Bank Deposit Pricing in the Euro Area*

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Abstract

We investigate the supply and demand drivers of bank deposit pricing in the Euro area during the period 2007–2024. We document that the pass-through of policy rates to sight deposit rates is low, asymmetric, varies across the monetary policy regimes, and decreases over time. We build and estimate an equilibrium model of bank deposit markets, and find that the price sensitivity of depositors exhibits large heterogeneity between households and firms, across countries, and over time. Our estimates suggest that rate-sensitive depositors increasingly switched to alternative, higher-yielding savings products over time, thereby decreasing the average rate-sensitivity of the remaining pool of sight deposits. In turn, banks' market power over sight deposits increased, thereby accounting for the sluggish increase in overnight deposit rates following the 2022 European Central Bank's policy rate hikes.

Keywords: Deposit pricing, price elasticity, bank market power.

JEL codes: G21, G28, E52, E43

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1 Introduction

The rapid monetary tightening undertaken by the European Central Bank (ECB) starting in 2022 has been associated with a limited pass-through to bank deposit rates (a.k.a the deposit beta, as in Drechsler, Savov, and Schnabl, 2017, among others) compared to previous policy rate increases. The goal of this paper is to investigate the causes of the decline in the deposit beta. We argue that the main reason is the changing behavior of heterogeneous depositors over time. Rate-sensitive depositors switched to alternative, higher-yielding savings products in 2022–2024, thereby decreasing the average rate-sensitivity of the remaining pool of overnight deposits. Hence, banks' market power in overnight deposits increased, and deposit rates responded sluggishly to the ECB's rate hikes.

Deposits are the main funding source for most banks, and thus the speed and level of deposit pass-through have crucial implications for banks' funding costs and profitability, and ultimately for the transmission of monetary policy and aggregate financial stability. The limited pass-through of ECB policy rates on deposit rates in 2022–2024 has spurred a heated debate about the factors underpinning the sluggishness in the remuneration of these important saving instruments. One set of explanations points to structural supply-side factors. For instance, some analyses emphasize the role of bank market structure in deposit pricing (Grodzicki, Klaus, Pancaro, and Reghezza, 2023), and the Dutch Competition Authority has recently launched a broad market study into the (lack of) competition in the deposit market in the Netherlands.[1] Other analyses focus on bank characteristics, most notably changes in their assets and liabilities over time. For example, on the asset side, the large amount of reserves held by banks may reduce their need to raise deposits (Messer and Niepmann, 2023), reflecting the strong expansion of the ECB's balance sheet. Because this balance sheet expansion is expected to be unwound only gradually and possibly not completely, the sluggishness of the deposit rate pass-through could become a more persistent phenomenon. Similarly, the increase in bank capital regulations following the 2008 Financial Crisis may make deposits a less important source of funding.

In this paper, we investigate the importance of these competing explanations by empirically analyzing the supply and demand determinants of banks' deposit rates in the Euro area. We combine several different data sources to compile a unique dataset of deposit markets in the Euro

[1] https://www.acm.nl/en/publications/acm-launches-market-study-functioning-dutch-savings-market.

area during the period 2007–2024. Our empirical investigation proceeds in two complementary steps. First, we provide a rich descriptive analysis of deposit pricing, most notably of deposit betas. Second, we estimate an equilibrium model of deposit markets that allows us to quantify the role of different demand and supply factors in deposit pricing, and to conduct counterfactual analyses that decompose the sources of declining deposit betas.

The first part of our analysis establishes four key patterns about deposit pricing in the Euro area. First, we document that the pass-through of policy rates to deposit rates is low: our estimate of the long-run deposit beta equals 0.247 for household sight deposits[2]. Second, we document that deposit betas have declined over time. For example, the deposit beta was approximately 0.3 during the 2007–2008 hiking cycle, and declined to approximately 0.1 during 2022–2024. Third, we find evidence for asymmetric deposit betas across monetary policy regimes: the deposit pass-through is higher when the ECB decreases policy rates than when the ECB increases policy rates. Moreover, we document a significant decline in the deposit pass-through when the ECB set negative policy rates in 2014–2022. Fourth, we document a weak correlation only between bank balance sheet characteristics (i.e., assets and liabilities) and their deposit pricing, suggesting that bank-side factors alone cannot account for the patterns in the data.

These empirical findings motivate us to develop and estimate a supply-and-demand model of deposit markets that can provide a unified account of these patterns. We build on the recent literature on IO-style models of bank competition (e.g., Egan, Hortaçsu, and Matvos, 2017; Xiao, 2020, among others). Depositors choose among differentiated bank deposit products, cash, and an outside option (e.g., money market funds), where depositors differ in their liquid asset holdings, which scale their rate sensitivity. Multi-product banks set deposit rates to maximize profits under Nash-Bertrand competition. The model yields an equilibrium relationship among deposit rates, banks' gross revenues from intermediation, and markdowns, with markdowns inversely related to depositors' rate sensitivity.

We estimate the depositors' side using two complementary approaches. A nested logit specification delivers transparent, illustrative evidence of across-market variation in depositors' behavior. These estimates confirm that firms are more rate-sensitive than households, that households in higher-income Northern European countries are more rate-sensitive than those in lower-income Southern European countries, and that the rate sensitivity of depositors varies with the monetary policy regime—most notably, depositors exhibit differential behavior during periods of

[2] Drechsler, Savov, and Schnabl (2021) report a deposit beta of approximately 0.4 in the US.

negative versus positive ECB policy rates. A richer mixed logit specification incorporates both observable heterogeneity (through household income and firm revenue distributions) and unobservable heterogeneity in depositors' liquid asset holdings. The mixed logit estimates reveal that higher-income households hold disproportionately large deposits and are more rate sensitive, and thus are significantly more likely to shift funds away from overnight deposits when market rates rise. During the period of negative policy rates (2014–2022), most depositors maintained similar probabilities of holding overnight deposits, reflecting a compressed yield curve and lack of attractive alternatives. When the ECB raised policy rates in 2022, the most rate-sensitive, high-balance depositors shifted to term deposits and outside options, whereas inertial, low-balance depositors remained in overnight accounts.

On the bank side, we validate the Nash-Bertrand pricing model and decompose observed deposit rates into gross revenues, the inverse own semi-elasticity (a measure of bank market power), and cross-elasticity adjustments. Our estimates imply that the average markdown equals 92 percent of gross revenue, indicating substantial bank market power over depositors. Tracing the evolution of markdowns over time reveals the central mechanism of the paper: markdowns on household overnight deposits bottomed out during the period of negative policy rates, increased thereafter, and peaked during 2022–2024. This rise in markdowns directly accounts for the declining deposit beta: when the ECB raised rates, banks did not proportionally increase deposit rates because the compositional shift in depositors simultaneously increased their market power.

We conduct counterfactual analyses to further understand and quantify the effects of this mechanism. We remove depositor heterogeneity by setting all depositors' rate sensitivity equal to the deposit-weighted average in 2008. We find that it would have raised household overnight deposit rates by an average of 31 basis points over the sample period, with the gap widening to 45 basis points in 2024. The counterfactual deposit beta during the 2022–2024 hiking cycle would have been approximately twice as large as its observed value. In contrast, removing bank heterogeneity produces deposit rates that closely track actual rates, confirming that the low deposit pass-through stems primarily from aggregate depositor behavior rather than from failures of competition among banks or differences in bank characteristics.

2 Related Literature

A large body of literature studies the role of banks in the transmission of monetary policy. Within this broader literature, our paper aims to contribute to and connect two related strands that focus on bank deposits. The first one is the strand on deposit pricing, which studies the relationship between policy rates and bank deposit rates. Hannan and Berger (1991) and Neumark and Sharpe (1992) document that US bank deposit rates adjust slowly and asymmetrically after changes in policy rates, most notably in banking markets with fewer competitors, and interpret this evidence in favor of price rigidities. Drechsler, Savov, and Schnabl (2017) and Drechsler, Savov, and Schnabl (2021) revisit and extend these empirical analyses with a novel interpretation based on banks' market power in deposit markets, and document its role in the transmission of monetary policy.[3]

The second strand develops and estimates IO-style models of bank competition; see Clark, Houde, and Kastl (2021) for an insightful overview. The most related papers focus on deposit markets in the United States: Dick (2008), Ho and Ishii (2011), Honka, Hortaçsu, and Vitorino (2017), among others, study depositors' choice among differentiated banks; Ishii (2007), Egan, Hortaçsu, and Matvos (2017), Xiao (2020), Wang, Whited, Wu, and Xiao (2022), and Aguirregabiria, Clark, and Wang (2025) study market equilibrium between depositors and banks. Albertazzi, Burlon, Jankauskas, and Pavanini (2022) estimate an equilibrium model of the Euro area banking sector to study multiple equilibria with bank runs. In a complementary paper, Egan, Hortaçsu, Kaplan, Sunderam, and Yao (2025) estimate a dynamic model of US deposit competition with inactive depositors, finding that this inertia accounts for large markups. Our paper shares the conclusion that depositor behavior is a first-order determinant of bank market power, but emphasizes a different mechanism: We focus on how the composition of heterogeneous depositors changes endogenously over the interest rate cycle, whereas they model inertia as a persistent friction.

We build and innovate in both strands of literature by providing descriptive evidence on the pass-through of policy rates to deposit rates, and estimate an equilibrium model of deposit markets in the Euro area—a setting in which policy rates exhibit new regimes (e.g., negative rates), bank deposits account for a larger share of household assets, and banks play a larger

[3] Eichenbaum, Puglisi, Rebelo, and Trabandt (2025) argue that state-dependent depositor inattention generates asymmetric pass-through to deposit rates, and embed this mechanism in a general-equilibrium model of monetary policy transmission.

financial intermediation role compared to US markets (Allen and Gale, 2000). The key innovation of our analysis is that we provide novel evidence on how depositors' changing behavior and composition over time affect bank market power and deposit pricing, and show that this mechanism accounts for the descriptive patterns on deposit betas.

Our results showing that the average rate sensitivity of depositors increased over time are consistent with the recent findings of Blickle, Li, Lu, and Ma (2024), who document that deposit flightiness in the US banking system increased during the 2022–2023 rate-hiking cycle. We complement their analysis by estimating an equilibrium model that decomposes the sources of changing deposit betas into demand-side and supply-side factors, and by studying the Euro area, where the prolonged period of negative policy rates creates distinct dynamics in depositor behavior. We focus on the implications for deposit pricing and bank market power, whereas they focus on financial stability; the two perspectives are complementary, as the compositional mechanism we identify is precisely the source of the deposit flightiness they document.

3 Data

We build a comprehensive dataset of deposit markets in the Euro area for the period 2007q3–2024q4 by combining several bank-level and macroeconomic variables from different ECB and commercial datasets.

Deposit Rates and Volumes. We obtain bank-level data on deposit rates and volumes from the ECB individual MFI interest rate statistics (IMIR) and the individual balance sheet items (IBSI) datasets for the period 2007q3-2024q4.

These datasets report three types of household deposits, and two types of corporate deposits. Household and corporate sight (or overnight) deposits are convertible into currency and transferable on demand by cheque, banker's order, debit entry or similar means, without significant delay, restriction or penalty. Household and corporate term deposits (or deposits with an agreed maturity) are non-transferable deposits that cannot be withdrawn before an agreed fixed term, or that can be withdrawn subject to a penalty only. Household deposits redeemable at notice are deposits for which the holder must respect a fixed period of notice before withdrawing the funds; in some cases, it may be possible to withdraw a certain amount in a specified period, or subject to the payment of a penalty. The datasets report separate entries for term deposits with a maturity of less than 24 months or more than 24 months, and for deposits redeemable with a notice of less than 3 months or more than 3 months.

The IMIR and IBSI datasets report data on stocks and flows for each deposit type. Specifically, stocks and flows are identical for sight deposits, because depositors are assumed to roll over these deposits overnight, but they differ for term deposits and deposits redeemable at notice. We will use data on flows in our empirical analysis, which allow us to precisely capture the flows from sight deposits to term deposits as interest rates increase, for example.

Moreover, we obtain household and firm cash holdings from the monetary aggregates of the Balance Sheet Items (BSI) statistics.

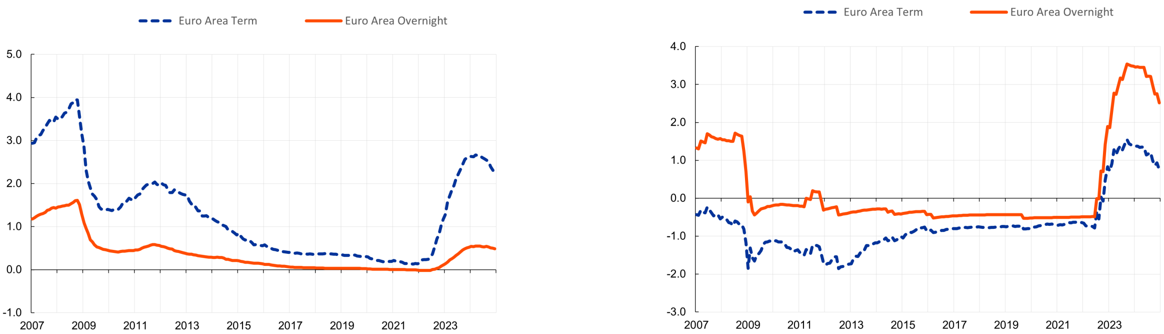
The sample of banks reporting in the IMIR and IBSI datasets has expanded over time, as different countries joined the reporting framework at different dates. Consequently, some of the statistics and figures for the early part of our sample period are based on fewer reporting banks and may appear less precise or more volatile. However, we have access to aggregate overnight deposit volumes and cash holdings from the BSI statistics for the full sample period. We use these aggregates to adjust the cash holdings in our bank-level dataset so that the ratio of overnight deposits to cash in our estimation sample matches the corresponding ratio in the aggregate data. This adjustment ensures that the relative size of the cash option is measured consistently over time, even as the composition of reporting banks changes.

Bank Characteristics. We collect several bank-level characteristics from different sources. The IBSI dataset reports some balance sheet variables, such as bank assets and bank liabilities, but their coverage before 2013 is limited. Thus, we complement them with data from Orbis, which reports more detailed data on bank capital variables, such as their Common/core equity tier 1 ratio, long-term debt, and their Basel 3 leverage ratio.

From Orbis, we also obtain the number of bank branches. We extract bank credit ratings from S&P Global Ratings, Moody's, Fitch Ratings, DBRS, and Scope Ratings using the "Centralised Securities Database" (CSDB), a proprietary ECB database, to measure bank-level credit risk. We harmonize credit ratings into a single numerical scale ranging from 1 (AAA) to 20 (SD/D) and take the arithmetic average when several ratings coexist.

We retrieve banks' excess liquidity held with the Eurosystem's National Central Banks from the ECB Counterparties database. Excess liquidity equals deposits with the Eurosystem (held in the current account and deposit facility) in excess of the minimum reserve requirements

Figure 1: Time-series of Deposit Rates and Spreads in the Euro Area



(a) Euro Deposit Rates

(b) Spreads between Euro Deposit and ECB Deposit Facility Rates

Notes: The left panel displays the volume-weighted average deposit rates on overnight deposits (solid line) and term deposits (dashed line). The right panel displays the difference between the ECB Deposit Facility Rate and the volume-weighted average deposit rates on overnight deposits (solid line) and term deposits (dashed line).

