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Reaching for yield: Evidence from households[☆]

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ABSTRACT

The literature has documented "reaching for yield"—the phenomenon of investing more in risky assets when interest rates drop—among institutional investors. We analyze detailed transaction data from a large brokerage firm to provide direct field evidence that individual investors also exhibit this behavior. 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 observe and discuss the phenomenon of "reverse reaching for yield."

1. Introduction

The previous decade has witnessed an unprecedented decline in interest rates, followed by a recent strong reversal. The prolonged regime of low interest rates has prompted an important debate on whether it induced investors to take on more risk and, as a result, stimulated higher stock market valuations. There is indeed growing evidence that movements in interest rates reshape portfolio decisions for both intermediaries and institutional investors, including banks, mutual funds, pension funds, and insurance companies (Chodorow-Reich, 2014; Becker and Ivashina, 2015; Ioannidou et al., 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018; Ioannidou et al., 2022; Begenau et al., 2024). In particular, these investors tend to increase their exposure to risky assets when the real interest rate drops, a phenomenon sometimes labeled "reaching for yield". Explanations based on institutional frictions and agency issues have been proposed. 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, would similarly reallocate their portfolios in response to interest rate movement. There is experimental evidence that, in a lab setting—in which most institutional frictions are absent—individuals still 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, using detailed transaction data of almost two million Chinese investors over an 11-year period, we present direct field evidence of reaching for yield amongst retail investors. We document how retail investors both rebalance their portfolios within their brokerage accounts and move money in and out of these accounts in response to changes in the prevailing interest rate. We further exploit our data to test different theories of reaching for yield by examining the heterogeneity in investors' responses.

We start by discussing how existing theories of portfolio choice can generate reaching for yield. In the classic Merton portfolio choice model (Merton, 1969) portfolios should respond to interest rate movement unless investors expect the raw equity return to change one-for-one with the riskless rate. This one-for-one relationship is a potentially strong assumption to make about household expectations,

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even from a rational perspective, and empirical evidence on this relationship has been mixed. For example, Campbell and Yogo (2006) and Ang and Bekaert (2007) find that interest rates negatively predict future expected returns over the next month to next quarter. Focusing on monetary policy surprises, Bernanke and Kuttner (2005) show that positive interest rate surprises lead to a reduction in equity excess returns in the short run but an increase over the longer run.[1]

An extended model of portfolio choice with labor income (Merton, 1971) produces an additional prediction: reaching for yield should be more pronounced among younger and less-wealthy households. 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 were used to the previous high rates would feel like they are losing money. This would encourage more risk-taking and result in "reaching for yield". Moreover, prospect theory suggests that reaching for yield should be more (less) pronounced when investors are trading at a loss (gain) since, when the current interest rate drops, it moves the investor further away from (closer to) the break-even point, thus reducing (increasing) their risk aversion.

In our empirical analysis we construct three measures of portfolio reallocation. As discussed in the literature (e.g., Calvet et al., 2009), the change in the risky share does not fully reflect portfolio reoptimization since it is also a function of return realizations. Therefore, our first measure is the *active* change in the risky share, computed as the difference between the actual risky share and the counterfactual risky share to be observed if the investor did not trade (e.g., Calvet et al., 2009). The second measure we consider is the ratio of total net equity flows to total account balance.

While the first two measures focus on portfolio rebalancing within the brokerage account, the third captures flows into and out of the account. When interest rates change, investors may reallocate money between their brokerage account and alternatives such as bank accounts and money market mutual funds. To capture such behaviors, we compute net withdrawals as a percentage of the total account balance.

Our three measures examine both trading *within* the brokerage account and trading *into and out of* the account. Our analysis is therefore robust to the additional consideration of the potential impact of interest rate changes on investor expenditures requirements. Consider, for example, that following an interest rate increase, investors are facing higher expenditure requirements; for example, due to higher mortgage payments.[2] This can force them to increase their withdrawals from the brokerage account and could create a mechanical relationship between interest rate changes and our third measure. However, there is no mechanical impact on asset allocation within the account, captured by the first two measures.

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, making it an ideal period for our study. While different interest rates are available to retail investors, arguably the most relevant for household portfolio decisions is the Shanghai Interbank Offered Rate (SHIBOR)—the rate offered by many wealth management products.

It is important to clarify that we are studying how investors respond not to interest rate *shocks* (namely monetary policy shocks), but to changes in interest rates, taking into account that such changes might reflect or respond to specific economic conditions. This approach is 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. Such studies do not try to isolate specific shocks to past returns. Likewise, we want to understand how investors respond to changes in interest rates in general, not just to changes in interest rates that are orthogonal to specific variables.[3] In extensions discussed below, we show that our results are robust to controls for expected returns and macroeconomic conditions, albeit the interpretation changes slightly. We also study responses to changes in the monetary policy rate only, for which the results are also robust and, if anything, economically larger.

Based on the previous discussion, our first measure of interest rate innovation is simply the change in interest rates over the period; we specifically call it an innovation rather than a shock, to clarify that important difference. As an alternative, we consider the residual from an AR(1) regression of interest rates. Likewise, this should not be interpreted as a shock. The goal here is to control, in a relatively simple way, for agents' interest rate expectations. Finally, we use changes in the *real* interest rate, finding even stronger results. Although these measures should not be interpreted as pure interest rate shocks, they are predetermined relative to investors' portfolio decisions, given the timing of our regressions. 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; that is, 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, the evidence supports reaching for yield. When interest rates increase, retail investors have a negative active change in their risky share and, on average, 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 to 36 basis points, as measured by the active risky share or net equity flows, respectively. In addition, we observe a 14.5–37.5-basis-points increase, depending on the interest variable considered, in funds transferred out of the brokerage account (likely to other money market mutual funds). Remarkably, these portfolio elasticities are close to those found in Giglio et al. (2021), which studies 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 how this behavior differs in the cross-section of individuals. In particular, we focus on the dimensions of heterogeneity implied by different theoretical channels; namely, wealth (proxied by account size), age, and past gains and losses. Consistent with the portfolio-choice model with riskless labor income (e.g., Merton, 1971), we find that less-wealthy investors are substantially more likely to reach for yield. Those in the bottom decile of the wealth distribution rebalance their portfolios up to three times more than those in the third decile, and up to seven times more than those in the sixth decile, depending on the specific portfolio rebalancing measure that we consider. The wealthiest are even less responsive to interest rate changes. For most measures of portfolio rebalancing, they have essentially a zero response, implying that the average effect documented above for the investor population is fully driven by those with medium and low account balances.

We also find age effects consistent with the predictions of life-cycle models in which labor income is a close substitute for bonds (e.g., Cocco et al., 2005): young investors, who have a higher ratio of human capital

[1] Recent work by Nagel and Xu (2024) finds that the stock market response to these shocks is mostly driven by changes in the default-free term structure of yields, not by changes in the equity premium.

[2] As discussed later in the paper, the institutional setting in China makes this scenario less relevant. Nonetheless, there still could be an increase in other interest expenses or other living costs.

[3] In the same spirit, the forecasting regressions in Campbell and Yogo (2006) and Ang and Bekaert (2007) study the unconditional relationship between interest rates and the equity premium, as opposed to a relationship conditional on holding other variables constant.

to financial wealth, are more likely to reach for yield. The differences across age deciles are economically large and similar to those obtained when studying the impact of wealth.

Interestingly, our cross-sectional results also show that both wealthier and older individuals can sometimes engage in "reverse reaching for yield" by increasing their allocation to risky assets when interest rates rise. We discuss how this behavior is a possible outcome of a Merton 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.[4]

We also find evidence supporting prospect theory as an explanation for "reaching for yield". In particular, we test whether investors trading at a loss exhibit stronger tendencies to reach 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 experiencing losses. This result is robust to the two measures of interest rate innovation we consider and to all three measures of portfolio rebalancing activities.

Importantly, our conclusions are robust to the inclusion of controls for proxies of future expected returns, such as the lagged dividend yield, past stock market returns, and past returns on the investors' own portfolios, and for macroeconomic conditions such as lagged GDP and consumption growth, inflation and house price growth, and exchange rate fluctuations. Consistent with the hypothesis that reaching for yield is partially driven by revisions in expectations of the equity premium, these additional results of "reaching for yield" are smaller in magnitude. However, the fact that, in virtually all regressions, the coefficients on interest rates remain both economically important and statistically significant suggests that the other channels we examine (wealth, human capital, and prospect theory) are also at work.

Having studied portfolio rebalancing across asset classes, we explore whether investors reallocate their portfolio of risky assets in response to *changes* in interest rates. More precisely, we consider whether investors either reinforce or partially offset the previously documented reaching for yield behavior by increasing or decreasing their risk-taking within their risky asset portfolios. We explore this possibility by constructing an average-weighted beta for each investor in each month and considering the change in this beta as our dependent variable. Under the Merton model (Merton, 1969), we would not expect to find any effect unless high- and low-beta assets respond differently to changes in interest rates. Consistent with this, although we find a statistically significant coefficient, its economic magnitude is negligible.

Many papers have documented the phenomenon of "reaching for yield" and studied its underlying mechanisms (e.g., Chodorow-Reich, 2014; Becker and Ivashina, 2015; Ioannidou et al., 2015; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018; Lian et al., 2019). The key innovation of our paper is to document retail investors reaching for yield. We not only document this phenomenon in a field setting, but also examine competing theories that can generate this behavior and find support for both models of portfolio choice with riskless labor income and prospect theory. Concurrent work by Agarwal et al. (2023) studies consumption responses and portfolio rebalancing in response to changes in monetary policy rates.[5] Korevaar (2023) and Boddin et al. (2024) study reaching for yield in the housing market.

The rest of the paper is organized as follows. In Section 2, we discuss theories that can explain reaching for yield by retail investors. In Section 3, we present our data and methodology. Section 4 contains our baseline empirical results. In Section 5, we study heterogeneity in behavior across investors and relate these results to the theoretical channels discussed in Section 2. We conclude in Section 6.

2. Theories

In this section, we study the potential explanations for reaching for yield behavior by retail investors. Existing theories of reaching for yield apply to different types of institutional investors, resulting from specific institutional or regulatory frictions that they face (see Chodorow-Reich, 2014; Hau and Lai, 2016; Di Maggio and Kacperczyk, 2017; Drechsler et al., 2018; Acharya and Naqvi, 2019; Barbu et al., 2021). In general, these models do not make predictions about reaching for yield behavior for households. One exception is Campbell and Sigalov (2022). They show that reaching for yield can result from imposing a sustainable spending constraint to an otherwise standard Merton model. Their theory mostly applies to endowments and sovereign wealth funds, but it can also characterize trusts or households with a consumption commitment.[6]

2.1. Alternative theories of reaching for yield

In this subsection, we first discuss existing theories of reaching for yield behavior by retail investors. Later we discuss several testable implications generated by these theories.

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 risk-free rate, σ is the volatility of stock returns, and γ is the coefficient of relative risk aversion.

From Eq. (1) we see that changes in the risk-free rate can affect the investor's portfolio share under three conditions: first, when the expected return on stocks (μ) does not move one-for-one with r; second and third, when interest rate movement is correlated with either the expected volatility of stock returns (σ) or risk aversion (γ).

For simplicity, we first consider the case in which σ and γ are independent of r.[7] The impact of changes in the riskless rate on the risky share is given by

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

The derivative $\frac{\partial(\mu-r)}{\partial r}$ 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, if μ responds less (more) than one-for-one with interest rates: the risky asset becomes a more (less) appealing investment when the riskless rate goes down, because its relative yield, measured by $(\mu - r)$, has increased. Only in the limiting case of one-for-one response will the risky share remain unchanged.

Only under special cases of relatively frictionless economies would the expected stock return move exactly one-for-one with the risk-free

[4] 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.

[5] They only observe flows to and from the brokerage account, while we also have the actual portfolios holdings and total balance within the account. On the other hand, their data allow them to study consumption responses, which we do not observe.

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

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

rate.[8] Empirically, the evidence is mixed. For instance, Bernanke and Kuttner (2005) 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.[9] Campbell and Yogo (2006) find that higher interest rates (three-month T-bills) negatively predict excess returns at both the monthly and quarterly horizons.[10] Likewise, Ang and Bekaert (2007) find that "for the post-Treasury Accord 1952–2001 sample, a 1% increase in the annualized short rate decreases the equity premium by about 2.16%". Theoretically, models of countercyclical risk and risk aversion would similarly imply a negative relationship.

Importantly, the relevant return expectations to include in Eq. (1) are the subjective expectations of each investor, which can easily deviate from fully rational expectations. Assuming that those move exactly one-for-one with interest rates is a particularly strong 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 movement. The model, however, does not provide much guidance on the cross-sectional variation in reaching for yield among investors.[11] In the next sections, we discuss models that can generate heterogeneous responses to interest rates.

We first extend the model to include riskless labor income, while maintaining the assumption of 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 (Y). The Merton model assumes the limit case of riskless labor income. Viceira (2001) and Cocco et al. (2005) show that this result extends to a model with risky labor income, as long as human capital remains a closer substitute for bonds than for stocks.

In this model, the derivative of the risky share with respect to the riskless rate, assuming again that both σ and γ are independent of r, is[12]

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

This is higher than the response obtained in the model without labor income in Eq. (2), particularly if the ratio of the present value of labor income to financial wealth is high. For an investor with a ratio of present value of labor income to financial wealth of three, for example, the portfolio share response is four 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, for example, 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). Under such preferences, fluctuations in asset prices, such as those induced by interest rate movement, have a direct impact on investors' risk aversion and consequently on 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 Eq. (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. Since risk aversion increases with the habit level, the optimal risky share falls when the habit increases.

In this context, suppose that a drop in interest rates raises asset prices. This would increase investors' financial wealth, resulting in lower risk aversion and a lower risky share.[13] Therefore, when investors have DRRA 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 Eq. (3), we discuss both channels simultaneously in Section 2.2 when presenting the different testable hypothesis.

2.1.4. Prospect theory

Under prospect theory, investors evaluate the current interest rate by comparing it to a reference level, such as the average historical level. When the current interest rate is below the historical level, investors feel that they are in the loss region; they become 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 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.

At the same time, prospect theory, especially the loss-aversion component, suggests that the way investors react to interest rate movement will also depend on whether they are 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, 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 in the gain region. Then a drop in interest rates will reduce the gain, moving this investor closer to the kink, increasing effective risk aversion. This makes it less likely that the investor will invest in risky assets. By contrast, if an investor is in the loss region, then the same drop in interest rates will increase 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 currently in the loss region are more likely to "reach for yield".

[8] 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.

[9] The result reverts at longer horizons but in our empirical specifications we consider a monthly frequency.

[10] In Appendix G, we repeat the analysis in Campbell and Yogo (2006) for the Chinese stock market and obtain similar conclusions.

