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Reaching for Yield: Evidence from Households

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Abstract

The existing literature has documented "reaching for yield"—the phenomenon of investing more in risky assets when interest rates are lower—among institutional investors. Using detailed transaction data from a large brokerage firm, we provide direct field evidence that reach for yield is also present in the trading behavior of individual investors. We further document significant heterogeneity in these responses as predicted by different theories. Consistent with models of portfolio choice with labor income, reaching for yield is more pronounced among younger and less wealthy individuals. Consistent with prospect theory, reaching for yield is more pronounced when investors are trading at a loss. Finally, we discuss the phenomenon of "reverse reaching for yield" and document such behavior among certain investor subgroups.

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1 Introduction

The previous decade has witnessed an unprecedented decline in interest rates, a trend that is now being rapidly reversed. There is growing evidence that movements in interest rates reshape investors' portfolio decisions. This has been documented for both intermediares and institutional investors, such as banks, mutual funds, pension funds, and insurance companies (Chodorow-Reich, 2014; Becker and Ivashina, 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018). In particular, it has been shown that these investors increase their risk exposure when the real interest rate drops, a phenomenon labelled as "reaching for yield". In parallel with the growing evidence, explanations based on institutional frictions such as funding constraints and agency issues have been proposed to explain this trading response to interest rate movements (Drechsler et al., 2018; Campbell and Sigalov, 2022).

However, it remains an open question whether retail investors, who do not face the same set of frictions or constraints, reallocate their portfolios in response to interest rate movements in a similar way. There is evidence showing that, in a lab setting where most institutional frictions are absent, individuals do increase their exposure to risky shares when interest rates drop (Lian et al., 2019). As a result, theories based on portfolio optimization with constraints or biases have been proposed to generate reaching for yield by retail investors (Lian et al., 2019; Campbell and Sigalov, 2022).

In this paper, we use detailed transaction data of almost two million Chinese investors over a 11-year period, and present direct field evidence that reaching for yield is also present in retail investors' trading behavior. We document how these investors both re-balance their brokerage account portfolios, and simultaneously move money in and out of those accounts, when the prevailing interest rate changes. We further exploit our data to test different theories of reaching for yield by examining the heterogeneity in investors' responses to interest rates.

We start by discussing alternative theories of reaching for yield based on the household's portfolio optimization. The classic Merton portfolio choice model (Merton, 1969) already implies that optimal portfolios should respond to interest rate movements, except in a limiting case where investors expect the equity return to change one-for-one with the riskless rate. This is a potentially strong assumption to make about household expectations, even from a rational perspective. For example, Bernanke and Kuttner (2005) show that positive (negative) interest rate surprises lead to a statistically and economically significant reduction (increase) in equity excess returns.[1] As we consider an extended model with labor income (Merton, 1971), we obtain additional predictions: reaching for yield should be more pronounced among younger and less wealthy individuals. This is because, in the model, the elasticity of the risky share to the interest rate increases in the ratio of human capital to financial wealth, which is typically higher for both younger and less wealthy individuals.

Prospect theory can also generate "reaching for yield" (Lian et al., 2019). When interest rates drop, investors who are used to the previous high rates would feel like they are now beginning to lose money. Under prospect theory, this feeling of a loss would encourage more risk-taking and result in "reaching for yield". Moreover, prospect theory suggests that reaching for yield should be more pronounced when investors are trading at a loss. Indeed, when the current interest rate drops, it moves the investor further away from the break-even point—that is, the most risk-averse point in the utility function—and reduces risk aversion. Conversely, for those who are trading at a gain, a lower interest rate reduces the size of the perceived gain and moves the investor closer to the break-even point, which, in turn, can lead to higher risk aversion and less "reaching for yield".

In our empirical analysis we construct three different measures to capture portfolio reallocation behavior. As discussed in the literature (e.g., Calvet et al., 2009), although the change in risky share is a simple and intuitive measure of portfolio re-balancing, it does not necessarily reflect actual portfolio re-optimization since it is also a function of return realizations.[2] Therefore, our first measure is the *active* change in the risky share, computed as

[1]A variance decomposition analysis reveals that this is driven to an almost equal extent by revisions in cash-flow forecasts and revisions in future excess returns.

[2]For example, when the realized return on risky assets exceeds the realized return on the safe asset, the risky share mechanically rises even if the investor does not change her portfolio.

the difference between the actual risky share and the counterfactual risky share that would have been observed if the investor did not trade (following Calvet et al. (2009)).[3] The second measure of portfolio reallocation that we consider is the ratio of total net equity flows to total account balance (at the beginning of each period). It measures the total value of new equity investments as a percentage of the total funds available to the investor.

While the first two measures focus on portfolio re-optimization within the brokerage account, the third one captures a different dimension of portfolio rebalancing: flows in and out of the account. When interest rates change, investors may respond by reallocating money between their brokerage account and other accounts such as bank accounts and money market mutual funds. To capture this additional channel, we further compute net withdrawals and express them as a percentage of the total balance (at the beginning of the period).

Our analysis covers the period from 2006 to 2016. During this 11-year window, the prevailing interest rates in the Chinese markets experienced substantial variation over time. While different interest rates are available to retail investors, the most relevant one for household portfolio decisions is the Shanghai Interbank Offered Rate (SHIBOR), which is offered by many wealth management products.

It is important to clarify that we are not studying how investors respond to interest rate shocks (e.g. monetary policy shocks). We are studying how investors respond to changes in interest rates, taking into account that such changes might reflect, or respond to, specific economic conditions. Our approach is therefore analogous to those regressing portfolio holdings or trading behavior on past stock returns to identify, for example, whether investors are contrarians or momentum traders, or whether they exhibit disposition effects. These studies don't try to isolate specific shocks to past returns, because that would only limit their conclusions: investors are momentum (contrarian) traders in response to those specific shocks to past returns. Likewise, we want to understand how investors respond to changes

[3]This counterfactual "no-trade" risky share is referred to as the passive risky share since it reflects movements in asset prices only.

in interest rates, not just changes in interest rates that are orthogonal to specific variables.[4]

Based on the previous discussion, our first measure of interest rate innovation is simply the change in interest rate over the period, and we specifically call it an innovation instead of shock, to clarify that important difference. As an alternative we also consider the residual from an AR(1) regression of interest rates. Likewise, this shouldn't be interpreted as a shock. The goal here is to control, in a relatively simple way, for agents' interest rate expectations. Although neither measure should be interpreted as a pure interest rate shock, given the timing of our regressions, they are both pre-determined relative to investors' portfolio decisions. For example, we regress the active change in risky share during month t, on the change in interest rates at the start of that same month, so from the first day of month $t-1$ to the first day of month t.

Across all three measures of portfolio rebalancing and both measures of changes in interest rates, we find supporting evidence for reaching for yield. When interest rates increase, retail investors have a negative active change in their risky share, and decrease their equity flows. They are also more likely to withdraw funds from their brokerage accounts. The magnitude of these effects is nontrivial. Consider a 100 basis point increase in the interest rate. First, this is associated with an average active reduction in risk exposure within the brokerage account of 5 basis points to 36 basis point, as measured by the active risky share or net equity flows, respectively. In addition, we observe a 14.5 to 37.5 basis points increase, depending on the interest the variable considered, in funds transferred out of the brokerage account (likely to other money market mutual funds). Remarkably, these portfolio elasticities are very similar to the ones found in Giglio et al. (2021), who document portfolio responses to expectations of future stock returns. Furthermore, these averages hide significant heterogeneity in investor responses, as discussed next.

Having documented that, on average, retail investors "reach for yield", we next examine

[4]For example, changes in interest rates might predict future improvements in economic conditions, and investors might expect this to be the case. Then that is a potentially important channel determining their portfolio reallocation behavior, and we want to include it in our analysis.

how this behavior differs in the cross-section. In particular, we focus on the dimensions of heterogeneity implied by different theoretical channels, namely wealth, age, and past gains and losses.

Consistent with portfolio choice models with labor income, we find that less wealthy investors are substantially more likely to engage in reaching for yield. They re-balance their portfolios by 2 to 3 times more than those in the middle of the wealth distribution. The wealthiest individuals are even less responsive to interest rate changes. In fact, for certain measures of portfolio rebalancing, richer individuals have essentially a zero response to interest rate movements, implying that the average effect documented above for the investor population is fully driven by those with medium and low account balances. It is striking that, in addition to a monotonically decreasing relationship between reaching for yield and wealth, the empirical pattern also reveals a convex relationship between these two variables, as predicted by the portfolio choice model with labor income.

We also find age effects consistent with the predictions of life-cycle models with labor income: young investors, who have a higher human capital to financial wealth ratio, are more likely to engage in reaching for yield.[5] The differences across age deciles are economically large and similar to the ones obtained when studying the impact of wealth.

Interestingly, our cross-sectional results also show that both wealthier and older individuals can sometimes engage in the "reverse reaching for yield" by increasing their allocation to risky assets when interest rates rise. We discuss how this behavior, though seemingly counter-intuitive, is a possible outcome of the portfolio choice model with labor income. If an increase in interest rates changes asset prices in such a way that the investor's wealth actually falls then the present value of his future labor income becomes relatively more important, and therefore the optimal risky share is now higher.[6] Although the evidence for "reverse reaching for yield" is only present in some of our specifications, it is interesting that

[5] With the noticeably exception of the very young agents, in some specifications.

[6] Alternatively the same result can arise if increases in interest rates are associated with increases in the present-value of future labor income. We discuss both possibilities in the paper.

this is particular theoretical prediction might actually be verified in the data.

We also find evidence in support of prospect theory. In particular, we test whether investors trading at a loss exhibits stronger tendencies of reaching for yield than those trading at a gain, after controlling for other individual characteristics. Consistent with prospect theory, reaching for yield is more pronounced when investors are currently suffering from losses, especially when portfolio return is measured based on last month's end price. This result is robust to the two measures of interest rate innovations we consider and to all three measures of portfolio rebalancing activities.

The rest of the paper is organized as follows. In Section 2 we discuss different theories that can explain reaching for yield by retail investors. In Section 3 we present our data and methodology. Section 4 contains our empirical results and we conclude in Section 5.

2 Theories

In this section we study potential explanations for reaching for yield behavior by retail investors. Existing theories of reaching for yield show how this behavior can be optimal for different types of institutional investors, as a result of specific institutional or regulatory frictions that they face (see Acharya and Naqvi (2019), Drechsler et al. (2018), Ozdagli and Wang (2019), Chodorow-Reich (2014), Di Maggio and Kacperczyk (2017), Drechsler et al. (2018) or Barbu et al. (2021)). In general, these models do not make predictions about reaching for yield type of behavior for households. One exception is Campbell and Sigalov (2022). They show that reaching for yield can result imposing a sustainable spending constraint to an otherwise standard Merton model. Their theory mostly applies to endowments and sovereign wealth funds, but it may also characterize trusts and even some households.[7]

[7]Since we only have access to brokerage account data we cannot directly test if their predictions also apply to our setting, as this would require data/evidence on consumption commitments.

2.1 Alternative theories of reaching for yield

In this subsection we first present alternative theories of reaching for yield behavior by retail investors. Later we discuss several testable implications based on these different economic channels.

2.1.1 Portfolio choice model without labor income

We start with the two-asset Merton model with i.i.d. returns (Merton, 1969). In this model the share of wealth invested in the stocks (α) is given by

$$\alpha = \frac{\mu - r}{\gamma\sigma^2}, \tag{1}$$

where μ is the expected equity return, r is the riskfree rate, σ^2 is the volatility of stock returns, and γ is the coefficient of relative risk aversion.[8]

From equation (1) we see that changes in the risk free rate can affect the investor's portfolio share under three conditions. First, if the expected return on stocks (μ) does not move one-for-one with r. We discuss the plausibility of this assumption below. Interest rate movements can also effect the optimal portfolio allocation if they are correlated with either the expected volatility of stock returns (σ) or with risk aversion (γ).

For simplicity, we first consider the case in which σ and γ are both independent of r.[9] Then, the impact of changes in the riskless rate on the risky share is given by

$$\frac{\partial\alpha}{\partial r} = \frac{\frac{\partial(\mu - r)}{\partial r}}{\gamma\sigma^2}, \tag{2}$$

[8] The multi-asset version of this is

$$\alpha = \frac{1}{\gamma}(\mu - r)\Sigma^{-1},$$

where μ now denotes the vector of expected returns on the different assets, r is a vector where all elements are equal to the riskless rate, and Σ is the variance-covariance matrix of returns.