(MRR), normalized by bank total assets. Occasionally, excess liquidity can be negative because of non-compliance with the MRR, or technical and operational errors.

Household Income and Firm Revenues. For each country, we retrieve the annual household income distribution in each country using the Household Finance and Consumption Survey (HFCS), and the annual firm revenue distribution from Orbis. Appendix A describes the HFCS and Orbis datasets in more detail, and explains how we construct the household income and firm revenue distributions used in the estimation.

Macroeconomic Variables. We obtain some country-level macroeconomic variables from the ECB Statistical Data Warehouse (SDW), such as the GDP per capita, the unemployment rate, and the inflation rate.

4 Empirical Patterns on Bank Deposit Pricing

The left panel of Figure 1 displays the time series of the volume-weighted average bank deposit rates in the Euro area, and the right panel displays them as spreads from the ECB's Deposit Facility Rate (DFR). The right panel shows the stark pattern that is the main focus of our paper, i.e., the extreme spreads between policy and bank deposit rates during 2022–2024.[4]

To understand this pattern, we perform a descriptive analysis of deposit rates during our sample period, establishing the following key facts: (1) The pass-through of policy rates into deposit rates is low, most notably for overnight deposits. (2) The pass-through has declined over time. (3) The pass-through of policy rates to deposit rates is asymmetric, i.e., it is higher in periods of declining rates than in periods of increasing rates. (4) The pass-through varies in the cross-section of banks and over time.

4.1 Fact 1: Deposit Betas Are Low

In this section, we investigate the pass-through of policy rates to deposit rates, following the analysis Drechsler, Savov, and Schnabl (2017, 2021). Specifically, we estimate the following regressions:

$$\Delta r_{i,j,t} = \alpha_j + \sum_{l=0}^{2} \beta_{jl} \Delta r^{€}_{t-l} + \delta_j X_{c,t} + \theta_i + \varepsilon_{i,j,t}, \quad (1)$$

where Δ denotes the first-difference operator; $r_{i,j,t}$ is the interest rate set by bank i on deposit product type j (i.e., household sight deposit, corporate sight deposit, term deposit) in quarter t; $r^{€}_t$ is the ECB DFR in quarter t. $X_{c,t}$ is the vector of the following macro control variables of country c (where bank i operates): the Herfindahl–Hirschman Index (HHI) of bank deposits, the first-difference of the 10-year domestic government bond yields, unemployment growth, inflation growth, and GDP growth. θ_i are bank fixed effects.[5] The parameter β_{j0} measures the short-run pass-through, and the sum $\sum_{l=0}^{l=2} \beta_{jl}$ measures the long-run pass-through (the coefficients of additional lags were either negligible or non-significant).

Table 1 reports coefficient estimates of three separate regressions using data on (1) household sight deposits; (2) corporate sight deposits; and (3) term deposits.[6] The estimates of the short-run deposit betas equal 0.147 for household sight deposits, 0.284 for firm sight deposits, and

[4] We use the DFR as our baseline policy rate throughout the paper. However, the ECB changed its monetary policy framework in October 2008 to full-allotment refinancing operations (Schnabel, 2024), which complicates the use of a single policy rate for the full sample. Figure B.1 in the Appendix confirms that the 2022–2024 spreads were the largest in the sample period when measured against the ECB's Main Refinancing Operation Rate.

[5] We include separate fixed effects for multinational banks present in different countries.

[6] We distinguish between household and corporate sight deposits because deposit guarantee schemes usually cover the former (subject to country-specific rules, such as the deposit amount being below a certain threshold) but not the latter, resulting in different price and risk elasticities. In contrast, term deposits tend to display more homogeneous dynamics between household and firm sight deposits; hence, we decide to pool them together.

Table 1: Deposit Betas

	(1) Sight, Households	(2) Sight, Firms	(3) Term
$\Delta r_t^{€}$	0.147***	0.284***	0.629***
	(0.015)	(0.019)	(0.025)
$\Delta r_{t-1}^{€}$	0.073***	0.100***	0.178***
	(0.012)	(0.016)	(0.025)
$\Delta r_{t-2}^{€}$	0.028***	0.030***	0.066***
	(0.008)	(0.011)	(0.017)
HHI_t	-0.196***	-0.221***	-0.606***
	(0.051)	(0.065)	(0.121)
Macro Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Observations	11,457	11,924	12,012

The dependent variable in columns (1)–(3) is the change in interest rates for household sight, corporate sight, and term deposits, respectively. The interest rate $r_t^{€}$ is the ECB DFR. The sample period is 2008q2 to 2024q4. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

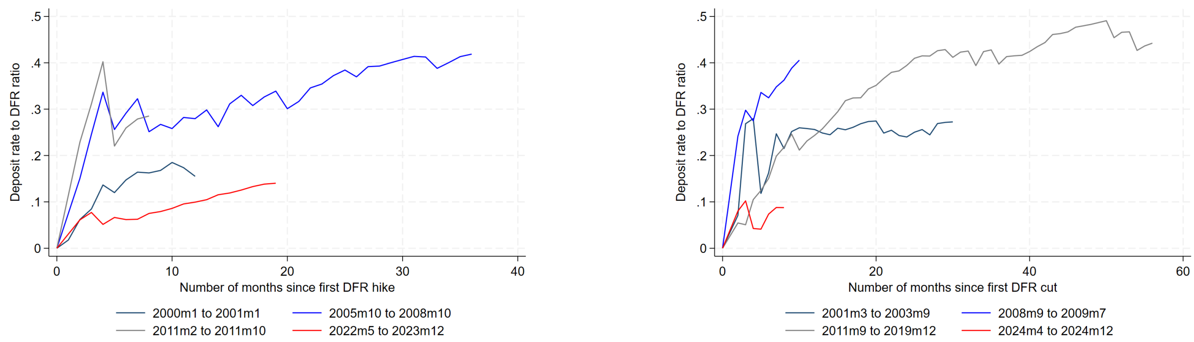
0.629 for term deposits, whereas the estimates of the long-run deposit betas equal 0.247 for household sight deposits, 0.414 for firm sight deposits, and 0.873 for term deposits. Hence, sight deposits display lower short- and long-run betas than term deposits, as well as a slower adjustment to their long-run values, as short-run deposit betas attain approximately 60 and 70 percent of their long-run values for sight and term deposits, respectively.

The lower deposit betas of sight deposits compared to those of term deposits are consistent with the "money-like" attribute of sight deposits, which provides a convenience yield that term deposits do not have. Moreover, the magnitudes of the household sight deposit betas are lower than the value of approximately 0.40 that Drechsler, Savov, and Schnabl (2017, 2021) estimate on US bank deposit data for the period 1997–2013.

Finally, the negative coefficient on the Herfindahl–Hirschman Index (HHI) is consistent with the idea that banks operating in a concentrated market structure can offer lower rates on their deposits without incurring deposit outflows, likely because customers face fewer alternatives.

A potential concern with our use of the DFR to estimate deposit betas is that the Main Refinancing Operations (MRO) rate was arguably the more relevant policy rate for banks for the early part of the sample—at least until October 2008, when the ECB shifted its operational framework to fixed-rate full allotment in its refinancing operations, which over time led to a large-scale expansion of excess liquidity and progressively made the DFR the binding floor

Figure 2: Simple Deposit Betas



(a) Interest rate hike

(b) Interest rate cut

Notes: The figure displays the ratio of the cumulative change of the average overnight deposit rate over the cumulative change of the DFR in periods of increasing ECB policy rates (left panel) and decreasing ECB policy rates (right panel). We define a period of increasing (decreasing) policy rates as a period during which the DFR increases (decreases), and spans from two months before the first rate increase (decrease) to three months after the last rate increase (decrease).

rate (Schnabel, 2024). However, two considerations assuage this concern. First, because our regressions are estimated in first differences, any level difference between the DFR and the MRO does not affect our estimates: what matters for identification is the co-movement of changes in deposit rates with changes in the policy rate, not their relative levels. Second, Table B.1 in the Appendix reports alternative estimates of equation (1) in which the main explanatory variable $r_t^{€}$ is the 3-month Euribor in quarter t, which tracks the MRO more closely during the pre-2010 period. The estimates of deposit betas are very similar to those reported in Table 1, just slightly lower: for example, the short- and long-run household sight deposit betas equal 0.106 and 0.213, respectively.

4.2 Fact 2: Deposit Betas Declined Over Time

We now document that deposit betas have declined over time. Figure 2 displays some illustrative evidence to this effect. Specifically, it displays the ratios of the cumulative change of the average overnight deposit rates to the cumulative change of the DFR (i.e., the "simple" deposit beta in the analysis of Drechsler, Savov, Schnabl, and Wang, 2026) for each period of increasing (left panel) and decreasing (right panel) ECB policy rates since 2000.

A few instructive patterns emerge from the panels of this figure. First, the left panel shows that deposit betas declined from approximately 0.30 to approximately 0.10 from the 2007–2008 to the 2022–2023 hiking cycles. Second, the right panel confirms that the decline in deposit betas over time occurred in periods of declining policy rates too. Third, the left panel suggests that the adjustment of deposit betas towards their long-run value was considerably slower in 2022–2023 compared to 2007–2008.

4.3 Fact 3: Deposit Betas Are Asymmetric

We now document that deposit betas are asymmetric across different ECB monetary policy regimes. To do so, we enrich our estimating equation as follows:

$$\Delta r_{i,j,t} = \alpha_j + \sum_{l=0}^{2} \beta^{+}_{jl} \Delta r^{€}_{t-l} \times \mathbb{1}(\Delta r^{€}_{t-l} > 0) + \sum_{l=0}^{2} \beta^{-}_{jl} \Delta r^{€}_{t-l} \times \mathbb{1}(\Delta r^{€}_{t-l} \leq 0) + \delta_j X_{c,t} + \theta_i + \varepsilon_{i,j,t}, \tag{2}$$

where the indicator variable $\mathbb{1}(\Delta r^{€}_{t-l} > 0)$ captures periods of increasing policy rates, and the variable $\mathbb{1}(\Delta r^{€}_{t-l} > 0)$ periods of stable of decreasing policy rates.[7] All other variables are as previously defined.

Columns (1)–(3) in Table 2 display the coefficient estimates of equation (2) using data on (1) household sight deposits; (2) corporate sight deposits; and (3) term deposits. Overall, both the short- and long-run betas for all deposits are lower when policy rates are increasing compared to when they are decreasing. Notably, the short- and long-run betas of household sight deposits equal 0.017 and 0.110, respectively, when rates are increasing, whereas they equal 0.213 and 0.356, respectively, when rates are decreasing. This asymmetric adjustment is often interpreted as one key manifestation of bank market power (Neumark and Sharpe, 1992): banks keep deposit rates low in the early phase of a hiking cycle to boost their net interest margins, whereas they respond swiftly to declining market rates in times of loose monetary policy.

We further investigate the asymmetry of deposit betas between periods of positive or (weakly) negative policy rates. Hence, we estimate regressions similar to (2) but with indicator variables $\mathbb{1}(r^{€}_{t-l} > 0)$ and $\mathbb{1}(r^{€}_{t-l} \leq 0)$ instead of $\mathbb{1}(\Delta r^{€}_{t-l} > 0)$ and $\mathbb{1}(\Delta r^{€}_{t-l} \leq 0)$, respectively. Columns (4)–(6) in Table 2 display the coefficient estimates of these regressions. Both the short- and long-run betas for all deposits are lower when policy rates are negative compared to when they are positive: The short- and long-run betas of household sight deposits equal 0.115 and 0.160,

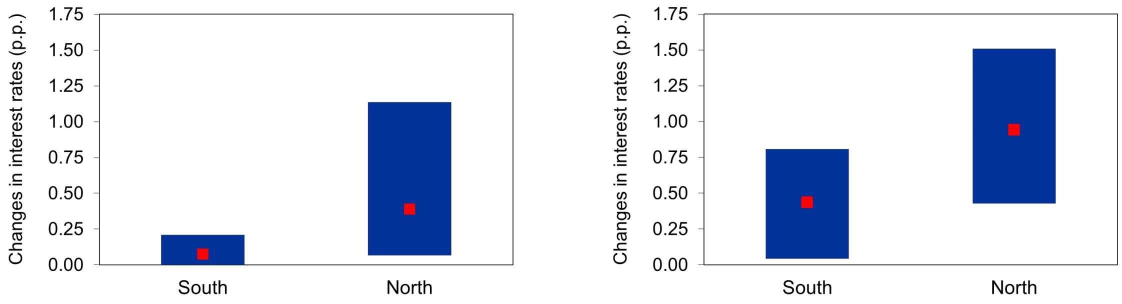
[7] Regression (2) is estimated over the period 2008q2 to 2024q4. The quarters with an increase in DFR during the sample period are: 2008q3, 2011q2–2011q3, 2022q3–2024q1.

Table 2: Deposit Betas across Monetary Policy Regimes

	(1) Sight, Households	(2) Sight, Firms	(3) Term	(4) Sight, Households	(5) Sight, Firms	(6) Term
$\Delta r_t^{€} \times \mathbb{1}(\Delta r_t^{€} > 0)$	0.017	0.099***	0.287***			
	(0.011)	(0.021)	(0.045)			
$\Delta r_t^{€} \times \mathbb{1}(\Delta r_t^{€} \leq 0)$	0.213***	0.380***	0.807***			
	(0.021)	(0.024)	(0.033)			
$\Delta r_{t-1}^{€} \times \mathbb{1}(\Delta r_{t-1}^{€} > 0)$	0.046***	0.028	0.281***			
	(0.014)	(0.026)	(0.053)			
$\Delta r_{t-1}^{€} \times \mathbb{1}(\Delta r_{t-1}^{€} \leq 0)$	0.097***	0.147***	0.128***			
	(0.018)	(0.018)	(0.036)			
$\Delta^+ r_{t-2}^{€} \times \mathbb{1}(\Delta r_{t-2}^{€} > 0)$	0.047***	0.086***	0.054			
	(0.011)	(0.020)	(0.039)			
$\Delta^- r_{t-2}^{€} \times \mathbb{1}(\Delta r_{t-2}^{€} \leq 0)$	0.046***	0.037***	0.105***			
	(0.009)	(0.011)	(0.022)			
$\Delta r_t^{€} \times \mathbb{1}(r_t^{€} > 0)$				0.143***	0.288***	0.642***
				(0.016)	(0.020)	(0.028)
$\Delta r_t^{€} \times \mathbb{1}(r_t^{€} \leq 0)$				0.115***	0.172***	0.360***
				(0.025)	(0.036)	(0.100)
$\Delta r_{t-1}^{€} \times \mathbb{1}(r_{t-1}^{€} > 0)$				0.074***	0.094***	0.166***
				(0.013)	(0.017)	(0.030)
$\Delta r_{t-1}^{€} \times \mathbb{1}(r_{t-1}^{€} \leq 0)$				-0.022	0.043	0.111
				(0.057)	(0.031)	(0.099)
$\Delta^+ r_{t-2}^{€} \times \mathbb{1}(r_{t-2}^{€} > 0)$				0.020**	0.020*	0.051***
				(0.008)	(0.012)	(0.020)
$\Delta^- r_{t-2}^{€} \times \mathbb{1}(r_{t-2}^{€} \leq 0)$				0.067**	0.091***	0.340***
				(0.028)	(0.029)	(0.111)
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,457	11,924	12,012	11,457	11,924	12,012

Notes: The dependent variable in columns (1) to (6) is the change in interest rates for household sight, corporate sight, and term deposits, respectively. The interest rate $r_t^{€}$ is the ECB DFR. The sample period is 2008q2 to 2024q4. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Figure 3: Change in interest rates between December 2021 and March 2024



(a) Household sight deposits

(b) Corporate sight deposits

Notes: change in deposit rates between December 2021 and March 2024. The blue bars represent the interquartile range. Country selection following Table 4.

respectively, when rates are negative, whereas they equal 0.143 and 0.237, respectively, when rates are positive. Competition from cash and the zero lower bound on deposit rates likely account for these differences: In some markets, we never observe negative interest rates on overnight deposits in our data, suggesting that regulatory or other (e.g., political) constraints imply that banks treat zero as an effective floor on deposit pricing (Altavilla, Burlon, Giannetti, and Holton, 2022).[8]

4.4 Fact 4: Deposit Betas across Markets and Banks

We now document how deposit betas vary across markets and banks. Figure 3 presents some intriguing, simple evidence on across-market differences. Specifically, it displays the change in interest rates on household (left panel) and corporate sight deposits in two sets of Euro area countries following the most recent round of ECB policy rate increases: Southern countries of the Euro area (Italy, Spain, Portugal, Greece, Slovenia, Malta, and Cyprus) and Northern countries (all others). This difference is geographic, but also broadly corresponds to differences in the yields of sovereign bonds, which on average are higher in Southern countries than in Northern countries during our sample period. The panels show that, on average, banks in Southern countries increased their deposit rates less than those in Northern countries.

