What Makes Depositors Tick?

Bank Data Insights into Households' Liquid Asset Allocation

Fernando Cirelli Arna Olafsson*

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Abstract

This paper provides a comprehensive analysis of depositor behavior using a unique panel of high-frequency individual bank account holdings and transactions, combined with survey data from bank customers. We examine who moves deposits, what triggers these movements, and where funds are allocated. Our findings reveal persistent heterogeneity in portfolio allocations and returns, with financial literacy, education, and wealth influencing these differences. Using both expected and unexpected income and expense shocks, we show that fluctuations in individual wealth shape portfolio adjustments. Finally, we demonstrate that wealthier individuals are more likely to reallocate funds toward higher-return assets during periods of policy tightening.

Keywords: Bank Deposit Stickiness, Household Finance, Monetary Policy Transmission

*Cirelli (f.cirelli@columbia.edu): School of International and Public Affairs, Columbia University. Address: 420 W 118th Street, New York, NY 10027; Olafsson (ao.fi@cbs.dk): Copenhagen Business school, Danish Finance Institute, CEPR; Olafsson gratefully acknowledges support from the Center for Big Data in Finance (grant no. DNRF167). We thank the bank providing the data for their collaboration and Ines Kishkill for her outstanding research assistance.

1 Introduction

What drives retail bank deposits is a central question in macroeconomics and finance. Retail bank deposits are a dominant, cost-effective and secure source of funding for banks, making it essential to understand their drivers to assess the stability of bank funding as well as the transmission of monetary policy (see, e.g., Hanson et al., 2015; Drechsler et al., 2017). Deposits also play two fundamental roles in the financial lives of households: as medium of exchange—as electronic payments take over cash and checks—and as a store of value—even the sole store of value for many—and their allocation can have profound implications for welfare (Campbell, 2006; Badarinza et al., 2016).

There is, however, little knowledge about what drives households' allocations to bank deposits. Existing studies have shown that aggregate deposit stickiness—which allows banks to manage liquidity risks arising from maturity mismatch—is partly explained by deposit insurance (Hanson et al., 2015), superior liquidity services (d'Avernas et al., 2023), and market power (Drechsler et al., 2021). However, we still know little about individual-level behavior of depositors. More specifically, who moves deposits, why, and where does the money go? This is the aim of this paper.

In this paper, we undertake a comprehensive investigation of individuals' bank deposit behavior using a unique data set, sourced from one of the largest banks in Iceland, servicing about one third of the population, providing detailed, high-frequency, transactional-level bank information on the financial choices of depositors. Our data allow us to track the funds after a portfolio adjustment, enabling us to investigate who moves them, in relation to the types of events that trigger the movement, and where the money comes from or goes as depositors either increase or withdraw their deposits. We complement the bank data with four surveys[1] conducted with bank customers, providing valuable insights into individuals' financial knowledge, preferences, education, and other relevant characteristics.

[1]These surveys were conducted in relation to other projects and the associated papers are still work in progress.

We begin by providing a descriptive analysis of safe liquid asset holdings. We show significant differences in individuals' portfolio allocations, despite assets in this class offering nearly identical non-pecuniary benefits but differing in their rates of return. Specifically, we show that portfolio returns within this asset class increase with individual wealth: individuals in the highest wealth decile achieve returns that are, on average, 4 percentage points higher. This difference arises from wealthier individuals allocating a larger share of their portfolios to higher-return assets. However, despite achieving higher returns, wealthier households forego a larger share of consumption, effectively bearing a higher cost of liquidity of around 5 percentage points of annual consumption. We use survey data to investigate the characteristics of depositors who, on average, hold lower-return portfolios. We find that financial literacy, knowledge of inflation's effects, and attention to bank balances stand out as significant factors explaining persistent differences in returns.

We then examine the events that trigger portfolio reallocations and track where funds are moved. Portfolio allocations are shown to respond to changes in individuals' wealth. Specifically, the share of high-return safe liquid assets, particularly savings deposits, increases as individuals become wealthier. The magnitude of this effect is substantial: during periods when individuals reach their peak wealth within the sample period, the share of low-return deposits is, on average, 20 percentage points lower. Using event studies of expected and unexpected income shocks, we further demonstrate that income increases trigger almost immediate portfolio reallocations into high-return deposits, typically within a few days. Conversely, reallocations from high- to low-return deposits occur precisely on the day individuals incur expenses requiring additional funds, suggesting that consumption drives the decrease in high-return liquid assets within the portfolio.

Finally, we examine how changes in interest rate spreads influence portfolio allocation. During periods of policy tightening, the spreads between low- and high-return deposits widen, increasing the relative cost of holding low-return deposits. In response to these changes, the evidence points to wealthy individuals being the ones most likely to reallocate funds from

low-return deposits to higher-return alternatives.

We contribute to the literature on the ability of banks to maintain a considerable and stable markup in deposit pricing (see, e.g., Hanson et al., 2015; Drechsler et al., 2021; Egan et al., 2021; d'Avernas et al., 2023; Li et al., 2023; DeMarzo et al., 2024; Kundu et al., 2024). Our paper contributes by providing a micro-founded behavioral perspective on the market power of banks in the deposit market and for the divergence of deposits to high- and low-rate deposit accounts: the depositors that hold substantial liquidity in low-interest checking accounts tend to have lower financial literacy and numeracy, a weaker understanding of inflation's effects, poorer decision-making abilities, and are typically older and less educated. Our findings also contribute to the literature on the importance of stable deposits for bank funding and the overall stability of the banking sector (see, e.g., Diamond and Dybvig, 1983; Hanson et al., 2024), as well as on how recent changes in financial technology may impact this (see, e.g., Erel et al., 2023; Jiang et al., 2023; Koont, 2023; Koont et al., 2024).

Finally, our paper contributes to the discussion on deposit stickiness by exploring alternative explanations. In Iceland, all transfers—both within and between banks—are cleared instantly. This implies that bank-to-bank transfer delays, which have been hypothesized to be among the driving factors behind deposit stickiness (see, e.g., Lu et al., 2024) cannot be relevant in our setting. Moreover, the limited number of deposit providers in Iceland significantly reduces search costs, another factor often cited as a source of deposit stickiness (see, e.g., Yankov, 2024). Given these institutional features, our setting allows us to assess the role of other mechanisms in explaining why households keep funds in low-yielding deposits.

The rest of the paper is organized as follows. Section 2 describes the data and the construction of key variables. Section 3 provides a descriptive analysis of holdings of safe liquid assets. Section 4 study events that trigger a portfolio reallocation. Section 5 presents a standard model whose predictions can be compared to our findings. Section 6 concludes.

2 Data

The data we use are provided by one of the largest banks in Iceland that provides us with access to comprehensive, detailed, and highly disaggregated panel of bank data, providing a nearly complete view of the personal finances of about 1/3 of the adult Icelandic population. More specifically, the data contain individual and family identifiers, detailed information on demographics, bank account transactions (time, location, merchant, product category, and transaction amount)—providing us with a detailed measure of individuals' consumption by category—all bank account balances, bank account overdraft limits and use, credit card transactions and limits, all loans (including, e.g., mortgages, car loans and leases, and consumer loans), and financial portfolios (including, e.g., daily information on portfolio composition and all sales and purchases of stocks, bonds, and funds). Furthermore, we can infer real estate owners and the value of real estate from real estate taxes that we observe in the transaction data.

The bank providing the data for this paper has collaborated with Copenhagen Business School to administer four online surveys 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 the project, and as a result, the questions varied across surveys. These surveys provide information of individuals' financial knowledge, understanding of inflation's effects, discounting and risk preferences, decision-making abilities, education levels, and other relevant characteristics. Details on the surveys can be found in Appendix B.

2.1 Using Bank Data to document Financial Behavior

Detailed and accurate high-frequency panel data on consumption and financial choices of individuals are notoriously hard to come by (see, e.g., Gelman et al., 2014; Kolsrud et al., 2018). Questions regarding consumption and many financial decisions, e.g., use of consumer

credit and investments in risky asset markets, are normally analyzed empirically using self-reported survey data. As discussed by, e.g., Kolsrud et al. (2018), such survey measures may be very problematic.

Survey responses rely on participants' recall of bank account balances at the interview day or their estimate of average balances while consumption measures are based on stylized questions regarding spending by broad categories over a certain period or an expenditure diary (e.g., the diary surveys of the Consumer Expenditure Survey, CEX, in the US and Living Costs and Food Survey, LCF, in the UK). Such survey based measures of consumption and financial decision making may suffer from measurement error (Zinman, 2009). Specifically, respondents may, e.g., have little incentive to answer the questions accurately, may not understand the wording of the questions, they may simply forget some of their past actions. Moreover, this type of measurement error or noise in survey-generated data can increase with the length of the recall period (de Nicola and Giné, 2014) Furthermore, survey can generate systematically biased data if respondents, e.g., suffer from either agreement or justification bias and report how they believe they should behave rather than how they behave in practice, concerns about surveyors sharing the information, or stigma about their consumption habits (Karlan and Zinman, 2008).

A sizable literature now avoids the problems associated with survey data by exploiting the recent availability of highly accurate register data to capture financial behavior, consumption, and wealth. These data are the most comprehensive in the Nordic countries and include, e.g., asset holdings by year-end and annual income. These annual snapshots are then used to infer financial behavior, e.g., stock market participation, portfolio diversification, etc. (see, e.g., Calvet et al., 2009; Olafsson and Pagel, 2018a) and to impute consumption and wealth returns (see, e.g., Koijen et al., 2014; Browning and Leth-Petersen, 2003; Sodini et al., 2016; Fagereng and Halvorsen, 2017; Fagereng et al., 2017, 2020; Bach et al., 2020; Fagereng et al., 2021). As discussed by Koijen et al. (2014), there are considerable discrepancies between the registry-based and survey-based measures.

However, although the use of register data to capture certain financial behaviors overcomes the problems associated with survey data, both types of data suffer from long reporting intervals. This low frequency of survey and register data challenges the analyses of various questions regarding aspects of personal finances that change frequently, e.g., the allocation of liquid wealth. For instance, yearly snapshots of an individual's bank account balances do not capture if individuals respond sluggishly to interest rate changes.

This study overcomes the problems associated with the use of surveys and register-based measures of financial behavior by using transaction-level administrative data from a retail bank and enriches it with experimental measures that can be used to explore the underlying mechanism for the patterns of behavior we document in the bank data.

2.2 Setting

Using data from Iceland has three main advantages when studying the allocation of liquid wealth. First, bank accounts in Iceland are personal and cannot be shared, 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 her spouse, and we can identify all transfers between the individual and her spouse. Second, the administrative bank data are more representative of the underlying population than bank data obtained from banks in other settings. This is because: i) there are not that many banks in Iceland and each of them services a large share of the population, ii) all adult individuals in Iceland need to have a bank account.[2] This is also reflected in that Iceland has the highest share of internet banking usage in Europe.[3] Olafsson and Pagel (2018b), Carvalho et al. (2024), and Gathergood and Olafsson (2024) discuss in more detail the representativeness of bank data in Iceland. Third, Icelandic consumers use electronic means of payments almost exclusively,[4]

[2]There are many reasons for this. For instance, checks are not used in Iceland and if individuals want to receive salary payments or state benefits, they need a bank account.

[3]According to Eurostat, 96 percent of Icelanders used internet banking in 2020. Source: https://ec.europa.eu/eurostat/databrowser/view/tin00099/default/table?lang=en

[4]ATM withdrawals make up approximately one percent of spending transactions by amounts or transactions volume.

which implies that the data capture the financial lives of the users better than transaction-level bank data in other settings would.

2.3 Sample selection

We use a panel dataset tracking the daily spending, income, borrowing, saving, and investing of 133,751 individuals, representing approximately 44.7% 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*, though we also report results for the entire dataset and for adult residents specifically.

We call a customer active if he or she is registered as living in Iceland and appear to be economically active, specifically individuals for whom we observe periodic monthly income arrivals (e.g., labor market income or unemployment benefits, pension payments, invalidity benefits, and student loans) and expenses that can be classified as consumption. This criterion excludes dormant account holders and individuals whose primary banking activities occur at other financial institutions. After applying this restriction, we are left with 93,637 active customers, accounting for 31.5% of the adult population.