[9] In this paper we do not explore the role of a potential correlation between stock return volatility and interest rate changes, but we consider changes in risk aversion, namely in the context of both habit formation and loss aversion (as in the case of prospect theory preferences).

where $\frac{\partial(\mu-r)}{\partial r}$ equals -1 if investors expect μ to remain constant and 0 if they instead expect the risk premium $(\mu-r)$ to remain constant. So, in this model, unless μ responds one for one with interest rates (or more than that), the risky asset becomes a more appealing investment when the riskless rate goes down, because its the relative yield, measured by $(\mu - r)$, has increased.

The Merton model is a partial equilibrium model, hence it is silent about the derivative of expected stock returns with respect to the interest rate. Only under special cases of relatively frictionless economies would the expected stock return move exactly one for one with the riskfree rate.[10] Bernanke and Kuttner (2005) study the empirical relation between interest rates and stocks returns, and find that positive (negative) interest rate surprises lead to a statistically and economically significant reduction (increase) in equity excess returns over the next two months.[11] Furthermore, a variance decomposition analysis reveals that this is driven almost equally by revisions in cash-flow forecasts and revisions in future excess returns. In addition, the relevant return expectations to include in equation (1) are the subjective expectations of each investor, which might arguably differ from fully rational expectations. Therefore, we conclude that assuming that (subjective) expectations of future stock returns move exactly one-for-one with interest rates is a particularly extreme assumption to make about household expectations.

2.1.2 Portfolio choice model with labor income

In the previous section, we showed that reaching for yield can be obtained in the Merton model if investor expectations about the excess market return are not neutral to interest rate movements. The model, however, does not provide much guidance on the cross-sectional variation in reaching for yield among investors.[12] In these next sections, we discuss models

[10] If we consider a consumption-based asset pricing model, this essentially assumes that the interest rate has no impact on consumption growth. This condition may be valid in simpler models, but can easily break down as we introduce different constraints, either on the household side or on the production side.

[11] In our empirical specifications we consider a monthly frequency.

[12] The model has cross-sectional predictions as a function of both risk aversion and expectations, but our data does not include direct information on those.

that directly speak to heterogeneous responses to interest rates.

We first extend the model to include riskless labor income, while still assuming complete markets (Merton, 1971). In this setting the portfolio rule depends on the ratio of the present value of future labor income (human capital) to current financial wealth:

$$\alpha = \left[1 + \frac{PV(Y)}{W}\right] \frac{\mu - r}{\gamma\sigma^2}, \tag{3}$$

where $PV(Y)$ denotes the present value of future labor income (Cocco et al., 2005). In this model, the partial derivative of the risky share with respect to the riskless rate, assuming again that both σ is and γ are independent of r, is[13]

$$\frac{\partial\alpha}{\partial r} = \left[1 + \frac{PV(Y)}{W}\right] \frac{\frac{\partial(\mu - r)}{\partial r}}{\gamma\sigma^2}. \tag{4}$$

This is higher than the response obtained in the model without labor income (equation (2)), particularly if the ratio of the present-value of labor income to financial wealth is high. For an investor with a present-value of labor income to financial wealth of 3, for example, the portfolio share response is 4 times larger than in the model without labor income.

2.1.3 Portfolio choice model with decreasing relative risk aversion (DRRA)

Another potential channel driving reaching for yield is a combination of preferences that deviate from constant relative aversion and changes in asset valuations resulting from changes in interest rates. Deviations from constant relative risk aversion can result from a consumption floor/commitment (e.g., Chetty and Szeidl, 2007)), habit formation (e.g., Abel, 1990; Constantinides, 1990; Campbell and Cochrane, 1999), or loss aversion (e.g., Barberis and Huang, 2001; Gomes, 2005; Barberis and Xiong, 2009), for example. Under such preferences, fluctuations in asset prices, such as those induced by interest rate fluctuations, have

[13]This particular derivation imposes two additional assumptions: constant wealth and constant present-value of future labor income. We relax both of these below, as they provide additional testable implications from the model.

a direct impact on investor's risk aversion and consequently their optimal risky share.

For simplicity we restrict our attention to the case without labor income. Under certain conditions (e.g., Campbell and Viceira, 2002; Calvet and Sodini, 2014), it can be shown that equation (1) becomes

$$\alpha = \left[\frac{\mu - r}{\gamma\sigma^2}\right]\left[1 - \frac{\lambda H}{W}\right], \tag{5}$$

where H is a habit or subsistence level and λ is a positive constant such that the product of the two represents the present-value of maintaining the habit over the agent's life-time. Risk aversion increases with the habit level, and hence the optimal risky share falls when the habit increases.

In this context, if decreases in interest rates lead to higher asset prices, the increase in financial wealth would lead to a lower degree of risk aversion and subsequently to a drop in the risky share.[14] Therefore, when investors have DRRA in preferences, there is an additional reaching for yield channel, through the wealth effects of interest change changes. Since wealth also appears in the portfolio choice model with labor income, as in equation (3), we discuss both channels simultaneously in the section (2.2), when presenting the different testable hypothesis.

2.1.4 Prospect Theory

Under prospect theory, investors evaluate the current level of interest rates by comparing it to a reference level, for example, the average historical level. When the current interest rate is below the historical level, investors feel that they are in the loss region, which makes them more risk tolerant and increase their risky shares. Conversely, when the current interest rate goes above the historical level, investors become more risk averse and reduce their holdings of risky shares (Lian et al., 2019). Therefore, even with the same current interest rate, investors will be more risk averse when past interests have been low and more risk taking when past interest rates have been high.

[14]The reverse would happen if investors' preferences exhibit increasing relative risk aversion.

At the same time, prospect theory, especially the loss aversion component of it, suggests that the way investors react to interest rate movements will also depend on whether they are currently in a gain or loss region. To understand the intuition, we start with two observations. First, under prospect theory, investors are less risk averse with a bigger gain and less risk-loving with a bigger loss—that is, their utility function exhibits diminishing sensitivity. Second, according to prospect theory, the most risk averse point along the utility function is the origin, the point where investors break even in their returns.

Suppose that an investor is currently in the gain region. Then a drop in interest rates will reduce the size of the gain, moving this investor closer to the kink. Because of a higher risk aversion and closer proximity to the kink, the effective risk aversion increases, making it less likely for the investor to invest in risky assets. By contrast, if an investor is currently in the loss region, then the same drop in interest rates will increase the size of the loss, making this investor more risk-averse (less risk-loving). At the same time, because of the investor is further away from the kink, this force will induce lower risk aversion. In most parameterizations of prospect theory, the second channel dominates, and the investor becomes less risk averse and more likely to invest in risky assets (Barberis and Xiong, 2009). Therefore, according to prospect theory, investors who are currently in the loss region are more likely to exhibit "reaching for yield".

2.2 Testable predictions

2.2.1 Age and wealth levels

We now discuss the different testable implications that will guide our empirical analysis. A first clear prediction from equation (4) is that, everything else equal (especially when future labor income is held constant), richer individuals should respond less (in absolute terms) to changes in interests rates, since W appears in the denominator.[15]

[15]Naturally the equation implies the opposite prediction for the present value of future labor income, but unfortunately we do not observe income in our data.

Hypothesis 1: $|\partial\alpha/\partial r|$ should be a decreasing function of W.

The derivation is provided in appendix 1.

Considering equation (4) in a life-cycle context yields a second testable implication. In a life-cycle model (see, for example, Cocco et al. (2005)), young agents have substantial wealth in the form of their future labor income, but have only accumulated limited financial wealth. As they get older, and approach retirement, they accumulate more wealth while the present-value of their future labor income is naturally decreasing.[16] Therefore, young (old) investors have a higher (lower) ratio of human capital to financial wealth. From equation (4) this implies that they should respond more (less) to changes in interest rates.

Hypothesis 2: $|\partial\alpha/\partial r|$ should be a decreasing function of age.

In our empirical analysis we will directly test both of these hypothesis.

2.2.2 Changes in wealth

Equation (4) was obtained under the assumption that μ and σ don't respond to changes in interest rates. Another implicit assumption is that current wealth remains unchanged. However, current wealth might decrease if the increase in interest rates leads to a reduction in the prices of the assets (stocks or bonds) that the investor holds. When interest rates increase the prices of bonds should decrease thus lowering the wealth of investors with bond portfolios. Stock holdings are potentially also affected. In fact, under the assumption that the equity premium does not change with interest rates then equity prices should also decrease as the present-discount value of dividends is now smaller.[17] In general, unless we consider the other extreme case, in which it is the stock return that remains constant (instead of the equity premium), or unless we have an exactly off-setting effect in expected dividends, then equity prices should also change in response to interest rate movements.

[16] After retirement wealth will typically start decreasing as well.

[17] This was the assumption required for ruling out reaching for yield in the context of the Merton model without labor income. So, even though that condition rules out reaching for yield in that model, it implies reaching for yield in the model with labor income, as discussed below.

If we take this effect into account then equation (4) is replaced with:[18]

$$\frac{\partial\alpha}{\partial r} = \left[1 + \frac{PV(Y)}{W}\right]\frac{\frac{\partial(\mu-r)}{\partial r}}{\gamma\sigma^2} - \frac{\mu - r}{\gamma\sigma^2}\frac{PV(Y)\frac{\partial W}{\partial r}}{W^2} \tag{7}$$

Intuitively, if an increase in interest rates decreases (increases) wealth then the ratio of human capital to financial wealth increases (falls). This increase (decrease) in the investor's implicit bond holdings leads to a higher (lower) optimal risky share. Therefore this second term adds (counteracts) to the impact of the first term in the equation thus increasing (reducing) the investor's response to change in the interest rate. [19]

Equation (7) provides a further testable implication from the portfolio choice model with labor income: individuals whose wealth is more (less) adversely affected by increases in interest rates should decrease their risky share by less (more) in response to these changes.

Hypothesis 3: $\partial\alpha/\partial r$ should be a decreasing function of $\partial W/\partial r$ (human capital channel).

We label hypothesis 3 as the "human capital channel" to distinguish it from the next hypothesis, which is also about the sign of $\partial W/\partial r$, and arises if investors have decreasing relative risk aversion, as discussed in section 2.1.3. Working from equation (5) we have

$$\frac{\partial\alpha}{\partial r} = \left[\frac{\frac{\partial(\mu-r)}{\partial r}}{\gamma\sigma^2}\right]\left[1 - \frac{\lambda H}{W}\right] + \left[\frac{\mu - r}{\gamma\sigma^2}\right]\left[1 - \frac{\lambda H}{W}\right]\left[\frac{\partial W}{\partial r}\frac{\lambda H}{W^2}\right], \tag{8}$$

Equation (8) shows that, if increases (decreases) in interest rates reduce (increase) investor wealth then this is another channel that can generate reaching for yield. In this

[18] A further implicit assumption in deriving equation (4) is that the present-value of future labor income also remains constant when interest rates change. However, to the extent that changes in interest rates affect economic activity they are also likely to have an impact on future labor income. In that case the derivative becomes:

$$\frac{\partial\alpha}{\partial r} = \left[1 + \frac{PV(Y)}{W}\right]\frac{\frac{\partial(\mu-r)}{\partial r}}{\gamma\sigma^2} + \frac{\mu - r}{\gamma\sigma^2}\frac{\frac{\partial PV(Y)}{\partial r}}{W}. \tag{6}$$

This equation provides one additional testable implication: individuals whose future labor income is more (less) negatively correlated with interest rates should change their portfolios more (less) in response to changes in interest rates. Unfortunately our data does not include individual income and therefore we cannot estimate $\partial PV(Y)/\partial r$ at the household level. Therefore we leave this as an untested hypothesis and only mention it for completeness.

[19] In fact, due to this channel, i.e. under equation (7), $\partial\alpha/\partial r$ can now also take positive values. We discuss this possibility in more detail later in this section.

context a more negative $\partial W/\partial r$ leads to a more negative $\partial\alpha/\partial r$ (i.e. more reaching for yield). Therefore the DRRA channel gives rise to the exact opposite prediction from the labor income model with CRRA preferences:[20]

Hypothesis 4: $\partial\alpha/\partial r$ should be a increasing function of $\partial W/\partial r$ (DRRA channel)

The discussion so far has considered the impact of interest rate changes, which is the focus of our paper. However, the two channels, human capital and DRRA are present whenever current financial wealth changes, regardless of the reason for that change. Therefore, they also imply more general versions of hypothesis 3 and 4, which we will refer to as hypothesis 3b and 4b respectively:

Hypothesis 3b: $\Delta\alpha$ should be a decreasing function of ΔW (human capital channel).

Hypothesis 4b: $\Delta\alpha$ should be an increasing function of ΔW (DRRA channel).

Even though hypothesis 3b and 4b are in direct conflict with each other, they highlight the importance of including a measure of (exogenous) ΔW in the regressions since it will affect the portfolio rebalancing behavior through these two different channels. The estimated regression coefficient will effectively reveal the relative importance of one channel (ratio of human capital to financial wealth) versus the other (DRRA).

