What Makes Depositors Tick?

Bank Data Insights into Households' Liquid Asset Allocation

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Abstract

We use transaction-level data from a major Icelandic bank—servicing about one third of the population—to study households' portfolio allocation within liquid, short-term, safe assets—checking, savings, and brokered liquid funds—that are identical in risk, maturity, and liquidity but offer different yields. These assets are the main source of liquid financial wealth for households and the largest source of funding for banks. Despite instantaneous, costless transfers, most households barely respond to interest-rate spreads. We find that wealthy households are roughly ten times more responsive than the average, place larger shares in high-yield assets, and earn about two percentage points higher returns on their liquid portfolios than low-wealth households. Survey evidence suggests that financial literacy and inflation knowledge amplify responsiveness to interest rates. We show that business-cycle fluctuations in the share of low-rate deposits are driven primarily by active reallocation among wealthy depositors. Also, we find that standard portfolio-choice models with state- or time-dependent frictions, calibrated to match our estimated moments, are able to reproduce cross-sectional holdings but overstate households' sensitivity to interest rates.

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1 Introduction

The allocation of household liquid safe assets is central to economics and finance as it links monetary policy, the banking sector, and the real economy. The distribution of liquid assets across households shapes the transmission of monetary and fiscal policy (Auclert et al., 2025). The stickiness of bank deposits—the main form of household liquid assets—affects bank lending (Hanson et al., 2015), and cyclical fluctuations in deposits influence financial intermediation over the business cycle (Drechsler et al., 2017). Furthermore, for most households, liquid, short-term, safe assets are both the largest component of their financial portfolios and key means to smooth consumption (Badarinza et al., 2016). Yet, despite their importance, we know little about the determinants of their allocation.

In this paper, we contribute to the understanding of household financial portfolio allocation where we focus on this important asset class, i.e., liquid, short-term, safe assets.[1] Although narrow in scope, this category is economically relevant: for the median household, it is the only form of financial wealth, and for the vast majority, it constitutes the largest share of their liquid financial portfolios. These assets are also central to the financial system, serving as a primary funding source for banks. Finally, an advantage of focusing on liquid, short-term, safe assets is that it provides a clean environment where risk, maturity, and liquidity remain constant across assets and time, allowing us to attribute variation in holdings to household characteristics.

To study household portfolio decisions, we leverage detailed transaction-level data from one of the largest banks in Iceland. The bank offers all clients access to multiple liquid, short-term, safe assets that are nearly identical in non-pecuniary characteristics but differ significantly in interest rates, with these differences widening over the business cycle. We document that despite transfers between these accounts being instantaneous and free of charge, there are substantial differences in portfolio holdings and returns across individuals, yet allocations remain largely unresponsive to interest rate spreads, except among wealthy households.

[1] These assets—defined more precisely in Section 2.4—include checking and savings accounts, and “liquid funds” held in brokerage accounts.

Central to our analysis is the richness of the data, which cover roughly a third of the Icelandic population on a daily basis between 2016 and 2024. We observe bank account balances, interest rates, inflows and outflows, card payments, and financial portfolios managed by an affiliated broker. These data are also contain information on demographics and have been linked to survey responses of the bank customers that measure financial literacy, inflation knowledge, expectations, and other individual characteristics. Furthermore, Iceland offers an ideal setting for our research because it is among the most advanced countries in digital banking, with near-universal use of online services and frictionless real-time transfers between accounts.

We begin by showing that wealth is a key determinant of portfolio allocation, while sensitivity to interest rate spreads is limited. Portfolio shares in low-return deposits fall sharply with wealth: individuals in the top asset decile hold, on average, more than 40 percentage points less in low-return accounts than those in the bottom decile. By contrast, sensitivity to interest rate spreads is modest: the share kept in low-return deposits declines by only about 0.1 percentage points for each 1-percentage point increase in the spread. We reinforce this finding by examining individual reallocation behavior. Wealthy households rebalance their portfolios more frequently than low-wealth households, yet the average frequency of reallocations, the number of transfers per month, and the size of transfers remain largely unresponsive to spreads.

These allocation differences translate directly into realized returns. Wealthy households earn, on average, about 2 percentage points more on their liquid portfolios than households at the bottom of the distribution. This difference in returns arises even though all clients have access to the same set of assets with identical risk, maturity, and liquidity. However, wealthy households also leave more money on the table, with the top wealth decile forgoing interest income equivalent to approximately 2.5 percent of their annual consumption, compared to a median of 0.3 percent.

We then explore heterogeneity in households' responses to changes in interest rate spreads. We find that the wealthiest individuals are roughly ten times more responsive than the average depositor: those in the top decile reduce their low-rate deposit share by about 1 percentage point for every 1-percentage-point increase in the spread, whereas those in the bottom 60 percent of the distribution hardly react at all. Consistent with these portfolio-share results, the probability of making a portfolio adjustment increases noticeably with spreads for wealthy individuals but shows little change for the majority of households. Going beyond wealth, we incorporate survey evidence and find that higher financial literacy and better inflation knowledge substantially amplify households' responsiveness to changing spreads.

Finally, we use our findings to provide new insights into the literature on monetary policy transmission and household portfolio choice. We first show that fluctuations in the share of low-cost deposits over the business cycle—crucial for bank lending—are driven primarily by wealthy individuals actively adjusting their portfolios in response to interest rate changes. Then, we use our estimated moments to discipline standard portfolio choice models. We show that while these models capture the cross-sectional distribution of holdings, they substantially overstate households' sensitivity to interest rate changes.

Related Literature

This paper contributes to several strands of the literature. First, we add new evidence to the study of household portfolio allocation (see, e.g., Guiso et al., 2002; Campbell, 2006) by documenting substantial heterogeneity in choices and returns within an asset class that lacks trading frictions and in which assets share common non-pecuniary characteristics. A related point is made in Fagereng et al. (2020), which we complement by highlighting the heterogeneous cyclical variation in returns.

We further show that portfolio sensitivity to interest rates is limited, in line with Koijen and Yogo (2019), and that responsiveness varies systematically with investor wealth and financial literacy, echoing themes emphasized in the household finance literature (see, e.g., Lusardi and Mitchell, 2014; Calvet et al., 2009).

We also contribute to the literature on deposit stickiness. In contrast to Lu et al. (2024), where transfer delays can generate inaction, in our setting all transfers—both within and across banks—are settled instantaneously. This rules out transfer frictions as a source of stickiness. Additionally, our findings speak to the broader literature on the importance of stable deposits for bank funding (Hanson et al., 2015; Egan et al., 2021; d'Avernas et al., 2023; DeMarzo et al., 2024; Kundu et al., 2024; Koont et al., 2024) and on the role of monetary policy in shaping lending through deposit reallocation (Drechsler et al., 2017; Li et al., 2023; Blickle et al., 2024; Argyle et al., 2024). We contribute to this literature by providing evidence on which factors shape deposit allocation in the cross-section and, more importantly, which depositors drive aggregate fluctuations.

Our findings also contribute to the literature on household inaction in response to financial incentives (Andersen et al., 2020b; Chetty et al., 2014; Andersen et al., 2025; Calvet et al., 2007). We innovate by studying inaction in a setting where reallocations are instantaneous and free, and the assets we study are nearly identical in non-pecuniary characteristics. Despite sizable potential gains, we document that households leave substantial interest income on the table.

Our study adds to a growing literature that uses transaction-level bank data, either from financial aggregators or directly from banks (see, e.g., Gelman et al., 2014; Baker, 2018; Olafsson and Pagel, 2018; Andersen et al., 2020a; Carlin et al., 2022; Gathergood and Olafsson, 2024), and a small but growing literature that links administrative records on financial behavior with survey evidence on the same individuals (see, e.g., Epper et al., 2020; Carvalho et al., 2024; Schnorpfeil et al., 2024). Our high-quality bank data—combining high-frequency information on deposits, broker balances, transfers, interest rates, and demographics—are precisely what is needed to investigate what drives portfolio adjustments.

Finally, we contribute to the growing literature that incorporates portfolio choice into macroeconomic models. Recent work builds on Baumol (1952) and Tobin (1956) by introducing costly reallocation between liquid and illiquid assets in incomplete-markets Aiyagari (1994) models (e.g., Kaplan and Violante, 2014; Kaplan et al., 2018; Auclert et al., 2020, 2025). Adjustment costs are typically disciplined by targeting the distribution of liquid assets to match observed marginal propensities to consume, but they are rarely confronted with evidence on actual reallocations, and liquid assets are often modeled as a single instrument whose returns move one-for-one with the policy rate. We provide direct evidence on within-household reallocations across liquid accounts, allowing us to discipline the elasticity of these movements. A notable exception is Alvarez et al. (2012), which also uses reallocation evidence to identify portfolio frictions. We show that models matched only to cross-sectional holdings reproduce portfolios but overstate responsiveness to interest rates. This elasticity is key for assessing households' responses to monetary policy.

2 Data

We use proprietary data from one of the largest banks in Iceland. The data set includes daily information on all individual bank account balances, the interest rates paid on each account, and overdraft limits and usage. It also provides the official account names and descriptions that we use to classify accounts. The data cover all loans—such as mortgages, car loans and leases, and consumer loans—as well as financial portfolios managed by an affiliated broker, with daily information on portfolio composition and all transactions. The data also contain all inflows and outflows from each account, accompanied by transaction descriptions that allow us to classify them. In addition, we observe debit and credit card expenditures, including credit limits and detailed information on the time, location, merchant, category, and amount of each transaction.

In addition to bank information, the data contain individual and family identifiers, allowing us to follow individuals and households over time, as well as demographic information, including age, gender, and registered place of residence. We also exploit that the bank data have been linked to survey information that were obtained through four online surveys administered to bank customers over the past few years. In all surveys, participants have similar characteristics to other bank customers as well as the general population. Each survey was tailored to address specific research questions related to different research questions, and as a result, the questions varied across surveys. Through the surveys, we obtain information on individuals' financial knowledge, understanding of inflation's effects, discounting and risk preferences, decision-making abilities, education levels, and other relevant characteristics.

2.1 Environment

Iceland provides an ideal setting to study questions related to household portfolio allocation in a digital financial environment. For context, its GDP per capita in 2023 was about 6% lower than that of the U.S. and approximately 30% higher than that of France, after adjusting for costs of living.[2] Crucially, Iceland is among the most advanced countries in the adoption of online banking and electronic payments. In 2021, 95% of Icelanders reported using internet banking, compared to, e.g., 75% in France and 45% in Italy.[3] Cash usage is also exceptionally low: in 2022, only 7% of transactions in Iceland were conducted in cash, while it was 50% in France and 70% in Italy.[4]

In addition, bank accounts in Iceland are personal, and, therefore, there are no joint accounts, even within households. The fact that there are no joint accounts in Iceland means that all transactions we observe are related to the individual under investigation and not to the spouse. Moreover, motives for holding funds in low-return accounts for precautionary reasons are limited: Interbank transfers are free and instantaneous, and unexpected bills are rare. Most bills are linked to a resident's social security number and appear automatically in their online banking interface without requiring explicit enrollment. Finally, 70% of surveyed customers at our partner bank report banking exclusively with that institution and not holding accounts elsewhere. A large share of those with other banking relationships report only having dormant accounts at other banks.

2.2 Sample selection

We use a panel data set tracking the daily balances, spending, income, borrowing, and financial investments of 133,751 individuals, representing approximately 49% of Iceland's total adult population. We observe account balances from January 2016 to September 2024, but transaction movements and interest rates are available only from January 2018 onward. Most of our analysis focuses on a subset of customers we define as *active*.

We call a customer active in any given month if he or she is an adult with a checking account at the bank, registered as residing in Iceland, and appears economically active. Specifically, we require individuals to have at least one monthly income inflow—such as labor income, unemployment or invalidity benefits, pension payments, or student loans—and at least one food-related expense in at least 8 of the past 24 months. This definition strikes a

[2] International Monetary Fund (2025)
[3] Eurostat (2025)
[4] Central Bank of Iceland (2024), European Central Bank (2022)

balance: a looser criterion would include many dormant or peripheral users, while a stricter one might exclude less active customers who might still contribute to patterns of deposit stickiness. After applying this filter, our sample consists of an average of 86,484 active customers per year, representing 32% of the adult population.

In addition, when computing results and regressions, we restrict the sample to individuals whose average balance during the relevant period (month, year, or other horizon under study) exceeds 3,000 ISK, in order to rule out temporary dormant accounts. Excluding this filter, or raising the threshold, does not affect any of our results.

2.3 Data Representativeness

In this section, we assess the representativeness of our data by comparing the sample of active clients to population-level data from Iceland across multiple dimensions. In surveys of bank clients, we found that 67% of bank customers bank exclusively with the collaborating bank and among those with multiple accounts, over 35% mention that they only have inactive accounts at other banks. The demographic distribution in our bank data closely aligns with the population distribution in Iceland, as shown in Table 1.

Our data set includes deposits from all individuals with an account in the collaborating bank. Figure 18 in the Appendix shows that the sum of deposits in all account types held by active clients accounts for an average of 20% of total household deposits reported by the Central Bank of Iceland. We interpret this as evidence supporting the representativeness of our deposit data.

We benchmark our expenditure data against national measures of consumer behavior. Specifically, we compare observed spending among bank clients with *household final consumption expenditure* reported by Statistics Iceland. Figure 19 shows that the distribution of expenses in our data set closely mirrors the shares reported for the general population in 2019, the only year with a category-level decomposition for individuals residing in Iceland, i.e., the only year that does not include tourists. The close match across multiple spending categories shows that our data set is representative and reliably captures broader patterns of consumer behavior. Moreover, Figure 20 shows that aggregate spending by active clients accounts for more than 20% of total household expenses in Iceland for most of the sample

Table 1: Demographics of Icelandic Adults and Active Bank Clients

	Iceland	**Active Clients**
Total	272,539	86,484
Women	49%	49%
Married	54%	55%
Residing in the capital	64%	64%
Children (if >0)	1.8	1.8
Age		
Mean	46.5	45.9
Shares:		
18-20	0.05	0.04
20-30	0.19	0.20
30-40	0.18	0.19
40-50	0.17	0.17
50-60	0.16	0.17
60+	0.25	0.23

Notes: This table compares the demographic composition of adults residing in Iceland to that of active clients in our sample over the study period. Reported values are time-series averages. "Active clients" are individuals that meet our activity criteria. Total population refers to January counts reported by Statistics Iceland; we report the average for that month in our data. Population figures come from national registers; sample statistics are based on the bank's internal data.

period.

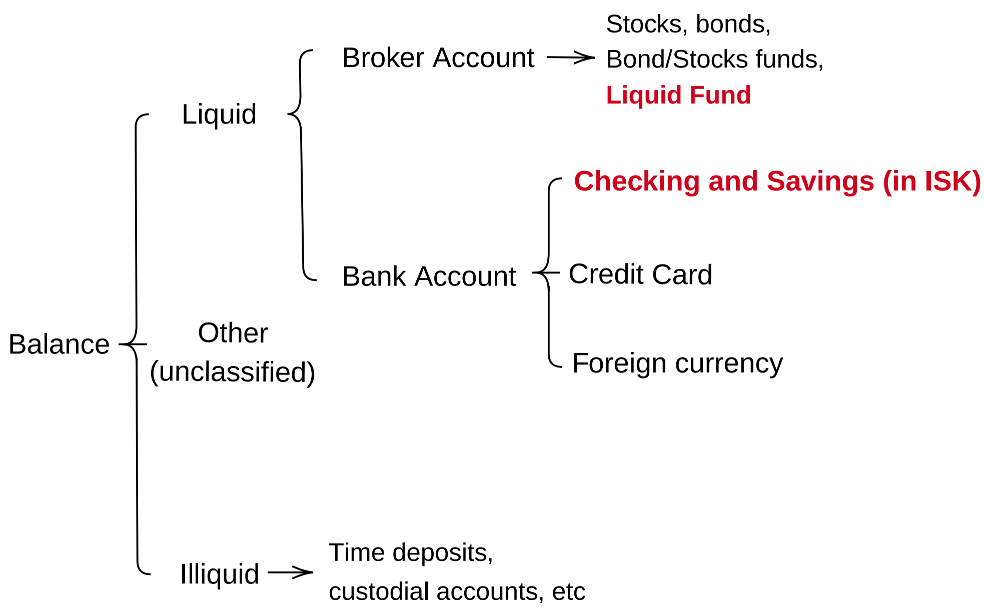
2.4 Account Types and Summary Statistics

A bank client can hold balances within the bank and in his or her associated brokerage account, if such an account is open. The bank offers a wide variety of account types. Using information provided by the bank, its public website, and the Internet archives, we classify these accounts into categories that are straightforward to interpret and comparable to other countries. Figure 1 summarizes this classification and includes representative examples.

Individual balances can be classified as *liquid*—meaning funds can be transferred at full value to an account that can be used for payments without any quantity restrictions or meaningful time delays[5]—or as *illiquid*, if they do not meet this criterion. Liquid accounts

[5]Transfers are immediate for all accounts studied except one, which has a delay of one business day. We provide further details on this account later.

Figure 1: Accounts Classification



Notes: This figure shows our classification of individual bank accounts into interpretable categories along with examples. Accounts highlighted in red are those we categorize as liquid, short-term, safe assets—the primary focus of our study.

include funds held either at the bank or at its affiliated broker. The bank offers a variety of checking and savings accounts in local or foreign currency, as well as prepaid credit cards. At the broker, funds can be invested in individual stocks, bonds, or investment funds with varying risk profiles. Illiquid accounts take several forms, including traditional time deposits, custodial accounts accessible only when the beneficiary reaches adulthood, and specialized savings accounts earmarked for purposes such as home purchases. A small share of accounts that could not be clearly categorized are labeled as *other*.

Checking account balances can be positive or negative, as most come with an overdraft facility, where account balances can be negative up to a limit based on credit history, income, and assets. Overdrafts dominate the unsecured consumer credit market in Iceland and are generally used extensively. Credit card balances can also be either positive (prepaid credit cards or regular credit card repayments) or negative (outstanding balances). Credit cards in Iceland are issued by banks and their balances are rarely rolled over on their due dates but rather paid in full, and if individuals lack funds to pay them, they can take an overdraft to pay the bill.

Table 2 provides summary statistics for the balances of active clients. All values are obtained by first computing them for each year and then averaging across the sample period. Monetary values are expressed in Euros as of September 2024.[6] Liquid safe assets, defined in detail in the next section, are by far the most common financial assets: Almost every individual in the sample holds a non-zero balance in either checking or savings accounts. Furthermore, on average, checking and savings accounts constitute the largest shares of individual portfolios. Despite their popularity, liquid, short-term, safe assets are highly concentrated: the top 10% of holders control close to 70% of total funds.[7] In contrast, foreign currency accounts and financial market accounts are less common and exhibit even higher concentration.

Table 2: Descriptive Statistics: Balances

	Share > 0	**Share of Total Assets**	**Share of Liquid Safe**	**Mean**	**Std. Dev.**	**P10**	**Median**	**P90**	**Share Top 10%**	**Share** < 0
(1)+(2)+(3): Liquid Safe asset	0.97	0.74		14186	52317	16	2092	35044	0.66	
Checking asset (1)	0.88	0.38	0.51	3091	12910	0	514	6649	0.69	
Savings (2)	0.78	0.36	0.48	10211	40823	0	1511	26032	0.74	
Liquid Funds (3)	0.02	0.01	0.01	884	22926	0	0	0	0.85	
Checking wealth	0.78			2086	13787	-3193	438	6567		0.19
Time deposits	0.19	0.05		2104	23887	0	0	136	0.97	
Other illiquid asset	0.30	0.14		2984	15858	0	0	4856	0.90	
FX asset	0.15	0.02		810	15401	0	0	8	0.97	
Broker	0.10	0.05		7701	100726	0	0	996	0.85	
Credit Card	0.08			-743	1687	-2335	-91	1		0.54
Other undefined	0.12	0.01		585	23770	0	0	1	0.97	

Notes: This table presents summary statistics of bank holdings of active clients. All values are obtained by first computing yearly averages and then averaging across all years within our sample period. Monetary values are in September 2024 Euros.

[6]For reference, the ISK/USD exchange rate averaged 129 ISK per US Dollar during the sample period.
[7]This concentration level matches that reported by Argyle et al. (2024) for the U.S.

Liquid, Short-Term, Safe Assets

This paper's focus is on individuals' allocation of liquid, short-term, safe assets, with only limited and explicitly noted exceptions.[8] Figure 1 highlights in red the account types included in this category: checking accounts, savings accounts, and "liquid funds" held at the broker. All assets in this category are liquid because transfers between them are free, involve almost no delays, and are not restricted in terms of time, amount, or frequency. In addition, they carry no price risk, as they have zero maturity.

Table 3 provides a detailed overview of the differences between these account types. Checking accounts can be used for payments—debit card transactions and credit card bills are settled through them—can be accessed via ATMs, and also function as a credit line due to an overdraft facility. Transfers from checking accounts to other banks are immediate and free of charge throughout the sample period. Moreover, checking deposits are insured up to EUR 100,000 under Icelandic legislation.[9] Savings accounts are nearly identical to checking accounts, with two key exceptions: they cannot be linked to payment cards and do not offer overdraft facilities. However, transfers between checking and savings accounts are instantaneous,[10] free, and unlimited in amount. Liquid funds are short-term money market funds offered through the associated broker. Transfers into and out of these funds may involve up to a 24-hour delay. The underlying assets are typically short-term government securities, virtually free of price risk.