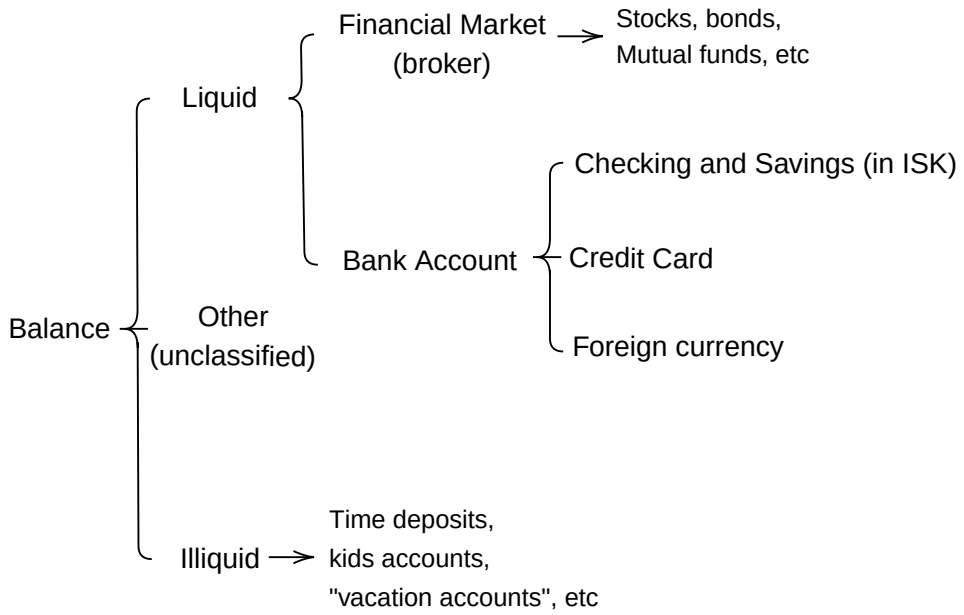
For the purposes of this paper, limiting the sample to individuals who appear to exclusively bank with the collaborating institution may not always be ideal, as dormant accounts could contribute significantly to deposit base stickiness. For questions where we do need to have a complete picture of the personal finances of individuals we do restrict our sample to active customers. We clearly specify in each exercise which population is being used.

2.4 Accounts Classification

We analyze the balance holdings of individuals within the bank and in their associated brokerage accounts, if such an account is open. The bank offers a wide variety of account types, whose names and characteristics change in some cases during the sample period. 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 presents a summary of this classification along with examples.

Figure 1: Accounts Classification



Individual balances can be *liquid*—meaning funds can be transferred to an account that can be used for payments at full value without time constraints—or *illiquid*, if they do not meet this criterion. Liquid accounts are further divided into funds held in bank accounts or in the brokerage account provided by the bank. We refer to balances held in the brokerage account as balances in the *financial market*. Bank accounts are categorized into classic checking and savings accounts, which offer a secure return in Icelandic Krona (ISK), and foreign currency accounts, whose return in ISK is uncertain. We also observe daily credit card balances. Finally, there is a small share of accounts that we could not classify and which we labeled as *other*.

Bank balances can be positive or negative, as most checking accounts 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 negative (outstanding balances). Credit cards in Iceland are issued by the 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 rather take an overdraft to pay the bill.

Table 1 provides a summary of account balances from both the individuals' and banks' perspectives. Each figure represents the time series average across the sample, with values reported in 2024 Icelandic Kronas.[5] Checking and savings accounts are by far the most common financial assets, as nearly every individual in the sample holds a non-zero balance in these accounts. On average, these accounts constitute the largest shares of individual portfolios. In contrast, holdings in foreign currency accounts and financial market accounts are relatively uncommon and exhibit a higher concentration of funds. For the bank, the bulk of funds come in the form of savings deposits, which are also relatively stable.

Table 1: Balances Descriptive Statistics

	Checking	**Savings**	**FX**	**Time Dep**	**Other Illiquid**	**Financial Market**
Individuals						
Share with Non-zero Holdings	0.97	0.8	0.15	0.1	0.3	0.12
Mean portfolio share	0.37	0.38	0.02	0.02	0.14	0.05
Share held by top 10% holders	0.68	0.70	0.92	0.80	0.66	0.76
Bank						
Mean share	0.14	0.54	0.04	0.08	0.17	-
Std. Dev. (share)	0.025	0.03	0.009	0.012	0.005	-

Note: Nominal amounts are in thousands of 2024 ISK. Statistics represent sample averages. The share held by top holders of each asset is calculated for each period, with the reported value being the time-series average.

2.5 Data Representativeness

One concern is whether individuals bank activities at one bank provide an accurate picture of their finances. In surveys to bank clients we found that 67% of bank customers say they

[5]For reference, the US/ISK exchange rate was $129 ISK per US Dollar during the sample period.

bank exclusively with the collaborating bank and among the ones with multiple accounts, over 35% mention that they only have inactive accounts at other banks.

Additionally, the distribution of age, gender, and family size in our bank dataset closely aligns with the population distribution in Iceland, as shown in Table 5 in the appendix.

Our dataset includes deposits from all individuals with an account in the collaborating bank. Figure 18 in the appendix shows that these deposits account for an average of 30% of total household deposits reported by the Central Bank of Iceland, with this share remaining stable over time. We interpret this as evidence supporting the representativeness of our deposit data.

Even though the bank serves a large share of the population and the demographics of the bank customers are similar to those of the nation in recent years a worry about representativeness may still exist. To provide more evidence on the representativeness of our data, we benchmark our expenditure data with measures of national consumer behavior. First, we compare observed spending among bank customers to data from the Household Final Consumption Expenditure collected by the Statistics Iceland. This comparison is not straightforward, as we observe outflows of funds from accounts, some of which cannot be classified as consumption or lack detailed categorization. Additionally, expenditure surveys include spending by tourists, who in a country like Iceland account for around 20% of total expenses (and close to 100% in categories like transportation and accommodation), but are absent from our dataset. Fortunately, in 2019, the statistical agency reported separate data on consumption by locals and tourists, enabling a more precise comparison with our bank data.

Figure 19 in the appendix illustrates how closely the expense shares in our dataset align with those reported for locals in the 2019 Household Final Consumption Expenditure by Statistics Iceland. The close match across multiple spending categories shows that our dataset is representative and reliable for capturing broader consumer behavior patterns.

3 Individual Liquidity Allocation

In this section, we analyze individuals' allocations of liquid safe assets. Through the bank individuals can access multiple short term assets, safe in nominal assets, which share similar non-pecuniary characteristics but, as we will show, differ significantly in their rates of return.

Understanding the allocation of liquid assets is of fundamental importance for households, banks, and the transmission of fiscal and monetary policy. For households, holding a large share of assets in low-return instruments can lead to substantial income losses and exacerbate wealth inequality Fagereng et al. (2020). For banks, deposits serve as a low-cost funding source, making it essential to preserve their deposit franchise value and ensure financial stability Drechsler et al. (2023). Deposits also play a central role in the transmission of monetary policy. During episodes of monetary tightening, depositors reallocate funds to higher-return alternatives, prompting banks to reduce credit supply in the short run Drechsler et al. (2017), while potentially increasing it in the long run Wang (fthc).

The Return on Safe Liquid Assets

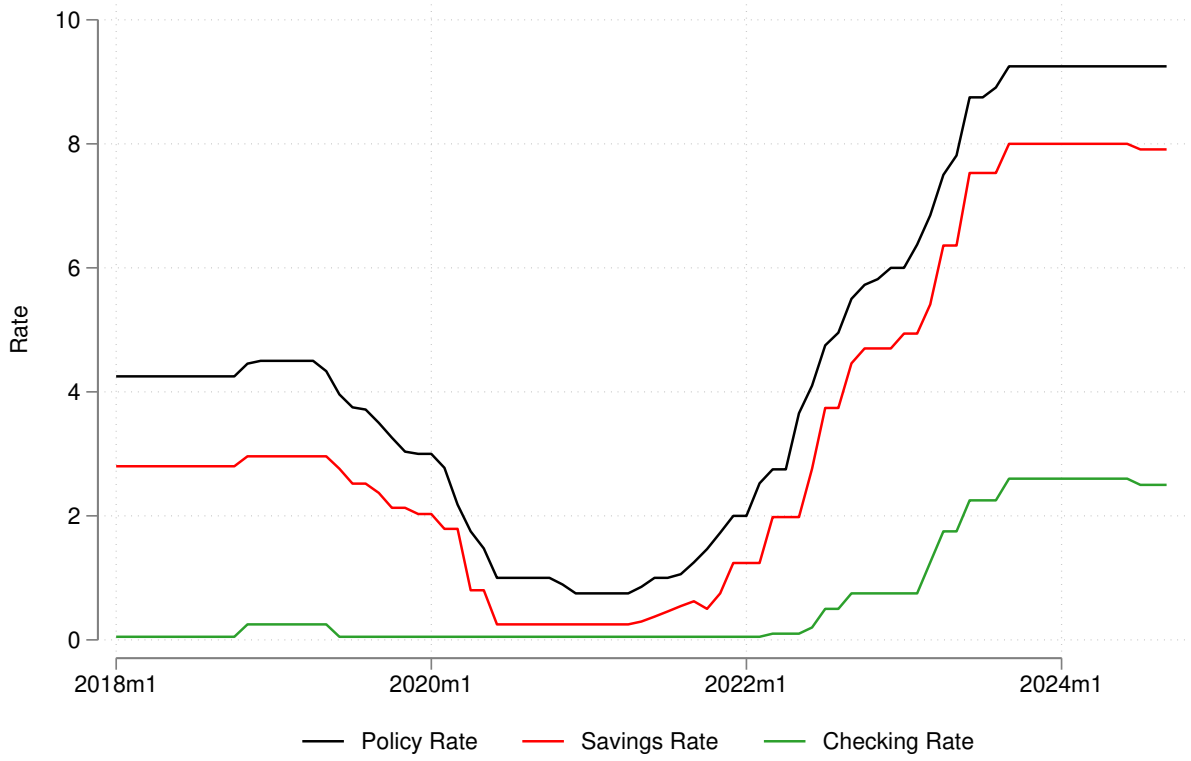
Individuals can hold liquid short term safe assets in the form of checking and savings accounts, and of liquid funds. Balances in savings and brokerage accounts are liquid in the sense that they can be instantly converted into checking (transaction) accounts without delay, anytime in the case of savings accounts and during trading hours in the case of liquid funds in the brokerage accounts. However, the interest rates offered by these accounts vary significantly.

Figure 2 presents the time series of interest rates for liquid accounts over the sample period. Among all available products, the figure reports the returns on high-yield checking and savings accounts, along with the central bank's policy rate, which serves as a proxy for the safe return available in the market.[6] The figure highlights that the spread—the difference

[6]Figure 11 in the appendix shows that the policy rate closely tracks the interest earned on an account labeled "liquid funds" offered by the bank's broker. Figure 12 compares the rates in the figure with those of similar products.

between the policy rate and deposit returns—is consistently positive and, in the case of checking accounts, widens as interest rates rise. This suggests that holding funds in deposits, particularly in checking accounts, becomes increasingly costly during periods of monetary tightening.

Figure 2: Interest Rates on Accounts



Note: The figure depicts the interest rates offered by the bank on its high-yield checking and savings accounts. Additionally, it shows the policy rate set by the central bank which closely tracks the return on liquid funds offered by the broker.

Our setting, where the high-rate and low-rate co-exist within the same institution, is ideal for testing the importance of interest rates in the allocation of liquid funds to low-rate and high-rate accounts as it allows us to control for various factors that have been suggested as explanations for the stickiness of deposits, like deposit insurance (Hanson et al., 2015) and superior liquidity services (d'Avernas et al., 2023).

Portfolio Allocations and the Cost of Liquidity

Given the substantial differences in returns between accounts offering nearly identical non-pecuniary benefits, we examine how individuals allocate their funds and the resulting costs. To guide our analysis, we use a simple model, which we outline below.

A Simple Model

Assume individuals live for two periods and have preferences over a consumption stream represented by the utility function:

$$U(c_1, c_2) = u(c_1) + \beta u(c_2),$$

where $u(c_t)$ has standard properties. We assume there is no uncertainty regarding the income process y_t individuals get or the returns on assets.

The individual chooses consumption (c_1, c_2) and total savings a. Savings can be allocated across J different safe assets, indexed by $j \in \{1, \ldots, J\}$, each offering a return r_j. Total savings a is the sum of savings across all assets, $a = \sum_{j=1}^{J} a_j$, where $a_j \in \mathbb{R}_+$ denotes the amount saved in asset j. All assets are assumed to be equally liquid, meaning they can be converted into consumption without cost or delay.

The individual follows a saving strategy $\alpha = (\alpha_1, \ldots, \alpha_J)^\intercal$, where $\alpha_j = \frac{a_j}{a}$ represents the share of the portfolio allocated to asset j. In this simple model, we assume the saving strategy α is exogenously given. The return on the portfolio under strategy α is then given by $r(\alpha) = \sum_{j=1}^{J} \alpha_j r_j$.

The problem of the individual that follows a strategy α is given by,

$$V(\alpha) = \max_{c_1, c_2, a} u(c_1) + \beta u(c_2)$$

subject to,

$$c_1 + a = y_1$$

$$c_2 = y_2 + a\,(1 + r\,(\alpha))$$

The first order necessary and sufficient condition for the solution is

$$u'\,(c_1) = \beta\ (1 + r\,(\alpha))\ u'\,(c_2)$$

The solution to this problem $(c_1(\alpha), c_2(\alpha), a(\alpha))$ is obtained from combining the first order condition with the budget equations.

