sets a higher deposit spread under a higher policy rate, i.e., an incomplete pass-through. We also show that the pass-through from policy rate to deposit rate is lower for banks with more inattentive depositors.

We find supportive evidence in the cross-section of banks. A bank with a one-standard-deviation higher depositor inattention sets a rate on savings account that is 10bp lower under a 2% policy rate. If the policy rate goes up by 1%, it raises the deposit rate by 3bp less.

[1] For existing deposits, interests are credited monthly and banks are not required to notify depositors rate changes in the interim, making policy rate change the only salient news on deposit spreads. See Regulation DD, 12 C.F.R. §1030.5(a)(2)(i), which states that "No notice under this section is required for... variable-rate changes," i.e., banks do not need to notify consumers any change in the interest rate and corresponding APY on variable-rate deposit accounts.

[2] Banks generally refrain from quoting negative rates to depositors. One primary reason is that depositors can always shift into cash that earns a zero nominal return. In the U.S., deposit rates have never dropped below zero. International evidence suggests that even when policy rates turn negative, deposit rates cluster at the zero lower bound (Heider, Saidi, and Schepens 2019).

Our inattention-based rate-setting framework also contributes a new instrument for isolating deposit flow sensitivity—a key input for the deposit franchise value calibration that is often obscured by endogenous rates.[3] As inattention varies geographically, for bank branches in peripheral counties with a small local deposit market, their rates follow the rate set at larger markets of the same bank (Drechsler, Savov, and Schnabl 2017, Begenau and Stafford 2023). Hence, their rates can be instrumented by inattention of other counties served by the same bank, constituting a leave-one-out (LOO) instrument that is plausibly exogenous à la Autor, Dorn, and Hanson (2013) and DellaVigna and Gentzkow (2019). We show that, a one-standard-deviation rise in depositor inattention reduces the deposit outflow response to a 1% increase in deposit spread by about 0.54%.

In addition, we enrich the model to revisit the observed sluggish rate adjustment following monetary policy changes and its asymmetric responses to policy rate cuts and hikes. We model short-run sluggishness in resetting deposit rate à la Calvo (1983). Under a higher policy rate, more banks set positive deposit rates that depend on the policy rate. In turn, our model predicts that a larger share of banks will adjust in response to a policy rate change starting from a higher policy rate, regardless of the direction of the rate change. Previously, Hannan and Berger (1991), Driscoll and Judson (2013) and others show that rate cuts trigger more banks to adjust than rate hikes. We show empirically that the asymmetry is driven by the level of the prevailing policy rate, since rate cuts tend to start with a higher level of policy rate. Finally, in studying the cross-section of banks that adjust, we allow banks to *endogenously* choose how quickly it revises deposit rates with a cost (Romer 1990, Gopinath and Itskhoki 2010). The optimal adjustment frequency is increasing in depositor inattention since there is larger marginal gain. We confirm empirically that banks with more inattentive depositors reset rates significantly faster following policy rate changes.

[3]Previous work addresses the endogeneity of deposit rates using bank-specific policy rate pass-through (Egan, Hortaçsu, and Matvos 2017); a Berry-Levinsohn-Pakes-style instrument based on rival banks' characteristics (Egan, Lewellen, and Sunderam 2022); and supply-side shifters such as salaries and non-interest expenses (Xiao 2020, Whited, Wu, and Xiao 2022).

Using the empirical moments estimated from data, we calibrate the model and compute the present value of inattentive deposits. We find U.S. banks collectively derive about $2.6 trillion in present value profits from their $5 trillion in non-interest-bearing (NIB) deposits and $10 trillion in savings deposits by the end of 2022. We discuss further policy implications of inattention-based deposit pricing. Because temporal monopoly hinges on locking in inattentive depositors, competition alone may not eliminate it: once a bank secures these depositors, it can continue to charge a monopoly deposit spread. By contrast, under an elasticity interpretation, a 10% increase in the aggregate attention index, for example, driven by digital banking tools that prompt depositors to check balances more often, would lower the deposit franchise value by roughly 6.6% for savings deposits and 8.4% in NIB deposits, wiping out an estimated $592 billion in aggregate.

Last, we discuss comparative statics of deposit franchise value with respect to policy rate changes, taking into account banks' endogenous rate setting and spread-sensitive deposit outflows. Consistent with Drechsler, Savov, and Schnabl (2021), we find that when the policy rate is low, banks optimally quote a zero deposit rate, and deposit franchise has *negative* duration. Intuitively, an increase in the policy rate widens the spread more than it accelerates outflows, so the deposit franchise value rises. However, once the policy rate is high enough, an increase in the policy rate leads to a larger loss from deposit outflows, which dominates the gain in deposit spread and results in a *positive* duration for the deposit franchise. In future work, it may be promising to test this prediction and to study its implications for bank hedging policy.

Literature and contribution. Deposits are the cornerstone of money aggregates, and a large body of work in banking centers on four puzzling facts around deposits: deposit rates consistently sit below the policy rate, the pass-through of policy rate to deposit rates is incomplete, short-run deposit rate adjustments are asymmetric after hikes and cuts, and deposits flows are sticky (e.g., Diebold and Sharpe 1990, Hannan and Berger 1991, Driscoll and Judson 2013, d'Avernas et al. 2023, Argyle et al. 2024). Prior papers attribute these to

search frictions, local market power, and depositor sophistication (Duffie and Krishnamurthy 2016, Yankov 2024, Drechsler, Savov, and Schnabl 2017, Fleckenstein and Longstaff 2024). We show depositor inattention is an important source of banks' market power, which helps explain these puzzling facts.

Our evidence and theory of banking on inattention add to the growing literature that links banks' funding costs and risks to their depositor base (e.g., Kashyap, Rajan, and Stein 2002, Hanson, Shleifer, Stein, and Vishny 2015, Drechsler, Savov, and Schnabl 2017, He and Manela 2016, Drechsler, Savov, and Schnabl 2021, Begenau and Stafford 2023, Egan, Lewellen, and Sunderam 2022, DeMarzo, Krishnamurthy, and Nagel 2024, Llambias and Ordonez 2024, Jiang, Matvos, Piskorski, and Seru 2024). In this line of research, our paper is most closely related to and complements the work of Blickle, Li, Lu, and Ma (2024) and Egan et al. (2025). Blickle, Li, Lu, and Ma (2024) build a dynamic bank run model which features heterogeneity in depositors' preferences for convenience and predicts time-varying deposit run risk. Egan et al. (2025) estimate a quantitative dynamic model with sticky deposits and bank competition. We provide direct evidence that inattention varies across depositors and develop an analytical model with closed-form solutions, suggesting that higher inattention leads to lower deposit rates, weaker pass-through, and lower flow sensitivity across banks. Our empirical analysis confirms these novel predictions, and we use the resulting empirical moments to estimate the deposit franchise value.

We propose that inattention helps explain the *convenience yield*, i.e., the systematic spread investors pay for holding safe and liquid assets (Krishnamurthy and Ma 2025). Because deposit spreads rise with the policy rate, prior work often needs a policy-rate-dependent convenience value in individuals' demand for safe assets, that can be motivated by transaction needs, search frictions, hedging demand, non-pecuniary benefits, and limited substitutability across liquid and safe assets (e.g., Baumol 1952, Miller and Orr 1966, Sidrauski 1967, Poterba and Rotemberg 1986, Kiyotaki and Wright 1993, Lagos and Wright 2005, Krishnamurthy and Vissing-Jorgensen 2011, Nagel 2016, Drechsler, Savov, and Schnabl 2017, Krishnamurthy

and Li 2023, Acharya and Laarits 2023, Choi, Kirpalani, and Perez 2024, Lu, Song, and Zeng 2024). We offer a complementary supply-side explanation for deposit pricing, highlighting the role of financial intermediaries (He and Krishnamurthy 2013): banks' temporal monopoly over inattentive depositors generates a positive deposit spread. Further, as the policy rate rises, banks widen the deposit spread—i.e., an incomplete pass-through to deposit rate—for higher profits, as they discount the future more heavily.

Our paper complements the emerging literature on how online banking and digital technology affect the banking sector (Erel, Liebersohn, Yannelis, and Earnest 2023, Koont 2023, Koont, Santos, and Zingales 2024, Jiang, Yu, and Zhang 2024). We highlight that digital nudges which increase balance management checking frequency weaken banks' temporal monopoly, and quantify the resulting decline in the deposit franchise value.

Methodologically, we provide a new method of measuring inattention. Using large-scale transaction-level data and machine learning techniques, we develop a statistical model that predicts inattention as a function of demographics and socioeconomic characteristics. This approach complements the existing approaches in behavioral economics, including experiments (e.g., Kahneman 1973, Gabaix, Laibson, Moloche, and Stephen 2003), structural estimates from revealed preferences (e.g., Abaluck and Adams-Prassl 2021), and survey evidence (for comprehensive reviews, see DellaVigna 2009 and Gabaix 2019), delivering a systematic, population-wide measure of inattention.

A population-wide measure of inattention has broad relevance in macro-finance research. Inattention shapes mortgage refinancing decisions (Andersen, Campbell, Nielsen, and Ramadorai 2020, Berger, Milbradt, Tourre, and Vavra 2024a,b, Byrne et al. 2023), household expectations of inflation and unemployment (Coibion and Gorodnichenko 2011, Piccolo and Gorodnichenko 2025, Garmaise, Levi, and Lustig 2024), managerial decision-making (Dessein, Galeotti, and Santos 2016, Dessein and Santos 2021), fiscal and monetary policy (Farhi and Gabaix 2020, Gabaix 2020, Eichenbaum, Puglisi, Rebelo, and Trabandt 2025),

and central bank communication (Coibion, Georgarakos, Gorodnichenko, and Weber 2023, Bauer, Pflueger, and Sunderam 2024), with important welfare and efficiency implications (Hébert and La'O 2023, Angeletos and Sastry 2025).

2. Data

Our empirical analysis integrates five complementary datasets. (i) Transaction-level Bank Statements from a leading analytics firm track checking and savings accounts for 26 million U.S. depositors at over 23,000 depository and lending institutions (2014–2022), allowing us to construct an individual inattention index. (ii) IRS Zipcode Level Tax Filings (2007–2021) merged to 2010 Census ZCTA5 demographics provide nationwide socioeconomic covariates through county identifiers for projecting inattention out of sample. (iii) The FDIC Summary of Deposits (2007–2021) gives annual branch-level deposit sizes for each bank, enabling county-level aggregation of deposit stocks. (iv) FFIEC Call Reports (2007–2021) supply quarterly bank-level deposit flows and calculated savings rates. (v) Weekly RateWatch surveys (2006–2022) record bank-reported yields on $25K money-market deposit accounts, for which we aggregate the data to bank-week averages and consider only the direction (sign) of each weekly rate change. Focusing on the sign, rather than the level, insulates our analyses on rate adjustment dynamics from systematic bank-level reporting bias on rates.

2.1. Transaction-Level Data on Depositors

We analyze bank account statements for over 26 million depositors at 23,000+ depository and lending institutions from 2014 to 2022 to construct and validate a depositor inattention measure and link it to deposit pricing.[4] These records include transaction-by-transaction details and balance information for each depositor's deposit accounts across banks. The granularity of these data allows us to track how depositors react to different income events based on the income source. We further infer individual characteristics that can influence depositor inattention, such as student loan payments, mortgage payments, entrepreneur

[4]The same provider supplies the data used in Baugh, Ben-David, Park, and Parker 2021.

status,[5] parental status, marital (relationship) status, investor status, retirement status, unemployment status, and wage-earner status, by manually analyzing text descriptions in the transactions. The specific keywords used to construct these variables are listed in Appendix B.1; we report the summary statistics in Table 1.

	N	Mean	SD	Median	25th Pct.	75th Pct.
Total Income	13,250,542	67,989.11	222,835.80	6,367.00	1,314.00	29,813.48
Child Credit	1,489,311	14,642.39	143,898.06	4,500.00	1,800.00	10,800.00
Investment Income	8,143,131	37,307.72	144,804.20	2,311.02	100.00	21,218.34
Salary Income	1,184,347	390,217.88	395,916.91	300,258.84	118,012.86	556,676.06
Social Security	2,448,039	46,459.04	63,231.73	21,564.90	5,637.00	63,973.00
Tax Refund	9,248,072	11,267.37	17,747.64	5,454.00	1,976.00	13,678.34
Student Loan	3,562,159	26,536.06	340,776.78	2,460.15	280.00	17,274.79
Mortgage	4,511,473	222,298.67	1,912,789.80	53,456.46	8,951.49	200,332.92
Indicator Variables						
Unemployed	26,521,334	3.64%				
Parent	26,521,334	6.64%				
Single	26,521,334	1.95%				
Female	26,521,334	33.82%				
Male	26,521,334	30.00%				
Entrepreneur	26,521,334	4.63%				

This table summarizes the key depositor-level characteristics derived from our transaction data, available from 2014 to 2022. Monetary variables (Total Income, Child Credit, Investment Income, Salary Income, Social Security, Tax Refund, Student Loan Payment, and Mortgage Payment) are expressed as the annual total per depositor in current dollars, averaged over the years in which the flow is observed. Indicator variables report the share of depositors who, at any point in the sample, are: Unemployed, Parents (if the depositor paid for childcare or received child tax credits), Single, Female, or Entrepreneurs (if the depositors linked to a business or corporate account).

Table 1: Depositor Characteristics

2.2. County-Income-Group Level IRS Tax Filings and County-Level Census Data

To predict inattention out of sample, we use IRS zipcode-AGI (adjusted gross income) level filings year by year from 2007 to 2021. The IRS tax filings are representative across the country and allow us to project the inattention measure over time nationwide. We construct

[5]Our inattention measure requires consistent labor income; this does not exclude depositors who also run side businesses. Nonetheless, bank-classified business accounts constitute a small share of the sample and are not central to our analysis.

socioeconomic and demographic characteristics from Form 1041 that match those observable at the individual level from the transaction-level database; we detail the variable construction in Appendix B.2. To map zipcodes to counties, we merge each year's IRS filings with the USPS zipcode-FIPS crosswalk (first-quarter snapshot) obtained from HUD's Office of Policy Development and Research. Additionally, we aggregate 2010 Census ZCTA5 data to derive demographic and socioeconomic information, such as ethnicity, gender, homeownership, and family structure, for each county, including key demographic variables available through Missouri Census Data Center as in Mian, Sufi, and Trebbi (2010).

2.3. County-Level Bank Deposits from FDIC Summary of Deposits

We use the FDIC's annual Summary of Deposits from 2007 to 2021, which reports each bank branch's total deposits, parent bank (RSSDID), and county as of June 30 of the year.

2.4. Bank-Level Rates and Flows from Call Reports

We obtain quarterly non-interest-bearing and savings deposit growth, and calculate the savings deposit rate as interest expense on savings deposits divided by the volume of savings deposits from Call Report filings between 2007 and 2021.

2.5. Branch-Level Deposit Rates from RateWatch

Our RateWatch sample reports the annual percentage yield for new deposits quote each week, beginning in 2006. We follow Drechsler, Savov, and Schnabl (2017) convention focusing on the most widely reported product in the sample period, the $25K money-market deposit accounts, then aggregate branch observations up to the bank-week level using weekly averages and compute the weekly changes in reported deposit rates. Note that we only use the *sign* of weekly rate changes to analyze the transitional dynamics of bank rate setting. This shields our analysis from any systematic bank-level reporting bias on rate levels.

3. Evidence and Measure of Depositor Inattention

We start with analyzing how depositors allocate their liquid balances after receiving income. We show that regular paychecks are drawn down from bank accounts quickly, whereas unpredictable income (tax refunds) remain idle on balance twice as long. The additional reaction time of depositors to unexpected income signals inattention. Consistent with that interpretation, we find banks serving inattentive depositors consistently quote lower deposit rates, suggesting inattention as a source of banks' market power in deposits (Drechsler, Savov, and Schnabl 2017).

3.1. Reactions to Expected and Unexpected Income

Ideally, we would estimate depositor reactions controlling for both idiosyncratic, individual fixed effects, and the growth in income over time. The dimensionality of our data—millions of depositors observed across thousands of pay cycles—makes such a specification infeasible. We adopt a two-step approach instead: first, we compute each depositor's cumulative net flow around every paycheck and scale it by the corresponding paycheck amount as in Baugh, Ben-David, Park, and Parker (2021). We then estimate the impulse response functions of the percentage changes in these normalized flows, for expected and unexpected income events separately.

To start with, for each account of depositor i and income type j, we compute the daily cumulative net flows of the account over the 14-day estimation window,

$$f_{ijt}^{\tau} = \sum_{k=0}^{\tau} (\text{inflows}_{ijk} - \text{outflows}_{ijk}), \quad 0 \leq \tau \leq 13,$$

where $\tau = 0$ corresponds to the event date and event time $\tau = 1, 2, \ldots, 13$ represent the subsequent dates to avoid overlapping events (given that the majority of labor income is disbursed biweekly or monthly).[6] Income vary in size; we scale these flows by the event-

[6] Although depositors often hold multiple accounts, we observe that most depositors receive any given income type j in a given month t in one primary account. For clarity, we therefore suppress the account subscript and pool each depositor's impulse responses across all their accounts.

specific income s_{ijt}, and obtain a *normalized flow*: $F^{\tau}_{ijt} = \frac{f^{\tau}_{ijt}}{s_{ijt}}$. For each event time τ, we aggregate the normalized flows to compute user i event type j specific averages $\overline{F^{\tau}_{ij}}$, and the standard deviations $\sigma\left(F^{\tau}_{ij}\right)$.[7]

Second, separately for each income type j, we estimate the impulse response function:

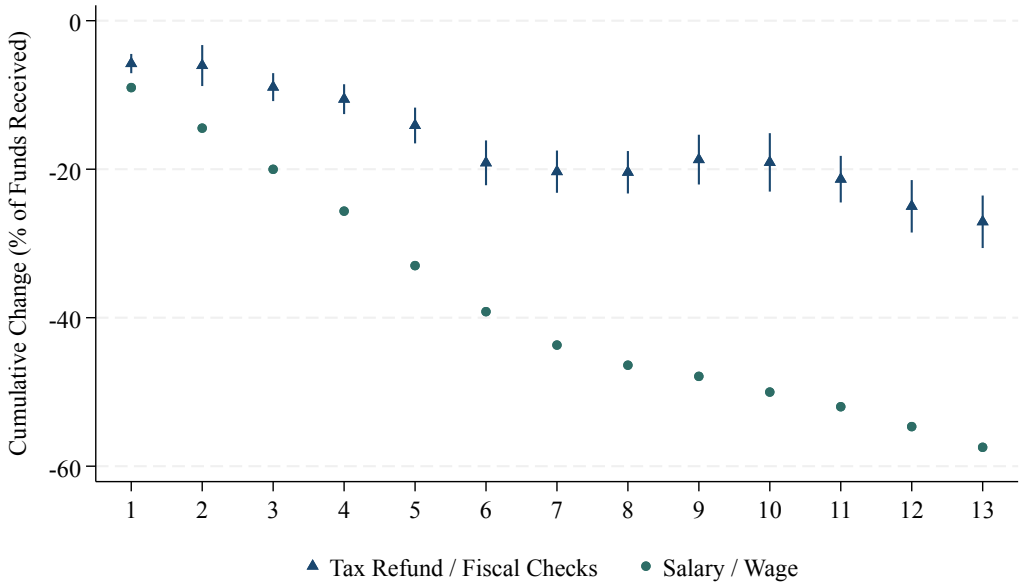
$$\overline{F^{\tau}_{ij}} = \sum_{\tau=0}^{13} \beta^{\tau}_{j} \mathbf{I}^{\tau} + \delta_i + \varepsilon_{ij},$$

where $\overline{F^{\tau}_{ij}}$ is depositor i's average normalized flow for income type j at event time τ, $\mathbf{I}^{\tau}$ is a dummy variable for event time τ, δ_i represents depositor-specific fixed effects, and ε_{ij} is the error term. Coefficients β^{τ}_{j} for each event type j traces the cumulative effect of income on balance over event time τ.

Figure 1 shows that on average, depositors deplete half of their expected labor income in two weeks after receiving the paychecks, whereas for unexpected income, that is, tax refund and fiscal checks, about 75% of the income still lingers on the account after two weeks.

Connection to the literature on marginal propensity to consume (MPC). Our findings that unexpected income lingers longer in deposit accounts than expected income are orthogonal to potential differences in MPCs out of transitory or permanent income. To clarify this point, note that in the frictionless benchmark, each dollar of income is either consumed (C), parked in low-yield deposit accounts that provide immediate liquidity (B), or invested in risky or safe assets with competitive yields such as money market funds (S), with $C + B + S = 1$. The MPC literature measures C; we measure the half-life of B. Differences in MPCs between expected (or likely permanent) and unexpected (transitory) income give only an upper bound for B but cannot explain our finding that unexpected income lingers longer in B. Because under full attention, the positive spread between money

[7] We report results from weighted least squares in the paper because under heteroskedasticity, weighted least squares help in two fronts: first, it yields the best linear unbiased estimator, and shifts how each depositor contributes to the fit based on the precision of their individual-level estimates as noisier estimates have a smaller influence (Greene 2012). The results are robust to use non-weighted, ordinary least squares.



The x-axis represents the number of days after the receipt of funds. The y-axis shows the cumulative change in balance as a *percentage* of the funds received in the corresponding bank account.
We compare the impulse responses for two income sources, salary/wages and tax refunds/fiscal checks, using a panel of 26 million depositors observed at the transaction level between 2014 and 2022. For each individual i and event type j, we first compute the cumulative net flows over a 14-day window, f_{ijt}^{τ} for $0 \leq \tau \leq 13$, where $\tau = 0$ denotes the event date and $\tau = 1, \ldots, 13$ represent subsequent dates. These flows are scaled by the event-specific income s_{ijt} to yield normalized flows across time, $F_{ijt}^{\tau} = f_{ijt}^{\tau}/s_{ijt}$, from which we compute user-event type averages $\overline{F_{ij}^{\tau}}$ and their standard deviations $\sigma\left(F_{ij}^{\tau}\right)$. We then estimate the IRF by regressing $\overline{F_{ij}^{\tau}}$ on event-time dummies with user fixed effects, i.e., $\overline{F_{ij}^{\tau}} = \sum_{\tau=0}^{13} \beta_j^{\tau} \mathbf{I}^{\tau} + \delta_i + \varepsilon_{ij}$, using weighted least squares with weights $w_{i\tau j} = 1/\sigma\left(F_{ij}^{\tau}\right)^2$. Due to computational limits with the large amount of depositor fixed effects, the graph plots β_j^{τ} estimated using a 1-in-100 random sample (sample size is 241,867 depositors); standard errors are clustered at the depositor level and confidence intervals are constructed via 500 bootstrap replications.

Figure 1: Cumulative net balance changes upon receipts of funds

market funds and deposits implies that any portion of $1 - C$ not needed as liquidity buffer should be swept into S.[8]

Put differently, we study the *allocation across safe assets* rather than the consumption-savings margin emphasized in the MPC literature (for reviews, see Parker 2011, Ramey 2025). In our sample, over 60% of depositors have used a brokerage account (Table 1),

[8]Indeed, if the only purpose of B is to provide liquidity for immediate future consumption, then a higher MPC out of permanent income should imply a higher B, the opposite of what we observe.

indicating access to competitive savings vehicles. The idle retail deposit balances—in the magnitude of trillions of dollars—cannot be explained by liquidity buffers alone: even under the view that only deposit accounts are liquid, precautionary saving motives explain about a quarter of the deposits left in bank accounts (Lu, Song, and Zeng 2024).

Additionally, our sample is dominated by high-income, unconstrained depositors whose average account holds tens of thousands of dollars. These depositors face few liquidity constraints, their persistent idle balances are best interpreted as evidence of inattention.[9]

Guided by the facts above, we estimate depositor-level local projections around expected and unexpected income to build an inattention measure. We observe muted responses to FOMC announcements and lumpier withdrawals among more inattentive depositors, suggesting the inattention measure is relevant for bank rate setting.

