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Reaching for Yield: Evidence from Households*

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Abstract

The existing literature has documented "reaching for yield"—the phenomenon of investing more in risky assets when interest rates drop—among institutional investors. In this paper, 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".

Keywords: reaching for yield, portfolio choice, retail investors, prospect theory.
JEL Codes: G11, G40, G50.

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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 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., 2023). In particular, these investors tend to increase their exposure to risky assets when the real interest rate drops, a phenomenon sometimes labelled "reaching for yield". In parallel with this evidence, explanations based on institutional frictions and agency issues have been proposed to account for "reaching for yield" (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 reallocate their portfolios in response to interest rate movements in a similar way. There is experimental evidence showing that, in a lab setting where 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 a 11-year period, we present direct field evidence that reaching for yield is also present in the trading behavior of 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 movements, 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, 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]

As we consider an extended model of portfolio choice with labor income (Merton, 1971), we obtain additional predictions: 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 now 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 re-optimization 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 re-balancing within the brokerage account, the third one captures flows in and out of the account. When interest rates change, investors may respond by reallocating money between their brokerage account and alternatives such as bank accounts and money market mutual funds. To capture such behaviors, we further compute net withdrawals as a percentage of the total account balance.

The three measures we use examine both trading *within* the brokerage account and trading *in and*

[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.

out of the account. As a result, our analysis is 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 an increase in mortgage payments.[2] This can force them to increase their withdrawals from the brokerage account and potentially create a mechanical relationship between interest rates changes and our third measure. However, there is no mechanical impact on their asset allocation within the account, which is 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 excellent period to conduct our study. While different interest rates are available to retail investors, arguably the most relevant one for household portfolio decisions is the Shanghai Interbank Offered Rate (SHIBOR), which represents the rate offered by many wealth management products.

It is important to clarify that we are not studying how investors respond to interest rate *shocks* (namely monetary policy shocks). We are interested in examining how investors respond 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. These studies do not try to isolate specific shocks to past returns. Likewise, we want to understand how investors respond to changes in interest rates, not just changes in interest rates that are orthogonal to specific variables.[3] In extensions discussed below, we show that our results are robust to the inclusion of various controls for expected returns and macroeconomic conditions, albeit the interpretation changes slightly. We also study responses to changes in the monetary policy rate only, where the results are also robust and, if anything, economically larger in magnitude.

Based on the previous discussion, our first measure of interest rate innovation is simply the change in interest rates over the period, and we specifically call it an innovation instead of shock, to clarify that important difference. As an alternative we also consider the residual from an AR(1)

[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.

regression of interest rates. Likewise, this shouldn't be interpreted as a shock. The goal here is to control, in a relatively simple way, for agents' interest rate expectations. Finally, we also use changes in the *real* interest rate, and we find even stronger results. Although these measures should not be interpreted as pure interest rate shocks, they are pre-determined 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, so from the first day of month $t-1$ to the first day of month t.

Across all three measures of portfolio rebalancing and both measures of changes in interest rates, the evidence is supportive of reaching for yield. When interest rates increase, retail investors have a negative active change in their risky share, and decrease their equity flows, on average. They are also more likely to withdraw funds from their brokerage accounts. The magnitude of these effects is nontrivial. Consider a 100 basis point increase in the interest rate. First, this is associated with an average active reduction in risk exposure within the brokerage account of 5 basis points to 36 basis point, as measured by the active risky share or net equity flows, respectively. In addition, we observe a 14.5 to 37.5 basis points increase, depending on the interest variable considered, in funds transferred out of the brokerage account (likely to other money market mutual funds). Remarkably, these portfolio elasticities are close to the ones 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 engage in reaching for yield. Those in the bottom decile of the wealth distribution re-balance their portfolios up to 3 times more than those in the 3rd decile, and up to 7 times more than those in 6th decile, depending on the specific portfolio rebalancing measure that we consider. The wealthiest individuals 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 where labor income is a close substitute for bonds (e.g. Cocco et al. (2005)): young investors, who have a higher human capital to financial wealth ratio, are more likely to engage in reaching for yield. The differences across age deciles are economically large and similar to the ones obtained when studying the impact of wealth.

Interestingly, our cross-sectional results also show that both wealthier and older individuals can sometimes engage in "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 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 in support of prospect theory as an explanation for "reaching for yield". In particular, we test whether investors trading at a loss exhibit stronger tendencies of reaching for yield than those trading at a gain, after controlling for other individual characteristics. Consistent with prospect theory, reaching for yield is more pronounced when investors are currently experiencing losses. This result is robust to the two measures of interest rate innovations we consider and to all three measures of portfolio rebalancing activities.

Importantly, our conclusions are robust to the inclusion of various controls for future expected returns, including lagged dividend-yield, stock market returns, and returns on the investors' own portfolios, and for macroeconomic conditions such as the lagged GDP growth. 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 re-balancing across asset classes, we also explore whether investors re-allocate their portfolio of risky assets in response to *changes* in interest rates. More precisely, we consider whether investors either re-enforce or partially offset the previously documented reaching

[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.

for yield behavior, by increasing or decreasing their risk taking within their risky asset portfolio. 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. Importantly, not only do we document this phenomenon in a field setting, we also examine competing theories that can generate this behavior and find supportive 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 re-balancing in response to changes in monetary policy rates.[5] Korevaar (2023) and Boddin et al. (2024) study reaching for yield in the context of the housing market.

The rest of the paper is organized as follows. In Section 2, we discuss different theories that can explain reaching for yield by retail investors. In Section 3, we present our data and methodology. Section 4 contains our baseline empirical results. In Section 5, we study heterogeneity in behavior across investor 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 Acharya and Naqvi (2019), Drechsler et al. (2018), Ozdagli and Wang (2019), Chodorow-Reich (2014), Di Maggio and Kacperczyk (2017), Hau and Lai (2016), Drechsler et al. (2018) or Barbu et al. (2021)). In

[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 allows them to study consumption responses, which we do not observe.

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

From equation (1) we see that changes in the risk free rate can affect the investor's portfolio share under three conditions. The first condition is when the expected return on stocks (μ) does not move one-for-one with r. In addition, interest rate movements can also effect the optimal portfolio allocation if they are correlated with either the expected volatility of stock returns (σ) or with risk aversion (γ).

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

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

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

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

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 the 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 riskfree 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 (3-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 equation (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 movements. 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.

[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 7, 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.

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 partial derivative of the risky share with respect to the riskless rate, assuming again that both σ is and γ are independent of r, is[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 (equation (2)), particularly if the ratio of the present-value of labor income to financial wealth is high. For an investor with a present-value of labor income to financial wealth of 3, for example, the portfolio share response is 4 times larger than in the model without labor income.

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

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

[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.