What is the cost of following strategy α? Let $\alpha^\star$ denote the portfolio that maximizes the return, and let $\gamma(\alpha, \alpha^\star)$ represent the share of consumption in the first period needed to compensate an individual for following strategy α instead of $\alpha^\star$. Formally,

$$\gamma(\alpha, \alpha^\star) : [0,1]^J \to \mathbb{R} \quad \text{such that} \quad V(\alpha; \gamma(\alpha, \alpha^\star)) = V(\alpha^\star),$$

where $V\,(\alpha; \gamma) = u\,((1+\gamma) \cdot c_1\,(\alpha)) + \beta u\,(c_2\,(\alpha))$. Proposition 1 below provides an approximation for $\gamma(\alpha, \alpha^\star)$, which quantifies the welfare loss incurred by not following the strategy that maximizes the return.

Proposition 1 (First-Order Losses from Strategy α)**.** *The welfare loss of following strategy α instead of the highest-return portfolio $\alpha^\star$ can be approximated by*

$$\gamma\,(\alpha, \alpha^\star) \approx \frac{1}{c_1(\alpha^\star)} \cdot \frac{a(\alpha^\star)}{1+r} \cdot (r - r(\alpha)) \tag{1}$$

Proof: See Appendix X

Given that all assets are safe and liquid, the highest-return portfolio $\alpha^\star$ allocates all weight to the asset with the highest return, which we assume to be liquid funds in the broker.

Thus, $r(\alpha^\star) = r$, where r is the return on liquid funds. Proposition 1 has a clear intuition: the cost of following strategy α is determined by the forgone interest, which is measured as the present value of wealth multiplied by the forgone interest, $\frac{a(\alpha^\star)}{1+r(\alpha^\star)} \cdot (r - r(\alpha))$. To express this cost in terms of shares of consumption in the first period, dividing by $c_1(\alpha^\star)$ is needed.

If we assume, as usually done in the literature, that deposits rate are well approximated by $r_j = \beta_j r$ with $\beta_j \leq 1$, we can express the return on liquid safe assets as $r(\alpha) = \sum_j \alpha_j \beta_j r$, which allows us to write log welfare loss as

$$\ln(\gamma) = \ln(a) + \ln(r - r(\alpha)) = \ln(a) + \ln(r) + \kappa(\alpha) - \ln(c), \tag{2}$$

where $\kappa(\alpha) \equiv \ln(1 - \beta^\intercal \cdot \alpha)$ is a function of the portfolio shares, and we approximate $\ln(1 + r) \approx 0$. The key takeaway from this equation is that a one percent increase in wealth a generate the same percentage loss on welfare as a one percent increase in the policy rate r,[7] holding constant the portfolio shares and consumption.

Return Heterogeneity and The Cost of Liquidity

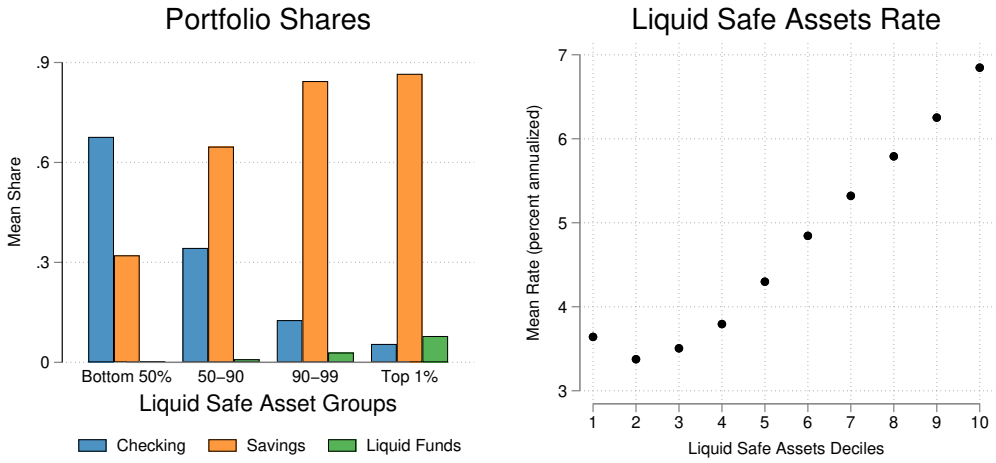
All elements of equation (1) are observed in our dataset: the portfolio allocation, α, the return on each asset, r_i, total funds saved, a, and consumption, c_1. We focus this section on analyzing portfolios during recent years of high interest rates.

The left panel of Figure 3 depicts the portfolio allocation, α, across the liquid safe asset distribution. Specifically, it groups individuals by their level of liquid safe assets at each point in time and calculates the average share of each asset within the liquid safe portfolio for members of each group during 2023 and 2024. It shows that wealthier households allocate a smaller share of their liquid portfolio to low-return checking deposits, favoring higher-return savings accounts instead. However, liquid funds held within the broker are not a commonly used asset category, even among the very wealthy.

A lower portfolio share allocated to low-return assets implies that wealthier households

[7] Percent increase in r, i.e. $\Delta r/r$, not percentage points.

Figure 3: Portfolio Shares and Return of Liquidity



Note: Plots use average data from year 2023 and 2024. Groups of households are computed at each point in time using their liquid safe asset holdings. Liquid asset rate is defined as the weighted average return on liquid assets.

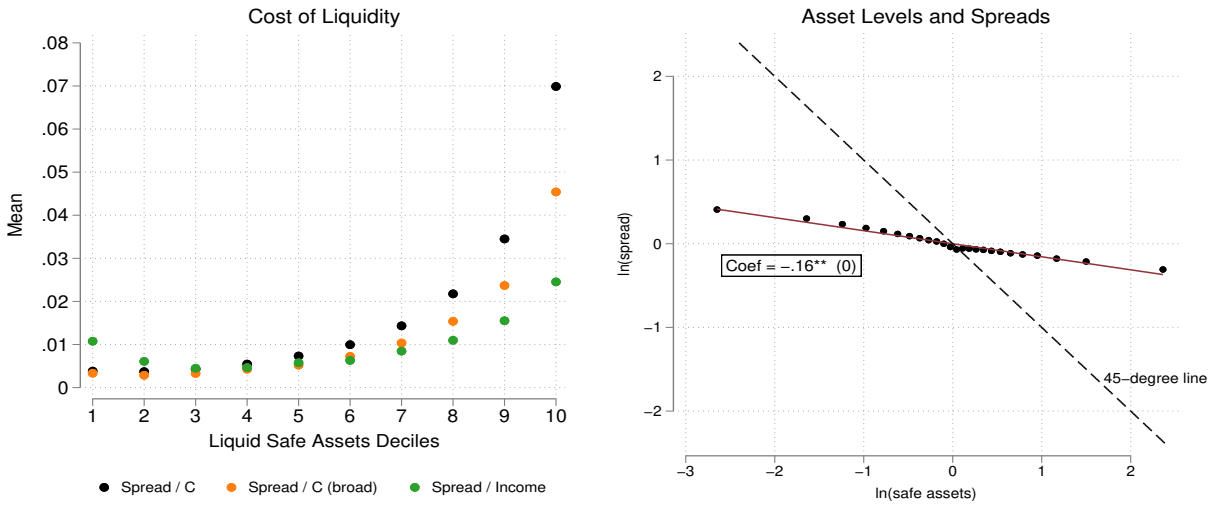
achieve higher returns on their portfolios making the return on liquid safe assets, $r(\alpha)$, wealth-dependent. The right panel of Figure 3 illustrates the average return on liquid assets during 2023 and 2024, grouped by deciles of liquid safe assets at each point in time. The wealth dependence of returns on assets with similar characteristics, and its implications for wealth inequality, have been highlighted in prior research (see Fagereng et al., 2020). However, less attention has been given to importance of the forgone interest income, $\gamma(\alpha, \alpha^\star)$.

A higher return on liquid assets reduces the cost per unit of liquidity, $r - r(\alpha)$, but does not necessarily lower the total cost, $\gamma(\alpha, \alpha^\star)$, as the latter scales with wealth relative to consumption. The left panel of Figure 4 illustrates the cost of liquidity, $\gamma(\alpha, \alpha^\star)$, in consumption-equivalent terms across different asset deciles. Specifically, it shows the twelve-month forgone interest income for individuals, expressed as a share of expenses over the same period.[8] The figure presents this cost using two different measures of consumption: one

[8]For each month t, the cost of liquidity is computed as: $\frac{\sum_{s=0}^{11}(r_{t-s}-r_{i,t-s})\cdot a_{i,t-s}}{\sum_{s=0}^{11} c_{i,t-s}}$, where $a_{i,t-s}$ is the total value of liquid assets held by individual i in month $t-s$, r_{t-s} is the safe return available in the market, and $c_{i,t-s}$ is the monthly value of consumption expenses.

(black dots) includes only outflows that can be confidently classified as consumption expenses, while the other (orange dots) treats any unclassified outflow as consumption. Additionally, it includes the same measure using income for comparison, in green dots.[9]

Figure 4: Cost of Liquidity and Assets Spread Relationship



Note: figure shows average data from years 2023 and 2024. Groups of households are computed at each point in time using their liquid safe asset holdings. The measure is computed as the cumulative forgone interest income on safe liquid assets during the last 12 months over the same period cumulative expenses. Consumption expenses in black dots is measured using only outflows identified as consumption, while orange dots include all unclassified expenses on it. Only individuals defined as active are use in the computation.

Figure 4 shows that while wealthier households earn higher returns on their liquid safe assets, the cost of liquidity increases with wealth. Moreover, the figure highlights that these costs are substantial for more than half of the population, ranging from 1 percent of annual consumption for the sixth decile to 5–7 percent for the wealthiest individuals, depending on the measure of consumption used.

The cost of liquidity increases with wealth, a, because individuals do not adjust their portfolios quickly enough as their wealth grows. Equation (2) shows that if the elasticity of

[9]Figure is computed using liquidity cost winsorized at 1% to prevent the mean growing due to outliers arising from very low consumption expenses. Figure 13 in the appendix shows the same figure using the median instead of the mean.

the spread, $r - r(\alpha)$, with respect to wealth is below one, then the cost of liquidity rises with wealth. The right panel of Figure 4 illustrates this relationship through a binscatter of the log of liquid safe assets against the log of the spread for individuals.[10] The estimated slope is -0.16, well below one in absolute terms, indicating that for each 1% increase in wealth, the spread on liquid safe assets declines by only 0.16% on average. The flat slope suggests that while individuals adjust their portfolios as they accumulate wealth, their response is insufficient to prevent liquidity costs from rising.

Portfolio Differences: Wealth, Spreads, and Persistent Heterogeneity

Since the cost of liquidity rises with both wealth and spreads for a given portfolio share, we now examine what drives portfolio allocation. Equation (2) shows that a 1 percentage point increase in wealth has the same effect on liquidity costs as a 1 percentage point increase in the policy rate. Given this, we ask whether individuals respond by reallocating their portfolios away from low-return assets as they accumulate wealth or as spreads widen.

We focus on active bank clients whose balances are at least \$3000 ISK every month and who are present in the entire sample (between January 2018 and September 2024). With these individuals, we estimate the following regression:

$$y_{it} = \beta_a \ \ln(a_{it}) + \beta_r \ \ln(r_t) + X'_{it} \cdot \alpha + \nu_i + \varepsilon_{it} \tag{3}$$

where y_{it} is the individual variable of interest in month t—i.e., the share in low-return checking deposits or the cost of liquidity in terms of consumption—$\ln(a_{it})$ are liquid safe assets of individual i on month t, r_t is the policy rate set by the central bank used as a proxy for the return on liquid funds, X'_{it} are other individual time-varying characteristics such age, and ν_i captures individual fixed effects. The goal of estimating ν_i is to understand whether there is persistent heterogeneity in portfolios and which are the individual characteristics of

[10] Specifically, it presents the binscatter from the regression $\ln(a_{it}) = \alpha_i + \beta \ln(r - r_{it}) + \varepsilon_{it}$ using a stable panel of active individuals. All variables are normalized to have mean zero.

individuals who persistently hold a larger share of their portfolio in low-return deposits or face higher costs on liquidity.

Table 2 shows that, as anticipated in Figure 3, the share on low return deposits correlates negatively with the level of assets of the individual (columns (1)-(2)). However, the better allocation of wealthy individuals, is not sufficient to offset the increasing cost of liquidity with wealth (columns (3)-(4)). The table also shows that, although wealth and interest rates have the same effect on liquidity costs if portfolios remain unchanged (equation (2)), the correlation between interest rates and portfolio shares is only about 1/7th as strong (column (2)). This suggests that portfolio allocations are more sensitive to wealth than to interest rates.

Table 2: Determinants of Liquid Safe Portfolio Allocation

	(1) Share in Checking	(2) Share in Checking	(3) Cost of Liquidity	(4) Cost of Liquidity
log liquid safe assets (a)	-9.848 (0.0823)	-7.823 (0.0786)	0.769 (0.00777)	0.431 (0.00498)
log Policy Rate (r)	-1.533 (0.0542)	-1.217 (0.0531)	0.611 (0.00671)	0.629 (0.00565)
age	1.225 (0.0485)	-0.231 (0.0865)	-0.0966 (0.00410)	-0.472 (0.0106)
age^2	-0.0105 (0.000470)	0.00167 (0.000772)	0.00109 (0.0000431)	0.00429 (0.000110)
FE	N	Y	N	Y
N	3035961	3035961	2614854	2614844
Adjusted R^2	0.194	0.716	0.271	0.693

Note: Regression of individual liquid portfolio share in checking deposits and the cost of liquidity. Left-hand variables are in percent (100s) as well as the policy rate r. Liquid safe assets are in real terms. The cost of liquidity is the 12-month forgone interest income in terms of consumption expenses winsorized at the 1% level. The panel of individuals is a stable panel of active individuals with at least $3000 ISK in liquid safe assets. The data frequency is monthly and the time spans between January 2018 and September 2024. Individually clustered standard errors in parentheses.