[11] 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.

[12] 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.

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

2.2. Testable predictions

2.2.1. Age and wealth levels

We now discuss the testable implications that will guide our empirical analysis. A first clear prediction from Eq. (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.[14]

Hypothesis 1. $|\partial\alpha/\partial r|$ is a decreasing function of W

The derivation is provided in Appendix A.

Considering Eq. (4) in a life-cycle context yields a second testable implication. In a life-cycle model (e.g., Cocco et al., 2005), young agents have substantial wealth in the form of their future labor income, but have accumulated only limited financial wealth. As they get older and approach retirement, they accumulate more wealth, and the present value of their future labor income is naturally decreasing.[15] Therefore, younger investors have a higher ratio of human capital to financial wealth and, according to Eq. (4), they should respond more to changes in interest rates.

Hypothesis 2. $|\partial\alpha/\partial r|$ is a decreasing function of age.

In our empirical analysis we will directly test both hypotheses.

2.2.2. Changes in wealth

Eq. (4) was obtained under the assumption that μ and σ do not respond to changes in interest rates. Another implicit assumption is that current wealth remains unchanged. However, when interest rates increase, bond prices should decrease, lowering the wealth of investors with bond portfolios. Stock holdings may also be affected. In fact, under the assumption that the equity premium does not change with interest rates, equity prices should also decrease as the present-discount value of dividends is now smaller.[16] 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 offsetting effect in expected dividends, then equity prices should also change in response to interest rate movement.

If we take this effect into account then Eq. (4) is replaced with[17]

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

Intuitively, if an increase in interest rates decreases wealth, then the ratio of human capital to financial wealth increases. This increase in the investor's implicit bond holdings leads to a higher optimal risky share. Therefore this second term adds to the impact of the first term in the equation, thus increasing the investor's response to change in the interest rate.[18]

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

Hypothesis 3. $\partial\alpha/\partial r$ is 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 Eq. (5), we have

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

Eq. (8) shows that, if increases in interest rates reduce investor wealth, then this is another channel that can generate reaching for yield. In this 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 a prediction exactly opposite to that of the riskless labor income model with CRRA preferences:[19]

Hypothesis 4. $\partial\alpha/\partial r$ is an increasing function of $\partial W/\partial r$ (DRRA channel).

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

Hypothesis 3b. $\Delta\alpha$ is a decreasing function of ΔW (Human capital channel).

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

Even though Hypotheses 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 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 reach for yield when they are already in the loss region. Conversely, if an investor is at a gain and the interest rate has just dropped, this would bring the investor closer to the origin—the point of 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 among those at a gain.

[14] 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.

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

[16] This is 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 next.

[17] A further implicit assumption in deriving Eq. (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 affect 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 negatively correlated with interest rates should change their portfolios more in response to changes in interest rates. Unfortunately, our data does not include individual income and therefore we cannot estimate $\partial PV(Y)/\partial r$ for each investor. Therefore we leave this as an untested hypothesis and only mention it for completeness.

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

[19] 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

As discussed, under the Merton model we can observe either reaching for yield or reverse reaching for yield, depending on whether, following changes in the interest rate, investors adjust their expected stock return by less or more than one-for-one.

One interesting implication of Eqs. (6) and (7) is that, under certain conditions, the optimal portfolio response in the model with labor income also leads to reverse reaching for yield. From Eq. (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 substitute for bonds, this implies a higher optimal risky share in financial wealth, potentially offsetting the other channels. From Eq. (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, in both Equations, the second term is not very large: it is divided by wealth in Eq. (6) and by the ratio of human capital to wealth squared in Eq. (7). However, if the first term is also particularly small, which can 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". This is naturally also more likely to happen 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 changes in interest rates.

3.1. Data

Our dataset includes account-level transaction data from a large national brokerage firm in China.[20] The company has branches in almost all of China's provincial districts and is a market leader in several regions. Moreover, it provides comprehensive capital market services, making all exchange-listed securities available to its clients. 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 that used by Odean (1998), for example. Each observation specifies the account, date, time, price, quantity, and security code. Before 2015, we know that this is the only brokerage account of a person, following the "one account per investor" regulation.[21] 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, including their age and education and for how long the account has been opened.

A few limitations of the data are worth noting. First, we do not observe holdings of mutual funds (except ETFs and other exchange-traded assets). However, ownership of mutual funds was quite small in the Chinese markets during the sample period (An et al., 2022). Second, the cash balance of the account is updated only whenever an investor makes a transaction. Therefore, if an investor deposits or withdraws cash but does not trade, the cash balance will not be updated. This concern, however, is largely mitigated by the fact that average Chinese retail investors trade a lot, with a monthly turnover (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' holdings of risk-free assets. We use withdrawals and additions to the brokerage account to infer the potential reallocation of funds to this additional safe asset category, as discussed below.

[20] This is the same data used in Gao et al. (2024) and Liao et al. (2022).

[21] The rule was lifted in April 2015 to allow investors to have up to 20 accounts at different brokerage firms. However, in 2016, the regulator has tightened the rule again to allow three accounts per investor.

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, then sum over all stocks:

$$A_{jt} = \sum_i Q^i_{jt} P^i_t, \tag{10}$$

where Q is the number of shares and P is the share price. The change in the risky share $\Delta\omega_{jt}$ is then simply the difference between the 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 Appendix D, 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 Eq. (11) is that it also reflects movements in asset prices. Therefore, it can take on non-zero values, even in the absence of rebalancing. To isolate the effect of an investor's active rebalancing decisions from the effect of changes in stock prices, we follow Calvet et al. (2009) and compute the active 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—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, as defined in the previous section.

As the right-hand–side of Eq. (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.

[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.

3.2.3. Net flow to equity

Our second measure 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, allowing us to calculate these flows. We can therefore compute 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:

$$Buys_{jt} = \sum_{d\in t}\sum_{i} B_j^{id} P^{id}; \tag{15}$$

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

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

The net flow into equity for 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. 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 the brokerage account. 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. 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. Because Yu'ebao has become the largest money market mutual fund, we use the SHIBOR as our measure of interest rates.[23] Fig. 1 shows the time-series plot of the (annualized) 1-month SHIBOR from October 2006 to December 2016.

Throughout our sample period, there is significant variation in the SHIBOR. There was a sharp decline—from around 3.5% to around 1%—in late 2008 following the Global Financial Crisis and the stock market crash. Once the economy began to recover, the SHIBOR steadily rose and peaked around 7%. Then, in 2015, following yet 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%. Such substantial variation in SHIBOR makes our period particularly well suited for studying the impact of interest rate changes on portfolio allocation.

3.3.2. Interest rate innovation

In our regressions we consider two measures of interest rate movement. As discussed, we are not interested in capturing interest rate shocks (e.g., monetary policy shocks). Our goal is to study how investors 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 discussed in Section 2.

Therefore, the first measure of interest rate innovation 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:

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

Fig. 2 plots the two measures of interest rate innovation over the sample period.

We can see these two series are very highly correlated and 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 innovation, we include other variables in our regressions, either as controls or to test our hypothesis. 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

Hypothesis 2 states that reaching for yield should be a decreasing function of age. Our data include age information for roughly a half the sample and we consider all investors aged from 30 to 80 in our analysis. We define 10 age groups: the first group is ages 30–35 and the others have a five-year step (36–40, 41–45, etc.). Table B.11 in Appendix B reports the distribution of investors across those age groups. 72.7% of our sample are in the five group between 36 and 60; the most populated is 46–50 (17.8% of sample). The 30–35 group comprises 9.4% of the sample while only 18% are older than 61.

3.4.2. Wealth

Hypothesis 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; we consider 10 wealth groups. Since wealth has a very right-skewed distribution, if we considered equal-sized deciles, the first would capture very limited variation, particularly when compared to the tenth. We instead set specific break points for each group, such that each of them captures a different segment of the wealth distribution and none is particularly small. Our break points (all in CNY) are 10K, 25K, 50K, 100K, 200K, 300K, 400K, 500K, and 1M.

[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.

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

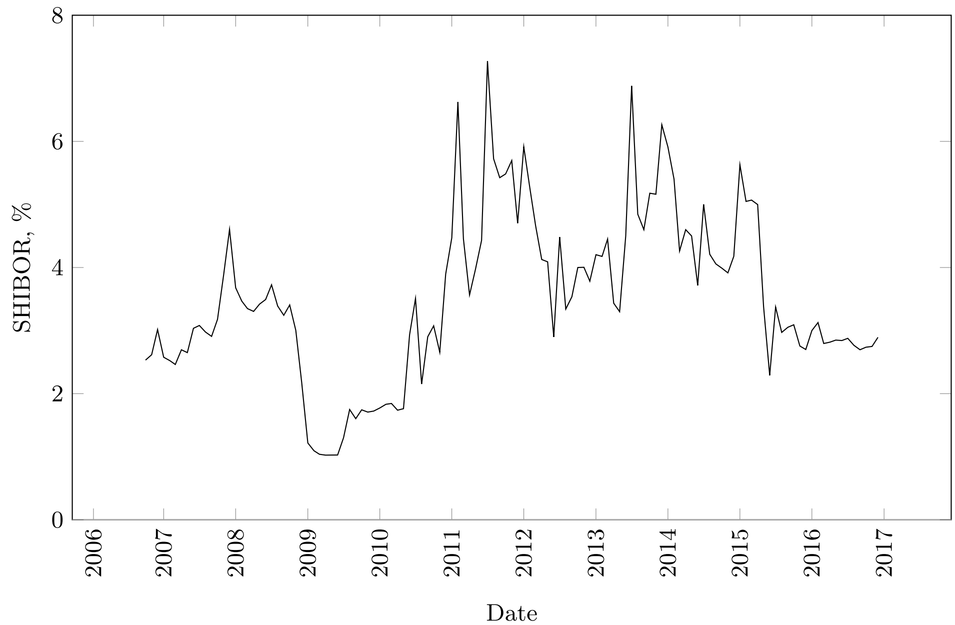

Fig. 1. Historical 1-month SHIBOR. Fig. 1 shows the time-series plot of the (annualized) 1-month SHIBOR over the period from October 2006 to December 2016.

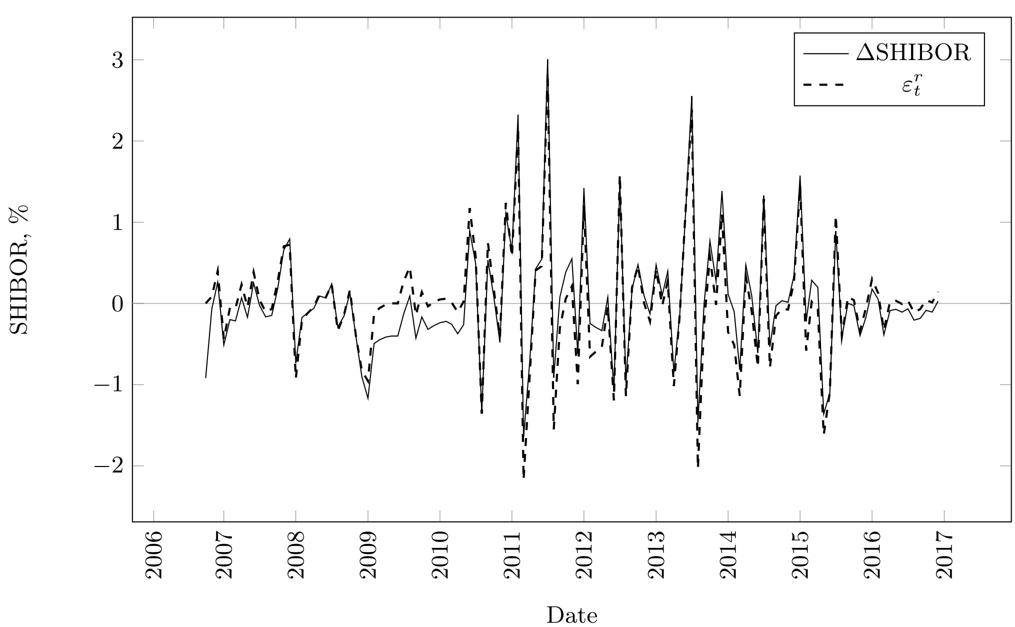

Fig. 2. Interest rate innovation.
Fig. 2 shows the time-series plot of two measures of interest rate innovation. The first is the simple change in interest rate (ΔSHIBOR). To obtain the second measure (ε_t^r), we fit an AR(1) process to the interest rate and use the error term as the innovation: $r_t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

We assign investors to a wealth group each month, based on current account value, and repeat the assignment procedure for every cross-section in the data. Therefore, an investor can switch wealth groups over time. Table B.12 in Appendix B provides the full distribution of investors across wealth groups. Around 20% have an account balance of less than 10K CNY, 18% have between 10K and 25K; 87% have less than 200K.

3.4.3. Passive change in wealth

As highlighted by Hypotheses 3b and 4b, another important variable implied by both models with riskless labor income and models with DRRA preferences is the change in investor's wealth. We obtain our measure of change in wealth induced by financial markets in three steps. First, for all assets that each investor holds at the start of the month, we compute the 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—that is has not executed any trades or moved any funds into our out of the account:

$$\Delta W_{jt}^p = A_{jt-1}^p - A_{jt-1} = \sum_i Q_{jt-1}^i (P_t^i - P_{t-1}^i). \tag{21}$$

Finally, we scale the passive change in wealth by the account balance in the previous month and convert it into a percentage value by taking the log:

$$\log \Delta W_{jt}^{p} = \ln\left(1 + \frac{A_{jt-1}^{p} - A_{jt-1}}{A_{jt-1} + C_{jt-1}}\right). \tag{22}$$

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. 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, so that $(P_t^i - \bar{P}_{jt}^i)$ 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 equals 1 if $Gains_{jt-1}$ is positive and 0 otherwise.

Since we do not observe the investors' actual reference point, 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 are reset every month. This assumption is particularly well suited for Chinese retail investors, whose average monthly turnover is around 100%. Fig. A.1 in Appendix C plots the series of monthly gains, while Column 8 in Table 1 provides detailed descriptive statistics.

3.4.5. Aggregate variables

Our specifications include aggregate variables as additional controls; namely, aggregate stock returns, the dividend-price ratio, and a set of macroeconomic indicators detailed below. We also consider the monetary policy rate as an alternative to our interest rate variable. Specifically, to control for macroeconomic conditions, we use the quarterly GDP growth series (seasonally adjusted quarterly GDP by expenditure series, retrieved from the National Bureau of Statistics of China), the monthly change in the consumer price index (seasonally adjusted as in Higgins et al. (2016)), the monthly consumption growth (seasonally adjusted monthly series of retail sales of consumer goods from Higgins et al. (2016)), the monthly percent change in the exchange rate with respect to the dollar (based on not seasonally adjusted monthly averages of the daily data of Chinese Yuan Renminbi to U.S. Dollar spot exchange rate series retrieved from FRED, Federal Reserve Bank of St. Louis), and the quarterly house price growth (the quarterly not seasonally adjusted index is provided by Bank for International Settlements and it is based on the prices of new dwellings in 70 cities in China).