We investigate more formally differences across countries and banks by estimating the fol-

[8]Negative rates are more common on corporate deposits than on household deposits: we observe negative rates in 360 and 1031 observations in the regressions of columns (1)–(2) or (4)–(5) of Tables 1 and 2, respectively.

lowing regression:

$$\Delta r_{i,j,t} = \alpha_j + \sum_{l=0}^{2} \beta_{jl}^{W} \Delta r_{t-l}^{€} \times W_{c,t-l} + \sum_{l=0}^{2} \beta_{jl}^{Z} \Delta r_{t-l}^{€} \times Z_{i,t-l} + \delta_j X_{c,t} + \theta_i + \varepsilon_{i,j,t}, \quad (3)$$

where $W_{c,t-l}$ are key aggregate macro variables at the country level, such as (the logs of) the aggregate GDP per capita and the unemployment rate; and $Z_{i,t-l}$ are bank characteristics, such as their (log) assets, the CET1 capital ratio, and an indicator variable equal to one if the bank rating is investment grade, and zero otherwise.

Table 3 reports the coefficient estimates.[9] It confirms that banks in countries with higher per capita GDP have higher betas than those in lower-income countries. One possible explanation (admittedly speculative at this stage, but the results of Section 6 will buttress it) is that depositors in higher-income countries are, on average, more likely to switch deposits across banks than those in lower-income countries, perhaps because the value of their deposits is larger and they are more financially sophisticated, and thus banks need to adjust their deposit rates closer to market rates. The table also shows that bank betas increase when the unemployment rate rises, perhaps because some depositors behave more thriftily and are more attentive to deposit rates when unemployment spikes.

Moreover, perhaps surprisingly, Table 3 shows weak evidence only that deposit betas are correlated with bank characteristics: it seems that larger banks (measured by their assets) and banks with lower capital ratios have slightly higher long-run betas across deposit types, but the economic magnitudes of the estimated coefficients are negligible.

One potential concern with the regressions of Table 3 is that the macro, aggregate variables are common for all banks within the same market, and thus they may absorb some bank characteristics that are identical for all banks within the same market. For example, if all banks in the same market have very similar capital ratios and these capital ratios vary across markets, then the macro variables could absorb this across-market variation. The data show that there is substantial heterogeneity between banks within the same market, assuaging some of these concerns. Nevertheless, we perform separate regressions with macro and bank variables, respectively. Tables B.4 and B.5 in the Appendix report the coefficient estimates of these separate regressions, which are almost identical to those reported in Table 3.[10]

[9] The number of observations is slightly lower than those in the regressions on Table 2 because some bank characteristics are missing.

[10] The regressions in Table 3 include bank fixed effects, which therefore absorb the persistent, cross-sectional

Table 3: Deposit Betas across Markets and Banks

	(1) Sight, Households	(2) Sight, Firms	(3) Term
$\Delta r_t^{€}$	-1.589**	-1.622***	-2.946***
	(0.625)	(0.526)	(0.612)
×Log (GDP per capita$_t$)	0.177***	0.184***	0.390***
	(0.068)	(0.058)	(0.060)
×Log (Unemployment Rate$_t$)	0.055*	0.045	0.201***
	(0.031)	(0.043)	(0.066)
×Log (Assets$_t$)	0.005	0.031**	-0.005
	(0.013)	(0.016)	(0.014)
×CET1 Ratio$_t$	-0.002	-0.013***	-0.028***
	(0.004)	(0.005)	(0.005)
×Investment Grade$_t$	0.020	-0.006	0.073
	(0.029)	(0.041)	(0.052)
$\Delta r_{t-1}^{€}$	-0.626	0.020	2.134***
	(0.607)	(0.360)	(0.751)
×Log (GDP per capita$_{t-1}$)	0.103	0.016	-0.231***
	(0.065)	(0.037)	(0.072)
×Log (Unemployment Rate$_{t-1}$)	0.024	0.043	-0.070
	(0.026)	(0.033)	(0.066)
×Log (Assets$_{t-1}$)	-0.019*	-0.007	0.023*
	(0.011)	(0.011)	(0.013)
×CET1 Ratio$_{t-1}$	-0.007**	-0.003	0.004
	(0.003)	(0.003)	(0.005)
×Investment Grade$_{t-1}$	-0.003	-0.080**	-0.014
	(0.024)	(0.035)	(0.054)
$\Delta r_{t-2}^{€}$	0.622	0.356	0.210
	(0.377)	(0.261)	(0.654)
×Log (GDP per capita$_{t-2}$)	-0.074*	-0.044	-0.039
	(0.042)	(0.028)	(0.066)
×Log (Unemployment Rate$_{t-2}$)	-0.067***	-0.033	0.035
	(0.024)	(0.035)	(0.058)
×Log (Assets$_{t-2}$)	0.020***	0.011	0.002
	(0.007)	(0.010)	(0.014)
×CET1 Ratio$_{t-2}$	0.002	0.001	0.013***
	(0.002)	(0.003)	(0.005)
×Investment Grade$_{t-2}$	-0.009	0.039	-0.010
	(0.014)	(0.029)	(0.048)
Macro Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Observations	9,662	9,756	9,954

The dependent variable in columns (1)–(3) is the change in interest rates for household, corporate sight, and term deposits, respectively. The interest rate $r_t^{€}$ is the ECB DFR. The sample period is 2008q2 to 2024q4. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Taken together, the four patterns documented in this section paint a consistent picture. The pass-through of policy rates to deposit rates is low, has declined over time, and displays

variation between banks. We have also estimated regressions with bank random effects, and the results are quite similar to those reported in Table 3.

pronounced asymmetries across monetary policy regimes; yet these patterns are only weakly related to bank balance sheet characteristics or market concentration. This suggests that bank-side factors alone cannot account for the dynamics of deposit betas and motivates us to develop a structural model that explicitly incorporates demand-side heterogeneity. Notably, the cross-country differences documented in Fact 4 (higher-income countries displaying higher deposit betas) and the time-series variation documented in Fact 2 (deposit betas declining across successive hiking cycles) point to a role for the composition and behavior of depositors in shaping banks' pricing decisions. The model we develop in the next section formalizes this intuition by allowing depositors to differ in their rate sensitivity as a function of their liquid asset holdings and by deriving the implications of this heterogeneity for banks' optimal markdowns.

5 Model

This section analyzes how the pricing of deposits affects households' and firms' supply of deposits and, implicitly, the deposit base composition. Sight deposit pass-through affects deposit supply as customers have the incentive to shift their money to higher-yield saving products, depending on the opportunity cost of holding money-like (sight) deposits in a high-interest rate environment.

5.1 Setup

In each market m and period t, there are I_{mt} potential consumers, either households or firms, indexed by i. We follow Ishii (2007) and Ho and Ishii (2011) by assuming that each consumer i decides to put (i.e., supply) an amount of liquid assets d_{imt} either into one of the J_{mt} bank deposit products, indexed by j, or into cash, or into an alternative product (e.g., a money market fund). These two non-bank products allow us to capture how the substitution between banking and non-banking products vary over time as market rates change, most notably in periods of negative rates or periods of increasing rates.

More formally, the indirect utility of consumer i choosing bank deposit product j in market m and period t equals:

$$U_{ijmt} = \alpha_{imt} d_{imt} r_{jmt} + \beta X_{jmt} + \xi_{jmt} + \varepsilon_{ijmt}, \tag{4}$$

where r_{jmt} is the interest rate on deposit product j in market m (i.e., a combination of country and segment, households or firms) and period t; X_{jmt} are observable attributes of deposit product j, such as the maturity period, as well as bank attributes, such as the number of branches and its credit rating; ξ_{jmt} is an unobservable attribute of each deposit product; and ε_{ijmt} is an idiosyncratic preference that depositor i has for deposit product j in market m and period t. The indirect utility of cash equals $\varepsilon_{i\emptyset mt}$; and the indirect utility of the outside option equals $U_{i0mt} = \alpha_{imt} d_{imt} r_{0t} + \varepsilon_{i0mt}$, where r_{0t} is a market return.

Crucially, the outside option's attractiveness scales with the depositor's rate sensitivity and liquid assets, just as for bank deposit products. This implies that when market rates rise, depositors with larger liquid asset holdings experience a greater increase in the utility of the outside option relative to bank deposits, and are thus more likely to shift funds away from overnight deposits. This is the key feature of the model: the exit of high-balance, rate-sensitive depositors from overnight deposits when policy rates rise endogenously increases banks' market power over the remaining, less elastic depositors.

Consumer i chooses product j with probability

$$P_{ijmt} = Pr\left(\varepsilon_{ijmt} : U_{ijmt} \geq U_{ikmt}, \forall k \neq j\right), \tag{5}$$

and the market share of product j equals

$$s_{jmt} = \frac{\int\int P_{ijmt}\left(\alpha_{imt}, d_{imt}\right) d_{imt} dF_{\alpha,d}(\alpha_{imt}, d_{imt})}{\int d_{imt} dF_d(d_{imt})}, \tag{6}$$

which is the deposit-weighted average probability, where $F_{\alpha,d}(\cdot,\cdot)$ is the joint cumulative distribution function of the interest rate sensitivity α_{imt} and of the liquid assets d_{imt}, and $F_d(\cdot)$ is the cumulative distribution function of liquid assets. Thus, the denominator $\int d_{imt} dF_d(d_{imt})$ is the total mass of liquid assets.

5.2 Bank Rate Setting

Banks choose the interest rates of their J_l deposit products to maximize their flow profits, given their lending rates and other costs:

$$\max_{r_{jmt}} \sum_{j \in J_l} \left(R_{lt} - r_{jmt} - c_{jmt}\right) q_{jmt} \quad \text{s.t.} \quad r_{jmt} \geq 0 \quad \forall j \in J_l^h, \tag{7}$$

where R_{lt} is the return on bank l's assets, which includes its lending rate and the return on the securities in its portfolio; c_{jmt} are the operating costs of offering product j; and $q_{jmt} = s_{jmt} \int d_{imt} dF_d(d_{imt})$ are product j's quantity of deposits. In some markets, we impose the non-negativity constraint on products in the set of bank l's deposit products $J_l^h \subseteq J_l$ to reflect the institutional feature that we recount in Section 4.3: in these markets, we never observe negative interest rates on deposits in our data. We do not impose this constraint in markets in which we observe negative rates.

The optimal rate on the deposit product j satisfies the first-order condition:

$$-s_{jmt} + (R_{lt} - r_{jmt} - c_{jmt}) \frac{\partial s_{jmt}}{\partial r_{jmt}} + \sum_{j' \neq j \in J_l} (R_{lt} - r_{j'mt} - c_{j'mt}) \frac{\partial s_{j'mt}}{\partial r_{jmt}} + \mu_{jmt} = 0, \tag{8}$$

where $\mu_{jmt} \geq 0$ is the Lagrange multiplier on the non-negativity constraint, with $\mu_{jmt} > 0$ only when the constraint binds (i.e., $r_{jmt} = 0$). When the constraint does not bind, $\mu_{jmt} = 0$ and the first-order condition reduces to the standard Nash-Bertrand pricing condition.

Solving for the optimal rate r_{jmt}, we obtain:

$$r_{jmt} = (R_{lt} - c_{jmt}) - \frac{s_{jmt}}{\frac{\partial s_{jmt}}{\partial r_{jmt}}} + \frac{\sum_{j' \neq j \in J_l} (R_{lt} - r_{j'mt} - c_{j'mt}) \frac{\partial s_{j'mt}}{\partial r_{jmt}}}{\frac{\partial s_{jmt}}{\partial r_{jmt}}} + \frac{\mu_{jmt}}{\frac{\partial s_{jmt}}{\partial r_{jmt}}}. \tag{9}$$

The first term is the gross revenue from raising an additional unit of deposits, which equals the return R_{lt} net of operating costs c_{jmt}; the second term is the inverse of the semi-elasticity of supply for product j; and the third term accounts for the cross-elasticities of the supply for bank l's other deposit products. The sum of the second and third terms corresponds to the bank's markdown on deposit product j. The fourth term captures the effect of the non-negativity constraint: because $\frac{\partial s_{jmt}}{\partial r_{jmt}} > 0$, a binding constraint ($\mu_{jmt} > 0$) pushes the optimal rate upward relative to the unconstrained solution, reflecting the fact that the bank would prefer to set a negative rate, but it is constrained to set zero. The non-negativity constraint is particularly relevant during the period of negative ECB policy rates (2014–2022), when banks' gross revenues from overnight deposits declined, but household deposit rates could not adjust downward.[11]

[11] The non-negativity constraint on product j also affects the optimal rates on other products offered by the same bank through the cross-elasticity terms. Specifically, when the constraint binds on product j, the bank's rate on product j is higher than its unconstrained optimum, making product j relatively more attractive. Because deposit products within the same bank are substitutes, this reduces demand for the bank's other products. The sign of the resulting adjustment on the other products' rates is in general ambiguous and depends on the full demand structure. In our estimates of Section 6, the spillover is positive, meaning that the constraint on product

6 Estimation and Results

We now describe our estimation in detail, as well as our estimation results.

6.1 Depositors: Nested Logit

We start by making some simplifying assumptions that deliver some nested logit linear regression equations. The main advantage of these regressions is that they illustrate in a transparent way some interesting across-market variations in depositors' behavior that our descriptive analyses of Section 4 suggested.

Specifically, we assume that the interest rate sensitivity α_{imt} and the amount of liquid assets d_{imt} vary across markets, but they are constant within markets. i.e., $\alpha_{imt} = \alpha_{mt}$ and $d_{imt} = d_{mt}$.