2.2.3 Previous gains or losses

As discussed in Section 2.1.4, under prospect theory, investors are more likely to engage in reaching for yield when they are already in the loss region. Conversely, if an investor is currently at a gain and the interest rate just experienced a drop, this would bring the investor closer to the origin—the point of the highest risk aversion—and the investor will become more risk averse. Therefore, prospect theory makes the following prediction regarding reaching for yield under gains and losses

Hypothesis 5: Reaching for yield is more prominent among investors at a loss than those at a gain.

[20] Naturally the prediction of a DRRA model with labor income would be ambiguous, depending on the relative importance of the two effects.

2.2.4 Reverse reaching for yield

One interesting implication of equations (6) and (7) is that, under certain conditions, the optimal portfolio response to an increase (decrease) in interest rates is actually to increase (decrease) the risky share. From equation (6) this can happen when a higher riskless rate is associated with a significant increase in the investor's human capital. Since human capital is a closer substitute for bonds this therefore implies a higher optimal risky share in financial wealth, potentially offsetting the other channels. From equation (7) we obtain the same logic but now when higher interest rates are associated with a sufficiently large decrease in investor wealth. As wealth falls the relative importance of human capital increases and we have the same logic as before.

It is important to note that the second term in both equations is not very large: it is divided by wealth in equation (6) and by the ratio of human capital to wealth squared in equation (7). However, if the first term is also particularly small, which will happen for investors who expect the equity premium to remain (almost) unchanged, then the second effect can indeed dominate, thus leading to reverse reaching for yield behavior. This is naturally also more likely to happen in cases when the two channels (decrease in wealth and increase in human capital) operate simultaneously (i.e. when combining both equations).

3 Data and Methodology

In this section, we first describe the data we use to analyze investor behavior. We then discuss how we measure both investor behavior and interest rate changes.

3.1 Data

Our dataset includes account-level transaction data from a large national brokerage firm in China.[21] The company has branches in almost all of China's provincial districts and

[21] This is the same data that is used in Gao et al. (2021) and Liao et al. (2021).

is a market leader in several regions. Moreover, it provides comprehensive capital market service to its clients, making all exchange-listed securities available to them. This enables us to observe the trades of all exchange-listed assets. The dataset includes every transaction record from 2006 to 2016, for a total of 2,002,777 investors, and the structure is similar to the one used by Odean (1998), for example. Each observation specifies the account, date, time, price, quantity, and security code. In addition, the data also have records of cash holdings, allowing us to calculate total account balance. For a large number of investors, we have some additional information, namely their age, education and for how long the account has been opened, for example.

A few limitations are worth noting about the data. First, we do not observe holdings of mutual funds (except for ETFs and other exchange-traded assets). However, ownership of mutual funds was quite small among the Chinese markets during the sample period (An et al., 2022). Second, cash balance at the account is not observed instantaneously. Instead, it is only updated whenever an investor makes a transaction. Therefore, if an investor deposits or withdraws cash from their account but does not trade, their cash balance will be not be updated. This concern, however, is largely mitigated by the fact that average Chinese retail investors trade a lot, with a monthly turnover (defined as the total transaction volume divided the average balance in a month) of around 100%. Third, while we observe the cash balance in the brokerage account, we do not observe bank accounts and therefore our data does not fully capture investors' holding of risk-free assets. Since we observe withdrawals and additions to the brokerage account we use these to infer the potential reallocation of funds to this additional safe asset category, as discussed below.

3.2 Measuring household behavior

Our objective is to study portfolio reallocation in response to changes in interest rates. In this section, we discuss four candidate measures of portfolio rebalancing behavior.

3.2.1 Change in risky share

The simplest measure of portfolio rebalancing is the change in the total risky share in the portfolio. We define risky share ω_{jt} as the value of equity holdings in investor j's portfolio by the end of month t (A_{jt}) over the sum of her equity holdings and cash holdings by the end of month t (C_{jt}):[22]

$$\omega_{jt} = \frac{A_{jt}}{A_{jt} + C_{jt}}. \tag{9}$$

To obtain the value of equity holdings A_{jt}, we first calculate the value of the holdings in each particular stock i, and then sum over all stocks:

$$A_{jt} = \sum_{i} Q^{i}_{jt} P^{i}_{t}, \tag{10}$$

where Q denotes the number of shares and P denotes share price. The change in the risky share $\Delta\omega_{jt}$ is then simply the difference between current and previous period's risky share:

$$\Delta\omega_{jt} = \omega_{jt} - \omega_{jt-1}. \tag{11}$$

The main advantage of this measure is its simplicity. However, as discussed below, it can be distorted by movements in asset prices. Therefore, in our main analysis we consider the three measures presented next. In the Appendix, we report consistent results obtained with the (simpler) change in risky share.

3.2.2 Active change in risky share

One potential issue with the change in risky share (equation 11) is that it also reflects movements in asset prices. Therefore, it can take on non-zero values, even in the absence of any rebalancing. To isolate the effect of an investor's active rebalancing decisions from the effect due to changes in stock prices, we follow Calvet et al. (2009) and compute the active

[22] We exclude bond and currency ETFs to avoid classifying them as either risky or riskless assets. In any case only 0.01% (0.04%) of our observations have positive bond (currency) ETF positions.

change in risky share. First, we compute the value of stock holdings under the counterfactual that there were no trades between $t-1$ and t (which we denote as A^p_{jt}):

$$A^p_{jt} = \sum_i Q^i_{jt-1} P^i_t. \tag{12}$$

We can then compute the passive risky share, i.e. the risky share that we would have observed in the absence of any trades, as:

$$\omega^p_{jt} = \frac{A^p_{jt}}{A^p_{jt} + C_{jt}}. \tag{13}$$

Finally, we can compute the active change in risky share from:

$$\omega^a_{jt} = \omega_{jt} - \omega^p_{jt}, \tag{14}$$

where ω_{jt} is risky share in the account j in month t defined in previous section.

As the right-hand-side of equation (14) shows, the active change in risky share isolates the changes that are due to actual portfolio rebalancing, as opposed to movements in asset prices.

3.2.3 Net flow to equity

The second measure that we consider is the total net flow to equity (scaled by account balance). If investors are reaching for yield, then we would expect an increase (decrease) in the net flows to equity when interest rates fall (increase). Our detailed data on investors' accounts include quantity and execution price for each transaction, thus allowing us to calculate these flows. First, we obtain the cumulative buys and sells for each account j in each month t by summing up the value of transactions on all stocks during the month:

$$Buys_{jt} = \sum_{d \in t} \sum_i B^{id}_j P^{id}; \tag{15}$$

$$Sells_{jt} = \sum_{d \in t} \sum_{i} S_j^{id} P^{id}, \tag{16}$$

where d denotes a given day in month t, i denotes the stock, and B and S denote the number of shares bought and sold, respectively.

The net flow into equity for the account j in month t can then be computed from the difference between total $Buys$ and $Sells$:

$$NetFlow_{jt} = Buys_{jt} - Sells_{jt}. \tag{17}$$

Finally, we scale the net flow by the account balance at the end of the previous month ($NetFlow_{jt}^{pp}$):

$$NetFlow_{jt}^{pp} = \frac{Buys_{jt} - Sells_{jt}}{A_{jt-1} + C_{jt-1}}. \tag{18}$$

3.2.4 Withdrawals

Our previous two measures capture portfolio rebalancing within the brokerage account. However, this might not reflect the total portfolio reallocation behavior of the investors. If these investors reach for yield then they are also more (less) likely to withdraw funds from the account when interest rates increase (decrease) in order to increase (decrease) their riskless asset holdings outside of the brokerage account. In order to capture this behavior, we consider a third measure of portfolio activity: the (net) withdrawal amount from the brokerage account ($Withdr$).

As discussed above, in our data, the broker records the cash position before and after each transaction. We use these recorded cash positions to backfill daily/monthly cash holdings and corresponding additions and withdrawals of funds in the account. We then scale these net withdrawals by the account value in the previous period to obtain our measure:

$$Withdr_{jt}^{pp} = \frac{\sum_{d \in t} Withdrawal_{jd}}{A_{jt-1} + C_{jt-1}}. \tag{19}$$

3.3 Interest rate

3.3.1 Interest rate variable

For a retail investor in the Chinese market, there are three main relevant interest rates: the bank deposit rate, the government bond yield, and the SHIBOR (Shanghai Interbank Offered Rate). Investors earn the first two types of rates by placing their money in banks either as deposits or by holding government bonds, respectively. The first option is more commonly used than the second.

With the arrival of mobile payments and associated wealth management products, the most relevant benchmark rate for retail investors has arguably become the SHIBOR rate. For instance, Alipay's flagship service, called Yu'ebao, is effectively a money market mutual fund that offers the SHIBOR rate and can be used for consumption purposes immediately. Yu'ebao grew incredibly popular and became the largest money market mutual fund.[23] Therefore, in our analysis, we use the SHIBOR as our measure of interest rates. Figure 1 shows the time-series plot of the (annualized) 1-month SHIBOR over the period from October 2006 to December 2016.

[INSERT FIGURE 1 HERE]

Throughout our sample, there is significant variation in the SHIBOR over time. For instance, the rate experienced a sharp decline—from around 3.5% to around 1%—in late 2008 following the Global Financial Crisis and the stock market crash. Later, once the economy began to recover, the SHIBOR steadily rose and peaked around 7%. Then, in 2015, following yet again another stock market crash, the People's Bank of China (PBoC) cut the interest rate, and as a result the SHIBOR fell to around 3%.

[23]See, for example, "Meet the Earth's Largest Money-Market Fund" (`https://www.wsj.com/articles/how-an-alibaba-spinoff-created-the-worlds-largest-money-market-fund-1505295000`), *The Wall Street Journal*, September 13, 2017

3.3.2 Interest rate innovations

In our regressions we consider two measures of interest rate movements. As discussed, we are not interested in capturing interest rate shocks (e.g. monetary policy shocks). Our goal is to study how investor respond to changes in interest rates, taking into account that those changes might be related to past/current economic conditions and/or expectations of future economic conditions.[24]. In fact, those are some of the channels that we have discussed in section 2.

Therefore, the first measure of interest rate innovations that we consider is the simple change in interest rate over the month. For the second measure we fit an AR(1) process to the interest rate and use the error term as the innovation:

$$r_t = a_r + \rho_r r_{t-1} + \varepsilon_t^r. \tag{20}$$

Figure 2 plots the two measures of interest rate innovations over the sample period.

[INSERT FIGURE 2 HERE]

We can see these two series are very highly correlated, and also exhibit very similar volatility. Consistent with this, our empirical results are very similar when we consider one measure or the other.

3.4 Other explanatory variables

In addition to the interest rates innovations, we include other variables in our regressions, either as controls or in order to test the different theoretical hypothesis that we have discussed.[25]

[24] And these would, in turn have an impact on expectations of future asset prices

[25] In some cases these variables appear as interactions with the change in interest rates, consistent with the theoretical predictions, and as described below.

3.4.1 Age

Hypotheses 2 states that reaching for yield should be a decreasing function of age. In our data we have age information for roughly a half of the sample, and we consider all investors aged from 30 to 80 in our analysis. We define ten age groups where the first group includes ages from 30 to 35 and all other groups have a 5-year step (i.e. 36 to 40, 41 to 45, etc).

Table A1 in Appendix 2 reports the distribution of investors across the different age groups. 72.7% of investors in our sample are in the five groups of ages between 36 and 60, and the most populated age group is the one between 46 and 50 (17.8% of sample). The younger group of investors aged between 30 and 35 comprises 9.4% of the sample while only 18% of our investors are older than 61.

3.4.2 Wealth

Hypotheses 1 states that reaching for yield should be a decreasing function of wealth. Our measure of investor wealth is the total account balance at the beginning of the month, and we consider ten wealth groups. Since wealth has a very right skewed distribution, if we considered equal-sized deciles, the first decile would capture very limited variation, particularly when compared to the tenth decile. Therefore, we instead set specific break points for each group, such that each of them captures a different segment of the wealth distribution and none of them is particularly small. More specifically, we use the following break points (all in CNY): 10K, 25K, 50K, 100K, 200K, 300K, 400K, 500K, and 1M.

We assign investors to a wealth group each month, based on their current account value, and repeat the wealth group assignment procedure for every cross-section in the data. Therefore, the same investor can switch across different wealth groups over time. Table A2 in Appendix 2 provides the full distribution of investors across wealth groups. Around 20% of the sample have an account balance of less than 10K CNY and 18% have between 10K and 25K. In total, 87% of the investors in the sample have less than 200K in assets and cash in their account.