Table 2 also shows a substantial increase in the R^2 when including individual fixed effects (even columns) compared to when they are excluded (uneven columns) highlighting the importance of fixed individual characteristics in explaining the heterogeneous portfolios. In

other words, some individuals consistently hold a higher return portfolio and pay a lower cost of liquidity, even after accounting for changes in wealth levels, age, and interest rates. The dispersion in the fixed-effect component is substantial, with a standard deviation of 30%, a 10th percentile of -40%, and a 90th percentile of 46%. These figures suggest that a significant share of individuals consistently hold more than 50 percentage points higher in low-return deposits within their portfolios.

Heterogeneous Portfolios

In this section, we show that the relationship between wealth and spreads varies across individuals with different characteristics. Specifically, we use survey data on bank customers to examine whether individuals with greater financial knowledge and skills adjust their portfolios to achieve higher returns as they accumulate wealth or, alternatively, if they face increasing spreads. In other words, we investigate whether portfolio sensitivity to wealth and interest rates depends on individual characteristics.

To do so, we classify individuals into terciles based on the number of correct responses to questions on financial literacy, inflation, and numeracy. We then estimate the following regression on the share of checking deposits in portfolios, incorporating interactions between survey variables, wealth, and the policy rate into equation (3):

$$\begin{aligned} y_{it} = \beta_a \ \ln(a_{it}) + \beta_r \ \ln(r_t) + X'_{it} \cdot \alpha + \nu_i + \\ + \beta_{ax} \ln(a_{it}) \cdot I_{i \in g} + \beta_{rx} \ln(r_t) \cdot I_{i \in g} + \beta_{ar} \ \ln(a_{it}) \cdot \ln(r_t) + \varepsilon_{it} \end{aligned}$$

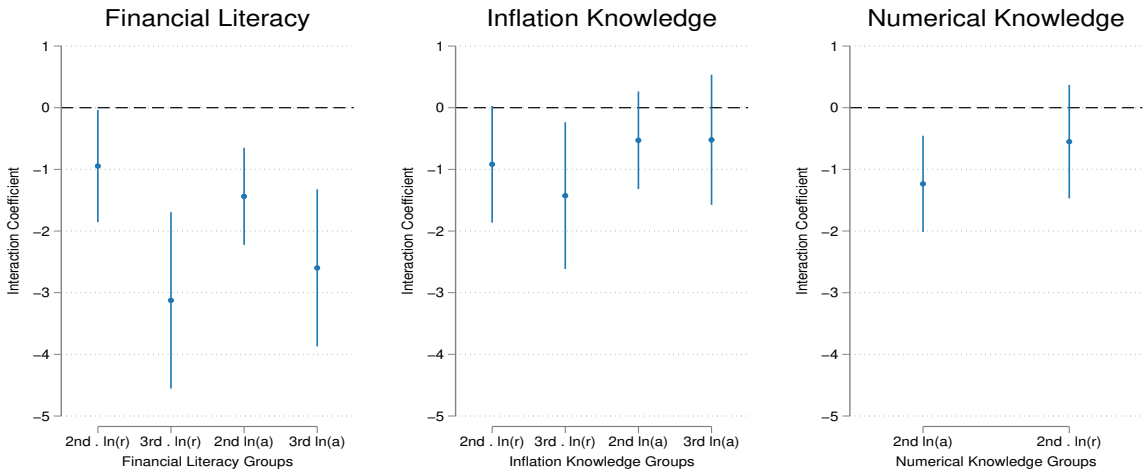
where $I_{i \in g}$ is an indicator function for each survey group, with $g \in \{1, 2, 3\}$.[11] Figure 5 presents the estimated interaction coefficients, while Table 4 reports the full regression results.

All panels in Figure 5 show that individuals with greater financial knowledge or skills hold

[11] Numerical knowledge could not be split into terciles, so we classify individuals into two groups: low or high numerical knowledge.

a lower share of checking deposits in their portfolios as spreads increase or as they become wealthier. Consider, for example, the left panel: when the policy rate rises by 1 percentage point, the share of checking deposits in the portfolio of an individual in the third tercile of financial literacy is 3 percentage points lower than that of an individual in the first tercile. Similarly, as an individual becomes 1 percent wealthier, those with the highest financial literacy hold, on average, 3 percentage points less in checking deposits. These effects are substantial compared to the baseline estimates reported in Table 2.

Figure 5: Sensitivity to Interest Rates and Wealth Across Individual Characteristics



Note: The figure presents the estimated interaction coefficients from the regression (4) of the share of checking deposits on wealth, the policy rate, and their interactions with individual characteristics. Individuals are grouped into terciles based on financial literacy, inflation knowledge, and numeracy (with numeracy split into two groups: low and high). Full regression results are reported in Table 4.

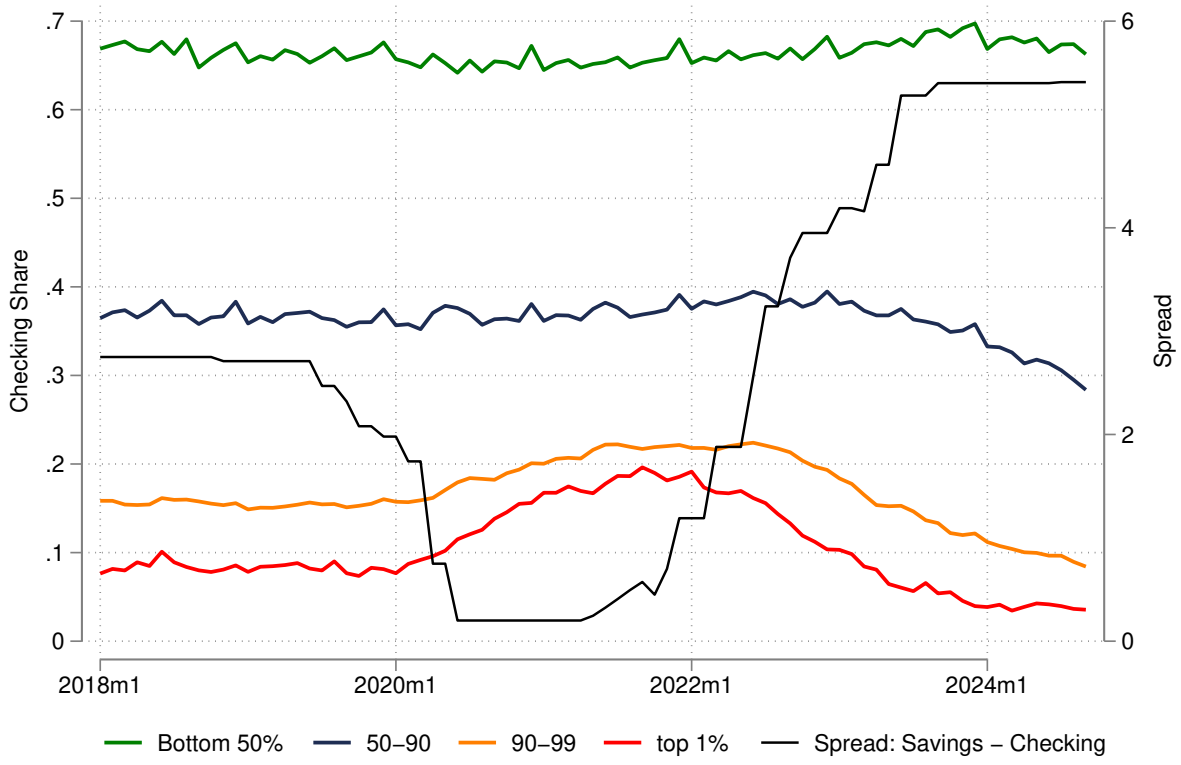
4 Portfolio Adjustments

This section investigates the events that trigger portfolio reallocations by depositors. Specifically, we examine what triggers funds to move, who moves them, and where they are reallocated. We begin by showing that portfolio allocation correlates strongly with fluctuations in individuals' wealth levels and appears to depend on the interest rate spread, but

only for wealthy individuals.

We first examine the time series of low-return checking deposit shares across individuals with different wealth levels. Figure 6 plots the average share of checking deposits in liquid safe assets, grouping individuals based on their liquid asset holdings at each point in time.[12] The figure shows the strong relationship between wealth levels and the allocation to low-return checking accounts. Notably, despite the return gap between checking and savings accounts (right axis) increasing more than fivefold between 2022 and 2024, the share of checking deposits remains remarkably stable across the wealth distribution, except for the wealthiest individuals, who seem to adjust their portfolios more actively.

Figure 6: Portfolio Share in Checking Account



Note: The figure shows the average share of checking deposits in the liquid safe asset portfolio for active individuals grouped by their wealth level at each point in time. The spread represents the difference in returns between standard savings and checking accounts.

[12] Figure 15 in the appendix replicates this analysis while keeping group membership fixed and a balanced panel, classifying individuals by their average asset level over the sample period.

To further assess the importance of wealth relative to the interest rate spread in shaping portfolio choices, we examine the impact of individual wealth fluctuations rather than just wealth levels. Specifically, we regress the share of low-return deposits in an individual's portfolio on fluctuations in their wealth, the level of the spread, and the interaction between the two. This allows us to not only evaluate whether the spread influences portfolio allocation but also determine whether individuals' relative wealth changes affect their sensitivity to the spread.

Let share_{it} denote the fraction of individual i's liquid safe assets allocated to checking deposits in month t, and let d_{it} represent the decile of individual i's liquid safe asset holdings in month t. Wealth deciles are calculated uniquely for each individual, ranking their wealth level from 1 (lowest) to 10 (highest) over the sample period. Lastly, let spread_t denote the spread between checking and savings accounts interest rates, normalized to have mean zero. Using a stable panel of active bank customers, we estimate the following regression:

$$\text{share}_{it} = \alpha \cdot \text{spread}_t + \sum_{j=1}^{10} \beta_j \cdot \text{I}_{(d_{it}=j)} + \sum_{j=1}^{10} \gamma_j \cdot \text{I}_{(d_{it}=j)} \cdot \text{spread}_t + X'_{it} \cdot \delta + \nu_i + \varepsilon_{it} \qquad (4)$$

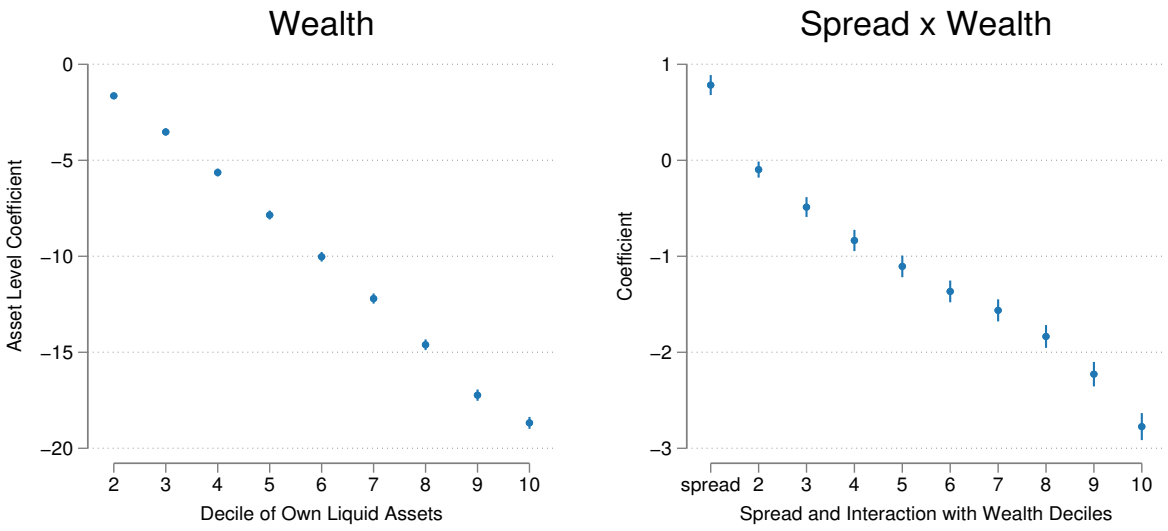
where $\text{I}_{(d_{it}=j)}$ is an indicator function equal to one if agent i is in decile j of their wealth at month t, ν_i is an individual fixed effect and X'_{it} are time varying controls such as age.