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

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

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

In this context, suppose that a drop in interest rates raises asset prices. This would increase investors' financial wealth, resulting in a lower level of risk aversion and a drop in the 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 equation (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 level of interest rates by comparing it to a reference level, for example, the average historical level. When the current interest rate is below the historical level, investors feel that they are in the loss region, which makes them more risk tolerant and increase their risky shares. Conversely, when the current interest rate goes above the historical level, investors become more risk averse and reduce their holdings of risky shares (Lian et al., 2019). Therefore, even with the same current interest rate, investors will be more risk averse when past interests have been low and more risk taking when past interest rates have been high.

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

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

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

2.2 Testable predictions

2.2.1 Age and wealth levels

We now discuss the different testable implications that will guide our empirical analysis. A first clear prediction from equation (4) is that, everything else equal (especially when future labor income is held constant), richer individuals should respond less (in absolute terms) to changes in interests rates, since W appears in the denominator.[14]

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

The derivation is provided in appendix 1.

Considering equation (4) in a life-cycle context yields a second testable implication. In a life-cycle model (see, for example, Cocco et al. (2005)), young agents have substantial wealth in the form of their future labor income, but have only accumulated limited financial wealth. As they get older and approach retirement, they accumulate more wealth, 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 equation (4), they should respond more to changes in interest rates.

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

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

[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.

2.2.2 Changes in wealth

Equation (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 are potentially also 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 off-setting effect in expected dividends, then equity prices should also change in response to interest rate movements.

If we take this effect into account then equation (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]

Equation (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.

[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 below.

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

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

This equation provides one additional testable implication: individuals whose future labor income is more 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, i.e. under equation (7), $\partial \alpha / \partial r$ can now also take positive values. We discuss this possibility in more detail later in this section.

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

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

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

Equation (8) shows that, if increases 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 the exact opposite prediction from the riskless labor income model with CRRA preferences:[19]

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

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

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

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

Even though 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 different channels. The estimated regression coefficient will effectively reveal the relative importance of one channel (ratio of human capital to financial wealth) versus the other (DRRA).

2.2.3 Previous gains or losses

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

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

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.

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 investors adjust their expected stock return by less or more than one for one, following changes in the interest rate.

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

It is important to note that, in both equations, the second term is not very large: it is divided by wealth in equation (6) and by the ratio of human capital to wealth squared in equation (7). However, if the first term is also particularly small, which 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 in cases when the two channels (decrease in wealth and increase in human capital) operate simultaneously (i.e. when combining both equations).

3 Data and Methodology

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

3.1 Data

Our dataset includes account-level transaction data from a large national brokerage firm in China.[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 service to its clients, making all exchange-listed securities available to them. This enables us to observe the trades of all exchange-listed assets. The dataset includes every transaction record from 2006 to 2016, for a total of 2,002,777 investors, and the structure is similar to the one used by Odean (1998), for example. Each observation specifies the account, date, time, price, quantity, and security code. Before 2015 we know that this is the only brokerage account of a person, following the "one investor – one account" 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, namely their age, education and for how long the account has been opened, for example.

A few limitations are worth noting about the data. First, we do not observe holdings of mutual funds (except for ETFs and other exchange-traded assets). However, ownership of mutual funds was quite small among the Chinese markets during the sample period (An et al., 2022). Second, cash balance at the account is only updated whenever an investor makes a transaction. Therefore, if an investor deposits or withdraws cash from their account but does not trade, their cash balance will be not be updated. This concern, however, is largely mitigated by the fact that average Chinese retail investors trade a lot, with a monthly turnover (total transaction volume divided the average balance in a month) of around 100%. Third, while we observe the cash balance in the brokerage account, we do not observe bank accounts and therefore our data does not fully capture investors' holding of risk-free assets. 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 that is used in Gao et al. (2021) and Liao et al. (2021).

[21] The rule was lifted in April 2015 to allow investors to have up to 20 accounts at different brokerage firms. However, in 2016, regulator has tightened the rule again to allow only up to three accounts for one 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, and then sum over all stocks:

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

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

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

The main advantage of this measure is its simplicity. However, as discussed below, it can be distorted by movements in asset prices. Therefore, in our main analysis we consider the three measures presented next. In Appendix 4, we report consistent results obtained with the (simpler) change in risky share.

3.2.2 Active change in risky share

One potential issue with the change in risky share (equation (11)) is that it also reflects movements in asset prices. Therefore, it can take on non-zero values, even in the absence of rebalancing.

[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.

To isolate the effect of an investor's active rebalancing decisions from the effect due to changes in stock prices, we follow Calvet et al. (2009) and compute the active change in risky share. First, we compute the value of stock holdings under the counterfactual that there were no trades between $t-1$ and t (which we denote as A^p_{jt}):

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

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

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

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

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

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

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

3.2.3 Net flow to equity

The second measure that we consider is the total net flow to equity (scaled by account balance). If investors are reaching for yield, then we would expect an increase (decrease) in the net flows to equity when interest rates fall (increase). Our detailed data on investors' accounts include quantity and execution price for each transaction, thus allowing us to calculate these flows. 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:

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

$$Sells_{jt} = \sum_{d \in t} \sum_i S^{id}_j P^{id}, \tag{16}$$

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

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

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

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

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

3.2.4 Withdrawals

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

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

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

3.3 Interest rate

3.3.1 Interest rate variable

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

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

[INSERT FIGURE 1 HERE]

Throughout our sample, there is significant variation in the SHIBOR over time. For instance, the rate experienced a sharp decline—from around 3.5% to around 1%—in late 2008 following the Global Financial Crisis and the stock market crash. Later, once the economy began to recover, the SHIBOR steadily rose and peaked around 7%. Then, in 2015, following yet again another stock market crash, the People's Bank of China (PBoC) cut the interest rate, and as a result the SHIBOR fell to around 3%. The substantial degree of variation in SHIBOR during our sample, makes this period particularly well suited for studying the impact of interest rate changes on portfolio allocation.

3.3.2 Interest rate innovations

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

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

[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

and use the error term as the innovation:

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

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

[INSERT FIGURE 2 HERE]

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

3.4 Other explanatory variables

In addition to the interest rates innovations, we include other variables in our regressions, either as controls or in order to test the different theoretical hypothesis that we have discussed. 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. In our data we have age information for roughly a half of the sample, and we consider all investors aged from 30 to 80 in our analysis. We define ten age groups where the first group includes ages from 30 to 35 and all other groups have a 5-year step (i.e. 36 to 40, 41 to 45, etc).

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

3.4.2 Wealth

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

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

3.4.3 Passive change in wealth

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

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

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

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

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

3.4.4 Previous gains and losses

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

$$Gains^{pp}_{jt} = \frac{\sum_i Q^i_{jt}(P^i_t - \bar{P}^i_{jt})}{A_{jt} + C_{jt}}, \tag{23}$$

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

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

3.4.5 Aggregate variables

In some of our specifications, we include aggregate variables as additional controls, namely aggregate stock returns, the dividend-price ratio, and GDP growth. Finally we also consider the monetary policy rate as our interest rate variable. We discuss these variables and data sources in the relevant sections.

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 significantly lower in the initial part of the sample. Therefore, the median balance in the sample corresponds to about 2 years worth of household income.