Table 3: Liquid, Short-Term, Safe Assets Characteristics

	Payments (Debit card / ATM / Overdraft)	Deposit Insurance	Liquidity (transfer to checking)	Transfers (other banks)
Checking	✓	✓	-	✓
Savings	✗	✓	Instant	✓
Liquid Funds	✗	✗	24 hours	✗

Notes: This table summarizes the differences across liquid, short-term, safe assets. A check mark indicates features available to bank clients for each account type, while a cross denotes unavailable features.

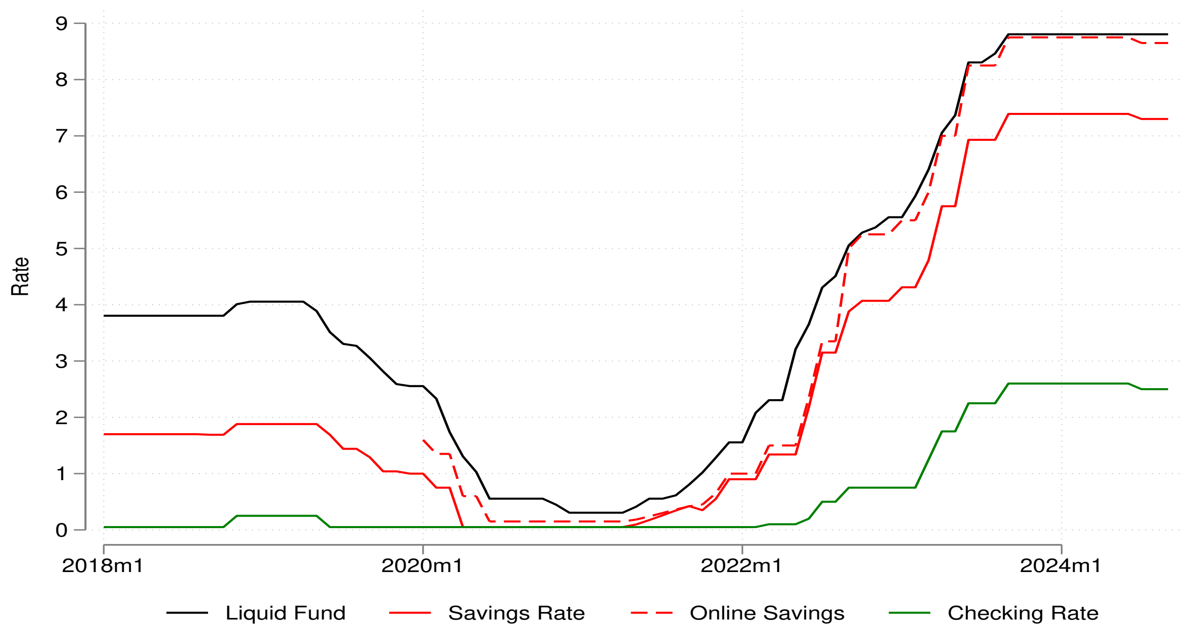
[8]Whenever results refer to other asset types, we make this explicit. For brevity, we sometimes use the terms "liquid assets" or simply "assets," but unless otherwise noted, these always refer to the category we define as "liquid, short-term, safe assets."

[9]Central Bank of Iceland (2025)

[10]Funds can be moved from a savings account to a checking account in seconds.

Despite their nearly identical characteristics, the products in this group offer significantly different interest rates throughout the sample period. Figure 2 presents the time series of interest rates for a selection of liquid, short-term, safe assets available to all bank clients over the sample period. Among all products available, the figure reports the returns on high-yield checking and savings accounts, a product labeled "Online Savings" that became available in 2020, and the net return (after operational costs) on the liquid fund offered through the broker.

Figure 2: Time Series of Interest Rates on Bank Accounts and the Liquid Fund



Note: This figure shows the interest rates offered by the bank on its high-yield checking and savings accounts, as well as on the "Online Savings" account introduced in 2020. It also includes the net return (after fees) on the liquid fund available through the broker.

Figure 2 highlights that the spread—the difference between the return on the liquid fund (the highest-yielding liquid safe asset) and deposit returns—is consistently positive and, in the case of checking accounts, widens as interest rates increase. This suggests that holding funds in deposits, particularly in checking accounts, becomes increasingly costly during periods of monetary tightening. The figure also shows that in recent years, all bank clients had access to high-return, safe assets through savings accounts at their bank—without needing to move funds elsewhere or forgo deposit insurance.[11] We are therefore studying portfolio allocation across assets that are nearly identical in terms of nonpecuniary characteristics: The assets in our category do not differ in risk, maturity, and liquidity. However, they offer markedly different interest rates that vary over time and transfers between them are frictionless.

Our setting, where high-rate and low-rate assets coexist within the same institution and where transfers are free and frictionless, is ideal for evaluating the importance of interest rates in the allocation of wealth between low- and high-return accounts, as it allows us to control for factors that have been suggested as explanations for the stickiness of deposits, such as deposit insurance (Hanson et al., 2015), superior liquidity services (d'Avernas et al., 2023), and delays in transfers (Lu et al., 2024). Finally, while our focus is limited to a narrow set of asset types, this category dominates in the financial portfolios of households. As shown in Table 2, participation is almost universal, for most households these assets constitute their only form of financial wealth as they do not invest in risky asset markets, and even among those that do invest in risky asset markets, for most they represent a substantial share of their overall financial portfolio.

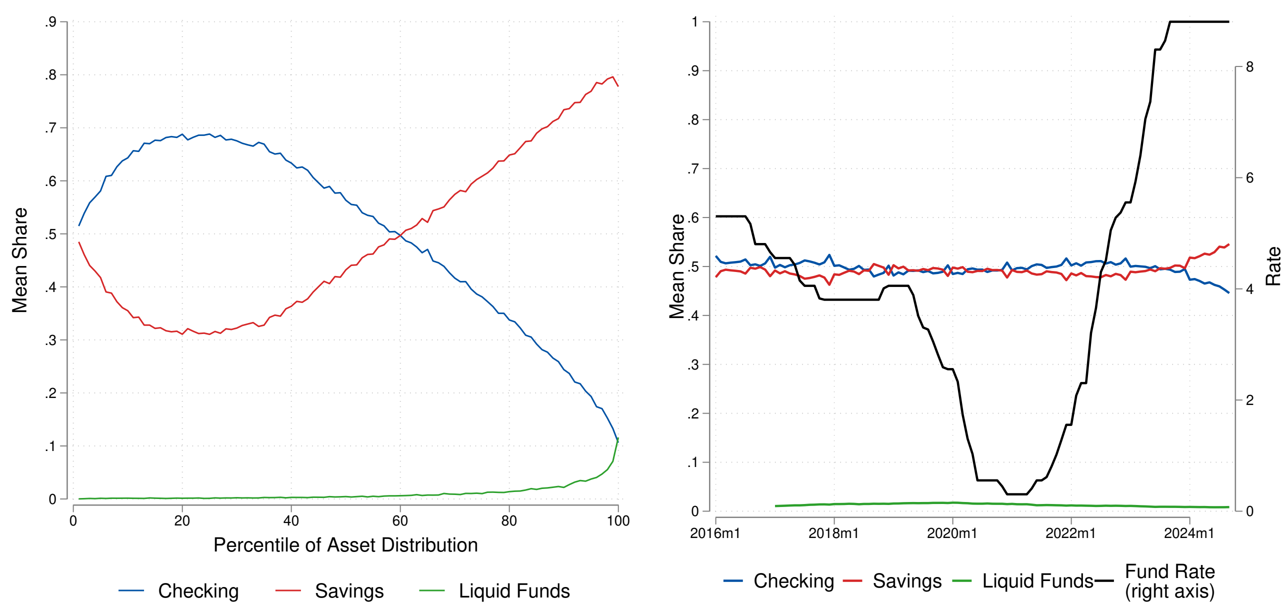
3 Portfolio Allocation and Adjustment

In this section, we study individuals' allocation of liquid, short-term, safe assets, namely, checking deposits, savings deposits, and liquid funds held at the broker. As discussed earlier, these assets are almost identical in their non-pecuniary characteristics, yet they offer substantially different interest rates. We begin by showing that wealthy individuals favor higher-return assets, but despite portfolio adjustments being nearly frictionless, the average portfolio response to return spreads is minimal. We then quantify the foregone interest income associated with observed asset choices. Finally, we study heterogeneity in responses to interest rate changes across wealth levels and individual characteristics.

[11] The bank openly advertised this account on its web portal. For instance, on August 8 2025, the first banner on the homepage read: "Get higher interest on your savings: 8.65% interest," referring to this account. The only difference from a traditional savings account is that it can be opened and managed exclusively through the online banking platform or mobile app.

We first illustrate our results in Figure 3. The left panel shows portfolio shares across the distribution of liquid, short-term, safe asset holdings, and the right panel shows the average—unweighted—monthly shares across the sample period. To construct the left panel, we compute each individual's average daily share in each asset class for a given year, then group individuals into percentiles based on their average holdings that year, and report the time-series average of each group. The right panel computes the average shares in each asset for all individuals for each month in the sample and plots it together with the rate on liquid funds, the highest-return liquid, short-term, safe asset.

Figure 3: Portfolio Shares across the Asset Distribution and Time



Notes: The left panel shows average portfolio shares across percentiles of liquid, short-term, safe asset holdings. The right panel shows unweighted average monthly portfolio shares across the sample period, plotted alongside the interest rate on liquid funds. Holdings of liquid funds are available only starting in 2017.

The left panel of Figure 3 shows that the share of high-return assets in the liquid, short-term, safe portfolios of households increases with wealth: Individuals in the top percentiles hold only about 20% of their liquid portfolio in checking deposits—roughly 50 percentage points less than those in the bottom percentiles. Savings deposits dominate the portfolios of wealthy individuals, accounting for the largest share of their liquid safe assets. The fact that liquid funds are a marginal asset class even among the wealthy can be explained by savings deposits offering nearly identical return (as shown in Figure 2) while preserving deposit insurance.

The right panel of Figure 3 shows that average portfolio shares are insensitive to changes in return spreads: Even as return spreads fluctuate from zero to over 6 percentage points—increasing the opportunity cost of holding low-return deposits—average household allocations show virtually no reallocation toward higher-yielding accounts. This lack of response occurs despite the fact that portfolio adjustments between these assets do not involve changes in risk, transaction costs, or delays.

We formalize this result by regressing the share of low-return checking deposits in an individual's portfolio on fluctuations in their wealth, the level of the interest rate, and several controls. We divide active individuals in the sample into asset deciles $d_{it} = \{1, 2, \ldots, 10\}$ using three different wealth definitions to capture different notions of wealth. In the first, we sort individuals into deciles based on their level of assets in a given month relative to others. In the second, we sort individuals into deciles by each individual's average level of assets across the entire sample period. In the third, deciles are calculated uniquely for each individual by ranking their monthly asset levels from 1 (lowest) to 10 (highest) over time, to capture their wealth relative to their own wealth history.

We estimate the following regression:

$$\text{share}^C_{it} = \alpha + \beta^r \cdot r^L_t + \sum_{j=1}^{10} \beta^a_j \cdot \mathbb{I}_{(d_{it}=j)} + X'_{it} \cdot \delta + \nu_i + \varepsilon_{it} \tag{1}$$

where share^C_{it} is the share of individual i's portfolio held in checking deposits among liquid, short-term, safe assets in month t; r^L_t is the interest rate on the liquid fund normalized to have mean zero;[12] $\mathbb{I}_{(d_{it}=j)}$ is an indicator function equal to one if individual i is in decile j in month t; ν_i denotes individual fixed effects, which we include in some specifications; and

[12] The interest rate on liquid funds is $r^L_t = r_t - c$, where r_t is the policy rate and c denotes fixed fees. Since these fees are proportional to the asset value, all variation comes from the policy rate. Using the policy rate instead of the spread allows us to include 2016–18, for which we lack bank interest rate data. As shown in Figure 2, however, spreads comove closely with the policy rate, so increases in the policy rate also imply higher costs of holding checking deposits. Moreover, the effect of the policy rate on portfolio shares is of main interest, as it is the rate directly controlled by monetary policy.

X'_{it} represents a vector of controls that includes individual age and age^2, a linear time trend, a gender dummy, a marriage dummy, the number of kids, and a dummy for whether the individual resides in the capital.

Table 4 corroborates that the share of low-return checking deposits declines with wealth. This pattern holds across all three decile definitions. Column (1) shows that individuals in the top decile of the asset distribution in month t hold, on average, a 42.6 percentage point lower share of checking deposits compared to those in the bottom decile. A similar gap is observed in column (2), where deciles are based on individuals' average asset levels over the sample period. Column (3) shows that the relationship also holds within individuals: When individuals are in the highest wealth decile relative to their own distribution, they hold on average 15.8 percentage points less in checking deposits compared to when they are in their lowest decile. This confirms that wealthier individuals—both in the cross section and over time—allocate a smaller share of their liquid portfolios to low-return assets.

Table 4 also shows that the share of low-return checking deposits declines only modestly as the interest rate on the highest-return liquid, short-term, safe assets, r_t^L, increases, and—as shown in Figure 2—spreads widen. To gauge the magnitude, column (1) indicates that a 1 percentage point increase in the liquid fund rate is associated with a 0.13 percentage point decrease in the share of checking deposits. This implies that the 9 percentage point increase in the liquid fund rate observed between 2021 and 2024—during which the spread between the liquid fund and checking deposits widened by over 6 percentage points—is associated with an average decline in the checking share of only about 1.2 percentage points.

There are a few additional results from Table 4 worth noting. First, we observe a negative time trend in the share of checking deposits, which may reflect improvements in the accessibility and usability of alternative accounts. Second, gender plays a significant role: female clients hold, on average, 8 percentage points less in low-return checking deposits compared to male clients with similar characteristics. Third, the substantial increase in the R^2 when individual fixed effects are included (column (3))—relative to when they are excluded (columns (1) and (2))—highlights the importance of persistent individual characteristics in explaining portfolio heterogeneity. Finally, other control variables, including marital status, place of residence and number of children, do not exhibit economically significant effects.

Table 4: The Share of Checking Deposits in Liquid, Short-Term, Safe Portfolios

	Decile Classifications		
	(1) Monthly levels	(2) Sample average	(3) Own wealth
Decile levels (relative to 1st)			
2.	9.62	-2.26	-0.10
	(0.19)	(0.42)	(0.06)
3.	10.08	-7.60	-1.29
	(0.23)	(0.43)	(0.08)
4.	6.39	-12.89	-2.87
	(0.25)	(0.43)	(0.09)
5.	-0.52	-17.35	-4.62
	(0.26)	(0.44)	(0.10)
6.	-8.71	-20.82	-6.38
	(0.27)	(0.44)	(0.10)
7.	-16.31	-26.50	-8.60
	(0.28)	(0.44)	(0.11)
8.	-24.02	-32.09	-10.85
	(0.29)	(0.45)	(0.12)
9.	-32.62	-39.36	-13.55
	(0.30)	(0.44)	(0.12)
10.	-42.65	-49.53	-15.67
	(0.31)	(0.43)	(0.13)
Liquid Fund rate (r^L)	-0.13	-0.18	-0.31
	(0.01)	(0.01)	(0.01)
age	0.86	0.99	-0.83
	(0.03)	(0.03)	(0.06)
age^2	-0.01	-0.01	0.01
	(0.00)	(0.00)	(0.00)
Female	-8.13	-8.44	
	(0.19)	(0.20)	
Time trend	-0.02	-0.03	-0.05
	(0.00)	(0.00)	(0.00)
# of kids	-0.44	-0.49	0.45
	(0.12)	(0.12)	(0.11)
Married	-1.65	-0.94	1.29
	(0.22)	(0.22)	(0.21)
Residing in Reykjavík	1.55	1.86	-0.07
	(0.21)	(0.21)	(0.28)
Constant	44.72	53.31	72.76
	(0.65)	(0.70)	(1.65)
FE	N	N	Y
N	7926422	7926422	7916002
adj. R^2	0.183	0.143	0.662

Notes: This table reports estimates from regression (1) of the share of checking deposits in portfolios on asset deciles, the liquid fund rate, and controls. We use three alternative decile definitions. In the first column, individuals are sorted each month based on their asset holdings relative to the rest of the sample. In the second, individuals are sorted based on their average asset holdings over the entire sample period. In the third, each individual's monthly asset holdings are ranked relative to their own asset distribution across the sample period. Standard errors are clustered at the individual level and shown in parentheses.

Instrumenting Rate Changes Using Monetary Policy Shocks

Interpreting the coefficient on r_t^L as causal requires addressing potential endogeneity concerns. The liquid fund rate comoves with the central bank's policy rate, which responds endogenously to macroeconomic conditions that may affect checking deposit shares. To address this endogeneity, we instrument changes in r_t^L using monetary policy surprises—unexpected changes in the policy rate around central bank announcements—following a well-established approach in the monetary economics literature.[13]

Unlike in the U.S., Iceland does not have a liquid market for government bond futures that can be used to infer monetary policy surprises around central bank meeting times—the standard approach in the literature. However, commercial banks in Iceland regularly publish forecasts of central bank decisions shortly ahead of the monetary policy meetings at which the policy rate, r_t, is set by the Monetary Policy Committee. We exploit this institutional feature and define a monetary policy surprise on date τ as the difference between the actual policy rate announced by the committee, r_τ, and the most recent forecast from our partner bank, r_τ^f:

$$\text{surprise}_\tau = r_\tau - r_\tau^f \tag{2}$$

We work with monthly data and define the monthly shock as the sum of all surprises within a given month.[14] Figure 14 shows the time series of changes in the central bank policy rate and the corresponding surprises. While most policy changes were anticipated, the figure reveals several sizable surprises—particularly during the tightening cycle following the Covid pandemic.[15]

We follow the literature on monetary policy transmission and use monetary policy surprises as instruments for changes in the interest rate on liquid assets. Specifically, we estimate a

[13] See Nakamura and Steinsson (2018).

[14] There is only one month with two central bank meetings—March 2020—when the committee met unexpectedly due to the Covid emergency. Given the unscheduled nature of this meeting, no bank forecast was available, so we assume a forecast of no change for that announcement.

[15] In Appendix A we show that these surprises generate impulse responses in macro variables aligned with previous studies.

version of equation (1) in six-month differences:

$$\Delta \text{share}_{it}^{C} = \alpha + \beta^{r} \cdot \Delta r_t^L + \beta^{a} \cdot \Delta \log\left(a_{it}\right) + \varepsilon_{it} \tag{3}$$

where Δx_t denotes the 6-month change in variable x, and $\log(a_{it})$ is the log of liquid safe assets held by individual i, in real terms.

We estimate equation (3) using two-stage least squares (2SLS), where the change in the liquid asset interest rate, Δr_t^L, is instrumented using the sum of the monetary policy surprises over the period:

$$\Delta r_t^L = \alpha + \gamma \cdot \sum_{\tau=0}^{5} \text{surprise}_{t-\tau} + \varepsilon_t \tag{4}$$

Table 5 presents the results, with column (1) reporting the OLS estimates and column (2) showing the 2SLS estimates using monetary policy surprises as instruments. Two points are worth noting. First, estimating the specification in six-month differences with wealth levels ($\log(a_{it})$)—as in equation (3)—yields a coefficient on β^r of similar magnitude to that obtained in levels with wealth deciles ($\mathbb{I}_{(d_{it}=j)}$), as in equation (1), suggesting the results are not sensitive to this transformation. Second, and more importantly, instrumenting for the change in interest rates in column (2) hardly changes the coefficient on Δr_t^L.

While we remain cautious about drawing strong causal claims, the similarity in the estimated coefficients across specifications—whether in levels, differences, or using monetary surprises as instruments—gives us some reassurance that the baseline estimate captures a meaningful relationship.

Further Evidence: Portfolio Adjustment Actions

Our data set allows us to observe both the direction and magnitude of fund transfers between different asset categories.[16] We use this information to reinforce our previous findings by showing that wealthy individuals reallocate funds between high- and low-return assets more frequently than low-wealth individuals, but the average reallocation frequency, number of transfers per month and size remain largely independent of interest rate spreads.

[16] We identify all transfers between bank accounts and to the bank's affiliated brokerage platform. Also, we use available transfer metadata to track movements to external brokers as accurately as possible.

Table 5: 6-Month Changes in the Share of Checking Deposits

	(1) OLS	(2) IV
$\Delta \log(a_{it})$	-2.72	-3.25
	(0.039)	(0.041)
Δr_t^L	-0.21	-0.18
	(0.012)	(0.017)
constant	-0.61	-0.63
	(0.010)	(0.012)
N	7005567	6666333
adj. R^2	0.018	0.025

Notes: This table reports estimates of equation (3). The dependent variable is the 6-month change in the share of checking deposits in liquid, short-term, safe assets. Column (1) reports OLS estimates. Column (2) reports 2SLS estimates instrumenting the change in the interest rate on liquid assets, Δr_t^L, with the sum of monetary policy surprises over the previous six months. Standard errors are clustered at the individual level.