Figure 7 presents the results on how within-individual variation in wealth and its interaction with the spread between savings and checking account interest rates are associated with liquid wealth allocations.[13] Technically, we are reporting correlations. In practice, our set of fixed effects does impose a bar though for selection, omitted-variable bias, and reverse causality. All regressions control for selection on time-invariant (un)observables by including individual fixed effects, and we always compare individuals' values to their own averages. The left panel shows the effects of individuals' wealth levels—the β_j coefficients in equation (4)—on the share of low-return checking deposits in their portfolios. The right panel illustrates the interaction between individuals' wealth deciles—the γ_j coefficients—and the spread between

[13] Table 3 in the appendix provides detailed regression estimates.

checking and savings account rates, the α coefficient.

Figure 7: Effect of Wealth Levels and Interest Rate Spreads on Checking Deposit Share



Note: The figure shows the estimated coefficients from equation (4). Deciles of individuals' wealth levels are calculated relative to each individual history of wealth in the dataset. The left panel plots the β_j coefficients, capturing the effect of changes in individuals' wealth. The right panel shows the γ_j coefficients, capturing the effect of the spread across different individual wealth levels. The panel is stable using only active individuals, and standard errors are clustered at the individual level.

The left panel reveals that as individuals wealth increases, they tend to hold a smaller share of their liquid wealth in checking deposits. The effect is substantial: moving from the lowest to the highest decile of their own wealth distribution reduces the share of checking deposits by almost 20 percentage points. The right panel highlights that individuals respond to increases in the cost of low-return deposits (as measured by the spread) by reducing their portfolio share, but this responsiveness is observed only during periods when they are relatively wealthy, compared to their own personal history. At the peak of their wealth during the sample period, a 1 percentage point increase in the spread is correlated with a 2 percentage point reduction in the share of checking deposits. In contrast, when individuals are at lower wealth levels, the share of low-return deposits appears largely unresponsive to changes in their cost.

Adjustment Frequency

Improving the administration of liquid safe assets can have a large benefit, even for individuals that do not save between payment days. That is, even individuals with little assets—typically referred to as hand-to-mouth—can benefit. Take a classical Baumol-Tobin model of cash management with two assets, but assume here that the low-return asset has return r_C and the high-return asset has return r_S—in reference to checking and savings accounts. Assume that the individual's income is deposited into the low-return account at the beginning of the period. Finally, suppose funds in the low-return account are needed to pay for consumption.

Take two individuals. Agent (a) never moves funds between accounts, meaning they get paid at the beginning of the month and use the funds in the low-return deposits to pay for consumption. Agent (b), on the other hand, moves funds into the high-return account as soon as they are paid and then transfers money back $N-1$ times to finance consumption, making a total of N fund movements. The interest income of agent b is given by

$$\text{income}_b(N) = \frac{c}{2} \cdot \left(\frac{N-1}{N} \, r_S + \frac{1}{N} \, r_C \right)$$

and note that $\text{income}_a = \frac{c}{2} \cdot r_C$ is the interest income of the individual (a) who receives their income in the checking account and never moves it to savings. The additional interest income that individual (b) earns is

$$\text{income}_b(N) - \text{income}_a = \frac{c}{2} \cdot \frac{N-1}{N} \; (r_S - r_C)$$

To understand the magnitude of this effect, note that making just one additional transfer between accounts ($N = 2$) results in a gain of

$$\text{income}_b(2) - \text{income}_a = \frac{c}{4} \cdot (r_S - r_C)$$

Under moderate interest rate conditions, where the spread between checking and savings

deposits is $r_S - r_C = 4\%$ annually, this additional income amounts to 1% of consumption. That is, even individuals who consume all their income can obtain significant benefits from moving funds between bank accounts within the same bank instantly and at no cost.

As a reference, this simple Baumol-Tobin modification predicts that if transferring funds between accounts incurs a cost κ in units of consumption, then the optimal number of transfers, $N^\star$, is given by

$$N^\star = \left[\frac{(r_S - r_C) \cdot c}{2\kappa}\right]^{1/2}$$

if $\frac{c}{2}\frac{r_S - r_C}{2} \geq 2\kappa$, and $N^\star = 0$ otherwise. The minimum threshold for a positive spread to induce transfers arises because income is assumed to be received in the low-return account, requiring at least two transactions—one in and one out of savings. This result implies that the frequency of reallocations increases with both the interest rate spread and the level of consumption.

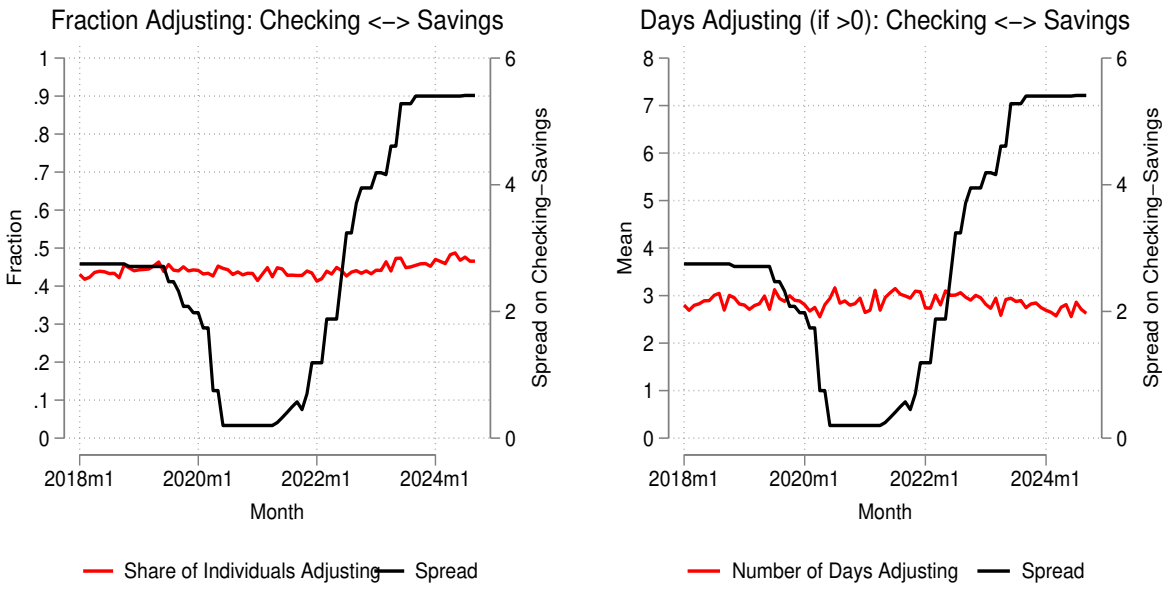
Our data set enables us to track the movement of funds between accounts within the bank and transfers to broker accounts. Figure 8 highlights that the reallocation of funds between accounts is relatively common, with 40% of individuals making at least one transfer per month between its own checking and savings accounts. The right panel further shows that, conditional on making at least one transfer in a month, individuals reallocate funds on an average of three days. However, the overall pattern remains largely unaffected by changes in the spread between checking and savings accounts. Both the share of individuals transferring funds and the average number of transfers remain consistent, regardless of whether the spread is zero or 5%, with only the top individuals exhibiting some adjustment, as shown in Figure 16 in the appendix.[14]

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We provide further evidence on the role of fund inflows and outflows in shaping portfolio allocations. Specifically, we calculate the share of individuals who, conditional on making a portfolio reallocation into their checking account on a given day, also exhibit an outflow of

[14] Figure 17 in the appendix shows a similar figure for movements to the broker account.

Figure 8: Adjustments



Note: Left: fraction of individuals moving funds between checking and savings at least once a month. Right: average number of days funds move between checking and savings conditional on at least one movement in the month. Calculation uses only active bank customers.

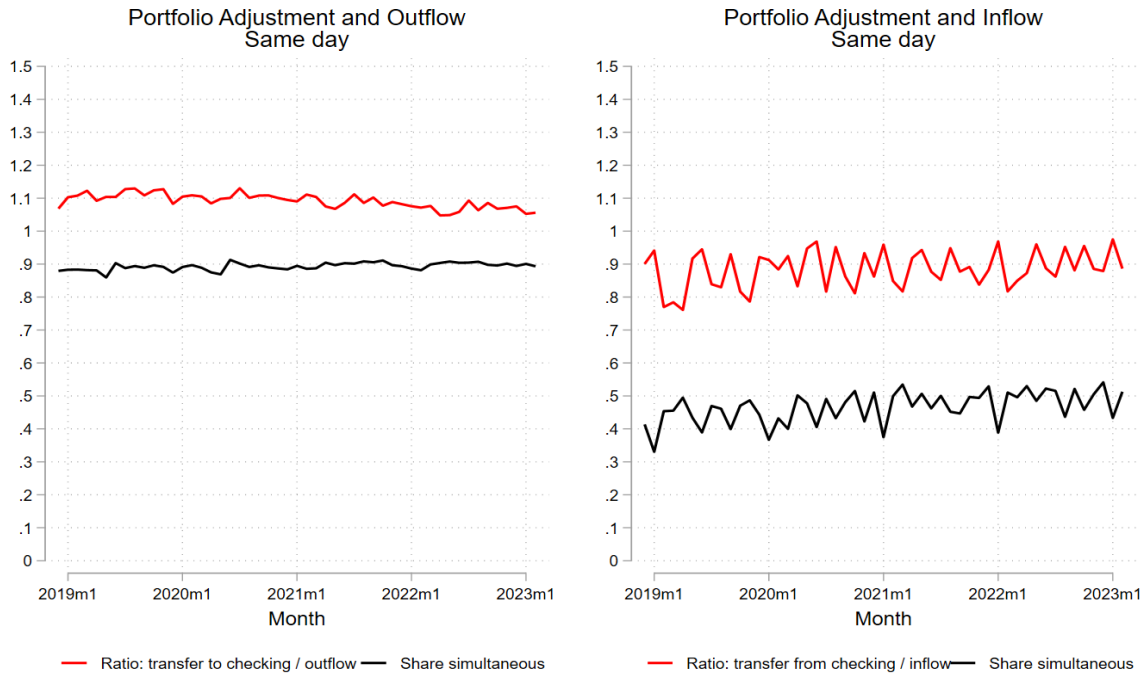
funds from the same account on that day.[15] The left panel of Figure 9 (black line) shows that 90% of all inflows into checking accounts are accompanied by simultaneous outflows. Furthermore, the red line illustrates the median size of inflows relative to outflows, indicating that the median inflow closely matches the outflow. This pattern suggests that inflows into checking accounts are largely driven by the need to consume or make payments.

The right panel of Figure 9 provides analogous information for reallocations out of checking accounts. The black line in the right panel shows the share of individuals who, conditional on reallocating funds from checking into a saving account on a given day, also received an inflow into checking on that same day. It reveals that approximately half of these individuals make such reallocations on days when they experience an income flow. Furthermore, the median

[15]While we cannot determine whether the outflow is for consumption purposes, we can rule out that it is directed to a broker account.

size of the transfer into a higher return account closely matches the inflow of funds into checking. This pattern highlights the importance of income inflows in driving reallocations from checking accounts to high-return accounts.

Figure 9: Portfolio Adjustments Following Expense and Income Flows



Note: The figure illustrates the share of individuals reallocating funds from checking accounts to higher-return accounts (right panel) and vice versa (left panel). The black line represents the share of individuals who, conditional on making a transfer into or out of checking, also experience a corresponding outflow or inflow of funds on the same day. The red line shows the median size of the transfer relative to the accompanying inflow or outflow.

4.1 Events Response

In this section, we examine how individuals adjust their portfolios in response to cleanly identify events. Specifically, we explore the impact of income changes—both anticipated and unanticipated—on portfolio allocation. We also investigate the role of large consumption expenses, such as house purchases and other atypical expenditures, in driving reallocation decisions. Lastly, we use unexpected movements in the policy rate to instrument for changes

in the cost of holding deposits to understand how sudden shifts in the cost of liquidity influence individuals' portfolio choices. By studying these events, we aim to shed light on the underlying mechanisms that prompt individuals to reevaluate their asset distribution.

4.2 Managing an Anticipated Income Change

All workers in Iceland receive holiday allowance amounting to a minimum of two accumulated working days for each worked month or 10.7%. Some workers get the allowance transferred monthly into an account which funds are automatically transferred separately into the clients checking or savings account on the 11th of May each year or the next working day thereafter. While workers can monitor the balance, they cannot access the funds until that specific day. This represents an example of funds that individuals anticipate will become liquid on a particular day, making it a fully anticipated income windfall.