[INSERT TABLE 1 HERE]

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

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

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

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

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

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

4 Reaching for Yield

4.1 Baseline results

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

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

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

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

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

Crucially, we do not assume that changes in interest rate are exogenous to household behavior. In that respect we take the same approach as studies who test whether investors are momentum traders or contrarians, or whether they exhibit a disposition effect, for example. Those 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 assessment, or in their risk preferences. In the same spirit, our goal here is to understand how investors respond 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 expectations about those economic conditions.

4.1.1 Regressions with account-level fixed effects

In Table 2, we report regressions where the vector X includes the passive change in wealth ($\log \Delta W^p$, thus capturing Hypothesis 3b and 4b) and the dummies for current wealth (proxied by account balance).[27] The standard errors on the interest rate innovations are clustered at the account level, since it only has time-series variation, while the standard errors on the passive change in wealth are time-clustered.

[INSERT TABLE 2 HERE]

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

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

Withdrawals from the brokerage account could also represent a response to higher expenditure requirements, in response to the increase in interest rates, such as higher mortgage expenses. This,

[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 ($\Delta\omega$, equation (11)) are reported in Appendix 4 (table A3) and yield the same conclusions.

however, would not impact the two measures of portfolio re-balancing within the brokerage account. In fact, to the extent that investors would be more likely to withdraw 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 the ones estimated in Giglio et al. (2021). They find that a 1 percentage point increase in expected stock returns is associated with a 70 basis point higher equity share. To compare with our baseline results we require an assumption about how investors expectations of future stock returns change when the interest changes. Suppose that, following a 1% increase in interest rates, the investors' expected that the stock return will increase by 50 basis points.[30] Then, our regressions imply an elasticity of the brokerage account portfolio to the expected return, of between 10 b.p. to 72 b.p., depending on the measures of portfolio rebalancing and interest rate innovation. To this, we would then add portfolio rebalancing outside of the account, as captured by account withdrawals. Our overall effect is therefore very similar to the estimates obtained by Giglio et al. (2021). Furthermore, we later show that these average responses mask substantial heterogeneity across investors.

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

[29]Furthermore, as shown in Appendix 6, surveys suggest that no more than 20% of stock holders have mortgage. In addition, in China although mortgage rates are typically only fixed for 2 or 5 years, so some investors might be exposed to interest rate risk. the rates are only re-set once a year, in January. Therefore, we wouldn't expect this to have a large impact on the regressions results, even for withdrawals, since they are estimated at a monthly frequency.

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

Since our data include some periods of significant stock market movements ("bubbles and crashes"), in Appendix 5 we report results using data from January 2009 to December 2014 only, 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 equation (2). Let's assume an investor with risk aversion of 5 and an expected return volatility of 20%. A -0.5% change in the risky share implies a value of $\frac{\partial(\mu-r)}{\partial r}$ of -0.1.[31] So, when interest rates increase by 1%, investors expect that the return on stocks will increase by 0.9%.[32] This highlights the underlying assumption behind "reaching for yield" in the context of the Merton model: it will occur as long as investors don't expect the return on stock to move exactly one-for-one with the riskess rate.

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

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

4.1.3 Regressions with age dummies

In the previous regressions, we didn't control for age because we included account-level fixed effects. In Table 3, we consider an alternative specification that replaces the fixed effects with age dummies. The age dummies are constructed from the 10 age groups defined in section 3. Both age

[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 the return on stocks to remain constant.

and wealth are included here "only" as controls. In the next subsections, we specifically consider our Hypotheses 1 and 2, and study how these two variables impact reaching for yield directly.

[INSERT TABLE 3 HERE]

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

4.2 Reaching for yield within risky assets

In our baseline results we consider portfolio re-allocation between risky and riskless assets. In this section we explore whether investors also reallocate their portfolio 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. Neither of those is a prediction of the simple Merton model, though. 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 denotes the vector of expected returns on the different assets, r is a vector where all elements are equal to the riskless rate, and Σ is the variance-covariance matrix of returns.

Equation (26) defines the efficient portfolio, the tangency portfolio in a CAPM setting. Changes in the riskless rate will impact the allocation between the riskless asset 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]

[33]More precisely, unless there is a change in the efficient portfolio. From equation (26), this will only happen

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 Chinese market proxied by the Shanghai Stock Exchange (SSE) Composite Index. We estimate betas on the 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, where the weights are 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. So that A_{jt}^{i} is the value of stock i in period t and A_{jt} is the total value of equity if the portfolio, and the ratio of the two is the share of this stock in investor's portfolio.

4.2.2 Results

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

[INSERT TABLE 4 HERE]

We find a positive and statistically significant coefficient in both regressions, but the economic magnitude of the coefficients 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 re-balancing 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 this model we should only observe a change in the composition

if there is a differential impact on the expected returns of the different assets, or on the different terms in the variance-covariance matrix.

of the risky portfolio if changes in the interest rate are expected to have a differential impact on different risky assets. In particular, we should only observe an increase or decrease in portfolio beta if investors expected that high and low beta stocks would be differentially impacted.

4.3 Results with changes in real interest rate

In our previous analysis we have considered changes in the nominal interest rate as our main explanatory variable, consistent with the previous literature on "reaching for yield" behavior. However, in the simple Merton model (equation (1)), 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. Figure 3 plots changes in both the nominal and real SHIBOR rates over time.

[INSERT FIGURE 3 HERE]

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 (equations (24) and (25)) but with changes in the real rate as our main right-hand-side variable. The results are reported in Table 5.

[INSERT TABLE 5 HERE]

Consistent with our previous results, we again find evidence in favor of reaching for yield across all six specifications, i.e. for all three measures of portfolio re-balancing and the two measures of

[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.

interest rate change. Comparing the results in Table 5 with those obtained 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 perfectly 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 impact on portfolio decisions in the second specification. We also note that expectations of the equity premium may fluctuate due to reasons beyond 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 potential correlation. Ideally we would like a middle ground, where 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 the results.

4.4.1 Proxies for subjective return expectations

In the US market, different variables have been proposed as predictors of excess equity returns, 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 papers 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.

In addition, 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., 2021). 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 they pay more attention to the returns on the assets that they actually own. In addition, it is a more relevant measure of expectations if it captures the expected return on the assets in which they actually invest.

In Appendix 8, 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 lagged stock market returns

In Table 6 we report results where we extended 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.

[INSERT TABLE 6 HERE]

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 engage in reaching for yield behavior, after controlling for the dividend yield and past returns. Relative to the baseline regressions, the coefficients are about 2/3 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 non-trivial effect coming from other the 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, the account withdrawal variable is likely to be a more noisy measure of portfolio rebalancing, since money taken out of the account can also be used for a variety of other purposes, such as consumption or paying back debt.

4.4.3 Results with lagged dividend-yield and lagged portfolio returns

In Table 7, we report results where we include the investors' 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 column (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 in the first four regressions and negative in the last two. This again suggests, on average, investors behave as momentum traders.