3.2. Measuring Depositor Inattention

The contrast in depositors' reactions to expected and unexpected income (Section 3.1) suggests a natural depositor-level measure of inattention: the difference in statistical half-lives, i.e., the extra days it takes a depositor to deplete half of an unanticipated income event relative to an expected one. However, this measure is inherently censored: it cannot capture depositors whose reaction times exceed our observation window before the next income arrives. For example, most wage earners and retirees in the U.S. receive paychecks and social securities monthly or biweekly. To avoid overlapping with the next biweekly or monthly pay cycle, in constructing the statistical half-life, one needs to cap the estimation window to at most 14 days, yet many individuals may not check or adjust their balances for 2, 3, or even 6 months. As a result, those with the longest delays—the most inattentive depositors—are dropped from this calculation.

To project the half-life estimates beyond 30 days, we apply individual-level local

[9]Inattention revealed by this overlooked margin—the safe asset allocation of unspent income—not only is helpful in explaining banks' deposit market power, but also potentially useful in generating heterogeneous MPCs as estimated in Shapiro and Slemrod (2003), Johnson, Parker, and Souleles (2006), Parker, Souleles, Johnson, and McClelland (2013), Orchard, Ramey, and Wieland (2025) and others.

projections up to 180 days:

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,s,h} + \beta_{i,s,h} I_{i,s,t} + \rho_{i,s,h}(y_{i,t-1} - y_{i,t-2}) + \varepsilon_{i,s,t,h},$$

where $y_{i,t+h}$ is the h-period account balance for depositor i, $\beta_{i,s,h}$ captures the dynamic effect at horizon h of an income shock of type s with magnitude $I_{i,s,t}$. We include the lagged balance difference $(y_{i,t-1} - y_{i,t-2})$ to account for persistence in balances or time-varying confounders.[10] Income events are indexed by type s, which include tax refunds and fiscal checks for unexpected income events, and salary and social security income for expected income events. We run these local projections separately for each depositor, using an estimation window of 180 days for each depositor (i.e., $h \leq 180$).

To capture depositor inattention, we first compute the *half life* of an income shock's effect on balances. From the period-by-period local projections above, the estimation horizon h represents the number of periods ahead at which we measure the change in depositor i's account balance following an income event. We define the half–life for unexpected events, $\text{HL}_i^{\text{unexp}}$, as the smallest h such that $\beta_{i,s,h} \leq 0.5\,\beta_{i,s,0}$, i.e., the time it takes for the effect to decay by at least one half. Note that if a depositor has $\beta_{i,s,0} \notin (0, 1]$, the income flow is either fully transferred out or not the main shock at the time of occurrence, in which case we exclude these depositors. We define HL_i^{exp} analogously for expected income.

Figure 2 plots the distribution of the half lives by type of income. Half-lives from expected income (salary and social securities) averages about 6 days, whereas half-lives from unexpected income (tax refunds and fiscal checks) averages about 25 days.

We then measure the depositor-level inattention using the difference of half–lives between unexpected and expected income, $\Delta\text{HL}_i = \text{HL}_i^{\text{unexp}} - \text{HL}_i^{\text{exp}}$. By construction, ΔHL_i captures each depositor's relative sluggishness in responding to unexpected versus expected income,

[10] In alternative specifications, we also include a deterministic trend to capture potential changes over time, and the prevailing 30-day flow volatility $\delta_{i,t}$ at time $t-1$; the inattention measure is robust to the additional controls.

where the responding time to expected income serves as a depositor-level baseline that might be due to liquidity constraints. We quantify the depositor-level inattention by ranking ΔHL_i across depositors. The difference in half lives, ΔHL_i, averages 19.23 days, with a median of 7 and a standard deviation of 29.57.

In Section 5, we aggregate the depositor-level inattention to county-income-group level, and use demographics from IRS tax filings and Census to train a predictive algorithm that extends this in-sample inattention measure nationwide.

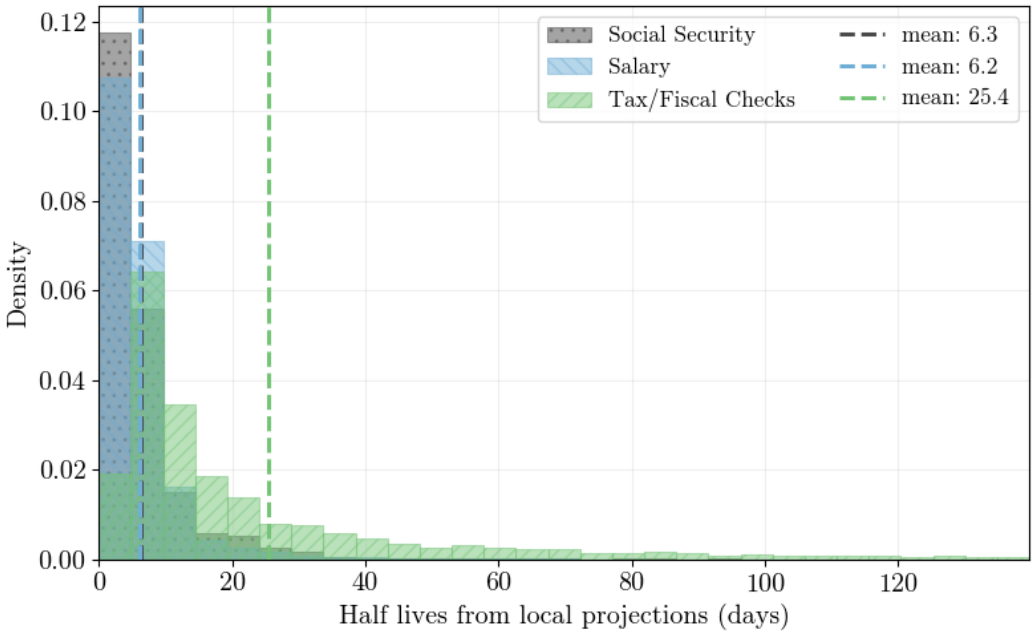


Figure 2: Distribution of half lives for expected and unexpected incomes

We compute half lives are via depositor-level local projections up to $h \leq 180$ days: $y_{i,t+h} - y_{i,t-1} = \alpha_{i,s,h} + \beta_{i,s,h} I_{i,s,t} + \rho_{i,s,h}(y_{i,t-1} - y_{i,t-2}) + \varepsilon_{i,s,t,h}$, where s indexes salary/social security (expected) and tax/fiscal checks (unexpected). For each s, HL_i^s is the smallest h with $\beta_{i,s,h} \leq 0.5\,\beta_{i,s,0}$; cases where $\beta_{i,s,0} \notin (0, 1]$ are excluded. Inattention is $\Delta\text{HL}_i = \text{HL}_i^{\text{unexp}} - \text{HL}_i^{\text{exp}}$. We use local projections, instead of statistical half lives to project half lives up to 180 days mitigate censoring from biweekly/monthly pay cycles.

3.3. Depositor Inattention and Rate Sensitivity Around FOMC Announcements

Depositor inattention is an important factor that affects depositors' reactions to monetary news. We check the weekly deposit flows out of bank accounts for individual depositors before

and after FOMC announcement weeks. Most bank interest payments are paid monthly (or at lower frequencies), hence in the three-week window around FOMC announcements, depositors are likely only reacting to the target rate changes. For each depositor i, we compute their total deposit balance changes Δm_{iw} as a percentage change from one week before FOMC announcement (starting Wednesday) to one week after FOMC announcement, and regress Δm_{iw} on target rate changes $\Delta \rho_w$. We plot individuals' high-frequency deposit flow sensitivity to policy rate against depositor inattention in Figure 3(a). Inattentive depositors have much smaller deposit outflow compared with attentive depositors, suggesting that inattention is associated with depositors' sensitivity to policy rate changes.[11]

Although inattentive depositors are less responsive to policy rate changes, the amounts they move when they do react are much larger. Panel (b) of Figure 3 shows that, in dollar terms, the deposit flows of the most inattentive group are nearly twice as volatile as those of the most attentive group. To examine this "lumpy" behavior more closely, we sort depositors into 20 equal-sized inattention bins (each with at least 100 observations to ensure reliable skewness estimates) and analyze the distribution of their flow responses across bins. Figure 3(c) shows that during rate hikes, inattentive depositors have more positive skewness, suggesting large outflows compared to attentive depositors.

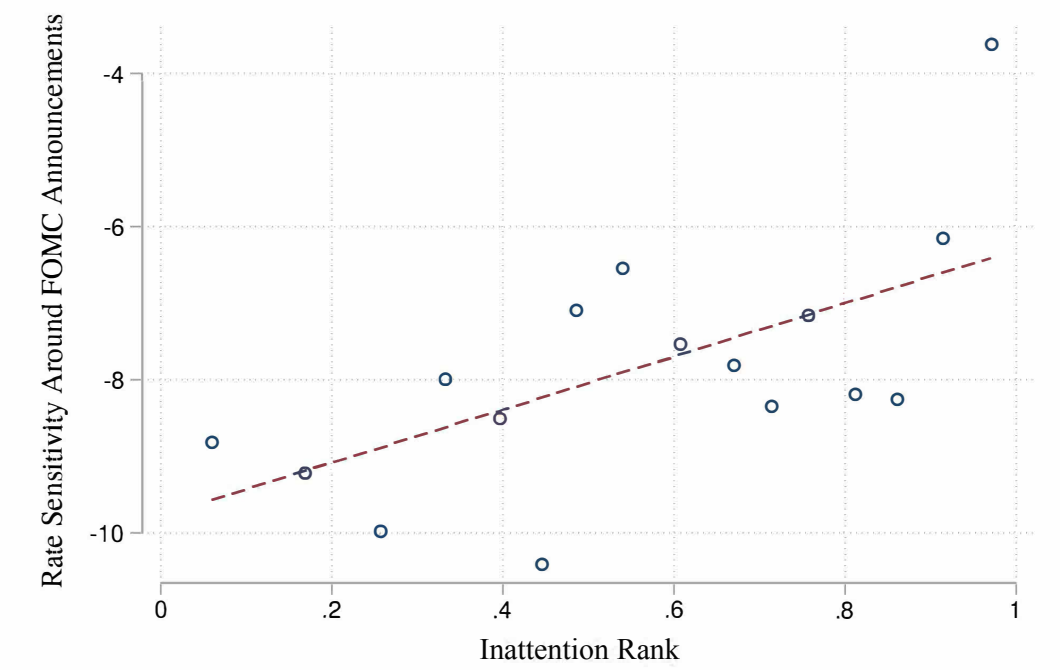
Depositor-level spread sensitivity. Above we highlight that depositors' immediate reactions to FOMC announcements vary with their level of inattention. Appendix C.1 extends this analysis by estimating each depositor's unconditional sensitivity to the deposit spread at monthly frequency. The resulting estimates mirror the announcement-based findings here, though they are modestly smaller in magnitude.

4. A Model of Banking on Inattention

Depositors are inattentive, and inattentive depositors are less rate sensitive. Motivated by these observations, we develop a dynamic banking model in which depositor inattention gives

[11] The results are robust to adding consumption volatility (measured as 12-month prevailing standard deviation of spendings scaled by average spending).

(a) Sensitivity to Policy Rate Changes



(b) Volatility in Dollar-Volume Flows

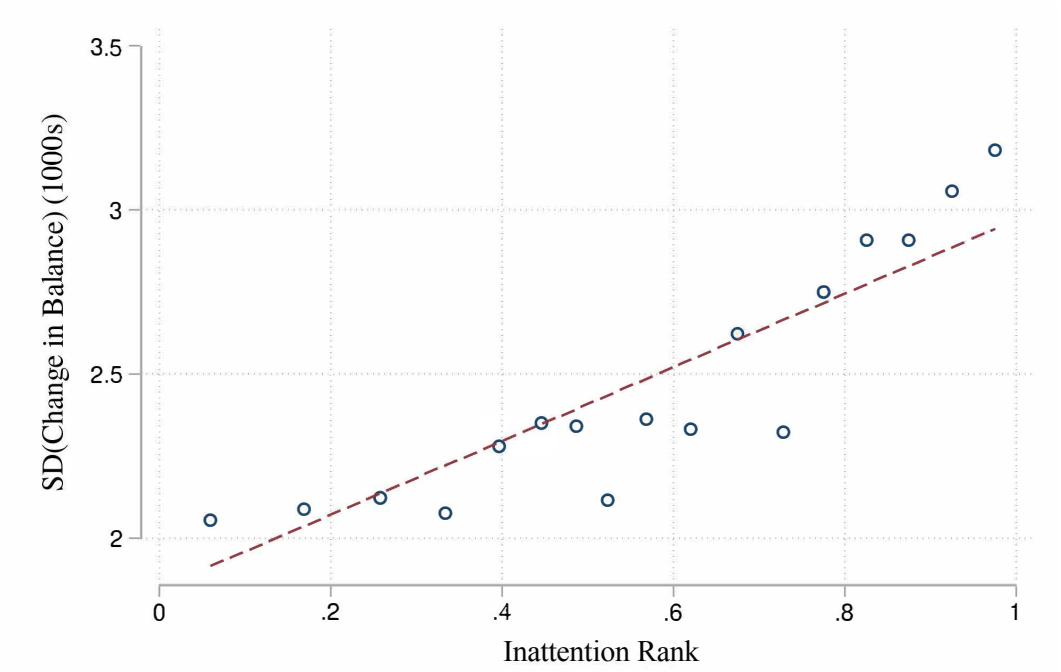
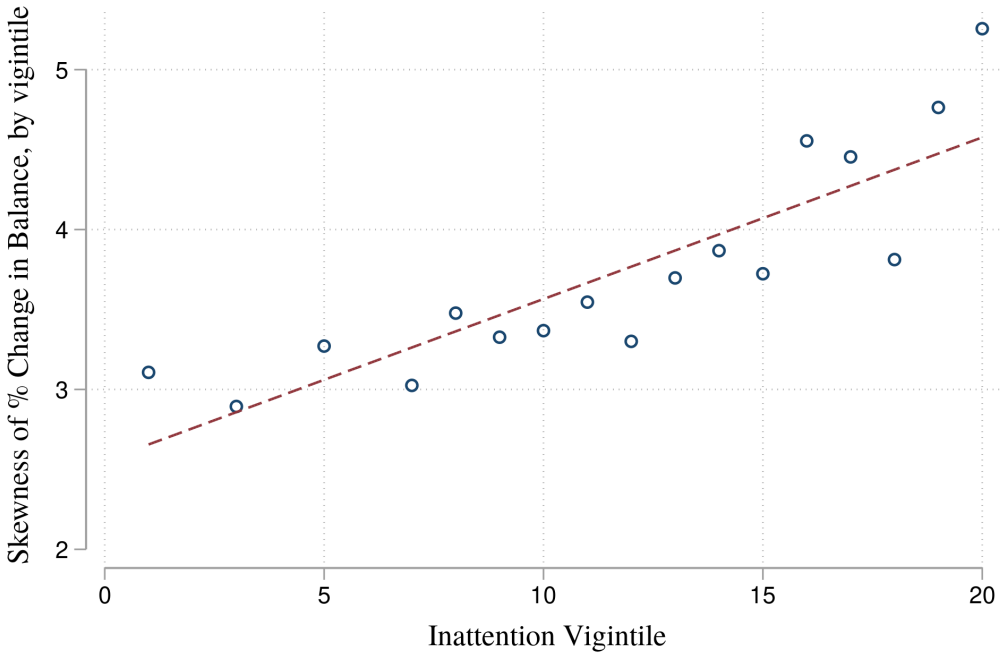


Figure 3: Reactions to policy rate changes, +/- 1 week around FOMC announcements

(c) Skewness of Flows



In all panels, Δm_{iw} is the percentage change in depositor i's total deposit balance from one week before to one week after the FOMC announcement (week defined from Wednesday to Wednesday), and $\Delta\rho_w$ is the change in the target federal funds rate at the FOMC meeting. In panel (a), we plot each depositor's high-frequency deposit flow sensitivity, the regression coefficient from $\Delta m_{iw} = \gamma\Delta\rho_w + \varepsilon_{iw}$ against depositor's inattention. Panel (b) reports the standard deviation of the raw change (in dollars) of depositor i's total deposit balance from one week before to one week after rate hike announcements by inattention rank. In panel (c), depositors are sorted into 20 inattention bins (each with at least 100 observations), and we plot the skewness of Δm_{iw} from one week before to one week after rate hike announcements, highlighting that inattentive depositors exhibit more positive skewness. The sample period is from 2014 to 2022.

Figure 3: Reactions to policy rate changes, +/- 1 week around FOMC announcements (Cont.)

rise to banks' market power in the deposit market (Drechsler, Savov, and Schnabl 2017). In equilibrium, deposit-rate pass-through is less than one-to-one, and smaller for banks with more inattentive depositors. The model also forms the basis for quantifying banks' franchise value of deposits. In addition, this model yields unique predictions on the sluggishness and asymmetry in short-run rate adjustments.

We start by introducing the inattentive depositors and setting up banks' optimization.

Inattentive depositors. Time runs from $t = 0$ to infinity. Starting from the initial $M_0 > 0$,[12] the deposit balance decays at rate $\tau^{-1}P(\rho - r)$ with $\tau \geq 0$ as

$$\dot{M}_t = -\underbrace{\tau^{-1}}_{\text{attention}} P(\underbrace{\rho_t}_{\text{policy rate}} - \underbrace{r_t}_{\text{deposit rate}})M_t \tag{1}$$

The term $\tau^{-1}P(\rho_t - r_t)$ captures the documented sensitivity of deposit outflows to the deposit spread and its dependence on inattention. With an increasing $P(\cdot)$, depositors are more likely to withdraw when they are more attentive (lower τ) or when the deposit spread $\rho_t - r_t$ is larger. This multiplicative form follows if each depositor has an independent Poisson strike with arrival rate τ^{-1} to check their account, and upon checking, they withdraw their entire balance with probability $P(\rho_t - r_t)$ from the bank account to invest in a money market fund that pays the policy rate ρ_t.

Assuming a constant policy rate ρ, we show that the bank optimally sets a constant deposit rate r, in which case the deposit balance evolves as

$$M_t = \mathrm{e}^{-\tau^{-1}P(\rho - r)t}M_0 \tag{2}$$

The term $\tau^{-1}P(\rho - r)$ ensures that deposit demand is upward-sloping in r, leading to a tradeoff for the bank between the profit margin and deposit outflows which we discuss next.

Banks' optimization. Given a balance M_t under temporal monopoly, the bank chooses a sequence of deposit rates (i.e., funding costs) $\{r_t \geq 0\}_{t\geq 0}$, subject to the zero lower bound, to maximize its deposit franchise value over existing deposits

$$\max_{\{r_t \geq 0\}_{t\geq 0}} V_0 \equiv \int_0^\infty \mathrm{e}^{-\rho t} \overbrace{(\rho_t - r_t)}^{\text{profit margin}} M_t \mathrm{d}t \tag{3}$$

[12] As Duffie (2019) emphasizes, the U.S. payment system operates entirely through banks. Wages and other inflows land directly in deposit accounts, which also serve as the primary source of liquidity for transfers, bill payments, and daily spending. As of 2024, the $18tn in outstanding deposits constitutes U.S. commercial banks' primary source of low-cost, stable funding.

subject to the law of motion of the deposit balance (1).

We evaluate the deposit franchise value based on existing deposits that decay over time, following Drechsler, Savov, Schnabl, and Wang (2025). We abstract from deposit inflows for two reasons. First, attracting new deposit inflows is costly.[13] In order to determine the values of inflows, we also need to measure the acquisition cost. Second, we take the depositor inattention parameter τ as given for each bank. As inattention varies across depositors, banks may actively attract more inattentive depositors, for example, by using targeted mailings with eye-catching sign-up offers to reach those who do not rate-shop proactively. Analyzing the dynamics with inattentive depositors sorting across banks is left for future work.

The bank optimally sets a constant deposit rate $r_t = r \geq 0$, and hence M_t follows (2). Further, it is more convenient to express the bank franchise value in terms of the deposit spread $x \equiv \rho - r \in (-\infty, \rho]$ as

$$\max_{x \in (-\infty, \rho]} V_0 = \frac{\overbrace{x}^{\text{profit margin}}}{\underbrace{\tau^{-1} P(x)}_{\text{decay rate}} + \underbrace{\rho}_{\text{discount rate}}} M_0 \tag{4}$$

As the bank will never set a negative deposit spread (which leads to a negative profit margin), the domain of interest is $x \in (0, \rho]$.

Throughout the paper, we assume that $P(x)$ is power function

$$P(x) = a + \left(\frac{x}{b}\right)^{\gamma}, \ x \in (0, b(1-a)^{1/\gamma}] \tag{5}$$

with $a > 0, b > 0, \gamma > 1$. A positive intercept $a > 0$ means that even with zero deposit spread, depositors may withdraw, which captures idiosyncratic liquidity needs. Further, $b > 0, \gamma > 1$ ensure that $P(x)$ is non-negative, increasing and convex, the last of which implies that the

[13] In reality, banks offer competitive promotional rates and sizable cash bonuses—particularly on checking and savings accounts with direct deposit setup—to attract new depositors. Theoretically, issuing new deposits creates dilution risk for existing depositors, raising existing depositors' probability of withdrawal (Jermann and Xiang 2023, Benetton, Hébert, and McQuade 2025).

bank franchise value V_0 is concave in x. Intuitively, an increasing and convex probability $P(x)$ means that the marginal withdrawal rate rises with the spread—small spreads only trigger the most sensitive depositors, while larger spreads push away more depositors.

Discussion on assumptions. The key ingredient of the theory is the deposit decay rate $\tau^{-1}P(x)$ in the deposit franchise value (4), which is increasing and convex in the deposit spread and is lower when depositors are more inattentive. As inattention weakens the deposit decay rate, banks' optimal rate-setting depends on the inattention of their depositors, generating unique cross-sectional predictions. While we adopt a particular functional form that is multiplicatively separable between inattention τ and withdrawal probability $P(x)$, the idea would carry across more broadly to alternative ways of modeling deposit decay that varies across banks.

4.1. Deposit Rate, Flow Sensitivity, and Deposit Franchise Value

We analyze the optimal deposit spread the bank sets and its properties. Under a constant policy rate ρ, the bank optimally sets a constant deposit spread $x \equiv \rho - r \in (0, \rho]$. The marginal change in bank franchise value associated with a marginal change in x is

$$\frac{\partial V_0}{\partial x} = \frac{\overbrace{\tau^{-1}P(x) + \rho}^{\text{gain from higher profit margin}} \quad \overbrace{- x\tau^{-1}P'(x)}^{\text{loss in quantity}}}{(\tau^{-1}P(x) + \rho)^2} M_0 \tag{6}$$

In choosing the optimal deposit spread x, the bank trades off the profit margin (deposit spread) and quantity (the size of deposits)— a higher profit margin x brings higher profits holding fixed deposits, but leads to a faster decay of deposit balances. Crucially, the quantity consideration is weaker when depositors are more inattentive (higher τ). If depositors are very inattentive, the profit margin consideration dominates, and the bank sets the highest deposit spread possible by choosing $x = \rho$. If depositors are only moderately inattentive, the bank offers an interior deposit spread $x < \rho$ (i.e., positive rate $r > 0$) to balance the profit margin and quantity considerations.

Proposition 1 (Optimal deposit rate and pass-through)**.** *Define*

$$u(\rho) \equiv \frac{(\gamma-1)(\rho/b)^{\gamma}-a}{\rho} \tag{7}$$

which increases in ρ*.*

1. *If* $\tau < u(\rho)$*, the bank sets*

$$r = \rho - b\left(\frac{\rho\tau + a}{\gamma - 1}\right)^{1/\gamma} \tag{8}$$

   with the following properties:

   (a) *the deposit rate* r *is lower when* τ *is higher, i.e.,* $\frac{\mathrm{d}r}{\mathrm{d}\tau} < 0$*;*

   (b) *the pass-through of policy rate to deposit rate is between zero and one, i.e.,* $\frac{\partial r}{\partial \rho} \in (0, 1)$*;*

   (c) *the pass-through to deposit rate is lower when* τ *is higher, i.e.,* $\frac{\partial^2 r}{\partial \rho \partial \tau} < 0$*.*

2. *If* $\tau \geq u(\rho)$*, the bank set a zero deposit rate* $r = 0$ *and has zero pass-through from the policy rate* ρ *to deposit rate.*

This proposition implies that the optimal deposit rate r decreases in τ until hitting 0 at $\tau = u(\rho)$. Since $u(\rho)$ increases in ρ, a higher policy rate leads more banks—especially those with inattentive depositors (high τ)—to set positive deposit rates.