Moreover, we assume that ε_{ijmt} in equation (4) follows a generalized extreme value distribution that yields a nested logit probability of household choice, with non-overlapping nests $B(j)$ (Cardell, 1997). Households first choose one product type among: (1) overnight deposits; (2) term deposits; (3) deposits redeemable at notice; (4) cash; or (5) the outside option. After they have chosen one product type, households choose the product among those offered by different banks within the chosen product type to maximize their utility. Because the data do not report any deposits redeemable at notice for firms, we allow firms to choose among the following product types: (1) overnight deposits; (2) term deposits; (3) cash; or (4) the outside option. After they have chosen one product type, firms choose the product among those offered by different banks within the chosen product type to maximize their utility.

Hence, the probability $P_{ijmt} = P_{jmt}$ that a household or firm chooses product j satisfies:

$$\begin{aligned} P_{jmt} &= P_{jmt|B(j)} P_{B(j)}, \\ P_{jmt|B(j)} &= \frac{\exp\left(\frac{\alpha_{mt} d_{mt} r_{jmt} + \beta X_{jmt} + \xi_{jmt}}{1-\lambda}\right)}{D_{B(j)}}, \\ P_{B(j)} &= \frac{D_{B(j)}^{1-\lambda}}{\sum_{B(j)} D_{B(j)}^{1-\lambda}}, \end{aligned} \tag{10}$$

where $P_{jmt|B(j)}$ and $P_{B(j)}$ are the probabilities of choosing product j within its nest $B(j)$ and choosing nest $B(j)$, respectively, which are constant across households or firms. The parameter λ governs the correlation of unobservable preferences ε_{ijmt} within each nest: when $\lambda = 0$, there is

j also pushes up the bank's rates on its other deposit products.

no correlation of unobservable preferences across products within nests, implying that products within and across nests are equally substitutable, and thus the deposit supply simplifies to a standard logit; when λ increases and approaches 1, the correlation of unobservable preferences within each nest increases, implying that products within nests become closer substitutes than those across nests. The term $D_{B(j)} = \sum_{j \in B(j)} \exp\left(\frac{\alpha_{mt} d_{mt} r_{jmt} + \beta X_{jmt} + \xi_{jmt}}{1-\lambda}\right)$ is the inclusive value of all products in nest $B(j)$.

In turn, because deposits and the rate-sensitivity parameter are homogeneous within market m, the aggregate market shares s_{jmt} correspond to the choice probabilities P_{jmt}. Thus, we obtain the following linear regression equation (Berry, 1994):

$$\log\left(s_{jmt}\right) - \log\left(s_{0mt}\right) = \alpha_{mt} d_{mt}(r_{jmt} - r_{0t}) + \beta X_{jmt} + \lambda \log\left(s_{jmt|B(j)}\right) + \xi_{jmt}, \qquad (11)$$

where s_{jmt} is the market share of product j, s_{0mt} is the market share of the outside option $j = 0$, and $s_{jmt|B(j)}$ is the market share of product j within its nest $B(j)$. In practice, the estimation of equation (11) faces the following challenges:

Liquid Assets. We do not have data on the average liquid assets d_{mt} across markets m and periods t, and thus we can identify a composite parameter $\tilde{\alpha}_{mt} = \alpha_{mt} d_{mt}$ only, which we will (perhaps loosely) refer to as the interest rate sensitivity.

Instruments. The interest rate r_{it} and the within-nest market share $s_{jmt|B(j)}$ are likely correlated with the unobservable product attribute ξ_{it} in the supply equation (11). Hence, we use instruments for these endogenous variables: (1) For the interest rate r_{it}, we use the yield of the German Bund at time t matched to the corresponding maturity of the deposit product: e.g., for overnight deposits, we use the 1-month yield; for term deposits up to 12 months, we use the 12-month yield. Moreover, following the descriptive evidence of Section 4, we allow negative and positive German Bund yields to affect deposit rates differently. These instruments exploit the variation in interest rates across the yield curve and over time (i.e., the rotation of the yield curve), and thus the variation across nests over time. (2) For the within-nest market share $s_{jmt|B(j)}$, we use the number of banks offering products in the nest.

Outside Option. Our data reports deposit quantities q_{jmt} and cash holdings, and thus converting them into market shares s_{jmt} requires assumptions on the market size. In many applications, the market size is assumed to be equal to (or a function of) the population of market m in period t, or other demographic or economic variables. However, Huang and Rojas (2013, 2014) document that inaccurate assumptions about the total market size can bias the parameter estimates. Thus, we adapt their procedure to our setting by estimating the following regression:

$$\log\left(q_{jmt}\right) = \tilde{\alpha}_{mt} r_{jmt} + \beta X_{jmt} + \eta_{mt} + \lambda \log\left(s_{jmt|B(j)}\right) + \xi_{jmt}, \tag{12}$$

where η_{mt} is a market m-period t fixed effect which absorbs the log quantity of the outside option as well as its return, i.e., $\eta_{mt} = \log(q_{0mt}) - \tilde{\alpha}_{mt} r_{0t}$.

Having obtained parameter estimates of equation (12), we assume that the return of the outside option r_{0t} is related to a market interest rate (the 3-month Euribor rate) according to $r_{0t} = \omega r_t$, where we estimate the parameter ω by a regression of η_{mt} on $\tilde{\alpha}_{mt} r_t$. In turn, this regression allows us to obtain an estimate of the quantity of funds q_{0mt} in the outside option and thus of the total market size.

6.1.1 Nested Logit Estimates

Table 4 reports the IV estimates of several specifications that use data from the flows of deposits.

Heterogeneity: Households versus Firms. The specification of column (1) investigates different sensitivities to interest rates between households and firms. The estimates of the coefficient $\tilde{\alpha}_{mt}$ equal 0.398 for households and 1.035 for firms. These values confirm that deposit products with higher interest rates attract a larger share of deposits, and their difference indicates that firms are more sensitive to rates than households. The coefficient λ of (the log of) within-nest market share equals 0.301, which suggests that households and firms view deposit products across nests as moderately close substitutes.

The coefficients $\tilde{\alpha}_{mt}$ of the interest rate and λ of the log of the within-nest market share are the key parameters that determine how the product market shares respond to interest rates; Appendix C reports the formulas of the semi-elasticities. These estimates imply that, on average, a one-percentage-point increase in the interest rate offered by a lender on its household deposits increases its market share by 0.533 percent compared to 1.354 percent on its firm deposits.

Although we focus primarily on interest rates, the coefficient estimates of the other variables are also noteworthy. Households and firms are more likely to deposit their money in banks

Table 4: Deposit Supply Estimates, Nested Logit

	(1) Households-Firms	(2) North-South	(3) Positive-Negative	(4) Income/Revenue
Interest Rate	0.398***	0.606***	0.634***	-1.073
	(0.051)	(0.063)	(0.063)	(0.741)
Δ Interest Rate, Firms	0.637***	0.506***	0.445***	1.368*
	(0.060)	(0.076)	(0.078)	(0.749)
Δ Interest Rate, South		-0.510***	-0.257***	
		(0.083)	(0.090)	
Δ Interest Rate, Firms * South		-0.112	-0.067	
		(0.128)	(0.141)	
Δ Interest Rate, Negative Policy Rates			0.614***	
			(0.134)	
Δ Interest Rate, Firms * Neg. Policy Rates			0.681***	
			(0.182)	
Δ Interest Rate, South * Neg. Policy Rates			-0.524***	
			(0.167)	
Δ Interest Rate, Firms * South * Neg. Rates			-0.712***	
			(0.267)	
Δ Interest Rate * Log(Household Income)				0.152**
				(0.073)
Δ Interest Rate, Firms * Log(Firm Revenue)				-0.027
				(0.076)
Deposits Redeemable at Notice:				
Less than 3 months	-0.367***	-0.358***	-0.510***	-0.400***
	(0.034)	(0.034)	(0.042)	(0.034)
More than 3 months	-2.345***	-2.433***	-2.692***	-2.501***
	(0.067)	(0.071)	(0.085)	(0.070)
Term Deposits:				
Less than 24 months	-5.100***	-4.975***	-5.170***	-5.117***
	(0.065)	(0.067)	(0.073)	(0.067)
More than 24 months	-6.627***	-6.574***	-6.962***	-6.717***
	(0.056)	(0.057)	(0.085)	(0.057)
Log Number of Branches	0.495***	0.511***	0.503***	0.514***
	(0.013)	(0.013)	(0.013)	(0.013)
Log Number of Employees per Branch	0.582***	0.603***	0.594***	0.620***
	(0.026)	(0.026)	(0.026)	(0.027)
Investment Grade	-0.154***	-0.170***	-0.159***	-0.160***
	(0.019)	(0.019)	(0.019)	(0.020)
Log Within-Nest Market Share	0.301***	0.281***	0.297***	0.269***
	(0.021)	(0.021)	(0.021)	(0.022)
ω	0.355***	0.360***	0.286***	0.361***
	(0.019)	(0.019)	(0.017)	(0.017)
Market-Date FE	Yes	Yes	Yes	Yes
Observations	54,739	54,739	54,739	54,739

Notes: The table reports the coefficient estimates of the nested logit deposit supply regression equation (12). Standard errors in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$

with more branches and more employees. Surprisingly, banks with higher credit ratings do not seem to attract more deposits, perhaps because the vast majority of depositors are insured. Moreover, households and firms prefer deposits with shorter maturities, particularly valuing the liquidity of overnight deposits. Specifically, the coefficients of columns (1) indicate that on average households require a premium of $\frac{6.627-5.100}{0.398} = 3.833$ percentage points to hold term deposits with a maturity of more than 24 months compared to term deposits with a maturity of less than 24 months.

Finally, the value of the parameter $\omega = 0.361$ indicates that the outside option has a return lower than the 3-month Euribor rate, thus suggesting that the main alternatives to bank deposits may be a mix of electronic money institutions and money market funds (Xiao, 2020; Im, Li, and Wang, 2025).

Heterogeneity: Northern versus Southern Europe. The specification of column (2) further investigates differences in the interest rate sensitivities of the deposit supply across countries. We split the sample into two groups of countries: Southern countries of the Euro area (Italy, Spain, Portugal, Greece, Slovenia, Malta, and Cyprus) and Northern countries. This difference is geographic, but also broadly corresponds to differences in the yields of sovereign bonds, which on average are higher in Southern countries than in Northern countries during our sample period.

The estimated difference in the interest-rate coefficient between households in Northern and Southern countries equals -0.510, implying that the rate sensitivity of Southern countries' households is significantly lower than that of Northern countries' households.

These estimates provide a micro-foundation for the cross-country differences in deposit betas documented in Figure 3 and Table 3: banks in Southern countries raised deposit rates less during 2022–2024 because their depositors are less rate-sensitive, not because of differences in bank characteristics.

Heterogeneity: Negative versus Positive Policy Rates. The specification of column (3) further investigates whether households and firms across Northern and Southern countries exhibit differential sensitivity to interest rates depending on the level of ECB policy rates. To understand this issue, we split the sample into two regimes depending on whether the ECB set strictly negative rates on its deposit facility (i.e., the period from June 11, 2014, to July 27,

2022) or not. In turn, we allow for the sensitivity to interest rates to depend on eight "types" that correspond to all combinations of households or firms, located in Northern or Southern countries, and during periods of negative or positive policy rates.

Overall, the coefficient estimates of the interest rate reported in column (3) imply that the average value of the sensitivity $\tilde{\alpha}_{mt}$ across markets (calculated with equal weights) equals 1.116 and its standard deviation equals 0.664, thereby suggesting that the interactions between the cross-sectional and time-series market characteristics uncover some important heterogeneity. Interestingly, the estimates imply that depositors are more sensitive during periods of negative policy rates. Finally, all other parameters are almost identical to those reported in columns (1)–(2).

Heterogeneity: Macro Observables. Column (4) reports the estimates of our richer nested logit specification, which assumes that the amount of liquid assets is a function of country-specific variables, that is, $d_{mt} = \sum_w \alpha^w_{mt} w_{mt}$, where the variables w_{mt} include the log of the average household income or the log of the average firm revenue of each country in period t. Moreover, we allow separate parameters α^w_{mt} between households and firms to allow income variables to affect deposits of households and firms differentially. Hence, we hold the parameters underlying the distribution of $\tilde{\alpha}_{mt}$ constant over time, but the distribution changes over time because of the dynamics of household incomes and firm revenues.

The coefficient estimates in column (4) imply that the average value of $\tilde{\alpha}_{mt}$ across markets (with equal weighting) equals 0.747 and its standard deviation across markets equals 0.338. The average is broadly similar to those reported in columns (1)–(3) and the standard deviation reaffirms the large observable heterogeneity of depositors.

This heterogeneity depends on the income variables in interesting ways. Most notably, households' $\tilde{\alpha}_{mt}$ increases with the level of household income, whereas the effect of firm revenue on their rate sensitivity is estimated very imprecisely, perhaps suggesting that firm heterogeneity within markets is more important than the heterogeneity between average firms across countries in accounting for their management of liquid assets and rate sensitivity.

Figure 4 zooms in on one set of estimates that play a prominent role in our analysis: the estimated outside option s_{0mt}. It portrays the average values (weighted by the estimated market size) of the market shares of the outside option s_{0mt} over time for households (solid line) and firms (dashed line), which display two noteworthy patterns. First, the market share of the

Figure 4: Market Shares of Outside Options

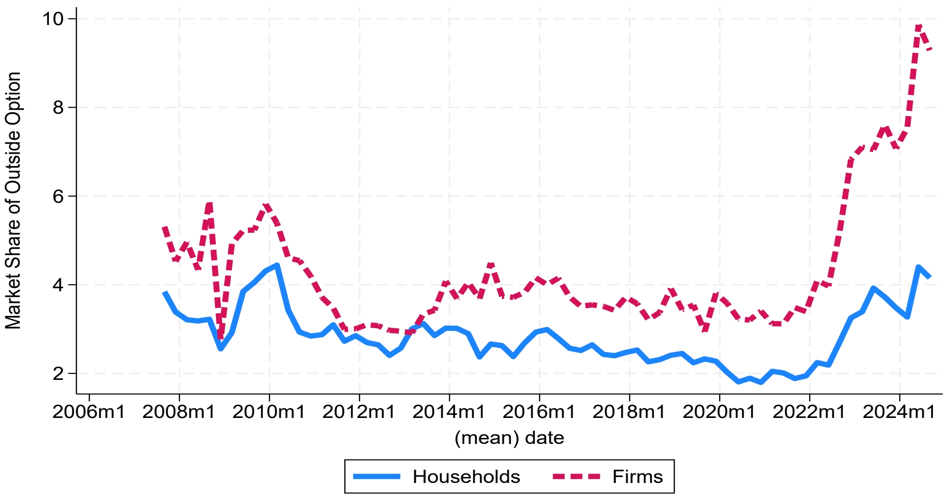


Figure 5: Time-series of Average s_{0mt}

Notes: The figure panel displays the averages of the estimated market share of the outside option for households (solid line) and firms (dashed line) over time.

outside options for firms is higher than that for households, consistent with their higher average rate sensitivity reported in Table 4. Second, the average market share of the outside option for both households and firms decreased from 2008 to 2022 and suddenly spiked when market and policy rates rose sharply from the second quarter of 2022.