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.[25] 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). For comparison, the average annual per-capita disposable income of Chinese households in 2016 (the latest year in our sample) was 23K RMB and was significantly lower in the subsample covering the first few years of trading. Therefore, the median balance in the sample corresponds to about two years' worth of household income.

The average risky share in the sample is 75%. The average *active* equity change in Eq. (14) is around 0.98%, indicating that investors' active trading has actually increased their equity exposure over the sample. Consistent with this, the mean monthly net equity flow as a percentage of account balance in Eq. (18) is 1.8%.[26] In any given month, there is both a significant fraction of investors who trade and a significant fraction who do not, with the 25th and 75th percentiles of the active risky share change being zero.

The mean withdrawal rate in Eq. (19) over the sample is −3.54%, revealing that investors are, on average, transferring more money into their brokerage accounts than they are taking out. As with the active risky share change and the net equity flows measure, here too we observe a nontrivial percentage of zeros. In any given month, many investors neither invest new money into their account nor withdraw any.

The mean passive change in wealth as a percentage of the account value (see Eq. (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 the previous month (see Eq. (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%).

4. Reaching for yield

4.1. Baseline results

As previously discussed, our empirical analysis considers three measures of household portfolio rebalancing: active change in risky share (ω^a), net equity flow ($NetFlow^{pp}$), and (net) withdrawals ($Withdr^{pp}$). Our baseline specifications 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 Eq. (20)). The regressions also include additional controls (denoted by X) and account-level fixed effects (denoted by f). More precisely, we estimate the following Equations:

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

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

where j is each individual investor and t is 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 1, 2010, to January 31, 2010, on the change in interest rates from December 1, 2009, to December 31, 2009. All other explanatory variables that capture changes are also measured over the same period (December 1, 2009, to December 31, 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 1, 2010, in the previous example).

Crucially, we do not assume that changes in interest rate are exogenous to household behavior. In that respect we take the same

[25] Summary statistics for age and wealth are reported in Appendix B.

[26] The maximum and minimum values of net equity flows can exceed 100% and −100% depending on the amount of cash additions and/or capital gains.

Table 1
Descriptive statistics.

Stats (1)	Acc. balance (2)	ω, % (3)	ω^a, % (4)	$NetFlow^{pp}$, % (5)	$Withdr^{pp}$, % (6)	$\log \Delta W^p$, % (7)	$Gains^{pp}$, % (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 reports summary statistics for the data. 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 (Eq. (14)) respectively. In Column 5 and 6, we include our two other measures of portfolio rebalancing, respectively net equity flows (Eq. (18)) and withdrawal rates (Eq. (19)). In Column 7, we report the passive change in wealth (Eq. (22)). Finally in Column 8 we show account gains and losses (Eq. (23)). For each variable we provide the total number of account-month observations in millions (N), the mean, the standard deviation (SD), minimum and maximum values, key percentiles of the distribution, 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^r_t		−0.0911***		−0.363***		0.375***
		(0.00161)		(0.00338)		(0.00312)
$\log \Delta W^p$	−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; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
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 dependent variables, the regression specifications are $y_{j,t+1} = \alpha + \beta \Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for Columns 1, 3, and 5 (where Δr_t is the change in interest rate) and $y_{j,t+1} = \alpha + \beta \varepsilon^r_t + \gamma X_{jt} + u_{j,t+1}$ for Columns 2, 4, and 6 (where ε^r_t is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, Eq. (22)), account-level fixed effects, and dummy variables for 10 wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε^r_t and on time-clustered SEs for $\log \Delta W^p$.

approach as studies that test whether investors are momentum traders or contrarians or whether they exhibit a disposition effect. Such studies regress current trading behavior on past stock returns. Naturally those past movements in prices were determined by changes in investors' expectations of future dividends, in their risk assessments, or in their risk preferences. In the same spirit, our goal here is to understand investors' responses to changes in interest rates, with the full understanding that those changes have an impact on future economic conditions and/or can result from changes in expectations about those economic conditions. Later in Section 4.4, we will also consider regression specifications which include financial and macroeconomic variables as controls.

4.1.1. *Regressions with account-level fixed effects*

In Table 2, we report regressions in which the vector X includes the passive change in wealth ($\log \Delta W^p$, thus capturing Hypotheses 3b and 4b) and the dummies for current wealth (proxied by account balance).[27] The standard errors on the interest rate innovation 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.

Table 2 shows that, on average, retail investors reach for yield. This conclusion is reached under all three measures of rebalancing behavior that we consider, and for both measures of interest rate innovation.[28]

Focusing first on the trading behavior inside the brokerage account, we find that, following a one-percentage-point increase in the interest rate (SHIBOR), the average investor decreases her active risky share by 5 to 9 basis points, depending on the measure of interest rate innovation. Similarly, net equity flows decrease by 20 to 36 basis points. 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 basis points to 37.5 basis points, 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 nontrivial.

Withdrawals from the brokerage account could also be a response to higher expenditure requirements due to the increase in interest rates; for example, higher mortgage expenses. This, however, would not affect the two measures of portfolio rebalancing within the brokerage account. In fact, to the extent that investors are more likely to withdraw

[27] 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 1.

[28] Results for the simple change in risky share ($\Delta\omega$, Eq. (11)) are reported in Appendix D (Table D.13) and yield the same conclusions.

their cash balances and leave their investments unchanged, such withdrawals would actually mechanically increase their risky share within the account.[29]

The portfolio elasticities documented above are remarkably similar to those estimated in Giglio et al. (2021). They find that a one percentage-point increase in expected stock returns is associated with a 70-basis-point increase in equity share. Comparing our results with their elasticity requires making an assumption about how investors' expectations of future stock returns change when the interest changes. Suppose that, following a 1% increase in interest rates, investors expected that the stock return would increase by 50 basis points.[30] Then, our regressions imply an elasticity of the brokerage account portfolio to the expected return of between 10 to 72 basis points, depending on the measures of portfolio rebalancing and interest rate innovation. Additionally, we have portfolio rebalancing outside the account, as captured by account withdrawals. Our overall effect is therefore similar to the estimates obtained by Giglio et al. (2021). Furthermore, we later show that these average responses mask substantial heterogeneity across investors.

Motivated by Hypotheses 3b and 4b, we have also included the passive change in wealth ($\log \Delta W^p$, Eq. (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 investor's implicit bond holdings are now a smaller fraction of her portfolio, lowering the optimal risky share. The negative coefficient for $\log \Delta W^p$ in the first four regressions indicates that the human capital channel is the dominating effect here. This does not, however, rule out DRRA in preferences. Our coefficient can only estimate the net effect of the two channels. In fact, when we consider the effect on withdrawals, the coefficient is again negative. This result, however, is consistent with the DRRA channel dominating in this context, since for this left-hand–side variable the prediction is reversed.

Since our data include some periods of significant stock market movement ("bubbles and crashes"), in Appendix E we report results using data from January 2009 to December 2014 only, thus excluding those periods. The conclusions remain unchanged.

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 Eq. (2). Let us assume an investor with a 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 do not 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 Merton model with labor income (Eq. (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 nontrivial 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 those implied by our simple calibration exercise.

4.1.3. Regressions with age dummies

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

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; the coefficients are now slightly smaller than those in the previous regressions, but still strongly significant.

4.2. Reaching for yield within risky assets

In our baseline results, we consider portfolio reallocation between risky and riskless assets. In this section, we explore whether investors also reallocate their portfolios of risky assets in response to movements in the interest rate.

One possibility is that, when interest rates increase, investors decrease their risk taking further by reducing the beta of their risky investment. An alternative possibility is that agents (partially) compensate for the reduction in total risky investments by increasing their beta exposure. The Merton model, however, produces neither of those predictions. The multiple risky asset version of the (Merton, 1969) model yields the following equation for the optimal risky share:

$$\alpha = \frac{1}{\gamma}(\mu - r)\Sigma^{-1}, \tag{26}$$

where α is now a vector with the share of wealth invested on each individual risky asset, μ is the vector of expected returns on the different assets, r is a vector in which all elements are equal to the riskless rate, and Σ is the variance–covariance matrix of returns.

Eq. (26) defines the efficient portfolio—the tangency portfolio in a CAPM setting. Changes in the riskless rate will affect the allocation between riskless assets and the efficient portfolio, but will not change the optimal allocation among risky assets, unless those assets exhibit different levels of correlation with the interest rate.[33]

[29] Furthermore, as shown in Appendix F, surveys suggest that no more than 20% of stockholders have a mortgage. In China, mortgage rates are typically only fixed for two or five years, which means that some investors are exposed to interest rate risk. The rates are, however, only re-set once a year (in January). Therefore, we do not expect this to have a large impact on the regressions results, since our regression specification is based on monthly observations.

[30] This is halfway between the full increase which 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 larger.

[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 of −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 return on stocks to remain constant.

[33] More precisely, unless there is a change in the efficient portfolio. From Eq. (26), this will happen only if there is a differential impact on the expected returns of the different assets, or on the different terms in the variance–covariance matrix.

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)
$\log \Delta W^p$	−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; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
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 1, 3, and 5 (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 2, 4 and 6 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, Eq. (22)), age dummies, and dummy variables for 10 wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$.

Table 4
Regression results for change in account beta with account fixed effects.

	$\Delta\beta^{mkt}$	
	(1)	(2)
Δr_t	0.000432***	
	(0.0000166)	
ε_t^r		0.000577***
		(0.0000173)
$\log \Delta W^p$	−0.000570***	−0.000564***
	(0.000211)	(0.000212)
Account FE	YES	YES
Wealth dummies	YES	YES
Observations	98,977,533	99,255,059
Adjusted R^2	−0.008	−0.008

Robust clustered standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
This table reports the results from our estimations for the change in average value-weighted account β with account-level fixed effects. The dependent variable measures the risk within the portfolio of stocks and is calculated with respect to the SSE Index (β_{jt}^{mkt}, Eq. (27)). Letting y_{jt} denote the dependent variable, the regression specification is (as before) $y_{j,t+1} = \alpha + \beta \Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for Column 1 (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 Column 2 (where ε_t^r is residual from the AR(1) model for interest rate). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, Eq. (22)), account-level fixed effects and dummy variables for 10 wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$.

4.2.1. *Investor portfolio betas*

In order to investigate the possibility of risk-shifting within the portfolio of risky assets, we compute a (value-weighted) average beta for each investor. More precisely, we first compute, for each asset, its beta with respect to the Chinese market, proxied by the Shanghai Stock Exchange (SSE) Composite Index. We estimate betas on a 12-month rolling basis by regressing daily stock return on market excess return.

We then use the individual asset betas β_{it}^{mkt} to compute a weighted average beta for each investor β_{jt}^{mkt} in each month, with the weights given by the investor's portfolio holdings in that same month:

$$\beta_{jt}^{mkt} = \sum_i \frac{A_{jt}^i}{A_{jt}} \beta_{it}^{mkt}, \tag{27}$$

where, as before, j, i, and t denote an investor, a stock, and a month, respectively. A_{jt}^i is thus the value of stock i in period t and A_{jt} is the total value of equity of the portfolio, and the ratio of the two is the share of this stock in the investor's portfolio.

4.2.2. *Results*

We now replicate the previous regressions (Eqs. (24) and (25)) with the change in (value-weighted) beta as our left-hand–side variable. The results are reported in Table 4.

In both regressions, we find a positive and statistically significant coefficient, but their magnitude is negligible. A one-percentage-point increase in the interest rates leads to an increase in the average beta of the risky asset portfolio of less than 0.001.

These regressions answer the question of whether, when interest rates change, investors adjust the beta of their risky investment in order to either reinforce or compensate the portfolio rebalancing across asset classes. We conclude that, on average, neither of these is happening and the portfolio beta remains almost unchanged. As discussed, this is largely consistent with the predictions of the simple Merton model, under which we should observe a change in the composition of the risky portfolio only if changes in the interest rate are expected to have a differential impact on different risky assets. In particular, we should observe an increase or decrease in portfolio beta only if investors expected that high-and low-beta stocks would be differentially affected.

4.3. *Results with changes in real interest rate*

We have so far considered changes in the nominal interest rate as our main explanatory variable, consistent with the literature on "reaching for yield". However, in the simple Merton model (in Eq. (1)),

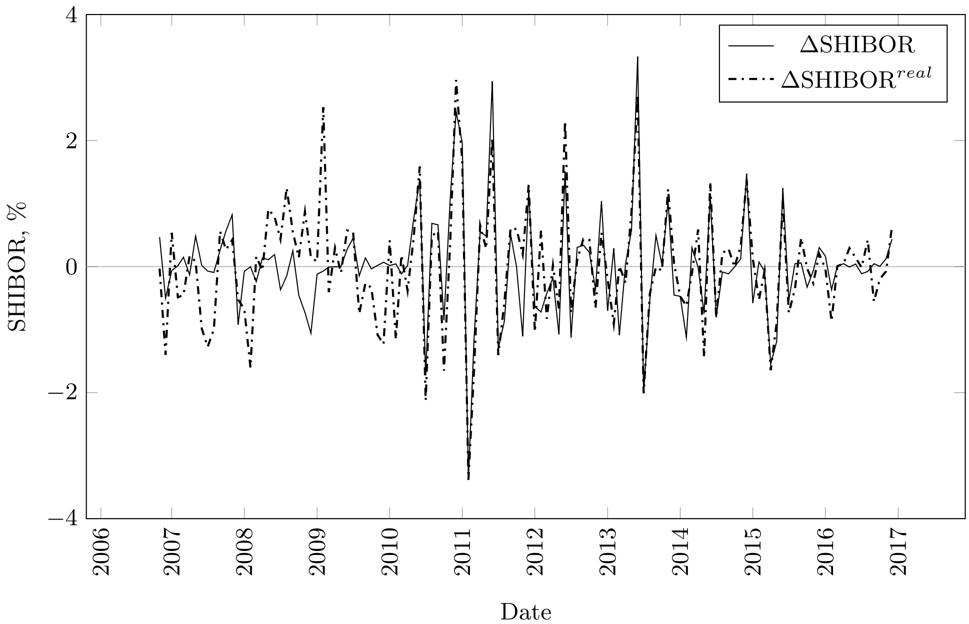

Fig. 3. Historical 1-month SHIBOR.
Fig. 3 plots the change in both the nominal (red) and real (blue) SHIBOR rates. Our inflation measure is computed using data for the Consumer Price Index in China from St. Louis FRED. We compute the growth rate over the previous year for each month to obtain the corresponding annual inflation rate. We obtain the real interest rate by subtracting the inflation rate from the SHIBOR rate.

the relevant moments are those referring to the real asset returns.[34] Therefore, in this section we repeat our previous analysis with changes in the real interest rate as our main explanatory variable.