Proposition 1 states that banks with moderately inattentive depositors ($\tau < u(\rho)$) choose positive deposit rates. Among them, banks with more inattentive depositors (higher τ) set a lower deposit rate r. The intuition comes from the first-order condition (6): with convex $P(x)$, the higher the deposit spread x (i.e., lower r), the larger the loss in quantity relative to gain due to profit margin $\tau^{-1}xP'(x) - \tau^{-1}P(x)$. The difference is modulated by τ^{-1}, as more inattentive deposits withdraw less, and equals ρ at the optimum. Thus, a bank with more inattentive depositors sets a lower rate r.

It further suggests that deposit spread x increases in ρ. That occurs because as ρ rises, future profits become less important, so banks increase spreads x to extract more from current deposits. Moreover, the sensitivity of x to ρ increases with τ—implying a lower pass-through to deposit rate when depositors are more inattentive—because the difference $\tau^{-1}xP'(x) - \tau^{-1}P(x)$ is modulated by τ^{-1}.

Proposition 1 highlights the impact of inattention on bank rate setting. Our model also makes predictions on the quantities of deposits. In (2), the deposit decay rate $\tau^{-1}P(\rho - r)$ depends on inattention τ and the deposit spread $\rho - r$, both of which vary across banks. Once we solve for the optimal r on τ according to Proposition 1, we can characterize the equilibrium deposit outflow across banks and analyze its dependence on inattention.[14]

Deposit rates for banks with high inattention τ. Proposition 1 predicts a kink in the rate-setting function across banks. It suggests that banks with very inattentive depositors set zero deposit rates and have zero pass-through from the monetary policy rate.

While we simply assume that the lowest deposit rate banks can set is zero, we note that in reality banks may post a small positive rate out of other concerns. While there is no federal floor on retail deposit rates, some accounts are explicitly "interest-bearing" (e.g., NOW accounts). Additionally, the CFPB Truth in Savings disclosures (Reg DD) requires banks to pay "interest" and to disclose the APY; banks are likely posting a de minimis rate to avoids advertising a 0% APY even in a low rate environment. For example, JPMorgan Chase retains 1bp interest rate on retail savings account from 2014 to 2025.

Proposition 2 (Deposit flow sensitivity under optimal deposit spread)**.** *Under the optimal deposit spread $x \equiv \rho - r$ characterized in Proposition 1, the deposit flow sensitivity w.r.t.*

[14]The dependence of r on τ is not a threat if we empirically study flow sensitivity of non-interest-bearing deposits with $r = 0$. In that case, the flow sensitivity is $(\Delta t)^{-1}\frac{\partial(\log M_{t+\Delta t} - \log M_t)}{\partial \rho} = -\tau^{-1}P'(\rho)$, whose magnitude declines in τ.

deposit spread is

$$(\Delta t)^{-1}\frac{\partial(\log M_{t+\Delta t}-\log M_t)}{\partial x}=-\tau^{-1}P'(x)=\begin{cases}-\tau^{-1}\frac{\gamma}{b}\left(\frac{\rho\tau+a}{\gamma-1}\right)^{1-1/\gamma}, & \tau<u(\rho)\\ -\tau^{-1}\frac{\gamma}{b}\left(\frac{\rho}{b}\right)^{\gamma-1}, & \tau\geq u(\rho)\end{cases} \tag{9}$$

which is continuous, with its magnitude declining in τ.

Thus, across banks, those with more inattentive depositors experience a lower flow sensitivity, despite that the deposit spread x is larger under a higher τ and hence the sensitivity $P'(x)$ is larger.

Proposition 3 (Deposit franchise value)**.** *The bank's deposit franchise value V_0 increases in τ, increases in ρ on $\rho\in[0,u^{-1}(0)]$, and decreases in ρ on $\rho\in(u^{-1}(0),\infty)$.*

Proposition 3 discusses the comparative statics of deposit franchise value (DFV) w.r.t. inattention τ and the policy rate ρ. It is intuitive that banks that face more inattentive depositors (higher τ) have a higher DFV, since the deposit decay rate $\tau^{-1}P$ is lower.

Regarding the policy rate ρ, it predicts that the DFV increases in ρ when ρ is small (specifically, $\rho<u^{-1}(0)$) and decreases in ρ otherwise. To understand this result, we start with the case of small ρ, where the optimal deposit rate is zero, and the DFV is given by

$$V_0=\frac{\overbrace{\rho}^{\text{profit margin}}}{\underbrace{\rho}_{\text{discount rate}}+\underbrace{\tau^{-1}P(\rho)}_{\text{deposit decay rate}}}M_0$$

As ρ increases, the profit margin, the discount rate and the deposit decay rate all go up. The profit margin force increases the DFV while the latter two forces decrease it. If the deposit decay rate is independent of ρ, the third force is shut off and it coincides with Drechsler, Savov, Schnabl, and Wang (2025), implying a DFV that is increasing in ρ. Under a convex $P(\rho)$, a higher ρ makes the marginal effect of the deposit decay rate force stronger. Thus when ρ is small, the deposit decay force is weak and the DFV increases in ρ. As ρ rises to

$\rho \in (u^{-1}(0), u^{-1}(\tau))$ where $r = 0$ still holds, the deposit decay force becomes strong enough to overturn the overall effect, leading to a DFV that decreases in ρ.

As ρ rises to $\rho > u^{-1}(\tau)$, the bank starts setting a positive deposit rate optimally, as characterized in Proposition 1. Under a positive optimal rate (or equivalently, a deposit spread $x \in (0, \rho)$), the DFV becomes

$$V_0 = \frac{\overbrace{x}^{\text{profit margin}}}{\underbrace{\rho}_{\text{discount rate}} + \underbrace{\tau^{-1}P(x)}_{\text{deposit decay rate}}} M_0$$

As ρ rises, the optimal deposit spread x changes, and the change in DFV is still governed by the same three forces (the profit margin, the discount rate, and the deposit decay rate). However, in this case, since the deposit spread x is optimally chosen to maximize the DFV, it balances the marginal effects of profit margin and the deposit decay rate. Hence a marginal increase in ρ affects the DFV only through the discount rate, which is envelope theorem. Hence, when the deposit rate r is optimally set to be positive under a large ρ, the DFV declines in ρ.

4.2. Sluggish Adjustment

Previously, we have considered the deposit spread, pass-through and deposit flows. In this subsection, we analyze banks' short-run rate adjustment dynamics in response to a policy change. We introduce adjustment frictions and consider a distribution of banks on $\tau \in [\underline{\tau}, \overline{\tau}]$ with cumulative density function $F(\cdot)$ which assigns positive density throughout. We start with a model with staggered rate setting under a constant frequency of adjustment following Calvo (1983). We show that, in response to a policy rate change, the higher the prevailing policy rate, the more banks adjust at any point in time. Then we extend the model to consider endogenous frequency of adjustment, similar to Romer (1990). We establish that banks with more inattentive depositors gain more from adjustment and thus choose to adjust more quickly.

4.2.1. Staggered Deposit Rate Setting

We start with a model of staggered rate setting following Calvo (1983). At time 0, the policy rate changes permanently from ρ to ρ'. A bank can only adjust its deposit rate when it receives a Poisson strike with intensity θ.

Proposition 4 (Aggregate share of adjusted banks)**.** *In response to a time-0 policy change from ρ to ρ' with arbitrary size of change, the share of banks that have adjusted their deposit rates by time t follows*

$$S_t = (1 - \mathrm{e}^{-\theta t})F(u(\bar{\rho})) \tag{10}$$

in which $\bar{\rho} \equiv \max\{\rho, \rho'\}$ is the event-peak rate*—the larger of pre- and post-change rates. Further, at any t, S_t increases in $\bar{\rho}$ for $\bar{\rho} \in (u^{-1}(\underline{\tau}), u^{-1}(\overline{\tau}))$.*

To understand this result, let us consider the share of banks that will eventually adjust their deposit rates in response to such a policy change. Proposition 1 suggests that, under any prevailing policy rate ρ, only banks with $\tau < u(\rho)$ will set a positive deposit rate. Hence, banks with $\tau > u(\rho)$ and $\tau > u(\rho')$ will always keep a zero deposit rate before and after the shock. The other banks will adjust when they get a Poisson strike, and thus the share of banks that have adjusted follows (10). If the policy rate $\bar{\rho}$ is high, more banks will adjust at any point in time, which is empirically testable.

Further, the theory predicts "roughly symmetric" responses to rate hikes and rate cuts—the path of adjustment share S_t is the same under the same event-peak rate $\bar{\rho}$, no matter whether the policy change is a rate hike or a rate cut. This has two implications: when we compare the path of S_t in response to a rate hike and a rate cut that start from the same prevailing ρ, then the rate hike triggers more banks to adjust since it corresponds to a higher event-peak rate $\bar{\rho}$. However, if we compare a rate cut from a prevailing ρ to a lower level with a rate hike starting from a lower level to exactly the same ρ, they trigger the same

paths of S_t, as two rate changes correspond to the same event-peak rate $\bar{\rho}$. In this sense, the responses are roughly symmetric.

However, previously, Driscoll and Judson (2013) and others noted that the adjustment path S_t is asymmetric across rate cuts and hikes: rate cuts trigger more banks to adjust than rate hikes. We revisit this finding and show that the different event-peak rates $\bar{\rho}$ between cuts and hikes may lead to the seemingly asymmetric result, since rate cuts often begin from a high rate whereas rate hikes are typically associated with low rates.

4.2.2. Endogenous Adjustment Frequency

Now we consider an extension with endogenous frequency of adjustment, similar to Romer (1990). At time 0 under a prevailing policy rate of ρ, the policy rate changes permanently by a small amount $\Delta\rho$. Banks choose a Poisson arrival rate $\theta \in [0, \infty)$ subject to a cost $C(\theta)$ with $C'(\theta) > 0, C''(\theta) \geq 0$ such that it can only adjust their rate r when it receives a Poisson strike. This setup allows for a discussion on which banks tend to adjust faster. A bank will choose a higher adjustment frequency θ if its profit gain from a quicker adjustment is higher, which generates a cross-sectional prediction related to its depositor inattention τ.

Proposition 5 (Endogenous adjustment frequency)**.** *In response to a small policy change $\Delta\rho$ starting from ρ, among the banks which set a positive deposit rate under ρ, the optimal adjustment frequency θ increases in τ when τ is small. That is, banks with more inattentive depositors adjust faster.*

4.3. Empirical Implications

Our rate-setting model is consistent with well-known aggregate facts including positive deposit spreads, incomplete pass-through of policy rates, and relatively muted flow sensitivity. In addition, it delivers unique, rich cross-sectional predictions linked to depositor inattention. We outline these predictions below to guide the empirical tests and calibration.

Cross-sectional variation in deposit rate, pass-through, and flow sensitivity. Proposition 1 predicts that, across banks, those with more inattentive depositors set a lower deposit rate r (or equivalently, a higher deposit spread x), and have a lower pass-through from the policy rate change to the deposit rate r (or equivalently, a higher pass-through into deposit spread x). Proposition 2 suggests that, banks with more inattentive depositors face flows that are less sensitive to changes in deposit spread x.

Sluggish rate adjustments. Although our central results focus on long-run effects, the model also delivers two unique predictions on short-run rate adjustments following policy rate changes. First, Proposition 4 suggests that, more banks will adjust in response to a policy rate change, when the prevailing policy rate ρ is higher. Consequently, policy rate cuts, which often happen under higher prevailing ρ, can trigger more banks to adjust than hikes. Second, Proposition 5 indicates that, among banks who set positive deposit rates, those with more inattentive depositors adjust faster in response to a policy rate change.

From cross-sectional evidence to deposit franchise value. Our model features three parameters (a, b, γ) which govern the level, slope, and curvature of the deposit decay rate $\tau^{-1}P(x)$. These parameters are informed by the three cross-sectional moments regarding deposit rate, pass-through, and flow sensitivity. Once we estimate these parameters, we can determine the deposit franchise value and its comparative statics w.r.t. inattention τ and policy rate ρ, following Proposition 3.

5. Evidence of Banking on Inattention

To examine how inattention shapes bank-level deposit flows and deposit pricing, we first project the in-sample inattention measure above to the full population: we map inattention to publicly available demographic and socioeconomic data, and train a statistical model that predicts inattention annually for every location-income cell nationwide. We next aggregate the predicted inattention: first to counties, weighting by local income; then to banks, weighting by each county's share of the bank's deposits. The bank-level inattention allows us

to test the model's predictions. Banks with more inattentive depositors experience weaker flow sensitivity, charge wider spreads, and pass on policy-rate changes less fully. All banks are slow to raise deposit rates after policy rate hikes, and inattentive banks are quicker to cut rate after rate cuts.

5.1. Predicting Inattention Using Public Datasets

The transaction-level data does not cover several key depositor demographics (e.g., age, family structure, race). To predict inattention, we first aggregate individual-level data to the county-income-group level and supplement it with other variables publicly available. Using the combined dataset, we train and cross-validate a predictive algorithm and then project it nationwide using IRS tax filings at the same county-income-group granularity. Below, we detail the steps to develop this algorithm, and Figure 4 outlines each estimation stage with the variables used for estimation.

We begin by constructing a merged dataset that includes county–income group averages of inattention, along with corresponding demographic and socioeconomic outcomes. In this step, we aggregate individual inattention measures by computing a weighted average. For each city–income group (c, g), we define the income-weighted inattention as $\alpha_{c,g} = \frac{\sum_{i\in(c,g)} \text{Income}_i \times \log(\Delta\text{HL}_i)}{\sum_{i\in(c,g)} \text{Income}_i}$; we standardize $\alpha_{c,g}$ to serve as the target variable for prediction.[15]

We predict the standardized inattention $\alpha_{c,g}$ with gradient boosting algorithm using features derived from our transaction data with demographic variables from the 2010 ZCTA-level Census via county FIPS codes (see Figure 4 for a summary of variables across datasets). Because some of the explanatory variables are highly skewed, we apply a log transformation when the skewness exceeds 3 and include county-level averages to capture potential social interactions that can affect depositor inattention (Eichenbaum, Puglisi, Rebelo, and Trabandt 2025). We split the merged dataset into an 80% training set and

[15]The raw half-life gap ΔHL_i is strictly positive and right-skewed as a fraction of depositors wait weeks or months, who then dominate the loss function used in our gradient boosting regression. We in turn transform the target variable to improve the predictive accuracy. The log scale compresses extreme values, stabilizes variance, and yields a distribution that is close to normal.

a 20% test set, employ five-fold cross-validation, and use randomized hyperparameter tuning to select the best model. The model produces predicted inattention levels $A(X_{c,g})$, where $X_{c,g}$ represents county-level socioeconomic and demographic characteristics.

We evaluate the selected model on the test dataset, where it explains approximately 72% of the out-of-sample variation in inattention, $\alpha_{c,g}$. The gradient boosting algorithm is highly effective at capturing meaningful variations in inattention by modeling flexible, non-linear interactions among demographic and socioeconomic variables. However, this complexity makes it difficult to pinpoint which variables are most useful in predicting inattention. For illustrative purposes, we perform a permutation test in which we randomly shuffle each feature and compute the average drop in R^2 over five trials. Although this method does not capture the combined or non-linear importance of features that work together, it provides useful insight into the *independent* contribution of each variable. Section 5.1 shows that several features cause a significant reduction in R^2 when permuted. The investment–related variables which capture average income share from investments, and shares of individuals with investment incomes are the most important independent contributor; permuting this group alone leads to a 2.9% drop in the overall out-of-sample R^2 of the pretrained model.

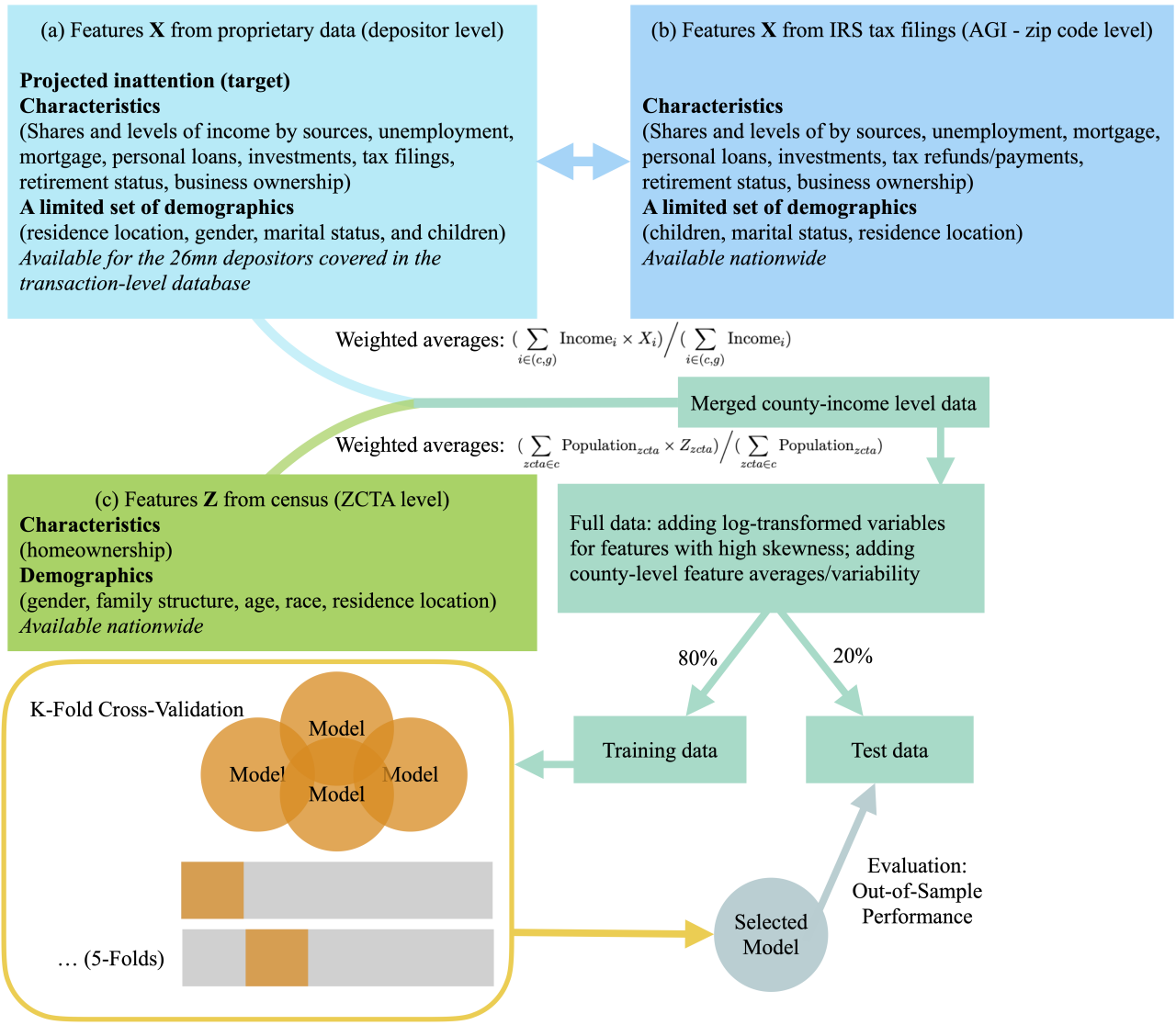
Finally, we apply the tuned model to all cities in the U.S. annually from 2007 to 2021. Since our proprietary dataset does not cover the entire U.S. population, we map in-sample explanatory variables in the model to corresponding variables derived from IRS administrative filing records (substituting dataset (a) with dataset (b) in Figure 4). Specifically, we extract measures from IRS Form 1040 corresponding to variables in the proprietary dataset. For example, to construct an "investment income" measure, we sum up reported net capital gains, dividends (ordinary and qualified), taxable interest, and, in some years, components of retirement income, which mirrors the investment income variable inferred from the transaction data. A complete list of variables derived from IRS tax filings, including their composite constructions, is provided in Table A-1. These variables are reported at zipcode–income group level; we aggregate them to the county–income group level

(the same level at which the predictive inattention model $A(X_{c,g})$ is trained). That is, for each county–income group (c, g) in year t, we obtain the predicted inattention $\hat{\alpha}_{c,g,t} = A(X_{c,g,t})$.

County-level inattention. We measure county–level inattention as an AGI-weighted average of county–income group–level inattention

$$\alpha_{ct} = \frac{\sum_g \text{AGI}_{cgt} \hat{\alpha}_{cgt}}{\sum_g \text{AGI}_{cgt}},$$

where AGI_{cgt} is the total adjusted gross income summed over all tax filings in income group g for county c in year t from IRS tax filings. We visualize the county-level inattention in Figure 6.

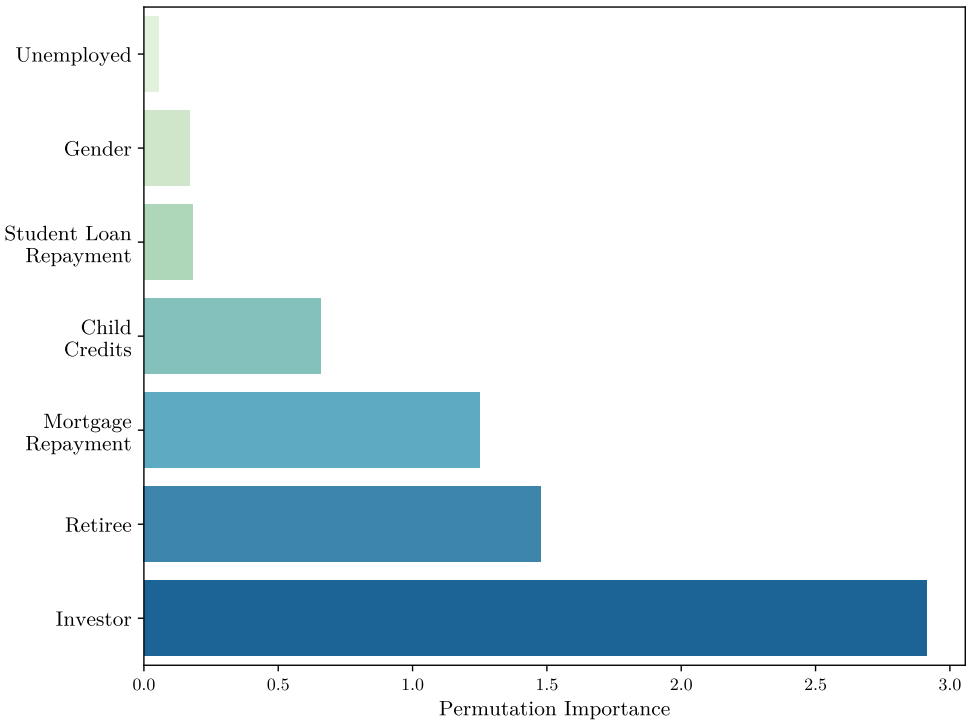


This chart lays out the data and method we use to predicting inattention. We combine proprietary data (**a**) and census data (**c**) to create a merged dataset that includes both the county–income group inattention and demographic and socioeconomic features to train a gradient boosting algorithm. Since variables can be highly skewed, we apply a log transformation when the skewness is above 3, and include county-level averages to account for local social interaction effects.

We then split the data into 80% training data and 20% test data; for the training data, we perform five-fold cross-validation and use randomized hyperparameter tuning to select the best model within the training dataset. We evaluate this selected model using the test dataset and report the out-of-sample performance.