[INSERT TABLE 7 HERE]

4.4.4 Results with lagged dividend-yield, lagged returns and lagged GDP growth

As a final extension, we further include lagged GDP growth to control for macroeconomic expectations and macroeconomic conditions. The results are reported in Tables 8 and 9. The coefficients on lagged interest rate, passive change in wealth, past returns and lagged dividend-yield all have similar magnitude and statistical significance to before. Once again, we conclude that, on average, Chinese investors exhibit reaching for yield behavior. The coefficient on the GDP growth variable itself is positive in columns (1) to (4) and negative in columns (5) and (6). This indicates that, following a period of higher GDP growth, retail investors tend to increase their investment in risky assets.

[INSERT TABLES 8 AND 9 HERE]

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 the People's Bank of China (PBC) monetary policy before

October 2015, so-called regulated-retail-interest-rate era.[35] 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, for example.[36]

Interest rates change for a variety of reasons, besides monetary policy shocks, namely in response to technology shocks or demand shocks. Figure 4 shows the time-series plot of the (annualized) 1-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 the paper is to study portfolio responses to changes in interest rates in general, not just the ones driven by monetary policy decisions. Nonetheless, it is also interesting to study those in isolation. We have re-estimated our previous regressions, replacing SHIBOR rate innovations with changes in the benchmark PBC policy rate. The results are reported in Table 10 below.

[INSERT TABLE 10 HERE]

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 negative in the regressions 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 the other variables are the same as in the previous regressions. Therefore, 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 exhibit reaching for yield behavior, 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 baseline specification

[35] 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.

[36] 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.

from section 4.1. Results for the extended specifications from section 4.4 are presented in Appendix 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.[37] More precisely here we focus on Hypothesis 1: reaching for yield should be a decreasing function of wealth.[38]

It is important to remember that Hypothesis 1 results from the equation (3), where the relevant state variable is the ratio of human capital to financial wealth, not financial wealth only. Since we do not observe labor income in our data, we can only control for wealth. However, to the extent that individuals with more wealth are also more likely to have higher income/human capital then that will work against us finding any effect in the data.[39] 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 in the data.

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

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

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

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

To facilitate the exposition, we present the implied portfolio response for each of the ten wealth

[37] 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) or Cocco et al. (2005)).

[38] 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.

[39] 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.

groups in Figures 5 and 6.

[INSERT FIGURES 5 AND 6 HERE]

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

5.1.1 Withdrawal rates

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

The differences across wealth groups are economically large. Consider Figure 5: while investors in wealth group 1 increase their withdrawals by 72 b.p. in response to a 100 b.p. movement in interest rates, for those in wealth group 3 the change in withdrawal rates is less than half of that (38 b.p.). Further up the wealth distribution investors are even less responsive and, as we reach wealth group 7, the change in withdrawal rate is essentially zero (4 b.p.).

This pattern is strikingly consistent with the predictions of the Merton model with labor income (equation (4)). In addition to the monotonic decay with wealth, the model also predicts a convex relationship such as the one obtained in Figure 5: as we move up in the wealth distribution the ratio of human capital to financial wealth becomes negligible and, consequently, a further increase in wealth doesn't change its value by as much as it does for less wealthy individuals.[40]

Giglio et al. (2021) show that wealthier investors reallocate their portfolios more in response to changes in expectations. Therefore, in the absence of the channel implied by hypothesis 1, we would have expected to find exactly the opposite result. Therefore, the isolated effect resulting from our channel is likely to be even stronger.

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

Finally, it is interesting to note that, in the specification with changes in interest rate (Figure 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 Figures 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 to see mostly negative changes. Indeed, for both figures, both measures, and across all 10 wealth groups, the responses to interest rate movements are negative, consistent with reaching for yield behavior.

As we compare the behavior of different investors we again find strong support for Hypothesis 1: less wealthy investors are more responsive to interest rate movements. Interestingly, the pattern is almost exactly the symmetric of the one observed in Panel (a). We observe a clear decreasing pattern (in absolute value) from wealth group 1 to wealth group 7, and essentially flat after that. As discussed before, this convex function of wealth is exactly predicted by equation (4). The magnitudes are larger when we consider the residuals from the AR(1) process as opposed to the simple changes in interest rates. From Panel (b) of Figure 5, a 100 b.p. interest rate innovation leads to a reduction in net equity flows as a percentage of the total account balance, of 54 b.p. for the first wealth group, compared with 35 b.p. for the third wealth group and 21 b.p. for the sixth.

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, for young investors the ratio of human capital to financial wealth is particularly higher, hence they should have a strong portfolio response to interest rates changes. As they get older, their human capital decreases and they accumulate more wealth, consequently the ratio of the two (and therefore the elasticity of the portfolio rule to interest rate fluctuations) falls.

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

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

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

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

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

[INSERT FIGURE 7 AND 8 HERE]

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

5.2.1 Withdrawal rates

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

Interestingly, the results in Figure 8 suggest that investors above age 56 (group 6 and higher), actually engage in reverse reaching for yield behavior: they transfer more money into their brokerage accounts (negative withdrawal rate) when interest rates increase. However, this pattern is not present in Panel (a) of Figure 7. Nevertheless, 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 Figures 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. The differences are again economically significant and the patterns are monotonic across all ten age groups, with the exception of the first age group in Figure 7 (i.e. when considering AR(1) residuals as the interest innovations).

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

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

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 currently trading at a gain, a (small) drop in interest rates pulls them closer to the kink and makes them more risk averse. In comparison, for someone currently trading at a loss, the same interest rate drop will pull them further away from the kink and can make them more risk taking (under certain parameterization). Therefore, we test how reaching for yield is correlated with an investor's current gain/loss position.

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

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

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

where Gain is given by equation (23) and measures the individuals (net) gains. In our analysis, we use measure gains relative to the stock price at the end of the preceding month, consistent with the very high turnover rates that we observe among our investors. Table 11 shows the estimation results.

[INSERT TABLE 11 HERE]

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

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

6 Conclusion

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

We discuss and test different theories of portfolio choice, that generate heterogeneous responses among households. Overall, we find that younger, less wealthy individuals display stronger reaching for yield, which provides empirical support for life-cycle models, and portfolio choice models where 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 this behavior. 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 changes in general. We don't try to isolate specific interest rate shocks, instead we want to understand how investors react when interest rates increase or decrease. It would be interesting to also study the response to monetary policy shocks, for example.

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Table 1: Descriptive statistics

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

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

Table 2: Results for baseline regression with account fixed effects

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.0468***		-0.199***		0.145***	
	(0.00156)		(0.00323)		(0.00291)	
ε_t^r		-0.0911***		-0.363***		0.375***
		(0.00161)		(0.00338)		(0.00312)
$\log \Delta W^p$	-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; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table 3: Results for baseline regression with age dummies

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.0444***		-0.222***		0.126***	
	(0.00276)		(0.00589)		(0.00543)	
ε_t^r		-0.0796***		-0.350***		0.322***
		(0.00285)		(0.00613)		(0.00576)
$\log \Delta W^p$	-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; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

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}, equation (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 ($\log\Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log\Delta W^p$.