6.2 Depositors: Mixed Logit

We now allow for observable and unobservable across- and within-market heterogeneity of deposits (Berry, Levinsohn, and Pakes, 1995). Specifically, we assume that liquid assets d_{imt} equal:

$$d_{imt}\left(y_{imt}, \nu_{imt}\right) = \exp\left(\alpha_m^0 + \alpha_m^y y_{imt} + \sigma_m \nu_{imt}\right), \tag{13}$$

where y_{imt} is either the log of household income (from the HFCS) or firm revenue (from Orbis); ν_{imt} is a standard normal draw; and $\alpha_m^0, \alpha_m^y,$ and σ_m are parameters that vary between households and firms. Thus, the parameters α_h^y and α_f^y correspond to the elasticities of liquid assets with respect to household income and firm revenue, respectively.

The specification (13) is parsimonious yet flexible along two important dimensions. First, because y_{imt} varies both across markets and over time, the distribution of $d_{imt}\left(y_{imt}, \nu_{imt}\right)$ inherits this variation: differences in average household income or firm revenue across countries generate cross-market heterogeneity in liquid assets, while their evolution over time generates changes in the distribution of deposits within each market. Second, the exponential form makes unobservable heterogeneity multiplicative, and thus the term $\exp\left(\sigma_m \nu_{imt}\right)$ scales liquid assets proportionally, so that the dispersion of $d_{imt}\left(y_{imt}, \nu_{imt}\right)$ around its observable component grows with the level of liquid assets, consistent with the empirical concentration of deposits among high-balance depositors that we will document below.

Moreover, we assume that the rate-sensitivity parameter is homogeneous across depositors ($\alpha_{imt} = \alpha$=1) because our aggregate data do not allow us to separately identify heterogeneity in deposits from heterogeneity in rate-sensitivity.[12] Hence, our estimates combine heterogeneity in liquid assets with heterogeneity in rate sensitivities.

Because the estimates of the parameter λ in Table 4 are quite low, we simplify the distribution of ε_{ijmt}, assuming that it follows a GEV distribution that yields a logit probability of depositors' individual choice.[13] Thus, the choice probability in equation (5) and the market share in equation (6) equal:

$$P_{ijmt} = \frac{\exp\left(\delta_{jmt} + \alpha d_{imt} r_{jmt}\right)}{\exp\left(\alpha d_{imt} r_{0mt}\right) + \sum_k \exp\left(\delta_{kmt} + \alpha d_{imt} r_{kmt}\right)} \tag{14}$$

$$s_{jmt} = \frac{\int\int P_{ijmt}\left(\alpha, d_{imt}\left(y_{imt}, \nu_{imt}\right)\right) d_{imt}\left(y_{imt}, \nu_{imt}\right) dF_{y,\nu}(y_{imt}, \nu_{imt})}{\int\int d_{imt}\left(y_{imt}, \nu_{imt}\right) dF_{y,\nu}(y_{imt}, \nu_{imt})}, \tag{15}$$

where $\delta_{jmt} = \beta X_{jmt} + \xi_{jmt}$ combines observable and unobservable non-price attributes of product j, and $F_{y,\nu}(\cdot,\cdot)$ is the joint distribution of the log of household income (or firm revenue) y_{imt} and the unobservable heterogeneity ν_{imt}.

We estimate the vector θ of the model parameters by GMM using the following procedure: (1) We numerically solve the system of market share equations (15) for the vector of unknown δ_{jmt} using the SQUAREM algorithm (Varadhan and Roland, 2008). (2) We construct moments by exploiting the orthogonality condition

$$E(\xi_{jmt} Z_{jmt}) = 0 \tag{16}$$

[12] In principle, we could add some micro-moments on household banking choices constructed from the HFCS to allow for richer heterogeneity in rate sensitivity, following Petrin (2002). However, we are not aware of datasets that allow us to construct comparable micro-moments on firm banking choices.

[13] In principle, we could combine approaches and estimate a random-coefficient nested logit model, following Grigolon and Verboven (2014).

between the unobservable characteristic ξ_{jmt} and the instruments Z_{jmt} described below. (3) We search for the vector θ of parameters that minimize the GMM criterion function:

$$\hat{\theta} \underset{\theta}{\operatorname{argmin}} \, \xi'(\theta) Z W Z' \xi(\theta), \tag{17}$$

where the weighting matrix W is the inverse of the covariance matrix of the instruments $E(Z'Z)$.[14]

Instruments. The mixed logit features additional parameters compared to the nested logit estimated previously, most notably the standard deviations σ_h and σ_f of the unobservable heterogeneity of the rate sensitivity across households and firms, respectively. Identifying these dispersion parameters requires instruments that shift the degree of rate differentiation across products within a market, rather than the level of rates alone. We therefore follow Gandhi and Houde (2025) and Borusyak, Chen, Hull, and Lei (2026) and construct "differentiation IVs" that capture the exogenous variation in how isolated each product is from its rivals in the interest rate space.

The construction proceeds in two steps common to both sets of instruments. First, we obtain fitted interest rates $\hat{r}_{jmt} = E\left(r_{jmt} | X_{jmt}, Z_{jmt}\right)$ from a first-stage regression of observed rates on the exogenous product and bank characteristics X_{jmt} and the exogenous instruments Z_{jmt} that exploit the rotation of the yield curve described above. These fitted rates serve as the exogenous component of each product's position in rate space.

Second, we use these fitted rates to construct two complementary sets of differentiation instruments. Following Gandhi and Houde (2025), the first set measures each product's "isolation" from rivals of the same type (e.g., overnight deposits, term deposits): for each product j, we count the number of rival deposit products of the same type whose fitted rates $\hat{r}_{kmt}$ lie within one quarter of the standard deviation of the standard deviation of the fitted rates of that type in market m and quarter t. A product with few nearby rivals is more isolated and thus faces a less elastic residual demand. Following Borusyak, Chen, Hull, and Lei (2026), the second set uses recentered instruments: j, we compute the average of $\hat{r}_{kmt}$ among rival products of the same type; we regress this average on the exogenous product and bank characteristics X_{jmt}; and we use the residual as the instrument. Both sets of instruments plausibly satisfy the exclusion

[14] Following Dubois and Lasio (2018), we approximate the market share of the outside option using the values estimated in the nested logit specification (4) in Table 4 and displayed in Figure 4.

restriction because, conditional on X_{jmt} and Z_{jmt}, the degree of rate differentiation across rivals reflects variation in market structure rather than any product-specific unobservable ξ_{jmt}. To further help identify the parameters governing observable heterogeneity y_{imt}, we interact both sets of instruments with the mean and standard deviation of y_{imt} in market m and quarter t.

In some specifications, we additionally include instruments that reflect the degree of differentiation across banks with respect to (the log of) the number of branches, constructed according to the same procedure described above for the rate differentiation instruments.[15]

6.2.1 Mixed Logit Estimates

Table 5 reports parameter estimates across two specifications: (1) relies solely on rate differentiation instruments, whereas (2) exploits both rate differentiation and branch differentiation instruments.

Depositors' Rate Sensitivities. The estimates in column (1) imply that the average household and firm rate sensitivity across markets (with equal weighting) equal 0.250 and 0.579, respectively, and their standard deviations within and across markets equal 0.193 and 0.255. The estimates in column (2) are very similar to those of column (1)—the average household and firm rate sensitivity across markets equal 0.257 and 0.684, respectively, and their standard deviations within and across markets equal 0.177 and 0.236—suggesting that the bank differentiation instruments bring limited additional useful information to the parameters' identification.

The estimates reveal important patterns in how depositors' liquid assets and rate sensitivities depend on their characteristics. In column (2), the elasticity of the rate sensitivity/liquid assets with respect to household income α_h^y equals 0.072, and to firm revenue α_f^y equals 0.085. These estimates suggest that higher-income households and higher-revenue firms hold larger amounts of liquid assets, consistent with economic intuition, and the relationship is stronger for households. Moreover, the standard deviation of unobservable household heterogeneity σ_h equals 0.615, and that of unobservable firm heterogeneity σ_f equals 0.158, suggesting that the variations in household and firm liquid assets beyond what household income and firm revenue capture are substantial.

The product and bank attribute estimates align closely with the nested logit results from

[15] The rate differentiation instruments exploit the rate variation across product types, whereas the branch differentiation instruments exploit the variation across banks.

Table 5: Deposit Supply Estimates, Mixed Logit

	(1) GMM-1	(2) GMM-2
Liquid Assets: $d_{imt} = \exp(\alpha_m^0 + \alpha_m^y y_{imt} + \sigma_m \nu_{imt})$		
α_h^0	-2.303***	-2.282***
	(0.068)	(0.066)
α_h^y	0.068***	0.072***
	(0.001)	(0.001)
σ_h	0.678***	0.615***
	(0.000)	(0.001)
α_f^0	-1.167***	-0.927***
	(0.078)	(0.075)
α_f^y	0.092***	0.085***
	(0.001)	(0.001)
σ_f	0.267***	0.158***
	(0.005)	(0.009)
Deposits Redeemable at Notice:		
Less than 3 months	-0.338***	-0.345***
	(0.073)	(0.073)
More than 3 months	-3.073***	-3.051***
	(0.092)	(0.091)
Term Deposits:		
Less than 24 months	-4.780***	-4.789***
	(0.093)	(0.094)
More than 24 months	-6.680***	-6.669***
	(0.082)	(0.082)
Log Number of Branches	0.659***	0.657***
	(0.008)	(0.008)
Log Number of Employees per Branch	0.937***	0.937***
	(0.012)	(0.012)
Investment Grade	-0.219***	-0.219***
	(0.021)	(0.021)
Market and Date FEs	Yes	Yes
Observations	54,739	54,739

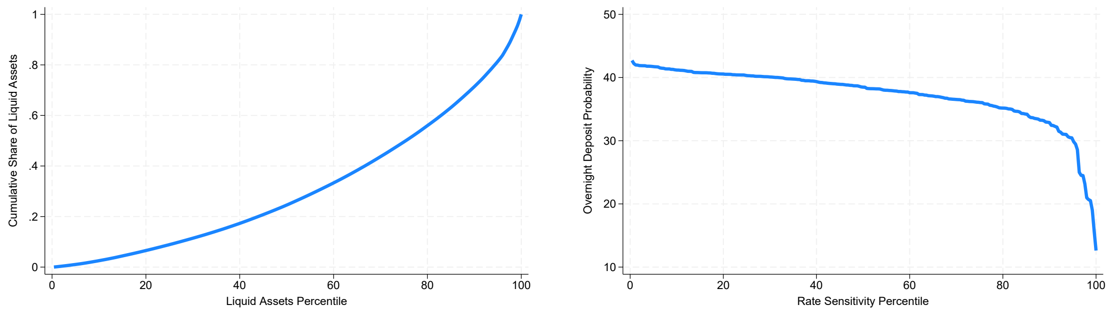
Notes: The table reports the coefficient estimates for the mixed logit deposit supply model. Standard errors in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4. Depositors strongly prefer overnight deposits to longer-maturity products. Banks with larger branch networks and more employees per branch attract significantly more deposits, whereas credit ratings show surprisingly little effect, possibly because deposit insurance neutralizes default risk concerns for most household depositors.

The Heterogeneity of Depositor Behavior. Figure 6 provides insights into the heterogeneous behavior of households. For illustrative purposes, we focus on households in one large market, Italy, which seems to have the most consistent data coverage during our sample period and is representative of the aggregate behavior. We use the estimates in column (1) of Table 5.

The left panel displays the cumulative distribution of household liquid assets/rate sensitivi-

Figure 6: Household Deposits



(a) Liquid Assets d_{imt} (b) Overnight Deposits

Notes: The left panel displays the cumulative share of household deposits d_{imt} at each percentile. The right panel displays the household probability of choosing overnight deposits at each percentile of deposits.

ties in 2024q1, revealing some meaningful concentration: the top 10 percent of depositors hold 28 percent of total household deposits. This convex relationship is consistent with the majority of bank deposit funding depending on a minority of depositors.

The right panel shows how the probability of choosing overnight deposits in 2024q1 varies across the distribution of household liquid assets. For households below the 90th percentile of liquid asset holdings, the overnight deposit probability declines gradually; however, it drops sharply for households above the 90th percentile. This divergence confirms our central hypothesis: following the ECB's 2022 rate hike, rate-sensitive depositors with larger balances shifted to term deposits and outside options as market rates rose, whereas inertial, low-balance depositors remained in overnight accounts despite unfavorable returns.

These patterns provide micro-foundations for the declining deposit betas documented in Section 4. As the most rate-sensitive depositors exit overnight deposit pools during rate-hiking cycles, the remaining depositors exhibit lower average elasticity. Banks optimally respond by increasing markdowns because the marginal depositor has become less responsive to interest rates. The counterfactual analyses in Section 7 quantify this mechanism precisely, but the patterns documented in Figure 6 already suggest its importance: the heterogeneity in liquid assets d_{imt} and thus rate sensitivity shape market dynamics and bank pricing power.

6.3 Banks

We now turn to the supply side, analyzing how banks set deposit rates given the estimated demand parameters. We solve the system of first-order conditions (8) to recover the net margin

$R_{lt} - r_{jmt} - c_{jmt}$ that lender l gains from each deposit product j. Because we impose the non-negativity constraint on household deposit rates, the equilibrium pricing equation includes the Lagrange multiplier μ_{jmt}. Our analysis then proceeds in three steps: (1) We validate the Nash-Bertrand pricing model through specification tests. (2) We decompose deposit rates into their constituent components: gross revenue, markdowns, and the shadow value of the non-negativity constraint. (3) We trace the evolution of markdowns over time to understand the declining deposit beta. We perform this analysis using the mixed-logit estimates of column (2) in Table 5.

6.3.1 Model Validation

Before interpreting our supply-side estimates, we validate the fundamental assumption that banks set deposit rates according to Nash-Bertrand competition as specified in Section 5.2. The Nash-Bertrand pricing condition in equation (9) states that the deposit rate set by a bank on deposit product j should equal its gross revenue minus a markdown, whose main component is the inverse of the semi-elasticity of depositors' supply of funds to product j. More precisely, a one-basis-point increase in a bank's markdown, reflecting greater market power over depositors, should translate into a one-for-one reduction in its deposit rate. Hence, testing whether the markdown enters the pricing equation with a coefficient of exactly -1 provides a direct specification test of the Nash-Bertrand framework.

To implement this test, we adapt the methodology used by Villas-Boas (2007) to our setting by estimating regressions that follow from equation (9):

$$r_{jmt} = [Gross\ \ Revenue_{jmt}] - [Markdown_{jmt}] + [Lagrange\ \ Multiplier_{jmt}], \tag{18}$$

where gross revenue combines returns R_{lt} and costs c_{jmt}; the markdown combines the inverse own-price semi-elasticity $\frac{s_{jmt}}{\frac{\partial s_{jmt}}{\partial r_{jmt}}}$ and cross-elasticity terms capturing multi-product pricing within banks; and the last term captures the shadow value of the non-negativity constraint on household deposit rates, which applies when $r_{jmt} = 0$.[16]

The key econometric challenge is that the estimated markdown may correlate with unobservable components of bank returns R_{lt} and costs c_{jmt}, inducing endogeneity bias. We address this using an instrumental variables strategy that exploits variation in the competitive envi-

[16] Pakes (2017) estimates similar regressions of prices on markups and costs.