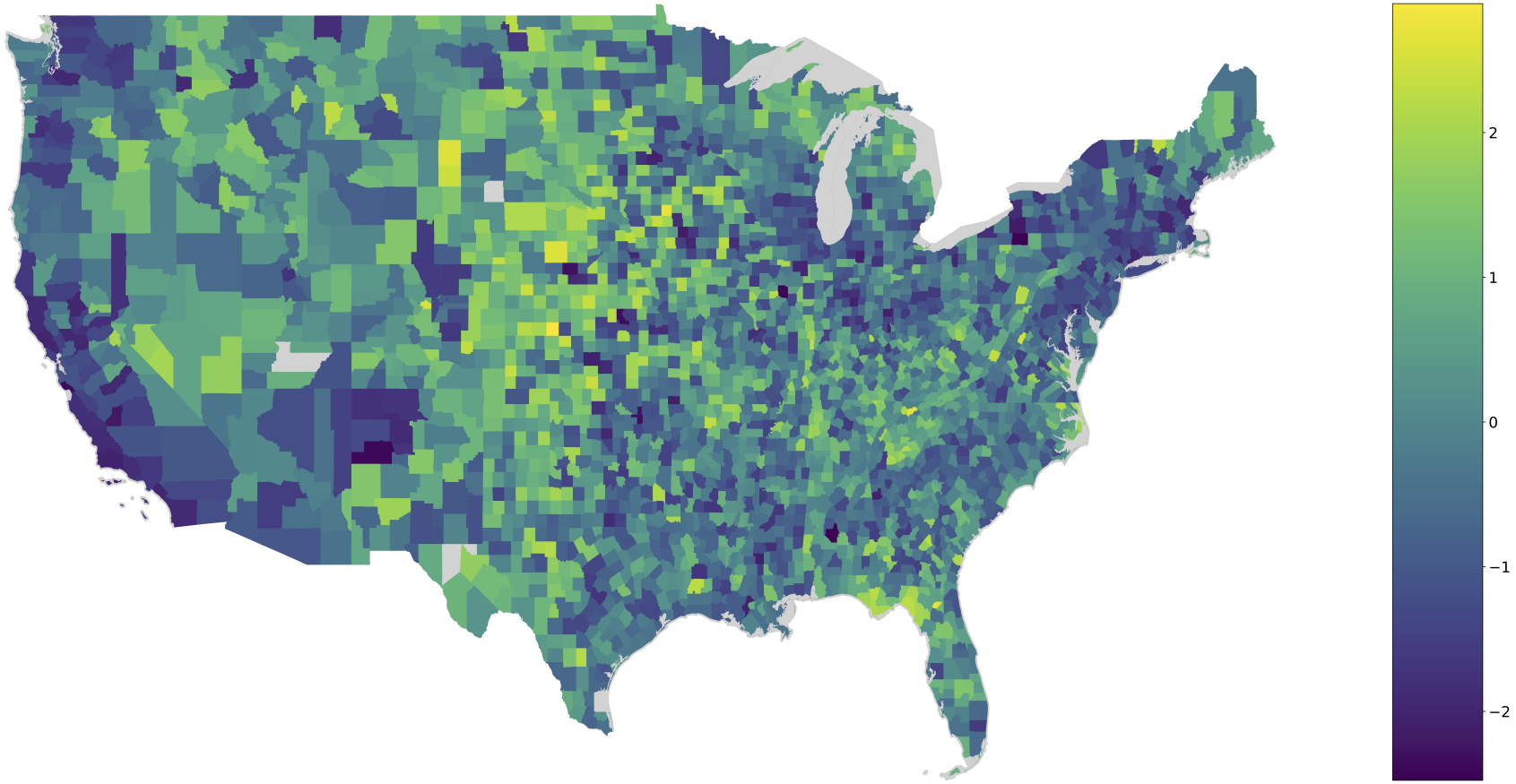
Finally, we apply this model on a national scale using publicly available micro-level IRS (**b**) to substitute proprietary data (**a**), and census data (**c**) for the years 2007 to 2021, providing a comprehensive measure of inattention across time and location.

Figure 4: Predicting inattention: Data and estimation steps



To isolate the relative importance of each variable, we perform a permutation test in which we randomly shuffle each feature and compute the average drop in R^2 over five trials. Note that this method underestimates the importance of features that interact non-linearly or work in tandem with other variables. We then display the top seven feature groups that *independently* contribute the most to the drop in R^2, with each group representing a set of related candidate features (e.g., share of investment as a percentage of total income, log-transformed values, local averages, etc.). Investor includes the number/share of depositors with brokerage account transactions and share of net investment income out of total income. Retiree (unemployed) includes the number/share of depositors with social security (unemployment benefits) credit transactions and share of social security income out of total income. Mortgage (student loans) repayment includes the number/share of depositors with mortgage payment (student loans) transactions. Child credits include the number/share of depositors with child tax credit transactions and share of child tax credits out of total income. Share/number of female/male is inferred based on keywords in Appendix B.1; we classify a depositor female when we observe more feminine product purchases than male product purchases from the associated accounts, and the rest male. In public data, gender is approximated by county-level census demographics.

Figure 5: Variables predicting inattention



This map displays the geographical distribution the predicted county-level inattention, α_{ct}, for the year 2018. Each county's predicted inattention is weighted by its total deposits, which are calculated as the sum of branch-level deposits reported by the FDIC in 2018. In counties without deposit data, we instead plot the simple average inattention for that area. Lighter (yellow) color with larger value of α_{ct} indicates a higher degree of inattention.

Figure 6: Mapping inattentive depositors

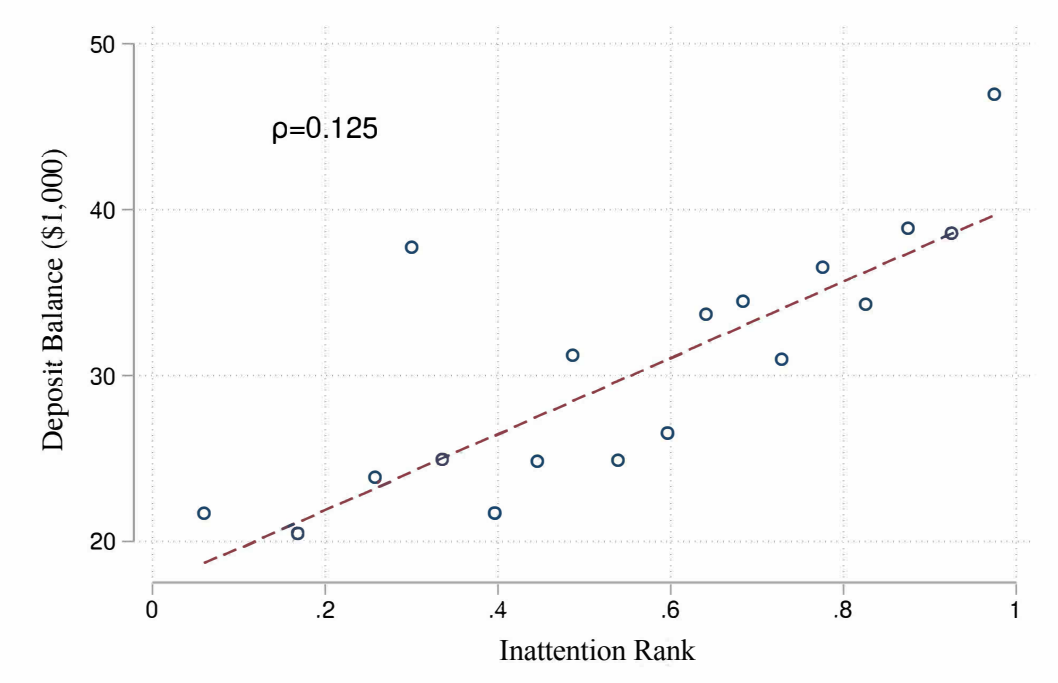
Bank-level inattention. Assuming that bank branches in the same locale face the same group of depositors as in Drechsler, Savov, and Schnabl (2017), using deposit-weighted averages of county-level inattention α_{ct}, we obtain bank-level inattention

$$\alpha_{bt} = \frac{\sum_c \text{Total Deposits}_{cbt} \hat{\alpha}_{ct}}{\sum_c \text{Total Deposits}_{cbt}}.$$

where $\text{Total Deposits}_{cbt}$ is the total deposits in county c for bank b in year t from the Summary of Deposits.

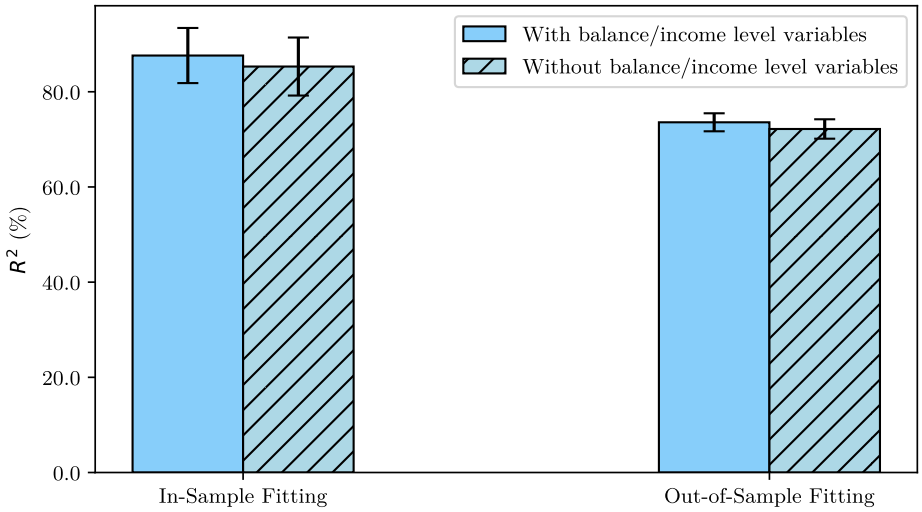
Appendix C.2 compares two separate regressions of county–bank–level annual deposit growth, one uses our predicted inattention, $\hat{\alpha}_{bt}$; the second aggregates the directly observed county measure, α_{ct}, up to the bank level using deposit weights as above. Both regressions yield similar sensitivities of deposit flows to policy rate changes, confirming that $\hat{\alpha}_{bt}$ is just as informative as aggregating the directly observed inattention in sample. Crucially, the predicted inattention allows us to move from the transaction-data coverage of roughly one-third of U.S. counties to nationwide coverage.

Relation with the size of deposit balances. Argyle et al. (2024) highlight that depositors with larger balances are more rate insensitive. Empirically, we find while inattentive depositors tend to have higher balances (Figure 7), this correlation does not imply that large balances *cause* inattention. In fact, we find that, at least statistically, high balances are likely a symptom rather than a cause of deposit stickiness. We run a head-to-head comparison between two predictive models. The baseline statistical model (that we used above to predict inattention), built on demographic data and income *shares* instead of *levels*, explains about 85% of the variation in the training data, with a standard error of 6.1% reflecting the uncertainty across trials. We then expand the model by adding balance and income level variables, such as sizes of balance, and levels of income by source, loans, and mortgages, to see if these factors would improve in-sample explanatory power and out-of-sample predictions. As shown in Figure 8, the expanded model increases the in-



This plot displays the correlation between depositor–level inattention and deposit balances. Inattention is measured by ranking ΔHL_i, which is the projected half-life difference between unexpected and expected income for each depositor i. The individual-level ranks are normalized between 0 and 1, where 1 indicates the highest level of inattention. Deposit balances are calculated by summing all bank account deposits for each depositor, using the values at the end of the sample period.

Figure 7: Inattention and deposit balance



This graph compares in-sample and out-of-sample explanatory power (R^2 in percentages) in two models: one model (left) includes additional *level* variables, such as balance sizes, income levels by sources of income, total income, loans, and mortgages; the other (in stripe pattern) uses only demographic transformations and income shares. For each model, we compute and plot the mean R^2 and its standard deviation (the error bar) across 100 random trials. The left set of bars displays the training (in-sample) performance, while the right set shows the test (out-of-sample) performance. The visualization illustrates that although there is a slight increase in both training and test R^2 when balance/income level variables are included, these additional variables do not significantly improve the model's fit.

Figure 8: Levels of income and balance only marginally improve inattention predictions

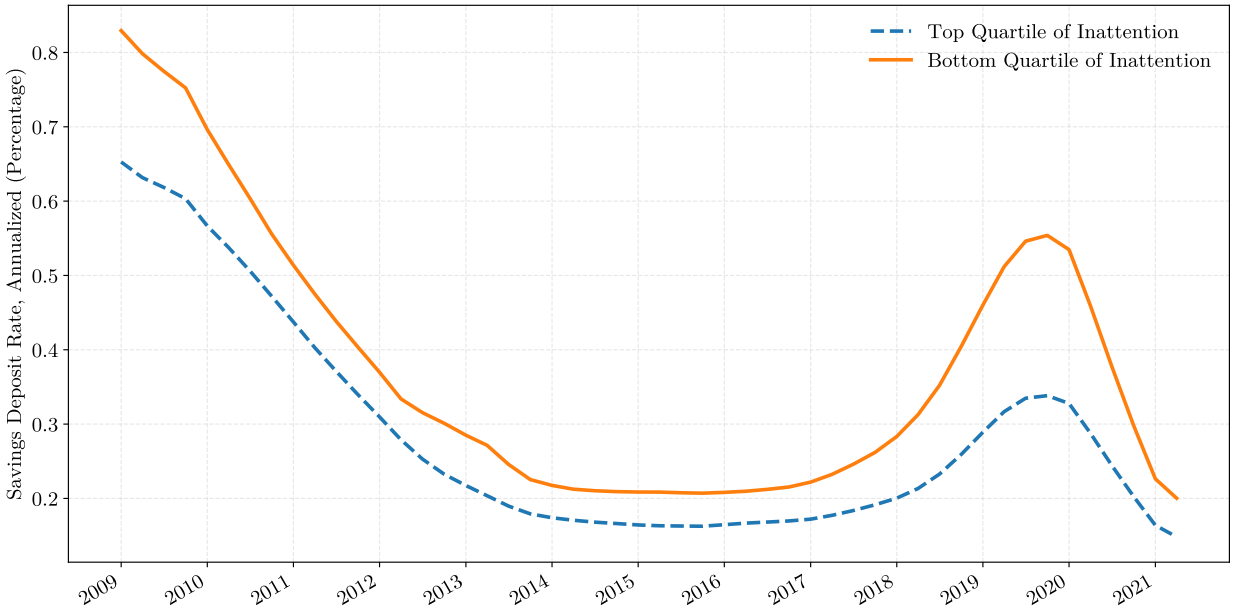
sample explanatory power to 88%, but the improvement in the out-of-sample performance is marginal: the test R^2 improved slightly from 72.18% (with the standard deviation of 2) to 73.59% (with the standard deviation of 1.9). The insignificant gains are well within the expected variability and suggest that while high balances are correlated with inattention, they do not add meaningful predictive power beyond what demographics and income shares already capture.

5.2. Time Series of Deposit Rates and Inattention

Leveraging our population-wide inattention measure, we sort banks into quartiles by their deposit-weighted inattention each year and then plot average savings deposit rates for the most attentive (bottom quartile) and least attentive (top quartile) banks in Figure 9. The gap

is visible in most years and across rate environments: banks serving less attentive depositors systematically post lower savings rates than banks serving more attentive depositors.

This figure aligns with our model's central mechanism: lower depositor attention weakens rate sensitivity, allowing banks to sustain wider spreads without triggering outflows. We next turn to testing the model's cross-sectional predictions, which will also inform the model parameters and quantify the importance of inattention.



We sort banks into quartiles each year according to their deposit-weighted inattention measure. The top quartile by inattention includes the 25% of banks with highest deposit-weighted inattention, and bottom quartile by inattention includes the 25% of banks with lowest deposit-weighted inattention. For each quartile we compute the average savings deposit rate, imputed as interest expense on savings deposits divided by the size of savings deposits, using U.S. Call Reports between 2007 and 2021 where the inattention measure is available. The figure plots top quartile (inattentive banks, blue dashed line) against bottom quartile (attentive banks, orange solid line). Both lines are 4-quarter moving averages.

Figure 9: Inattention and deposit rates

5.3. Cross-Sectional Evidence on Flow Beta, Deposit Rate, and Pass-Through

We now test the model's qualitative predictions in the cross-section of banks. Proposition 1 implies that banks serving a more inattentive depositor base have (i) a wider deposit spread

and (ii) a higher spread beta. Additionally, we show that inattentive depositor base have a smaller flow beta for non-interest-bearing deposits.

Non-interest-bearing deposits' flow beta. We estimate

$$\Delta \log m_{bt} = \sum_{k=-4}^{0} \beta_k \Delta \rho_{t-k} + \epsilon_{bt},$$

where $\Delta \log m_{bt}$ is the growth of non-interest-bearing deposits for bank b in quarter t and $\Delta \rho_t$ is the quarterly change in the policy rate. As checking deposits earn zero deposit rate, $\Delta \rho_t$ is also the change in the bank's deposit spread. Hence the deposit flow beta, defined as $\sum_{k=-4}^{0} \beta_k$ following Drechsler, Savov, and Schnabl (2017), reflects the sensitivity of deposit outflows to a 1 pp deposit spread increase over the past five quarters, mapping to the flow sensitivity in our model.

Figure 10(a) reveals a clear inverse relationship: banks with more inattentive depositors display lower deposit flow betas. For a one percent policy rate change, banks with one-standard-deviation higher inattention experience 0.46% less deposit outflows in non-interest-bearing deposits.

Deposit spread beta. Figure 10(b) plots the savings deposit spread beta, estimated from

$$\rho_t - r_{bt} = \sum_{k=-4}^{0} \beta_k \rho_{t-k} + \epsilon_{bt},$$

where r_{bt} is the rate offered by bank b on its savings deposits in quarter t. Banks with more inattentive depositors have a markedly higher pass-through: banks with one-standard-deviation higher depositor inattention pass through a one-percentage-point rate change about 3 basis points less.

Deposit spread. Deposit spread is on average higher for banks with more inattentive depositors. In Figure 10(c), we plot the bank-level deposit spread in savings deposits against the inattention in depositor base at 2019Q3, during which period the prevailing policy rate

is close to the target 2%; we report in appendix the average deposit spread plotted against average bank-level inattention during sample period in Figure A-3. Banks with one-standard-deviation more inattentive depositors post 10 basis points higher spread.

Our model predicts a policy-rate–dependent break point at $\tau = u(\tau)$. Consistent with this, Figure A-3(c) plateaus at high τ. We report a linear fit for simplicity, since in 2019Q4 most banks are interior.

(a) Flow Beta

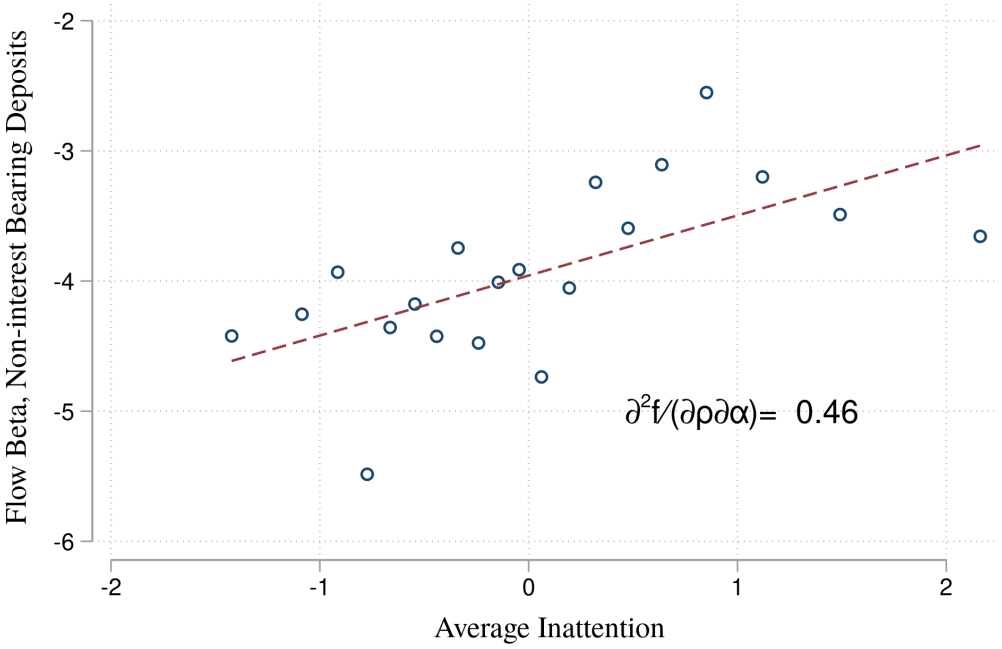
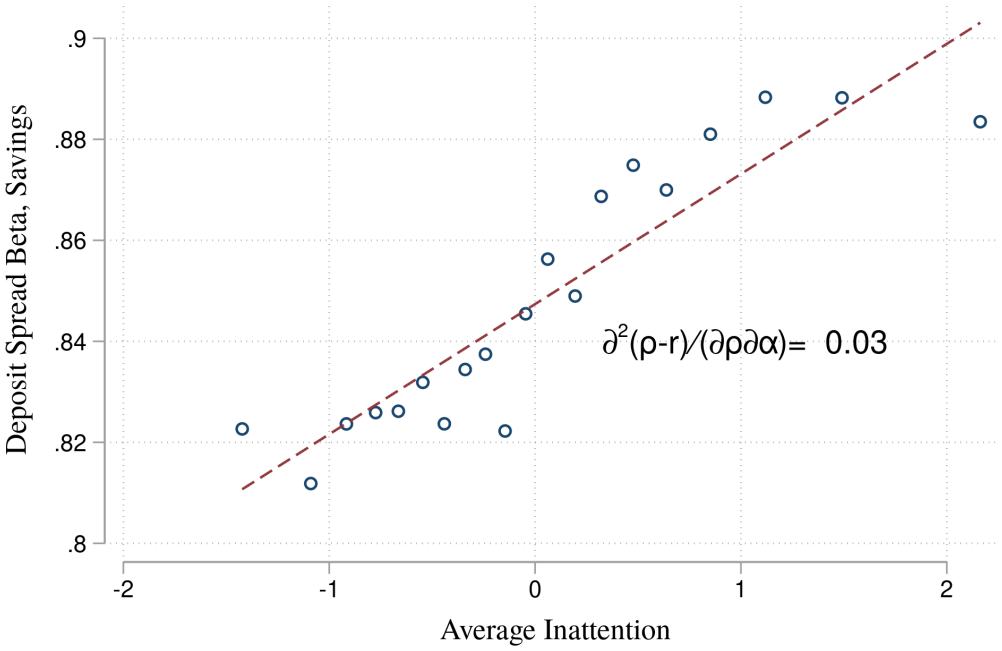


Figure 10: Flow beta, deposit spread, deposit spread beta and inattention

Panel (a) and (b) panel sorts banks by the average (year-normalized) inattention of their depositor base during the sample period. Flow beta takes the sum of coefficients from a five-quarter lagged regression of *non-interest-bearing* deposit growth on policy rate changes; it measures the % change in deposits triggered by a 1 pp spread increase. Deposit spread beta is the sum of five-quarter lagged coefficients from regressing the savings deposit spread on past policy rates; higher values indicate greater pass through to spread. Panel (c) uses the snapshot from 2019Q3 to demonstrate the relation between the level of spread and bank-level inattention at 2019Q3, at which point in time the policy rate is at 2.2%. The sample consists of all banks from Call Reports between 2008 and 2021, with at least 40 quarters of observations.