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)	
$\varepsilon_t^{r\,real}$		-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_{jt}^c denote each of the three the dependent variables (conditional), the regression specifications are $y_{j,t+1}^c = \alpha + \beta \Delta r_t + \gamma X_{jt} + u_{j,t+1}$ for columns 2, 4 and 6 (where Δr_t^{real} is the change in real interest rate), and $y_{j,t+1}^c = \alpha + \beta \varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) model for real interest rate). The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and $\varepsilon_t^{r\,real}$ 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	116166277	116487592	116232207	116554658	116232207	116554658
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 $y_{j,t+1} = \alpha + \beta \varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ 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, market return in previous month proxied by SSE index (mkt_t^{SSE}) 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 mkt_t^{SSE}, $\log \Delta W^p$ and $\log DP_t$.

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	116166277	116487592	116232207	116554658	116232207	116554658
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 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 ($\log \Delta W^p$), 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 $\log DP_t$.

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 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 ($\log \Delta W^p$), account-level fixed effects and dummy variables for 10 different wealth groups, returns for SSE index (mkt_t^{SSE}), 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. Regression additionally includes gross domestic product monthly gross growth rate $gGDP_t = \frac{GDP_t}{GDP_{t-1}}$) normalized and seasonally adjusted (OECD). Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$, mkt_t^{SSE} and $\log DP_t$.

Table 8: Results for baseline regression with account fixed effects, controlling for past market return, dividend yield and GDP growth

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.0165***		-0.0904***		-0.00934***	
	(0.00156)		(0.00323)		(0.00291)	
ε_t^r		-0.0377***		-0.209***		0.109***
		(0.00169)		(0.00351)		(0.00319)
$\log \Delta W^p$	-0.0632***	-0.0633***	-0.148***	-0.148***	-0.0819***	-0.0815***
	(0.0139)	(0.0138)	(0.0224)	(0.0223)	(0.0182)	(0.0183)
mkt_t^{SSE}	0.0222***	0.0216***	0.0914***	0.0894***	-0.121***	-0.119***
	(0.00720)	(0.00723)	(0.0279)	(0.0278)	(0.0347)	(0.0345)
$\log DP_t$	-1.082***	-1.077***	-5.289***	-5.224***	7.326***	7.261***
	(0.160)	(0.157)	(0.672)	(0.650)	(0.845)	(0.839)
$gGDP_t$	0.0439***	0.0513***	0.621***	0.672***	-0.585***	-0.618***
	(0.00149)	(0.00156)	(0.00368)	(0.00382)	(0.00456)	(0.00467)
Observations	116166277	116487592	116232207	116554658	116232207	116554658
Adjusted R^2	0.011	0.011	0.021	0.021	0.057	0.056

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

Table 9: Results for baseline regression with account fixed effects, controlling for investors' portfolio return, dividend yield and GDP growth

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr_t	-0.00462***		-0.116***		0.133***	
	(0.00158)		(0.00327)		(0.00295)	
ε_t^r		-0.0289***		-0.249***		0.274***
		(0.00170)		(0.00354)		(0.00323)
$\log \Delta W^p$	-0.0621***	-0.0623***	-0.143***	-0.144***	-0.0885***	-0.0880***
	(0.0138)	(0.0137)	(0.0225)	(0.0224)	(0.0198)	(0.0199)
rp_{jt}	0.0254***	0.0251***	0.0591***	0.0578***	-0.0110	-0.00995
	(0.00560)	(0.00559)	(0.0107)	(0.0107)	(0.0102)	(0.0103)
$\log DP_t$	-1.118***	-1.111***	-5.484***	-5.399***	7.653***	7.539***
	(0.173)	(0.168)	(0.700)	(0.676)	(0.881)	(0.868)
$gGDP_t$	0.0569***	0.0628***	0.626***	0.688***	-0.521***	-0.594***
	(0.00149)	(0.00156)	(0.00370)	(0.00384)	(0.00456)	(0.00467)
Observations	116166277	116487592	116232207	116554658	116232207	116554658
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, 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 $y_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ 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. Regression additionally includes gross growth rate $gGDP_t = \frac{GDP_t}{GDP_{t-1}}$) normalized and seasonally adjusted (OECD). Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$, rp_{jt} and $\log DP_t$.

Table 10: Results for regression with benchmark lending rate changes, account fixed effects, controlling for dividend yield, past returns and lagged GDP growth

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔBLR_t	-0.275***	-0.172***	-2.925***	-2.125***	4.312***	2.804***
	(0.0115)	(0.0114)	(0.0255)	(0.0252)	(0.0252)	(0.0249)
$\log \Delta W^p$	-0.0674***	-0.0660***	-0.153***	-0.146***	-0.0789***	-0.0899***
	(0.0143)	(0.0142)	(0.0259)	(0.0266)	(0.0180)	(0.0205)
$\log DP_t$	-1.166***	-1.206***	-5.773***	-5.982***	8.031***	8.310***
	(0.169)	(0.181)	(0.627)	(0.679)	(0.784)	(0.872)
mkt_t^{SSE}	0.0271***		0.122***		-0.161***	
	(0.00800)		(0.0287)		(0.0343)	
rp_{jt}		0.0262***		0.0676***		-0.0217**
		(0.00670)		(0.0120)		(0.00943)
$gGDP_t$	0.0271***	0.0287***	0.628***	0.544***	-0.640***	-0.414***
	(0.00190)	(0.00190)	(0.00455)	(0.00456)	(0.00540)	(0.00539)
Observations	99839679	99523838	99901698	99584503	99901698	99584503
Adjusted R^2	0.012	0.012	0.025	0.025	0.065	0.063

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 innovations 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 different 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 2, 4 and 6 (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 3, 5 and 7. Regression additionally controls for gross growth rate of GDP $gGDP_t = \frac{GDP_t}{GDP_{t-1}}$) normalized and seasonally adjusted (OECD). Sample is truncated to period from October 2006 to October 2015 reflecting the shift in monetary policy in late 2015. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$, mkt_t^{SSE}, rp_{jt} and $\log DP_t$.

Table 11: Results for regression controlling for past gains (monthly gains) and account fixed effects

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta r_t \times \mathbf{1}\{\text{Gain} < 0\}$	-0.140***		-0.304***		0.183***	
	(0.00203)		(0.00409)		(0.00390)	
$\Delta r_t \times \mathbf{1}\{\text{Gain} > 0\}$	0.0752***		-0.0623***		0.0939***	
	(0.00232)		(0.00511)		(0.00447)	
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\}$		-0.180***		-0.476***		0.453***
		(0.00208)		(0.00422)		(0.00406)
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\}$		0.0346***		-0.204***		0.265***
		(0.00253)		(0.00555)		(0.00490)
$\log \Delta W^p$	-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 2, 4 and 6 (where Δr_t is the change in interest rate), and $y_{j,t+1} = \alpha + \beta_1 \varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta \varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). Gain < 0 (Gain > 0) is a dummy equal to one if account experiences losses (gains) where account performace is computed from equation 23, with the price at the start of the month as the reference price. $\log \Delta W^p$ represents the passive change in wealth. The vector X_{jt} includes the passive change in wealth ($\log \Delta W^p$, equation (22)), account-level fixed effects and dummy variables for 10 different wealth groups. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$.