This event provides a useful example to study how individuals manage an income inflow, in this case, one that is fully anticipated. To understand their behavior, we conduct the following event study:

$$y_{i,t+s} = \alpha + \beta_s \cdot \mathrm{a}_t + \varepsilon_{i,t+s} \tag{5}$$

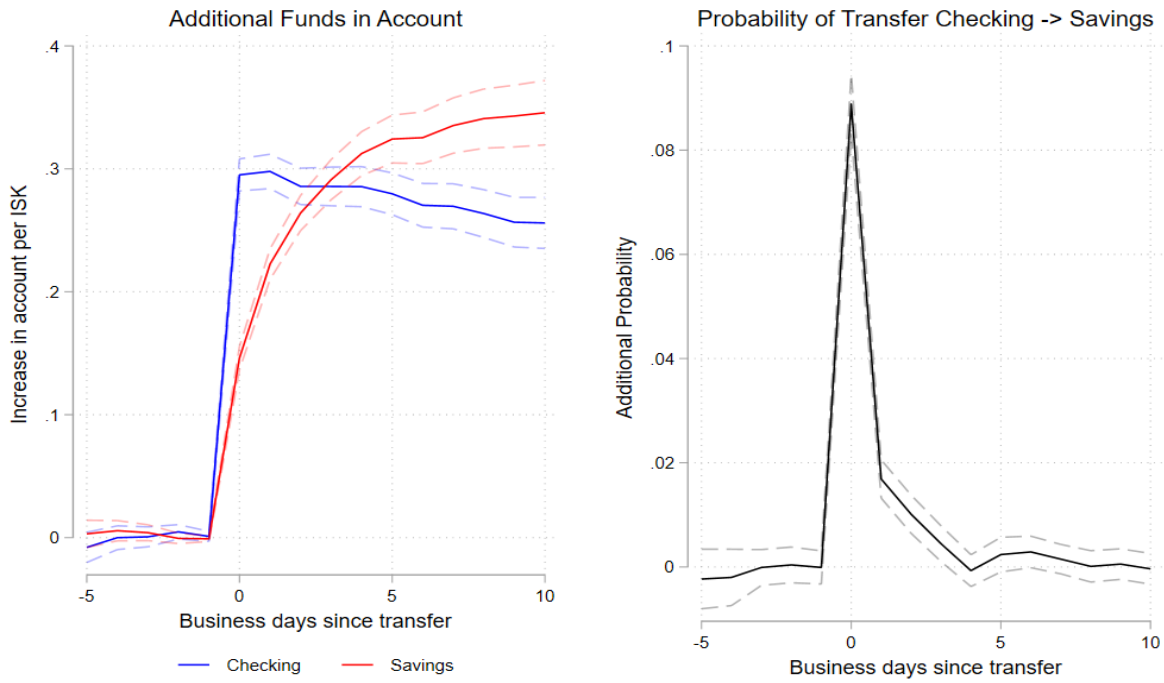
where t represent May 11th, the day of the transfer, and s denote the business days surrounding that transfer, with $-5 \leq s \leq 10$. We run two specifications. In the first, $y_{i,t+s}$ represents the ISK value in the checking and savings accounts on the day corresponding to $t+s$, and a_t is the ISK amount that became liquid on May 11th. This specification is run only for individuals who receive the transfer. In the second specification, a_t is an indicator function that equals one if the individual received a transfer from the vacation account, and $y_{i,t+s}$ is another indicator that equals one if the individual reallocates funds between checking and savings on the day $t+s$.

Figure 10 displays the estimated results from both specifications. In both the left and right panels, we observe that despite the transfer being fully anticipated, there is no change

in the size of funds nor any significant reallocation of funds before the transfer. The left panel shows that the vacation allowance increases funds in both checking and savings accounts. On average, individuals allocate 30 cents of each additional Krona to their checking account and another 15 cents to their savings account on the day of the transfer. Notably, the balance in savings accounts continues to grow in the days following the holiday allowance transfer, while funds in the checking account decline.

As funds can be directly deposited into savings accounts, the question arises whether individuals actively manage their portfolio. The right panel confirms that, indeed, on the exact day of the transfer and the following days, individuals move funds from the checking account into the higher-return savings account. We see this as additional evidence that individuals quickly respond to additional income by reallocating funds.

Figure 10: Response to Transfer from Vacation Account



Note: the left panel plots the change in the balance of checking and savings accounts following an anticipated vacation allowance transfer. The right panel shows the additional probability of reallocating funds between checking and savings accounts after the transfer.

4.3 Managing an Unanticipated Income Shock

4.4 Portfolio Response to a Monetary Policy Shock

5 Quantitative Model

6 Conclusion

Retail deposits are generally considered sticky, allowing banks to maintain a low deposit beta. However, regular events throughout history remind us that deposits sometimes move. Deposits thus appear to be considered both sticky and volatile. Existing studies have examined various potential explanations for deposit insensitivity to interest rates, including deposit insurance (Hanson et al., 2015), superior liquidity services (d'Avernas et al., 2023), and market power (Drechsler et al., 2021) as well as the volatile nature of deposits (see, e.g., Blickle et al., 2024). However, there is quite limited evidence on the deposit allocations of individuals coming from settings where researchers are able to follow the money, i.e., where it is possible to observe the money comes from, how depositors allocate them to different accounts or investments, as well as how various characteristics and circumstances interact with these behaviors.

In this paper, we combine high-frequency, comprehensive, and detailed panel of bank data, providing a close-to-full picture of the financial lives of individuals, and experimental data from a series of surveys administered to bank customers, to perform comprehensive analysis of deposit behavior that reconcile these seemingly contrasting deposit dynamics. We document significant heterogeneity in portfolio allocation among assets with similar characteristics but large differences in rates of return. Specifically, wealthier, more educated individuals with higher financial literacy consistently achieve higher returns on liquid safe assets.

We also show that portfolio allocations respond to changes in wealth, with wealthier individuals reallocating funds to higher-return assets. Moreover, this reallocation occurs almost immediately after income is received. Conversely, reductions in high-return deposits

happen when individuals incur large expenses. Finally, our evidence points to wealthier individuals as the ones most likely to reallocate towards high-return assets following an increase in deposit spreads.

To sum, our analysis of depositor behaviors using detailed individual-level, high-frequency panel of bank data over a long period of time provides new and valuable insights regarding the mobility of bank deposits. Our findings provide useful knowledge as to how to design interventions aimed to minimize the financial stability risk of the banking system.

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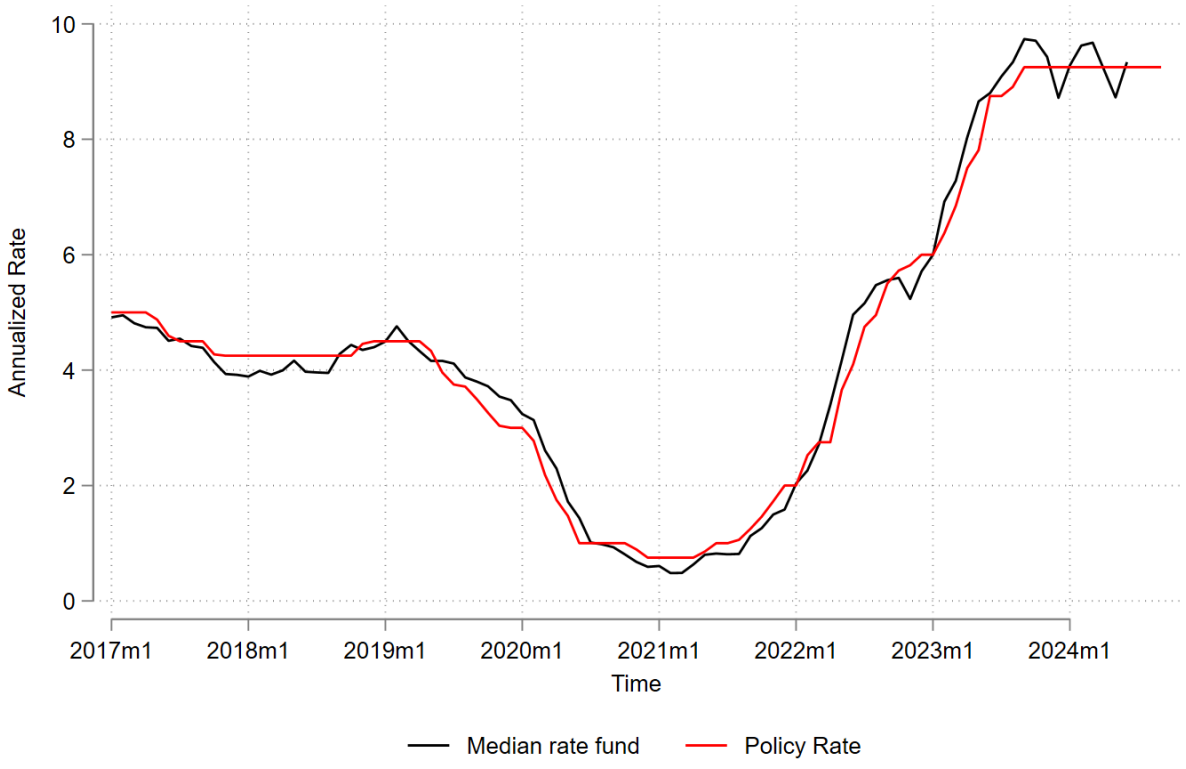
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A Additional Figures and Tables

Return on Liquid Funds

Figure 11 compares the Central Bank of Iceland's policy rate with the median realized three-month returns on liquid funds in the bank's broker. Specifically, if p_t denotes the log price of a fund share in month t, the black line represents the median across individuals of the annualized return, $\text{per}_{50}\left(p_{t+3} - p_t\right)$. The almost negligible variance in the return on liquid funds across individuals suggests that the bank offers a single, unique liquid fund. As shown in the figure, the realized return on the fund closely tracks the central bank's policy rate.

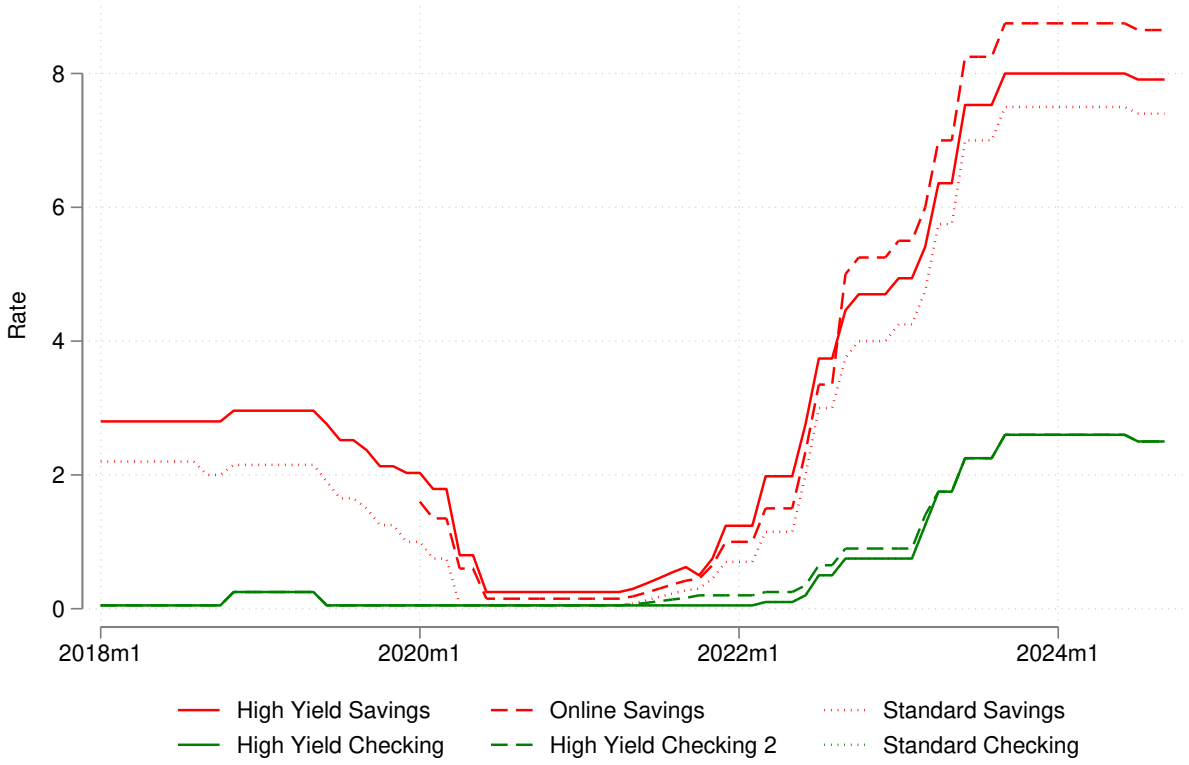
Figure 11: Return on Liquid Funds vs Policy Rate



Return Bank Accounts

The bank offer multiple tiers of products. Figure 12 shows the interest rate paid by the bank on some of these accounts.

Figure 12: Interest Rates on Accounts



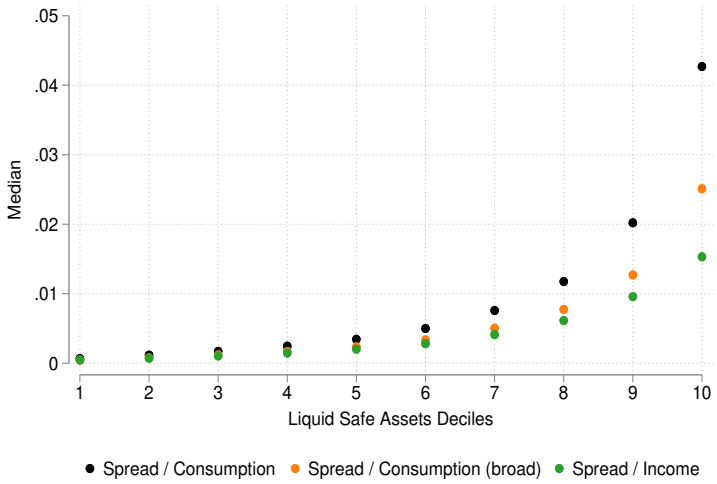
Note: The figure depicts the interest rates offered by the bank on different versions of the same product.