(b) Deposit Spread Beta



(c) Deposit Spread

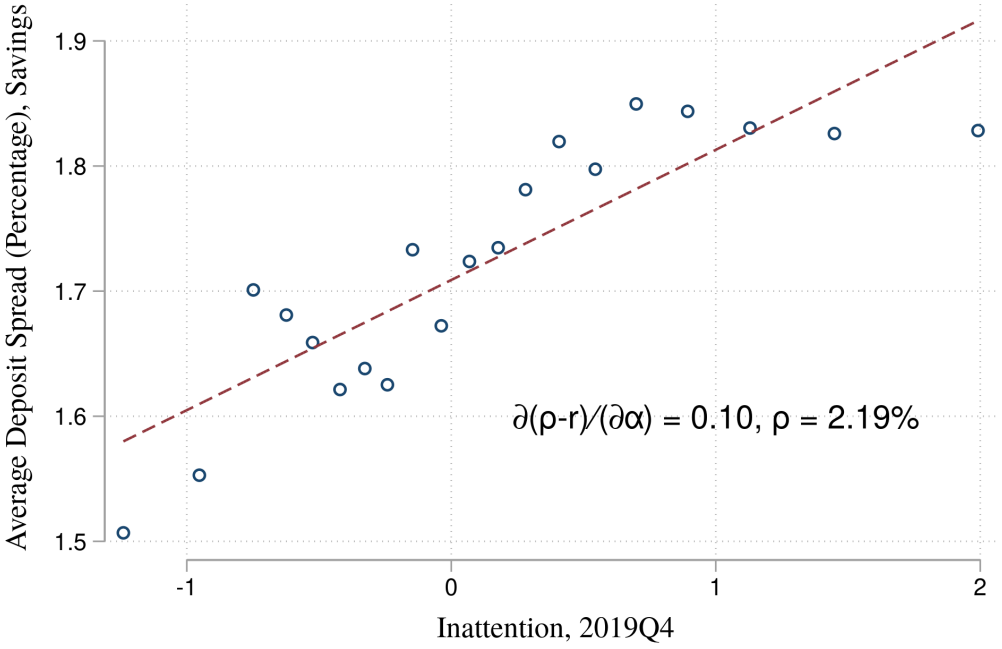


Figure 10: Flow beta, deposit spread, deposit spread beta and inattention (Cont.)

5.4. Deposit Flow Sensitivity: the Leave-One-Out Spread Instrument

Proposition 2 predicts that deposit outflows are less sensitive to the spread when depositors are more inattentive. Testing this prediction is challenging because depositor inattention affects both deposit flows and the spread x_{bt}. Specifically, Section 4 suggests that we can approximate the rate setting function as:

$$x_{bt} = \beta_0 + \beta_1 \alpha_{bt} + \beta_2 \alpha_{bt} \rho_t + \beta_3 \rho_t + \delta_b + \upsilon_{bt}, \tag{11}$$

where deposit spread of bank b at quarter t is $x_{bt} = \rho_t - r_{bt}$, and r_{bt} is the savings deposit rate, calculated as the ratio of deposit expenses to savings deposits from Call Reports. The bank-level deposit-weighted inattention $\alpha_{bt} = \sum_c w_{cbt} \alpha_{cbt}$, and bank b's deposit weight of deposits at county c in quarter t is w_{cbt}, which sum up to 1 across counties for a given bank ($\sum_c w_{cbt} = 1$).

Note that bank b *chooses* x_{bt} as a function of the bank's depositor inattention α_{bt} and the policy rate ρ_t (Eq. (11)). A naive regression of flows on spreads would therefore confound demand with the bank's own pricing response to attention. Our solution is a leave-one-out (LOO) instrument, which we construct in three steps. First, we estimate the bank-level rate-setting function in (11); second, we form a LOO deposit-weighted inattention measure that removes county j's inattention, $\alpha_{-j,bt}$; third, we "predict" the bank–county spread for county j by plugging the LOO deposit-weighted inattention measure into the estimated rate-setting function to construct the LOO spread instrument x^{LOO}_{jbt}. Intuitively, this instrument works based on a simple fact: within a multi-county bank, centralized pricing transmits the inattention mix of *other* counties into the posted rate, especially for peripheral markets where local branches do not set rates.[16] Because county j is excluded from $\alpha_{-j,bt}$, local demand shocks in j cannot mechanically drive x^{LOO}_{jbt}; and it remains relevant whenever the bank prices largely at the deposit-weighted inattention level.

[16] Banks may set a single uniform rate (Begenau and Stafford 2023) or delegate pricing to a few rate-setting branches (Drechsler, Savov, and Schnabl 2017). Our research design is orthogonal to this discussion, as we do not analyze major branches and focus on the minor branches which follow the lead rate.

We implement this design and report results below. First, Column 1 of Table 2 reports the bank-level rate-setting regression from estimating (11): deposit spreads increase with the policy rate, with a bank's deposit-weighted inattention, and with their interaction.

Taking the fitted coefficients from (11), we construct the LOO rate instrument for the deposit spread at the bank–county level:

$$x_{jbt}^{LOO} = \hat{\beta}_0 + \hat{\beta}_1 \alpha_{-j,bt} + \hat{\beta}_2 \alpha_{-j,bt} \rho_t + \hat{\beta}_3 \rho_t + \hat{\delta}_b,$$

where $\alpha_{-j,bt} = \frac{\sum_{c \neq j} w_{cbt} \alpha_{ct}}{1 - w_{jbt}}$ is the inattention the bank b faces weighted by deposit sizes in counties other than j.

Taking stock, this rate instrument is valid under two conditions: first, for a periphery county j with a small deposit share w_{jbt} so that the omission of county j hardly changes α_{bt}, the deposit-weighted average of depositor inattention faced by bank b at quarter t; in other words, bank b offering the same rate for the same deposit product does not set rate based on inattention of depositors in county j with small deposit size (assuming branches in the periphery county does not set rates). Empirically, we restrict the sample of bank-county pairs to counties with less than 50% of total bank deposits at a given time, and banks with more than 10 counties. In addition, inattention of any counties other than j cannot be correlated with errors $x_{jt} - \hat{x}_{jt}$, which is realistic as banks are present at large number of counties, and we also add time-region fixed effects in the fully saturated specification.

We then estimate banks' deposit flow sensitivity using a two-stage least-square specification, proxying rates and their interactions with inattention and local market power as highlighted in Drechsler, Savov, and Schnabl (2017) using the LOO instrument x_{jbt}^{LOO}. with additional bank, county, and state-year fixed effects that accounts for idiosyncratic and trending deposit growth:

First stages:

$$\Delta x_{jbt} = \eta_1 \alpha_{bt} \Delta x_{jbt}^{LOO} + \eta_2 \Delta x_{jbt}^{LOO} + \eta_3 \alpha_{bt} + \eta_4 \text{HHI}_{jt} + \eta_5 \text{HHI}_{jt} \Delta x_{jbt}^{LOO} + \delta_j + \delta_b + \delta_{s(j)t} + \epsilon_{jbt},$$

$$\alpha_{bt} \Delta x_{jbt} = \theta_1 \alpha_{bt} \Delta x_{jbt}^{LOO} + \theta_2 \Delta x_{jbt}^{LOO} + \theta_3 \alpha_{bt} + \theta_4 \text{HHI}_{jt} + \theta_5 \text{HHI}_{jt} \Delta x_{jbt}^{LOO} + \delta_j + \delta_b + \delta_{s(j)t} + \epsilon_{jbt},$$

$$\text{HHI}_{jt} \Delta x_{jbt} = \iota_1 \alpha_{bt} \Delta x_{jbt}^{LOO} + \iota_2 \Delta x_{jbt}^{LOO} + \iota_3 \alpha_{bt} + \iota_4 \text{HHI}_{jt} + \iota_5 \text{HHI}_{jt} \Delta x_{jbt}^{LOO} + \delta_j + \delta_b + \delta_{s(j)t} + \epsilon_{jbt},$$

Second stage:

$$\Delta \log m_{jbt} = \zeta_1 \widehat{\Delta x_{jbt}} + \zeta_2 \widehat{\alpha_{bt} \Delta x_{jbt}} + \zeta_3 \alpha_{bt} + \zeta_4 \widehat{\text{HHI}_{jt} \Delta x_{jbt}} + \zeta_5 \text{HHI}_{jt} + \delta_j + \delta_b + \delta_{s(j)t} + \varepsilon_{jbt}.$$

We report the estimated results in column 2–4 in Table 2. The leave-one-out instrument is a generated regressor, so we report bootstrapped standard errors throughout the estimates. The leave-one-out rate instruments along with bank-level inattention, county-level HHI, and bank-county fixed effects explain 96% of variations in bank rate and its interaction with inattention; in the second stage, we show that deposit outflows are larger in counties with higher deposit spread. Column 5 indicates that a 1% rise in the annualized deposit spread leads to smaller deposit outflows in counties with inattentive depositors: raising inattention by one standard deviation cuts the outflow response by about 0.54%. Columns 6-7 show that outflows' rate sensitivity is robustly lower with higher inattention, with bank-year controls that absorb bank-level time trends in deposit growth, and additional county-level fixed effects that account for idiosyncratic deposit growth. For later valuation of inattentive depositor's franchise value, we use the fully saturated estimate from column 6, that one standard deviation higher inattention leads to 0.56% less outflows with 1% higher spread.

5.5. "Asymmetric" Sluggishness in Rate Adjustments

Our model predicts that when the policy rate is sufficiently low and depositor inattention is high, less banks reset rate when policy rate changes as they are stuck at the corner solution of setting deposit rate at its minimum of zero rather than the positive interior solution implied

		First Stages			Second Stage		
	Spread (x_{bt})	ΔSpread (Δx_{bt})	Inatt.·ΔSpread ($\alpha_{jbt} \cdot \Delta x_{jbt}$)	HHI · ΔSpread ($\text{HHI}_{jt} \cdot \Delta x_{jbt}$)	ΔLog(Deposits) ($\Delta \log m_{jbt}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ρ_t	0.761***						
	(0.002)						
$\alpha_{bt} \cdot \rho_t$	0.003*						
	(0.002)						
α_{bt}	0.058***						
	(0.004)						
Δx_{jbt}^{LOO}		-0.788**	1.869	1.022**			
		(0.608)	(0.243)	(0.312)			
$\alpha_{jbt} \cdot \Delta x_{jbt}^{LOO}$		0.001	1.023***	-0.001			
		(0.002)	(0.008)	(0.001)			
$\text{HHI}_{jt} \cdot \Delta x_{jbt}^{LOO}$		0.008*	0.003	1.046***			
		(0.002)	(0.001)	(0.009)			
$\widehat{\alpha_{jbt} \cdot \Delta x_{jbt}}$					0.543***	0.477***	0.560***
					(0.116)	(0.080)	(0.088)
$\widehat{\text{HHI}_{jt} \cdot \Delta x_{jbt}}$					0.438	0.642*	0.515**
					(0.228)	(0.248)	(0.198)
$\widehat{\Delta x_{jbt}}$					0.106	0.000	0.000
					(30.910)	(0.000)	(0.000)
HHI_{jt}		0.005	-0.012***	0.024***	0.687**	0.715***	0.692***
		(0.002)	(0.002)	(0.003)	(0.360)	(0.354)	(0.348)
α_{jbt}		0.004	0.051***	-0.012***	1.192***	1.096***	1.036***
		(0.001)	(0.004)	(0.002)	(0.221)	(0.219)	(0.199)
Observations	95,296	146,753	146,753	146,753	146,753	146,753	146,753
Adjusted R^2	0.90	0.98	0.96	0.97			
F-stat			281.10				
Bank f.e.	Y	Y	Y	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y	Y
State-Year f.e.	Y	Y	Y	Y	Y	Y	N
Bank-Year f.e.	N	N	N	N	N	Y	N

Column 1 reports OLS estimates from the bank-level rate-setting equation $x_{bt} = \beta_0 + \beta_1 \alpha_{bt} + \beta_2 \alpha_{bt} \rho_t + \beta_3 \rho_t + \delta_b + \upsilon_{bt}$, where the spread $x_{bt} = \rho_t - r_{bt}$ is measured at the end of June, r_{bt} is the bank's savings-deposit rate, and ρ_t is the year-end policy rate. Inattention is deposit-weighted, $\alpha_{bt} = \sum_c w_{cbt} \alpha_{cbt}$ with $\sum_c w_{cbt} = 1$. Using the fitted coefficients, we construct a leave-one-out (LOO) spread for county j: $x_{jbt}^{\text{LOO}} = \hat{\beta}_0 + \hat{\beta}_1 \alpha_{-j,bt} + \hat{\beta}_2 \alpha_{-j,bt} \rho_t + \hat{\beta}_3 \rho_t + \hat{\delta}_b$, $\alpha_{-j,bt} = \frac{\sum_{c \neq j} w_{cbt} \alpha_{cbt}}{1 - w_{jbt}}$. Columns 2-7 present two-stage least-squares (2SLS) results for county-level deposit growth, with the first-stage regressions shown in columns (2)–(4). Deposit growth is calculated from the FDIC Summary of Deposits (end-June each year). Standard errors in columns 2-7 are based on 500 bootstrap replications (sampling clusters of banks).

Table 2: Deposit flow (spread) sensitivity in the cross-section

by first-order conditions. Incorporating adjustment costs, we further predict that inattentive banks reset rates faster following policy rate changes.

We take these predictions to data by tracking whether banks reprice their money market deposit accounts (MMDAs) around FOMC announcements. Weekly rate adjustment data are obtained from RateWatch, which reports the MMDA rates that banks post each week by account size. Following Drechsler, Savov, and Schnabl (2017), we focus on $25,000 accounts, also the most populated category in our sample. We emphasize the frequency of adjustments for two reasons. First, any level error in RateWatch quotes does not distort the timing or sign of changes, so bank-specific biases drop out. Second, earlier work on rate adjustment stickiness (e.g., Hannan and Berger 1991, Driscoll and Judson 2013) also relies on frequency measures.

For the most recent tightening cycle, defined by the first hike announcement of December 2015 and extending through 2019, only a small fraction of banks raised MMDA rates. In contrast, following the first rate cut of September 2007 in the 2007–2010 easing cycle, rate reductions were implemented promptly. We plot the "first cut" and "first hike" in solid black in Figure 11. These patterns reproduce the well-known "asymmetric rate-setting" evidence highlighted by Driscoll and Judson (2013). Consistent with our rate-level interpretation, however, we find that for hikes occurring at similarly high prevailing policy rates, e.g. January 2006, the fraction of banks that update and the speed of those updates are roughly *symmetric* to the cut in September 2007.

Introducing an adjustment cost into the model implies a sluggish short-run adjustment from policy to deposit rates: banks optimally delay, yet the gains from resetting are larger and resets occur faster when depositors are more inattentive. Figure 12 illustrates this cross-sectional heterogeneity. Sorting banks into quartiles by depositor inattention, those in the highest-inattention quartile lower MMDA rates most rapidly after the cut, followed in order by the second and third quartiles; banks with the most attentive depositors adjust last. The

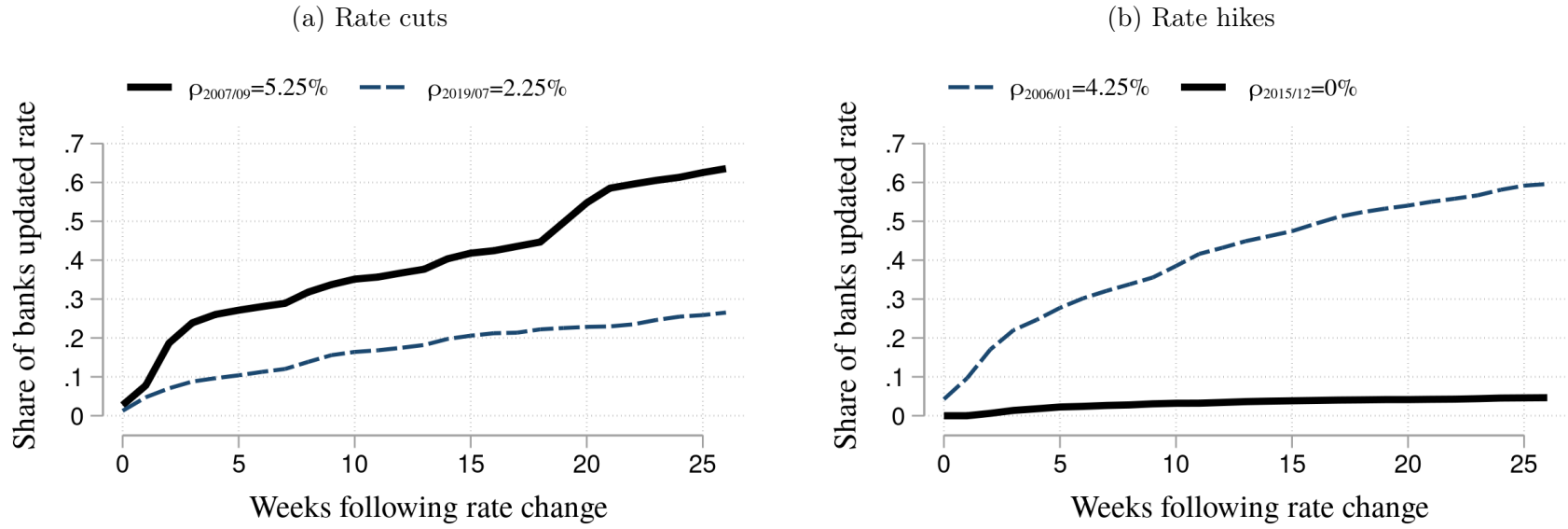
impulse response visualizations center on two high-rate events (January 2006 and September 2007) in which even the most inattentive banks eventually reprice at prevailing policy rate levels of roughly 5%, and as a result, the differences in the impulse responses are likely not driven by banks stuck at zero rate and never adjust in a low rate environment.

Table 3 further formalizes this cross-sectional test using weeks-to-adjustment regressions. We include FOMC announcements that has a hike or cut news and exclude announcements preceded by another move of the same sign within the previous six months. We then regress the number of weeks until the first same direction MMDA reset on depositor inattention, including event fixed effects that absorb trends across announcement periods, the level of the policy rate, and the size of the rate change. For both hikes and cuts, deposits from more inattentive depositors are associated with *faster* rate resets at the weekly frequency. Note that we truncate the dependent variable at 26 weeks (6 months post FOMC announcements) to compute the week-to-adjustment: if a bank has not updated within that horizon, it is coded as 26. This truncation introduces an *upward* bias, banks with highly inattentive customers should in principle remain at the zero-rate corner solution even longer so the bias works against our finding that higher inattention accelerates adjustments.

	(1) Hike	(2) Cut	(3) Diff.
α	-0.229*	-0.807***	0.578***
	(0.128)	(0.095)	(0.155)
Event f.e.	Y	Y	
Mean(WK)	11.226	9.995	
SD(WK)	4.386	7.138	
N	2,419	5,963	

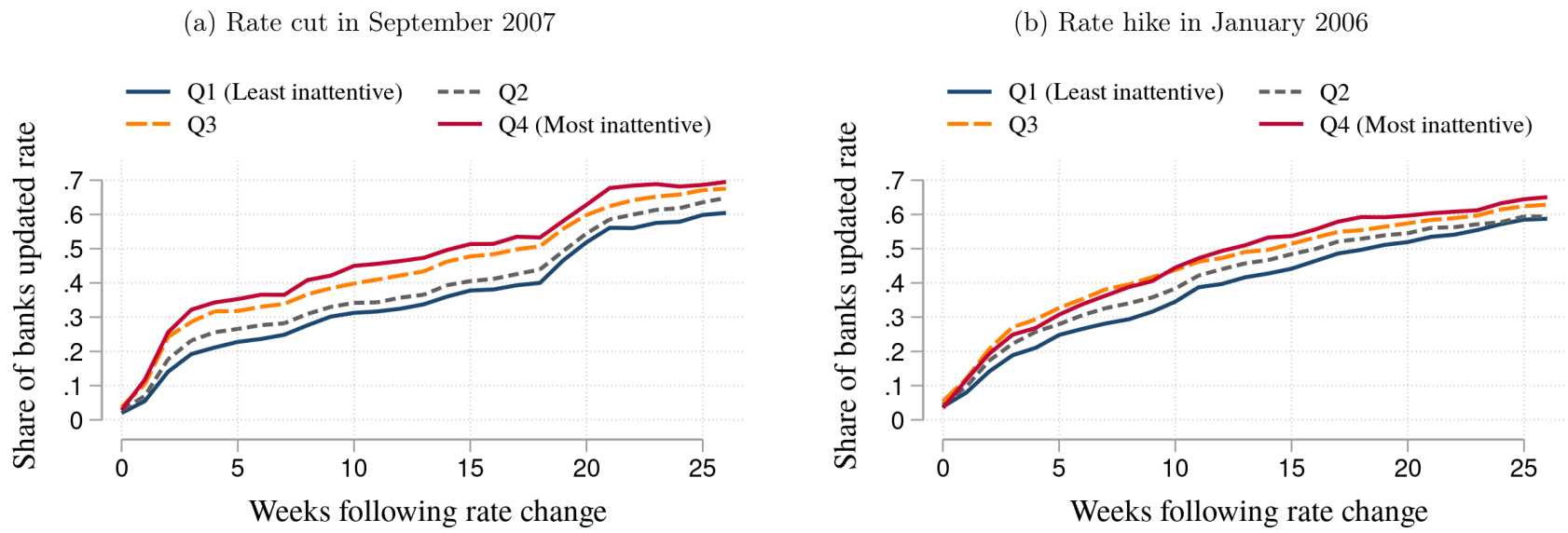
The dependent variable is the number of weeks between an FOMC announcement and the first same direction adjustment in a bank's reported $25,000 MMDA rate. Column (1) covers announcements that raised the target federal funds rate ("Hike"), column (2) those that lowered it ("Cut"), and column (3) reports the coefficient difference. α is bank-level depositor inattention. Both regressions include announcement fixed effects which also controls for the level and size of the policy rate change. Mean(WK) and SD(WK) are the unconditional mean and standard deviation of weeks-to-adjustment within each subsample. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Standard errors are clustered at bank level.

Table 3: Weeks to first rate adjustments and inattention



The figure plots the cumulative share of U.S. commercial banks that change the reported rate in the same direction as policy rate changes on $25,000 money market deposit accounts (MMDAs) in the weeks surrounding FOMC announcements. Week 0 is the week of the FOMC announcement (vertical dashed line). Left panel: the first rate cut of the 2007–10 easing cycle (18 Sep 2007). Right panel: the first rate hike of the 2015–19 tightening cycle (16 Dec 2015). MMDA quotes come from RateWatch.

Figure 11: "Asymmetric" deposit rate adjustments



The figure plots the cumulative share of U.S. commercial banks that change the reported rate in the same direction as policy rate changes on $25,000 money market deposit accounts (MMDAs) in the weeks surrounding FOMC announcements, for four quartiles of banks sorted by depositor inattention (α; Q1 = most attentive, Q4 = least attentive). The two panels focus on two FOMC announcements: the September 2007 cut (left) and the January 2006 hike (right). Week 0 is the FOMC announcement week. MMDA rate data is from RateWatch. Quartile assignments are fixed within an event, based on the mean of α at the corresponding announcement week.

Figure 12: Inattention and the speed of deposit rate adjustments

6. The Deposit Franchise Value and Its Comparative Statics

We calibrate the model parameters to inform the level and, more importantly, the comparative statics of the deposit franchise value (DFV). Although the dependence of DFV on the policy rate and inattention is of considerable interest for banking stability and monetary policy, it is difficult to estimate empirically due to the limited time-series variation in the policy rate. The theory-guided calibration therefore delivers counterfactuals and comparative statics that would otherwise be difficult to obtain.

6.1. Calibration

Identifying assumption. In our model, the decay rate of deposit balance is $\tau^{-1}P(\rho - r)$, in which τ varies across depositors but $P(\cdot)$ is the same. As $\tau^{-1}P$ is the sufficient statistic, τ and P are not separately identified. In the data, we measure the half-life of income rather than the half-life of balance. We identify the variation in τ in the cross-section under the assumption that τ is proportional to the ratio of the half-life of unexpected income to the half-life of expected income, as follows.

Recall that HL^{exp} is the half-life of expected income and HL^{unexp} the half-life of unexpected income. We assume each balance check triggers the same withdrawal probability $\tilde{P}$ of the income, which may or may not coincide with the withdrawal probability P of the overall deposit balance. By definition of a half-life, we have

$$\exp(-\tilde{P} \cdot HL^{\text{exp}}) = \frac{1}{2}, \quad \exp(-\tau^{-1}\tilde{P} \cdot \ HL^{\text{unexp}}) = \frac{1}{2}$$

Canceling out $\tilde{P}$ from these two equations yields $\tau = \frac{HL^{\text{unexp}}}{HL^{\text{exp}}}$. For each depositor i, the ratio $\tau_i \equiv HL_i^{\text{unexp}}/HL_i^{\text{exp}}$ is an empirical proxy for the depositor's inattention parameter. We further note that the cross-sectional variation in τ_i is mostly driven by variation in HL_i^{unexp}.