4.3.1. Real interest rate

We construct the real SHIBOR rate by subtracting the corresponding inflation rate in China over the same period. Our measure of inflation is constructed from the Consumer Price Index in China obtained from St. Louis FRED. Fig. 3 plots changes in both the nominal and real SHIBOR rates over time.

Although the two series track each other very closely for most of the sample, there are some periods with noticeable differences, particularly in the first half of the sample.

4.3.2. Results

We now repeat our baseline regressions (Eqs. (24) and (25)) but with changes in the real rate as our main right-hand–side variable. The results are reported in Table 5.

Consistent with our previous results, we find evidence in favor of reaching for yield across all six specifications; that is, for all three measures of portfolio rebalancing and the two measures of interest rate change. Comparing the results in Table 5 with those in Table 2, the estimated coefficients are now larger (in absolute value) in all cases. Therefore, by considering changes in the real (as opposed to nominal) riskless rate, in line with the theory, we obtain stronger results.

4.4. Results with additional control variables

In this section, we extend the baseline regressions to include controls for subjective expected returns. The two sets of results—those without controlling for expected returns and these—have different implications for the determinants of reaching for yield. In the first set, we allow changes in interest rates to affect the optimal portfolio allocation by changing investors' beliefs about the equity risk premium. In the second set, to the extent that we can control for investor beliefs, we shut down the belief channel while allowing for other channels of reaching for yield.

In other words, if changes in interest rates affect optimal portfolios only through the belief channel and we fully control for these beliefs, then changes in interest rates should have no effect on portfolio decisions in the second specification. We also note that expectations of the equity premium may fluctuate for reasons other than changes in interest rates. If such fluctuations are correlated with changes in interest rates within our sample period, then the second specification has the advantage of controlling for that correlation. Ideally, we would like a middle ground, in which we control only for changes in expected returns which are not driven by the change in interest rate. Since that is not possible in our setting, we report and compare both set of results.

4.4.1. Proxies for subjective return expectations

In the US market, various predictors of excess equity returns have been proposed, including the dividend yield (e.g., Campbell and Shiller, 1988), the riskless rate (e.g., Campbell and Yogo, 2006), *cay* (e.g., Lettau and Ludvigson, 2001), and the volatility risk premium (e.g., Bollerslev et al., 2009). The riskless rate is the main variable of interest is our analysis. Computing the volatility risk premium requires implied volatility data, which is not available for the Chinese market during our sample period. For *cay*, to the best of our knowledge, no paper has constructed this variable for the Chinese market, possibly because high-quality data on consumption and wealth are hard to acquire. This leaves us with the dividend-price ratio.

We also explore past stock market returns as a potential measure of subjective beliefs about future returns, based on the mounting empirical evidence on return extrapolation (Greenwood and Shleifer, 2014; Da et al., 2021), which also holds true in the Chinese market (Liao et al., 2022). As a further alternative, we consider the return on the investor's own portfolio, in the spirit of the experience effect (Malmendier and Nagel, 2011). This is arguably a better proxy for investor expectations than the market return, if investors pay more attention to the returns on the assets they actually own. In addition, it is a more relevant measure

[34] If we write the Merton model in nominal terms, inflation drops out since it subtracts from both terms on the numerator. There is only a role for inflation if it correlates differently with the returns on the risky and riskless assets, in which case we obtain an additional hedging term in the portfolio rule.

Table 5
Regression results for baseline specification with account fixed effects and change in real interest rate.

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t^{real}	−0.177***		−0.639***		0.666***	
	(0.00148)		(0.00307)		(0.00277)	
ϵ_t^{real}		−0.175***		−0.759***		0.808***
		(0.00151)		(0.00317)		(0.00292)
$\log \Delta W^p$	−0.0669***	−0.0662***	−0.168***	−0.166***	−0.0563**	−0.0590**
	(0.0193)	(0.0192)	(0.0263)	(0.0261)	(0.0255)	(0.0255)
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 estimations using change in real interest rate with account-level fixed effects. 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 $y^c_{j,t+1} = \alpha + \beta\Delta r_t^{real} + \gamma X_{jt} + u_{j,t+1}$ for Columns 1, 3, and 5 (where Δr_t^{real} is the change in real interest rate) and $y^c_{j,t+1} = \alpha + \beta\epsilon_t^{real} + \gamma X_{jt} + u_{j,t+1}$ for Columns 2, 4, and 6 (where ϵ_t^{real} is residual from the AR(1) model for real interest rate). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, Eq. (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t^{real} and ϵ_t^{real} and on time-clustered SEs for $\log \Delta W^p$. To proxy the inflation level, we use the monthly data for Consumer Price Index in China from St. Louis FRED. We subtract the CPI from SHIBOR to get the real rate and obtain the change in SHIBOR and AR(1) residuals as explained in Section 3.3.2.

Table 6
Results for baseline regression with account fixed effects, controlling for market return and dividend yield.

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	−0.0151***		−0.0695***		−0.0291***	
	(0.00156)		(0.00323)		(0.00291)	
ϵ_t^r		−0.0276***		−0.0778***		−0.0118***
		(0.00162)		(0.00337)		(0.00311)
$\log \Delta W^p$	−0.0634***	−0.0635***	−0.151***	−0.151***	−0.0794***	−0.0791***
	(0.0138)	(0.0138)	(0.0231)	(0.0232)	(0.0175)	(0.0175)
mkt_t^{SSE}	0.0220***	0.0215***	0.0887***	0.0883***	−0.118***	−0.118***
	(0.00711)	(0.00716)	(0.0264)	(0.0265)	(0.0331)	(0.0333)
$\log DP_t$	−1.093***	−1.091***	−5.449***	−5.411***	7.477***	7.432***
	(0.168)	(0.166)	(0.688)	(0.677)	(0.845)	(0.841)
Observations	116,166,277	116,487,592	116,232,207	116,554,658	116,232,207	116,554,658
Adjusted R^2	0.011	0.011	0.021	0.021	0.056	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 our baseline estimations with account-level fixed effects as in Table 2 in the paper, but appended with past market return and dividend yield as additional factor. 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 1, 3 and 5 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta\epsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for Columns 2, 4, and 6 (where ϵ_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$), account-level fixed effects, and dummy variables for 10 wealth groups, market return in previous month proxied by SSE index (mkt_t^{SSE}), and dividend yield ($\log DP_t$)—a logarithm of the ratio of the summation of the dividends paid on the stock portfolio over the past 12 months over price. Statistical significance is based on account-clustered SEs for Δr_t and ϵ_t^r and on time-clustered SEs for mkt_t^{SSE}, $\log \Delta W^p$ and $\log DP_t$.

of expectations if it captures the expected return on the assets in which they actually invest.

In Appendix H, we report estimation results based on forecasting regressions of stock market returns on the lagged dividend yield and the lagged stock market return, in the context of the Chinese market. In both cases, we find weak (and marginally significant) predictability.

4.4.2. Results with lagged dividend yield and stock market returns

Table 6 reports results from extending the baseline regression by including the lagged return on the SSE index and the lagged divided yield. The coefficient on the SSE index is positive and statistically significant in the first four regressions (those for the active risky share and net equity flows) and negative and statistically significant in the last two (those for withdrawals). These results are consistent with the notion that retail investors are, on average, trend-chasing.

In Columns (1) to (4), we again find that an increase (decrease) in interest rates is associated with a decrease (increase) in the risky share within the brokerage account, measured by either the active risky share or the net equity flow. Therefore, on average, retail investors reach for yield, after controlling for the dividend yield and past returns. Relative to the baseline regressions, the coefficients are about two-thirds smaller, suggesting that part of the effect in the baseline regressions was due to a revision in investors' risk premium expectations. However, the fact that the coefficients remain statistically significant suggests that there is still a nontrivial effect from the other channels.

In Columns (5) and (6), the coefficient on account withdrawals is negative. Later, we show that the coefficient turns positive under most of the alternative specifications we consider. Arguably, account withdrawal is likely to be a more noisy measure of portfolio rebalancing, since money taken out of the account can be used for a variety of other purposes, such as consumption or paying debt.

4.4.3. Results with lagged dividend yield and portfolio returns

In Table 7, we report results of including the investor's lagged portfolio return (rp_{jt}) instead of the lagged market return as a control for subjective beliefs. In Columns (1) and (4), the interest rate coefficients remain negative and significant. Furthermore, in Columns (5) and (6), the interest rate coefficients remain positive and significant, as in our baseline regressions. Quantitatively, we again observe a reduction in the estimated coefficients, with those in the new regressions being on average 60% smaller (in absolute value) than those in the baseline regressions. The coefficient on the lagged portfolio return is positive

Table 7
Results for baseline regression with account fixed effects, controlling for investors' portfolio return and dividend yield.

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	−0.00274*		−0.0950***		0.116***	
	(0.00158)		(0.00327)		(0.00295)	
ε_t^r		−0.0167***		−0.116***		0.159***
		(0.00164)		(0.00341)		(0.00315)
$\log \Delta W^p$	−0.0624***	−0.0626***	−0.146***	−0.147***	−0.0861***	−0.0857***
	(0.0137)	(0.0137)	(0.0232)	(0.0233)	(0.0191)	(0.0191)
rp_{jt}	0.0252***	0.0249***	0.0567***	0.0562***	−0.00894	−0.00855
	(0.00559)	(0.00560)	(0.0105)	(0.0105)	(0.00996)	(0.01000)
$\log DP_t$	−1.132***	−1.129***	−5.641***	−5.588***	7.783***	7.702***
	(0.179)	(0.176)	(0.712)	(0.699)	(0.883)	(0.873)
Observations	116,166,277	116,487,592	116,232,207	116,554,658	116,232,207	116,554,658
Adjusted R^2	0.011	0.011	0.021	0.021	0.055	0.055

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 as in Table 2 in the paper, but appended with past investors' return and dividend yield as additional factor. 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 1, 3 and 5 (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 2, 4 and 6 (where ε_t^r is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$), account-level fixed effects and dummy variables for 10 different wealth groups, investors' return in previous month (rp_{jt}) calculated as difference between the current market value of open positions and the value of the position at the start of the previous month scaled by account value in the previous month, and dividend yield ($\log DP_t$) is a logarithm of the ratio of the summation of the dividends paid on the stock portfolio over the past 12 months over price. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$ and $\log DP_t$.

in the first four regressions and negative in the last two. This again suggests that, on average, investors behave as momentum traders.

4.4.4. Results with lagged dividend yield, returns, and macroeconomic variables

As a final extension, we control for macroeconomic expectations and conditions by including lagged GDP growth, consumption growth, inflation rate, changes in the exchange rate, and changes in the real estate price index. For the variables with a quarterly frequency (lagged GDP growth and the real estate price index), we use the most recent quarterly data available for each month in the sample (denoted by t^*). The results are reported in Table 8.

In all regressions, the coefficients on lagged interest rate, passive changes in wealth, past market returns, and lagged dividend yield all have magnitude and statistical significance similar to our previous results.[35] We again conclude that, on average, Chinese investors reach for yield. In Table 8, the coefficient on GDP growth is positive in Columns (1)–(4) and negative in Columns (5)–(6). This indicates that, following a period of higher GDP growth, retail investors tend to increase investment in risky assets.

In general, it is hard to interpret the coefficients on the various macroeconomic variables due to their collinearity. For our main variable of interest, however, the coefficient on interest rate changes remains statistically significant in all regression, with a similar economic magnitude to before. Likewise, the coefficients on the other controls, including dividend yield, past market return and passive change in wealth, all remain significant and largely unchanged.

4.5. Results with changes in monetary policy rates

In this section, we study the portfolio reallocation behavior of retail investors in response to changes in monetary policy rates. The benchmark lending rate (BLR) and benchmark deposit rate (BDR) were the main instruments for People's Bank of China (PBC) monetary policy before October 2015—the so-called regulated-retail-interest-rate era.[36] Most of the times, deposit and lending interest rates were adjusted simultaneously and by the same magnitude, so the two are virtually equivalent. In our analysis, we use changes in monetary policy rates and not monetary policy shocks, such as those constructed in Bernanke and Kuttner (2005) from Federal funds futures data.[37]

Interest rates can change for reasons other than monetary policy shocks; namely, in response to technology shocks or demand shocks. Fig. 4 shows the time-series plot of the (annualized) one-month SHIBOR, compared with benchmark lending and deposit rates over the period from October 2006 to December 2016. The SHIBOR tracks the deposit rate very closely, but is much more volatile. The main goal of our paper is to study portfolio responses to changes in interest rates in general, not just those driven by monetary policy decisions. Nonetheless, it is interesting to study the latter in isolation. We have re-estimated our previous regressions, replacing SHIBOR rate innovation with changes in the benchmark PBC policy rate. The results are reported in Table 9 below.

We again find evidence in favor of reaching for yield. The interest rate coefficient is negative in the regressions for the risky share and net equity flows and for withdrawals. The magnitude of the estimated coefficients is in fact more than one order of magnitude larger than the one obtained in the previous regressions (with changes in SHIBOR). The coefficients on most other variables are the same as in the previous regressions.[38] Thus, when we focus on changes in the monetary policy rate, we obtain the same conclusions as before, with the results actually becoming quantitatively larger.

5. Heterogeneous responses

Having established that, on average, investors in our sample reach for yield, we now explore heterogeneity in responses along the different dimensions of data suggested by the theoretical channels discussed in Section 2. The results in this section build on the baseline specification from Section 4.1. Results for the extended specifications from

[35] We get similar results when we include the investor's lagged portfolio return (rp_{jt}), instead of the lagged market return, as a control for subjective beliefs.

[36] Since interest rates were liberalized in 2015, the central bank has de-emphasized benchmark rates and focused on using its growing arsenal of quasi-monetary policy tools to fine tune liquidity and interest rates.

[37] We cannot replicate their methodology in our setting. The shortest maturity bond futures in China is two years and, moreover, this market was shut down between 1995 until 2013.

[38] The coefficient on some of the macroeconomic variables are now changed relative to the previous regressions but, as argued before, these variables are highly collinear and are included primarily as controls.

Table 8
Results for baseline regression with account fixed effects, controlling for past market return, dividend yield and lagged macroeconomic indicators.