The left panel of Figure 4 shows the share of individuals in each asset decile who make at least one transfer in a month between checking and savings accounts.[17] The figure reveals that transferring funds between checking and savings deposits is relatively common, with 40% of individuals making at least one transfer in a given month. More importantly, it shows a clear wealth gradient: wealthy individuals adjust their portfolios in approximately half of all months, whereas low-wealth individuals do so in only one third of them.[18]

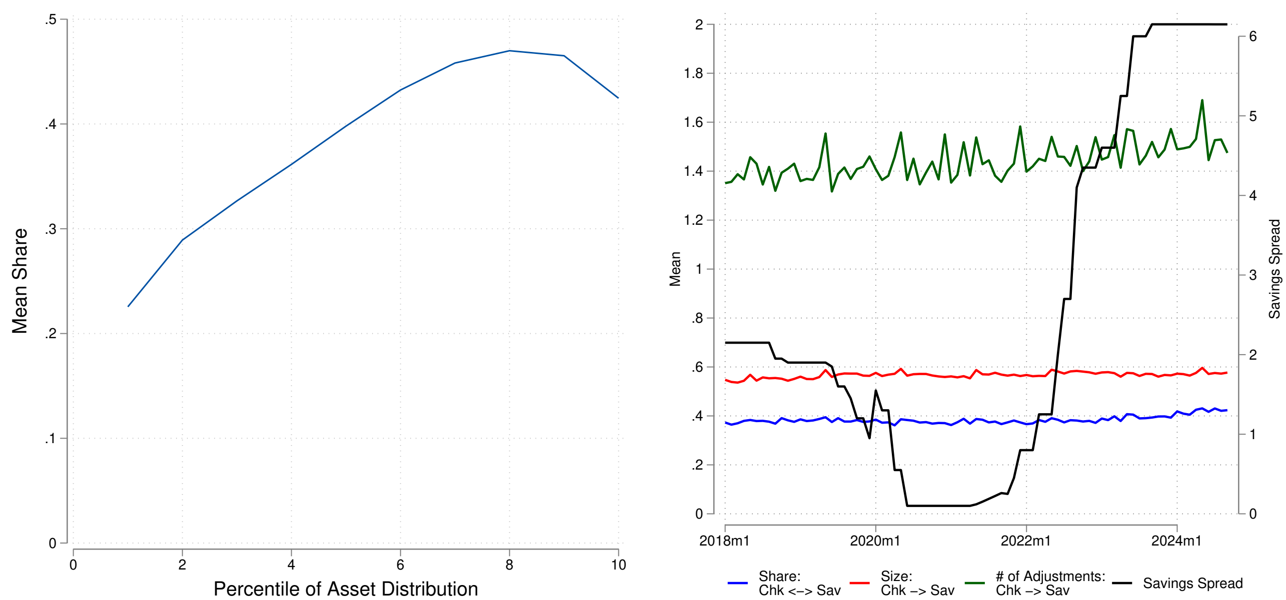
The right panel of Figure 4 shows that the average frequency of adjustments—indicated by the blue line—remains largely independent of interest rate spreads. Despite the opportunity cost of holding checking deposits increasing several-fold between 2021 and 2024, individuals do not systematically alter their adjustment behavior in response to these price changes. A similar pattern emerges when examining the number of transfers from checking to savings (green line): conditional on making at least one transfer in a given month, individuals make approximately 1.4 transfers a month regardless of the spread level. Finally, the average transfer size—measured as the transfer value divided by total checking account balances

[17] The transfer is in any direction. Figure 22 in the Appendix shows the time series of the share of inward and outward transfers separately.

[18] Figure 23 in the Appendix shows the share transferring out of checking into time deposits and brokerage accounts, confirming that these flows are negligible compared to checking-savings transfers.

immediately before the transfer—remains constant at approximately 60%, further confirming the insensitivity to interest rate.

Figure 4: Portfolio Adjustments across the Asset Distribution and Time

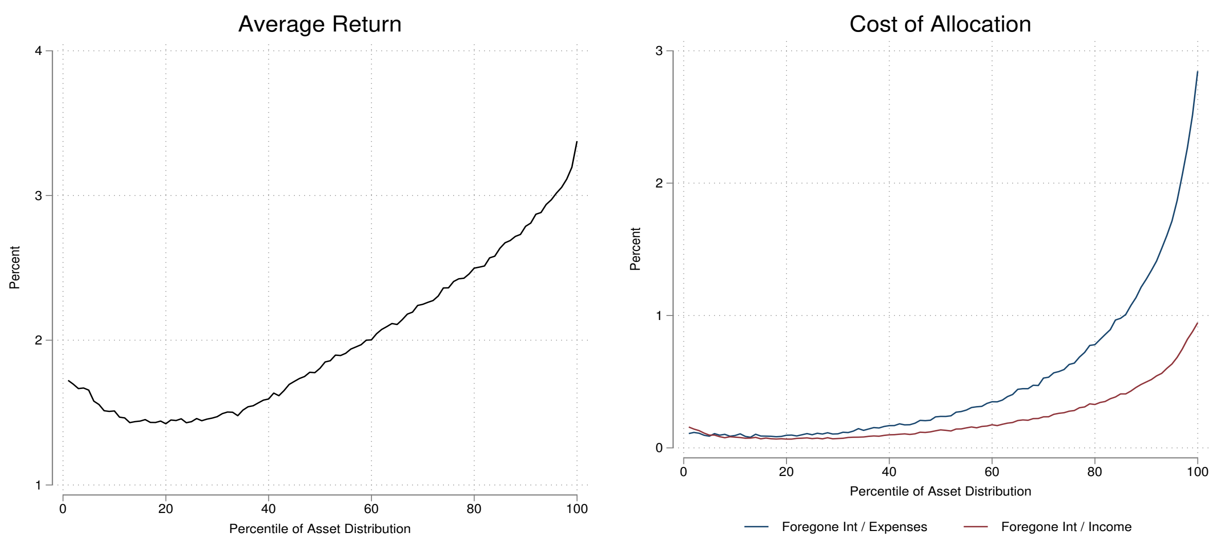


Notes: The left panel shows the share of individuals in each asset decile who make at least one transfer between checking and savings accounts in a given month. Asset deciles are computed monthly using liquid safe short-term assets, and the sample average is taken across sample period. The right panel displays three time series: the monthly share of individuals making at least one transfer between checking and savings in any direction (blue line), the average number of monthly transfers out of checking into savings conditional on making at least one transfer (green line), and the average transfer size out of checking into savings as a percentage of pre-transfer checking balances (red line). The black line shows the interest rate spread between the highest liquid return rate and the checking rate (right axis).

Return Heterogeneity and Foregone Interest Income

Lower portfolio shares in low-return assets allow wealthier households to earn systematically higher returns on their portfolios, making the return on liquid, short-term, safe assets wealth dependent. The left panel of Figure 5 illustrates this relationship by plotting the weighted average return on these assets by wealth percentiles, where individuals are grouped each year based on their average asset holdings. The figure reveals that households in the top percentiles earn returns that are approximately 2 percentage points higher than those in the bottom percentiles during the sample period. Importantly, this return gap does not reflect differences in risk, maturity, or liquidity; it arises solely from differences in how households allocate their liquid, short-term, safe assets.[19]

Figure 5: Return Heterogeneity and Foregone Interest Income by Wealth



Notes: The left panel shows the weighted average return on liquid, short-term, safe assets by wealth percentiles, where individuals are grouped annually based on their average liquid asset holdings. The right panel displays the foregone interest income as a percentage of individual annual consumption expenditure sorted by wealth percentile. The cost is calculated as the difference between the maximum available return on liquid funds and each individual's actual portfolio return, multiplied by total liquid assets and normalized by consumption. After-tax returns are computed using a capital income tax rate of 22%, consistent with the Icelandic tax code since 2018. Cost measures are winsorized at the 2.5th and 97.5th percentiles to mitigate the influence of outliers.

The wealth dependence of returns on assets with similar characteristics—and its implications for wealth inequality—has been emphasized in prior research (see Fagereng et al., 2020). Our setting, in which households allocate across assets that are nearly identical in risk, liquidity, and maturity, allows us to directly quantify the interest income forgone from not selecting the highest-return option—what we refer to as the "cost" of portfolio allocation. A higher return on assets reduces the *unit* cost per Krona invested, but it does not necessarily

[19]The return gap is not driven by product availability: all assets considered are accessible to all bank clients. Banks offer premium accounts with tiered conditions, but the differences across tiers are minimal, and even the highest tier has been dominated by online savings accounts since their introduction.

reduce the *total* cost, as the latter scales with wealth. To formalize this, we define the cost of individual i's portfolio allocation at time t as the forgone interest income, normalized by consumption expenditures:

$$\text{cost}_{it} = \frac{\left(r_t^L - r_{it}\right) a_{it}}{c_{it}} \tag{5}$$

Here, r_t^L denotes the return on the liquid fund at time t—the highest available rate among liquid safe assets—while r_{it} is the return on individual i's liquid portfolio. All rates are after tax. The term $(r_t^L - r_{it})$ thus captures the forgone spread, that is, the return gap relative to the allocation that maximizes returns. The product $(r_t^L - r_{it})a_{it}$ represents the total forgone interest income. By dividing this by c_{it}, individual i's consumption expenditure at time t, we express the cost in consumption-equivalent units. Equation (5) therefore measures how much consumption is effectively left on the table by individual i in the allocation of liquid, short-term, safe assets.[20] To compute this, we use total forgone after-tax interest income and consumption expenditures over a twelve-month period.[21]

The right panel of Figure 5 shows that while wealthier households earn higher returns on their liquid safe assets, the cost—forgone interest income in consumption-equivalent terms—increases substantially with wealth. The figure reveals that these costs are significant across the wealth distribution, ranging from 0.33 percent of annual consumption for the sixth decile to close to 3 percent for the wealthiest individuals. Although high-wealth households allocate more efficiently, their larger asset balances result in higher absolute losses.[22] In the next section, we examine whether households at different points in the wealth distribution adjust their portfolios differently in response to changes in returns.

[20] Importantly, we do not interpret a higher cost as evidence of suboptimal behavior. There may be valid reasons for choosing lower-yielding allocations. Instead, the measure can be read as: if such reasons exist, then the measured cost is what would be required to rationalize the observed allocation.

[21] We winsorize a_{it}/c_{it} at the 2.5th and 97.5th percentiles to mitigate the influence of outliers. To compute after-tax returns, we apply a capital income tax rate of 22%, consistent with the rate in place in Iceland since 2018. We also replicate the analysis using income during the year in place of consumption expenditure.

[22] Figure 21 in the Appendix displays the asset-to-consumption and asset-to-income ratios for individuals ranked by wealth deciles.

3.1 Heterogeneity in Response to Interest Rates

The average insensitivity to interest rate changes does not imply that no individuals respond to them. In this section, we explore whether there is heterogeneity in the response to interest rate changes across individuals. We begin by examining whether individuals with different levels of wealth react differently to changes in interest rates. We then use survey data to go beyond wealth and investigate other individual characteristics that may be a source of heterogeneity.

Heterogeneous Responses Across Wealth Levels

To examine whether wealthier individuals are more responsive to interest rate changes—and to the resulting increase in the spread—we estimate equation (1) augmented with an interaction between wealth deciles and the interest rate:

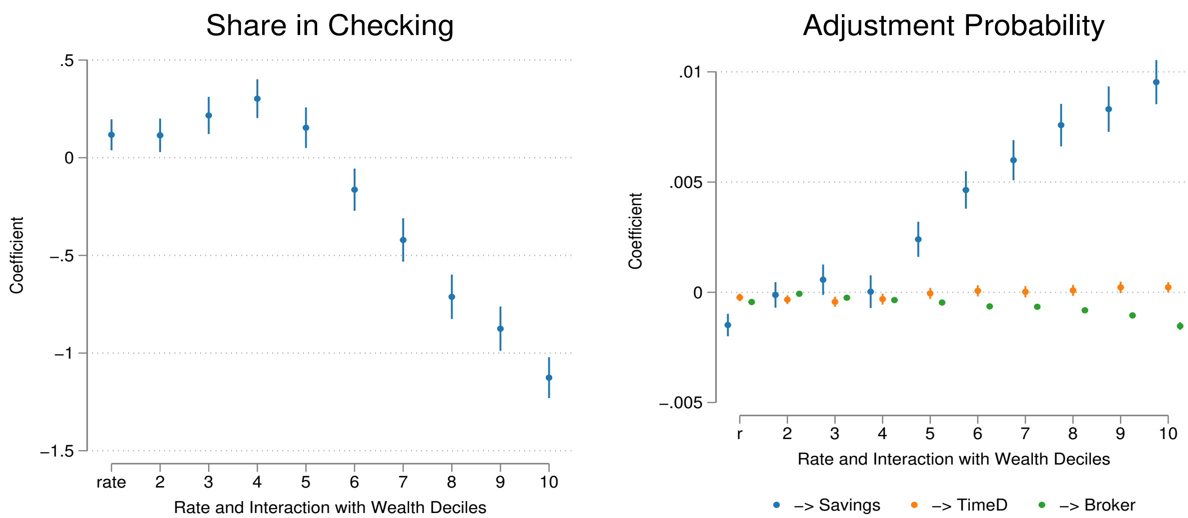
$$\text{share}_{it}^{C} = \alpha + \beta^{r} \cdot r_t^L + \sum_{j=1}^{10} \beta_j^a \cdot \mathbb{I}_{(d_{it}=j)} + \sum_{j=1}^{10} \beta_j^{ar} \cdot \mathbb{I}_{(d_{it}=j)} \cdot r_t^L + X_{it}' \cdot \delta + \nu_i + \varepsilon_{it} \tag{6}$$

the coefficients of interest are $\left\{\beta_j^{ar}\right\}_{j=1}^{10}$, which capture how the sensitivity of portfolio shares to interest rates varies across the wealth distribution. We also estimate the same equation using, as the dependent variable, an indicator $tr_{it}^{c,k} \in \{0,1\}$ for whether individual i transferred funds from a checking account to another asset k in month t, where k denotes savings deposits, time deposits, or a broker account. In this specification the interaction terms, β_j^{ar}, reflect how the likelihood of these reallocation decisions to interest rate changes varies by wealth level.

Figure 6 plots the estimated coefficients β^r and $\left\{\beta_j^{ar}\right\}_{j=1}^{10}$ from equation (6), using monthly wealth deciles for both outcomes under investigation: (i) the share of checking deposits in liquid portfolios, and (ii) the probability of reallocating funds from checking deposits into higher-yielding assets. The figure reveals the key result: Wealthier individuals are more responsive to changes in interest rates. That is, while they already hold portfolios with higher average returns—as shown in the previous section—they also actively shift toward higher-return assets as interest rate spreads widen.

The left panel shows that wealthier individuals reduce the share of their portfolio held in

Figure 6: Interest Rate Sensitivity by Wealth Decile



Notes: This figure plots the estimated coefficients on interest rates, β^r, and the interaction terms between interest rates and monthly wealth deciles, $\left\{\beta_j^{ar}\right\}_{j=1}^{10}$, from equation (6). The left panel shows the estimated effect of interest rate changes on the share of checking deposits; the right panel shows the effect on the probability of reallocating into higher-return accounts.

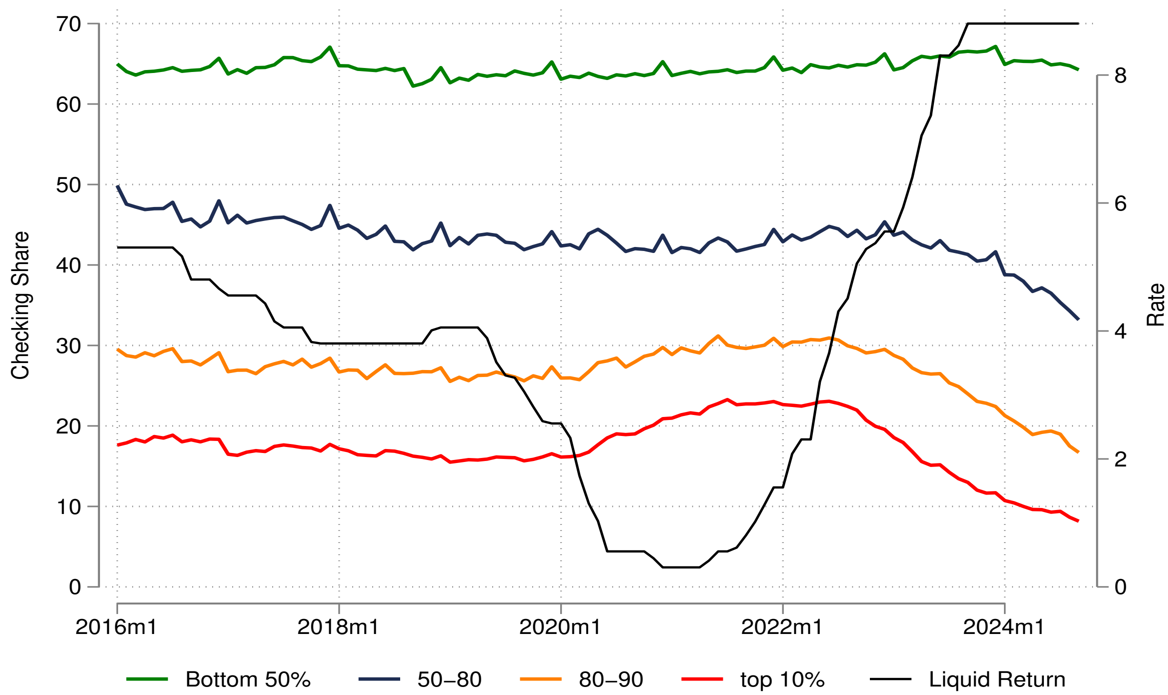
low-return checking deposits more strongly in response to rising interest rates. For instance, individuals in the top decile decrease their checking share by 1.15 percentage points for each 1 percentage point increase in the liquid fund rate—almost ten times the average sensitivity reported in Table 4.[23] The right panel illustrates a similar pattern in adjustment behavior. The wealthiest decile increases the probability of reallocating funds from checking to savings by roughly 1 percentage point for every 1 percentage point rise in the interest rate. In contrast, individuals in lower deciles show little to no increase in adjustment frequency. Transfers into time deposits or brokerage accounts, however, display minimal responsiveness to interest rates across all wealth groups.

The heterogeneity in sensitivity across wealth levels is observed in the raw data shown in Figure 7, which plots the average share of checking deposits in liquid safe asset portfolios by monthly wealth decile groups. The left axis shows the share of checking deposits across deciles, while the right axis plots the interest rate on liquid funds, a measure of the opportunity

[23]See Table 9 for the full set of regression coefficients by decile.

cost of holding funds in checking accounts. Over the monetary policy easing and tightening cycle observed during the sample period, only individuals in the top deciles appear to adjust their portfolio allocations in response to changes in the spreads. In particular, the red and orange lines—representing the top deciles—exhibit a clear negative correlation with the level of interest rates, consistent with more active reallocation toward higher-yielding assets.

Figure 7: Share of Checking Deposits in Liquid Portfolios by Wealth Decile



Notes: This figure shows the time series of average shares of checking deposit in liquid portfolios (left axis) for each wealth decile (monthly classification) and the liquid fund rate (right axis).

Beyond Wealth: The Role of Individual Characteristics

Do financially informed individuals adjust their holdings of liquid safe assets more in response to interest spread changes? To investigate this, we use survey data collected from the bank clients to link portfolio behavior with financial knowledge. We examine whether individuals with higher financial literacy, better awareness of current inflation, and a clearer understanding of how inflation affects asset values reduce their share of low-return liquid assets more than others when the interest rate spread increases.[24]

To assess individuals' financial knowledge, the survey asked bank clients to answer four standard questions commonly used in the financial literacy literature (see Lusardi and Mitchell, 2014). These questions cover key concepts: compound interest, the impact of inflation on purchasing power, the relationship between bond yields and bond prices, and differences in mortgage payments across maturities. Based on the number of correct answers, we classify individuals into two groups: those with high financial literacy, who scored above the median number of correct responses, and those with low financial literacy, who scored at or below the median.

To evaluate individuals' knowledge about inflation, we use two distinct measures. The first captures inflation rate perception. Clients are asked to state the inflation rate over the past 12 months, and we compute the absolute error as the linear distance between their response and the actual inflation rate. Based on this measure, we classify individuals into two groups: those with high precision, whose response deviates from actual inflation by no more than two percentage points, and those with low precision, whose error exceeds that threshold.

The second measure captures inflation-related knowledge through a set of eight questions that cover the effects of inflation on purchasing power, future interest rates, the stock market, and related topics. As with financial literacy, we classify individuals into two groups: those with high inflation knowledge, who answered more questions correctly than the median respondent, and those with low inflation knowledge.