Cross-sectional moments. Our model makes unique predictions on the cross-sectional variation of deposit rates, pass-through, and flow sensitivity across banks. The signs of these

empirical relations confirm our theoretical predictions, and their magnitudes informs the model parameters (a, b, γ) which govern the withdrawal probability $P(x) = a + (x/b)^\gamma$.

Proposition 6 (Calibration)**.** *Given (τ, ρ) which satisfy $\tau < u(\rho)$, the comparative statics of the deposit spread, deposit spread pass-through, and the flow sensitivity w.r.t. inattention τ are governed by the model parameters (a, b, γ) as, with $x \equiv \rho - r$,*

$$d_1 = \frac{\partial x}{\partial \tau} = \frac{b\rho}{\gamma} \frac{(a + \rho\tau)^{1/\gamma - 1}}{(\gamma - 1)^{1/\gamma}}, \tag{12}$$

$$d_2 = \frac{\partial^2 x}{\partial \rho \partial \tau} = \frac{b(a\gamma + \rho\tau)}{\gamma^2} \frac{(a + \rho\tau)^{1/\gamma - 2}}{(\gamma - 1)^{1/\gamma}}, \tag{13}$$

$$d_3 = (\Delta t)^{-1} \frac{\partial^2 (\log M_{t+\Delta t} - \log M_t)}{\partial x \partial \tau} = \frac{(a\gamma + \rho\tau)}{b\tau^2} \frac{(a + \rho\tau)^{-1/\gamma}}{(\gamma - 1)^{1 - 1/\gamma}}, \tag{14}$$

Conversely, the model parameters (a, b, γ) are pinned down by these three moments as

$$\gamma = 1 + \frac{\rho^2 d_2}{\tau^2 d_1^2 d_3}, \quad a = \rho\tau \frac{\gamma\rho - d_1/d_2}{\gamma(d_1/d_2 - \rho)}, \quad b = \frac{d_1 \gamma}{\rho} \frac{(\gamma - 1)^{1/\gamma}}{(a + \rho\tau)^{1/\gamma - 1}} \tag{15}$$

This proposition suggests that we can determine model parameters (a, b, γ) using empirical moments (d_1, d_2, d_3). Note that, the theory-predicted moments (d_1, d_2, d_3) vary with (τ, ρ). As a back-of-the-envelope calibration, we treat our empirical moments $(\hat{d}_1, \hat{d}_2, \hat{d}_3)$ are reflecting the theory-predicted moments at the average $(\bar{\tau}, \bar{\rho})$ during our sample period. Hence, we have

$$\gamma \approx 1 + \frac{\bar{\rho}^2 \hat{d}_2}{\bar{\tau}^2 \hat{d}_1^2 \hat{d}_3}, \quad a \approx \bar{\rho}\bar{\tau} \frac{\gamma\bar{\rho} - \hat{d}_1/\hat{d}_2}{\gamma(\hat{d}_1/\hat{d}_2 - \bar{\rho})}, \quad b \approx \frac{\hat{d}_1 \gamma}{\bar{\rho}} \frac{(\gamma - 1)^{1/\gamma}}{(a + \bar{\rho}\bar{\tau})^{1/\gamma - 1}} \tag{16}$$

In Section 5 we have estimated these three regressions: the level of the deposit spread, the deposit spread beta, and the deposit flow sensitivity to spread on the standardized projected inattention $Z_\alpha \equiv \frac{\alpha - \bar{\alpha}}{\mathrm{SD}(\alpha)}$, where $\mathrm{SD}(\alpha)$ is the cross-sectional standard deviation of α averaged across years (Figure 10, Table 2). All resulting coefficients are therefore interpreted with one–standard-deviation change in α. Take the level regression as an example. Let β_Z

denote the semi-elasticity of the deposit spread r with respect to Z_α: $\frac{\partial r}{\partial Z_\alpha} = \beta_Z$. Because $Z_\alpha = (\alpha - \bar{\alpha})/\mathrm{SD}(\alpha)$, we have $\frac{\partial r}{\partial \alpha} = \frac{\beta_Z}{\mathrm{SD}(\alpha)}$. The projected inattention α is linked to the model parameter τ through $\tau = 1 + \frac{180\, e^\alpha}{\mathrm{HL}^{\exp}}$ and hence $\frac{d\alpha}{d\tau} = \frac{1}{\tau - 1}$. Applying the chain rule yields

$$\frac{\partial r}{\partial \tau} = \frac{\beta_Z}{\mathrm{SD}(\alpha)} \frac{1}{\tau - 1}.$$

Therefore, dividing each coefficient by $\mathrm{SD}(\alpha)(\tau - 1)$ gives us the corresponding empirical moments for d_1, d_2, d_3.

We summarize these key data moments and corresponding model parameters in Table 4. We set the model's inattention parameter in our calibration to the sample average across all depositors, $\bar{\tau} = \frac{1}{N}\sum_{i=1}^{N} \tau_i$. We choose the policy rate $\bar{\rho}$ to be the prevailing rate in 2019Q3 and estimate the sensitivity of deposit rate with respect to inattention at the same time.

Moment / Parameter	Symbol	Value
Mean inattention	$\bar{\tau}$	2.60
Deposit spread v. inattention†	$\frac{\partial x}{\partial \tau}\Big\vert_{\bar{\tau}, \rho = \rho_{2019Q3}}$	0.0025
Deposit beta v. inattention†	$\frac{\partial^2 x}{\partial \rho\, \partial \tau}\Big\vert_{\bar{\tau}}$	0.075
Deposit flow sensitivity v. inattention††	$\partial^2 \Delta \log M / \partial x\, \partial \tau \vert_{\bar{\tau}}$	1.4
Policy rate	ρ	0.022
Calibrated withdrawal probability $P(\rho - r) = a + ((\rho - r)/b)^\gamma$		
	a	0.0068
	b	0.048
	γ	1.61

† Estimated in Figure 10; note that changes in spread levels with respect to changes in inattention is evaluated in 2019Q3. †† Estimated in Table 2. All α-related coefficients in Figure 10 and Table 2 are obtained for one–standard–deviation changes in α are converted to per–unit changes in τ using $\sigma(\alpha) = 0.25$ together with the $\hat{\alpha} \to \tau$ mapping in the text. Rates and flows are annualized.

Table 4: Moments and parameters for calibration

6.2. Deposit Franchise Value

We compute the deposit franchise value separately for savings deposits with positive deposit rates and for non-interest-bearing deposits in the aggregate. We then further examine the deposit franchise value across banks.

6.2.1. Savings Deposits

When the bank pays a strictly positive rate, the present value of the deposit franchise is

$$V_0 = \frac{\rho - r}{\rho + \tau^{-1}P(\rho - r)} M_0 = \tau b \frac{(a + \rho\tau)^{1/\gamma - 1}}{\gamma(\gamma - 1)^{1/\gamma - 1}} M_0 = \frac{d_2 \rho \left(d_2 \rho^2 + d_1^2 d_3 \tau^2\right)}{d_1^3 d_3^2 \tau^3} M_0. \tag{17}$$

Plugging in our estimates d_1, d_2, d_3 and $\bar{\rho}, \bar{\tau}$, we get $V_0 = 0.18 M_0$, which means that the bank derives a discounted sum of profits of 18 cents per 1 dollar of deposit. By the end of 2022, U.S. banks held roughly $10 trillion in savings deposits; under the calibration, they derive about $1.8 trillion in present value profits from these deposits.

Appendix D.3 provides additional empirical benchmarks of DFV based on banks' observed willingness to pay (proxied by bonuses and promotional rate offers). Banks' observed WTP is of similar magnitude to, but typically below, our calibrated DFV, which supports our calibration since the cost of attracting deposits must not exceed the profit.

6.2.2. Non-Interest-Bearing Deposits

Section 4 highlights that banks optimally pay a zero rate when depositors are highly inattentive ($\tau \geq \frac{(\gamma-1)(\rho/b)^{\gamma} - a}{\rho}$). Even when this threshold is not met, typically at higher policy rate levels, banks are compelled to pay zero on non-interest-bearing accounts by regulation: Regulation Q barred interest on demand deposits until 2011, and large non-interest-bearing (NIB) deposits persist throughout 2008–2022, amounting to roughly one-third to one-half of savings deposits(Figure A-5). Empirically, we find the flow sensitivity of non-interest-bearing deposits to policy rate changes closely matches that of savings deposits: the flow beta estimated in Figure 10 for non-interest-bearing deposits is similar to the leave-one-out

estimate in Table 2 for savings deposits. Assuming the withdrawal probability $P(\rho - r)$ is the same across the deposit products, we analyze the DFV of NIB deposits.

Let $P(x) = a + (x/b)^{\gamma}$ be the withdrawal probability and let $\bar{\tau}$ denote mean depositor inattention. Matching the three empirical moments in Table 4 yields

$$P(x) = 0.0068 + \left(\frac{x}{0.048}\right)^{1.61}, \qquad h(x) = \bar{\tau}^{-1} P(x).$$

At the sample average spread of 50 bp ($x = 0.005$), the implied annual withdrawal hazard is $h(0.005) \simeq 1.27\%$.

For non-interest-bearing deposits, the deposit franchise value is

$$V_0 = \frac{\rho}{\tau^{-1}(a + (\rho/b)^{\gamma}) + \rho} M_0 \tag{18}$$

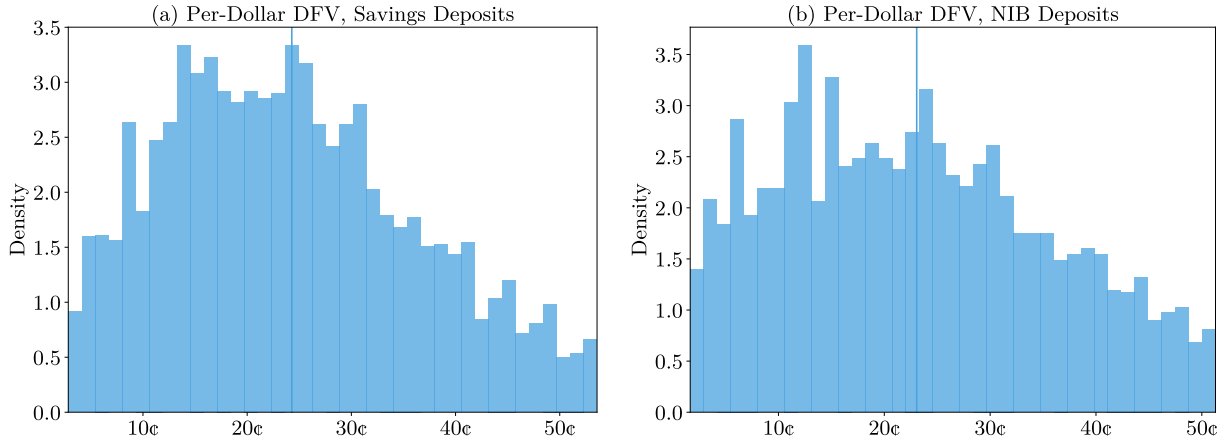
Evaluated at $\bar{\rho}$ and $\bar{\tau}$ as before, $V_0 = 0.16\, M_0$, i.e. the bank earns a profit of 16 cents per dollar of non-interest-bearing deposits. This is lower than for savings deposits because the zero-rate constraint is not optimal at the policy rate of 2.2% with inattention $\bar{\tau} = 2.6$; the higher withdrawal hazard outweighs the larger interest margin. By the end of 2022, U.S. banks held roughly $5 trillion in savings deposits; under the calibration, they derive about $0.8 trillion in present value profits from these deposits.

6.2.3. The Cross-Section of Deposit Franchise Value

We summarize the cross-section of deposit franchise value using bank-level deposit data for 2019Q4. We report per–dollar DFV, which is the object relevant for the pricing implications of inattention, and *total* DFV to document the scale and concentration of franchise value across banks. In the calibration, we hold (a, b, γ) fixed across banks, which allows us to highlight the role of inattention though it likely understates the actual cross-sectional heterogeneity.

Figures 13 show the cross–sectional distributions of DFV per dollar of deposits, $v^k_{0,i}$, across

banks indexed by i and deposit accounts indexed by k. Total DFV $V_{0,i}^k = M_{0,i}^k v_{0,i}^k$ reflects both the DFV per dollar, and the size of deposits. In 2019Q4, the six largest institutions account for roughly one half of aggregate DFV for both savings and non-interest-bearing deposits, reflecting deposit concentration. Table 5 list the top six banks by total DFV for savings and non-interest-bearing deposits, reporting *Bank Name*, *DFV*, and *DFV per dollar*. The banking industry's deposit-size distribution concentrates DFV at the very top of the bank size distribution.



Equations (17) and (18) imply per–dollar DFV for savings deposits is $v_{i,0}^* = \frac{b\tau_i}{\gamma}\left(\frac{\gamma-1}{\rho\,\tau_i+a}\right)^{\frac{\gamma-1}{\gamma}}$ and non–interest–bearing deposits is $v_{i,0}^0 = \frac{\rho\,\tau_i}{a+(\rho/b)^\gamma+\rho\,\tau_i}$, with parameters $\rho = 0.02$, $a = 0.0068$, $b = 0.048$, and $\gamma = 1.61$ calibrated in Section 6.1. Bank–level attention $\alpha_{i,2019}$ is constructed by aggregating county–level inattention projections with 2019 deposit weights from the FDIC Summary of Deposits: $\alpha_{i,2019} = \sum_c w_{ic,2019}\,\alpha_{c,2019}$, $\quad w_{ic,2019} \equiv \frac{\text{deposits}_{ic,2019}}{\sum_{c'}\text{deposits}_{ic',2019}}$, which is then used to compute the bank-level inattention index τ_i as detailed in Section 6.1.

Figure 13: The cross-section of deposit franchise value, 2019Q4

6.3. The Impact of Digital Banking

For savings deposits, the elasticity of DFV with respect to inattention is

$$\frac{\mathrm{d}\log V_0}{\mathrm{d}\log\tau} = \frac{a\gamma+\rho\tau}{\gamma(a+\rho\tau)} = \frac{d_2\rho}{d_1}. \tag{19}$$

(a) Savings Deposits			(b) Non-interest-bearing Deposits		
Bank Name	DFV (mn)	DFV (¢/$)	Bank Name	DFV (mn)	DFV (¢/$)
Wells Fargo	147.11	13.59	Wells Fargo	45.30	11.35
Bank of America	141.36	12.38	Bank of America	44.77	10.06
JP Morgan Chase	102.65	10.88	JP Morgan Chase	34.01	8.51
SunTrust and BB&T	54.25	19.27	SunTrust and BB&T	16.44	17.68
TD Bank	35.26	14.46	PNC Bank	10.04	13.73
Citi Bank	34.94	10.31	BNY Mellon	9.96	18.32

Equations (17) and (18) imply DFV for savings deposits is $v^*_{i,0} = \frac{b\tau_i}{\gamma}\left(\frac{\gamma-1}{\rho\,\tau_i+a}\right)^{\frac{\gamma-1}{\gamma}} D_i^s$ and non–interest–bearing deposits is $v^0_{i,0} = \frac{\rho\,\tau_i}{a+(\rho/b)^\gamma+\rho\,\tau_i} D_i$, with parameters $\rho = 0.02$, $a = 0.0068$, $b = 0.048$, and $\gamma = 1.61$ calibrated in Section 6.1. Size of bank-level savings deposits D_i^s and non-interest-bearing deposits D_i are from Call Reports. Bank–level attention $\alpha_{i,2019}$ is constructed by aggregating county–level inattention projections with 2019 deposit weights from the FDIC Summary of Deposits: $\alpha_{i,2019} = \sum_c w_{ic,2019}\,\alpha_{c,2019}$, $\quad w_{ic,2019} \equiv \frac{\text{deposits}_{ic,2019}}{\sum_{c'}\text{deposits}_{ic',2019}}$, which is then used to compute the bank-level inattention index τ_i as detailed in Section 6.1.

Table 5: Banks with largest deposit franchise value, 2019Q4

Under our calibration, $\frac{\partial \log V_0}{\partial \log \tau} = 0.66$, implies that a 1 percent decline in τ reduces the deposit franchise value V_0 by roughly 0.66%.

Similarly, for NIB deposits,based on our calibration, the elasticity of NIB deposits with respect to inattention is $\frac{\partial \log V_0}{\partial \log \tau} = 0.84$.

Taking stock, higher depositor inattention raises deposit franchise value. However, in our framework, the DFV and incomplete rate pass through are not from a lack of competitors in the number of banks. When depositors are inattentive, they also do not check anyone else's offer—so whichever bank already holds their money is a monopolist over that depositor for that stretch of time. Hence every bank sets its spread at the level that maximizes profit conditional on being compared only at those infrequent wake-up moments. When regulators charter a new bank or allows a money market fund (MMF) to tap into the Federal payment system, the newcomer can indeed offer an attractive headline rate, but it eventually inherits the same problem: it only loses newly acquired depositors when they look around again and decide to move. Anticipating this, the entrant would again settle on the very same

spread as the incumbents; otherwise it would leave money on the table anticipating depositor inattention. In short, adding more banks does not little to move the deposit franchise due to inattention. What does work is anything that keeps depositors alert, for example, digital banking (Koont, Santos, and Zingales 2024). FinTech companies that push rate alerts, open-banking APIs that make comparison of rates effortless, or disclosure rules that force banks to highlight better offers all reduce the average length of those inattentive periods. With less time to exploit each "captive" depositor, banks find it profitable to quote narrower spreads, and the franchise value of inattention shrinks accordingly. Suppose digital banks succeed in lowering depositor inattention by 10%. Mapping this to our measurement, since the half-life of expected income is about 5 days and that of unexpected income is about 13 days, it corresponds to a reduction of the latter by 1.3 days. Based on our calibration, a 10% increase in attention would lower the deposit franchise of savings deposits by 6.6% and of non-interest-bearing deposits by 8.4%.

6.4. Dollar Duration of Deposit Franchise Value

When banks optimally set a non-zero rate, the dollar duration of deposit franchise value is

$$Dur^* = -\frac{\mathrm{d}V_0}{\mathrm{d}\rho} = \frac{d_2\left(d_2\rho - d_1\right)\left(d_2\rho^2 + d_1^2 d_3\tau^2\right)^2}{d_1^6 d_3^3 \tau^5} M_0 \tag{20}$$

Plugging in the empirical moments, we have $\frac{\mathrm{d}V_0}{\mathrm{d}\rho} = -2.8M_0$, which suggests if the policy rate goes up by 1%, the bank loses 2.8 cents of deposit franchise.

For non-interest-bearing deposits, the dollar duration of deposit franchise value is

$$Dur^0 = -\frac{\partial V_0}{\partial \rho} = -M_0 \frac{a\tau + \tau(1-\gamma)(\rho/b)^\gamma}{\left[a + (\rho/b)^\gamma + \rho\tau\right]^2} \tag{21}$$

Plugging in the calibrated parameters using the empirical moments, we have $\frac{\partial V_0}{\partial \rho} = -3.6\, M_0$, meaning a 1% rise in ρ reduces franchise value by 3.6 cents per dollar; the duration of non-

interest-bearing deposits is higher than the duration of savings deposits. When the bank is forced to pay zero, it cannot "hedge" rate hikes by passing through them more generously with depositors; the entire policy rate shock widens the spread less than the acceleration of depositor attrition, the franchise's marked-to-market value falls faster, i.e. it has a longer (more negative) duration.

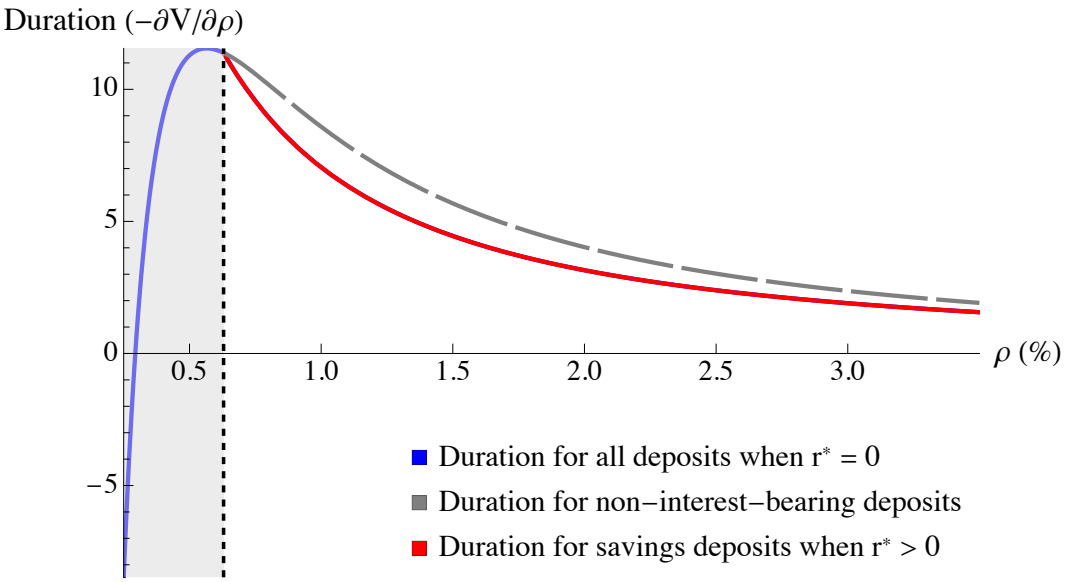


Figure 14: Durations of DFV

The figure plots the model-implied deposit franchise duration for non-interest-bearing (NIB) and savings deposits over policy rates ρ. Durations are computed from the baseline calibration summarized in Table 4. At very low rates ($\rho < 30$ bp) banks optimally post a zero deposit rate, franchise value rises as rates fall, generating *negative* duration for both deposit types. For intermediate rates (30 bp $\leq \rho \leq$ 63 bp) outside options become attractive and outflows start; at this point duration turns positive while posted deposit rates remain at zero. Once the policy rate exceeds 63 bp, banks optimally pay a positive deposit rate for savings deposits; the duration of savings deposits then drops below that of NIB deposits because banks can adjust the savings rate to trade off margin against attentive outflows, whereas NIB accounts must still pay zero.

When policy rate is sufficiently low and inattention is high ($\tau > \frac{(\gamma-1)\left(\rho/b\right)^{\gamma}-a}{\rho}$), banks *optimally* post a zero rate for all deposits. In this case, the duration of deposit franchise is *negative*: an increase in the policy rate raises the spread one-for-one but since inattentive depositors are insensitive to rate and do not withdraw much faster, the net present value rises. Deposits therefore hedge interest rate risk, as emphasized by Drechsler, Savov, and Schnabl

(2021). For example, under the calibration, at a policy rate of $\rho = 25$bp, $\frac{dV_0}{d\rho} = 8.4M_0$, that is, a 1bp rise in policy rate adds 8.4 cents per dollar of franchise value, i.e. a *negative* duration of 8.4. When the Fed sets low rates and banks optimally set zero rate for deposits for a prolonged period, deposits may have large, negative duration. However, as policy rate increases and banks start to post positive deposit rates, deposit franchise value for existing depositors turns into positive duration. Figure 14 plots the duration of non-interest-bearing and savings deposits across policy rate levels. When the policy rate is near zero there is no higher yield outside alternative, so even fully attentive depositors stay put. The franchise value therefore rises rapidly as the rate falls, giving these deposits negative duration. As the policy rate climbs ($30\text{bp} < \rho < 63\text{bp}$), outside options improve; deposit outflows begin while banks still post a zero deposit rate and duration becomes positive here. Once the policy rate is high enough ($\rho > 63\text{bp}$), banks optimally pay a positive rate. Note at this point the duration of savings deposits starts to diverge from non-interest-bearing deposits: duration risk is lower for savings deposits, as banks now start to optimize to balance the decay of attentive depositors and profit margin, which is no longer optimized when they are forced to set zero rate for non-interest-bearing deposits.