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	−0.0131***		−0.0723***		0.0104***	
	(0.00162)		(0.00335)		(0.00300)	
ε^r_t		−0.0137***		−0.128***		0.0574***
		(0.00171)		(0.00356)		(0.00328)
$\log \Delta W^p$	−0.0670***	−0.0671***	−0.158***	−0.159***	−0.0676***	−0.0673***
	(0.0143)	(0.0143)	(0.0228)	(0.0227)	(0.0173)	(0.0173)
mkt^{SSE}_t	0.0169**	0.0166**	0.0835***	0.0830***	−0.107***	−0.107***
	(0.00704)	(0.00703)	(0.0264)	(0.0261)	(0.0332)	(0.0331)
$\log DP_t$	−1.201***	−1.199***	−5.455***	−5.394***	7.724***	7.659***
	(0.170)	(0.168)	(0.748)	(0.721)	(0.920)	(0.919)
$gGDP_{t^*}$	0.000533***	0.000429***	0.0210***	0.0216***	−0.0394***	−0.0398***
	(0.000129)	(0.000130)	(0.000284)	(0.000287)	(0.000288)	(0.000290)
ΔCPI_t	−0.0798***	−0.0795***	−0.0956***	−0.0887***	0.216***	0.213***
	(0.000767)	(0.000777)	(0.00169)	(0.00171)	(0.00197)	(0.00198)
$gCons_t$	0.0315***	0.0314***	0.194***	0.191***	−0.157***	−0.154***
	(0.00133)	(0.00133)	(0.00275)	(0.00275)	(0.00247)	(0.00247)
$\Delta Exchange_t$	−0.191***	−0.191***	−0.578***	−0.586***	0.811***	0.825***
	(0.00257)	(0.00255)	(0.00556)	(0.00554)	(0.00554)	(0.00553)
$gRealEstate_{t^*}$	−0.0664***	−0.0663***	−0.373***	−0.372***	0.482***	0.476***
	(0.000852)	(0.000846)	(0.00197)	(0.00196)	(0.00214)	(0.00212)
Observations	116,166,277	116,487,592	116,232,207	116,554,658	116,232,207	116,554,658
Adjusted R^2	0.011	0.011	0.021	0.021	0.057	0.057

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 as in Table 2 in the paper, but appended with past market return, dividend yield and growth rate of GDP as additional factors. 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 1, 3, and 5 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta\varepsilon^r_t + \gamma X_{jt} + u_{j,t+1}$ for Columns 2, 4, and 6 (where ε^r_t is residual from the AR(1) interest rate model). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$), account-level fixed effects and dummy variables for 10 wealth groups, returns for SSE index (mkt^{SSE}_t), and dividend yield ($\log DP_t$)—a logarithm of the ratio of the summation of the dividends paid on the stock portfolio over the past 12 months over price. Regression additionally includes the most recent quarterly growth rate of nominal gross domestic product ($gGDP_{t^*}$), the change in consumer price index (ΔCPI_t), the growth rate of (nominal) consumption ($gCons_t$), the monthly percent change in the exchange rate with respect to the dollar ($\Delta Exchange_t$), and the most recent quarterly house price growth ($gRealEstate_{t^*}$). Statistical significance is based on account-clustered SEs for Δr_t, ε^r_t and all macroeconomic indicators and on time-clustered SEs for $\log \Delta W^p$, mkt^{SSE}_t and $\log DP_t$.

Section 4.4 are presented in Appendices 9, 10 and 11, and provide the same conclusions.

5.1. Heterogeneous responses: Wealth

We first consider one of the predictions of the portfolio-choice model with riskless labor income.[39] More precisely, we focus on Hypothesis 1: reaching for yield is a decreasing function of wealth.[40]

Note that Hypothesis 1 results from Eq. (3), in which the relevant state variable is not financial wealth but rather the ratio of human capital to financial wealth. Since we do not observe labor income in our data, we can only control for wealth. However, to the extent that wealthier individuals are also more likely to have higher income/human capital, then that will work against finding effect in the data.[41] Furthermore, Giglio et al. (2021) show that wealthier investors reallocate their portfolios more in response to changes in expectations, which will also work against finding our prediction confirmed in the data.

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

$$y_{j,t+1} = \alpha + \beta\Delta r_t + \beta^W(\Delta r_t I_{W_{jt}}) + \gamma I_{W_{jt}} + \phi X_{it} + f_j + u_{j,t+1}, \quad (28)$$

$$y_{j,t+1} = \alpha + \beta\varepsilon^r_t + \beta^W(\varepsilon^r I_{W_{jt}}) + \gamma I_{W_{jt}} + \phi X_{it} + f_j + u_{j,t+1}, \quad (29)$$

where, as before, $y_{j,t+1}$ is 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 responses for the 10 wealth groups in Figs. 5 and 6.

Fig. 5 reports the results obtained when interest rate innovation are measured as the AR(1) residual, whereas Fig. 6 plots the results when interest rate innovation are measured as the simple first difference. For each figure, Panel (a) plots results for (net) withdrawal rate (for which we expect mostly positive coefficients) and Panel (b) plots the results for the other two variables (for which we expect mostly negative coefficients).

5.1.1. Withdrawal rates

In both Figs. 5 and 6, Panel (a) reveals a strong decreasing pattern for the response of (net) withdrawal rates to interest rate movement as a function of wealth. Consistent with Hypothesis 1, the response is much more significant among less-wealthy investors and approaches zero for those in wealth groups 6 and above.

The differences across wealth groups are economically large. Consider Fig. 5: while investors in wealth group 1 increase their withdrawals by 72 basis points in response to a 100-basis-point movement

[39] As discussed, this prediction extends to models with risky labor income, as long as human remains a closer substitute for bonds than for stocks (e.g., Viceira, 2001; Cocco et al., 2005).

[40] 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.

[41] 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.

Table 9
Results for regression with benchmark lending rate changes and account fixed effects, controlling for dividend yield, past returns, and lagged macroeconomic indicators.

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔBLR_t	−0.430***	−0.307***	−3.007***	−2.251***	4.017***	2.707***
	(0.0112)	(0.0111)	(0.0246)	(0.0243)	(0.0239)	(0.0238)
$\log \Delta W^p$	−0.0675***	−0.0661***	−0.154***	−0.147***	−0.0770***	−0.0885***
	(0.0142)	(0.0141)	(0.0266)	(0.0269)	(0.0176)	(0.0198)
$\log DP_t$	−1.092***	−1.123***	−5.363***	−5.531***	7.742***	7.973***
	(0.166)	(0.174)	(0.619)	(0.656)	(0.802)	(0.861)
mkt_t^{SSE}	0.0271***		0.118***		−0.154***	
	(0.00745)		(0.0255)		(0.0309)	
rp_{jt}		0.0262***		0.0651***		−0.0187*
		(0.00663)		(0.0121)		(0.00998)
$gGDP_{t^*}$	−0.0000454	−0.00133***	−0.0112***	−0.0172***	0.00612***	0.0147***
	(0.000127)	(0.000127)	(0.000279)	(0.000281)	(0.000282)	(0.000284)
ΔCPI_t	0.195***	0.215***	0.852***	0.879***	−0.479***	−0.439***
	(0.00473)	(0.00473)	(0.00993)	(0.00994)	(0.00917)	(0.00918)
$gCons_t$	−0.00384***	−0.00868***	0.0895***	0.0611***	−0.0654***	−0.0194***
	(0.00146)	(0.00146)	(0.00302)	(0.00302)	(0.00269)	(0.00269)
$\Delta Exchange_t$	−0.121***	−0.116***	−1.012***	−0.990***	1.107***	1.086***
	(0.00272)	(0.00272)	(0.00599)	(0.00599)	(0.00609)	(0.00611)
$gRealEstate_{t^*}$	−0.00341***	−0.0139***	−0.00324	−0.0665***	0.0936***	0.199***
	(0.000957)	(0.000957)	(0.00218)	(0.00218)	(0.00232)	(0.00233)
Observations	99,839,679	99,523,838	99,901,698	99,584,503	99,901,698	99,584,503
Adjusted R^2	0.012	0.012	0.026	0.025	0.065	0.064

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 account-level fixed effects replacing interest rate innovation with benchmark interest rate changes resulting from policy announcements, appended with past returns, market or investor-portfolio, dividend yield. 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 $y_{j,t+1} = \alpha + \beta \Delta BLR_t + \gamma X_{jt} + u_{j,t+1}$ (where ΔBLR_t is the change in benchmark lending rate). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$), account-level fixed effects and dummy variables for 10 wealth groups, dividend yield ($\log DP_t$) is a logarithm of the ratio of the summation of the dividends paid on the stock portfolio over the past 12 months over price. Returns for SSE index for Columns 1, 3, and 5 (mkt_t^{SSE}) or investors' return in previous month (rp_{jt}) calculated as difference between the current market value of open positions and the value of the position at the start of the previous month scaled by account value in the previous month for Columns 2, 4, and 6. Regression additionally includes the most recent quarterly growth rate of nominal gross domestic product ($gGDP_{t^*}$), the change in consumer price index (ΔCPI_t), the growth rate of (nominal) consumption ($gCons_t$), the monthly percent change in the exchange rate with respect to the dollar ($\Delta Exchange_t$), and the most recent quarterly house price growth ($gRealEstate_{t^*}$). Statistical significance is based on account-clustered SEs for Δr_t, ε_t^r and all macroeconomic indicators and on time-clustered SEs for $\log \Delta W^p$, mkt_t^{SSE}, rp_{jt} and $\log DP_t$.

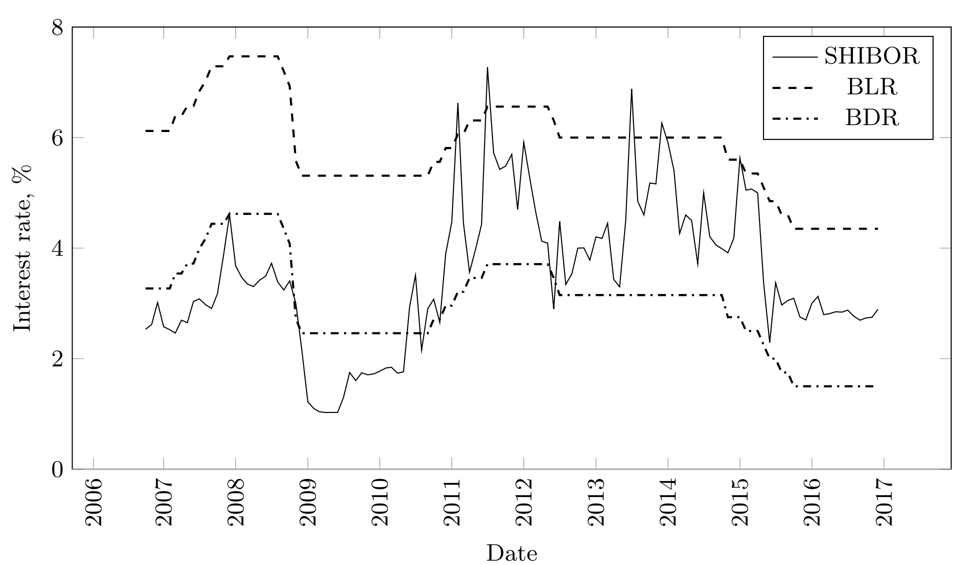

Fig. 4. Historical interest rates.
Fig. 4 shows the time-series plot of the (annualized) 1-month SHIBOR and benchmark lending and deposit rates from October 2006 to December 2016.

in interest rates, the change in withdrawal rates for those in wealth group 3 is half of that (38 basis points). 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 basis points).

This pattern is strikingly consistent with the predictions of the Merton model with labor income (Eq. (4)). In addition to the monotonic decay with wealth, the model also predicts a convex relationship such as that obtained in Fig. 5: as we move up in the wealth distribution

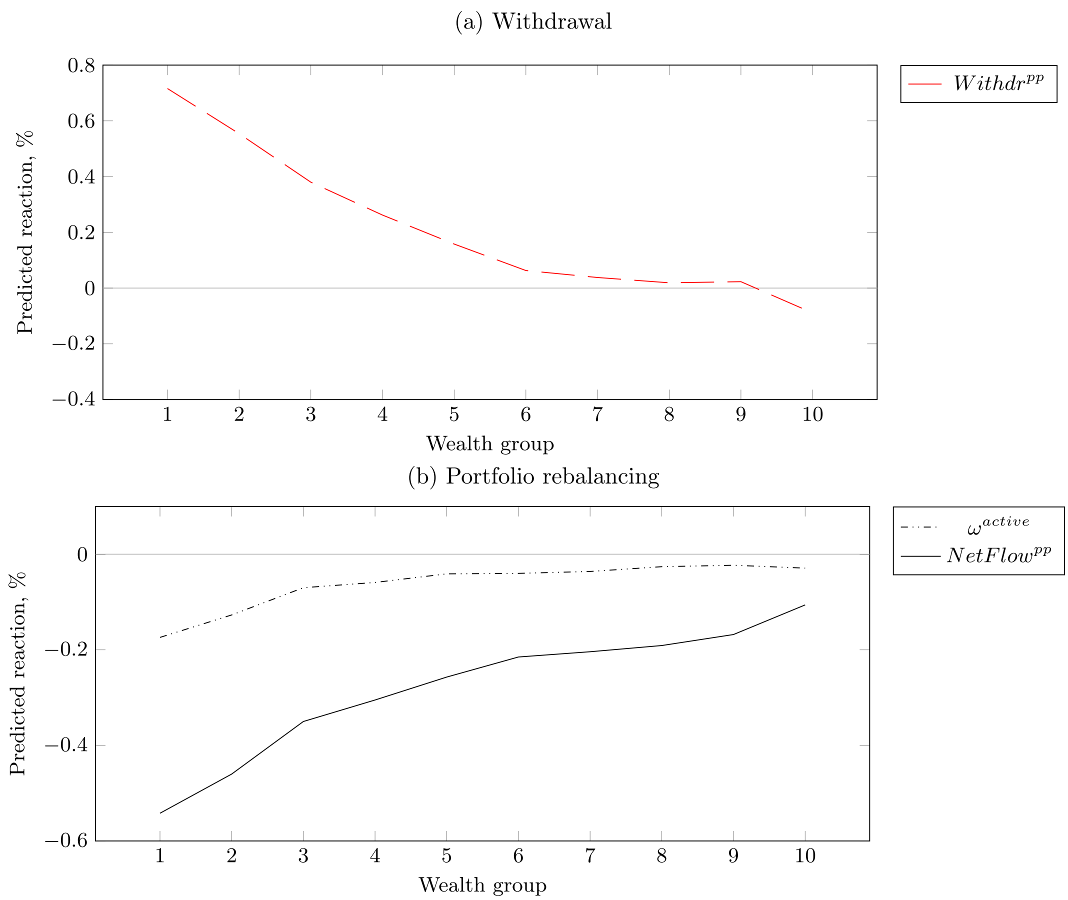

Fig. 5. Effect of AR(1) interest rate innovation on investor behavior by wealth group.
Fig. 5 plots the result from regressions of investor behavior proxies on change in interest rate interacted with wealth group dummies. Investor behavior proxies are active change in risky share, net flow into equity, and withdrawals (the latter two as share of previous balance). The interest rate innovation correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of the interaction effect of change in SHIBOR and wealth group. All regressions also include the passive change in wealth, wealth dummies, and account fixed effects.

the ratio of human capital to financial wealth becomes negligible and, consequently, a further increase in wealth does not change its value by as much as it does for less-wealthy individuals.[42]

Giglio et al. (2021) show that wealthier investors reallocate their portfolios more in response to changes in expectations. In the absence of the channel implied by Hypothesis 1, we would expect to find exactly the opposite result. Therefore, the isolated effect resulting from our channel is likely to be even stronger than in our baseline specification. Note that, in the specification with changes in interest rate (Fig. 6), 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 result was discussed as a possible outcome in Section 2.2.4.