To assess the influence of individual characteristics we estimate the following specification:

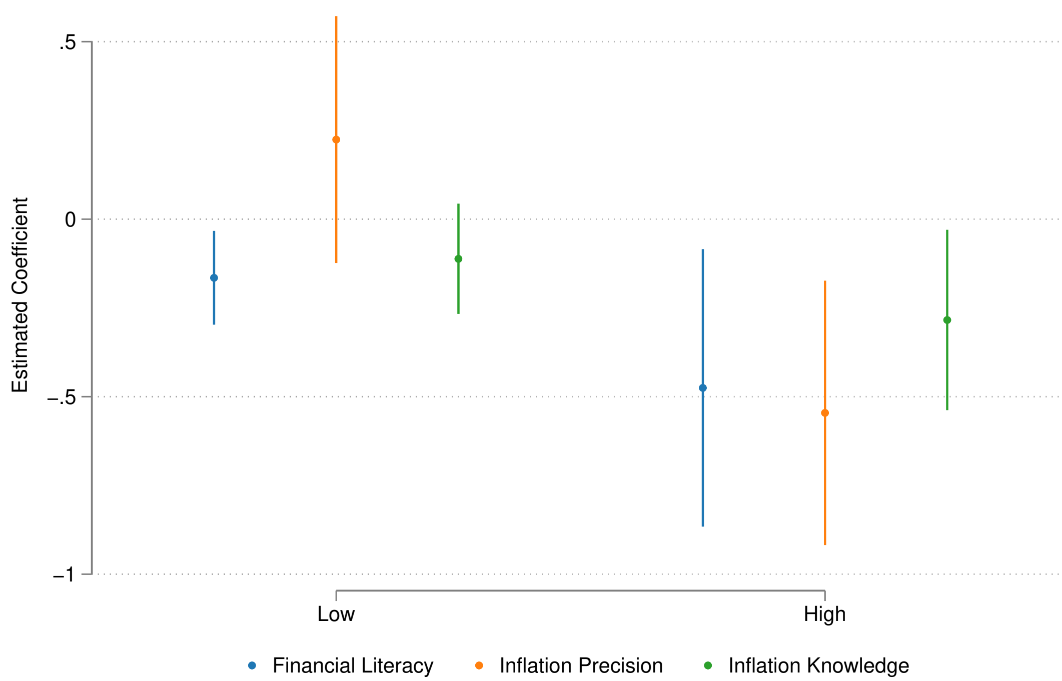
$$\Delta \text{ share}_{it}^{C} = \alpha + \beta^{r} \cdot \Delta \ r_t^L + \beta^{sr} \cdot \text{survey}_i \cdot \Delta \ r_t^L + \beta^{a} \cdot \Delta \ln(a_{it}) + \varepsilon_{it} \tag{7}$$

where Δx_t denotes the 6-month change in variable x_t, defined as $\Delta x_t \equiv x_t - x_{t-6}$, and survey_i denotes the individual characteristic of interest: a high financial literacy indicator, a high inflation knowledge indicator, or high inflation precision indicator. This approach allows us to evaluate how each characteristic correlates with sensitivity to the interest rate spread (via β^{sr}).

[24] The exact survey questions and the distribution of answers are provided in Appendix B.

Figure 8 presents the results, and Table 11 in the Appendix reports the corresponding regression estimates.[25] The figure shows that individual characteristics shape how people respond to interest rate changes (β^{sr}). Individuals with high financial literacy, more precise inflation perceptions, and better knowledge of inflation effects reduce their share of checking deposits more when spreads increase than those with lower scores. The estimated magnitudes are similar across indicators: on average, individuals with low financial knowledge do not adjust their portfolio in response to interest rate changes, whereas those with high knowledge reduce their share in checking deposits by 0.5 percentage points for every 1 percentage point increase in interest rates.

Figure 8: Return Sensitivity and Individual Characteristics



Notes: This figure plots the estimated coefficients β^{sr} from regression (7), showing how sensitivity to interest rate changes varies with individual characteristics. Each bar corresponds to a separate regression using one of the survey-based indicators: high financial literacy, high inflation knowledge, and high inflation perception precision. Error bars represent 95% confidence intervals based on standard errors clustered at the individual level. All variables are measured in 6-month changes.

[25] Table 12 also includes a version that allows for heterogeneity in responses by average wealth levels.

4 Discussion

In this section, we highlight new insights that inform the literature on the relation between monetary policy and financial intermediation, as well as models of household portfolio choice widely used in household finance and macroeconomics. We begin by documenting that fluctuations in the share of cheap core deposits over the business cycle—crucial for bank lending—are primarily driven by wealthier individuals actively adjusting their portfolios in response to return spread changes, rather than by shifts in the distribution of deposit holdings across the wealth spectrum.

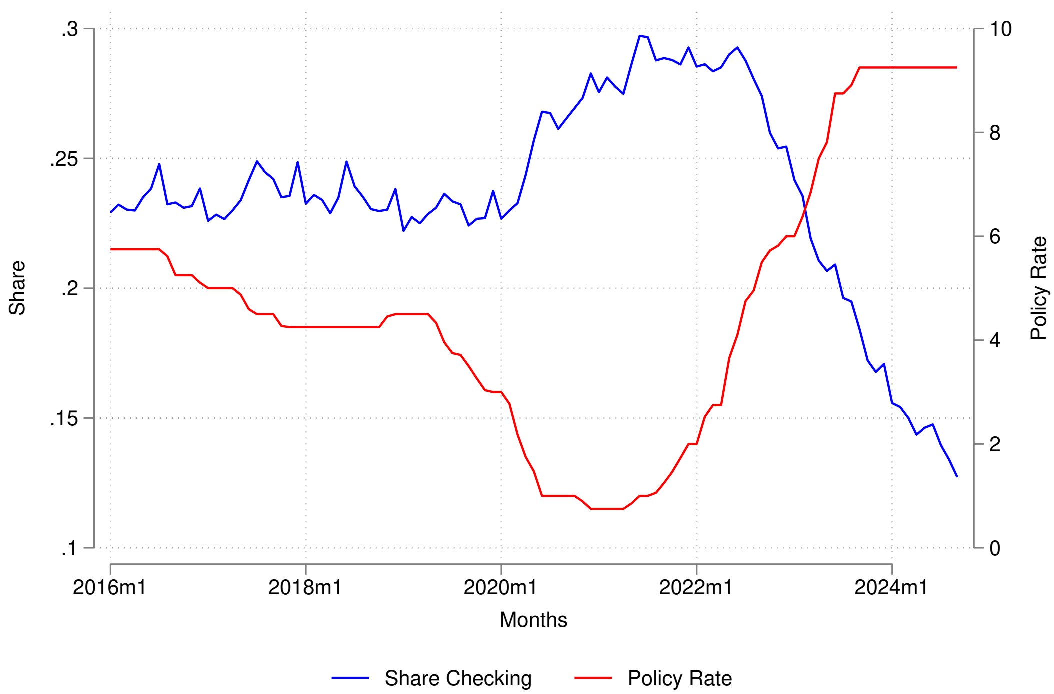
We then use the estimated moments to discipline parameters in portfolio choice models commonly used in macroeconomics and household finance. We show that a standard incomplete markets model with two assets, calibrated to match the observed frequency of portfolio adjustments, captures well the cross-sectional distribution of portfolio shares. However, it overstates the sensitivity of households' portfolio choices to interest rate changes—suggesting that the portfolio response to interest rates, which is central to monetary policy transmission, may be more muted than these models typically imply.

4.1 Who and What Drives Aggregate Deposit Fluctuations?

Low-yield deposits are central to bank lending, as they are not perfectly substitutable by other funding sources and directly affect banks' credit supply (Kashyap and Stein, 1995). Although it is well documented that the share of low-yield deposits declines when central banks raise policy rates (Drechsler et al., 2017), what drives these aggregate shifts remains an open question. In particular, it is not known whether the decline reflects active portfolio reallocation in response to yield changes, or whether it rather stems from either heterogeneous income changes (Salgado et al., 2019) or shifting consumption desires (Sterk and Tenreyro, 2018) that coincide with the monetary cycle and, as shown earlier, also shape portfolio choices. To shed light on the relative importance of these channels, we exploit the Covid-19 recession episode.

In our setting—where the interest rate on savings deposits closely tracks the yield available through brokered alternatives—we examine whether individuals reallocate funds from low-yield checking accounts into high-yield savings accounts as interest rates rise.[26] We refer to the sum of checking and savings deposits as *core deposits*. Figure 9 plots the evolution of the share of checking deposits within core deposits at the bank level, along with the central bank policy rate. Consistent with findings from other countries, we observe a negative correlation: as policy rates increase—and the spread widens—the share of funds held in low-return checking deposits declines.[27]

Figure 9: Policy Rate and Share of Checking Deposits



Notes: This figure plots the evolution of the aggregate share of checking deposits relative to total checking plus savings deposits of active clients alongside the central bank policy rate.

[26]Because savings rates are competitive with brokered alternatives, households have little incentive to move funds outside the bank—such as into money market funds. This justifies our focus on internal reallocations between checking and savings accounts, which still raise the marginal cost of funding for banks. Figure 24 in the Appendix shows that deposits as a share of total bank liabilities at the institution under study remained stable over the cycle and even increased during the Covid period.

[27]Figures Figure 25 and Figure 26 in the Appendix compare the evolution of the share of checking deposits within core deposits for active clients at our partner bank and for the full population across all Icelandic banks, showing that this pattern holds at the national level. They also show that the share of core deposits remains stable over the cycle, both at our bank and in the aggregate. This stability is expected, as the spread between savings deposits and outside alternatives does not widen during this period.

The aggregate share of checking deposits, s_t, can be written as a weighted average of group-level shares s_{gt}, with weights ω_{gt} given by each group's share in total core deposits. Its fluctuations can be decomposed into two components: a *redistribution* term and a *portfolio adjustment* term:[28]

$$s_t = \sum_g \omega_{gt} \cdot s_{gt} \quad \longrightarrow \quad \Delta s_t \approx \underbrace{\sum_g \Delta\omega_{gt} \cdot s_{gt-\tau}}_{\text{Redistribution}} + \underbrace{\sum_g \omega_{gt-\tau} \cdot \Delta s_{gt}}_{\text{Portfolio Adjustment}} \tag{8}$$

The first term, *Redistribution*, captures movements in the aggregate checking share due to changes in the distribution of core deposit balances across groups g, $\Delta\omega_{gt}$, interacted with heterogeneity in groups checking shares, $s_{gt-\tau}$. Based on our earlier findings, if funds shift towards low-wealth individuals—who tend to hold a higher fraction of their deposits in checking accounts—this redistribution will mechanically increase the aggregate share of checking deposits. In other words, movements in s_t can reflect shifts in who holds deposits, even if individuals' own portfolio shares remain unchanged.

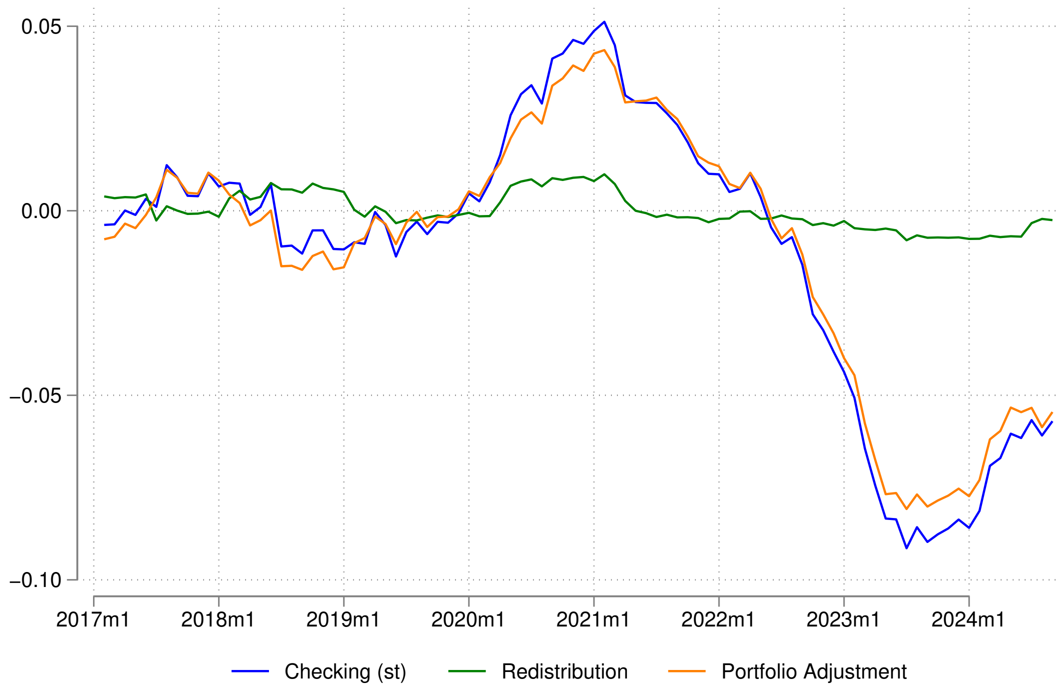
The second term, *Portfolio Adjustment*, captures movements in the aggregate checking share due to individuals adjusting their own portfolios, Δs_{gt}. That is, even if the distribution of core deposits across individuals remains unchanged, shifts in the checking share within individual portfolios can drive aggregate changes.

Figure 10 decomposes the 12-month change in the aggregate checking share into *Redistribution* and *Portfolio Adjustment* components, grouping individuals each month by deciles of core deposits. The figure shows that variation in the aggregate checking share is driven primarily by *portfolio adjustment*—changes in the share of checking deposits within individual portfolios—rather than by *redistribution* across wealth groups. Even during the Covid-19 recession—when household savings rose due to limited consumption opportunities and government transfers—most of the change in aggregate checking shares reflects within-household portfolio decisions, not shifts in the distribution of core deposits.

Redistribution across individuals of different wealth levels contributes little to the overall

[28] Specifically, given a group of individuals g: $s_{gt} \equiv \frac{\text{checking}_{gt}}{\text{checking}_{gt}+\text{savings}_{gt}}$ and $\omega_{gt} \equiv \frac{\text{checking}_{gt}+\text{savings}_{gt}}{\sum_g \left(\text{checking}_{gt}+\text{savings}_{gt}\right)}$ where $\text{checking}_{gt} = \sum_{i \in g} \text{checking}_{it}$ and equivalently for savings. The decomposition ignores the cross-product term $\sum_g \Delta\omega_{gt} \cdot \Delta s_{gt}$, which is later shown to be quantitatively negligible.

Figure 10: Decomposition of Changes in the Aggregate Checking Share



Notes: This figure shows the 12-month change in the aggregate share of checking deposits, decomposed into two components: *Portfolio Adjustment* (green), capturing changes in individuals' checking shares within their own portfolios, and *Redistribution* (orange), capturing changes due to shifting weights in the distribution of core deposits across individuals.

change because core deposits are highly concentrated among the wealthiest households. Individuals in the top decile alone hold over 60% of total core deposits, meaning that substantial shifts in wealth would be required to affect the aggregate share of checking deposits. During the Covid recession, there is a modest redistribution toward lower-wealth individuals—the share of core deposits held by the top 10% declines from 66.6% in 2019 (pre-pandemic) to 64.2% in 2021 (i.e., during the downturn)[29]—but this change is not large enough to significantly move the aggregate checking share.

Therefore, because changes in the aggregate are not driven by redistribution, we must focus on the factors that cause individuals' checking shares to fluctuate Δs_{gt} to understand what drives aggregate deposit shares Δs_t. Given the concentration of core deposits, this

[29] Figure 27 in the Appendix shows the distribution of core deposits by wealth group. Figure 28 next to it shows the average share of checking deposits in core deposits by wealth levels for different years.

ultimately means understanding what makes wealthy depositors tick.

One possibility is that relatively uniform savings patterns during the Covid recession led to temporary shifts in deposit allocations. Another is that changes in interest rate spreads account for the observed aggregate variation. While average responses to interest rates are modest, wealthy households are significantly more responsive, suggesting that rate movements may explain much of the aggregate reallocation, even if income effects are the main driver for most households. To explore this, we estimate a more flexible specification than those used in previous sections:

$$\begin{aligned} s_{it} = & \underbrace{\beta^r \cdot r_t^L + \sum_{j=1}^{10} \beta_j^{ar} \cdot \mathbb{I}_{(d_{it}=j)} \cdot r_t^L}_{\text{Interest rate terms}} \\ & + \sum_{j=1}^{10} \beta_j^a \cdot \mathbb{I}_{(d_{it}=j)} + \sum_{j=1}^{10} \beta_j^{a \log(a)} \cdot \mathbb{I}_{(d_{it}=j)} \cdot \log(a_{it}) + X_{it}'\delta + \alpha + \varepsilon_{it} \end{aligned} \tag{9}$$

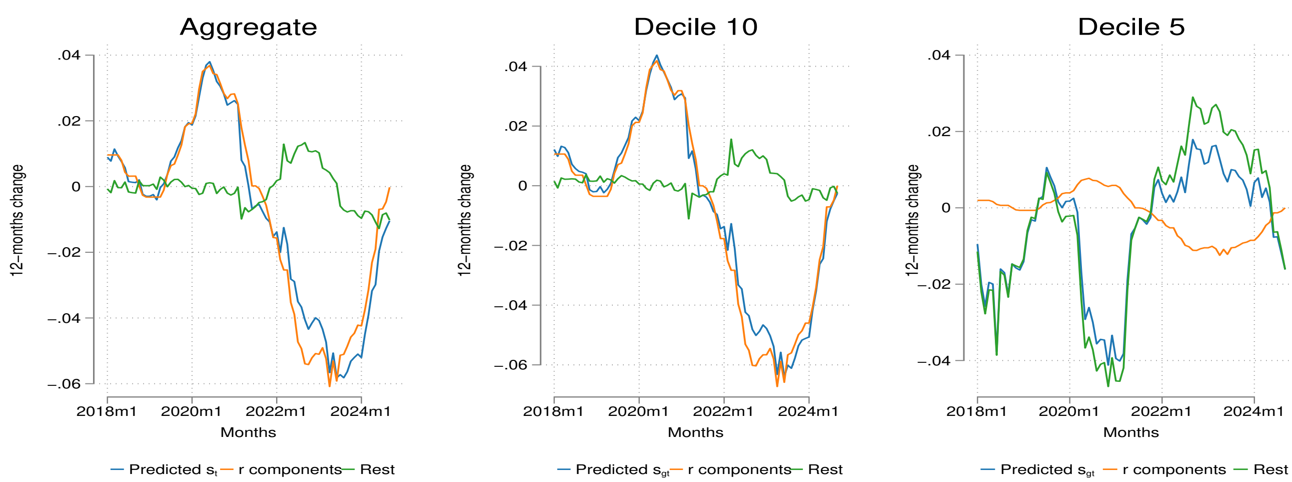
where s_{it} is individual i's share of checking in core deposits, r_t^L is the interest rate on the liquid fund, d_{it} denotes individual i's decile of core deposits at time t, a_{it} is their level of real core deposits, and X_{it} includes controls such as a polynomial in age, gender, and wealth group-specific time trends. This specification generalizes the baseline regression in the paper by allowing for decile-specific slopes in both the interest rate, the time trend, and the log of assets, $\log(a_{it})$. The rationale is that both the rank and the level of wealth within the group may shape portfolio responses during the cycle.

We aggregate individual-level predictions from equation (9) to construct a predicted aggregate share, $\widehat{s}_t = \sum_i \omega_{it} \cdot \widehat{s}_{it}$, and decompose its predicted yearly change, $\Delta\widehat{s}_t$, into the component driven by interest rate movements and the component driven by all other regressors.[30]

The left panel of Figure 11 shows that nearly all the predicted variation in the aggregate series is explained by the interest rate terms in equation (9), with wealth and other controls contributing little. This highlights the central role of interest rate movements in driving aggregate changes in the share of checking deposits.

[30] Figure 29 shows that the predicted changes in aggregate checking shares, $\Delta\widehat{s}_t$, closely track the observed changes. The interest rate component is computed as the 12-month difference in the predicted value of the terms labeled "Interest rate" in equation (9).

Figure 11: Decomposing Aggregate Changes in the Share of Low-Return Deposits



Notes: This figure decomposes 12-month changes in the model-predicted share of checking deposits into the portion explained by interest rate movements and the portion explained by all other covariates in equation (9). The left panel shows aggregate changes, the center panel shows the decomposition for the top wealth decile, and the right panel for the fifth wealth decile. Wealth deciles are constructed using core deposit balances. Interest rate effects are computed by holding all covariates constant except the interest rate.

The center and right panels decompose changes in the predicted average checking share for the top and middle wealth groups, $\Delta\widehat{s}_{gt}$.[31] For the fifth wealth decile (right panel), interest rates explain only a small share of the variation; most changes are associated with other covariates. By contrast, for the top wealth decile (center panel), the contribution of other factors is minimal, and interest rates account for virtually all of the observed fluctuations. This difference has direct implications for aggregate dynamics: Because wealthy households both hold the majority of deposits and respond strongly to interest rate changes, aggregate shifts in checking shares are largely the result of their portfolio adjustments to interest rates.

4.2 A Portfolio Choice Model with Adjustment Frictions

We study the predictions of household portfolio adjustment models and compare them to empirical moments from the data. Employing our novel empirical results, we discipline the

[31] Figure 30 shows that the decomposition also closely captures the actual changes in checking shares for each group.

frictions embedded in models commonly used in household finance and macroeconomics, assess their performance, and evaluate whether the frictions that best fit the evidence are primarily state- or time-dependent.