6.5. Demographics, Inattention, and the Deposit Franchise

In Section 5, we forecast transformed depositor inattention α_{ct} using gradient boosting, which flexibly captures non-linear interactions. To summarize which observable features are most predictive in a transparent way, we also fit a sparse linear model (LASSO) on 2010 county demographics with $\alpha_{c,2010}$ as the target. LASSO selects a concise set of covariates and yields signs indicating whether a one-standard-deviation increase in a predictor is associated with more or less attention.

We summarize the correlational patterns from the sparse linear model at a high level. Gender and race correlate with inattention: counties with larger shares of women, non-Latino Whites, and Asians tend to be more attentive (lower inattention). Age structure

also matters—more children (under 18) is associated with higher inattention. Household composition and tenure point in the same direction as attentiveness: places with more renters, unmarried-partner households, and single-mother households are, on average, more attentive. These associations are descriptive rather than causal; illustrative magnitudes and full estimates appear in Appendix Table A-4.

7. Conclusion

Our main finding is that depositor inattention is a key source of banks' market power in the deposit market. Drawing on transaction records for millions of depositors, we provide direct evidence that many depositors manage their bank accounts only sporadically, and that depositor inattention varies systematically with demographics and socioeconomic characteristics. We develop a dynamic model in which the bank enjoys temporal monopoly power over inattentive depositors and faces a simple trade-off: raising the spread boosts profits, but also increases spread-sensitive outflows. The model predicts and the data confirm that depositor inattention explains cross-bank differences in deposit spreads, monetary policy pass-through, and outflow sensitivity.

We use the empirical moments to calibrate the valuation of deposit franchise. We estimate that U.S. banks derive about 18 cents of franchise value per dollar of savings deposits, which aggregates to roughly $2.6 trillion as of the end of 2022, and that a 10% increase in depositor attention would erase 6.6% (8.4%) of deposit franchise value for savings (NIB) deposits at a 2% policy rate.

Our findings speak to several policy questions. First, rate hikes widen spreads especially for inattentive banks, muting monetary pass-through to deposit rates. Central banks thus face attention-dependent multipliers when assessing the effectiveness of monetary policy. Second, franchise value hinges on inattention. Hence, digital banking services that nudge households to monitor balances more frequently may erode a key cushion in bank funding.

This paper highlights systematic inattention to deposit holdings, opening several research

avenues. First, how does attention to liquidity fluctuate over the business cycle and with shifts in economic uncertainty, and what does that imply for banks' funding stability? Second, what happens when changes in the interest rate and attention strike simultaneously, as in regional banking crisis in 2023? Finally, the welfare implication of digital banking hinges on whether higher deposit rates fully compensate households for the cost of paying attention—an open issue for future research.

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Online Appendix for

Banking on Inattention

A. Proofs

Proof of Proposition 1. First, to establish the interior solution, we notice from (6) that

$$\left.\frac{\partial V_0}{\partial x}\right|_{x=0} = \frac{1}{\rho + \tau^{-1}a} M_0 > 0$$

which means that the optimal $x > 0$. Without constraint $x^* \leq \rho$, the optimal x satisfies

$$\frac{\partial V_0}{\partial x} = \frac{\rho + \tau^{-1}P(x) - \tau^{-1}xP'(x)}{(\tau^{-1}P(x) + \rho)^2} M_0 = 0$$

And the 2nd-order derivative evaluated at this optimal x is

$$\left.\frac{\partial^2 V_0}{\partial x^2}\right|_{x^*} = \frac{-\tau^{-1}xP''(x)}{(\tau^{-1}P(x) + \rho)^2} M_0 \tag{22}$$

which is negative since P is convex. Thus V_0 increases from $x = 0$ until the optimal x and then decreases afterward. This optimal x satisfies

$$xP'(x) - P(x) = \rho\tau$$

or equivalently,

$$r = \rho - Q^{-1}(\rho\tau)$$

in which $Q^{-1}(\cdot)$ is defined implicitly by

$$Q(x) \equiv xP'(x) - P(x) = (\gamma - 1)\left(\frac{x}{b}\right)^{\gamma} - a \tag{23}$$

and hence $Q^{-1}(y) = b\left(\frac{y+a}{\gamma-1}\right)^{1/\gamma}$ and

$$r = \rho - b\left(\frac{\rho\tau + a}{\gamma - 1}\right)^{1/\gamma} \tag{24}$$

Thus, the bank sets an interior $r \in (0, \rho)$ when $\rho > Q^{-1}(\rho\tau)$, which simplifies to

$$\tau < \frac{(\gamma-1)(\rho/b)^{\gamma} - a}{\rho} \tag{25}$$

The RHS is decreasing in ρ and denoted as $u(\rho)$ in the proposition for simplicity.

Regarding the comparative statics:

(a) For $\frac{\partial r}{\partial \tau}$, from (8), we have $\frac{\partial r}{\partial \tau} = -(Q^{-1})'(\rho)$. Further, from (23), we have $Q' = xP''$ and hence $(Q^{-1})' = \frac{1}{Q'} = \frac{1}{(x-c)P''}$. Hence, $\frac{\partial r}{\partial \tau} = -\frac{1}{xP''}\rho$ which is negative since $P'' > 0$.

(b) For $\frac{\partial r}{\partial \rho}$, from (8, 23), we have $\frac{\partial r}{\partial \rho} = 1 - (Q^{-1})'\tau = 1 - \frac{1}{xP''}\tau$ which is less than one if $P'' > 0$. To verify that it is positive, we plug in $x = b\left(\frac{\rho\tau+a}{\gamma-1}\right)^{1/\gamma}$ and get

$$\frac{\partial r}{\partial \rho} = 1 - \frac{b\tau}{\gamma(\gamma-1)^{1/\gamma}(\rho\tau + a)^{1-1/\gamma}}$$

which is decreasing in τ. Then we use (25) to bound it as

$$\frac{\partial r}{\partial \rho} > 1 - \frac{b/\rho}{\gamma(\gamma-1)^{1/\gamma}} \frac{(\gamma-1)(\rho/b)^{\gamma} - a}{(\gamma-1)^{1-1/\gamma}(\rho/b)^{\gamma-1}} = 1 - \frac{1}{\gamma} + \frac{a}{\gamma(\gamma-1)(\rho/b)^{\gamma}}$$

which is positive since $a > 0, \gamma > 1$.

(c) For $\frac{\partial^2 r}{\partial \rho \partial \tau}$, from (8), we have

$$\frac{\partial^2 r}{\partial \rho \partial \tau} = -(Q^{-1})' - (Q^{-1})''(\rho\tau) = -(Q^{-1})' - (Q^{-1})''Q$$

The inverse function Q^{-1} satisfies

$$(Q^{-1})' = \frac{1}{Q'}$$
$$(Q^{-1})'' = -\frac{Q''}{(Q')^3}$$

Hence we get

$$\frac{\partial^2 r}{\partial \rho \partial \tau} = -\frac{1}{Q'} + \frac{QQ''}{(Q')^3} = \frac{QQ'' - (Q')^2}{(Q')^3}$$

which is negative if $QQ'' - (Q')^2 < 0$ and $Q' > 0$ with the latter equivalent to $P'' > 0$. For the former, we plug in $Q = (\gamma - 1)(x/b)^\gamma - a$ and get

$$QQ'' - (Q')^2 = -\frac{\gamma(\gamma-1)^2}{b^2}\left(\frac{x}{b}\right)^{2\gamma-2} - a\frac{\gamma(\gamma-1)^2}{b^2}\left(\frac{x}{b}\right)^{\gamma-2} < 0$$

□

Proof of Proposition 2. For $\tau \geq u(\rho)$, we have $r = 0$ and thus the deposit flow sensitivity w.r.t. deposit spread is

$$(\Delta t)^{-1}\frac{\partial(\log M_{t+\Delta t} - \log M_t)}{\partial(\rho - r)} = -\tau^{-1}P'(\rho) = -\tau^{-1}\frac{\gamma}{b}\left(\frac{\rho}{b}\right)^{\gamma-1}$$

For $\tau < u(\rho)$, we plug in the optimal r from Proposition 1 and get

$$(\Delta t)^{-1}\frac{\partial(\log M_{t+\Delta t} - \log M_t)}{\partial(\rho - r)} = -\tau^{-1}P'(\rho - r) = -\tau^{-1}\frac{\gamma}{b}\left(\frac{\rho\tau + a}{\gamma - 1}\right)^{1-1/\gamma}$$

The absolute value declines in τ. □

Proof of Proposition 3. For $\rho < u^{-1}(\tau)$, we have

$$V_0 = \frac{\rho}{\rho + \tau^{-1}P(\rho)} M_0$$

and hence

$$\begin{aligned}
\frac{\mathrm{d}V_0}{\mathrm{d}\tau} &= \frac{\rho\tau^{-2}P(\rho)}{[\rho + \tau^{-1}P(\rho)]^2} M_0 > 0 \\
\frac{\mathrm{d}V_0}{\mathrm{d}\rho} &= \frac{\tau^{-1}\left[P(\rho) - \rho P'(\rho)\right]}{\left[\rho + \tau^{-1}P(\rho)\right]^2} M_0 = \frac{\tau^{-1}\left[a - (\gamma-1)(\rho/b)^{\gamma}\right]}{\left[\rho + \tau^{-1}P(\rho)\right]^2} M_0
\end{aligned}$$

the latter of which is positive when $\rho < b\left(\frac{a}{\gamma-1}\right)^{1/\gamma} = u^{-1}(0)$.

For $\rho > u^{-1}(\tau)$, we have

$$V_0 = \frac{x}{\rho + \tau^{-1}P(x)} M_0$$

which $x = x^*(\rho, \tau)$ optimally chosen to maximize V_0. Hence, the DFV satisfies

$$\frac{\mathrm{d}V_0^*}{\mathrm{d}\tau} = \frac{\partial V_0}{\partial x}\frac{\partial x^*}{\partial \tau} + \frac{\partial V_0}{\partial \tau} = \frac{\partial V_0}{\partial \tau} = \frac{x\tau^{-2}P(x)}{[\rho + \tau^{-1}P(x)]^2} M_0 > 0$$

where the first term drops out since $\frac{\partial V_0}{\partial x} = 0$ at x^*, which is essentially the envelope theorem. The same holds for $\frac{\mathrm{d}V_0^*}{\mathrm{d}\rho}$

$$\frac{\mathrm{d}V_0^*}{\mathrm{d}\rho} = -\frac{x}{[\rho + \tau^{-1}P(x)]^2} M_0 < 0$$

□

Proof of Proposition 4. Before the change in policy rate, banks set their optimal rate ρ established in Proposition 1. After the policy rate change, when a bank receives a Poisson strike to adjust their deposit rate, they will set the optimal deposit rate under ρ'. Further,

according to Proposition 1, with $u(\rho) \equiv \frac{(\gamma-1)(\rho/b)^{\gamma}-a}{\rho}$, only banks with $\tau < u(\rho)$ will set a positive rate under ρ and only those with $\tau < u(\rho')$ will set a positive rate under ρ'. Thus, with $\bar{\rho} \equiv \max\{\rho, \rho'\}$, banks with $\tau > u(\bar{\rho})$ will set a zero rate before and after the shock, and those with $\tau < u(\bar{\rho})$ will adjust their rate after shock. As banks can only adjust when they receive a Poisson strike with intensity θ, the share of banks that have adjusted their deposit rates hence follows

$$S_t = (1 - \mathrm{e}^{-\theta t})F(u(\bar{\rho}))$$

Since $u(\rho) \equiv \frac{(\gamma-1)(\rho/b)^{\gamma}-a}{\rho} = (\gamma-1)b^{-\gamma}\rho^{\gamma-1} - a\rho^{-1}$ increases in ρ, so is $F(u(\rho))$. Thus S_t increases in $\bar{\rho}$. □

Proof of Proposition 5. When a bank receives a Poisson strike to adjust their deposit rate, they will set the optimal deposit rate under $\rho' \equiv \rho + \Delta\rho$ established in Proposition 1. We denote the post-shock optimal rate as r' and the pre-shock optimal rate as r.

Suppose the bank receives the Poisson strike at time T, its discounted profit from time T onward is

$$V_T = \frac{\rho' - r'}{\rho' + \tau^{-1}P(\rho' - r')}M_T \tag{26}$$

Hence its time-0 discounted sum of profits is

$$\begin{aligned} V_0(T) =& \int_0^T \mathrm{e}^{-\rho' t}(\rho' - r)M_0\mathrm{e}^{-[\tau^{-1}P(\rho'-r)]t}\mathrm{d}t + \mathrm{e}^{-\rho' T}V_T \\ =& \frac{(\rho' - r)(1 - \mathrm{e}^{-[\rho' + \tau^{-1}P(\rho'-r)]T})}{\rho' + \tau^{-1}P(\rho' - r)}M_0 + \frac{(\rho' - r')\mathrm{e}^{-[\rho' + \tau^{-1}P(\rho'-r)]T}}{\rho' + \tau^{-1}P(\rho' - r')}M_0 \end{aligned} \tag{27}$$

where we plug in $M_T = \mathrm{e}^{-\tau^{-1}P(\rho'-r)T}M_0$.

Thus, the expected profits under an adjustment probability θ is

$$\begin{aligned}\mathrm{E}[V_0] =& \int_0^\infty V_0(T)\theta \mathrm{e}^{-\theta T}\mathrm{d}T \\ =& \frac{\rho' - r}{\rho' + \tau^{-1}P(\rho' - r)} M_0 + \underbrace{\left(\frac{\rho' - r'}{\rho' + \tau^{-1}P(\rho' - r')} - \frac{\rho' - r}{\rho' + \tau^{-1}P(\rho' - r)}\right)}_{\text{instantaneous profit gain}} \underbrace{\frac{\theta}{\theta + \rho' + \tau^{-1}P(\rho' - r')}}_{\text{Calvo-adjusted discount}} M_0\end{aligned} \tag{28}$$

The bank maximizes the profits net of cost $\mathrm{E}[V_0] - C(\theta)$. The optimal adjustment probability θ satisfies

$$\frac{\partial \mathrm{E}[V_0]}{\partial \theta} = C'(\theta)$$

In terms of the comparative statics w.r.t. τ, we have

$$\frac{\partial^2 \mathrm{E}[V_0]}{\partial \theta^2}\frac{\partial \theta}{\partial \tau} + \frac{\partial^2 \mathrm{E}[V_0]}{\partial \theta \partial \tau} = C''(\theta)\frac{\partial \theta}{\partial \tau} \tag{29}$$

which implies

$$\frac{\partial \theta}{\partial \tau} = \frac{\frac{\partial^2 \mathrm{E}[V_0]}{\partial \theta \partial \tau}}{C''(\theta) - \frac{\partial^2 \mathrm{E}[V_0]}{\partial \theta^2}} \tag{30}$$

Since $C''(\theta) > 0$, $\frac{\partial \theta}{\partial \tau}$ has the same sign as $\frac{\partial^2 \mathrm{E}[V_0]}{\partial \theta \partial \tau}$, if $\frac{\partial^2 \mathrm{E}[V_0]}{\partial \theta^2} < 0$ which we show next.

From (28), the marginal gain from a higher θ is

$$\frac{\partial \mathrm{E}[V_0]}{\partial \theta} = \underbrace{\left(\frac{\rho' - r'}{\rho' + \tau^{-1}P(\rho' - r')} - \frac{\rho' - r}{\rho' + \tau^{-1}P(\rho' - r)}\right)}_{\text{instantaneous profit gain}} \underbrace{\frac{\rho' + \tau^{-1}P(\rho' - r')}{[\theta + \rho' + \tau^{-1}P(\rho' - r')]^2}}_{\text{change in Calvo-adjusted discount}} M_0 \tag{31}$$

The instantaneous profit gain is second-order in $\Delta r \equiv r' - r$, since r' is the profits-maximizing

choice and r is suboptimal. We have

$$\begin{aligned}
\text{instantaneous profit gain} &= \frac{\rho' - r'}{\rho' + \tau^{-1}P(\rho' - r')} - \frac{\rho' - r}{\rho' + \tau^{-1}P(\rho' - r)} \\
&= \frac{1}{2} \underbrace{\frac{\tau^{-1}xP''(x)}{[\tau^{-1}P(x) + \rho]^2}}_{\text{concavity of profits function}} (\Delta r)^2 + O((\Delta r)^3) \\
&= \frac{1}{2} \underbrace{\frac{\tau^{-1}xP''(x)}{[\tau^{-1}P(\bar{x}) + \rho]^2}}_{\text{concavity of profits function}} \left(\underbrace{\frac{\mathrm{d}r}{\mathrm{d}\rho}}_{\text{pass-through}} \right)^2 (\Delta\rho)^2 + O((\Delta\rho)^3) \qquad (32) \\
&= \frac{(\gamma - 1)^{\gamma^{-1}+2}\tau}{2b\gamma^3(a + \rho\tau)^{\gamma^{-1}+1}} \left(\gamma - \frac{b\tau(a + \rho\tau)^{\gamma^{-1}-1}}{(\gamma - 1)^{\gamma^{-1}}} \right)^2 (\Delta\rho)^2 + O((\Delta\rho)^3) \qquad (33)
\end{aligned}$$

Further,

$$\text{change in Calvo-adjusted discount} = \frac{(\gamma - 1)\gamma\tau(a + \rho\tau)}{(a\gamma + (\gamma - 1)\theta\tau + \gamma\rho\tau)^2} \qquad (34)$$

As both terms are linear and increasing in τ when τ is small, $\frac{\partial\theta}{\partial\tau}$ is quadratic and increasing in τ when τ is small. Hence, the optimal θ increases in τ. □

B. Data Appendix

B.1. Extracting Characteristics from Transactions

Below we list the keywords we used to construct depositor-level characteristics. All processing takes place on the provider's secure servers with only aggregated results downloaded. **No individual depositor was identified throughout the analysis**.

- Student loans: Loan–servicing payments that qualify for the student-loan interest credit to match the observation in IRS tax filing data. We flag transactions whose description field contains any of the following servicer-related keywords:
  `usdoe`, `student`, `education`, `studnt`, `stdnt`, `navient`, `edfinancial`, `fedloan`, `great lakes`, `mohela`, `granite state`, `pheaa`, which are relevant student

loan servicers according to Federal Student Aid (https://studentaid.gov/announcements-events/loan-servicer-updates).

- Child: Payments or credits related to child support, child benefits, or children's goods and services.
  - **Credits** — transaction description contains any of:

    `childctc`, `child suppt`, `child sup`, `kychildpay`, `tx children`, `fam sup`, `child tax`, `child benefit`, `childsupp`, `peachcare for kids`
  - **Debits** — transaction description contains any of:

    `pottery barn kids`, `children's hosp`, `abercrombie kid`, `childrens hc`, `childrens med`, `children hosp`, `childrens ho2`, `child car`, `child dev`, `kid care`, `highlights for children`, `boston children`, `childrens medica`, `children's healt`, `seattle children`, `childrens healt`, `kids r kids`, `bright horizons`, `kindercare`, `the learning experience`, `learning care`, `seeking sitters`
- Single: Recurring charges to dating platforms are assumed to indicate single status. Transactions are flagged if transaction description contains any of the following, *excluding* unrelated phrases such as `tinder box`, `match box`, `bumble bee`, etc.
  - `eharmony.com`, `badoo`, `gotinder`, `bumble`, `successfulmatch`, `match.com`, `tinder`, `okcupid`, `matchcom`, `catholic match`, `grindr`, `elitesingles`, `plenty of fish`
- Women: Including transactions that target women's personal care and apparel. Transaction description field contains any of the following patterns are flagged:
  - both `victoria` and `secret`
  - `sephora`
  - both `nail` and `spa`
  - `birchbox`, `stitch fix`, `cora.life`, `mylola`
  - `aritzia`, `forever21`, `ann taylor` (or `anntaylor`)
  - the generic term `beauty`

- Men: Including transactions that signal men's grooming or leisure activities. Transactions are flagged if the corresponding description contains:
  - `barber`
  - `great clips`
  - `dollar shave club`
  - both `golf` and `club`
- Investment: manually collected in Blickle, Li, Lu, and Ma (2024).
- Social security / retired: identified via social security agency keywords.
- Unemployed: identified via unemployment benefit payout with state-by-state keywords.
- Income: pre-classified by data provider.
- Mortgage: pre-classified. 'Mortgage' payments in transaction category by data provider.
- Small business: has an active business account.

B.2. Variable Construction Using IRS Tax Filings

Table A-1 tabulates the construction of county-income group level socioeconomic demographic variables from IRS.

C. Additional Empirical Results

C.1. Individual Depositor's Sensitivity to Deposit Spreads: a Ratio Estimator

Because we do not know, nor do we wish to assume, exactly how a depositor's inattention translates into the spread that her bank offers. To sidestep this, we estimate rate sensitivity *within* narrow inattention bins of depositors. Specifically, we sort all depositors by their inattention into 25 bins to obtain within-bin rate sensitivity estimates. Let m_{it} be the balance across a depositor i's checking and savings accounts in month t, x_{it} the deposit spread, ρ_t the federal funds rate, and inattention of depositor i. The *deposit spread sensitivity*

$$s_i = \frac{\partial \log m_{it}}{\partial x_{it}}$$

Table A-1: IRS-Derived Measures Matching Variables Inferred from Transactional Data

Name	**Aggregate Metric**	**IRS Code (Years Available)**
Returns	Sum	n1(2007–2021)
Exemptions	Sum	n2(2007–2021)
Single	Simple Averages/Shares	MARS1(2013–2021)
Joint	Simple Averages/Shares	MARS2(2007–2021)
Salaries	Simple/Weighted Averages/Shares	00200(2007–2021)
Investment Income	Simple/Weighted Averages/Shares	00300(2007–2021)+00600(2007–2021) +00650(2008–2021) +23900(2007–2008) +01000(2009–2021) +01400(2007–2021) +01700(2007–2017,2019–2021) +01400(2007–2017,2019–2021) +01750(2018)
Business Income	Simple/Weighted Averages/Shares	00900(2007–2021)
Unemployment	Simple/Weighted Averages/Shares	02300(2007–2021)
Social Security	Simple/Weighted Averages/Shares	02500(2007–2021)
Tax Payment	Simple/Weighted Averages/Shares	18425(2007–2021) 11900(2007–2008,"gt0")+11901(2009–2021)
Tax Refund	Simple/Weighted Averages/Shares	00700(2007–2021) 11900(2007–2008,"lt0")+11902(2009–2021)
Mortgage	Simple/Weighted Averages/Shares	18500+19300(2007–2021);number of returns avail. 2007&2009-2021
Child	Simple/Weighted Averages/Shares	07220(2007–2017)+07225(2018–2021);number of returns avail. 2007&2009-2021
Student Loan	Simple/Weighted Averages/Shares	03210(2013–2021)

IRS 5-digits are reported with total amount (A) and numbers of filings (N) in each year between 2007 – 2021 except for 2008 where numbers of filings are not available. Each variable is computed as both a simple and a weighted average, and as shares out of total income (for amount) or number of returns. Composite measures (e.g., Regular Income, Retirement Income) are defined by the sum of IRS fields (or max – when computing numbers of returns).

measures the percentage change in balances induced by a one-percentage-point change in deposit spread.

However, depositors can self select into different banks, and unfortunately our transaction-level data does not reveal which banks a given depositor uses. The observed comovement between $\log m_{it}$ and x_{it} mixes true rate sensitivity with endogenous sorting across banks (rates) and depositors.