5.1.2. Changes in risky share and net equity flows

In Panel (b) of Figs. 5 and 6, we report results for the other two measures of portfolio rebalancing (active change in risky share and net equity flows), for which we expect mostly negative changes. Indeed, for both figures, for both measures, and across all 10 wealth groups, the responses to interest rate movement are negative, consistent with reaching for yield.

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 movement. Interestingly, the tendency of reaching for yield is decreasing (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 Eq. (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 Fig. 5, a 100-basis-point interest rate innovation leads to a reduction in net equity flows as a percentage of the total account balance, of 54-basis-point for the first wealth group, compared with 35 basis points for the third wealth group and 21 basis points for the sixth.

5.2. 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 (e.g., Cocco et al., 2005). Intuitively, because the ratio of human capital to financial wealth is particularly higher for young investors, they should have a strong portfolio response to interest rate changes. As they get older, their human capital decreases and they accumulate more wealth, so 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 (Eqs. (24) and (25)) interaction terms between interest rate innovation and dummy variables for the age groups:

$$y_{j,t+1} = \alpha + \beta \Delta r_t + \beta^{age}(\Delta r_t I_{age_{jt}}) + \gamma I_{age_{jt}} + \phi X_{it} + u_{j,t+1}, \tag{30}$$

[42] 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 Eq. (2).

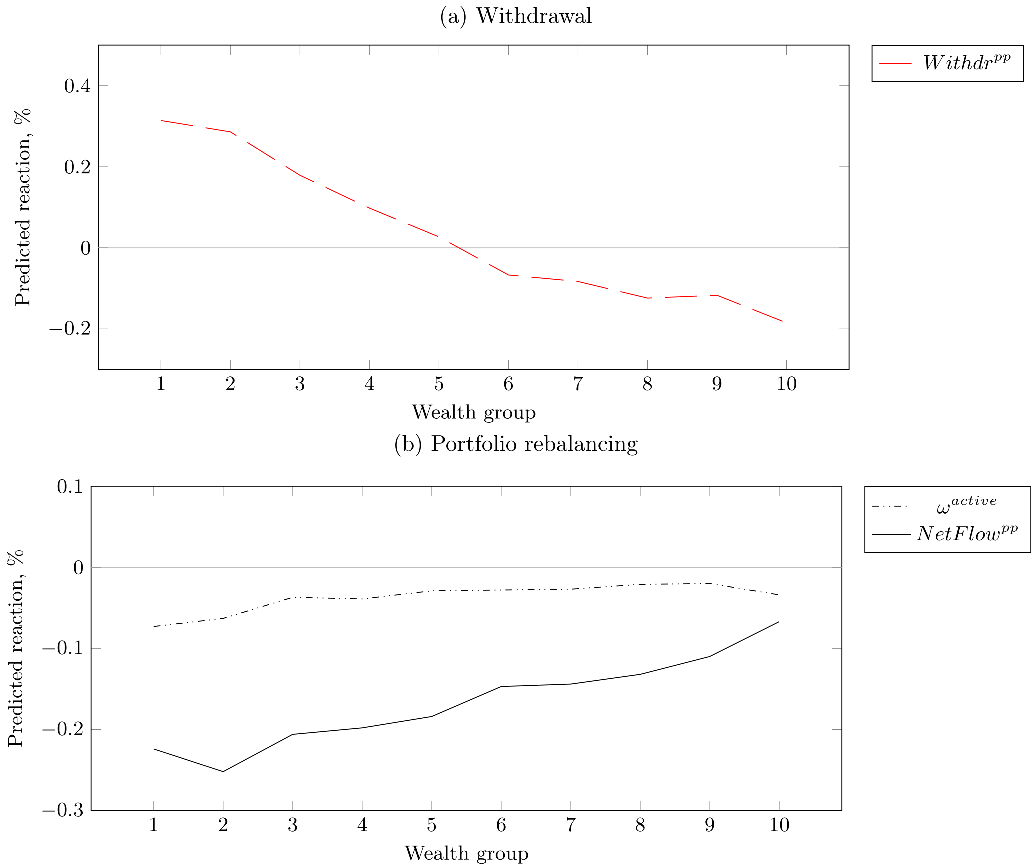

Fig. 6. Effect of interest rate changes on investor behavior by wealth group.
Fig. 6 plots the result from regressions of investor behavior proxies on change in interest rate interacted with wealth group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (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 the interaction effect of change in SHIBOR and wealth group. All regressions also include the passive change in wealth, wealth dummies and account fixed effects.

$$y_{j,t+1} = \alpha + \beta \epsilon_t^r + \beta^{age}(\epsilon_t^r I_{age_{jt}}) + \gamma I_{age_{jt}} + \phi X_{it} + u_{j,t+1}, \tag{31}$$

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

The implied portfolio responses for each of the age groups are presented in Figs. 7 and 8 for the specification with the AR(1) interest rate innovation and the one with interest rate changes, respectively.

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.

5.2.1. Withdrawal rates

Consistent with Hypothesis 2, Panel (a) of Fig. 8 shows a pronounced decreasing pattern of withdrawal rates as a function of age. In fact, withdrawal rates decrease monotonically across all age groups. While the youngest investors (age group 30–35) withdraw 54 basis points of their account value in response to a 100 basis points increase in interest rates, those in the age group 50–55 (group 5) withdraw only 3 basis points of their account balance.

Interestingly, the results in Fig. 8 suggest that investors above age 56 (group 6 and higher), actually engage in reverse reaching for yield: 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 Fig. 7. In both cases, we observe a perfectly monotonic decreasing pattern, as predicted by the theory.

5.2.2. Changes in risky share and net equity flows

In Panel (b) of Figs. 7 and 8, 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 do. The differences are again economically significant and the patterns are monotonic across all age groups, with the exception of the first age group in Fig. 7 (i.e., when considering AR(1) residuals as the interest innovation).

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 three 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 do.

5.3. Prospect theory

We now 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 trading at a gain, a (small) drop in interest rates

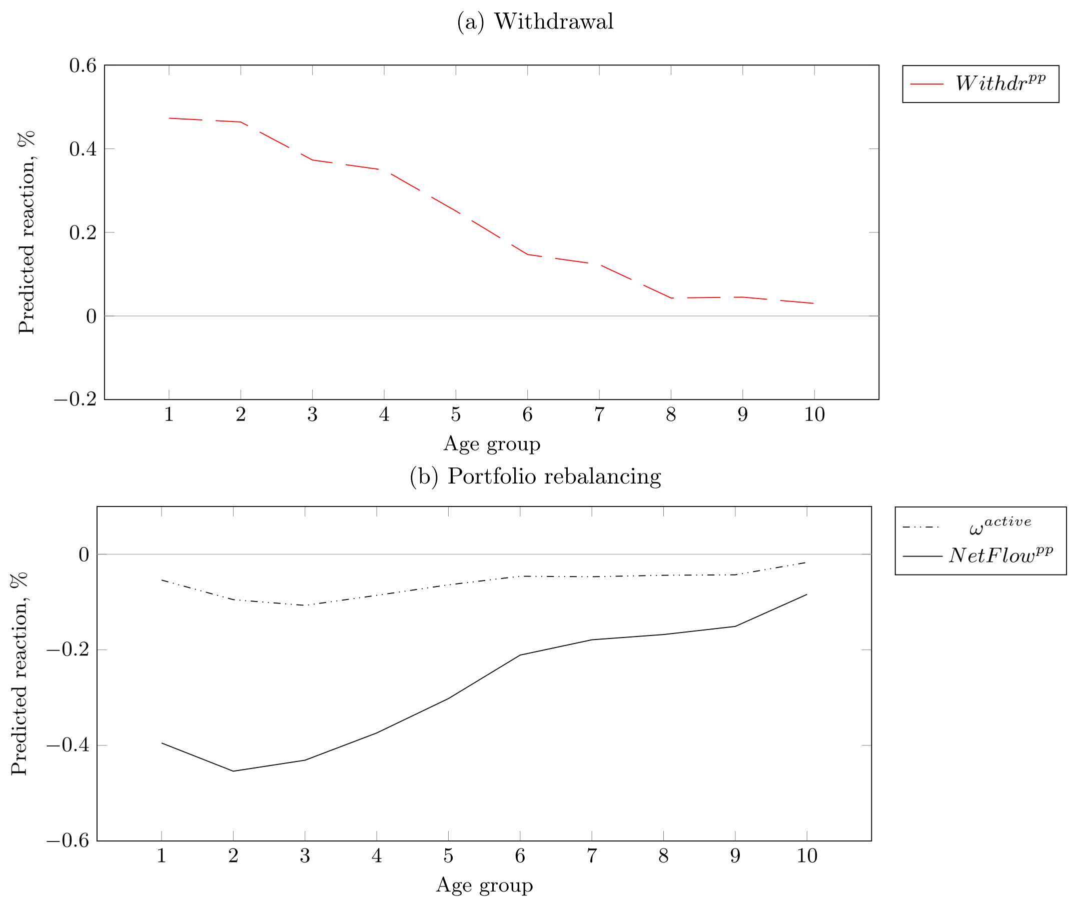

Fig. 7. Effect of AR(1) interest rate innovation on investor behavior by age groups.
Fig. 7 shows the result from regressions of investor behavior proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovation correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of coefficients for the interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and age dummies.

pulls them closer to the kink and makes them more risk-averse. For someone 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 parameterizations). Therefore, we test how reaching for yield is correlated with an investor's gain/loss position.

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

$$y_{j,t+1} = \alpha + \beta_1 \Delta r_t \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta r_t \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}, \tag{32}$$

$$y_{j,t+1} = \alpha + \beta_1 \varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta \varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}, \tag{33}$$

where Gain is given by Eq. (23) and measures the individual's (net) gains. In our analysis, we measure gains relative to the stock price at the end of the preceding month, consistent with the very high turnover rates observed among our investors. Table 10 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-basis-point interest rate innovation leads to a 14-basis-point decrease in active risky shares holding. Interestingly, those trading at a gain exhibit reverse reaching for yield. Among these investors, a 100-basis-point interest rate innovation is associated with a 7.5-basis-point increase in active risky shares holding. Similarly, in Column (2), in which we measure interest rate innovation using the AR(1) residual, those trading at a loss exhibit a much stronger tendency to reach for yield.

Columns (3)–(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 innovation. For both dependent variables and both measures of interest rate innovation, reaching for yield is larger when investors are trading following losses. These results again support prospect theory as a driver of reaching for yield by retail investors.

6. Conclusion

The literature has documented the existence of reaching for yield among institutional investors. We present new field evidence to document it among retail investors. Our results show that reaching for yield does not need to stem from the institutional frictions on which the literature has typically focused.

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 for portfolio-choice models in which labor income is a close substitute for bonds. 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 reaching for yield. These results are robust to adding controls for both future expected returns and macroeconomic conditions.

In this paper, we measure portfolio reallocation in response to interest rate changes in general. We do not try to isolate specific interest rate shocks, instead we want to understand how investors react when

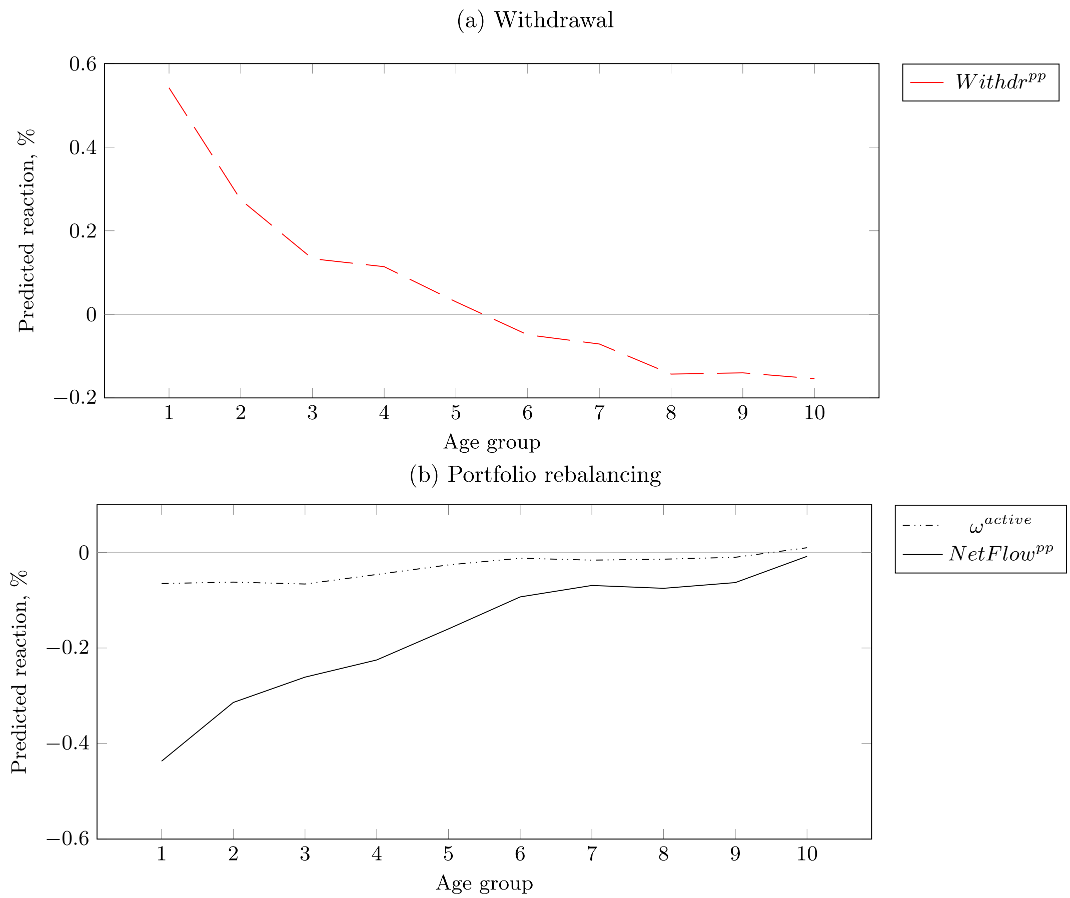

Fig. 8. Effect of interest rate changes on investor behavior by age group.
Fig. 8 shows the result from regressions of investor behavior proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (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 coefficients for the interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and age dummies.