The framework builds on a two-asset Baumol–Tobin model with income risk and incomplete markets.[32] Households receive a stochastic income stream y_t and can save in two assets: low-yield deposits d_t earning rate r_t^d, and higher-yield deposits b_t earning r_t with $r_t > r_t^d$. Markets are incomplete: households cannot fully insure against idiosyncratic income shocks.

Portfolio reallocation faces two possible frictions, and we solve versions of the model with each friction in isolation. First, moving funds across accounts entails a fixed monetary cost F.[33] This friction generates state-dependent (s, S) inaction regions, as in many applications in economics where financial incentives determine whether adjustment is made. Second, with exogenous probability λ each period, households receive an "adjustment opportunity" that allows costless portfolio rebalancing. This friction is meant to captures time-dependent inaction or inattention.[34]

The household that begins the period with liquid cash-on-hand w and can rebalance between low- and high-yield deposits solves:

$$V^A(w, b) = \max_{c, d', x} u(c) + \beta \mathbb{E}\left[V(y', d', b')\right]$$

subject to:

$$\begin{aligned} c + d' &= w + x \\ b' &= b(1 + r) - x \\ d' &\geq \underline{d}\,;\; b' \geq \underline{b} \\ y' &= \Gamma(y, \epsilon') \end{aligned}$$

where x is the value of the transfer between high- and low-yield deposits, $\underline{d}$ and $\underline{b}$ exogenous borrowing limits, and $\Gamma(y, \epsilon')$ is the Markov process for income that describes the transition between y and y' with ϵ' being the value of an iid shock. We normalize average income to

[32] These models are widely used in macroeconomics and finance; (see, e.g., Kaplan and Violante, 2014; Melcangi and Sterk, 2024; Cocco et al., 2005).

[33] Modeling the cost as a monetary rather than utility cost is standard practice in the literature, from Baumol (1952) and Tobin (1956) to Cocco et al. (2005), Kaplan and Violante (2014), and others.

[34] For an application see Auclert et al. (2020).

have mean 1: $\mathbb{E}(y) = 1$.

The household's problem when not adjusting is:

$$V^N(w,b) = \max_{c,d'} u(c) + \beta \mathbb{E}\left[V(y',d',b')\right]$$

subject to:

$$\begin{aligned} c + d' &= w \\ b' &= (1+r)\,b \\ d' &\geq \underline{d} \\ y' &= \Gamma(y,\epsilon') \end{aligned}$$

Finally, the household's beginning-of-period problem depends on the friction governing funds reallocation:

State-Dependent Friction (fixed cost F):

$$V(y,d,b) = \max\{\, V^A(w-F,\, b),\ V^N(w,\, b)\,\}.$$

Time-Dependent Friction (opportunity with probability λ):

$$V(y,d,b) = \lambda\, V^A(w,\, b) + (1-\lambda)\, V^N(w,\, b).$$

where liquid cash-on-hand is

$$w \equiv y + d(1+r^d).$$

Calibration and Mapping to the Data

Some parameters are taken from external sources, while others are chosen to match moments in the data. The model period is one month. Preferences over consumption are CRRA $u(c) = c^{1-\sigma}/(1-\sigma)$ with an intertemporal elasticity of substitution (IES) = 0.5, i.e. $\sigma^{-1} = 1/2$. Idiosyncratic income follows a lognormal AR(1) process::

$$\log y' = \rho\, \log y + \sigma_\epsilon\, \epsilon',$$

where ϵ' is i.i.d. standard normal.

For the income process we adopt a U.S. calibration widely used in the literature. Following Floden and Lindé (2001) and Auclert et al. (2024), we target an annual persistence of 0.91 and choose the innovation variance so that the cross-sectional standard deviation of (annual) log gross earnings is 0.92. Because these targets are annual while the model period is monthly, we select monthly (ρ, σ_ϵ) so that the simulated monthly process, when aggregated to the annual frequency, reproduces the targeted persistence and dispersion.[35] The implied monthly parameters are $\rho = 0.988$ and $\sigma_\epsilon = 0.145$.

For asset returns, we interpret the low-yield deposits as checking deposits and set their annual real return to $r^d = -3\%$ and the high-return deposits as savings deposits and set their annual return to $r = 1\%$. These values are consistent with a zero nominal return on checking deposits, a 4% nominal return on savings accounts, and an assumed inflation rate of 3%, roughly in line with pre-Covid inflation levels. We assume that agents are not allowed to borrow, so $\underline{d}$ and $\underline{b}$ are set to zero.

We calibrate the discount factor and portfolio adjustment parameters to match selected moments in the data as described below. The empirical moments of portfolio shares and returns are computed using average daily asset holdings. Because the model is in discrete time, we must assume an intra-period timing of consumption and, when a portfolio reallocation occurs, the timing of the adjustment within the period. We assume consumption is distributed evenly over the month at a constant rate, and that reallocations take place at the midpoint of the month.[36]

We set the discount factor β to match the lower tail of the liquid asset distribution. The goal is to capture the idea that limited adjustment may partly reflect low wealth. Specifically, we target the ratio of average liquid assets to annual consumption for individuals in the 5th decile, which is 0.28—roughly three months of consumption.[37] We then calibrate the trading-friction parameters, F or λ, to match the share of individuals making at least one monthly transfer between checking and savings accounts, which is 40%. Table 6 reports the

[35]Specifically, we simulate the monthly AR(1) process, construct annual income as $y_t^A = \sum_{m=0}^{11} y_{t+m}$, compute $\log y_t^A$, and then search over (ρ, σ_ϵ) to match the annual AR(1) persistence 0.91 and the standard deviation 0.92.

[36]See Appendix C.1 for the exact derivations.

[37]See footnote of Figure 21 in the Appendix for details on the computation.

parameters that managed to match the selected moments exactly. The obtained value of F corresponds to 0.1% of average monthly income.[38]

Table 6: Internally Calibrated Parameters

	State-Dependent	**Time-Dependent**
F	0.001	
λ		0.4
β	0.9755	0.9815

Notes: This table reports the internally calibrated parameters for each model: the discount factor β and the trading-friction parameters, F or λ. These are simultaneously chosen to match the ratio of average liquid assets to annual consumption for households in the 5th decile (0.28) and the observed share of households making at least one monthly transfer between checking and savings accounts (40%).

Results

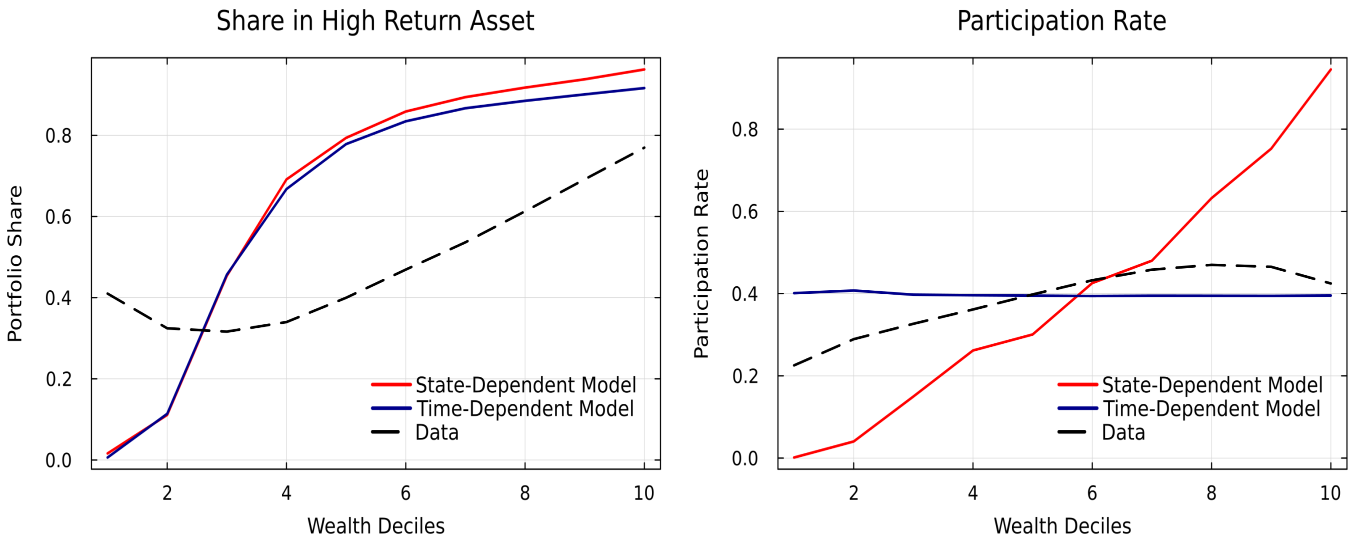
We begin by evaluating how the models replicate the cross-sectional allocation of liquid assets. The left panel of Figure 12 shows that both the state- and time-dependent specifications generate an increasing share of high-return assets across wealth deciles, consistent with the empirical profile in Figure 3 (reproduced in the figure). While the models capture the upward gradient, they predict a much steeper slope: for instance, the share for households in the 8th decile is overstated by more than 20 percentage points relative to the data.

The models reach this cross-sectional pattern even though they display very different likelihoods of rebalancing between accounts across the wealth distribution. The right panel of Figure 12 shows that, in the time-dependent specification, the share of individuals rebalancing is flat at 40% across deciles—by construction, rebalancing occurs only when an exogenous trading opportunity arrives. By contrast, in the state-dependent specification individuals endogenously choose to rebalance in an (s, S) fashion.[39] Because wealth and income comove in these models, higher-wealth households are more likely to hit the adjustment boundary and move funds from low-return to high-return accounts, so rebalancing likelihood rises with

[38] For reference, with a per-capita disposable income of roughly \$50,000 US dollars per year in Iceland, this implies an adjustment cost of about \$4 each month the individual decides to adjust.

[39] See Figure 31 in the Appendix for an example of the policy function.

Figure 12: Portfolio Shares and Rebalancing Rates Across Wealth Deciles in the Models



Notes: The left panel plots average annual shares of high-return assets across wealth deciles; the right panel plots monthly participation rates, defined as the share of individuals who rebalance between accounts in a given month. Dashed lines represent the data moments.

wealth.

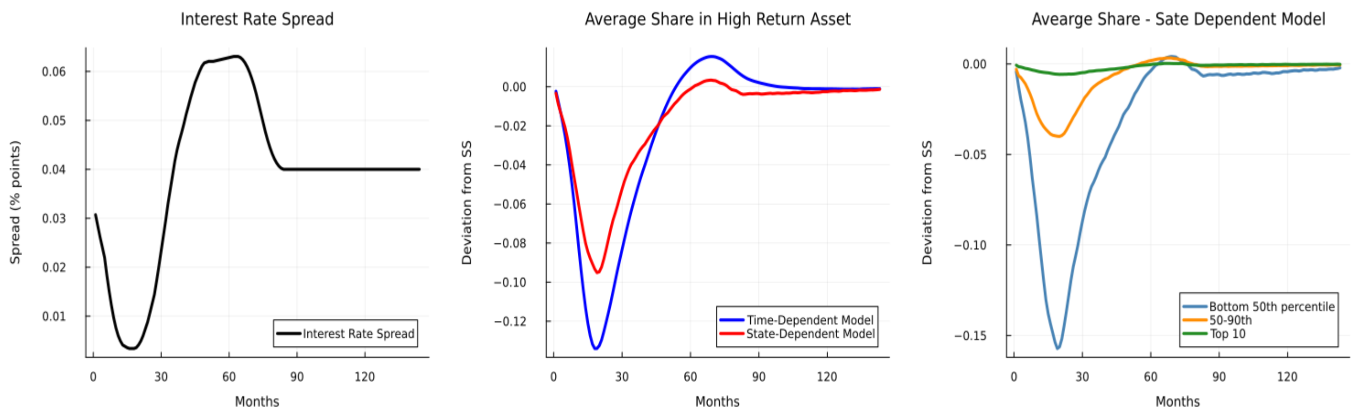
Overall, both types of frictions generate broadly similar implications for households' portfolio allocation across the wealth distribution, despite generating very different likelihoods of rebalancing between accounts. The cross-sectional predictions are not far from the data, suggesting that these simple mechanisms can go a long way toward capturing observed heterogeneity in portfolio choices. However, calibrating the models to match cross-sectional moments does not guarantee that they generate the right dynamics over the business cycle. This distinction is particularly relevant as heterogeneous-agent models have recently been popularized to study monetary policy transmission. In these models, households that are not at their borrowing constraint adjust consumption in response to interest-rate changes according to the Euler equation.[40]

We next show that both types of models overestimate the portfolio response to interest rates. To illustrate this, we initialize the economy in steady state and expose agents to a perfect-foresight path of interest rates on high- and low-return assets that replicates the

[40]See Kaplan et al. (2018).

evolution observed during the Covid-19 cycle.[41] The left panel of Figure 13 plots the implied spread, $r - r^d$, which first compresses as policy rates fall to the lower bound and subsequently widens as rates increase during the recovery.

Figure 13: Model Responses to an Interest-Rate Shock



Notes: The left panel shows the path of the spread, $r - r^d$, generated by the assumed interest-rate shock. The center panel plots the average share of high-return assets across all households in each model. The right panel displays the average share of high-return assets by wealth deciles in the state-dependent specification.

The center panel of Figure 13 shows that the average portfolio shares in the models fluctuate strongly with the spread, in stark contrast to the near-flat profile in the data (Figure 3). This excessive sensitivity arises under both types of frictions. In the state-dependent economy, the share of households that rebalance moves sharply with the spread, while in the time-dependent economy participation remains mechanically constant (Figure 33); nonetheless, portfolio shares still swing widely whenever trading opportunities arrive. The right panel highlights a further discrepancy: Unlike in the data (Figure 7), where responsiveness is concentrated among higher-wealth households, the models predict that fluctuations are largest among low-wealth households.[42]

Overall, we build on popular models of portfolio adjustment and show that, while they do a reasonable job of matching cross-sectional patterns, they struggle to reproduce the business-cycle response to an interest-rate shock. In particular, they overstate the sensitivity of portfolio

[41]The path is constructed using the bank's rates on high-return savings and checking deposits. Real rates are obtained by subtracting median household inflation expectations from the central bank inflation expectation survey. See Figure 32 for the exact path.

[42]As shown in Figure 34, this pattern also arises in the time-dependent specification.

shares to interest-rate fluctuations and misrepresent the distribution of responsiveness across the wealth distribution. Our results point to the need for additional mechanisms beyond simple trading frictions to account for the heterogeneous portfolio adjustments observed in the data.

5 Conclusion

This paper studies how individuals allocate their liquid, short-term, safe assets—checking, savings, and brokered liquid funds—that are identical in risk, maturity, and transfer frictions but offer different yields. This asset class dominates the financial portfolios of households: Participation is nearly universal; for most households their financial portfolios consists exclusively of liquid, short-term, safe asset; and even among those that do participate in risky assets markets, these assets constitute the largest share of their financial portfolio for most. This asset class is also important to banks as it constitutes the largest share of bank liabilities.

Using a panel of detailed and comprehensive individual transaction-level bank data linked to rich demographics and survey data, we show that most households adjust only modestly to movements in interest rates. In contrast, wealthy households are an order of magnitude more responsive than the average. They also allocate larger shares to higher-yield options and earn substantially higher returns on their liquid portfolios—about two percentage points per year. Survey measures of financial literacy and inflation knowledge are strongly associated with greater responsiveness.

Our portfolio-action evidence clarifies the aggregate picture of low-cost deposit fluctuations. Business-cycle movements in the share of low-rate deposits are driven primarily by a relatively small group of active, wealthier depositors who move funds when spreads widen. This reflects both the high concentration of deposits among these households and the fact that they are the only ones who respond significantly to rate changes.

A simple portfolio framework with either state-dependent or time-dependent frictions can reasonably match the cross-section of holdings, but both specifications overstate households' sensitivity to interest-rate spreads. This tension is informative: models that fit average allocations need additional ingredients—for instance, limited attention, information frictions, or salience—to reproduce the weak behavioral response we observe in the bulk of the distribution.

These findings have important implications for banks and for monetary policy. If most depositors remain inattentive while a minority of affluent households arbitrage spreads, deposit betas and funding costs will depend disproportionately on the behavior of that group. On the policy side, heterogeneous pass-through implies that rate changes transmit unequally through household liquid returns. Light-touch interventions—clearer disclosure of product yields, default "sweep" rules from checking to higher-yield accounts, or periodic reminders—could raise average cash returns without restricting choice, though the effectiveness of such tools remains an empirical questions. Future work could test targeted information or salience interventions, and track the role of mobile design and aggregators.

Taken together, the evidence points to a simple message: Even when safe, liquid options are near-perfect substitutes and transfers are easy, most households do not chase yield. A small, financially savvy share does, and their actions drive aggregate adjustments. Recognizing this heterogeneity is essential for modeling portfolio choice, for understanding banks' deposit pricing, and for gauging how monetary policy reaches households' liquid balances.

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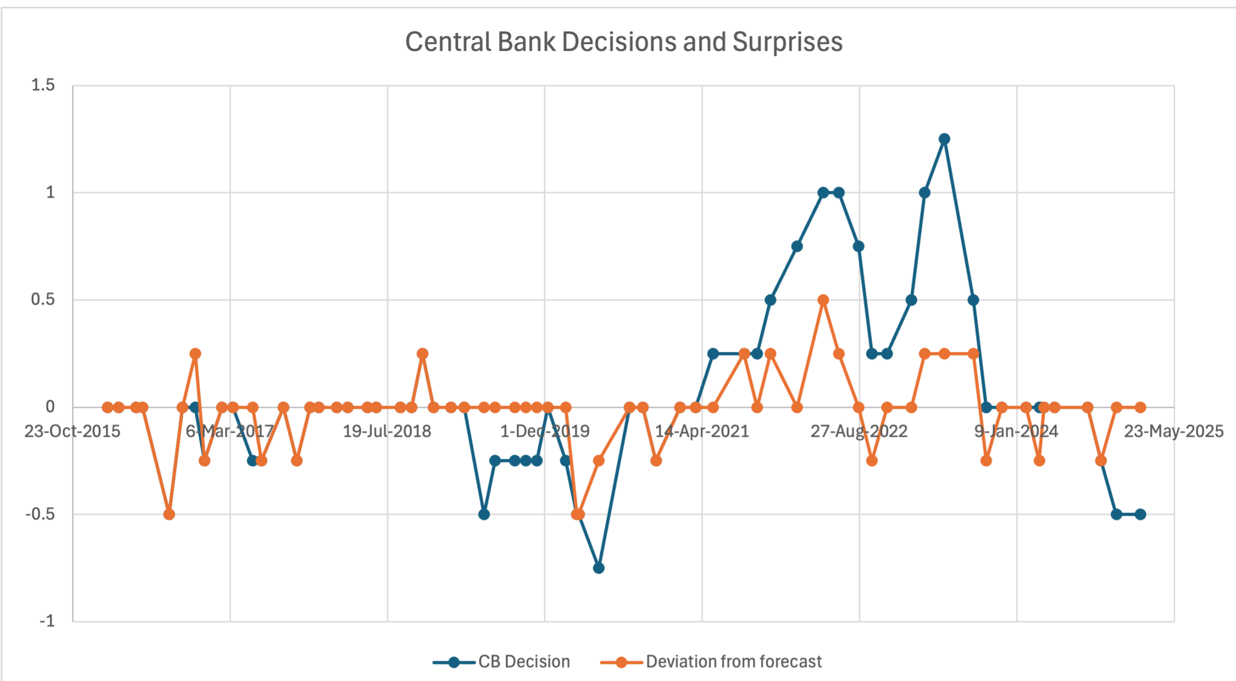
A Monetary Policy Surprises

We define a monetary policy surprise as the difference between the announced policy rate and the most recent forecast. Aggregating these at the monthly level, we construct a series of monetary policy shocks. This Appendix provides further evidence on the validity of this measure as an instrument for identifying the effects of monetary policy.

Figure 14 displays the time series of monetary policy surprises together with the Central Bank's decisions on the policy rate.

Figure 14: Monetary Policy Shocks



Notes: This figure displays changes in the Central Bank of Iceland's policy rate (blue line) and the corresponding monetary policy surprises (orange line), measured as the difference between the actual rate change and the most forecast from our partner bank. Surprises are aggregated at the monthly level.