Liquidity Cost

Figure 13 reproduces the computations of Figure 4 but shows the median cost per group.

Figure 14 computes the cost of liquidity using aggregate data from Iceland. The Iceland Central Bank reports monthly data on current accounts and sight deposits, which maps to our definition of checking and savings deposits. Additionally, the Iceland statistical agency reports yearly consumption expenditure measures of local households. We can combine

Figure 13: Cost of Liquidity



Note: figure shows average data from years 2023 and 2024. Groups of households are computed at each point in time using their liquid safe asset holdings. The measure is computed as the cumulative forgone interest income on safe liquid assets during the last 12 months over the same period cumulative expenses. Consumption expenses in black dots is measured using only outflows identified as consumption, while orange dots include all unclassified expenses on it. Only individuals defined as active are use in the computation.

this information with interest rates reported in Figure 2 and compute a measure of income lost using only aggregate data. To get the interest rate on deposits we need to assume a distribution over checking and savings deposits, which we assume to be a constant 50%.

Portfolio Share for Constant Groups

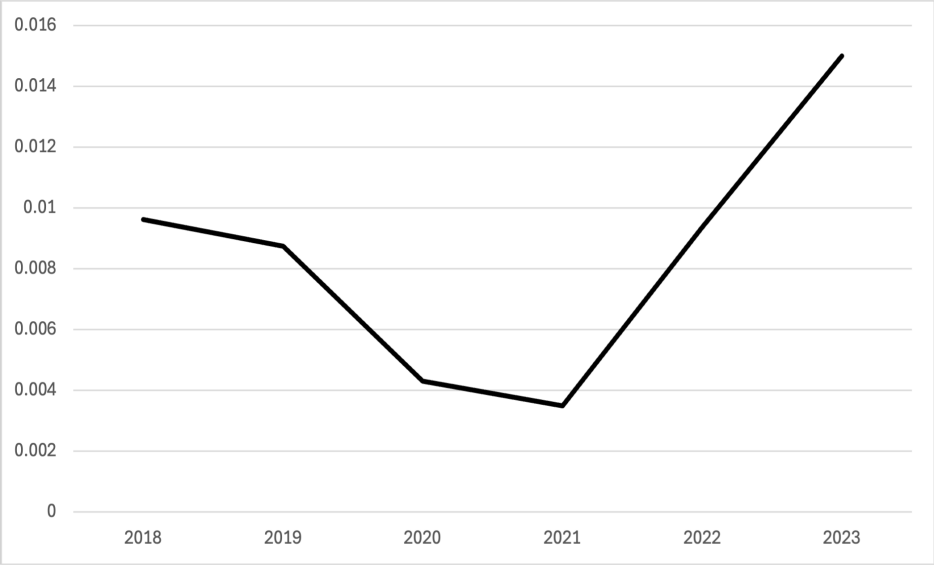
Regression Results

Adjustment for Groups Size

Adjustment to Broker

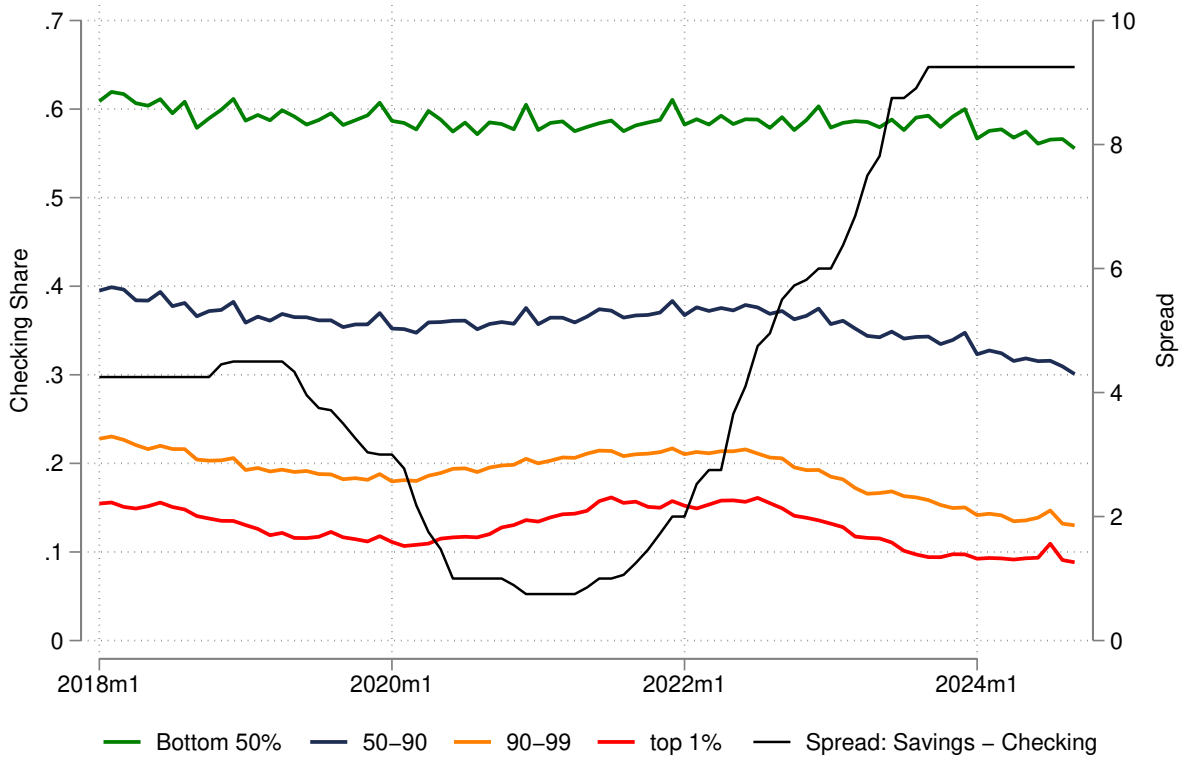
Additional

Figure 14: Cost of Liquidity - Aggregate Data



Note: the figure computes the cost of liquidity using aggregate data from Iceland. For deposits, it uses sight and current accounts as reported by the Central Bank. For consumption expenses, it uses consumption by local as reported by Statistics Iceland. The spread on deposits is the difference between the Policy Rate and a portfolio that allocated 50% on savings and 50% on checking using rates in Figure 2.

Figure 15: Portfolio Share in Checking Account



Note: The figure shows the average share of checking deposits in the liquid safe asset portfolio for active individuals. The panel of individuals is balanced and individuals are grouped according to their average level of assets during the period. The spread represents the difference in returns between standard savings and checking accounts.

Table 3: Checking Share, Own Wealth and Spreads

	(1) Share Checking
I_1	0 (.)
I_2	-0.0164 (0.000694)
I_3	-0.0352 (0.000916)
I_4	-0.0564 (0.00106)
I_5	-0.0785 (0.00118)
I_6	-0.100 (0.00127)
I_7	-0.122 (0.00135)
I_8	-0.146 (0.00142)
I_9	-0.172 (0.00150)
I_{10}	-0.187 (0.00158)
spread	0.00784 (0.000532)
$I_1 \times$ spread	0 (.)
$I_2 \times$ spread	-0.000968 (0.000428)
$I_3 \times$ spread	-0.00487 (0.000526)
$I_4 \times$ spread	-0.00835 (0.000564)
$I_5 \times$ spread	-0.0111 (0.000575)
$I_6 \times$ spread	-0.0137 (0.000579)
$I_7 \times$ spread	-0.0156 (0.000586)
$I_8 \times$ spread	-0.0184 (0.000605)
$I_9 \times$ spread	-0.0223 (0.000651)
$I_{10} \times$ spread	-0.0277 (0.000718)
age	-0.00471 (0.000785)
age^2	0.0000336 (0.00000731)
constant	0.686 (0.0211)
N	4324026
adj. R^2	0.675

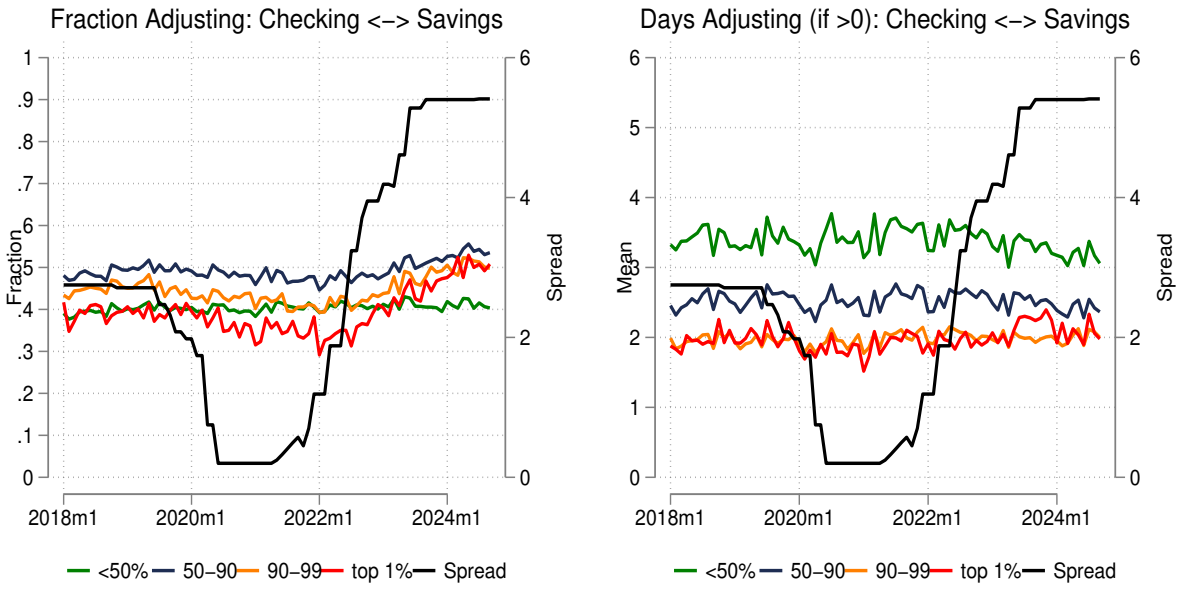
Note: Regression of individual share in checking deposits in liquid safe assets, expressed in shares. The spread is the percentage points difference between the return on savings and checking accounts in the bank rate r normalized to have mean zero. Individual levels of wealth are calculated uniquely for each individual, ranking their wealth from 1 to 10. The panel of individuals is a stable panel of active individuals with at least \$3000 ISK in liquid safe assets. The data frequency is monthly and the time spans between January 2018 and September 2024. Individually clustered standard errors in parentheses.

Table 4: Interacted Regression

	(1) Share Checking	(2) Share Checking	(3) Share Checking
ln(a)	0.315	-0.192	-0.119
	(0.311)	(0.306)	(0.289)
ln(r)	6.892	7.243	5.595
	(1.119)	(1.104)	(1.012)
1.FinLit·ln(a)	0		
	(.)		
2.FinLit·ln(a)	-1.437		
	(0.402)		
3.FinLit·ln(a)	-2.598		
	(0.650)		
1.FinLit·ln(r)	0		
	(.)		
2.FinLit·ln(r)	-0.946		
	(0.464)		
3.FinLit·ln(r)	-3.124		
	(0.730)		
ln(a)ln(r)	-0.466	-0.500	-0.404
	(0.0815)	(0.0796)	(0.0754)
age	-0.793	-0.864	-1.593
	(0.304)	(0.299)	(0.288)
age2	-0.000996	-0.000778	0.0102
	(0.00332)	(0.00327)	(0.00301)
1.Inflation·ln(a)		0	
		(.)	
2.Inflation·ln(a)		-0.529	
		(0.403)	
3.Inflation·ln(a)		-0.521	
		(0.538)	
1.Inflation·ln(r)		0	
		(.)	
2.Inflation·ln(r)		-0.918	
		(0.482)	
3.Inflation·ln(r)		-1.427	
		(0.607)	
1.Numerical·ln(a)			0
			(.)
2.Numerical·ln(a)			-1.235
			(0.398)
1.Numerical·ln(r)			0
			(.)
2.Numerical·ln(r)			-0.551
			(0.469)
Constant	88.40	88.28	97.94
	(7.390)	(7.271)	(7.089)
FE	Y	Y	Y
N	390001	406187	328870
Adj. R^2	0.533	0.530	0.546

Note:

Figure 16: Adjustments

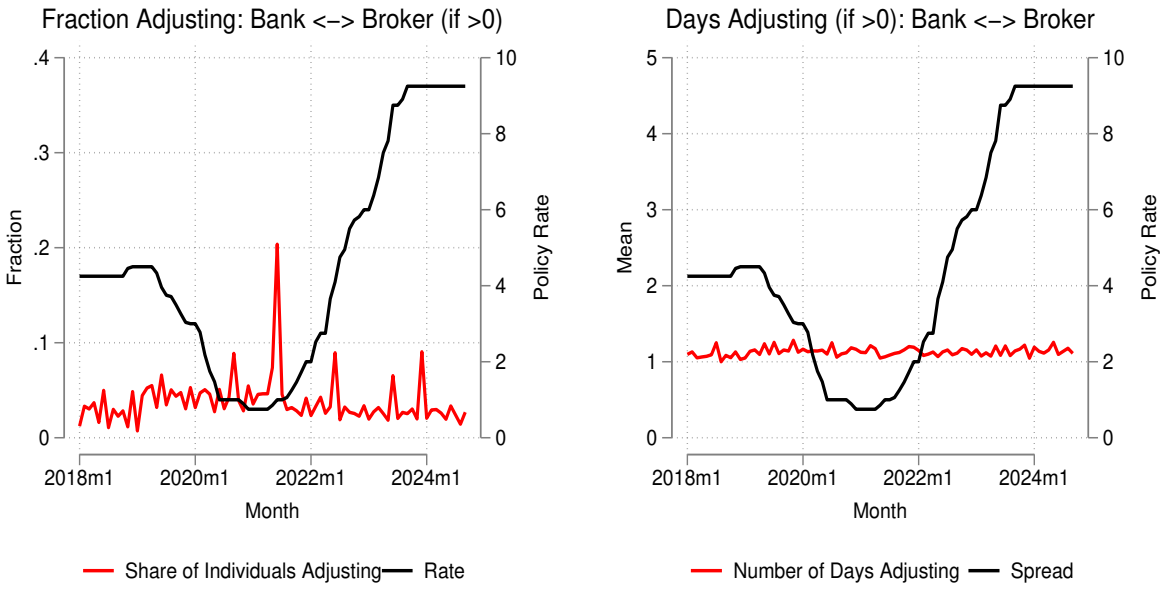


Note: Left: fraction of individuals moving funds between checking and savings at least once a month. Right: average number of days funds move between checking and savings conditional on at least one movement in the month. Calculation uses only active bank customers. Groups are calculated using liquid safe assets at each month.