3.4.3 Passive change in wealth

As highlighted by Hypotheses 3b and 4b, another important variable implied by both models of labor income and models with DRRA preferences, is the change in investor wealth. We obtain our measure of change in wealth induced by financial markets in two steps. First, for all assets that each investor holds at the start of the month, we compute their change in value over that month. Second, we aggregate these for each account, to obtain the total change in portfolio value that would have resulted from these price movements. We call this measure the passive change in wealth (ΔW^p), since it will be equal to the actual change in account value if the investor has remained passive, i.e. has not executed any trades, or moved any funds in our out of the account:

$$\Delta W^p_{jt} = A^p_{jt-1} - A_{jt-1} = \sum_i Q^i_{jt-1}(P^i_t - P^i_{t-1}). \tag{21}$$

We scale the passive change in wealth by the account balance in previous month and convert into a percentage value by taking logs:

$$ln\Delta W^p_{jt} = \ln\left(1 + \frac{A^p_{jt-1} - A_{jt-1}}{A_{jt-1} + C_{jt-1}}\right). \tag{22}$$

Naturally these changes in wealth are not necessarily the result of changes in interest rates. However, according to both the DRRA channel and the human capital channel, we should control for them in our regressions, regardless of the underlying mechanism responsible for the movements in asset prices.

3.4.4 Previous gains and losses

Hypothesis 5 states that reaching for yield should be more pronounced for investors with previous losses versus those with previous gains, relative to their reference points. We calculate gains and losses as the difference between the current market value of open positions and a reference price. We further scale gains by account value:

$$Gains_{jt}^{pp} = \frac{\sum_i Q_{jt}^i (P_t^i - \bar{P}_{jt}^i)}{A_{jt} + C_{jt}}, \tag{23}$$

where $\bar{P}_{jt}^i$ represents the individual-specific reference price, and therefore $(P_t^i - \bar{P}_{jt}^i)$ measures the gain or loss relative to that reference point. In the regression analysis, we use an indicator function for positive gains $\mathbf{1}\{\text{Gain} > 0\}$, which takes value 1 if $Gains_{jt-1}$ is positive and 0 otherwise.

Since we do not observe the actual reference point of the investors, we consider the price at the start of the previous month as the reference point. In this case, our measure ("monthly gains") corresponds to the gain or loss over the previous month. Under this specification, reference prices get reset every month. This assumption is particularly well suited for Chinese retail investors whose average monthly turnover is around 100%. Figure A1 in Appendix 3 plots the series of monthly gains, while Column 8 in Table 1 provides detailed descriptive statistics.

3.5 Descriptive statistics

Table 1 reports summary statistics for several variables in our data: account balance, risky share, the three measures of rebalancing behavior (active change in risky share, net equity flow, and withdrawal rate), passive wealth change, and monthly gains.[26] In an average month, the average investor in our sample holds around 168K RMB (approximately 23.5K US dollars) in her account. However, this is a very skewed distribution as previously discussed, with a median value of 40K RMB (approximately 6K US dollars).

[INSERT TABLE 1 HERE]

The average risky share in the sample is 75%. The average *active* equity change (equation (14)) is around 0.98%, indicating that investors' active trading has actually increased their

[26] Summary statistics for age and wealth are reported in Appendix 2.

equity exposure over the sample. Consistent with this, the mean monthly net equity flow as a percentage of the account balance (equation (18)) is 1.8%.[27] We can also observe that, in any given month, there is both a significant fraction of investors that trade and a significant fraction who do not trade, with the 25th and 75th percentiles of the active risky share change being equal to zero.

The mean withdrawal rate (equation (19)) over the sample is −3.54%, revealing that investors are on average transferring more money into their brokerage accounts than what they are taking out. As with the active risky share change and the net equity flows measure, here we also observe a non-trivial percentage of zeros. In any given month, there is a large number of investors who do not invest new money into account, and do not make any withdrawals either.

The mean passive change in wealth as a percentage of the account value (equation (22)) is close to zero (−0.05%), indicating that asset valuations have remained fairly constant during the sample period. There is, however, a significant dispersion around this mean. The 10th percentile is −11.63%, while the 90th percentile of 11.45%. Naturally this dispersion reflects both time-series and cross-sectional variation in our sample.

The final variable in Table 1 is monthly gains and losses as a percentage of the account value in previous month (equation 23). The mean is slightly negative (-0.6%), indicating that on average investors' portfolios are at a loss. At the same time, the variation of gains and losses in the portfolios is quite high (the standard deviation is 11.57%).

[27]The maximum and minimum values of net equity flows are not limited to 100% and −100% and can exceed those depending on the amount of cash additions and/or capital gains.

4 Reaching for Yield

4.1 Baseline results

As previously discussed, in our empirical analysis we consider three measures of household portfolio rebalancing behavior: active change in risky share (ω^a), net equity flow ($NetFlow^{pp}$), and (net) withdrawals ($Withdr^{pp}$). In our baseline specifications, we regress each of these variables (denoted below as y), against either changes in interest rates (Δr) or the residuals from the AR(1) process (ϵ^r, from equation (20)) as described in the previous section. The regressions also include additional controls (denoted by X) and account-level fixed effects (denoted by f). More precisely we estimate the following equations:

$$y_{j,t+1} = \alpha + \beta \Delta r_t + \gamma X_{j,t} + f_j + u_{j,t+1}; \tag{24}$$

$$y_{j,t+1} = \alpha + \beta \varepsilon_t^r + \gamma X_{j,t} + f_j + u_{j,t+1}, \tag{25}$$

where j denotes each individual investor, and t denotes calendar time (in months).

It is important to clarify the timing of the variables in the regressions. The left-hand-side variable measures changes over the current month, while the explanatory variables are computed at the start of that month. So, for example, we regress the change in risky share from January 1st, 2010 to January 31st, 2010, on the change in interest rates from December 1st, 2009 to December 31st, 2009. All other explanatory variables that capture changes are also measured over the same period (December 1st, 2009 to December 31st, 2009 in the previous example), and those that capture values at a point in time are evaluated at the start of the month (so January 1st, 2010, in the previous example).

4.1.1 Regressions with account-level fixed effects

In Table 2, we report regressions where the vector X includes the passive change in wealth ($ln\Delta W^p$, thus capturing Hypothesis 3b and 4b) and the dummies for current wealth (proxied by account balance).[28] The standard errors on the interest rate innovations are clustered at the account level, since it only has time-series variation, while the standard errors on the passive change in wealth are time-clustered.

[INSERT TABLE 2 HERE]

Table 2 shows that, on average, retail investors engage in reaching for yield. This conclusion is present under all three measures of rebalancing behavior that we consider, and for both measures of interest rate innovation.[29]

Focusing first on the trading behavior inside the brokerage account, we find that, following an interest rate (SHIBOR) increase of one percentage point, the average investor decreases her active risky share by 5 b.p. to 9 b.p., depending on the measure of interest rate innovation. Similarly, net equity flows decrease by 20 b.p. to 36 b.p. In addition, to rebalancing her portfolio within the brokerage account, the investor also withdraws funds from the account. More specifically, we observe an increase in account withdrawals of 14.5 b.p. to 37.5 b.p., depending on the interest rate variable being considered. Since these withdrawals are likely to be invested in money market mutual funds, the total reduction in risk exposure is non-trivial.

The portfolio elasticities documented above are remarkably similar to the ones estimated in Giglio et al. (2021). They find that a 1 percentage point increase in expected stock returns is associated with a 70 basis point higher equity share. To compare with our baseline results we require an assumption about how investors expectations of future stock returns change when the interest changes. Suppose that, following a 1% increase in interest rates, the investors' expected stock return increases by 50 basis points.[30]. Then, our regression imply an elasticity of the brokerage account portfolio to expected return, of between 10 b.p. to 72

[28] In this specification the wealth dummies are included only as controls. Later we will interact them with the interest rate variable to test the wealth channel implied by Hypothesis 2.

[29] Results for the simple change in risky share ($\Delta\omega$, equation (11)) are reported in Appendix 4 (table A3) and yield the same conclusions.

[30] This is half way between the full increase that would imply no reaching for yield, and no adjustment in the expectation of future stock returns. If we instead assume that investors expect the stock return to move almost one for one with interest rates, then our implied portfolio elasticities are even much larger.

b.p., depending on the measures of portfolio rebalancing and interest rate innovation. To this, we would then add portfolio rebalancing outside of the account, as captured by account withdrawals. Our overall effect is therefore very similar to the estimates obtained by Giglio et al. (2021).

Furthermore, we later show that these average responses mask substantial heterogeneity across investors. We will show that the effect is significantly larger for young investors and for those with less wealth, consistent with the predictions of models with labor income. In addition, we document that certain groups of investors actually exhibit "reverse reaching for yield" which, although perhaps somewhat counter-intuitive, was a possible implication from the portfolio choice model with labor income. In the next sections, we explore and document this rich heterogeneity.

Motivated by Hypotheses 3b and 4b, we have also included the passive change in wealth ($ln\Delta W^p$, equation (22)) in the regressions. If investors have DRRA then an increase in wealth should lead to a higher risky share, since risk aversion is now lower. On the other hand, the human capital channel implies the opposite: higher wealth decreases the ratio of human capital to financial wealth and therefore the investors implicit bond holdings are now a smaller fraction of her portfolio. As a result, the optimal risky share is now lower. The negative coefficient for $ln\Delta W^p$ in the first four regressions indicates that the human capital channel is the dominating effect here. Importantly, this does not rule out DRRA in preferences. Our coefficient can only estimate the net effect of the two channels. In fact, when we consider the impact on withdrawals, the coefficient is again negative but, since for this left-hand-side variable the prediction is reversed, that is now consistent the DRRA channel dominating in this context.

Since our data includes some periods of significant stock market movements ("bubbles and crashes"), in Appendix 5 we report results using data from January 2009 to December 2014 only, which excludes those periods. Likewise we also re-estimate our regressions with the added restriction that the dependent variable is different from zero, so that we are only focusing on investors that actually rebalance their portfolios (see Appendix 6). Our conclusions remain: in both cases, across all three measures of portfolio rebalancing, and for both measures of interest rate innovations, we find evidence of reaching for yield.

4.1.2 A simple calibration

It is interesting to consider what our estimation results imply in the context of the portfolio choice models discussed in Section 2.

If we consider the Merton model without labor income, the implied change in risky share is given by equation (2). Let's assume an investor with risk aversion of 5 and an expected return volatility of 20%. A −0.5% change in the risky share implies a value of $\frac{\partial(\mu-r)}{\partial r}$ of −0.1.[31] So, when interest rates increase by 1% investors expect that the return on stocks will increase by 0.9%.[32] This highlights the underlying assumption behind "reaching for yield" in the context of the Merton model: it will occur as long as investors don't expect the return on stock to move exactly one-for-one with the riskess rate.

If we repeat this calculation in the context of the portfolio choice model with labor income (equation (4)) then, for a ratio of human capital to financial wealth of 3 for example, the implied value of $\frac{\partial(\mu-r)}{\partial r}$ is even smaller, −0.025. This is enough to generate the non-trivial portfolio rebalancing that we observe in the data.

As mentioned above, Giglio et al. (2021) document that retail investors adjust their portfolios only moderately in response to changes in their expectations of future returns. Their results therefore suggest that the underlying changes in expectations are larger than the ones implied by this calibration exercise.

[31] As discussed, the full change in risky share includes the portfolio reallocation within the brokerage account and (likely) also the withdrawals from that account. For the purposes of this illustration we are combining those two effects into an approximate total response if −0.5%

[32] Naturally this is an average belief. In the extreme, it could arise if 90% of investors expect the equity premium to remain constant, while the other 10% expect the return on stocks to remain constant.

4.1.3 Regressions with age dummies

In the previous regressions we didn't control for age because we included account-level fixed effects. In Table 3, we consider an alternative specification that replaces the fixed effects with age dummies. The age dummies are constructed from the 10 age groups defined in section 3. Both age and wealth are included here "only" as controls. In the next subsections, we specifically consider our Hypotheses 1 and 2, and study how these two variables impact reaching for yield directly.

[INSERT TABLE 3 HERE]

The number of observations in these regressions is reduced to approximately 40% of the original sample (about 42 million compared with about 116 million before), reflecting the availability of the age variable in our data. Nevertheless, the results in Table 3 are very similar to those obtained in Table 2. The point estimates for the coefficients are very close to the previous ones. The more substantial differences are in the regressions for withdrawals where the coefficients are now slightly smaller than in the previous regressions, but they all remain strongly significant.