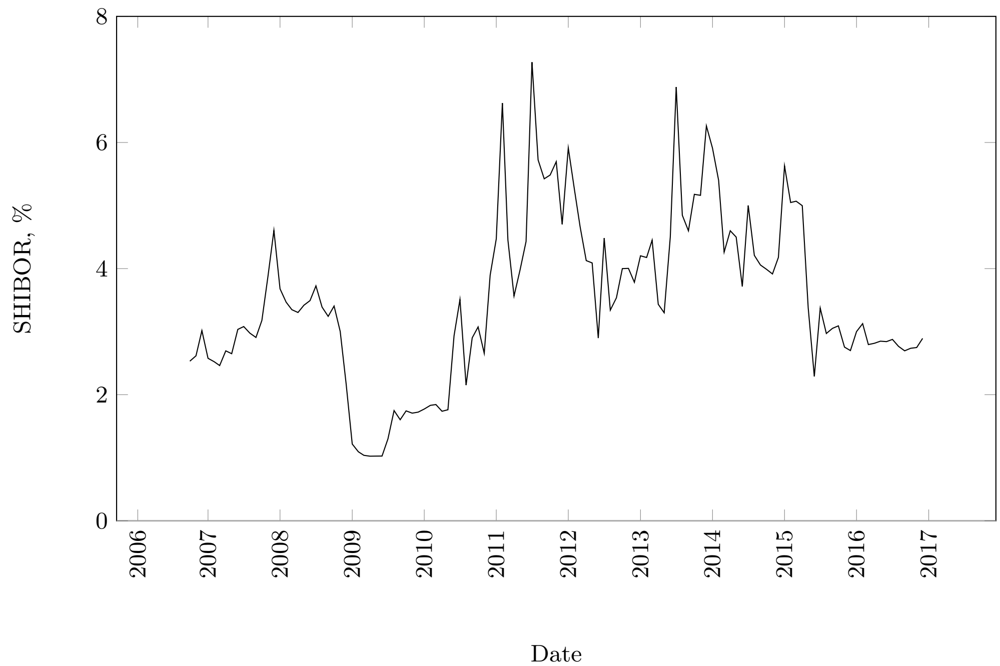


Figure 1: Historical 1-month SHIBOR

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

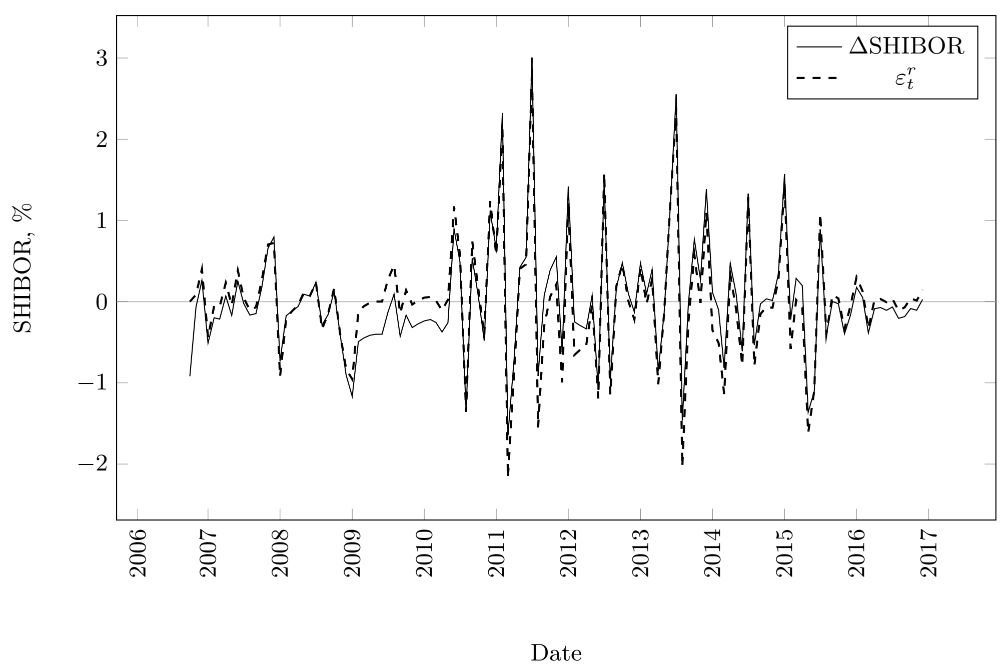


Figure 2: Interest rate innovations

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

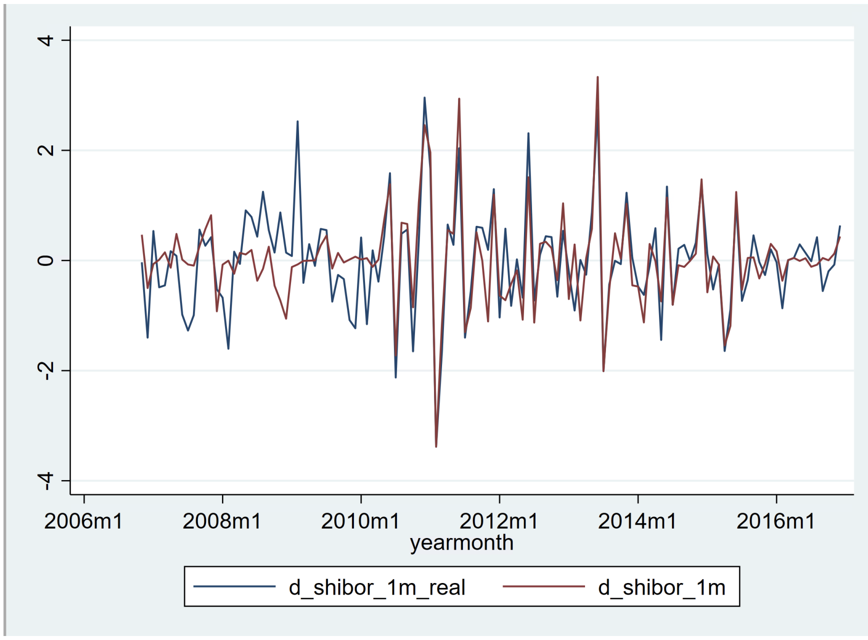


Figure 3: Change in nominal and real SHIBOR time series

The Figure 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 SHIBOR rate.