Table 10
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)	
$\varepsilon^r_t \times \mathbf{1}\{\text{Gain} < 0\}$		−0.180***		−0.476***		0.453***
		(0.00208)		(0.00422)		(0.00406)
$\varepsilon^r_t \times \mathbf{1}\{\text{Gain} > 0\}$		0.0346***		−0.204***		0.265***
		(0.00253)		(0.00555)		(0.00490)
$\log \Delta W^p$	−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 1, 3, and 5 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta_1 \varepsilon^r_t \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta \varepsilon^r_t \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for Columns 2, 4, and 6 (where ε^r_t 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 performance is computed from Eq. (23), with the price at the start of the month as the reference price. $\log \Delta W^p$ represents the passive change in wealth. The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, Eq. (22)), account-level fixed effects, and dummy variables for 10 wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε^r_t and on time-clustered SEs for $\log \Delta W^p$.

interest rates increase or decrease. It would be interesting, however, to also study the response to monetary policy shocks.

CRediT authorship contribution statement

Francisco Gomes: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Cameron Peng:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Oksana Smirnova:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Ning Zhu:** Resources, Data curation.

Declaration of competing interest

The authors have nothing to disclose.

Appendix A. Derivation of Hypothesis 1

To simplify the notation, we first define

$$\Gamma \equiv \frac{\partial(\mu - r)/\partial r}{\gamma \sigma^2} \tag{34}$$

so that we can rewrite Eq. (4):

$$\frac{\partial \alpha}{\partial r} = \left[1 + \frac{PV(Y)}{W}\right]\Gamma. \tag{35}$$

From this,

$$\frac{\partial \alpha / \partial r}{\partial W} = -\frac{PV(Y)}{W^2}\Gamma. \tag{36}$$

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

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

From Eq. (36), the sign of Γ is also the sign of $\partial\alpha/\partial r$, so we can rewrite 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 B. Summary statistics for age and wealth groups

Table B.11 shows the distribution of investors in the sample, across the age groups. The vast majority of investors are younger than 60, with the largest age group being 46–50, followed by 41–45.

Table B.12 shows the distribution of investors in the sample, across the 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 criterion for defining the cutoff points.

Appendix C. Descriptive statistics for gains and loses

In this Appendix we plot the time series of average monthly portfolio gains (Eq. (23)) across all investors in our sample. This is the variable that we use in the regression testing the loss aversion channel.

Table B.11
Age distribution of investors.

Age group (1)	N (2)	Minimum age (3)	Maximum age (4)
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 age distribution of investors in the sample across age groups. 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 B.12
Wealth distribution of investors.

Wealth group (1)	N (2)	Min(CNY) (3)	Max(CNY) (4)
1	24.41	0.01	9999.99
2	20.98	10 000	24 999.99
3	18.53	25 000	49 999.99
4	17.79	50 000	99 999.98
5	14.13	100 000	199 999.98
6	6.21	200 000	299 999.88
7	3.53	300 000	399 999.88
8	2.29	400 000	499 999.94
9	4.87	500 000	999 999.88
10	4.19	1 000 000	2.85E+06
Total	116.92	0.01	2.85E+06

This table shows the distribution of investors in the sample across wealth groups. 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 D. Baseline regressions for risky share

In this appendix we repeat our baseline "reaching for yield" regressions with the (simple) risky share as the left-hand-side variables. We obtain the same conclusions as when we consider the other measures.

Appendix E. Baseline regression estimated with data from 2009 to 2014

In this appendix we repeat our baseline "reaching for yield" regressions excluding the "boom-bust" periods in the Chinese stock market. We obtain the same conclusions as when we consider the full sample. (See Table E.14).

Appendix F. Institutional details and descriptive statistics for mortgages in China

In China, mortgages are exclusively adjustable rate mortgages. Any interest rate changes announced by the central bank are applied to all existing mortgages with a maturity exceeding one year, starting January in the following year. The maximum mortgage term is 30 years for newly built residential properties and 20 years for secondhand residential properties, with an additional requirement that the borrower's age plus mortgage term should not exceed 65 years. Moreover, second mortgages are not easily obtainable, as all mortgages are for property purchases only.

To gain insight about home ownership and mortgage utilization, we use the data from the China Family Panel Studies (CFPS), an annual longitudinal survey conducted by Peking University. It collects

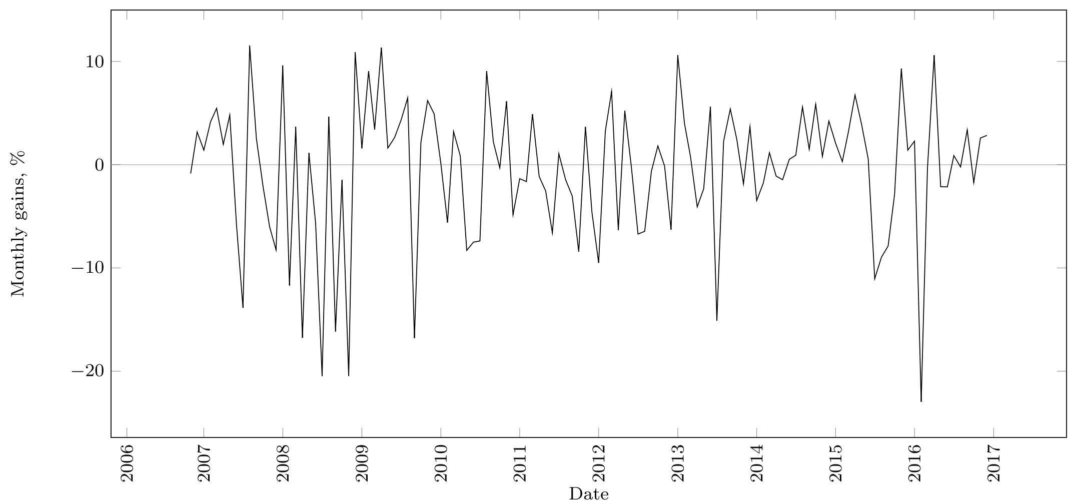

Fig. A.1. Average monthly account gains and losses.
Fig. A.1 plots the sample average of monthly account gains, computed from Eq. (23), with the price at the start of the month as the reference price. The gains are weighted by account balance.

Table D.13
Results for baseline regression for $\Delta\omega$.

(1)	(2)	(3)	(4)	(5)
Δr_t	−0.0979***		−0.117***	
	(0.00252)		(0.00451)	
ε_t^r		−0.140***		−0.156***
		(0.00258)		(0.00460)
$\log \Delta W^p$	−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 (Eq. (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). $\log \Delta W^p$ represents the passive change in wealth and all specifications include dummies for the 10 age groups. The first two regressions include account-level fixed effects while the other two include age fixed effects. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$.

Table E.14
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)
$\log \Delta W^p$	−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; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
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 ($\log \Delta W^p$, Eq. (22)), account-level fixed effects and dummy variables for the 10 wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$.

Table F.15
Mortgage ownership in China in 2010–2016, CFPS.

Year	Owners, %	Mortgage, %	
		All	Stockholders
(1)	(2)	(3)	(4)
2010	86.44%	3.19%	13.41%
2012	87.85%	4.23%	9.29%
2014	82.09%	7.18%	13.89%
2016	84.25%	9.12%	19.65%
Total	84.03%	7.08%	16.42%

Table F.15 presents data from the China Family Panel Studies on home ownership and mortgages in China from 2010 to 2016. Column (2) indicates the percentage of households that own a house in China in each year. Column (3) shows the percentage of all households with a mortgage. Lastly, Column (4) provides the percentage of stock owners with a mortgage.

comprehensive longitudinal data on individuals and families in China, with a particular focus on both economic and non-economic wellbeing.

Column (2) of Table F.15 shows that the percentage of households that own a house in China was high and relatively stable over the sample, with an average of 84.03%. Nevertheless, even with the high rate of home ownership, there is not a significant demand for mortgages as a financial instrument in China.

Based on Column (3) of Table F.15, only 3.19% of surveyed households had a mortgage in 2010. Even though mortgage ownership in China has shown some growth over the years, as evidenced by the increasing percentages of households with a mortgage, the rate of growth appears to be moderate, with the percentage of homeowners with a mortgage increasing only to 9.12% by 2016.

Note that the percentage of stock owners with a mortgage (Column (4)) is moderate and remained relatively stable at around 13–14% between 2010 and 2014, before increasing to 19.65% in 2016.

Overall, the data suggests that while there has been some growth in mortgage ownership in China, the rate of growth has been moderate, and the percentage of homeowners with a mortgage remains relatively low compared to the US. At the same time no more than a fifth of stock owners simultaneously hold a mortgage.

Appendix G. Stock returns and lagged interest rate in the Chinese stock market

In this appendix we replicate the analysis in Campbell and Yogo (2006), using data on the Shanghai Stock Exchange (SSE) Index and the CSMAR value-weighted index return as proxies for the Chinese stock market and the SHIBOR rate as our interest rate variable. More precisely, we estimate

$$\log RetX_t = \alpha + \beta \cdot \log SHIBOR^{3m}_{t-1} + u_t \tag{37}$$

where $\log RetX_t$ is the logarithm of market excess returns, calculated by subtracting the one-month SHIBOR from either the SSE Index or the CSMAR value-weighted index in current month (month t), and $\log SHIBOR^{3m}_{t-1}$ is the logarithm of the three-month SHIBOR in the previous month ($t-1$). We first estimate this regression for the period of 2006 to 2016, the same period considered in our paper, at the monthly frequency. The results are shown in Table G.16.

We find that, similar to Campbell and Yogo (2006), interest rates predict excess stock returns negatively and significantly, with $\hat{\beta}$ equal to −2.11 (−2.36) for the SSE Index (CSMAR value-weighted index). In terms of magnitude, Campbell and Yogo (2006) report normalized coefficients $\tilde{\beta}$ (Table 5 in their paper), computed as

$$\tilde{\beta} = \hat{\beta} \cdot \frac{\hat{\sigma}_e}{\hat{\sigma}_u}, \tag{38}$$

where $\hat{\sigma}_u$ is the standard deviation of the residuals from Eq. (37) and $\hat{\sigma}_e$ is the standard deviation of the residuals from the following regression:

$$\log SHIBOR^{3m}_{t-1} = \gamma + \delta_1 \cdot \log SHIBOR^{3m}_{t-2} + \delta_2 \cdot \log SHIBOR^{3m}_{t-3} + e_t. \tag{39}$$

Table G.16
Predictive performance of lagged interest rate.

Dev. var. $\log RetX_t$	(1) Full sample	(2) 2009–2014	(3) Full sample	(4) 2009–2014
	SSE Index		CSMAR	
$\log SHIBOR^{3m}_{t-1}$	−2.11***	−1.62**	−2.36***	−1.78**
	(0.625)	(0.67)	(0.668)	(0.704)
Observations	122	71	122	71
Adjusted R^2	0.068	0.0931	0.072	0.101
F	11.36	5.82	12.52	6.4

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
This table reports the results from a univariate predictive regression of stock excess returns on lagged stock excess returns: $\log RetX_t = \alpha + \beta \cdot \log SHIBOR^{3m}_{t-1} + u_t$, where $RetX_t$ is market excess return, that is, the difference between a return for the SSE-index (Columns (1) and (2)) or CSMAR value-weighted index with dividends reinvested in current month (Columns (3) and (4)) and the risk-free return (1-month SHIBOR). The sample covers the period from 2006 to 2018 at monthly frequency. Columns (1) and (3) use the full sample, while Columns (2) and (4) are based on the subsample spanning January 2009 to December 2014 and excludes boom and bust periods.

Table H.17
Predictive performance of dividend-price ratios.

Dev.var. $\log RetX_t$	(1) Full sample	(2) 2006–2008	(3) 2009–2016
$\log(D/P)_t$	0.0544*	0.0994	0.0239
	(0.0290)	(0.0626)	(0.0333)
Observations	123	27	95
Adjusted R^2	0.020	0.055	−0.005
F	3.520	2.518	0.516

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
This table reports the results from a univariate predictive regression of stock excess returns on dividend-price ratio: $\log RetX_t = \beta_0 + \beta_1 \cdot \log DP_{t-1} + \epsilon_t$, where $RetX_t$ is market excess return, that is a return for aggregate equal-weighted market portfolio with dividends reinvested over risk free return (1-month SHIBOR) and DP_{t-1} is dividend-price ratio calculated as the ratio of the summation of the dividends paid on the stock portfolio over the past 12 months ($\log \frac{D^{12}_t}{P_t}$). Both variables are in logarithms. The sample covers the period from 2006–2018 at monthly frequency. Column (1) uses the full sample, while Columns (2) and (3) are based on the subsamples before and after 2009.

Table H.18
Predictive performance of lagged market return.

Dev.Var. $\log RetX_t$	(1) Full sample	(2) 2009–2014
$\log RetX_{t-1}$	0.201**	0.150
	(0.0911)	(0.115)
Constant	−0.0154	−0.0195*
	(0.0108)	(0.0109)
Observations	122	71
Adjusted R^2	0.032	0.009
F	4.860	1.714

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
This table reports the results from a univariate predictive regression of stock excess returns on lagged stock excess returns: $\log RetX_t = \beta_0 + \beta_1 \cdot \log RetX_{t-1} + \epsilon_t$, where $RetX_t$ is market excess return, that is a return for aggregate equal-weighted market portfolio with dividends reinvested over risk-free return (1-month SHIBOR). The sample period is 2006–2018 at monthly frequency. Column (1) uses the full sample, while Column (2) is based on the subsample spanning January 2009 to December 2014 and excludes boom and bust periods.

The normalized coefficients can be interpreted as the standard deviation of the change in expected returns relative to the standard deviation of the innovation to returns. We estimate a normalized coefficient of −0.086 (−0.089) for the SSE (CSMAR) regression (this compares with −0.017 in Campbell and Yogo (2006))

As previously discussed, our data include periods of dramatic market movement (“bubbles and crashes”). Therefore, we repeat the previous regression for the more stable period (January 2009 to December 2014) and obtain similar results: the estimated $\hat{\beta}$ is −1.62 for the SSE

Table K.19
Results for regression controlling for past gains (monthly gains), account fixed effects, dividend yield, and past market return.