4.2 Heterogeneous responses: wealth

Having established that, on average, investors in our sample exhibit reaching for yield behavior, we now turn to one of the predictions of the portfolio choice model with labor income. More precisely here we focus on Hypothesis 1: reaching for yield should be a decreasing function of wealth.[33]

It is important to remember that Hypothesis 1 is based on the asset allocation rule implied by portfolio choice model with labor income (equation (3)). The relevant variable in the model is the ratio of human capital to financial wealth, not financial wealth only. Since

[33] Note that this refers to the level of wealth, so it is a different prediction from the role of changes in wealth which is captured by the passive wealth change variable.

we do not observe labor income in our data, we can only control for wealth. However, to the extent that individuals with more wealth are also more likely to have higher income/human capital then that will work against us finding any effect in the data.[34] Furthermore, Giglio et al. (2021) show that wealthier investors reallocate their portfolios more in response to changes in expectations, which will work against finding our prediction in the data.

To test hypothesis 1, we extend the previous regressions (equations (24) and (25)) to include interaction terms between the interest rate innovation and dummy variables for the different wealth groups ($I_{W_{jt}}$):

$$y_{j,t+1} = \alpha + \beta \Delta r_t + \beta^W (\Delta r_t I_{W_{jt}}) + \gamma I_{W_{jt}} + \phi X_{it} + f_j + u_{j,t+1} \tag{26}$$

$$y_{j,t+1} = \alpha + \beta \varepsilon_t^r + \beta^W (\varepsilon^r I_{W_{jt}}) + \gamma I_{W_{jt}} + \phi X_{it} + f_j + u_{j,t+1} \tag{27}$$

where, as before, $y_{j,t+1}$ denotes one of our four measures of household portfolio rebalancing, X_{it} includes passive change in wealth, and the f_j are account-level fixed effects. The dummy variables for wealth correspond to the 10 wealth groups described in section 3.

To facilitate the exposition, we present the implied portfolio response for each of the ten wealth groups in Figures 3 and 4.

[INSERT FIGURES 3 AND 4 HERE]

Figure 3 reports the results obtained when interest rate innovations are measured as the AR(1) residual, whereas Figure 4 plots the results when interest rate innovations are measured as the simple first difference. For each of these two figures, Panel a) plots results for (net) withdrawal rate (for which we expect mostly positive coefficients), while Panel b) plots the results for the other two variables (for which we expect mostly negative coefficients).

[34] Conditional on the age we would expect a high correlation between wealth and income, but this should be much weaker unconditionally. As individuals age their wealth tends to increase while their human capital is falling. Hypothesis 2, which we test below, tries to capture fluctuations in the ratio of human capital to financial wealth, by exploiting these typical life-cycle patterns.

4.2.1 Withdrawal rates

In both Figures 3 and 4, Panel (a) reveals a strong decreasing pattern for the response of (net) withdrawal rates to interest rate movements as a function of wealth. Consistent with Hypothesis 1, the response is much more significant among the less wealthy investors, and becomes close to zero for those in wealth groups 6 and above.

The differences across wealth groups are economically large. Consider Figure 3: while investors in wealth group 1 increase their withdrawals by 72 b.p. in response to a 100 b.p. movement in interest rates, for those in wealth group 3 the change in withdrawal rates is less than half of that (38 b.p.). Further up the wealth distribution investors are even less responsive and, as we reach wealth group 7, the change in withdrawal rate is essentially zero (4 b.p.).

This pattern is strikingly consistent with the predictions of the portfolio choice model with labor income (equation 4). In addition to the monotonic decay with wealth, the model also predicts a convex relationship such as the one obtained in Figure 3: as we move up in the wealth distribution the ratio of human capital to financial wealth becomes negligible and, consequently, a further increase in wealth doesn't change its value by as much as it does for less wealthy individuals.[35]

Finally, it is interesting to note that, in the specification with changes in interest rate (Figure 4) the implied responses for the more wealthy investors, although small, are actually positive: these investors are doing the exact opposite of reaching for yield. This perhaps surprising result was discussed as a possible outcome when we presented the theoretical predictions from the portfolio choice models.

Giglio et al. (2021) show that wealthier investors reallocate their portfolios more in response to changes in expectations. Therefore, in the absence of the channel implied by hypothesis 1, we would have expected to find exactly the opposite result. Therefore, the

[35]Another way to see the same result is that, as wealth increases, the portfolio allocation converges to the Merton solution without labor income. Hence the change in interest rate converges to one implied by equation (2).

isolated effect resulting from our channel is likely to be even stronger.

4.2.2 Changes in risky share and net equity flows

In Panel (b) of Figures 3 and 4, we report results for the other two measures of portfolio rebalancing (active change in risky share and net equity flows), for which we expect to see mostly negative changes. Indeed, for both figures, both measures, and across all 10 wealth groups, the responses to interest rate movements are negative, consistent with reaching for yield behavior.

As we compare the behavior of different investors we again find strong support for Hypothesis 1: less wealthy investors are more responsive to interest rate movements. Interestingly, the pattern is almost exactly the symmetric of the one observed in Panel (a). We observe a clear decreasing pattern (in absolute value) from wealth group 1 to wealth group 7, and essentially flat after that. As discussed before, this convex function of wealth is exactly predicted by equation (4). The magnitudes are larger when we consider the residuals from the AR(1) process as opposed to the simple changes in interest rates. From Panel (b) of Figure 3, a 100 b.p. interest rate "innovation" leads to a reduction in net equity flows as a percentage of the total account balance, of 54 b.p. for the first wealth group, compared with 35 b.p. for the third wealth group and 21 b.p. for the sixth.

4.3 Heterogeneous responses: age

We now consider Hypothesis 2: reaching for yield should be more pronounced among young investors, as implied by taking the portfolio choice model with labor income into a life-cycle context. Intuitively, for young investors the ratio of human capital to financial wealth is particularly higher, hence they should have a strong portfolio response to interest rates changes. As they get older, their human capital decreases and they accumulate more wealth, consequently the ratio of the two (and therefore the elasticity of the portfolio rule to interest rate fluctuations) falls.

We test this hypothesis by adding, to our baseline regressions (equations (24) and (25)), interaction terms between the interest rate innovation and dummy variables for the different age groups that we have previously defined:

$$y_{j,t+1} = \alpha + \beta \Delta r_t + \beta^{age}(\Delta r_t I_{age_{jt}}) + \gamma I_{age_{jt}} + \phi X_{it} + u_{j,t+1} \tag{28}$$

$$y_{j,t+1} = \alpha + \beta \varepsilon_t^r + \beta^{age}(\varepsilon_t^r I_{age_{jt}}) + \gamma I_{age_{jt}} + \phi X_{it} + u_{j,t+1} \tag{29}$$

where, as before, we omit account level fixed effects because we are including age as a separate regressor, and X_{it} includes passive change in wealth.

The implied portfolio response for each of the ten age groups are presented in Figures 5 and 6, respectively for the specification with the AR(1) interest rate innovation and the one with interest rate changes.

[INSERT FIGURE 5 AND 6 HERE]

Just as we did in the previous subsection (when studying wealth effects), we separate the results for withdrawal rates (Panel (a)), for which we expect positive coefficients, from those for the other two dependent variables (Panel (b)), for which we expect negative coefficients.

4.3.1 Withdrawal rates

Consistent with Hypothesis 2, Panel (a) of Figure 6 shows a pronounced decreasing pattern of withdrawal rates as a function of age. In fact, withdrawal rates decrease monotonically across all ten age groups. While the youngest investors (age group 30-35) withdraw 54 b.p. of their account value in response to a 100 b.p. increase in interest rates, those in the age group 50-55 (group 5) withdraw only 3 b.p. of their account balance.

Interestingly, the results in Figure 6 suggest that investors above 56 (group 6 and higher), actually engage in reverse reaching for yield behavior: they transfer more money into their brokerage accounts (negative withdrawal rate) when interest rates increase. However, this pattern is not present in Panel (a) of Figure 5. Nevertheless, in both cases we observe a perfectly monotonic decreasing pattern, as predicted by the theory.

4.3.2 Changes in risky share and net equity flows

In Panel (b) of Figures 5 and 6 we report the responses for the other two measures of portfolio rebalancing: active change in risky share and net equity flows. Consistent with Hypothesis 2, the age pattern for net equity flows (as a percentage of account balance) is essentially the opposite of the pattern observed in Panel (a) for withdrawal rates: following increases in interest rates, young households decrease equity flows by more than older households. The differences are again economically significant and the patterns are monotonic across all ten age groups, with the exception of the first age group in Figure 5 (i.e. when considering AR(1) residuals as the interest innovations).

When considering active changes in the risky share, the age pattern is less clear. From age 41 the behavior of the active risky share is consistent with Hypothesis 2, with older investors responding less to changes in interest rates, but the differences are much less pronounced than for net equity flows. However, for first two age groups we now observe an increasing pattern (in absolute value).

Overall, across the 3 different measures of portfolio rebalancing, we find supporting evidence for Hypothesis 2, young investors reallocate their portfolios by more in response to interest rate changes than older ones.

4.4 Prospect theory

We move on to consider Hypothesis 5, which states that reaching for yield should be more prevalent among investors trading at a loss than at a gain. As discussed, under prospect theory, the most risk-averse point is the origin (or the kink), where investors break even in their portfolio return. For someone currently trading at a gain, a (small) drop in interest rates pulls them closer to the kink and makes them more risk averse. In comparison, for someone currently trading at a loss, the same interest rate drop will pull them further away from the kink and can make them more risk taking (under certain parameterization). Therefore, we test how reaching for yield is correlated with an investor's current gain/loss position.

Specifically, we test this hypothesis by running the following regressions:

$$y_{j,t+1} = \alpha + \beta_1 \Delta r_t \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta r_t \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}, \tag{30}$$

$$y_{j,t+1} = \alpha + \beta_1 \varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta \varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}, \tag{31}$$

where Gain is given by equation (23) and measures the individuals (net) gains. In our analysis, we use measure gains relative to the stock price at the end of the preceding month.

Table 4 shows the estimation results. Columns (1) and (2) report results for the active change in risky share. Consistent with prospect theory, conditional on passive changes in wealth, investors trading at a loss become more risk-seeking after an interest rate drop. In column (1), only those trading at a loss reach for yield: a 100 b.p. interest rate innovation leads to a 14 b.p. decrease in active risky shares holding. Interestingly, those trading at a gain actually exhibit reverse reaching for yield. Among these investors, a 100 b.p. interest rate innovation is associated with a 7.5 b.p. increase in active risky shares holding. Similarly, in column (2) where we measure interest rate innovations using the AR(1) residual, those trading at a loss exhibit a much stronger tendency of reaching for yield.

Columns (3) to (6) report results for the other two measures of portfolio rebalancing, (net) flows into equities and (net) withdrawals from the account, under the two specifications of interest rate innovations. For both dependent variables and both measures of interest rate innovations, reaching for yield is larger when investors are trading following losses. These results again support prospect theory as a driver of reaching for yield behavior by retail investors.[36].

[36]In Appendix 7 we show result for regressions where we restrict the dependent variable to have non-zero values. We are thus focusing on investors who are actively rebalancing only. The results are again supportive of the prospect theory predictions.

5 Conclusion

The existing literature has documented the existence of "reaching for yield" among institutional investors. In this paper, we present new field evidence to document the same phenomenon among retail investors. Our results show that reaching for yield does not need to stem from institutional frictions, as what the existing literature has typically focused on.

We discuss and test different theories of portfolio choice, that generate heterogeneous responses among households. Overall, we find that younger, less wealthy individuals display stronger reaching for yield, which provides empirical support for life-cycle models, and portfolio choice models with labor income. We also find stronger reaching for yield when investors are trading at a loss, which provides empirical support for prospect theory as a further explanation of this behavior.

In this paper we measure portfolio reallocation in response to interest changes in general. We don't try to isolate specific interest rate shocks, instead we want to understand how investors react when interest rates increase or decrease. It would be interesting to also study the response to monetary policy shocks, for example, as this would be particularly useful to understand the transmission mechanism of monetary policy.