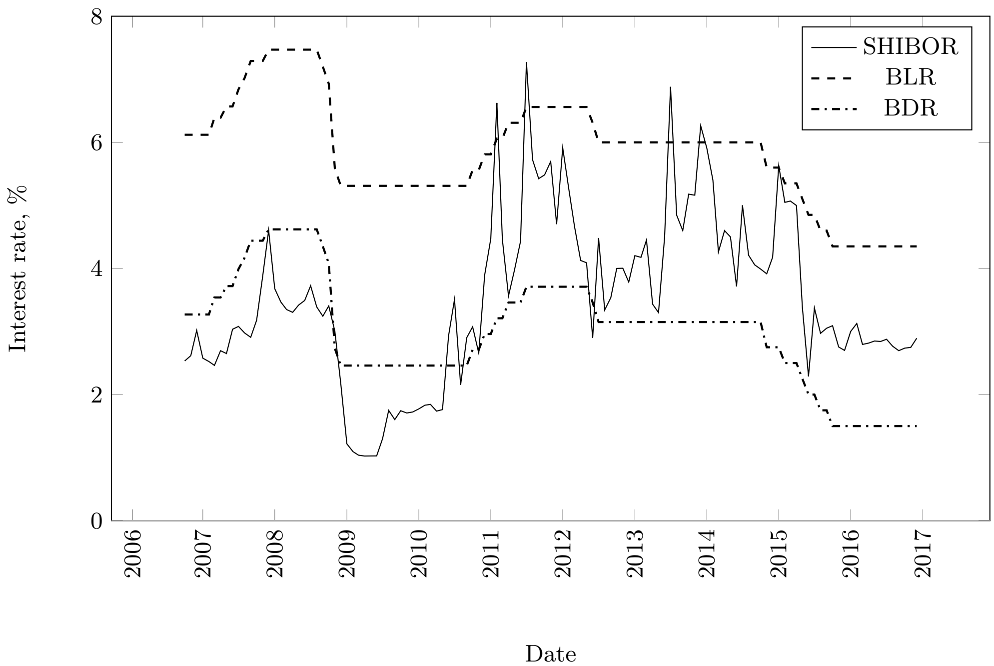
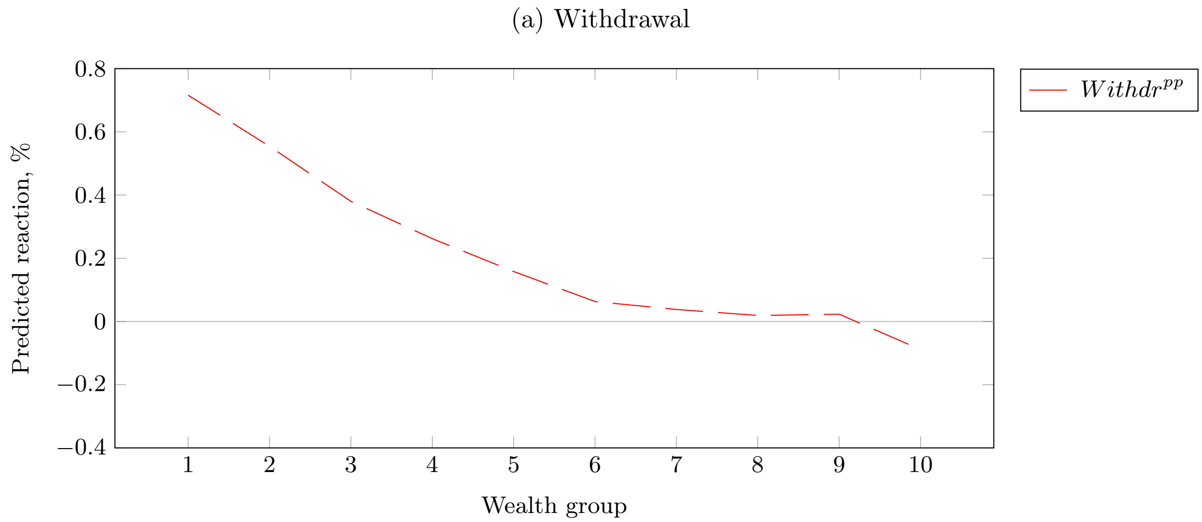


Figure 4: Historical interest rates

Figure 4 shows the time-series plot of the (annualized) 1-month SHIBOR, benchmark lending and deposit rates over the period from October 2006 to December 2016.



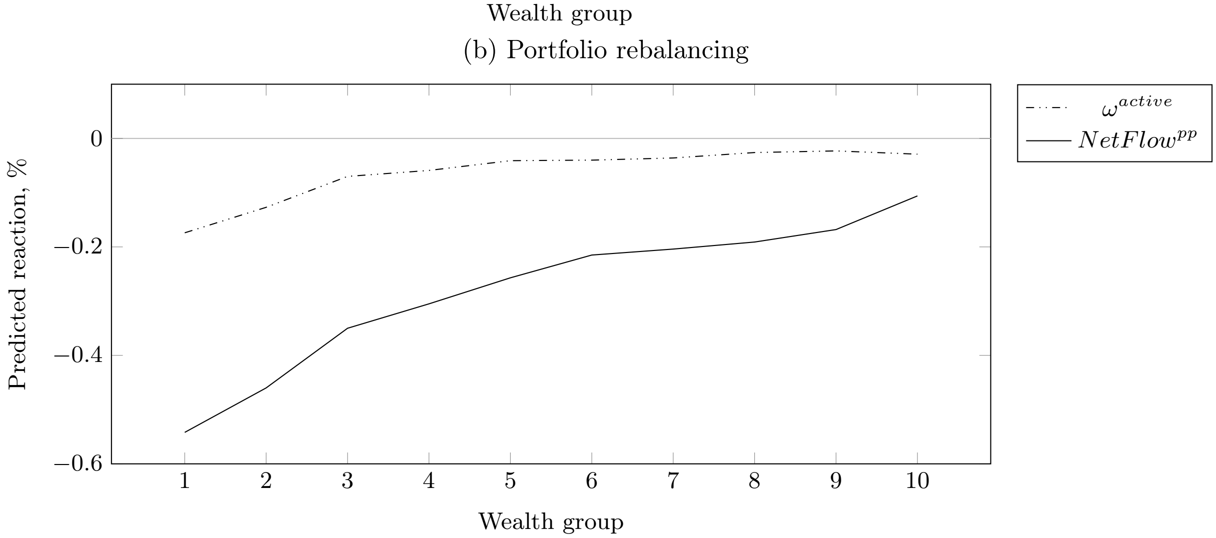
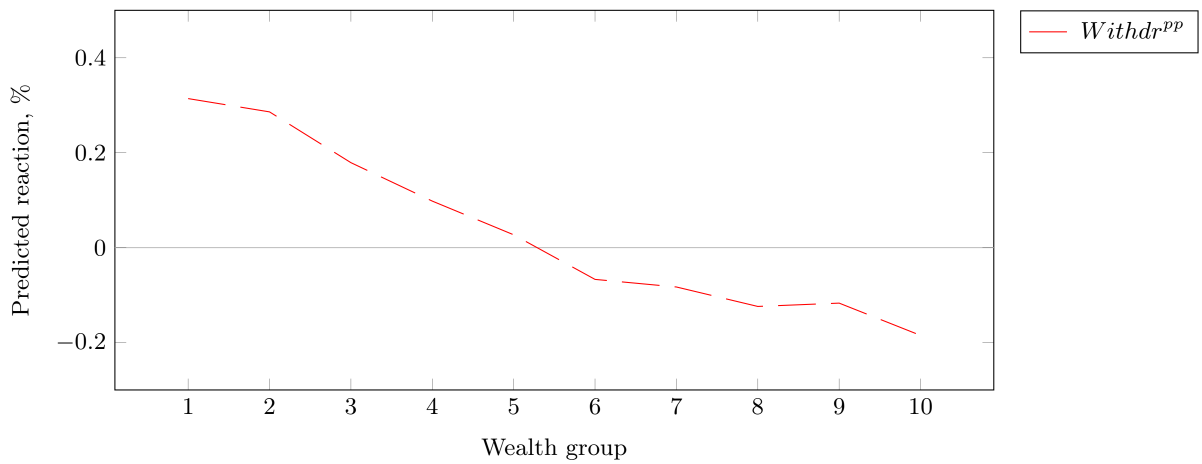