Instead, under the assumption that given a depositor, the policy rate change influences deposit balances only through the deposit spread, we instead estimate two reduced-form slopes with respect to policy rate ρ_t:

$$\gamma_i = \frac{\partial \log m_{it}}{\partial \rho_t}, \qquad \beta_i = \frac{\partial x_{it}}{\partial \rho_t},$$

This ratio recovers the causal response of deposit flows to rates without taking a stand on banks' pricing rules or depositor sorting:

$$\underbrace{\partial ln(m_{it})/\partial \rho_t}_{reduced-form\ \gamma_i} = \underbrace{\partial ln(m_{it})/\partial x_{it}}_{rate\ spread\ sensitivity\ s_i} \cdot \underbrace{\partial x_{it}/\partial \rho_t}_{pass-through\ \beta_i}$$

Empirically, we exploit heterogeneity in inattention to form Q bins of depositors sorted by their inattention levels $q = 1, \ldots, Q$. Within each bin, we estimate:

$$\Delta \log m_{it} = \gamma_q \Delta \rho_t + \delta_i + \varepsilon_{it}, \qquad i \in q, \tag{35}$$

$$x_{it} = \beta_q \rho_t + \delta_i + \upsilon_{it}, \qquad i \in q. \tag{36}$$

Specification (35) estimates the sensitivity of balances on policy rate for depositors in a given inattention group, controlling for depositor fixed effect δ_i, and specification (36) estimates the pass-through of policy rate to deposit spread faced by depositors in a given inattention

group.[17] We then estimate the rate sensitivity of depositors as

$$\hat{s}_q = \hat{\gamma}_q / \hat{\beta}_q. \tag{37}$$

Appendix C.1 summarizes the rate sensitivity of depositors inferred from (37) for 25 bins of depositors sorted by inattention. The most attentive depositor group on average has a rate sensitivity of -6.8%; that is, for every one-percentage-point increase in deposit spread, the attentive depositors move 6.8% account balances out in the following month. On the far right side, for the most inattentive depositors, the rate sensitivity is about -1.5%; that is, for every one-percentage-point increase in deposit spread, the inattentive depositors move 1.5% account balances out in the following month.

C.2. Predicted Bank-Level Inattention and Deposit Flows Across Counties

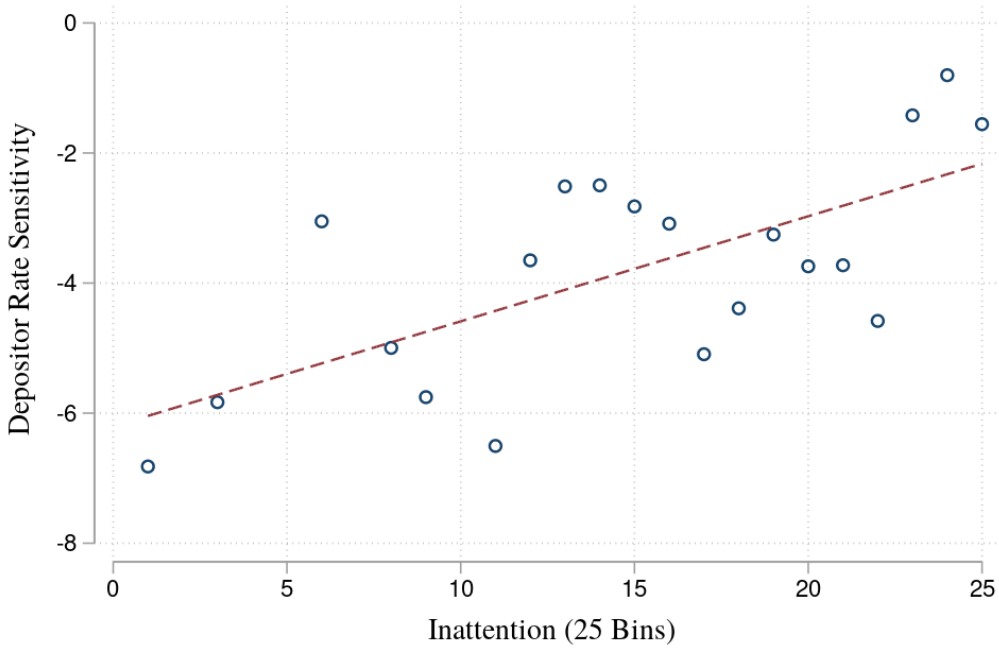
We regress county-bank level annual deposit growth,

$$\Delta m_{bct} = \beta_0 \Delta\rho_t + \beta_1 \alpha_{ct} \cdot \Delta\rho_t + \beta_2 \alpha_{ct} + \beta_3 \text{HHI}_{ct} \cdot \Delta\rho_t + \beta_4 \text{HHI}_{ct} + \delta_b + \delta_t + \varepsilon_{bct},$$

on the annual change in the federal funds rate, $\Delta\rho_t$, its interaction with county-level inattention (α_{ct} or the projected $\hat{\alpha}_{ct}$), county-level deposit-market Herfindahl index HHI_{ct} and its interaction with $\Delta\rho t$ capture local deposit market competitiveness (Drechsler, Savov, and Schnabl 2017). Additionally, δ_b and δ_t collect bank and year fixed effects, which account for unobserved idiosyncratic and common trends in deposit growth.

Appendix C.2 shows that for a given bank, higher inattention consistently make deposit flows less sensitive to policy rate changes. Columns 1-3 use the inattention measure observed directly for the subset of counties covered by the transaction-level sample (2014-2022); columns 4-6 replicate the exercise with the projected measure available for all counties back to 2007. In every specification, the interaction term $\alpha_{ct} \times \Delta\rho_t$ is positive and significant,

[17] We regress the level of the spread x_{it} on the level of the policy rate ρ_{it} because first-differencing doubles measurement noise in x_{it}, which is already volatile at the individual level.



The figure plots the rate (spread) sensitivity across $Q = 25$ bins of depositors sorted by their inattention rank. We estimate within-bin regressions for each bin q:
$\Delta \log m_{it} = \gamma_q \Delta\rho_t + \delta_i + \varepsilon_{it}, \quad x_{it} = \beta_q \rho_t + \delta_i + \upsilon_{it}, \quad i \in q,$
where m_{it} is depositor i's total balance, x_{it} is the deposit spread faced by depositor i, and ρ_t is the federal funds rate. Each regression includes depositor fixed effects δ_i and clusters standard errors at the depositor level. We then recover the rate sensitivity as $\hat{s}_q = \hat{\gamma}_q / \hat{\beta}_q$ and plot it against bin index q, where bin 1 contains the most attentive depositors and bin 25 contains the most inattentive. A negative $\hat{s}_q$ indicates that higher deposit rates induce outflows, and its magnitude falls as inattention increases.

Figure A-1: Depositor's rate (spread) sensitivity

indicating that higher inattention dampens the outflow response to policy rate increases. Controlling for county fixed effects (columns 2 and 5) and for time-varying local market concentration (columns 3 and 6) leaves the result roughly unchanged.

These results confirm that the projected inattention $\hat{\alpha}_{bt}$ is as informative for bank deposit flow sensitivity to policy rate changes as the directly observed measure, while extending coverage from a subsample of depositors from roughly one-third of U.S. counties to the national level.

	(a) Using observed α			(b) Using projected $\hat{\alpha}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\alpha \times \Delta\rho$	0.154**	0.153**	0.155**			
	(0.068)	(0.068)	(0.068)			
$\hat{\alpha} \times \Delta\rho$				0.589***	0.404***	0.372***
				(0.043)	(0.048)	(0.049)
HHI $\times \Delta\rho$			-0.002			0.287***
			(0.082)			(0.059)
Bank FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
County FE	N	Y	Y	N	Y	Y
Observations	123,622	123,622	123,622	38,4117	384,117	384,117

This table reports estimates from the cross-sectional regression $\Delta m_{bct} = \beta_0 \Delta\rho_t + \beta_1 (\alpha_{ct} \times \Delta\rho_t) + \beta_2 \alpha_{ct} + \beta_3 (\text{HHI}_{ct} \times \Delta\rho_t) + \beta_4 \text{HHI}_{ct} + \delta_b + \delta_t + \varepsilon_{bct}$, where Δm_{bct} is the log-difference in deposits for bank b in county c during year t, $\Delta\rho_t$ is the annual change in policy rate, α_{ct} measures county-level depositor inattention (directly observed for 2014-2022, and projected as $\hat{\alpha}_{ct}$ for 2007-2022), HHI_{ct} is the county Herfindahl-Hirschman index, and δ_b and δ_t are bank and year fixed effects. Columns (1)-(3) use observed α_{ct} (2014-2022) with the 123,622 county-bank-year observations available with observed α_{ct}; Columns (4)-(6) use projected $\hat{\alpha}_{ct}$ (2007-2022) with 384,117 observations. All columns include bank and year FE; Columns (2) and (5) add county fixed effects; Columns (3) and (6) also include the $\text{HHI}_{ct} \times \Delta\rho_t$ interaction. Standard errors (in parentheses) are clustered at the bank level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A-2: Deposit Flows in the Cross Section

C.3. Asymmetric Sluggishness

We replicate the asymmetry results in Driscoll and Judson (2013) with the two in-sample rate hike and cut cycles in Figure A-2.

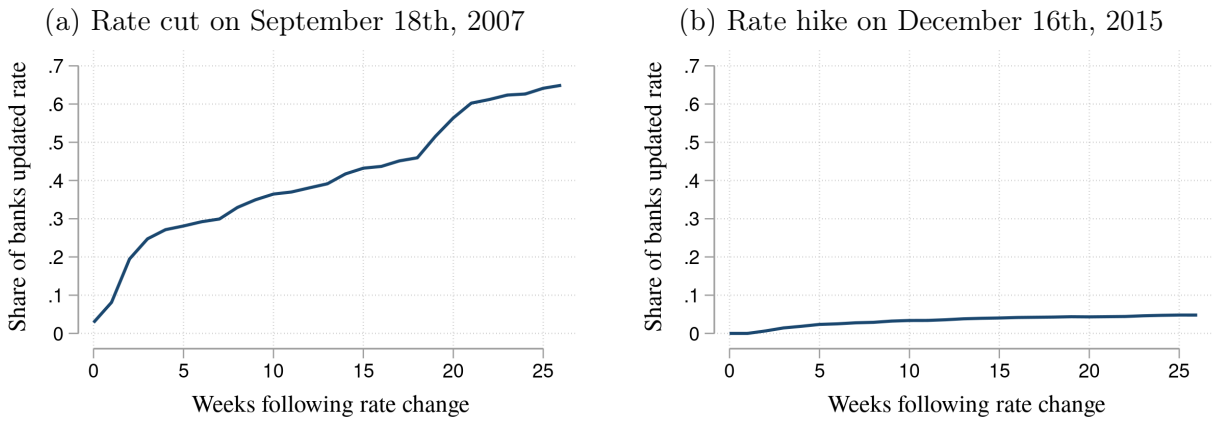


Figure A-2: Short-run asymmetry in rate pass-through

C.4. Average Spread and Inattention

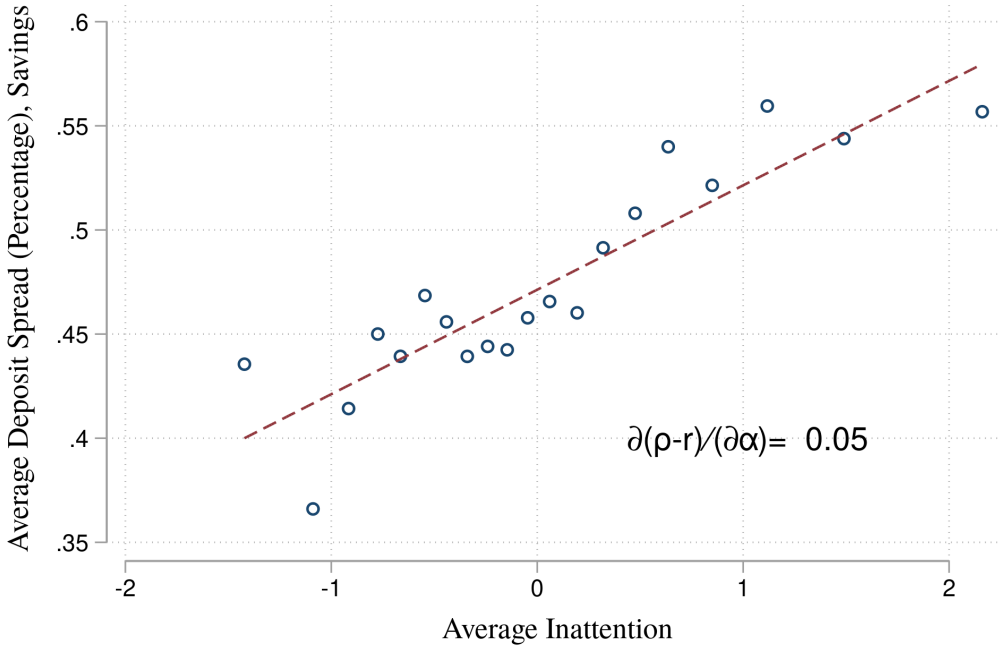


Figure A-3: Average spread and inattention

D. Additional Calibration Results

D.1. Duration Difference between Savings and NIB deposits

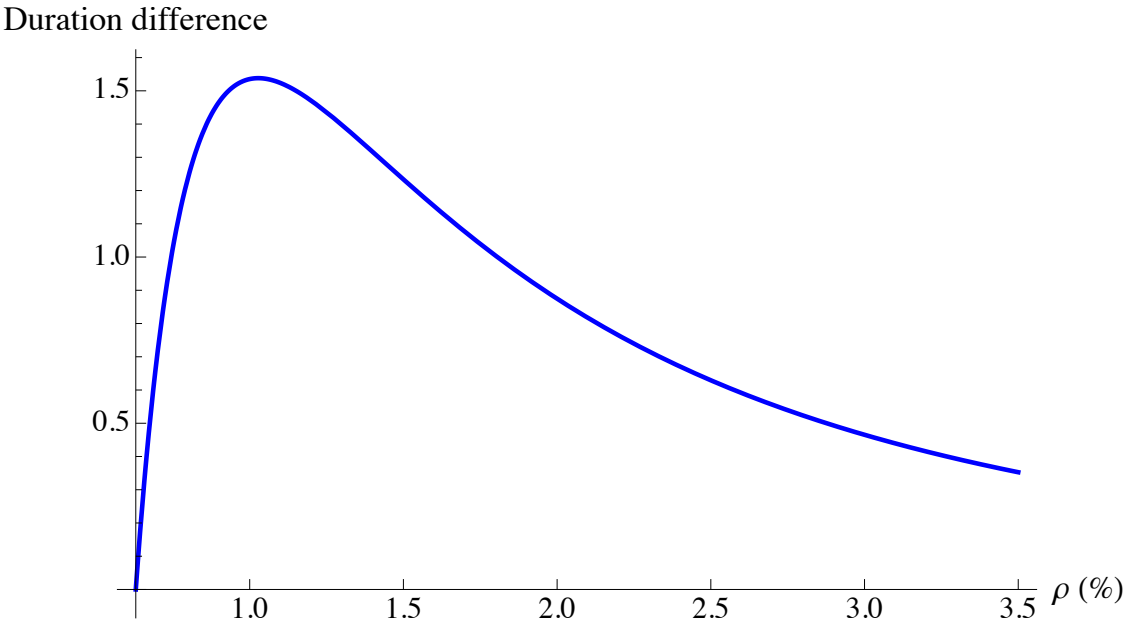


Figure A-4: Duration difference between savings / non-interest-bearing deposits

The figure plots the the difference between the franchise value duration of non-interest-bearing (NIB) deposits and that of savings deposits for the baseline calibration. A positive wedge indicates that NIB balances load more heavily on interest rate risk than savings balances. The wedge attains maximum of roughly 1.5 around $\rho = 1\%$. At the 2% policy rate benchmark, the wedge is approximately 1, implying that every dollar of NIB deposits carries roughly one additional bond-equivalent year of duration risk compared with a dollar of savings deposits. As the policy rate rises further, the discounting future profit margin dominates, and the wedge gradually narrows, reaching about 0.4 when ρ is 3.5%.

D.2. Non-Interest-Bearing Deposit Size

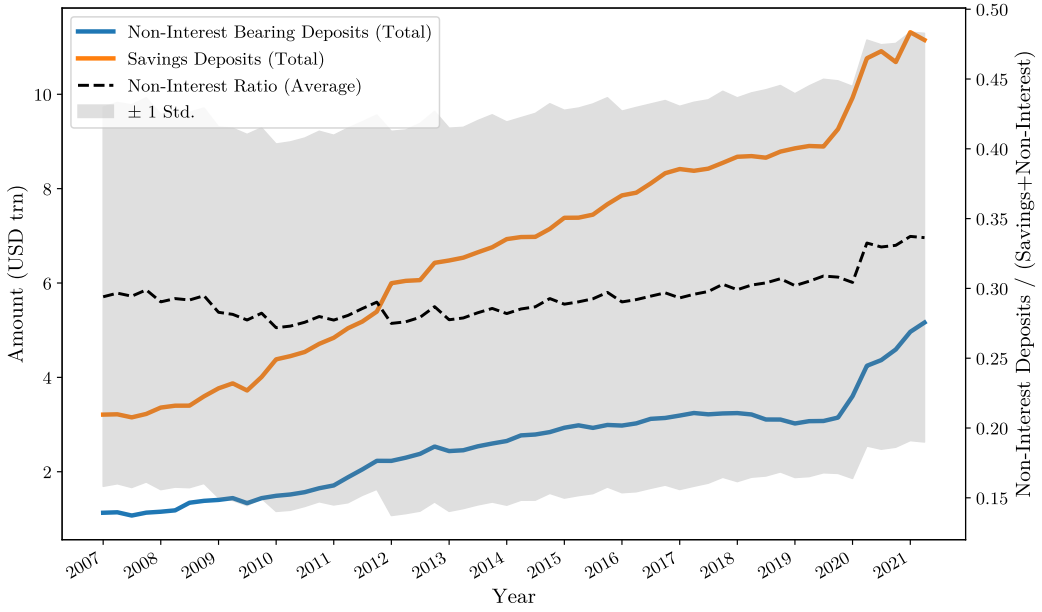


Figure A-5: Size of non-interest bearing deposits over time

The figure plots the time variation of core retail deposits using Call Report data. The left-hand axis plots the aggregate stock of non-interest-bearing deposits (NIB) and savings deposits (solid orange). The right-hand axis shows the non-interest-deposit ratio as NIB / (NIB + Savings), averaged across banks each quarter (black dashed). The grey band represents +/- one within-quarter standard deviation of this ratio across banks, illustrating the cross-sectional dispersion in reliance on zero-rate funding.

D.3. Banks' Willingness-to-Pay for an Inattentive Depositor

Banks' willingness-to-pay (WTP) for a new depositor must not exceed the present value of the profit it expects to earn from that customer's deposit balances. Under our baseline calibration, an averagely inattentive savings depositor yields about \$0.18 of franchise value per dollar, implying a bank would pay at most 18 cents per dollar for new deposits. Below, we discuss why our DFV implied willingness-to-pay is only a theoretical upper bound of banks' true WTP for two reasons.

First, banks cannot directly observe a new depositor's inattention level ex ante; depositors attracted by promotional rates might be more rate-sensitive and attentive than the average existing depositors. Thus banks need to discount the \$0.18-per-dollar franchise value by the probability that the customer will remain inattentive. As a simple back-of-the-envelope calculation, let $p \in [0, 1]$ denote the share of promo–induced new customers who ultimately behave like the average inattentive depositor ($\bar{\tau}$). Expected value per dollar of balance is then $p \times 0.18$. For instance, if only $p = 0.5$ of new depositors stay beyond the teaser period, the bank values a \$10,000 account at $0.5 \times 0.18 \times 10000 = \$900$, and will not spend more than \$900 in up-front incentives.

In practice, banks often screen depositors—such as asking for "qualifying activities" (e.g., direct deposits or maintaining a large balance every day) or residence in specific areas—and offer front-loaded cash bonuses or temporary rate bumps that hopefully lock in inattentive depositors. Table A-3 summarizes some representative promotional offers as of 2025 and converts them into empirical WTP estimates under a conservative assumption that *promo seekers depart immediately after the minimum period required for the promotion* (i.e., $p = 0$). Chase's 20 cents per dollar suggests it anticipates a higher-than-average depositor inattention among those responding to its offer; except for Chase, empirical WTPs cluster between 1 and 8 cents per dollar, far below the 18 cents per dollar maximum implied by the DFV. In addition, entry to the deposit market is not competitive. Starting a new bank in the

U.S. faces regulatory hurdles; from 2010 to 2023, U.S. has averaged six new banks per year despite having more than 4,000 incumbents. Entry barriers suggest incumbent banks rarely need to pay fully competitive rates to attract deposits away from rivals, pushing acquisition costs well below the deposit franchise value of new deposits.

Bank	Incentive	Eligibility	Cost	WTP (¢/$)
U.S. Bank	$400 cash bonus	$5,000 direct deposits	$400	8.0
Chase	$300 cash bonus	$1,500 daily balance[a]	$300	20.0
PNC	$400 cash bonus	$5,000 direct deposits	$400	8.0
TD Bank	$200 cash bonus	$10,000 daily balance[b]	$200	2.0
Citibank	promo rate, 4.25% (3mo)	$25,000 daily balance	≈ $266	1.1
SoFi	promo rate, 4.00% (6mo) +$300[c]	$5,000 direct deposits	≈ 310	3.1
Wells Fargo	promo rate, 4.60% (12mo)	$10,000 daily balance	≈ $460	4.6

[a] Chase also allows qualification via $500 of direct deposits within 90 days; using that threshold would imply a WTP of 60 cents per $1. We report the more conservative $1.5k balance requirement.
[b] TD Bank's offer is valid for *selected states* only.
[c] SoFi has an additional 0.20pp rate boost for six months, which adds about $10 of extra interest on a $10k balance; the one-time cash bonus is up to $300 depending on the size of direct deposits.
Note that promotions often have multiple tiers of cash/rate bonuses, in which case we report only the maximum promotion available applied to the maximum balance/direct deposit tier.

Table A-3: Promotional offers for depositor acquisition

Finally, when would the deposit franchise value *equal* banks' WTP for a new dollar of deposits? In a frictionless, perfectly competitive deposit market, competition drives the expected net profit on each new dollar to zero, and DFV equals WTP if banks expect that the average promotion takers are as inattentive as their existing customers. Note that even with perfect competition, the cross-sectional heterogeneity of depositors still bear important redistribution implications: as long as banks cannot perfectly price discriminate(i.e., depositor types are not fully known), cross-subsidies may persist across demographic groups, with the attentive depositors more than compensated by banks'

promotions and others pay more for banks' franchise value.

D.4. Demographics and Inattention

	β_α	$s.e._\alpha$	β_τ	$s.e._\tau$	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
% Under 18	0.061	0.008	0.022	0.003	23.542	3.042
% Black	0.009	0.003	0.003	0.001	8.864	13.690
% Householder	0.205	0.009	0.070	0.003	39.074	3.236
% Female	-0.231	0.011	-0.077	0.004	50.070	1.942
% Asian	-0.027	0.007	-0.008	0.002	1.233	2.493
% White (Non-hispanic)	-0.013	0.001	-0.004	0.000	78.080	18.896
% Renter	-0.020	0.003	-0.006	0.001	28.118	7.169
% Unmarried Partner	-0.334	0.037	-0.113	0.012	2.401	0.543
% Single Moms	-0.165	0.021	-0.054	0.007	6.418	2.066
$\bar{\tau}_{2010}$					2.346	0.322

All demographic covariates are expressed as percentages of the county population and are constructed from the 2010 Decennial Census five-digit ZIP Code Tabulation Area (ZCTA) file available through Missouri Census Data Center. For each variable we compute a population-weighted average across all ZCTAs within a county. % Under 18 is the share of residents younger than 18; % Black, % Asian, and % Non-Hispanic White are the shares of individuals who identify with those single-race categories, the latter excluding any Hispanic or Latino origin; % Female is the share of residents identifying as female; % Householder is the share of adults listed as the householder of their housing unit; % Renter Occupied is the share of occupied housing units that are rented rather than owned; % Unmarried Partner denotes households in which the householder cohabits with an unmarried partner; and % Single Moms denotes families headed by a female householder with own children under 18 and no spouse present. The dependent variables are two alternative measures of depositor inattention: $\alpha_{c,2010}$, the predicted annual inattention measure at county level detailed in Section 5, and $\tau_{c,2010} = 180e^{\alpha_{c,2010}}$, the inattention measured in days corresponding to model parameter. Columns 1–2 present coefficients (β_α) and robust standard errors from an OLS regression of $\alpha_{c,2010}$ on the demographic variables selected by the post-LASSO procedure; Columns 3–4 repeat the regression using $\tau_{c,2010}$; Columns 5–6 report county-level means and standard deviations for each covariate as well as $\tau_{c,2010}$.

Table A-4: Post-LASSO OLS: Demographics and inattention