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Table 1: Descriptive statistics

Stats	Acc. Balance	ω, %	ω^a, %	$NetFlow^{pp}$, %	$Withdr^{pp}$, %	$ln\Delta W^p$, %	$Gains^{pp}$, %
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	118,613,350	118,556,263	118,536,384	116,920,015	116,920,015	116,920,015	116,603,018
Mean	0.168	75.00	0.98	1.80	-3.54	-0.05	-0.60
SD	0.40	33.78	17.32	32.20	30.23	10.40	11.57
Min	0.00	0.00	-49.81	-100.07	-215.33	-37.66	-42.79
p5	0.00	0.00	-14.17	-43.20	-30.50	-18.88	-21.34
p10	0.00	0.00	-1.79	-14.96	-1.62	-11.63	-13.26
p25	0.01	62.21	0.00	0.00	0.00	-3.87	-4.74
p50	0.04	93.35	0.00	0.00	0.00	0.00	0.00
p75	0.13	98.85	0.00	0.00	0.06	4.84	4.54
p90	0.39	99.75	0.98	18.32	1.49	11.45	11.35
p95	0.75	99.91	9.60	49.72	15.07	16.24	16.58
Max	2.85	100.00	97.63	174.87	69.26	29.30	36.45
N (ID)	2.00	2.00	2.00	1.94	1.94	1.94	1.93
# of months	59.22	59.22	59.22	60.41	60.40	60.40	60.29

This table shows descriptive statistics for our sample. Column 2 reports total account balance in millions of CNY. Column 3 reports the risky share while column 4 display active change in risky share (equation 14) respectively. In columns 5 and 6 we include our two other measures of portfolio rebalancing, respectively net equity flows (equation 18) and withdrawal rates (equation 19. In column 7 we report the passive change in wealth (equation 22). Finally in column 8 we show account gains and losses (23). For each variable we provide the total number of account-months observations in millions (N), the mean, the standard deviation (SD), minimum and maximum values and key percentiles of the distributions, the number of unique account observations in millions (N (ID)), and the average number of months we observe for each investor.

Table 2: Results for baseline regression with account fixed effects

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.0468***		-0.199***		0.145***	
	(0.00156)		(0.00323)		(0.00291)	
ε_t^r		-0.0911***		-0.363***		0.375***
		(0.00161)		(0.00338)		(0.00312)
$ln\Delta W^p$	-0.0660***	-0.0663***	-0.165***	-0.166**	-0.0597***	-0.0588**
	(0.0134)	(0.0134)	(0.0242)	(0.0243)	(0.0250)	(0.0252)
Account FE	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	116,166,277	116,487,592	116,232,207	116,554,658	116,232,207	116,554,658
Adjusted R^2	0.010	0.010	0.017	0.017	0.048	0.048

robust account-clustered or time-clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from our baseline estimations with account-level fixed effects. The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y_{jt} denote each of the three the dependent variables, the regression specifications are $y_{j,t+1} = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

Table 3: Results for baseline regression with age dummies

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.0444***		-0.222***		0.126***	
	(0.00276)		(0.00589)		(0.00543)	
ε_t^r		-0.0796***		-0.350***		0.322***
		(0.00285)		(0.00613)		(0.00576)
$ln\Delta W^p$	-0.0573***	-0.0574***	-0.148***	-0.149***	-0.102***	-0.101***
	(0.0140)	(0.0140)	(0.0244)	(0.0244)	(0.0219)	(0.0220)
Age dummies	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	41,654,841	41,748,668	41,662,949	41,757,002	41,662,949	41,757,002
Adjusted R^2	0.004	0.004	0.006	0.006	0.009	0.009

robust account-clustered or time-clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from our baseline estimations with age dummies. The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y_{jt} denote each of the three the dependent variables, the regression specifications are $y_{j,t+1} = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), age dummies and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

Table 4: Results for regression controlling for past gains (monthly gains) and account fixed effects

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta r_t \times \mathbf{1}\{\text{Gain} < 0\}$	-0.140***		-0.304***		0.183***	
	(0.00203)		(0.00409)		(0.00390)	
$\Delta r_t \times \mathbf{1}\{\text{Gain} > 0\}$	0.0752***		-0.0623***		0.0939***	
	(0.00232)		(0.00511)		(0.00447)	
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\}$		-0.180***		-0.476***		0.453***
		(0.00208)		(0.00422)		(0.00406)
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\}$		0.0346***		-0.204***		0.265***
		(0.00253)		(0.00555)		(0.00490)
$ln\Delta W^p$	-0.0658***	-0.0660***	-0.165***	-0.165***	-0.0598**	-0.0591**
	(0.0135)	(0.0134)	(0.0243)	(0.0243)	(0.0251)	(0.0254)
Account FE	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	116,166,277	116,487,592	116,232,207	116,554,658	116,232,207	116,554,658
Adjusted R^2	0.011	0.010	0.017	0.017	0.048	0.048

robust account-clustered or time-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from our regression estimations including interactions of interest rate change with gains and losses dummy. The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y_{jt} denote each of the four the dependent variables, the regression specifications are $y_{j,t+1} = \alpha + \beta_1 \Delta r_t \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta r_t \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta_1 \varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta\varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). Gain < 0 (Gain > 0) is a dummy equal to one if account experiences losses (gains) where account performace is computed from equation 23, with the price at the start of the month as the reference price. $ln\Delta W^p$ represents the passive change in wealth. The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

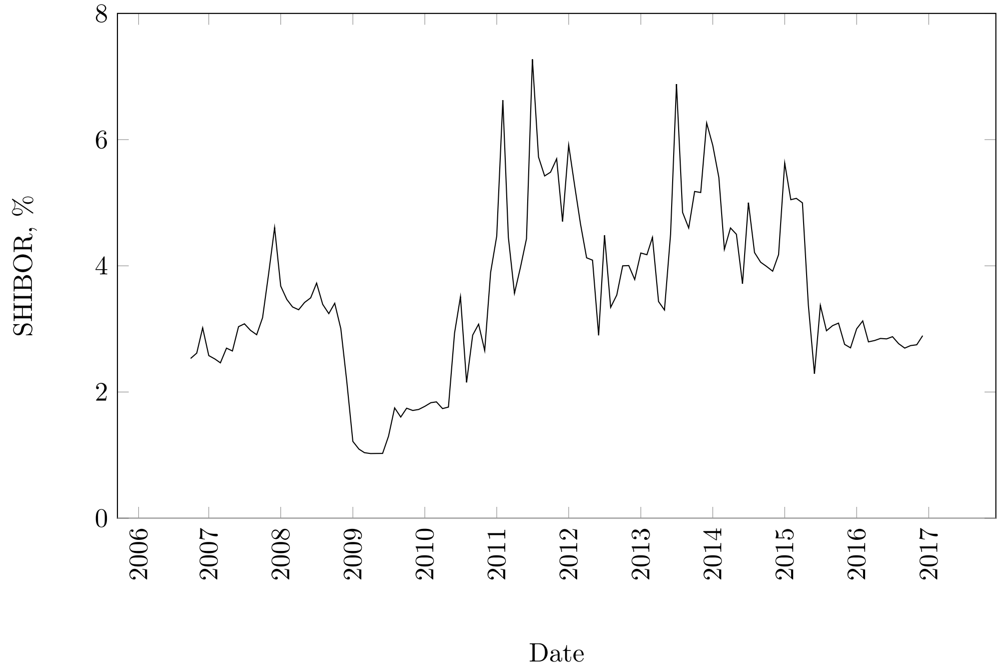


Figure 1: Historical 1-month SHIBOR

Figure 1 shows the time-series plot of the (annualized) 1-month SHIBOR over the period from October 2006 to December 2016.

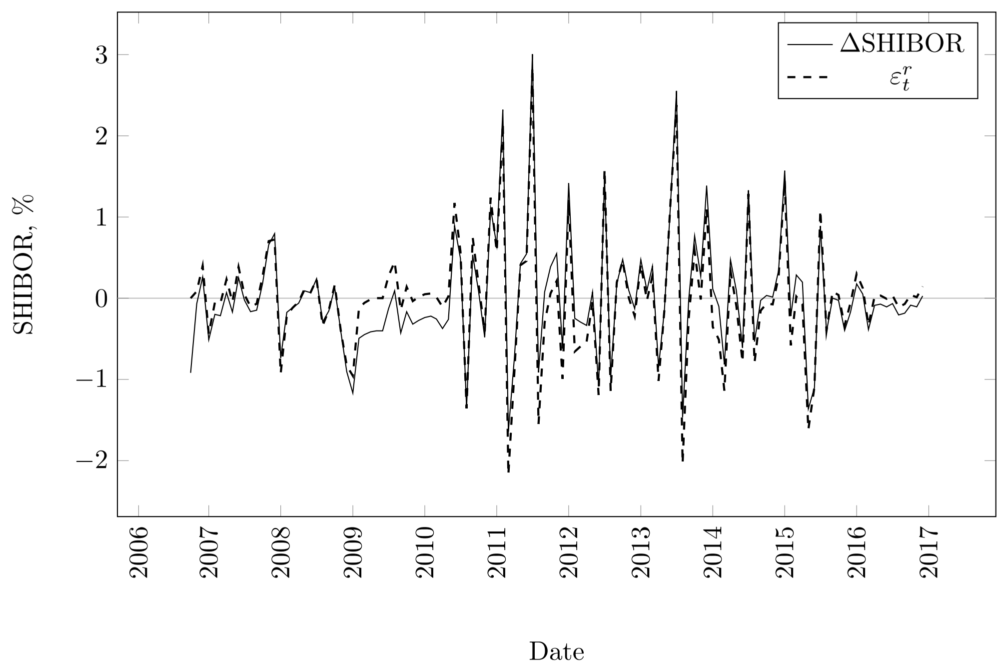
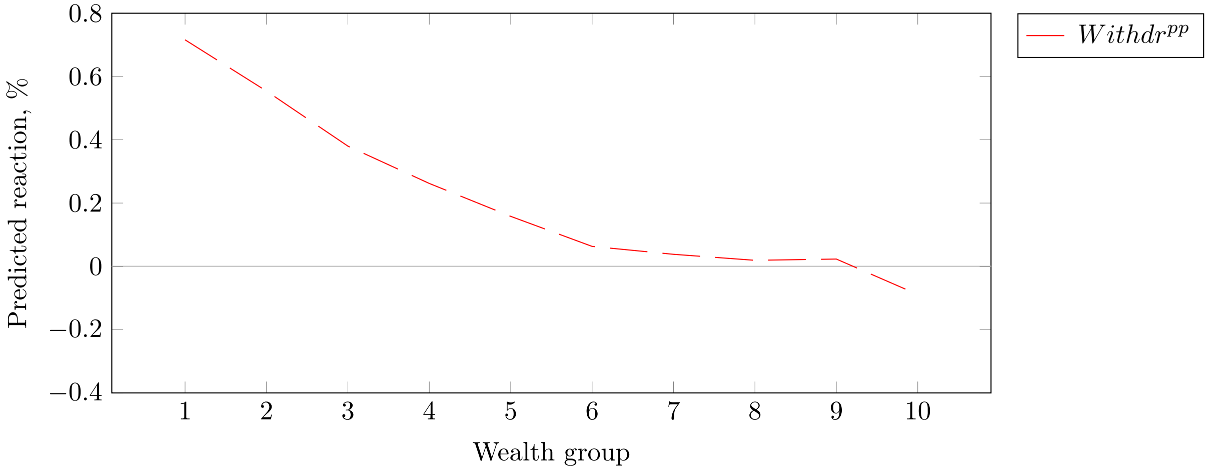


Figure 2: Interest rate innovations

Figure 2 shows the time-series plot of two measures of interest rate innovations. For the first measure is the simple change in interest rate (ΔSHIBOR). To obtain the second measure (ε_t^r), we fit an AR(1) process to the interest rate and use the error term as the innovation: $r_t = a_r + \rho_r r_{t-1} + \varepsilon_t^r$.

(a) Withdrawal



(b) Portfolio rebalancing

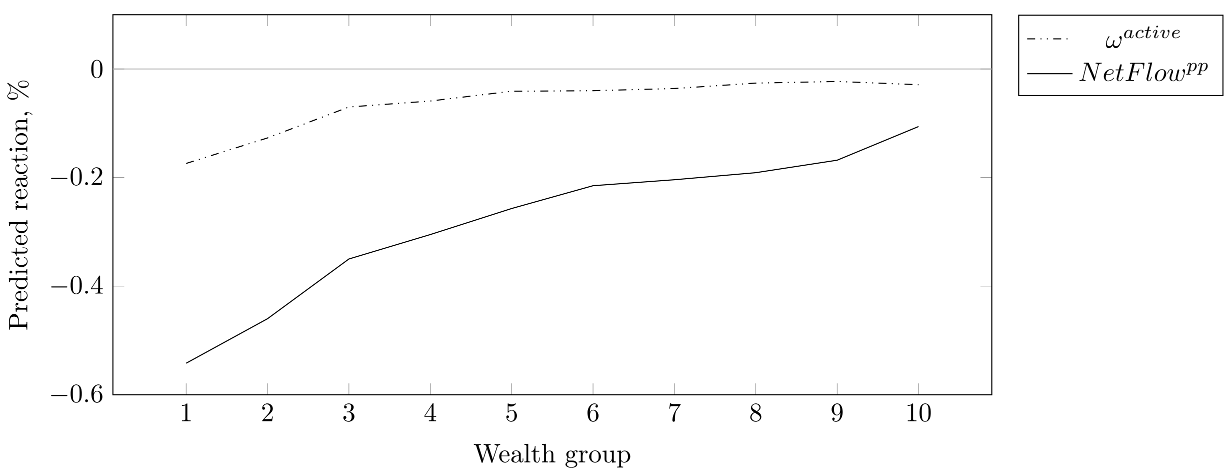


Figure 3: Effect of AR(1) interest rate innovations on investor behavior by wealth groups

Figure 3 plots the result from regressions of investor behaviour proxies on change in interest rate interacted with wealth group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovations correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of interaction effect of change in SHIBOR and wealth group. All regressions also include the passive change in wealth, wealth dummies and account fixed effects.