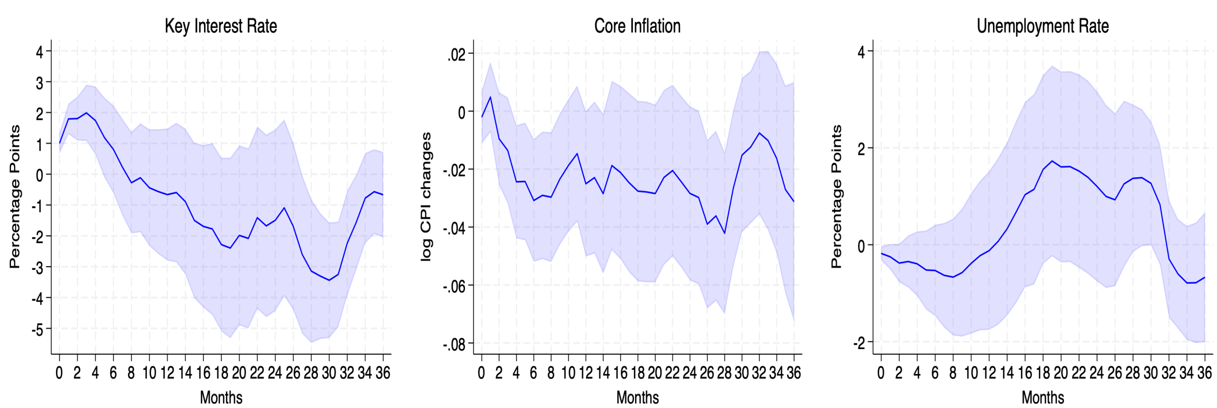
To assess the validity of our monetary policy shocks, we estimate the impulse responses of macroeconomic variables using local projections à la Jordà (2005):

$$y_{t+h} = \alpha_h + \beta_h \cdot \text{shock}_t + \sum_{\ell=1}^{p} \delta'_{h,\ell} w_{t-\ell} + \varepsilon_{h,t} \tag{10}$$

where y_{t+h} denotes the macroeconomic variable of interest h months after the shock at time t, and shock_t is the monthly monetary policy surprise, as previously defined, and normalized to generate a 1 percentage point increase in the central bank policy rate in the following month. The vector $w_{t-\ell} = (x_{t-\ell}, y_{t-\ell}, \text{shock}_{t-\ell})$ includes the ℓ lagged values of the dependent variable, the shock, and other control variables x_t.

We focus on the coefficient β_h, which captures the effect of a monetary policy surprise at time t on a macroeconomic variable y_{t+h} observed h months later. Specifically, we study the impact of shocks on the Icelandic central bank policy rate, log of core CPI, and the unemployment rate. The control vector includes two lags of the dependent variable, the shock, and the other macroeconomic variables under study. Figure 15 presents the estimated impulse responses over a 36-month horizon. The responses are broadly consistent with findings from similar economies (see Holm et al., 2021): after the shock, the policy rate initially increases and then reverts, core inflation declines modestly, and the unemployment rate rises. However, the short sample size constrains statistical power, resulting in imprecise estimates.

Figure 15: Impulse Responses to Monetary Policy Shocks



Notes: Estimated impulse responses of the central bank policy rate, core CPI, and the unemployment rate to a monetary policy shock normalized to generate a 1-percentage point increase in the policy rate. Responses are based on local projections over a 36-month horizon with two lags of each variable included as controls. Shaded areas denote 90% confidence intervals.

B Surveys

This Appendix provides details on the survey used to collect data on inflation expectations, inflation and financial knowledge. The survey was administered to 4,085 individuals, of whom 4,059 successfully merged with our main data set after applying the active client filter used throughout this paper. The following sections present the complete survey questions as they appeared to respondents, along with the distribution of correct answers where applicable.

B.1 Financial Knowledge Questions

This Appendix provides the exact wording of the survey questions used to assess financial literacy. These questions follow standard formulations widely used in the literature (see, e.g., Lusardi and Mitchell, 2014). The correct answer to each question is shown in **bold**.

1. Suppose you had 1,000 kr. in a bank account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
   - **More than 1,020 kr.**
   - Exactly 1,020 kr.
   - Less than 1,020 kr.
   - Don't know
   - Prefer not to say
2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
   - More than today
   - Exactly the same
   - **Less than today**
   - Don't know
   - Prefer not to say
3. If interest rates rise, what will typically happen to bond prices?
   - They will rise
   - **They will fall**

- They will stay the same
- There is no relationship between bond prices and the interest rate
- Don't know
- Prefer not to say

4. Please tell me whether this statement is true or false: A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.
   - **True**
   - False
   - Don't know
   - Prefer not to say

B.1.1 Distribution of Correct Answers on Financial Knowledge

A total of 4,058 individuals provided valid responses to the financial literacy questions. Table 7 presents the distribution of correct answers among respondents.

Table 7: Distribution of Correct Answers on Financial Literacy Questions

Number of Correct Answers	Frequency	Percent
0	190	4.7
1	416	10.3
2	1,042	25.7
3	1,933	47.6
4	477	11.7
Total	**4,058**	**100.0**

The median number of correct responses is 3. For our analysis, we classify individuals as having high financial literacy if they scored above the median, i.e., answered all 4 questions correctly.

B.2 Inflation Awareness Question

To capture individuals' perceptions of recent inflation, the survey included a question asking respondents to identify whether there was inflation or deflation over the past year and to estimate its magnitude. The question was presented as follows:

"We would like to ask you about the rate of inflation or deflation over the past 12 months. Inflation refers to the percentage increase in overall prices in the economy, most commonly measured by the Consumer Price Index (CPI). Deflation is the opposite of inflation and indicates a percentage decrease in prices.

Over the past 12 months, do you think there was inflation or deflation?

Please select one:

- Inflation
- Deflation

What do you think the rate of [inflation if selected above / deflation if selected above] was over the past 12 months? Please give your best estimate as a percentage (0 or greater):

Over the past 12 months, I think the rate of [inflation/deflation] was: ___%."

B.2.1 Distribution of Inflation Perception Deviations from Actual Inflation

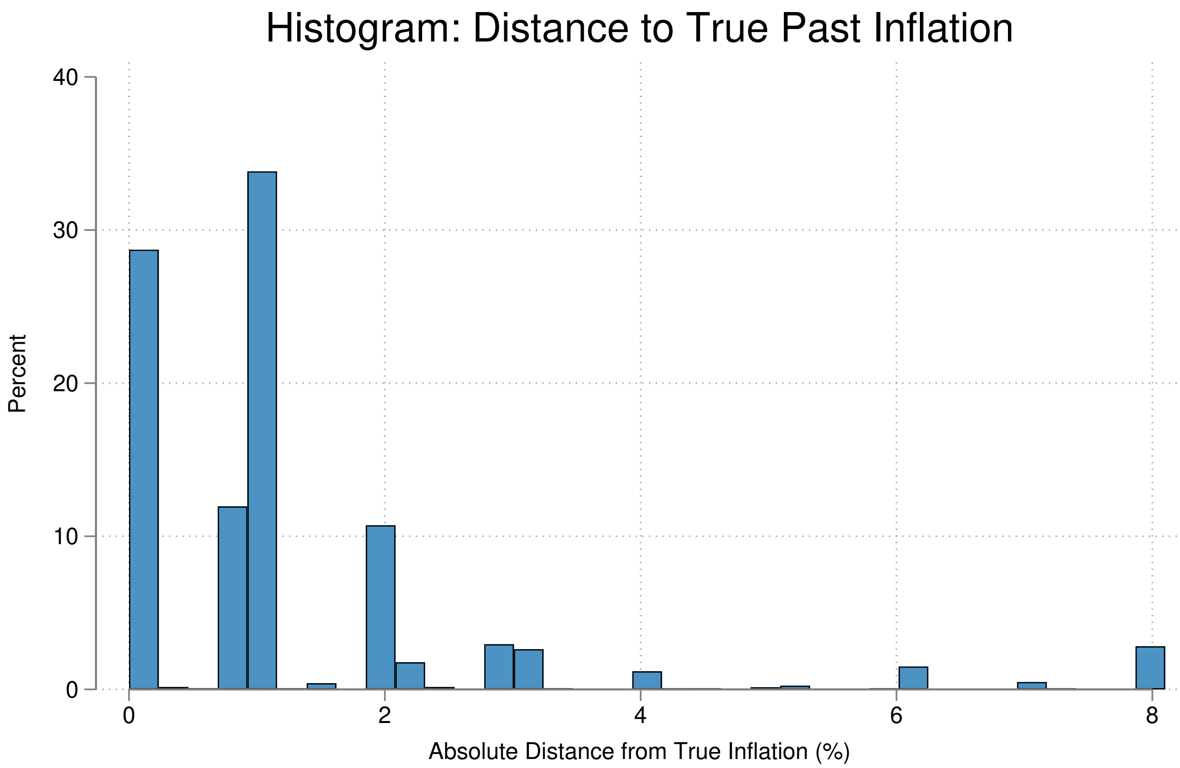
The survey was conducted between June and September 2023, with over 80% of respondents completing it in June and nearly all of the remaining 20% in September. To measure the actual rate of inflation, we use the 12-month inflation rate published by the Central Bank of Iceland, which stood at 8.9%, 7.6%, 7.7%, and 8.0% in June, July, August, and September 2023, respectively. A total of 3,733 individuals provided valid responses to the past inflation level.

Figure 16 shows the distribution of absolute errors in respondents' perceptions of the inflation rate over the past 12 months. The figure plots the absolute distance between each individual's reported inflation rate and the actual rate at the time of the survey.

B.3 Inflation Knowledge Questions

This Appendix provides the exact wording of the survey questions used to assess knowledge of the effects of inflation on asset prices and purchasing power. The correct answer to each question is shown in **bold**. Note that for some questions, multiple answers may be considered

Figure 16: Histogram of Errors on Inflation Level



correct due to the inherent imprecision of economic relationships between response options. In these cases, we consider the question correctly answered if the participant chooses any of these answers.

When you expect inflation to be much higher for the next five years than today, what do you think happens to the following:

Future interest rates on mortgages and other loans

- **Go up**
- Go down
- No change
- Don't know

The amount of goods and services that can be bought in five years time with a fixed salary level

- Go up
- **Go down**
- No change
- Don't know

The value of stocks today

- Go up
- **Go down**
- No change
- Don't know

The future growth rate of the Icelandic economy. Please note that in the last 10 years (2013 through 2022) the average growth rate of the Icelandic economy has been 3.1% per year.

- **Lower than average**
- Higher than average
- About average
- Don't know

Future unemployment rate.

- **Go up**
- Go down
- **No change**
- Don't know

Future house prices

- **Go up**
- Go down
- No change
- Don't know

Do you think that an individual expecting high inflation should do the following?:

Adjust their purchases of durable goods

- **Buy any planned durable goods sooner rather than later.**
- Postpone buying any planned durable goods.
- Buy a cheaper version of the planned durable goods
- It depends. Please explain:

If an individual needed to take a mortgage to buy a home, what type of a mortgage should she take? Should she take a CPI-indexed loan or a non-CPI indexed mortgage and should it be a fixed-rate or a variable-rate mortgage?

- Fixed-rate CPI indexed mortgage
- **Fixed-rate non-CPI indexed mortgage**
- Variable-rate CPI indexed mortgage
- **Variable-rate non-CPI indexed mortgage**

B.3.1 Distribution of Correct Answers on Inflation Knowledge

A total of 4,034 individuals provided valid responses to the inflation knowledge questions. Table 8 presents the distribution of correct answers among respondents.

Table 8: Distribution of Correct Answers on Inflation Knowledge Questions

Number of Correct Answers	Frequency	Percent
0	23	0.57
1	72	1.78
2	185	4.59
3	417	10.34
4	779	19.31
5	992	24.59
6	907	22.48
7	526	13.04
8	133	3.30
Total	**4,034**	**100.0**

The median number of correct responses is 5. For our analysis, we classify individuals as having high inflation knowledge if they scored above the median, i.e., answered 6 or more questions correctly.

C Model Appendix

C.1 Mapping to Data

We assume that when an agent chooses to consume c_t in month t, consumption occurs continuously at a constant rate over the period. Consider an individual who enters period t with cash-on-hand $w_t = y_t + d_t(1 + r^d)$, prior to any transfer into or out of the high-return asset. Suppose a portfolio adjustment of size $b'_t - b_t$ takes place at time $\tau \in [0, 1]$ within the period. Then, the average holdings of low-return (deposit) assets in period t are given by:

$$\begin{aligned} \overline{d}_t &= \int_0^\tau (w_t - c_t \cdot h)\, dh + \int_\tau^1 (w_t - c_t \cdot h) - (b'_{t+\tau} - b_t)\, dh \\ &= \frac{w + d'}{2} + \left(b'_{t+\tau} - b_t\right) \cdot \left(\tau - \frac{1}{2}\right) \end{aligned}$$

and the average holdings of high-return assets are,

$$\overline{b}_t = \tau \cdot b_t + (1 - \tau) \cdot b'_{t+\tau}$$

The share of low-return deposits in the portfolio is then computed as,

$$\text{share low}_t = \frac{\overline{d}_t}{\overline{d}_t + \overline{b}_t}$$

The average return on assets,

$$\text{average return}_t = \text{share low}_t \cdot r^d + (1 - \text{share low}_t) \cdot r$$

The forgone interest for not maximizing the return on the portfolio is

$$\text{forgone interest}_t = \overline{d}_t \cdot (r - r^d)$$

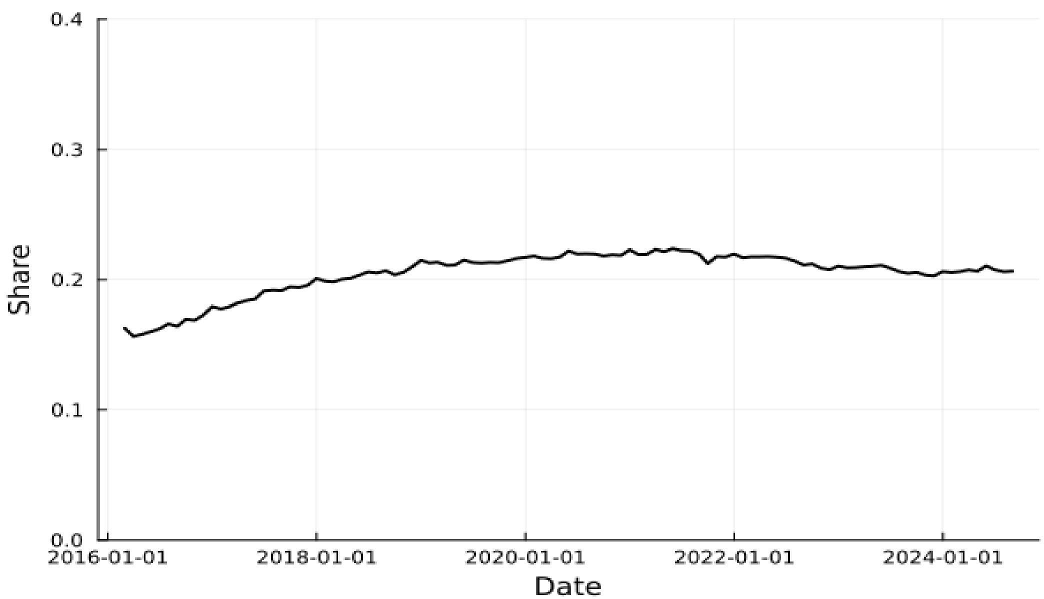
The size of the transfer as a share of the current level of liquid assets is:

$$\text{Transfer size} = \frac{b' - b}{w - c \cdot \tau} = \frac{b' - b}{w \cdot (1 - \tau) + (a + b' - b) \cdot \tau}$$

In the baseline, we assume that the reallocation occurs at the midpoint of the period $\tau = 1/2$.

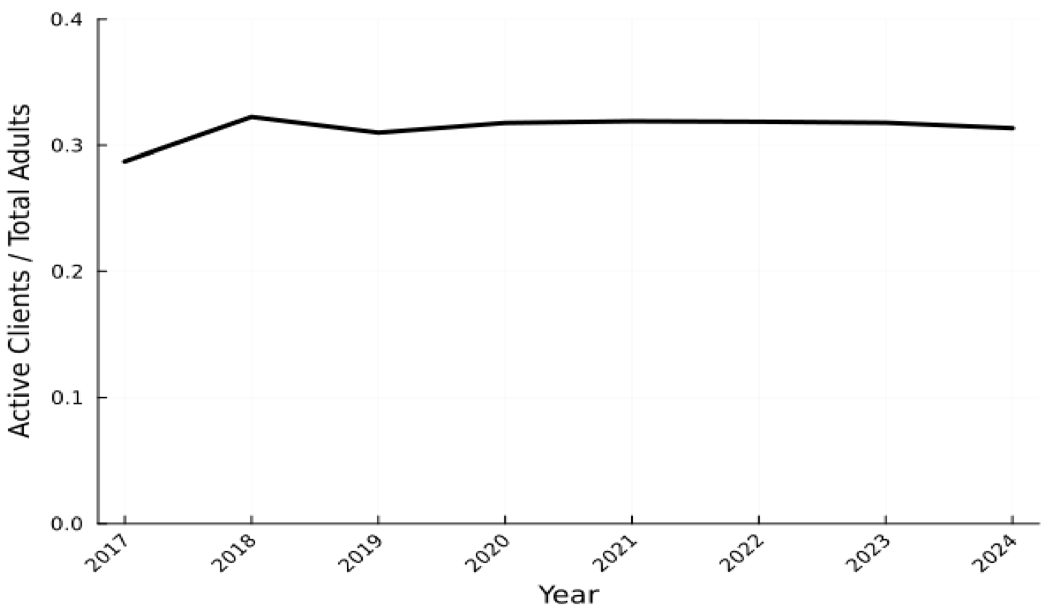
D Additional Figures and Tables

Figure 17: Share of Household Deposits Held by Active Clients



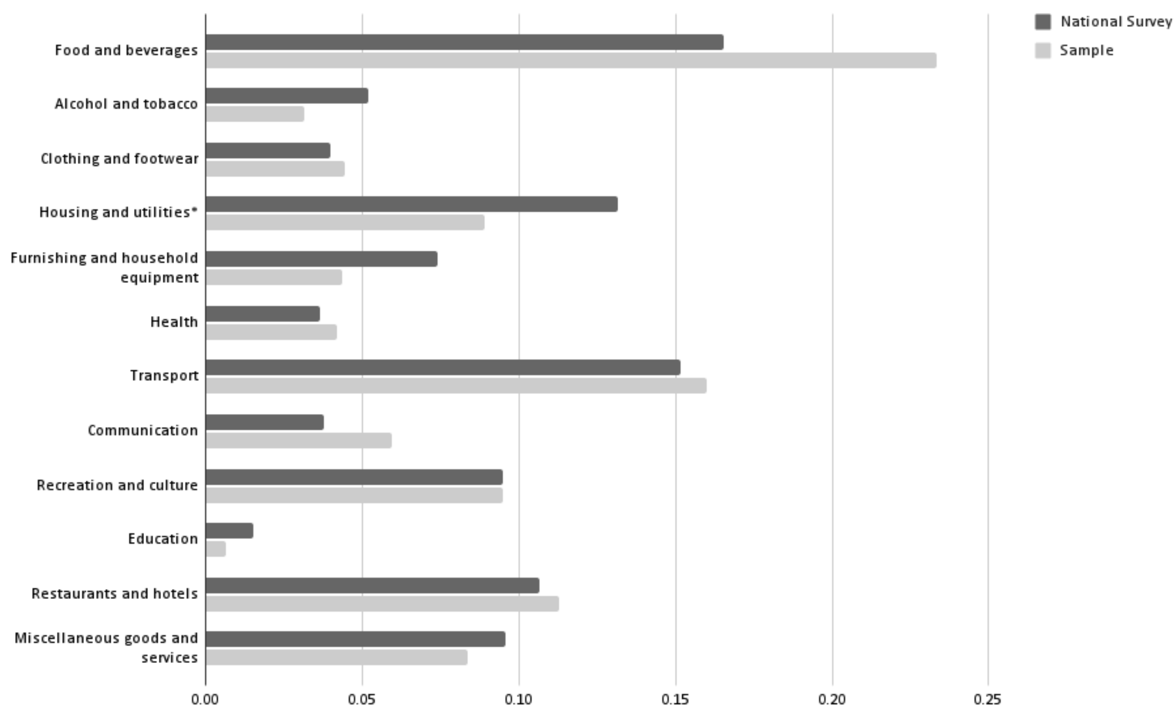
Notes: This figure displays the proportion of total household deposits held by active clients at the collaborating bank as a share of aggregate household deposits reported by the Central Bank of Iceland. Both the bank-specific and aggregate deposit figures are calculated using end-of-month values (last business day).