Table 6: Bank Estimates

	(1) Interest Rate All	(2) Interest Rate Households	(3) Interest Rate Firms	(4) Gross Revenue All	(5) Gross Revenue Households	(6) Gross Revenue Firms
Markdown	-0.593***	-0.587***	-0.705**			
	(0.075)	(0.068)	(0.241)			
Deposits Redeemable at Notice:						
Less than 3 months	0.418***	0.396***		0.393***	0.344***	
	(0.012)	(0.014)		(0.015)	(0.015)	
More than 3 months	0.832***	0.810***		0.758***	0.707***	
	(0.024)	(0.028)		(0.027)	(0.027)	
Term Deposits:						
Less than 24 months	0.634***	0.655***	0.616***	0.594***	0.595***	0.601***
	(0.022)	(0.038)	(0.028)	(0.024)	(0.046)	(0.024)
More than 24 months	1.030***	0.971***	1.116***	0.877***	0.746***	1.079***
	(0.030)	(0.041)	(0.034)	(0.010)	(0.014)	(0.015)
Log Number of Branches	0.020*	0.027*	0.023	0.064***	0.084***	0.045***
	(0.010)	(0.012)	(0.019)	(0.007)	(0.010)	(0.007)
Log Number of Employees per Branch	0.021**	0.025**	0.027*	0.038***	0.053***	0.034***
	(0.007)	(0.010)	(0.011)	(0.007)	(0.011)	(0.009)
Investment Grade	-0.028***	-0.039***	-0.004	-0.041***	-0.061***	-0.001
	(0.008)	(0.010)	(0.014)	(0.008)	(0.010)	(0.013)
Log(Assets)	0.079***	0.096***	0.041**	0.117***	0.141***	0.055***
	(0.009)	(0.011)	(0.013)	(0.007)	(0.010)	(0.008)
Non-Interest Expenses/Assets	0.039***	0.055***	0.007	0.048***	0.071***	0.004
	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)
Lagrange Multiplier	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,283	32,497	19,786	52,283	32,497	19,786
R^2				0.667	0.592	0.659

Notes: Columns (1)–(3) report coefficient estimates of the regression approximating equation (9), whose dependent variable is the interest rate r_{jmt}. Columns (4)–(6) report coefficient estimates of the regression equation (19), whose dependent variable is the gross margin h_{jmt}. Standard errors in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$.

ronment. Specifically, we instrument the markdown with the log of the number of banking competitors offering products of the same type as product j, and its interaction with the average log household income or firm revenue in market m. These instruments satisfy the relevance condition because, on average, additional competitors reduce each bank's market share and thus increase the magnitude of the own-price semi-elasticity, making the markdown smaller; similarly, a higher household income increases the rate sensitivity and thus the own-price semi-elasticity of depositors. These instruments plausibly satisfy the exclusion restriction because the number of competitors and its interaction with income should affect deposit rates only through competitive pressure on markdowns, not through direct effects on bank asset returns or operating costs specific to product j.

Columns (1)–(3) in Table 6 report the IV estimates. Specification (1) includes both household and firm products, specification (2) includes household products only, and specification

(3) includes firm products only. The estimates provide encouraging support for the Nash-Bertrand pricing model. Deposit products facing lower inverse semi-elasticities (i.e., higher semi-elasticities) feature higher interest rates. In the full sample (Column 1), the estimated coefficient on the markdown equals -0.593, although we can reject the null hypothesis that it equals the theoretical value of -1 at conventional significance levels. The household-only sample (Column 2) yields a similar estimate of -0.587. The firm-only estimate in column (3) of -0.705 is larger in absolute value and has larger standard errors as well, making it statistically indistinguishable from its theoretical value of -1. Taken together, these coefficients suggest that the Nash-Bertrand framework is a reasonable description of bank deposit pricing. Nevertheless, we should acknowledge that banks are multi-product firms and the cross-selling of complementary products is a common business practice, which may account for some departure from Bertrand-Nash pricing on individual products (Basten and Juelsrud, 2026).

Columns (1)–(3) in Table 6 also report estimates of the Lagrange multiplier μ_{jmt} on the non-negativity constraint on household rates. For tractability, we assume that the multiplier is common across lenders and periods, so that $\mu_{jmt} = \mu$ for all household deposit products. The Lagrange multiplier estimates are virtually zero: the estimated coefficients round to -0.000 in the pooled sample (column 1), the household-only sample (column 2), and the firm-only sample. Although theory predicts a non-negative shadow value, the magnitude of these estimates is minimal. Economically, this implies that the non-negativity constraint on household deposit rates contributed negligibly to equilibrium pricing on average across our sample, consistent with the fact that the constraint was not uniformly binding across all banks and periods during the negative rate episode.

6.3.2 Determinants of Gross Revenue

Having validated the pricing model, we turn to understanding what drives gross revenue $h_{jmt} \equiv R_{lt} - c_{jmt}$, decomposing it into observed product attributes X_{jmt}, observed bank attributes Z_{lt}, and unobservable product and bank attributes ν_{jmt}:

$$h_{jmt} = \gamma_X X_{jmt} + \gamma_Z Z_{lt} + \nu_{jmt}. \tag{19}$$

Columns (4)–(6) of Table 6 report estimates of equation (19). Specification (4) includes both household and firm products, specification (5) household products only, and specification (6) firm products only.

Deposit products requiring longer commitment periods generate substantially higher returns. According to the estimates of column (4), relative to overnight deposits, redeemable deposits with notice periods under 3 months earn 0.393 basis points higher return, and those with longer notice periods earn 0.758 basis points more. Term deposits exhibit even steeper maturity premia: products with maturities under 24 months earn 0.877 basis points more than overnight deposits, while those exceeding 24 months earn 0.594 basis points more.

These maturity premia reflect the opportunity cost banks face when locking in deposit funding at fixed rates. During our sample period, the yield curve was typically upward-sloping (except during the sovereign debt crisis and briefly in 2022–2023), meaning banks could invest term deposits in higher-yielding, longer-duration assets. The premia also compensate banks for reduced flexibility, because overnight deposits allow continuous repricing as market conditions change, whereas term deposits fix funding costs.

Larger banks, measured by their branch networks, or their number of employees, or their total assets, earn higher gross revenues on deposits, thereby suggesting economies of scale in deposit-taking. Several mechanisms could drive these scale economies. Larger branch networks may enable banks to gather deposits at lower marginal costs while investing them in higher-yielding assets through diversification and market power in lending markets. More employees per branch could indicate relationship banking that generates cross-selling opportunities: for example, depositors who trust their bank may also borrow, purchase wealth management services, or hold transaction accounts, increasing the total profitability of the deposit relationship beyond interest margin alone. This interpretation aligns with Basten and Juelsrud (2026), who document significant cross-selling synergies in bank-household relationships.

Surprisingly, banks with investment-grade credit ratings earn slightly lower gross revenues (4.1 basis points) than those with lower credit ratings, though the estimate becomes smaller and statistically insignificant in Column (6). This result possibly reflects portfolio composition: highly-rated banks may invest deposits more conservatively, accepting lower returns in exchange for safety. Because our gross revenue measure combines asset returns and operating costs, safer banks with lower-yielding asset portfolios naturally exhibit lower gross revenues, all else equal.

Table B.7 in the Appendix reports regressions similar to those in Table 6 using a smaller sample of banks for which we could retrieve their excess reserves held at central banks and their Tier 1 common capital ratio, both normalized by assets. Perhaps surprisingly, the estimated co-

Table 7: Interest Rate Decomposition

	Interest Rate	Gross Revenue	Inverse Own Semi-Elasticity	Cross Elasticity
Overnight Deposits	23	295	-263	-10
	(45)	(93)	(69)	(44)
Household Deposits	19	330	-297	-14
	(39)	(82)	(51)	(53)
Firm Deposits	31	220	-189	-0
	(56)	(68)	(40)	(3)

Notes: This table presents the decomposition of interest rates (in bps) according to equation (9). Products are weighted by their deposit amounts. Standard deviations across products in parentheses.

efficients on excess reserves and Tier 1 capital ratios are unstable across specifications and small in economic magnitude, consistent with the weak evidence on the effects of bank characteristics on deposit betas documented in Section 4.4.

6.4 The Evolution of Bank Market Power

We now examine the central mechanism of our paper: how depositors' heterogeneity accounts for the dynamics of markdowns over time, driving the declining deposit beta. Table 7 decomposes observed interest rates on overnight deposits into their three components from equation (9): gross revenue, the inverse own semi-elasticity, and cross-elasticity adjustments for multi-product banks.

Pooling all overnight deposit products over time, our estimates imply that the average deposit rate of 23 bps follows from the difference between gross revenues equaling 295 bps and the average markdown (the inverse own semi-elasticity plus the cross-elasticity) equaling 272 bps. Thus, the markdown equals 92 percent of gross revenue, which means that banks enjoy substantial market power over depositors.

Comparing household and firm overnight deposits reveals some interesting differences. Household deposits earn lower interest rates (19 versus 31 bps). This pattern reflects firms' greater rate sensitivity documented in Section 6: because firms respond more to rate changes than households do, banks offer higher rates (smaller markdowns) to retain their deposits.

Overall, Table 7 indicates that markdown differences between households and firms qualitatively match interest rate differences in the respective overnight deposit rates. The quantitative differences in markdowns between households and firms are larger than the corresponding differences in deposit rates, perhaps suggesting that banks may earn higher returns/margins on household deposits than on firm deposits, likely due to lower operating costs of serving household depositors.

Comparison to Existing US Estimates. Our estimated average revenues align well with prior research on US banks and deposits.

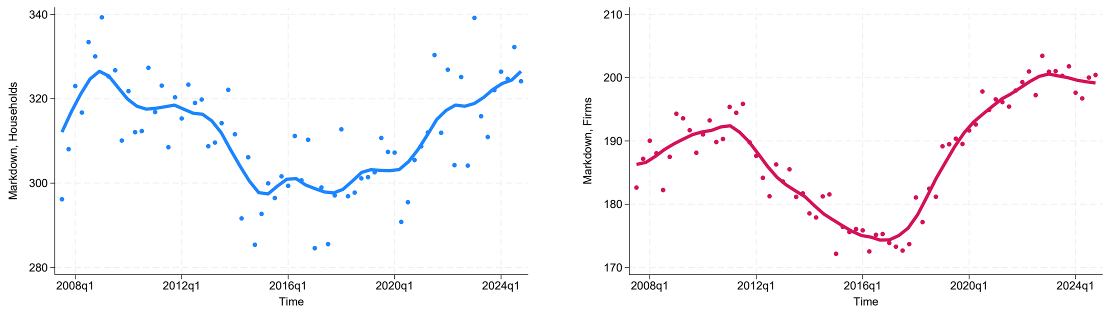
According to Table 7, Euro area banks enjoy a spread of $295 - 23 = 272$ bps, slightly higher than the intermediation spreads that Philippon (2015) documents for US banks. However, these differences in intermediation spreads are consistent with the corresponding differences in deposit betas between US and Euro area banks. Drechsler, Savov, and Schnabl (2017) estimate a long-run deposit beta of approximately 0.40 for US household sight deposits during 1997–2013, whereas our estimate in Table 1 equals 0.247 for the Euro area during 2007–2024. Lower pass-through rates translate directly into larger markdowns and larger intermediation spreads: when policy rates rise, Euro area banks increase deposit rates less than US banks, thereby extracting higher net revenues from the intermediation process. Our structural decomposition in Table 7 confirms this mechanism, as markdowns account for 92 percent of gross revenues in the Euro area, higher than comparable US estimates (Drechsler, Savov, and Schnabl, 2021).

The consistency of our gross revenue estimates across independent methodologies and banking systems strengthens confidence in our framework and estimates, and the differences in deposit betas and markdowns highlight important institutional variation in the extent of bank market power across these two financial systems.

Markdown Dynamics and Declining Deposit Betas. Figure 7 traces the evolution of markdowns on overnight deposits from 2007 to 2024. For household deposits (panel a), markdowns fluctuated around 309 basis points during 2007–2021, with a downward trend in the period of negative policy rates when the yield curve was compressed. However, markdowns increased sharply starting in 2022, reaching 326 basis points by 2024q1. Firm deposit markdowns (panel b) display similar dynamics. Markdowns bottomed out during the period of negative rates, and then peaked during the 2022 rate hiking cycle.

These dynamics directly account for the declining deposit beta documented in Section 4. When the ECB raised rates in 2022–2023, banks did not proportionally increase deposit rates because their markdowns rose simultaneously. The estimated model reveals that this sluggish pass-through is the equilibrium consequence of rising markdowns driven by compositional change

Figure 7: Markdowns, Overnight Deposits



(a) Average Markdown, Households

(b) Average Markdown, Firms

Notes: The panels display the deposit-weighted average markdown for household (left panel) and firm (right panel) overnight deposits over time. The dots are the averages in each quarter; the lines display the local polynomial fit.

in the depositor pool: the most rate-sensitive depositors shifted funds to term deposits and outside options (e.g., money market funds) as these alternatives became attractive after many years of low interest rates. As rate-sensitive depositors exited, the remaining pool of overnight deposits consisted disproportionately of inertial, low-balance depositors who value liquidity and convenience over yield maximization. Banks optimally responded to this compositional shift by exploiting the reduced elasticity of marginal depositors and thus increasing their markdowns. The estimates in Tables 4 and 5 quantified this heterogeneity; the markdown analysis now shows its direct pricing implications.

Critically, this mechanism differs from structural explanations for low deposit betas based on market concentration or bank balance sheet characteristics. The regressions in Table 3 showed that bank-level variables (e.g., assets or credit ratings) have minimal predictive power for deposit betas, a finding that is perhaps puzzling at the descriptive stage. The markdown analysis now provides the explanation: the main driver is a demand-side phenomenon common to all banks within a market, namely the change in the composition of depositors remaining in overnight accounts.

The counterfactual analyses in Section 7 will further formalize this intuition, quantifying how deposit rates would have evolved absent heterogeneity in depositor rate sensitivity.

7 Counterfactual Analyses

We use our estimated model to perform counterfactual analyses that quantify the relative importance of depositor and bank heterogeneity for deposit market outcomes. These exercises illuminate the mechanisms behind declining deposit betas and allow us to assess how alternative depositor characteristics and bank attributes would affect rates, bank profits, and depositor welfare.

Our counterfactual computations follow Morrow and Skerlos (2011). For each counterfactual scenario, we: (1) modify the relevant parameters while holding all others at their estimated values; (2) resolve for depositor choices given the new parameter values; (3) compute banks' optimal rate responses to the new depositor behavior; (4) iterate between steps (2)–(3) until convergence to a new equilibrium. We perform all counterfactuals using the mixed logit demand estimates in column (1) of Table 5.

7.1 The Role of Depositor Heterogeneity

Our first set of counterfactuals examines how heterogeneity in depositor rate sensitivity and liquid assets affects equilibrium outcomes.