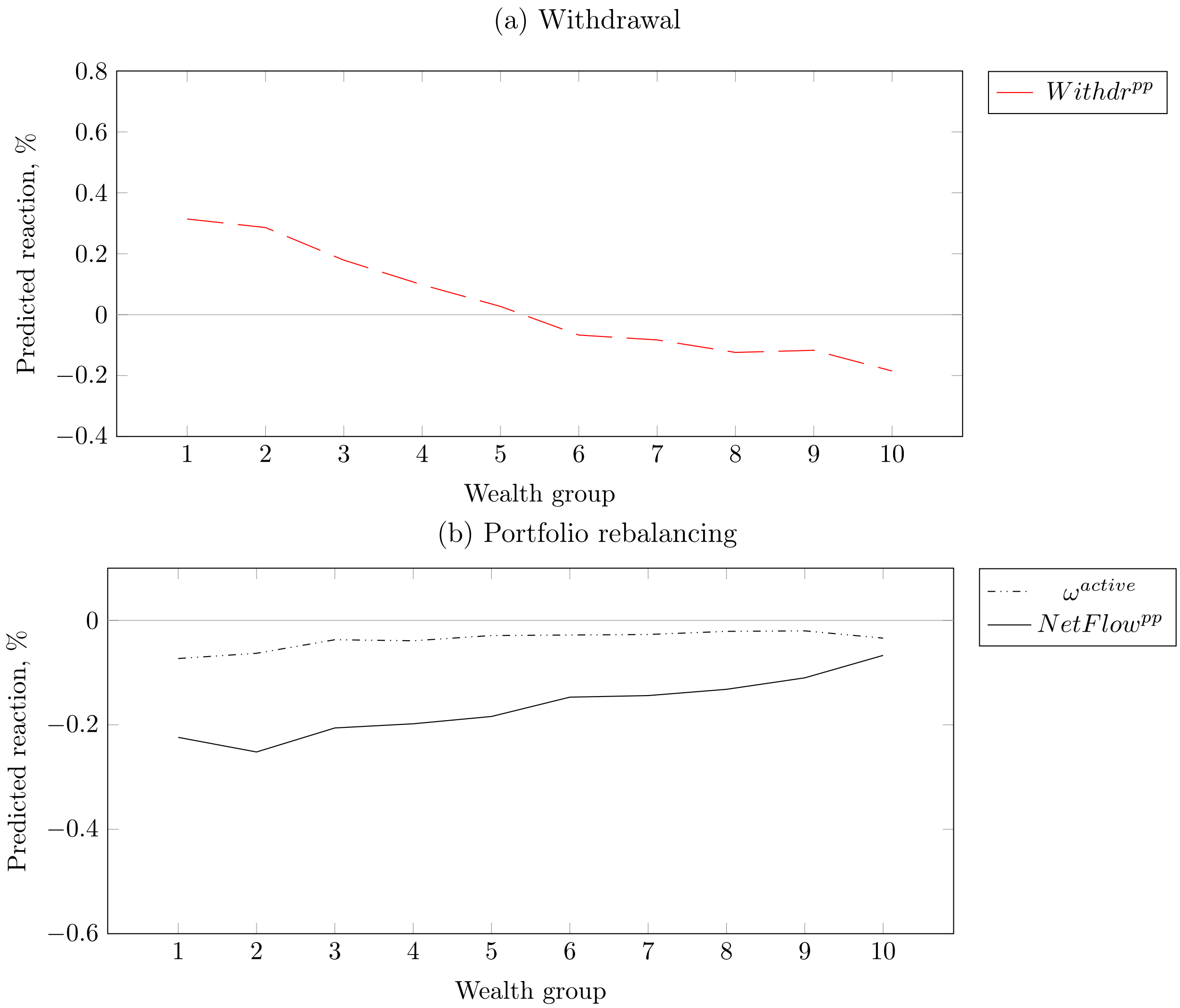


Figure 4: Effect of interest rate changes on investor behavior by wealth groups

Figure 4 plots the result from regressions of investor behaviour proxies on change in interest rate interacted with wealth group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The change in interest rate is the change in 1-month SHIBOR at the beginning of each month. Each line reflects the values of interaction effect of change in SHIBOR and wealth group. All regressions also include the passive change in wealth, wealth dummies and account fixed effects.

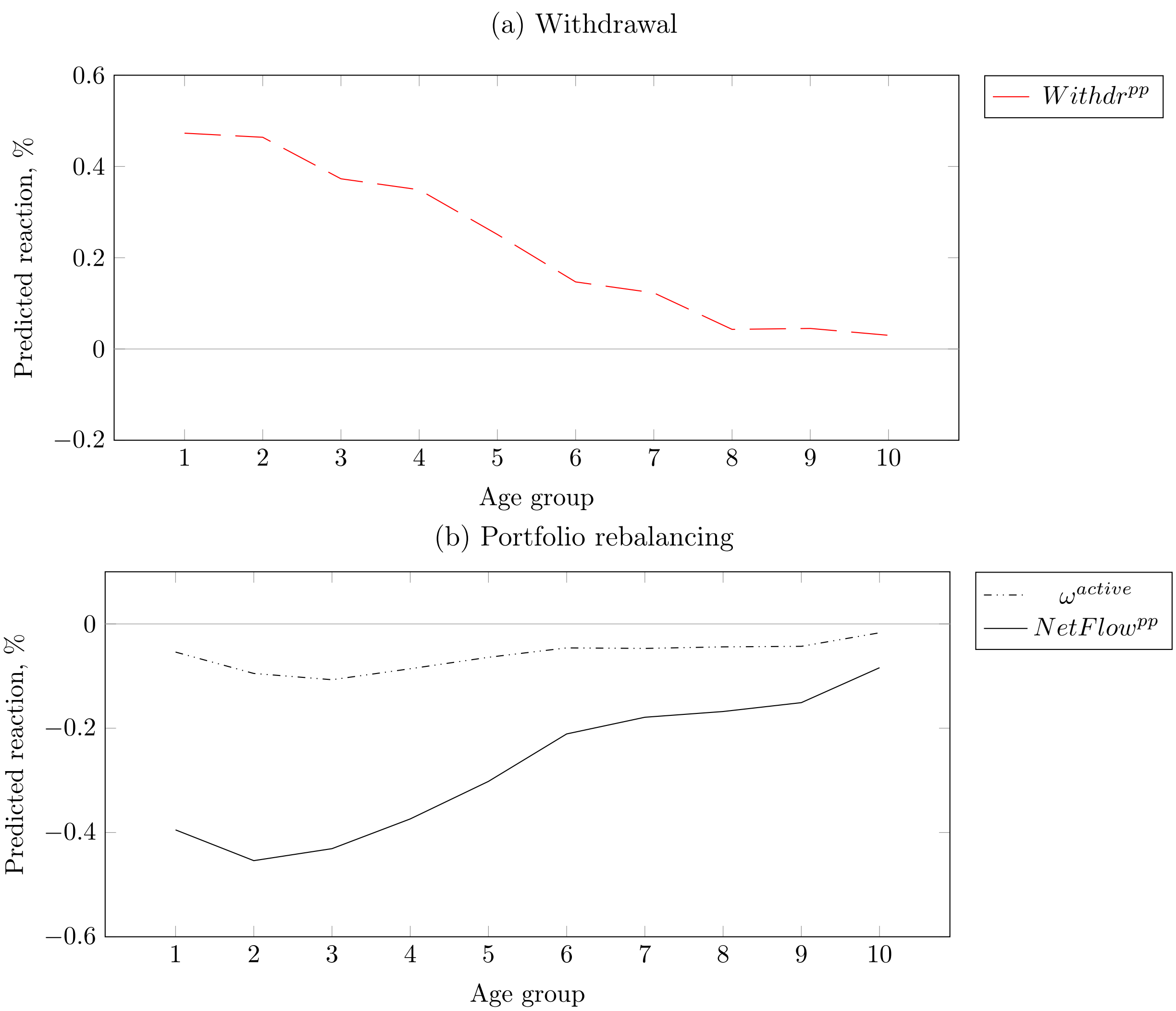
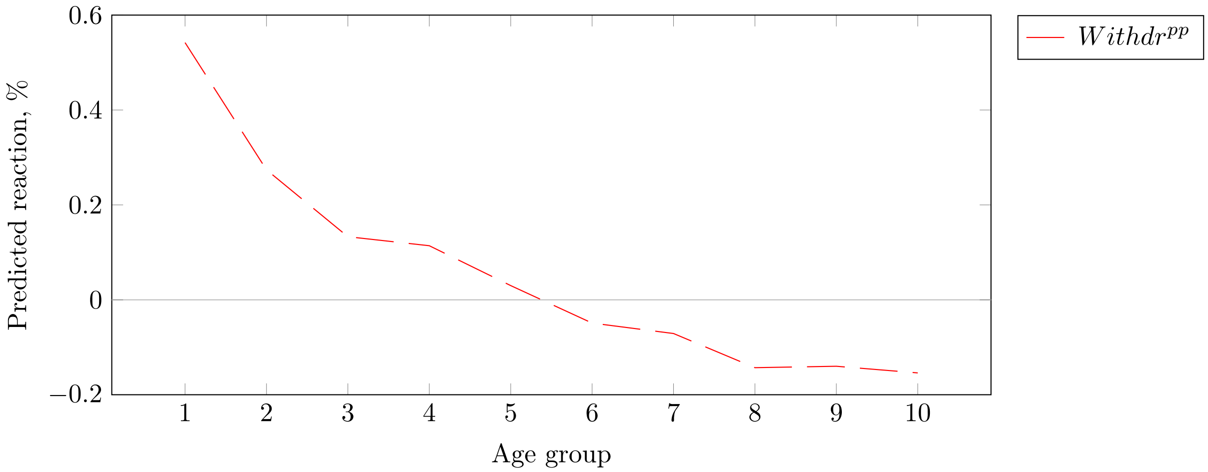


Figure 5: Effect of AR(1) interest rate innovations on investor behavior by age groups

Figure 5 shows the result from regressions of investor behaviour proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovations correspond to the residuals from an AR(1) process for SHIBOR.. Each line reflects the values of coefficient for interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and age dummies.

(a) Withdrawal



(b) Portfolio rebalancing

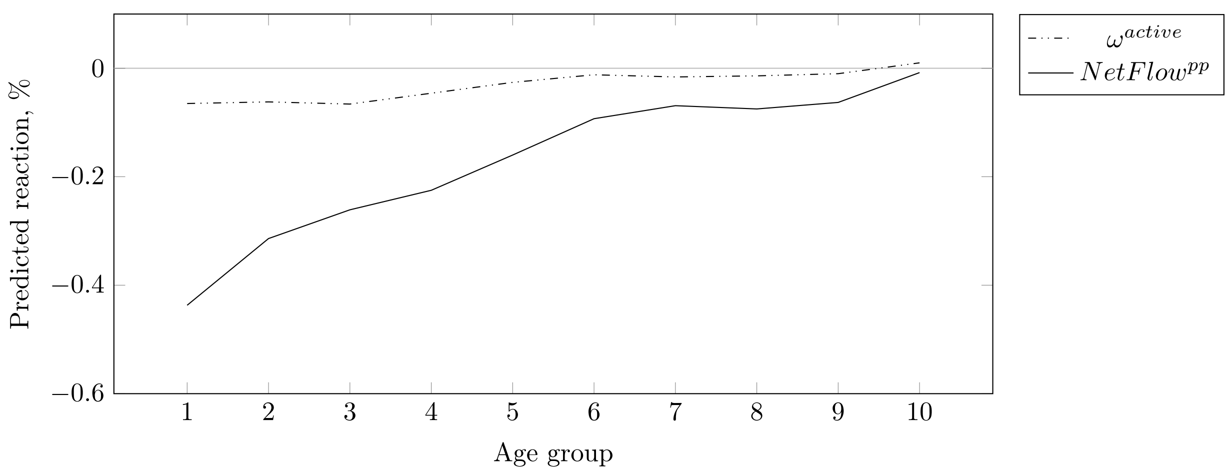


Figure 6: Effect of interest rate changes on investor behavior by age groups

Figure 6 shows the result from regressions of investor behaviour proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The change in interest rate is change in 1-month SHIBOR at the beginning of each month. Each line reflects the values of coefficient for interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and age dummies.