Figure 18: Ratio of Active Clients over Total Adults in Iceland



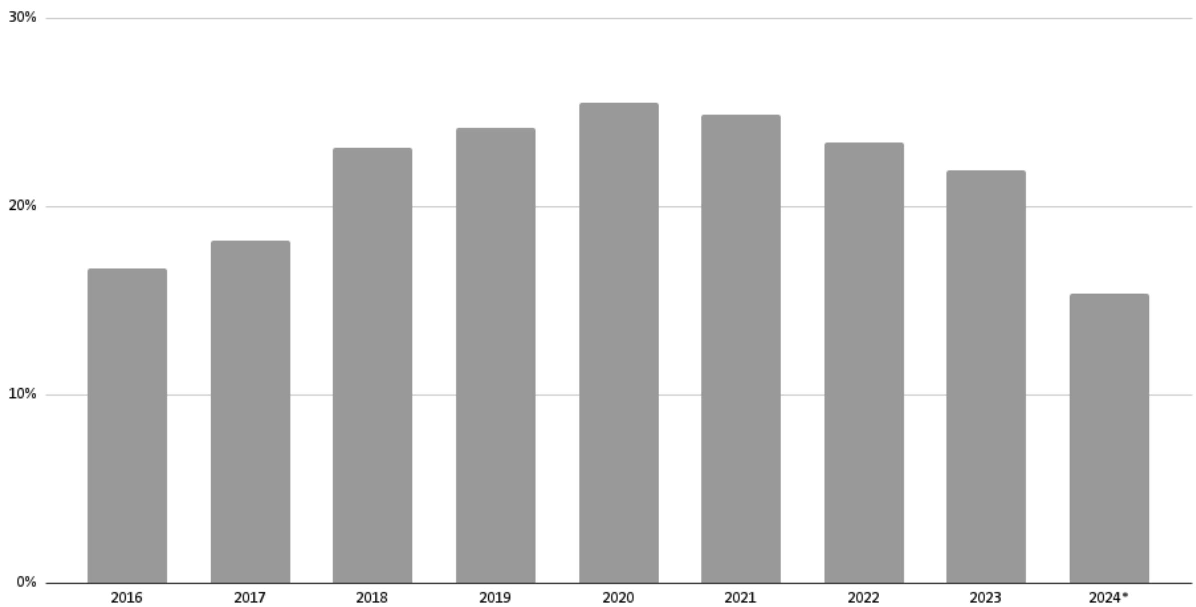
Notes: This figure shows the ratio of active bank clients to the adult population residing in Iceland. The ratio is computed by first taking the annual average number of active clients and then dividing it by the total adult population reported by Statistics Iceland.

Figure 19: Distribution of Expenses



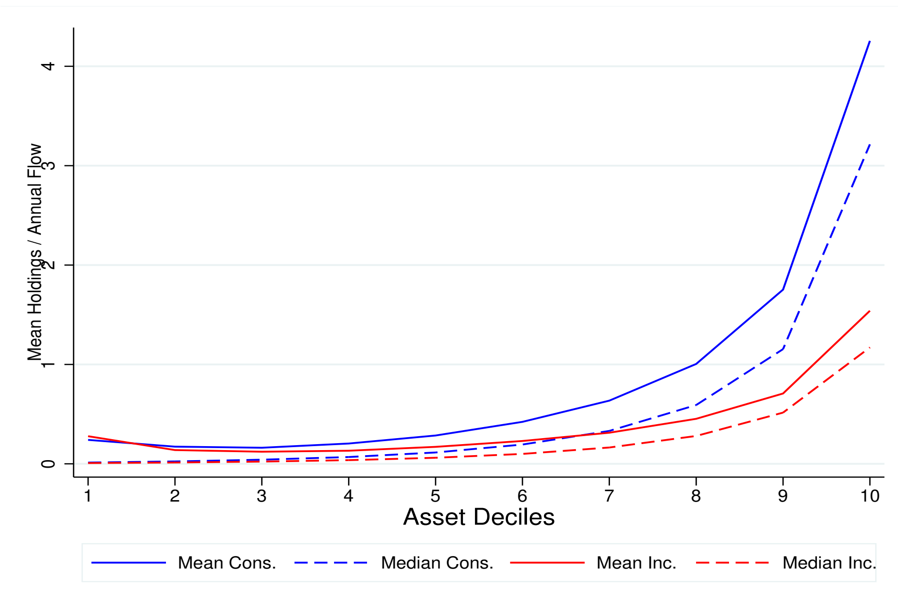
Notes: This figure compares the percentage distribution of household expenses in our sample of active clients with the Statistics Iceland survey of household consumption by residents in 2019. The comparison is restricted to expense categories that we can classify. *'Housing and Utilities' excludes imputed rental value for owner-occupied dwellings.

Figure 20: Share of Expenses



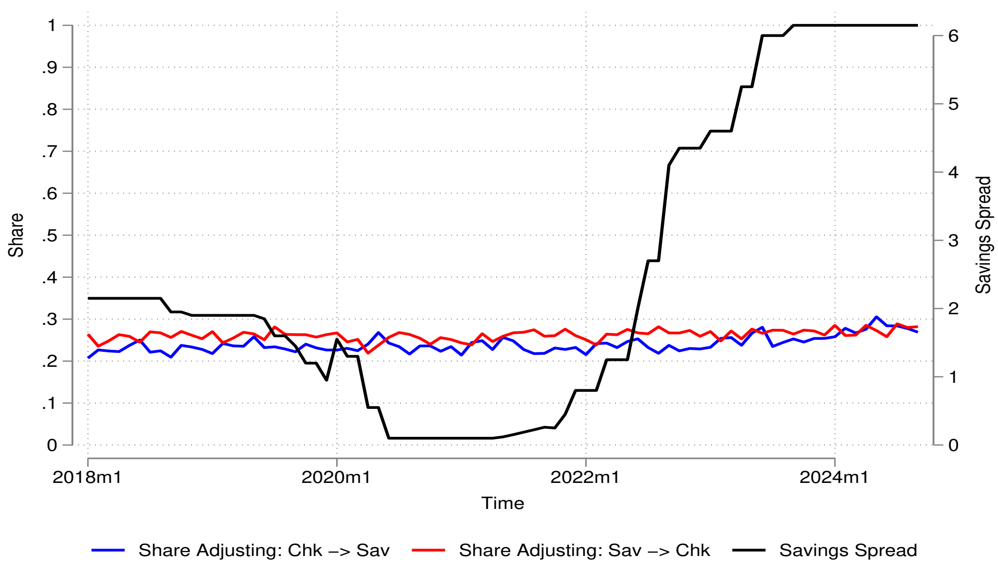
Notes: This figure reports the share of national household expenses, as measured by Statistics Iceland, within the aggregate of our sample of active clients. Expenses in the sample include only those outflows that we are able to classify into a category. Survey data exclude the imputed rental value of owner-occupied dwellings. *Data for 2024 reflect January–September only.

Figure 21: Average Assets Holdings over Annual Consumption and Income



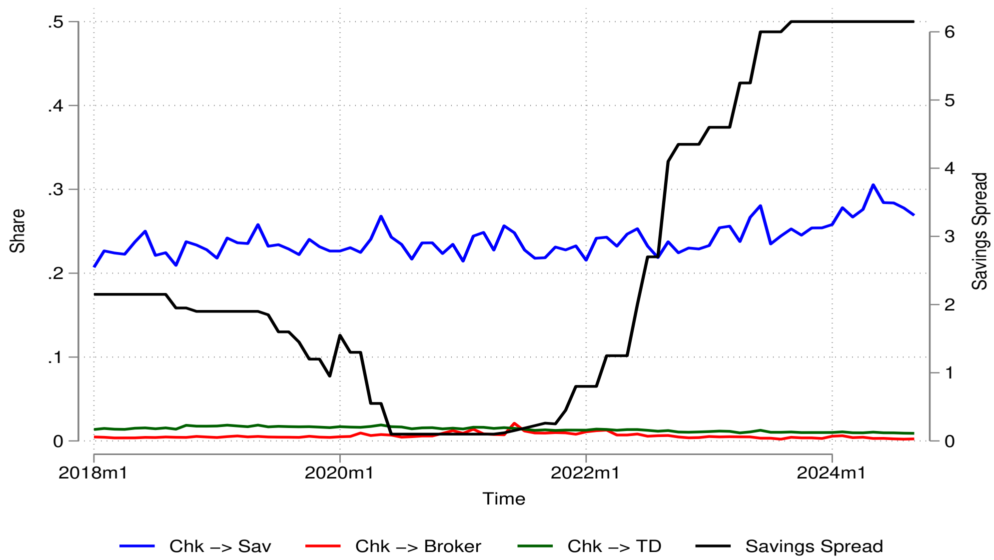
Notes: This figure shows the mean and median liquid safe asset holdings for each wealth decile. Asset holdings are computed as the average holding for each individual per year. Consumption and income are computed as annual sums for each individual. The plot displays the mean and median ratios of average annual asset holdings to total consumption or income for each wealth decile across all years. Wealth deciles are ranked by average annual asset holdings.

Figure 22: Directional Transfer Patterns: Checking and Savings Flows Over Time



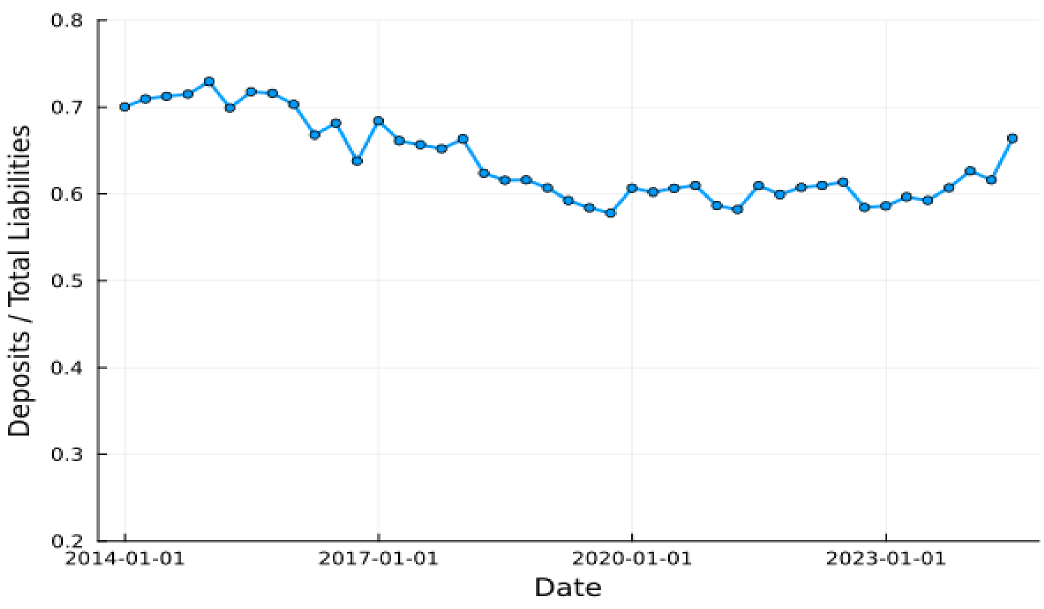
Notes: This figure shows the monthly share of individuals making transfers between checking and savings accounts by direction. The blue line shows the share transferring funds out of checking into savings, while the red line shows the share transferring funds from savings into checking. The black line displays the interest rate spread between the maximum savings rate and checking rate.

Figure 23: Transfer Destinations from Checking Accounts Over Time



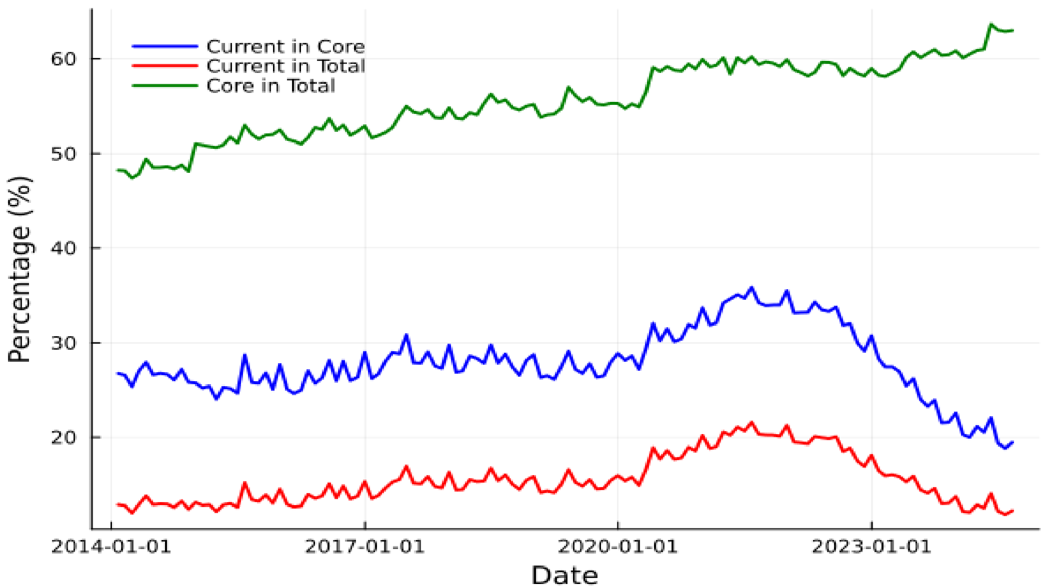
Notes: This figure shows the monthly share of individuals transferring funds out of checking accounts to different destinations. The blue line shows transfers to savings accounts, the red line shows transfers to brokerage accounts, and the green line shows transfers to time deposits. The black line displays the interest rate spread between the maximum savings rate and checking rate.

Figure 24: Deposits as a Share of Total Liabilities at the Partner Bank



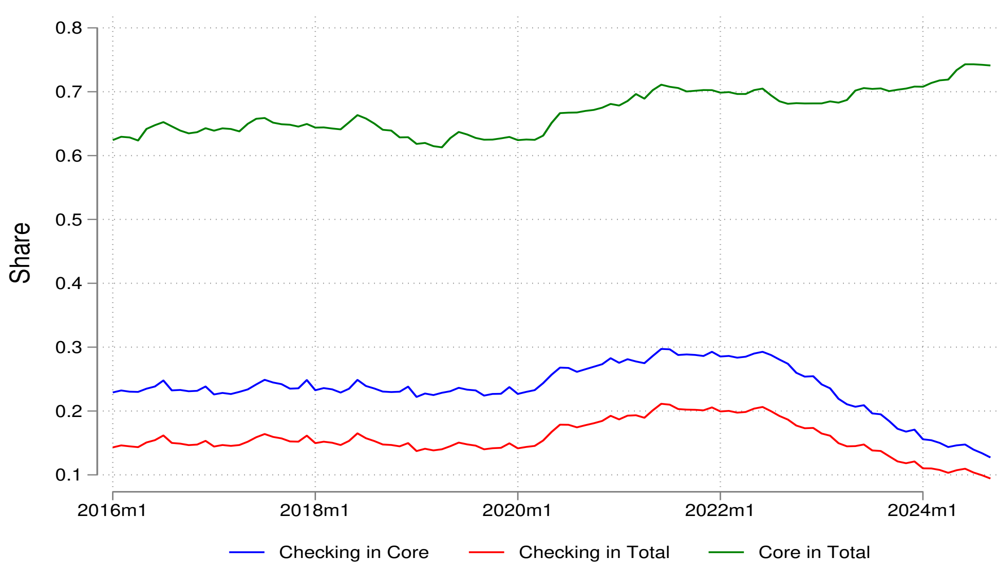
Notes: This figure shows the evolution of total deposits as a share of total liabilities for the partner bank between 2014 and 2024. Information comes from public quarterly balance sheets.

Figure 25: Aggregate Deposit Shares Across Icelandic Banks



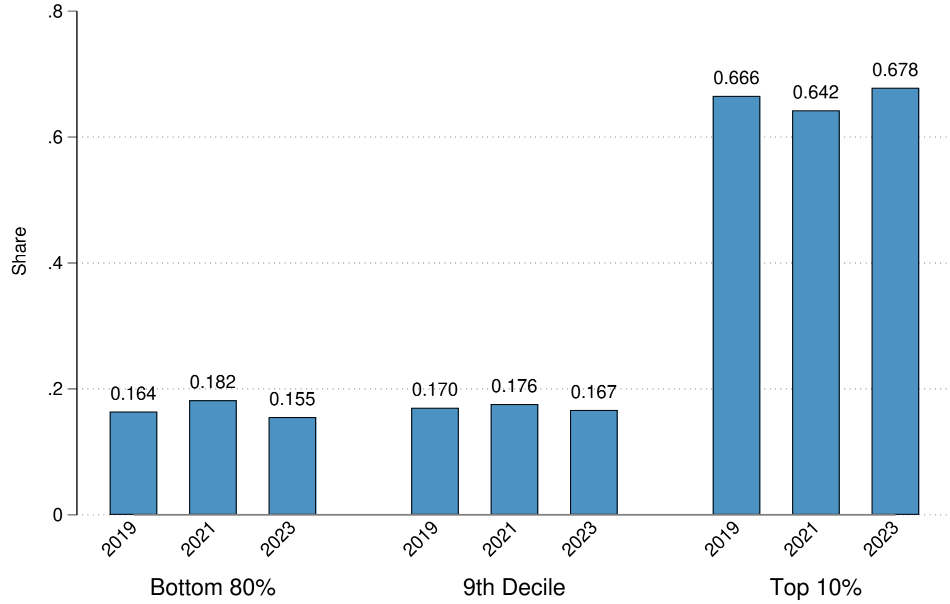
Notes: This figure shows the evolution of deposit shares across all banks in Iceland between 2014 and 2024. Data are sourced from the Central Bank of Iceland. Core deposits are defined as the sum of sight deposits (óbundin innlán) and current accounts (veltiinnlán). Total deposits include core deposits plus indexed deposits, holiday pay accounts, supplementary pension accounts, and other rerm deposits.

Figure 26: Deposit Shares for Active Clients at the Bank



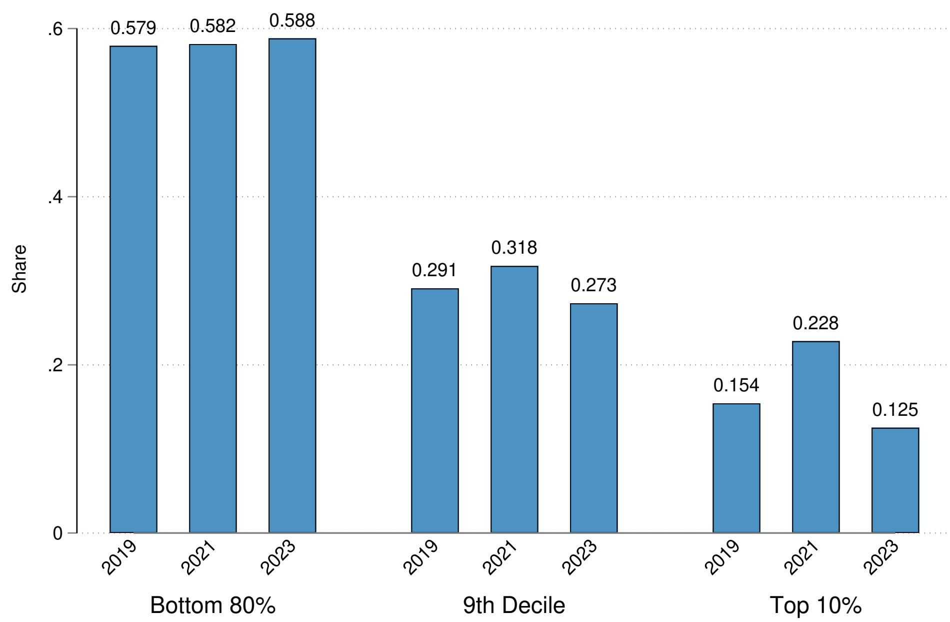
Notes: This figure shows the evolution of deposit shares for active clients at our partner bank between 2016 and 2024. Core deposits are defined as the sum of checking and savings deposits. Total deposits include core deposits plus all other forms of deposits held at the bank.

Figure 27: Share of Core Deposits Held by Wealth Group



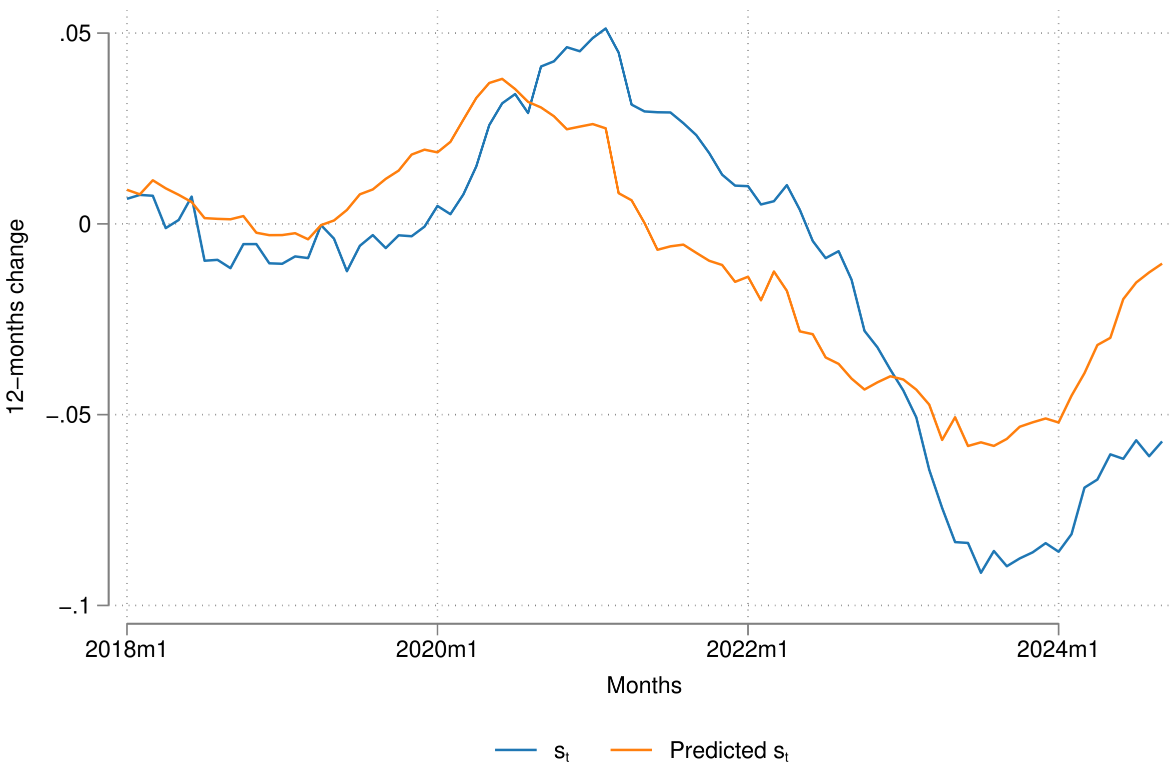
Notes: This figure shows the share of total core deposits held by different wealth groups.