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta r_t \times \mathbf{1}\{\text{Gain} < 0\}$	−0.138***		−0.320***		0.210***	
	(0.00205)		(0.00411)		(0.00391)	
$\Delta r_t \times \mathbf{1}\{\text{Gain} > 0\}$	0.145***		0.258***		−0.341***	
	(0.00233)		(0.00511)		(0.00447)	
$\epsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\}$		−0.146***		−0.336***		0.265***
		(0.00209)		(0.00422)		(0.00405)
$\epsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\}$		0.141***		0.289***		−0.406***
		(0.00256)		(0.00559)		(0.00493)
$\log \Delta W^p$	−0.0629***	−0.0630***	−0.150***	−0.150***	−0.0803***	−0.0802***
	(0.0139)	(0.0139)	(0.0232)	(0.0232)	(0.0175)	(0.0175)
$\log DP_t$	−1.126***	−1.118***	−5.515***	−5.470***	7.540***	7.495***
	(0.174)	(0.170)	(0.700)	(0.688)	(0.846)	(0.844)
mkt_t^{SSE}	0.0217***	0.0215***	0.0882***	0.0883***	−0.118***	−0.118***
	(0.00709)	(0.00714)	(0.0262)	(0.0263)	(0.0329)	(0.0331)
Observations	116,166,277	116,487,592	116,232,207	116,554,658	116,232,207	116,554,658
Adjusted R^2	0.011	0.011	0.021	0.021	0.056	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 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 1, 3, and 5 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta_1 \epsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta \epsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for Columns 2, 4, and 6 (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 performance is computed from Eq. (23), with the price at the start of the month as the reference price. $\log \Delta W^p$ represents the passive change in wealth. The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, Eq. (22)), account-level fixed effects, and dummy variables for 10 wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ϵ_t^r and on time-clustered SEs for $\log \Delta W^p$.

Index and −1.78 for the CSMAR value-weighted index. The corresponding implied $\tilde{\beta}$ coefficients are −0.066 and −0.067, respectively, and the regression coefficients are again statistically significant at the 1% confidence level.

Appendix H. Forecasting regressions in the Chinese stock market

In this appendix we first estimate predictive regressions for stock returns using the lagged dividend yield as the predicting variable. More precisely, we estimate:

$$\log RetX_t = \alpha + \beta \cdot (D/P)_{t-1} + \varepsilon_t. \tag{40}$$

This has been studied, in the context of the Chinese stock market, by Nie and Yin (2022). They argue that an institutional change in 2008 produced a distinct influence on the dividends policy of Chinese-listed firms and affected the information conveyed by dividends.[43] Motivated by this finding, they estimate the predictive regression separately for the pre- and post-2008 periods and, consistent with the regime shift hypothesis, find a statistically significant coefficient on the dividend-price ratio for the pre-2008 period, but not for the post-2008 period. Our estimation results are reported in Table H.17.

Our full sample period is 2006–2016 and, in our analysis, the β coefficient is only marginally significant. After splitting the sample as in Nie and Yin (2022), we similarly find a larger coefficient for the pre-2009 sample, but it is insignificant.

We next consider the lagged stock market return as a predictor by estimating the following regression:

$$\log RetX_t = \alpha + \beta \cdot \log(RetX)_{t-1} + \varepsilon_t. \tag{41}$$

The results are shown in Table H.18.

For the full sample (Column(1)), we obtain a positive and statistically significant coefficient (0.201). However, if we exclude the "bubble-and-crash" episodes (Column(2)), the coefficient is no longer statistically significant.

Appendix I. Wealth effects from regressions with controls for expected returns

In this appendix we repeat the analysis in Section 5.1, in which we study heterogeneity in portfolio responses to interest rate changes as a function of wealth-but in the context of the regressions with controls for expected returns (Section 4.4). As before, for past returns, we use either the lagged market return or the investor's past portfolio return. The results are shown in Fig. A.2.

Under these specifications, we again find a monotonic relationship between wealth and reaching for yield, as predicted by the theory: investors with less wealth will more for yield more strongly. As a reminder, the prediction of the theory is a negative relationship with the ratio of wealth to the present value of future labor income. Since these two variables are likely positively correlated in the data, the fact that we only observe the former actually makes it more striking that we are still able to uncover this relationship.

The results in Fig. A.2 reveal a large number of wealth groups that exhibit reverse reaching for yield. It may, therefore, be tempting to deduce that investors, on average, would also show such a behavior. However, note that the wealth groups are not equally populated, as we have instead used to economically relevant wealth cutoffs. As a result, almost two-thirds (63.92%) of our investors are in the bottom three groups. These investors are responsible for reaching for yield at the aggregate level.

Appendix J. Age effects from regressions with controls for expected returns

In this appendix, we repeat the analysis in Section 5.2, in which we study heterogeneity in portfolio responses to interest rate changes

[43] More precisely, the Chinese stock market operated under the unique Semi-Mandatory Dividend Rule, which was later revised significantly in 2008. In 2004, the China Securities Regulatory Commission (CSRC) announced that listed firms that have not paid a dividend to shareholders for three years cannot apply for seasoned equity offerings (SEOs). Furthermore, the Rule strictly stipulated in 2006 that SEOs must be preceded by cash dividend payments equal to at least 20% of the issuing firm's net profits for the previous three years—and as a result, this proportion subsequently rose to 30% in 2008.

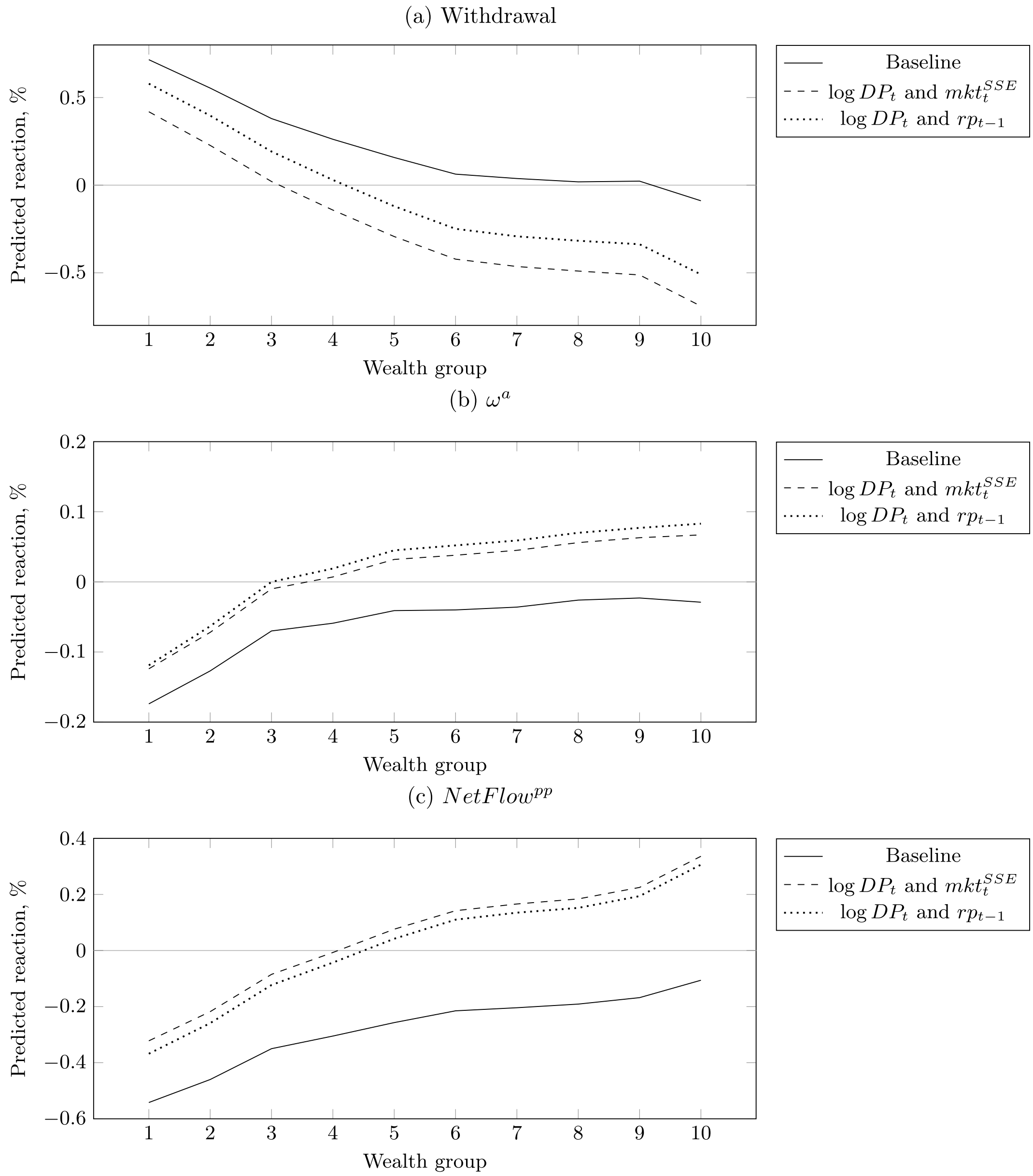

Fig. A.2. Effect of interest rate changes on investor behavior by wealth group, controlling for past stock market returns.
Fig. A.2 plots the result from regressions of investor behavior proxies on change in interest rate interacted with wealth group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovation correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of the interaction effect of change in SHIBOR and wealth group. All regressions also include the passive change in wealth, wealth dummies and account fixed effects. Regressions additionally control for dividend-price ratio in combination with either investor's past return or previous month stock market returns (SSE Index).

as a function of age in the context of the regressions with controls for expected returns (Section 4.4). As before, for past returns, we use either the lagged market return or the investor's past portfolio return. The results are shown in Fig. A.3

We find the same patterns as in baseline specification: younger agents are more actively reaching for yield.[44] This, again, aligns well with the theory. In terms of the overall magnitude, consistent with the results in Section 4.4, the inclusion of additional controls reduces the size of reaching for yield. This also coincides with more cases showing the opposite; namely, reverse reaching for yield.

Appendix K. Prospect theory channel with controls for expected returns

In this Appendix, we repeat the analysis in Section 5.3, in which we study heterogeneity in portfolio responses to interest rate changes as a function of previous gains and losses, in the context of the regressions with controls for expected returns (Section 4.4). The results are shown in Table K.19.[45]

We obtain the same patterns of reaching for yield as in Section 5.3: investors trading at a loss reach for yield, while those trading at a gain engage in reverse reaching for yield. As in all previous cases,

[44] As in the baseline results, the first age group is an exception to, otherwise, perfectly monotonic relationship.

[45] Results when controlling for the lagged own portfolio return are similar and available upon request.

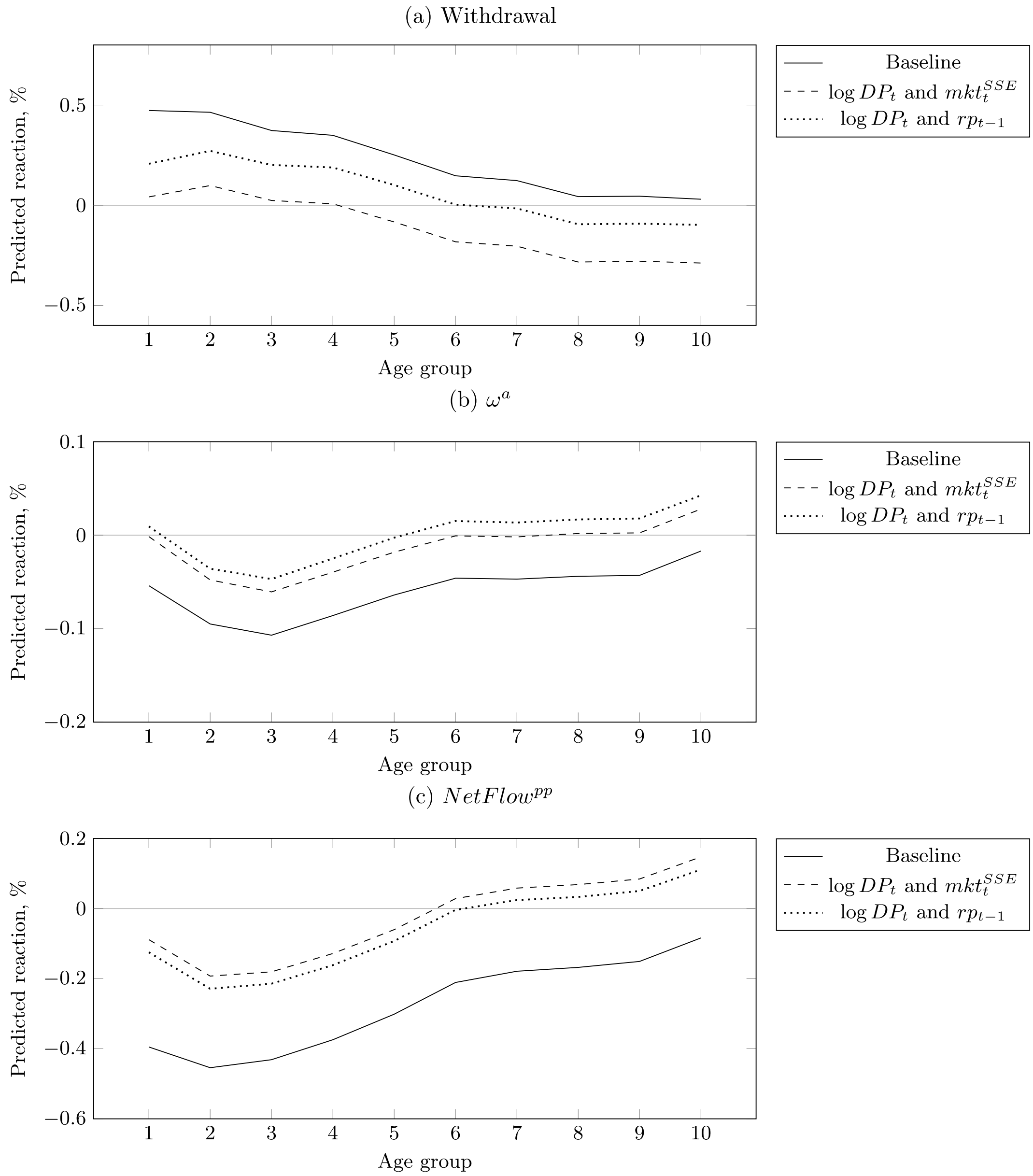

Fig. A.3. Effect of AR(1) interest rate innovation on investor behavior by age group, controlling for past stock market returns.
Fig. A.3 shows the result from regressions of investor behavior proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovation correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of coefficient for the interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and wealth dummies. Regressions additionally control for dividend-price ratio combination with either investor's past return or previous month stock market returns (SSE Index).

the coefficient on the lagged market return is positive in the first four specifications (those for the active risk share and for net equity flows) and negative in the other two (withdrawals), while the coefficient on the dividend yield has the opposite sign, consistent with retail investors behaving as trend-chasers.

Data availability

Code and Data for Reaching for Yield (Original data) (Mendeley Data)

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