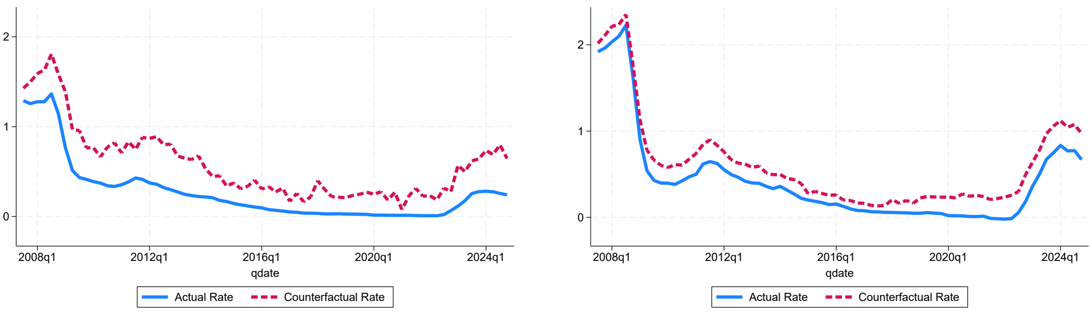
Specifically, we assume all depositors in market m and period t share identical rate sensitivity and liquid assets, which we set equal to the deposit-weighted average sensitivity in market m in 2008Q1. Hence, this counterfactual removes observable income/revenue-driven heterogeneity and unobservable heterogeneity in deposits, but preserves differences in average sensitivity across markets.[17]

Figure 8 displays the actual and counterfactual deposit rates on overnight deposits for households (panel a) and firms (panel b). Several interesting patterns emerge. First, household overnight deposit rates would have been, on average, 31 bps higher than actual rates during our sample period. The gap widens in 2022–2024, equaling 45 bps in 2024q1. This reflects our core finding: when rate-sensitive depositors exit overnight deposits, markdowns rise because the remaining depositors are less elastic. Homogenizing depositors by their average sensitivity yields a counterfactual world in which banks cannot exploit compositional shifts.

Second, the patterns are qualitatively similar but quantitatively smaller for firm deposits. Counterfactual rates exceed actual rates on average by 19 bps during 2007–2024, and by 29 bps in 2024q1.

[17]We also considered a second case, in which we further homogenize depositors by setting all households and firms to have the same average rate sensitivity over time (equal to the respective deposit-weighted average sensitivity estimated in 2008Q1). Thus, this second case eliminates cross-country differences (e.g., between Northern and Southern Europe) and over time, while preserving the difference between households and firms. Results are quite similar to those described below.

Figure 8: Counterfactual Rates on Overnight Deposits, No Depositors Heterogeneity



(a) Rates, Households (b) Rates, Firms

Notes: The panels display the actual (solid line) and counterfactual (dashed line) average interest rates on household (left panel) and firm (right panel) overnight deposits over time in a counterfactual market with no depositor heterogeneity.

Counterfactual Deposit Betas. To quantify the impact of depositor heterogeneity on deposit pricing dynamics, Figure 9 traces the evolution of simple deposit betas, computed as the ratio of cumulative deposit rate changes to cumulative DFR changes for the period 2022–2024. The figure also displays the simple beta of Figure 2 for 2022–2024, enabling transparent comparison between actual and counterfactual outcomes.

The stark divergence during 2022–2024 quantifies our central finding: declining deposit betas primarily reflect changing depositor composition rather than structural market factors. Absent heterogeneity, banks would have raised rates by a larger amount during this period, implying a long-term beta of 0.11, almost twice as large as the observed one of 0.06.

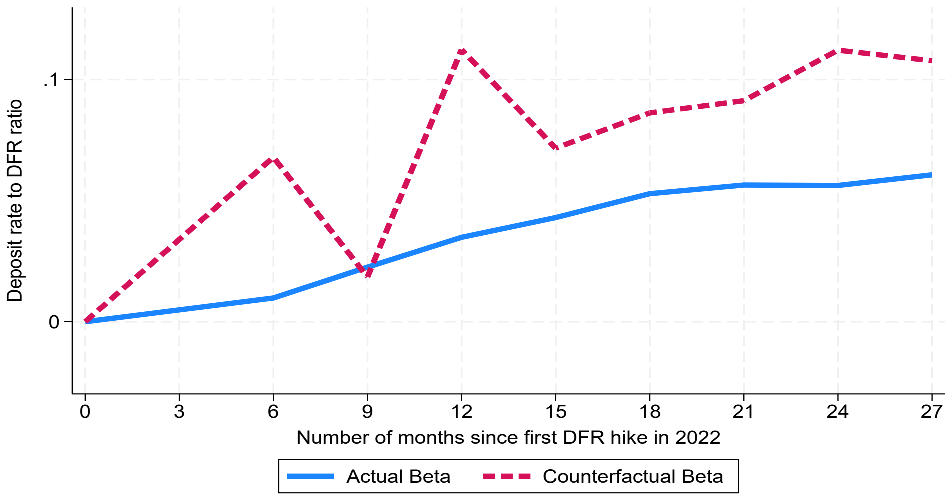
7.2 The Role of Banks' Heterogeneity

Our second counterfactual examines how heterogeneity across banks affects deposit pricing. Specifically, this counterfactual eliminates the role of bank characteristics (assets, branches, capital ratios, etc.) in determining gross revenues, while preserving heterogeneity in costs between overnight deposits, term deposits, and deposits redeemable at notice within markets.

Figure 10 displays actual and counterfactual deposit rates under this scenario. Surprisingly, this counterfactual produces rates that closely track actual rates, typically within a few basis points: the average difference between counterfactual and actual rates is bps for both households and firms during our sample period.

The limited impact of bank heterogeneity stands in stark contrast to the large effects of

Figure 9: Counterfactual Deposit Betas in 2022–2024



depositor heterogeneity. This asymmetry is consistent with the weak correlations between bank characteristics and deposit betas documented in Table 3. The rate decomposition in Table 7 shows that markdowns account for the vast majority of gross revenues, so cross-bank variation in costs is a second-order determinant of deposit rates. Moreover, because depositors are inelastic, a bank offering marginally higher rates attracts relatively few additional deposits, weakening the competitive pressure on deposit pricing.

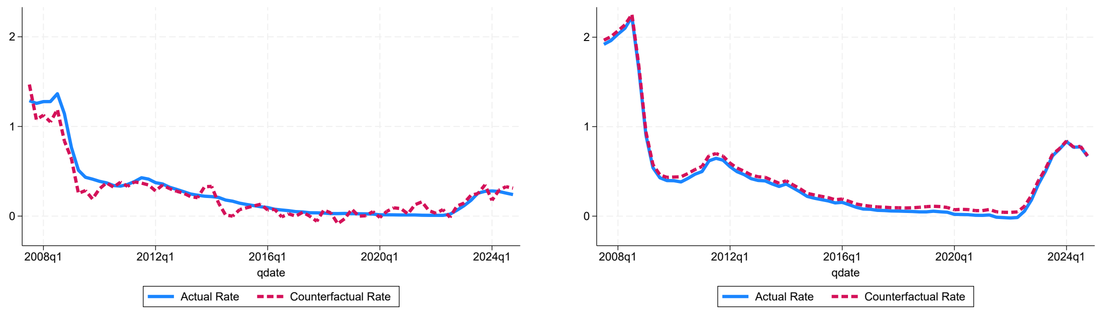
Taken together, these results cast doubt on the view that the main explanations for the sluggish deposit betas in 2022–2024 center on bank balance sheets, such as the accumulation of excess liquidity from ECB refinancing operations and asset purchases or higher capital requirements, because these explanations operate precisely through the bank channels that our counterfactual finds to have limited bearing on equilibrium deposit rates.

8 Conclusion

This paper investigates the causes of the decline in deposit betas in the Euro area. We combine several data sources to compile a comprehensive dataset of deposit markets during the period 2007–2024, and estimate an equilibrium model of deposit supply and demand that features rich heterogeneity in depositors' rate sensitivity.

Our central finding is that the changing composition of depositors in overnight accounts

Figure 10: Counterfactual Rates on Overnight Deposits, No Bank Heterogeneity



(a) Rates, Households

(b) Rates, Firms

Notes: The panels display the actual (solid line) and counterfactual (dashed line) average interest rates on household (left panel) and firm (right panel) overnight deposits over time in a counterfactual market with no bank heterogeneity.

primarily accounts for the declining deposit beta. Higher-income households and higher-revenue firms hold disproportionately large deposits and are significantly more responsive to interest rate differentials. During the prolonged period of negative ECB policy rates (2014–2022), a compressed yield curve led nearly all depositor types to maintain similar allocations to overnight deposits. When the ECB raised policy rates in 2022, the most rate-sensitive depositors shifted funds to term deposits and outside options such as money market funds, whereas inertial, low-balance depositors remained in overnight accounts. Banks optimally responded to this compositional shift by increasing markdowns, which rose by approximately 40 percent relative to pre-2020 levels. Our counterfactual analyses confirm the quantitative importance of this mechanism: removing depositor heterogeneity would have more than doubled the deposit beta during the 2022–2024 hiking cycle. In contrast, removing bank heterogeneity has limited effects on equilibrium deposit rates.

Beyond the specific findings, our analysis illustrates the value of integrating descriptive and structural approaches in the study of deposit markets. The descriptive patterns that we document in Section 4 (i.e., low and declining deposit betas; asymmetric pass-through across monetary policy regimes; and cross-country heterogeneity) are consistent with several competing explanations at the descriptive stage. The estimated model disciplines the interpretation by estimating depositors' rate sensitivity and banks' markdowns jointly, thus showing that the descriptive patterns follow from a common mechanism, namely the endogenous change in the composition of the depositor pool over the interest rate cycle.

These findings carry several implications. For monetary policy transmission, our results suggest that the effectiveness of the deposit channel depends not only on the level of policy rates but also on their recent history. A prolonged period of low or negative rates compresses the distribution of depositor behavior, as most depositors find it optimal to remain in overnight accounts. The subsequent normalization then triggers a compositional shift that weakens pass-through precisely when central banks seek to tighten financial conditions. More broadly, this mechanism implies that deposit betas are state-dependent in a way that standard reduced-form pass-through regressions cannot capture: the same policy rate increase can generate very different deposit rate responses depending on the composition of the depositor pool at the time of the increase.

For financial regulation and competition policy, the limited role of bank characteristics and market concentration in explaining deposit betas suggests that interventions targeting market structure alone may have modest effects on deposit pricing. Our results suggest a complementary, and arguably more important, channel: even in a competitive banking market, deposit rates will respond sluggishly to policy rate increases if the remaining pool of overnight depositors is composed predominantly of rate-insensitive individuals. Policies aimed at increasing depositors' financial literacy, their awareness of alternative savings products, or their ability to compare and switch between deposit products could alter the composition of the depositor pool and, through banks' equilibrium pricing responses, raise the level of deposit rates. Similarly, the recent growth of digital platforms that aggregate and compare deposit rates across banks could increase the effective rate sensitivity of retail depositors, with potentially significant effects on pass-through.

Finally, our analysis points to implications for financial stability. The compositional dynamics we document create a feedback loop: when policy rates rise, the exit of rate-sensitive depositors increases banks' market power over the remaining depositors, boosting net interest margins in the short run. However, this same mechanism implies that banks become increasingly reliant on a base of inertial depositors whose behavior during periods of financial stress, when perhaps salience and attention to deposit rates may suddenly increase, is difficult to predict from their behavior in normal times. Understanding the stability of this "inertial" deposit base under stress scenarios is an important question that we leave for future research.

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APPENDIX

A Household Income and Firm Revenue Distributions

A.1 Household Finance and Consumption Survey

Overview. The Household Finance and Consumption Survey (HFCS) is the Eurosystem's harmonised survey of household finances across European Union member states. It provides rich cross-sectional information on household balance sheets, income, and consumption, and is the primary source for the household income distributions used in our analysis.

The survey has been conducted in four waves, with reference years broadly corresponding to 2010, 2014, 2017, and 2021.[A.1] Spain is a partial exception: an initial round conducted in 2008 was assigned a distinct country code to differentiate it from the 2011 collection round, both of which are contained within the 2010 wave. We assign reference years 2008 and 2011 to Spain accordingly, while maintaining the standard reference year of 2010 for all other countries in that wave. Within-wave revisions also occur: for instance, the 2010-wave data used in this study correspond to the updated release of March 2020, rather than the initial April 2013 release.

Country coverage and sample sizes vary across waves. Wave 2010 covers 16 countries; Wave 2014 adds Estonia, Hungary, Ireland, Latvia, Poland, and an expanded Slovenia sample; Wave 2017 further incorporates Croatia and Lithuania; and Wave 2021 adds the Czech Republic while Poland exits. Sample sizes per country typically range from 1,000 to 6,000 households per wave. This staggered entry reflects the phased implementation of the HFCS across member states and differences in national sampling strategies.

Fitting Income Distributions. Each wave is multiply imputed: five separate imputed datasets (implicates) are provided to reflect uncertainty in the imputation procedure. We average across the five implicates to obtain a single cross-sectional snapshot of the income distribution for each survey wave.

The income variable we use is `DI2000`, which measures total gross household income. This variable aggregates employment and self-employment income, rental income from real estate, returns on financial investments, pension benefits, and transfers from both public programmes and private sources, thus capturing the full scope of household economic resources.

[A.1] The HFCS also permits the construction of a panel using the subsample of households surveyed in multiple waves, but this approach is considered experimental and lacks dedicated longitudinal weights.

For each reference year and country, we fit a log-normal distribution to gross household income using cross-sectional survey weights to ensure representativeness of the underlying population. The reference years included are $t \in \{2010, 2014, 2017, 2021\}$ for all countries in our sample, and $t \in \{2008, 2011, 2014, 2017, 2021\}$ for Spain.

Because the HFCS is conducted only every three to four years, we linearly interpolate the parameters of the fitted log-normal distributions between survey waves to obtain annual income distributions for each country.

A.2 Orbis

Overview. Orbis is a global commercial database maintained by Moody's that compiles financial information on over 580 million private and publicly listed companies from more than 170 national sources.[A.2] Its standardised cross-country format makes it well suited for constructing comparable firm revenue distributions across European countries.

We collect annual operating revenues from 2007 to 2021 for firms headquartered in the European countries covered by the HFCS. A firm is included in our sample if it reports operating revenues in at least one of the ten years preceding its last available observation. Revenues were downloaded in USD and converted to EUR using annual average exchange rates published by the ECB.[A.3]

Fitting Firm Revenue Distributions. For each country and year, we restrict the sample to firms with strictly positive operating revenues and fit a log-normal distribution to the resulting revenue data.

[A.2]Accessed October 19, 2025. See https://www.moodys.com/web/en/us/capabilities/company-reference-data/orbis.html.

[A.3]Daily rates are averaged to the annual level. Source: https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-usd.en.html.

B Robustness Checks

This appendix presents supplementary figures and tables showing robustness checks for the descriptive analyses in Section 4, as well as for the model estimation results in Section 6.

Figure B.1 replicates the right panel of Figure 1 using the ECB's Main Refinancing Operation Rate as the policy rate.

Table B.1 replicates Table 1 using the 3-month Euribor in quarter t as the main explanatory variable $r_t^{€}$.

Table B.2 reports the estimates of an error-correction model of the pass-through of the Euribor rate to deposit rates.