Figure 28: Share of Checking in Core Deposits by Wealth Group



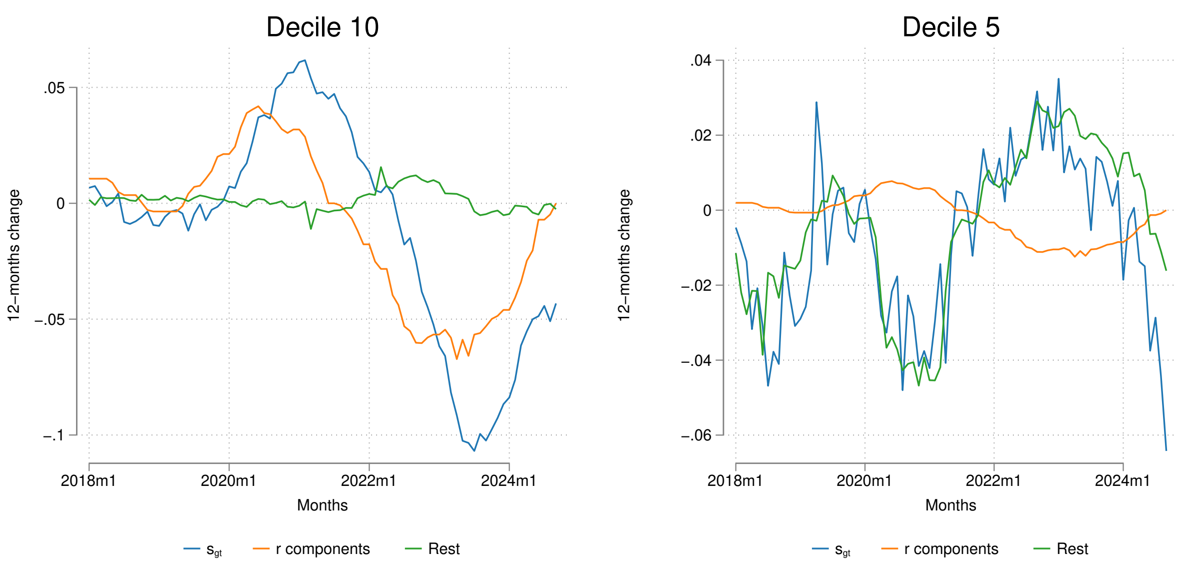
Notes: This figure shows the average share of checking accounts in core deposits held by different wealth groups.

Figure 29: Aggregate Fit



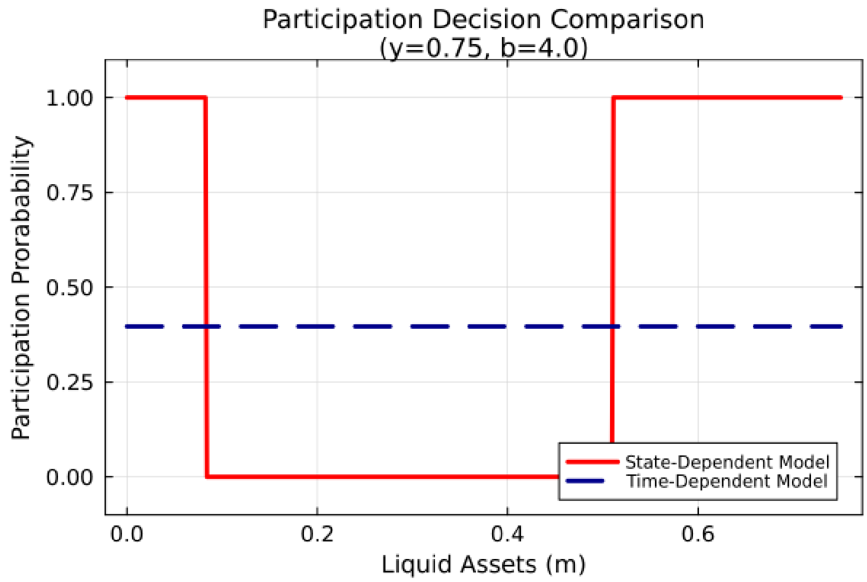
Notes: This figure shows the 12-month change in the aggregate share of checking deposits comparing the observed change in the aggregate share, Δs_t, with the predicted change from our model, $\Delta \widehat{s}_t$.

Figure 30: Decomposing Aggregate Changes in the Share of Low-Return Deposits



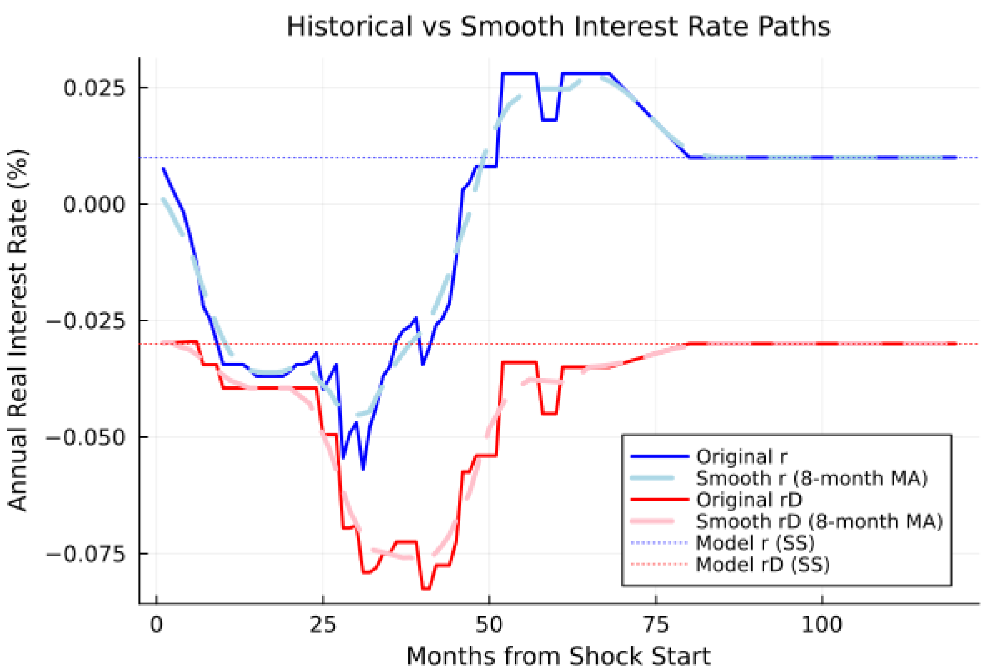
Notes: This figure plots 12-month changes in the actual share of checking deposits for the top wealth decile (left panel) and the fifth wealth decile (right panel), together with the corresponding model-predicted decomposition into the portion explained by interest rate movements and the portion explained by all other covariates in equation (9). Wealth deciles are constructed using core deposit balances. Interest rate effects are computed by holding all other covariates constant at their observed values and varying only the interest rate terms.

Figure 31: Rebalancing Likelihood for Different Models



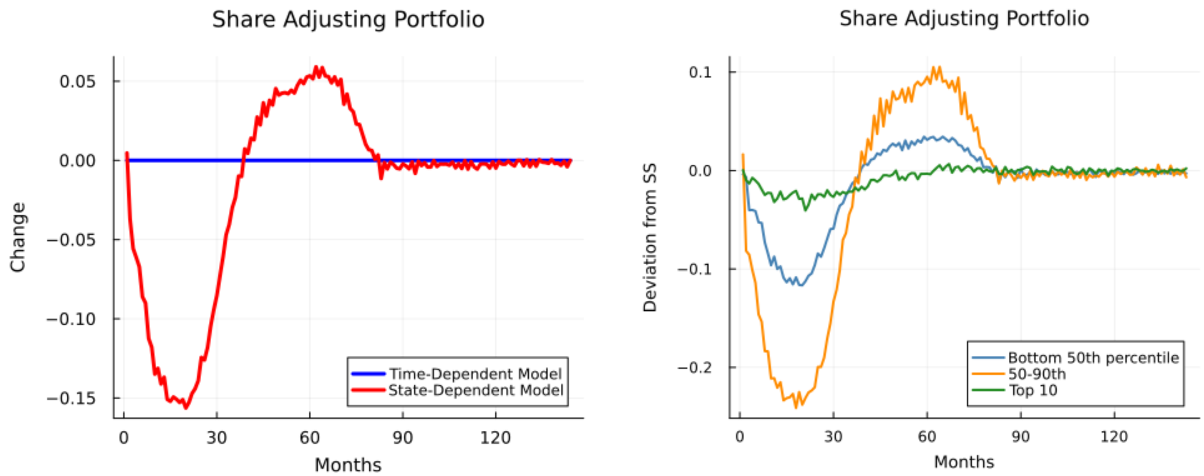
Notes: This figure plots the rebalancing decision between high- and low-return accounts for an individual with income $y = 0.75$ and holdings in the high-return account of $b = 4$ in the calibrated models.

Figure 32: Interest-Rate Paths Used in the Model



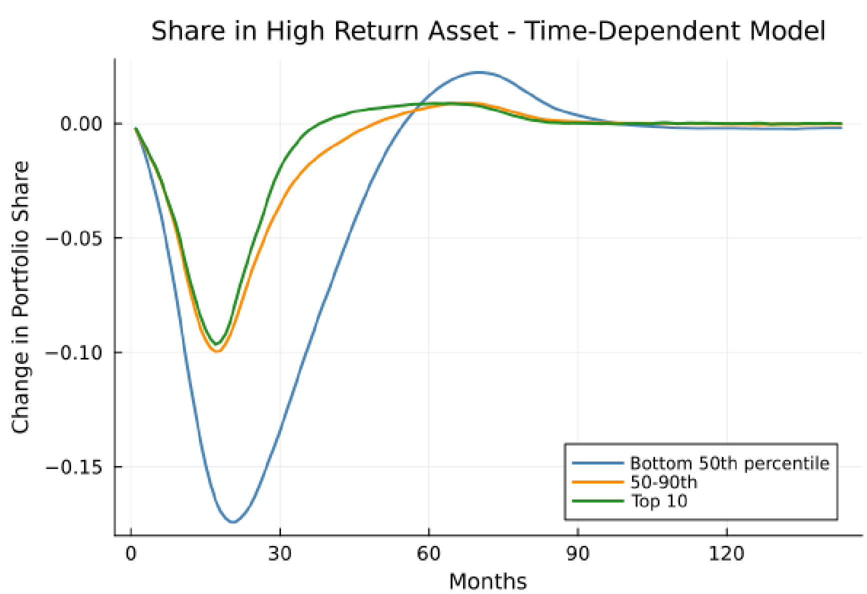
Notes: This figure plots the nominal interest rates on liquid funds (blue) and checking deposits (red). Solid lines show the data, dashed lines the 8-month moving averages used in the model, and dotted lines the steady-state values. Real rates are obtained by subtracting median household inflation expectations obtained from the inflation expectation survey of the Central Bank of Iceland.

Figure 33: Rebalancing Responses in the Models



Notes: This figure shows the change in the share of households rebalancing their portfolios following the interest-rate shock. The left panel plots the average rebalancing share across all households in both the state- and time-dependent models. The right panel shows the rebalancing share by wealth group in the state-dependent specification.

Figure 34: Portfolio Share Responses in the Time-Dependent Model



Notes: This figure shows changes in the share of high-return assets by wealth decile in the time-dependent model following the interest-rate shock.

Table 9: Share of Checking Deposits in Liquid, Short-Term, Safe Portfolios

	(1) Monthly levels	(2) Sample average	(3) Own wealth
Decile levels (relative to 1st)			
2.	9.618	-2.187	0.123
	(0.192)	(0.426)	(0.0562)
3.	10.08	-7.500	-0.940
	(0.226)	(0.432)	(0.0751)
4.	6.392	-12.79	-2.471
	(0.246)	(0.434)	(0.0879)
5.	-0.522	-17.25	-4.220
	(0.261)	(0.441)	(0.0970)
6.	-8.711	-20.72	-6.003
	(0.273)	(0.444)	(0.104)
7.	-16.31	-26.40	-8.256
	(0.282)	(0.445)	(0.110)
8.	-24.02	-32.01	-10.52
	(0.291)	(0.448)	(0.115)
9.	-32.63	-39.29	-13.17
	(0.301)	(0.444)	(0.120)
10.	-42.66	-49.46	-15.16
	(0.311)	(0.431)	(0.126)
Liquid Fund rate (r^L)	0.118	0.551	0.585
	(0.0405)	(0.0421)	(0.0278)
2.#r^L	0.115	-0.342	-0.151
	(0.0437)	(0.0588)	(0.0224)
3.#r^L	0.217	-0.555	-0.391
	(0.0486)	(0.0608)	(0.0272)
4.#r^L	0.302	-0.670	-0.619
	(0.0507)	(0.0625)	(0.0290)
5.#r^L	0.154	-0.791	-0.765
	(0.0531)	(0.0628)	(0.0296)
6.#r^L	-0.164	-0.891	-0.849
	(0.0550)	(0.0642)	(0.0300)
7.#r^L	-0.421	-0.985	-1.017
	(0.0567)	(0.0649)	(0.0305)
8.#r^L	-0.712	-1.012	-1.178
	(0.0579)	(0.0633)	(0.0316)
9.#r^L	-0.875	-1.127	-1.521
	(0.0580)	(0.0620)	(0.0337)
10.#r^L	-1.126	-0.979	-1.922
	(0.0534)	(0.0578)	(0.0373)
age	0.851	0.985	-0.895
	(0.0289)	(0.0294)	(0.0574)
age^2	-0.00802	-0.00937	0.0102
	(0.000293)	(0.000300)	(0.000511)
Female	-8.134	-8.439	
	(0.193)	(0.196)	
Time Trend	-0.0168	-0.0331	-0.0488
	(0.00164)	(0.00177)	(0.00306)
# of kids	-0.435	-0.475	0.446
	(0.115)	(0.118)	(0.113)
married	-1.660	-0.941	1.256
	(0.216)	(0.221)	(0.208)
Residing in Reykjavík	1.530	1.861	-0.0649
	(0.206)	(0.210)	(0.275)
constant	44.83	53.25	73.62
	(0.655)	(0.700)	(1.644)
N	7926422	7926422	7916002
adj. R^2	0.184	0.143	0.663

Notes: This table reports estimates from regression (6), which augments regression (1) by interacting asset deciles with the liquid fund rate. The dependent variable is the share of checking deposits in portfolios. We use three alternative decile definitions. In the first column, individuals are sorted each month based on their asset holdings relative to the rest of the sample. In the second, individuals are sorted based on their average asset holdings over the entire sample period. In the third, each individual's monthly asset holdings are ranked relative to their own asset distribution across the sample period. Standard errors are clustered at the individual level and shown in parentheses.

Table 10: Adjustment Probability: Wealth and Interest Rate Sensitivity Across Deciles

	(1) Checking -> Savings	(2) Checking -> Time Deposits	(3) Checking -> Broker
Monthly decile levels (relative to 1st)			
2.	0.0304	0.00379	0.000861
	(0.00117)	(0.000355)	(0.000106)
3.	0.0619	0.00598	0.00200
	(0.00150)	(0.000456)	(0.000130)
4.	0.101	0.00697	0.00325
	(0.00172)	(0.000512)	(0.000152)
5.	0.142	0.00585	0.00435
	(0.00189)	(0.000547)	(0.000168)
6.	0.176	0.00540	0.00548
	(0.00203)	(0.000595)	(0.000189)
7.	0.208	0.00351	0.00646
	(0.00219)	(0.000584)	(0.000217)
8.	0.230	0.00247	0.00804
	(0.00238)	(0.000599)	(0.000260)
9.	0.246	0.00239	0.00963
	(0.00266)	(0.000641)	(0.000309)
10.	0.245	0.00158	0.0154
	(0.00314)	(0.000695)	(0.000468)
Liquid Fund rate $\left(r^L\right)$	-0.00148	-0.000230	-0.000439
	(0.000259)	(0.0000884)	(0.0000292)
2.#r^L	-0.000119	-0.000334	-0.0000667
	(0.000296)	(0.000101)	(0.0000331)
3.#r^L	0.000572	-0.000431	-0.000245
	(0.000352)	(0.000117)	(0.0000383)
4.#r^L	0.0000293	-0.000309	-0.000352
	(0.000378)	(0.000126)	(0.0000454)
5.#r^L	0.00240	-0.0000492	-0.000462
	(0.000407)	(0.000127)	(0.0000494)
6.#r^L	0.00464	0.0000676	-0.000637
	(0.000432)	(0.000130)	(0.0000532)
7.#r^L	0.00599	0.0000238	-0.000654
	(0.000464)	(0.000131)	(0.0000575)
8.#r^L	0.00759	0.0000869	-0.000815
	(0.000491)	(0.000127)	(0.0000627)
9.#r^L	0.00831	0.000224	-0.00105
	(0.000525)	(0.000133)	(0.0000679)
10.#r^L	0.00953	0.000227	-0.00153
	(0.000510)	(0.000118)	(0.0000895)
age	-0.00296	0.000192	0.000136
	(0.000284)	(0.0000729)	(0.0000278)
age^2	-0.00000364	-0.00000417	-0.00000272
	(0.00000289)	(0.000000694)	(0.000000272)
Female	0.0806	0.00688	-0.00551
	(0.00187)	(0.000503)	(0.000206)
Time Trend	0.000399	-0.0000758	0.0000734
	(0.0000188)	(0.00000638)	(0.00000297)
# of kids	-0.00899	-0.000944	0.000195
	(0.00112)	(0.000324)	(0.000128)
Married	0.0176	0.000324	0.00147
	(0.00216)	(0.000579)	(0.000216)
Residing in Reykjavík	0.00743	0.00165	0.00345
	(0.00198)	(0.000541)	(0.000186)
constant	0.168	0.0121	-0.00458
	(0.00638)	(0.00167)	(0.000644)
N	6363304	6363304	6363304
adj. R^2	0.054	0.003	0.006

Notes: This table reports estimates from regression (6). The dependent variables are indicator variables for whether individual i transferred funds from a checking account to savings deposits (column 1), time deposits (column 2), or broker accounts (column 3) in month t. The coefficients capture baseline differences in reallocation probability across wealth deciles and their interaction with the liquid fund rate. Standard errors are clustered at the individual level and shown in parentheses.

Table 11: Rate Sensitivity and Individual Characteristics

	(1) $\Delta\text{share}_{it}^{C}$	(2) $\Delta\text{share}_{it}^{C}$	(3) $\Delta\text{share}_{it}^{C}$
Δr_t^L	-0.165	0.224	-0.112
	(0.0674)	(0.177)	(0.0792)
$\Delta \ln(a_{it})$	-3.357	-3.422	-3.374
	(0.183)	(0.190)	(0.184)
survey $\cdot \Delta r_t^L$	-0.475	-0.546	-0.284
	(0.199)	(0.190)	(0.130)
constant	-0.822	-0.807	-0.829
	(0.0475)	(0.0491)	(0.0477)
N	326231	301464	324077
adj. R^2	0.025	0.026	0.025

Notes: This table reports estimates from regression (7). Each column includes a separate indicator, survey_i, capturing high financial literacy (column 1), high inflation knowledge (column 2), or high inflation precision (column 3). All regressions are estimated in 6-month differences. Standard errors are clustered at the individual level.

Table 12: Rate Sensitivity, Individual Characteristics and Average Wealth

	(1) $\Delta\text{share}_{it}^C$	(2) $\Delta\text{share}_{it}^C$	(3) $\Delta\text{share}_{it}^C$
Δr_t^L	1.091	1.405	1.238
	(0.501)	(0.539)	(0.503)
$\Delta \ln(a_{it})$	-3.356	-3.422	-3.374
	(0.183)	(0.190)	(0.184)
survey $\cdot \Delta r_t^L$	-0.434	-0.521	-0.259
	(0.200)	(0.190)	(0.130)
$\ln(\bar{a}_i) \cdot \Delta r_t^L$	-0.0957	-0.0910	-0.103
	(0.0373)	(0.0386)	(0.0376)
constant	-0.823	-0.809	-0.830
	(0.0475)	(0.0491)	(0.0478)
N	326231	301464	324077
adj. R^2	0.025	0.026	0.025

Notes: This table reports estimates from regression (7), extended to include interactions between each survey-based indicator, survey_i, and average individual wealth $\bar{a}_i$. Each column includes a separate indicator for high financial literacy (1), high inflation knowledge (2), or high inflation perception precision (3). All regressions are estimated in 6-month differences. Standard errors are clustered at the individual level.