Table 5: Comparison of Population and Sample Characteristics

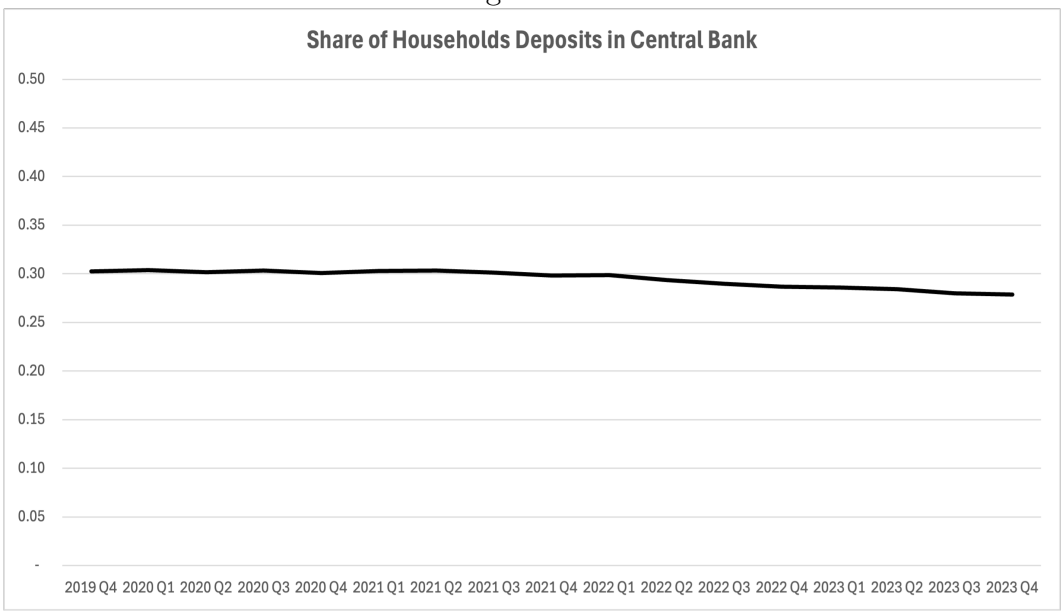
	Mean (SD)		Difference in Means
	Population (1)	Sample (2)	(1) - (2)
Female	0.50 (0.50)	0.51 (0.50)	-0.01
Married	0.41 (0.49)	0.46 (0.50)	-0.05
Capital Region	0.64 (0.48)	0.71 (0.45)	-0.07
Age	46.34 (18.35)	47.70 (17.18)	-1.36
Age $\leq$ 20	0.03 (0.18)	0.01 (0.10)	0.02
20 $<$ Age $\leq$ 30	0.20 (0.40)	0.18 (0.39)	0.01
30 $<$ Age $\leq$ 40	0.19 (0.39)	0.17 (0.38)	0.01
40 $<$ Age $\leq$ 50	0.17 (0.37)	0.18 (0.38)	-0.01
50 $<$ Age $\leq$ 60	0.16 (0.37)	0.19 (0.39)	-0.03
60 $<$ Age	0.26 (0.44)	0.27 (0.45)	-0.01
Family Size	1.75 (8.11)	2.13 (1.21)	-0.38

Figure 17: Adjustments



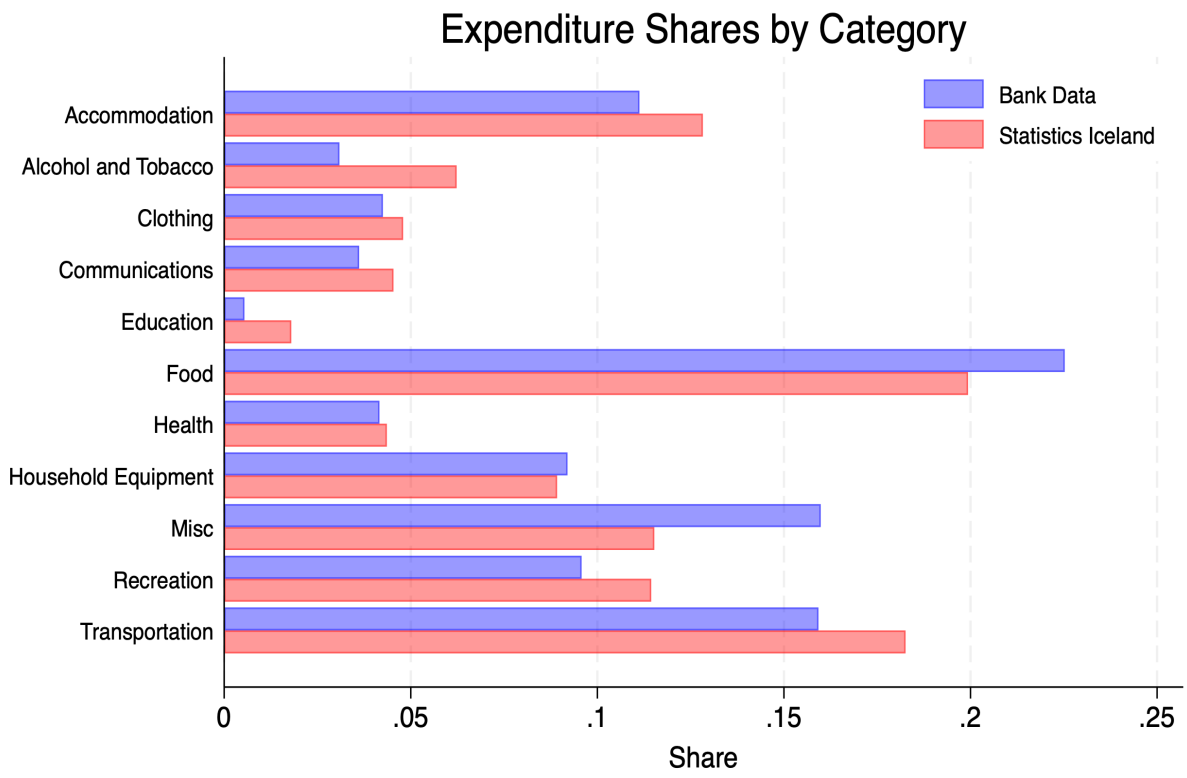
Note: Left: fraction of individuals moving funds between the bank and the broker at least once a month for those individuals with positive funds in the broker. Right: average number of days funds move conditional on at least one movement in the month. Calculation uses only active bank customers.

Figure 18:



Note: The figure shows the share of household deposits held at the collaborating bank relative to total household deposits reported by the Central Bank of Iceland.

Figure 19:



Note: Shares from the Statistic of Iceland correspond to consumption by locals in 2019 excluding housing.

Figure 20: Liquid Portfolio Share in Checking Deposits, Liquidity Cost, and Attention



B Survey Administration by the Bank

In October 2021, the bank sent out two short emails with invitations to participate two different surveys administered by Copenhagen Business School. The first one was only sent to married or cohabiting individuals where both spouses were active customers of the bank, based on certain activity filters we imposed, while the other survey was sent to all other active customers. In the survey for couples, 23,640 invitations were sent and of those 2,026 (8.6%) completed the survey while in the other survey 76,654 invitations were sent and 3,388 (4.4%) of these completed within a few days and the survey was thus closed as we lacked funding to pay more participants. Compared to the timing of responses and the time in the field in other surveys, we would have expected about twice as high response rate if the survey had stayed in the field as long in the field for a couple of weeks as is common. In June 2023, the bank sent again a short email to customers, this time to around 51,546 active customers, inviting them to participate in a survey on financial decision-making administered by Copenhagen Business School. Bank customers then received 1-2 reminders about the survey, in June and September. In total, 5,736 customers completed the survey (11.1%). In October, the bank sent out another email to all individuals that completed the survey in 2023 and still passed the activity filters to invite them to participate in a follow up survey. This time 5,665 invitations were sent out and of those, 2,388 (42.2%) completed the survey. The response rates in these surveys are relatively high response (For instance, Schnorpfeil et al. (2024a) report 1.8% and Schnorpfeil et al. (2024b) report 6.8%).

In all surveys, participants were informed that the survey data would not be available to the employees of the bank and that the researchers working with their information would not have access to any personally identifiable data. An important aspect of this is the design of the survey and payment setup, allowing us to contact bank customers without getting any contact information and to pay incentives, that were transferred directly into their bank accounts, without collecting any payment details. The way this was done is that we provided

the bank with a list of anonymized IDs of the individuals we wanted them to invite to participate in the survey and a unique survey link for each. The bank kept a bridge file that was used to obtain the email addresses of these individuals and used this to email survey invitations to the selected customers that contained the unique link we provided them with. Once an individual participates, we can link the responses using the unique link to his or her anonymized ID and thereby to the anonymized administrative bank data. Every day the bank then received a list of anonymized IDs and the bank then used the bridge file to transfer the incentives directly to the bank accounts of the individuals. This way, we never got hold of any contact information of the individuals (for example, email addresses) in our survey sample, and we did not have to collect any payment information to be able to pay them for their participation.

In all surveys, survey participants have similar characteristics to other bank customers as well as the population in general. The surveys were tailored to the specific research questions under investigation in the project associated with each survey. Some topics appear in several surveys while others only in one of them. The number of observations for each measure obtained from the surveys thus varies. There are two main elements of this survey. Examples of the content of the surveys include a set of incentivized experiments involving choice under risk, consisting of a standard task of allocating an endowment across risky assets which enable us to obtain measures of risk preferences and decision-making ability (see, e.g., Carvalho et al., 2024), a qualitative assessments of time preferences, asking participants to evaluate their own willingness to postpone a benefit to receive a larger benefit in the future, as well as a qualitative decision-making ability assessment, asking participants to evaluate their own skills at avoiding financial mistakes, as well as tests of individuals' understanding of the link between inflation, the economy, and households financial and labor market outcomes. Other information we obtain from the survey data include, e.g., education level, fields of education, labor market status, inflation expectations, knowledge about past inflation, and assessment of ability to cope with unexpected expense shocks.

C Model Numerical Solution

The model is solved numerically using methods of efficient value function iteration following J. Druedahl [...]. The key to speed up the computation is to nest value functions and pre-compute the expectation.

Let's write the value function for the non-adjusters calling m the total amount of liquid assets at the beginning of the period

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

subject to,

$$\begin{aligned} m' &= (y + m - c)(1 + r^D) \\ m' &\geq 0 \\ y' &= \Gamma(y, \epsilon') \\ b' &= b(1 + r) \end{aligned}$$

also, define

$$w(y, m', b') = \beta \mathbb{E}\left[V(y', m', b')\right]$$

as the pre-computed expectation of the future value (use a dense grid here, probably the same a in the adjusting case).

With this at hand, the problem of the adjusting individual becomes

$$V^A(y, m_A) = \max_{b'} V^N(y, m, b')$$

subject to,

$$m = m_A + b(1+r) - b'$$

$$b' \geq 0 \; ; \; m \geq 0$$

$$y' = \Gamma\left(y, \epsilon'\right)$$

Let's use that the income process follows an AR(1) in logs

$$\ln y' = \rho \ln y + \sigma_\varepsilon \, \varepsilon'$$

and approximate it using 7 gridpoints and Gaussian quadrature nodes.