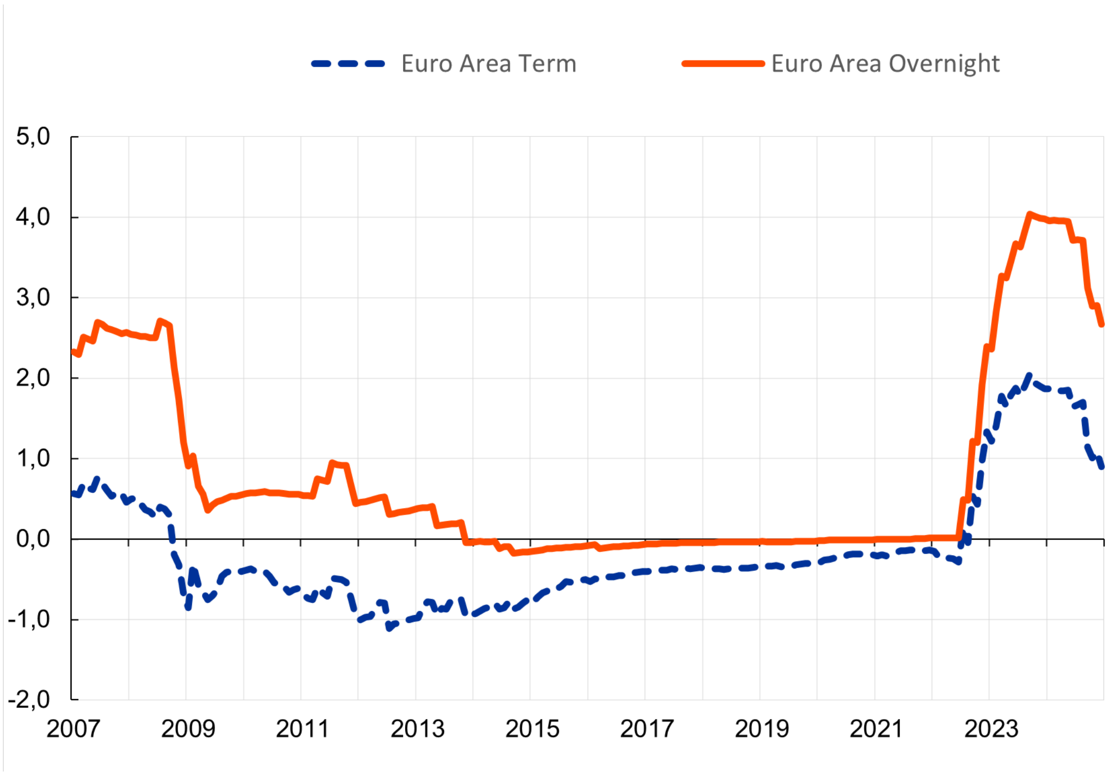
Table B.3 displays the long and short-run interest rate pass-through estimated from the coefficients of the error correction model estimated in Table B.2. These values are very similar to those obtained from Tables 1 and B.1.

Tables B.4 and B.5 check the robustness of the results in Table 3 by using aggregate macro controls only and bank characteristics only, respectively.

Table B.6 reports the coefficient estimates of regressions that study the correlation between simple betas and bank characteristics across different monetary policy regimes.

Table B.7 replicates the regressions in Table 6 using a smaller sample of banks for which we could retrieve their excess reserves held at central banks and their Tier 1 common capital ratio, both normalized by assets. The table shows inconclusive evidence that their reserves or Tier 1 capital ratios affect their deposit rates or gross revenues.

Figure B.1: Time-series of Spreads in the Euro Area, MRO



Notes: The figure displays the difference between the ECB Main Refinancing Operations Rate and the volume-weighted average deposit rates on overnight deposits (solid line) and term deposits (dashed line).

Table B.1: Deposit Betas, Euribor

	(1) Sight, Households	(2) Sight, Firms	(3) Term
$\Delta r_t^{€}$	0.106***	0.201***	0.461***
	(0.014)	(0.016)	(0.022)
$\Delta r_{t-1}^{€}$	0.096***	0.162***	0.303***
	(0.012)	(0.016)	(0.021)
$\Delta r_{t-2}^{€}$	0.011	-0.010	-0.032**
	(0.007)	(0.010)	(0.014)
HHI_t	-0.149***	-0.148**	-0.446***
	(0.050)	(0.065)	(0.120)
Macro Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Observations	11,457	11,924	12,012

Notes: The dependent variable in columns (1)–(3) is the change in interest rates for household, corporate sight, and term deposits, respectively. The interest rate $r_t^{€}$ is the 3-month Euribor. The sample period is 2008Q2 to 2024Q4. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table B.2: Deposit Pass-through, Error-correction Model

	(1) HH-SI	(2) NFC-SI	(3) DTE
L.IR	-0.100***	-0.128***	-0.231***
	(0.013)	(0.013)	(0.012)
L.Δ IR	0.041	-0.084	-0.197***
	(0.040)	(0.052)	(0.022)
L. Short-term rate	0.021***	0.045***	0.171***
	(0.003)	(0.004)	(0.010)
Δ Short-term rate	0.094***	0.187***	0.454***
	(0.013)	(0.014)	(0.019)
L.Δ Short-term rate	0.066***	0.104***	0.314***
	(0.014)	(0.017)	(0.023)
L.Δ Long-term rate	-0.005***	-0.010***	0.003
	(0.002)	(0.003)	(0.006)
N	11458	12268	11974
Macro controls	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes

Notes: The dependent variable in columns (1) to (3) is the interest rates for household, corporate sight, and term deposits, respectively. HH-SI, NFC-SI, and D-TE refer to interest rates for household sight, corporate sight, and term deposits, respectively. The short-term interest rate is the 3-month Euribor. The sample period is 2008Q2 to 2024Q4. The following macroeconomic control variables were included: the change in the long-term nominal yield, unemployment growth, inflation growth, real GDP growth, and the change in the Herfindahl-Hirsch index of deposit volumes. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table B.3: Short and Long-run Interest Rate Pass-through

	HH-SI	NFC-SI	D-TE
Long-run	0.205***	0.361***	0.715***
	(0.014)	(0.019)	(0.011)
Short-run	0.097***	0.187***	0.441***
	(0.011)	(0.012)	(0.017)
HH Index	-0.217**	-0.512**	-1.917**
	(0.075)	(0.100)	(0.227)
Speed of adjustment	-0.11	-0.13	-0.21
Macro controls	yes	yes	yes
Bank fixed effects	yes	yes	yes
Observations	11,452	12,213	11,926
Adjusted R-squared	23%	29%	40%

Notes: Long and short-run interest rate pass-through estimated from the coefficients of the error correction model estimated in Table B.2. HH-SI, NFC-SI, and D-TE refer to interest rates for household sight, corporate sight, and term deposits, respectively.

Table B.4: Deposit Betas across Markets

	(1) Sight, Households	(2) Sight, Firms	(3) Term
$\Delta r_t^{€}$	-1.559***	-1.687***	-3.551***
	(0.581)	(0.486)	(0.688)
×Log (GDP per capita$_t$)	0.177***	0.199***	0.405***
	(0.061)	(0.051)	(0.068)
×Log (Unemployment Rate$_t$)	0.058**	0.098***	0.271***
	(0.025)	(0.031)	(0.064)
$\Delta r_{t-1}^{€}$	-0.577	-0.055	2.583***
	(0.583)	(0.354)	(0.762)
×Log (GDP per capita$_{t-1}$)	0.065	0.003	-0.255***
	(0.061)	(0.036)	(0.075)
×Log (Unemployment Rate$_{t-1}$)	0.024	0.061**	-0.057
	(0.024)	(0.027)	(0.065)
$\Delta r_{t-2}^{€}$	0.519	0.338	0.053
	(0.358)	(0.251)	(0.630)
×Log (GDP per capita$_{t-2}$)	-0.044	-0.028	0.006
	(0.037)	(0.024)	(0.061)
×Log (Unemployment Rate$_{t-2}$)	-0.039*	-0.020	0.010
	(0.021)	(0.027)	(0.057)
Macro Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Observations	10,586	10,958	11,016

The dependent variable in columns (1)–(3) is the change in interest rates for household, corporate sight, and term deposits, respectively. The interest rate $r_t^{€}$ is the ECB DFR. The sample period is 2008Q2 to 2024Q4. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table B.5: Deposit Betas across Banks

	(1) Sight, Households	(2) Sight, Firms	(3) Term
$\Delta r_t^{€}$	-0.017	0.006	0.763***
	(0.136)	(0.144)	(0.180)
$\times$Log (Assets$_t$)	0.015	0.041***	0.013
	(0.013)	(0.014)	(0.016)
$\times$CET1 Ratio$_t$	0.000	-0.010**	-0.026***
	(0.004)	(0.005)	(0.006)
$\times$Investment Grade$_t$	0.027	0.002	0.084
	(0.030)	(0.039)	(0.057)
$\Delta r_{t-1}^{€}$	0.272**	0.222**	0.023
	(0.118)	(0.104)	(0.166)
$\times$Log (Assets$_{t-1}$)	-0.014	-0.004	0.015
	(0.011)	(0.010)	(0.014)
$\times$CET1 Ratio$_{t-1}$	-0.005**	-0.003	0.001
	(0.002)	(0.003)	(0.005)
$\times$Investment Grade$_{t-1}$	0.005	-0.086**	-0.031
	(0.024)	(0.034)	(0.055)
$\Delta r_{t-2}^{€}$	-0.113*	-0.064	-0.054
	(0.063)	(0.092)	(0.163)
$\times$Log (Assets$_{t-2}$)	0.013*	0.007	0.003
	(0.007)	(0.009)	(0.014)
$\times$CET1 Ratio$_{t-2}$	0.002	0.001	0.011**
	(0.002)	(0.003)	(0.005)
$\times$Investment Grade$_{t-2}$	-0.001	0.041	-0.022
	(0.014)	(0.027)	(0.048)
Macro Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Observations	9,662	9,756	9,954

The dependent variable in columns (1)–(3) is the change in interest rates for household, corporate sight, and term deposits, respectively. The interest rate $r_t^{€}$ is the ECB DFR. The sample period is 2008Q2 to 2024Q4. Standard errors are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table B.6: Simple Betas and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NFC				Households			
	Tight	Loose	Negative	Full	Tight	Loose	Negative	Full
CET1 ratio	0.004	-0.028	0.023	0.001	0.010	0.060	0.007	0.001
	(0.008)	(0.039)	(0.023)	(0.000)	(0.008)	(0.036)	(0.019)	(0.000)
Non-Interest Expenses/Assets	-0.063	-0.133	0.214**	0.003	-0.020	-0.068	0.075	0.006
	(0.045)	(0.100)	(0.092)	(0.004)	(0.038)	(0.075)	(0.151)	(0.003)
Log (Assets)	0.041*	0.036	-0.029	-0.004	0.015	0.109	0.000	-0.002
	(0.021)	(0.138)	(0.067)	(0.003)	(0.016)	(0.113)	(0.069)	(0.002)
Credit rating	-0.020**	-0.038	0.016	0.000	-0.017**	-0.010	0.029	-0.001
	(0.009)	(0.036)	(0.025)	(0.001)	(0.007)	(0.055)	(0.027)	(0.001)
Log (Number of branches)	-0.011	0.037	0.037	0.000	-0.015*	-0.142***	-0.047	-0.001*
	(0.010)	(0.068)	(0.037)	(0.001)	(0.008)	(0.048)	(0.056)	(0.001)
N	101	69	98	125	99	67	97	125

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The table shows the results of the cross-sectional regressions of the simple beta of sight deposits for non-financial corporate (NFC) and households (HH). The dependent variable is the simple deposit beta calculated as the ratio between the cumulative change in the sight deposit interest rate and the cumulative change in the ECB deposit facility rate. Tight, easing, and negative rate MP regimes refer to the periods 2022Q3–2024Q1, 2011Q4–2013Q1, and 2014Q2–2022Q2, respectively. Columns (4) and (8) refer to the estimations using the simple beta estimated over the full sample period ranging from 2007Q3 to 2024Q4.

Table B.7: Bank Estimates, Sample with Excess Liquidity and Tier 1 Capital Ratio

	(1) Interest Rate All	(2) Interest Rate Households	(3) Interest Rate Firms	(4) Gross Revenue All	(5) Gross Revenue Households	(6) Gross Revenue Firms
Markdown	-0.412***	-0.726***	-0.128			
	(0.093)	(0.143)	(0.250)			
Deposits Redeemable at Notice:						
Less than 3 months	0.338***	0.285***		0.307***	0.253***	
	(0.011)	(0.021)		(0.015)	(0.015)	
More than 3 months	0.709***	0.607***		0.594***	0.535***	
	(0.027)	(0.046)		(0.027)	(0.027)	
Term Deposits:						
Less than 24 months	0.526***	0.533***	0.495***	0.475***	0.496***	0.463***
	(0.021)	(0.045)	(0.028)	(0.025)	(0.045)	(0.025)
More than 24 months	0.939***	0.746***	1.039***	0.749***	0.617***	0.947***
	(0.032)	(0.073)	(0.031)	(0.011)	(0.015)	(0.016)
Log Number of Branches	0.029	0.155***	-0.041	0.148***	0.235***	0.025**
	(0.020)	(0.040)	(0.021)	(0.009)	(0.014)	(0.009)
Log Number of Employees per Branch	0.053***	0.164***	-0.010	0.136***	0.227***	0.012
	(0.015)	(0.032)	(0.014)	(0.010)	(0.015)	(0.012)
Investment Grade	-0.064***	-0.098***	-0.066**	-0.089***	-0.124***	-0.031
	(0.010)	(0.017)	(0.020)	(0.009)	(0.011)	(0.017)
Log(Assets)	0.040***	0.012	0.042*	0.045***	0.002	0.089***
	(0.006)	(0.010)	(0.017)	(0.009)	(0.013)	(0.009)
Non-Interest Expenses/Assets	0.006	-0.015*	0.027***	-0.006	-0.024**	0.023**
	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)	(0.007)
Excess Liquidity/Assets	0.054	-0.333**	0.316*	-0.034	-0.465***	0.540***
	(0.070)	(0.117)	(0.136)	(0.082)	(0.110)	(0.116)
Tier 1 Capital Ratio	-0.000	0.007*	-0.003*	0.006***	0.012***	0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
Lagrange Multiplier	-0.000**	-0.000**	-0.000***	-0.000**	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,420	22,706	13,714	36,420	22,706	13,714
R^2				0.729	0.691	0.663

Notes: This table reports the coefficient estimates of regressions similar to those in Table 6 using a smaller sample of banks for which we could retrieve their excess reserves held at central banks and their Tier 1 common capital ratio, both normalized by assets. Columns (1)–(3) report coefficient estimates of the regression approximating equation (9), whose dependent variable is the interest rate r_{jmt}. Columns (4)–(6) report coefficient estimates of the regression equation (19), whose dependent variable is the gross margin h_{jmt}. Standard errors in parentheses * $p < .10$, ** $p < .05$, *** $p < .01$.

C Model: Nested Logit Elasticities

Given the nested logit demand, the semi-elasticity of the product market share with respect to its own interest rate equals:

$$\frac{\partial \log(s_{jmt})}{\partial r_{jmt}} = \frac{\alpha_{mt}}{1-\lambda}(1 - s_{jmt|B(j)}) + \alpha_{mt} s_{jmt|B(j)} - \alpha_{mt} s_{jmt}. \tag{C.1}$$

The semi-elasticity of the product market share with respect to the interest rate of a different product k in the same nest ($B(k) = B(j)$) equals:

$$\frac{\partial \log(s_{jmt})}{\partial r_{kmt}} = -\alpha_{mt} \frac{\lambda}{1-\lambda} s_{kmt|B(k)} - \alpha_{mt} s_{kmt}. \tag{C.2}$$

The semi-elasticity of the product market share with respect to the interest rate of a different product l in a different nest ($B(l) \neq B(j)$) equals :

$$\frac{\partial \log(s_{jmt})}{\partial r_{lmt}} = -\alpha_{mt} s_{lmt}. \tag{C.3}$$