Appendix 1: Derivation of Hypothesis 1

To simplify the notation, we first define

$$\Gamma \equiv \frac{\partial(\mu - r)/\partial r}{\gamma\sigma^2} \tag{32}$$

so that can re-write equation (4) as:

$$\frac{\partial\alpha}{\partial r} = \left[1 + \frac{PV(Y)}{W}\right]\Gamma \tag{33}$$

From this

$$\frac{\partial\alpha/\partial r}{\partial W} = -\frac{PV(Y)}{W^2}\Gamma \tag{34}$$

So the sign of $\frac{\partial\alpha/\partial r}{\partial W}$ is the opposite of the sign of Γ, i.e.

$$\begin{cases} \partial\alpha/\partial r \text{ is a negative function of } W & \text{if } \Gamma > 0 \\ \\ \partial\alpha/\partial r \text{ is a positive function of } W & \text{if } \Gamma < 0 \end{cases}$$

From equation (34), the sign of Γ is also the sign of $\partial\alpha/\partial r$ so we can re-write the previous result as

$$\begin{cases} \partial\alpha/\partial r \text{ is a negative function of } W & \text{if } \partial\alpha/\partial r > 0 \\ \\ \partial\alpha/\partial r \text{ is a positive function of } W & \text{if } \partial\alpha/\partial r < 0 \end{cases}$$

combining these two terms, $|\partial\alpha/\partial r|$ is a negative function of W.

Appendix 2: Summary Statistics for Age and Wealth Groups

Table A1 shows the distribution of investors in the sample, across the different age groups. The vast majority of investors are younger than 60, with the largest age group being 46 to 50, followed by 41 to 45.

Table A1: Age Distribution of Investors

Age group	N	Min age	Max age
1	3.77	30	35
2	6.12	36	40
3	6.55	41	45
4	7.60	46	50
5	6.07	51	55
6	4.50	56	60
7	3.56	61	65
8	2.24	66	70
9	1.23	71	75
10	0.74	76	80
Total	42.36	30	80

This table shows the distribution of investors in the sample, across the different age categories that we consider in our regression specifications. Column 2 reports the number of investors in each category, in millions. columns 3 and 4 report, the corresponding minimum and maximum ages, respectively.

Table A2 shows the distribution of investors in the sample, across the different wealth groups. Wealth is proxied by the individual's account balance. The first wealth group is the largest, but all others are quite sizeable as well, which was an important criteria for defining the cutoff points.

Table A2: Wealth Distribution of Investors

Wealth group	N	Min,CNY	Max,CNY
1	24.41	0.01	9999.99
2	20.98	10000	24999.99
3	18.53	25000	49999.99
4	17.79	50000	99999.98
5	14.13	100000	199999.98
6	6.21	200000	299999.88
7	3.53	300000	399999.88
8	2.29	400000	499999.94
9	4.87	500000	999999.88
10	4.19	1000000	2.85E+06
Total	116.92	0.01	2.85E+06

This table shows the distribution of investors in the sample, across the different wealth categories that we consider in our regression specifications. Column 2 reports the number of investors in each category, in millions. Columns 3 and 4 report the corresponding minimum and maximum account balance, respectively.

Appendix 3: Descriptive statistics for gains and loses

Figure A1 plots the sample average of monthly account gains, computed from equation 23, with the price at the start of the month as the reference price. The gains are weighted by account balance.

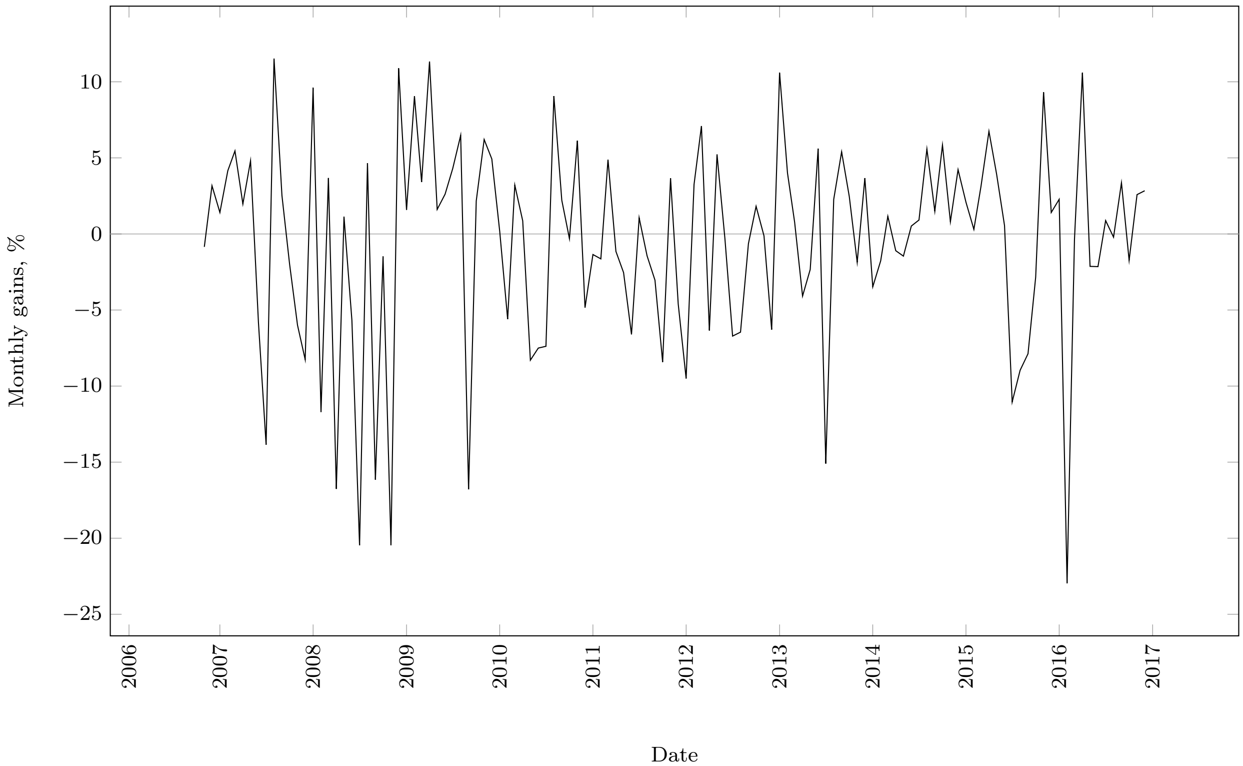


Figure A1: Average monthly account gains and losses

Appendix 4: Baseline regressions for risky share

Table A3: Results for baseline regression for $\Delta\omega$

Δr_t	-0.0979***		-0.117***	
	(0.00252)		(0.00451)	
ε_t^r		-0.140***		-0.156***
		(0.00258)		(0.00460)
$ln\Delta W^p$	-0.111***	-0.112***	-0.119***	-0.120***
	(0.0280)	(0.0280)	(0.0283)	(0.0283)
Account FE	YES	YES	NO	NO
Age Dummies	NO	NO	YES	YES
Wealth dummies	YES	YES	YES	YES
Observations	116,178,891	116,501,010	41,658,032	41,752,048
Adjusted R^2	-0.007	-0.007	0.003	0.003

robust account-clustered or time-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from our baseline regressions when the dependent variable is the change in risky share (equation 11). The specification in columns 2 and 4 is $\Delta\omega_{j,t+1} = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ (where Δr_t is the change in interest rate), while columns 3 and 5 report results for $\Delta\omega_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). $ln\Delta W^p$ represents the passive change in wealth, and all specifications include dummies for 10 different age groups. The first two regressions include account-level fixed effects while the other two include fixed effects for age. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

Appendix 5: Baseline regression estimated with data from 2009 to 2014

Table A4: Results for baseline regression using the data from 2009 to 2014

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr	-0.0293***		-0.107***		0.0206***	
	(0.00159)		(0.00324)		(0.00282)	
ε_t^r		-0.104***		-0.358***		0.302***
		(0.00167)		(0.00343)		(0.00306)
$ln\Delta W^p$	-0.0872***	-0.0872***	-0.223***	-0.223***	-0.0675**	-0.0675**
	(0.0150)	(0.0150)	(0.0274)	(0.0276)	(0.0286)	(0.0287)
Account FE	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	70,406,551	70,406,551	70,406,551	70,406,551	70,406,551	70,406,551
Adjusted R^2	0.002	0.002	0.017	0.018	0.055	0.056

robust account-clustered or time-clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from estimations with account-level fixed effects using the data from January 2009 to December 2014 only.The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y_{jt} denote each of the three the dependent variables, the regression specifications are $y_{j,t+1} = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

Appendix 6: Baseline regressions conditional on non-zero dependent variable

Table A5: Regression results for baseline specification with account fixed effects conditional on non-zero dependent variable

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.104***		-0.581***		0.680***	
	(0.00291)		(0.00847)		(0.00646)	
ε_t^r		-0.164***		-0.525***		0.655***
		(0.00303)		(0.00898)		(0.00686)
$ln\Delta W^p$	-0.108***	-0.109***	-0.422***	-0.421**	-0.0860***	-0.0858**
	(0.0220)	(0.0219)	(0.0531)	(0.0531)	(0.0421)	(0.0422)
Account FE	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	64,321,276	64,502,569	47,096,460	47,247,022	52,540,448	52,701,019
Adjusted R^2	0.013	0.013	0.041	0.041	0.101	0.100

robust account-clustered or time-clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from estimations with account-level fixed effects and conditional on non-zero dependent variable change. The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y^c_{jt} denote each of the three the dependent variables (conditional), the regression specifications are $y^c_{j,t+1} = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y^c_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

Table A6: Regression results for baseline specification with age dummies conditional on non-zero dependent variable

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.0740***		-0.398***		0.446***	
	(0.00441)		(0.0123)		(0.00982)	
ε_t^r		-0.117***		-0.355***		0.401***
		(0.00456)		(0.0129)		(0.0103)
$ln\Delta W^p$	-0.0900***	-0.0901***	-0.345***	-0.345***	-0.145***	-0.145***
	(0.0213)	(0.0213)	(0.0469)	(0.0470)	(0.0327)	(0.0327)
Age dummies	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	26,384,926	26,444,835	20,310,007	20,361,261	22,459,562	22,513,626
Adjusted R^2	0.007	0.007	0.022	0.022	0.035	0.035

robust account-clustered or time-clustered standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from our estimations with age dummies and conditional on non-zero dependent variable change. The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y_{jt}^c denote each of the three the dependent variables (conditional), the regression specifications are $y_{j,t+1}^c = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y_{j,t+1}^c = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.

Appendix 7: Regressions with gains and losses, conditional on non-zero dependent variable

Table A7: Results for regression controlling for past gains/losses (monthly) with account fixed effects and conditional on non-zero dependent variable

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta r_t \times \mathbf{1}\{\text{Gain} < 0\}$	-0.325***		-1.093***		1.024***	
	(0.00424)		(0.0126)		(0.00950)	
$\Delta r_t \times \mathbf{1}\{\text{Gain} > 0\}$	0.124***		-0.109***		0.314***	
	(0.00384)		(0.0112)		(0.00881)	
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\}$		-0.372***		-1.037***		1.064***
		(0.00431)		(0.0130)		(0.00971)
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\}$		0.0686***		-0.0114		0.183***
		(0.00421)		(0.0123)		(0.00964)
$ln\Delta W^p$	-0.108***	-0.108***	-0.422***	-0.421***	-0.0861**	-0.0864**
	(0.0220)	(0.0220)	(0.0530)	(0.0530)	(0.0423)	(0.0424)
Account FE	YES	YES	YES	YES	YES	YES
Wealth dummies	YES	YES	YES	YES	YES	YES
Observations	64,321,276	64,502,569	47,096,460	47,247,022	52,540,448	52,701,019
Adjusted R^2	0.013	0.013	0.041	0.041	0.101	0.100

robust account-clustered or time-clustered standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the results from our regression estimations including interactions of interest rate change with gains and losses dummy and conditional on non-zero dependent variable. The three dependent variables are the active change in risky share, net equity flows, and withdrawal rates. Letting y^c_{jt} denote each of the three the dependent variables (conditional), the regression specifications are $y^c_{j,t+1} = \alpha + \beta_1 \Delta r_t \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta r_t \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t is the change in interest rate), and $y^c_{j,t+1} = \alpha + \beta_1 \varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta\varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). Gain < 0 (Gain > 0) is a dummy equal to one if account experiences losses (gains) where account performace is computed from equation 23, with the price at the start of the month as the reference price. The vector X_{jt} includes the passive change in wealth ($ln\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $ln\Delta W^p$.