Figure 5: Effect of AR(1) interest rate innovations on investor behavior by wealth groups

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

(a) Withdrawal



(b) Portfolio rebalancing

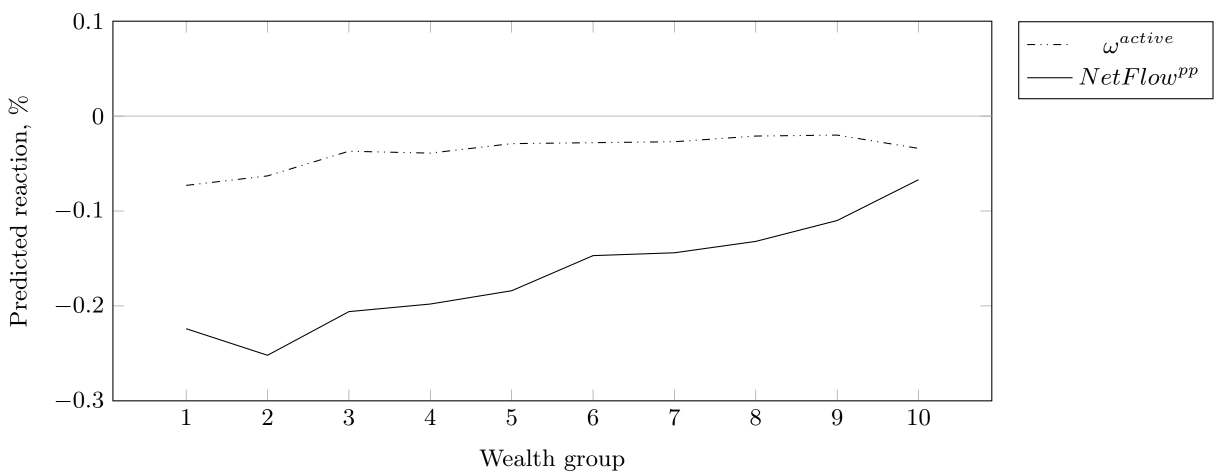


Figure 6: Effect of interest rate changes on investor behavior by wealth groups

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

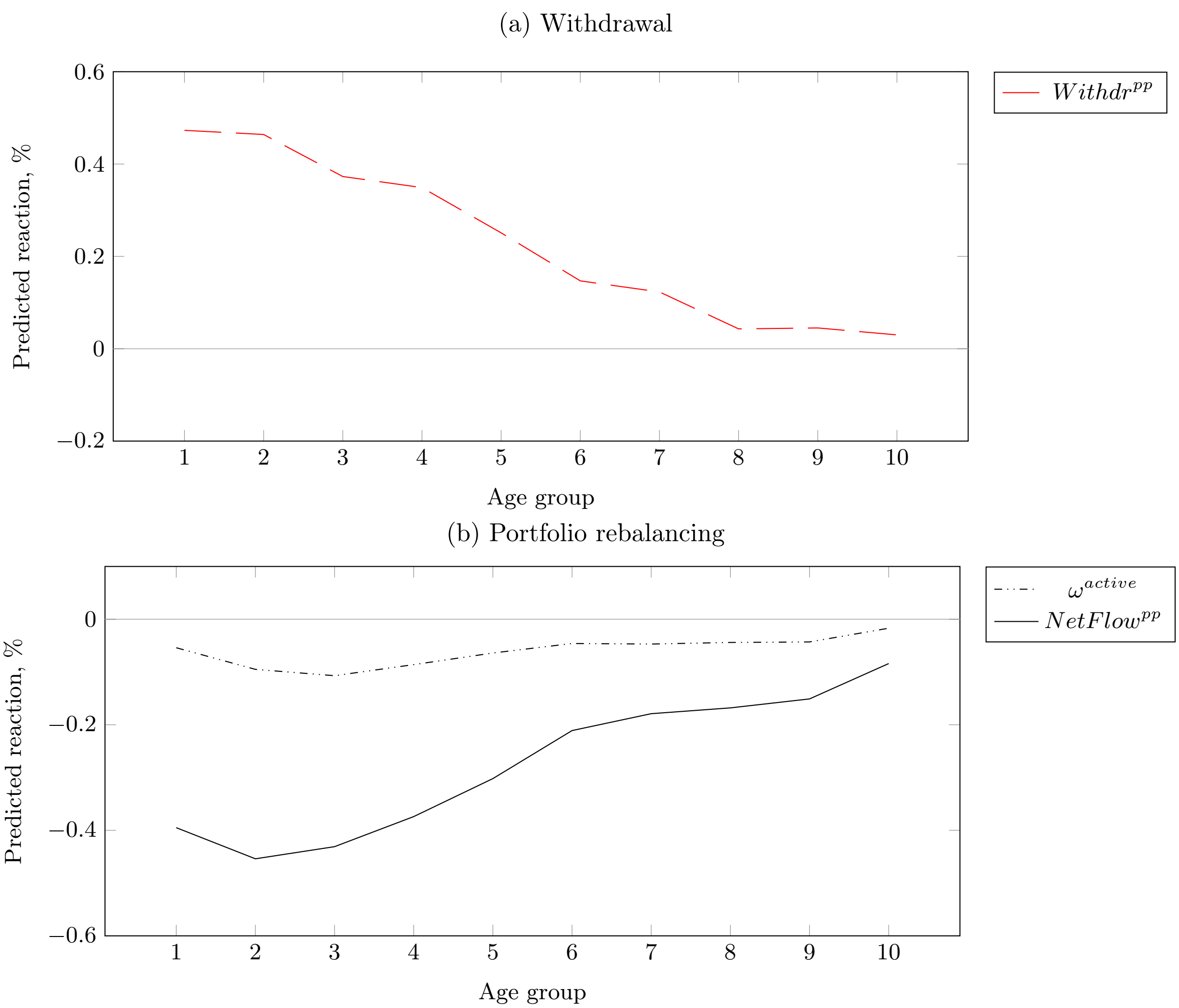


Figure 7: Effect of AR(1) interest rate innovations on investor behavior by age groups

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

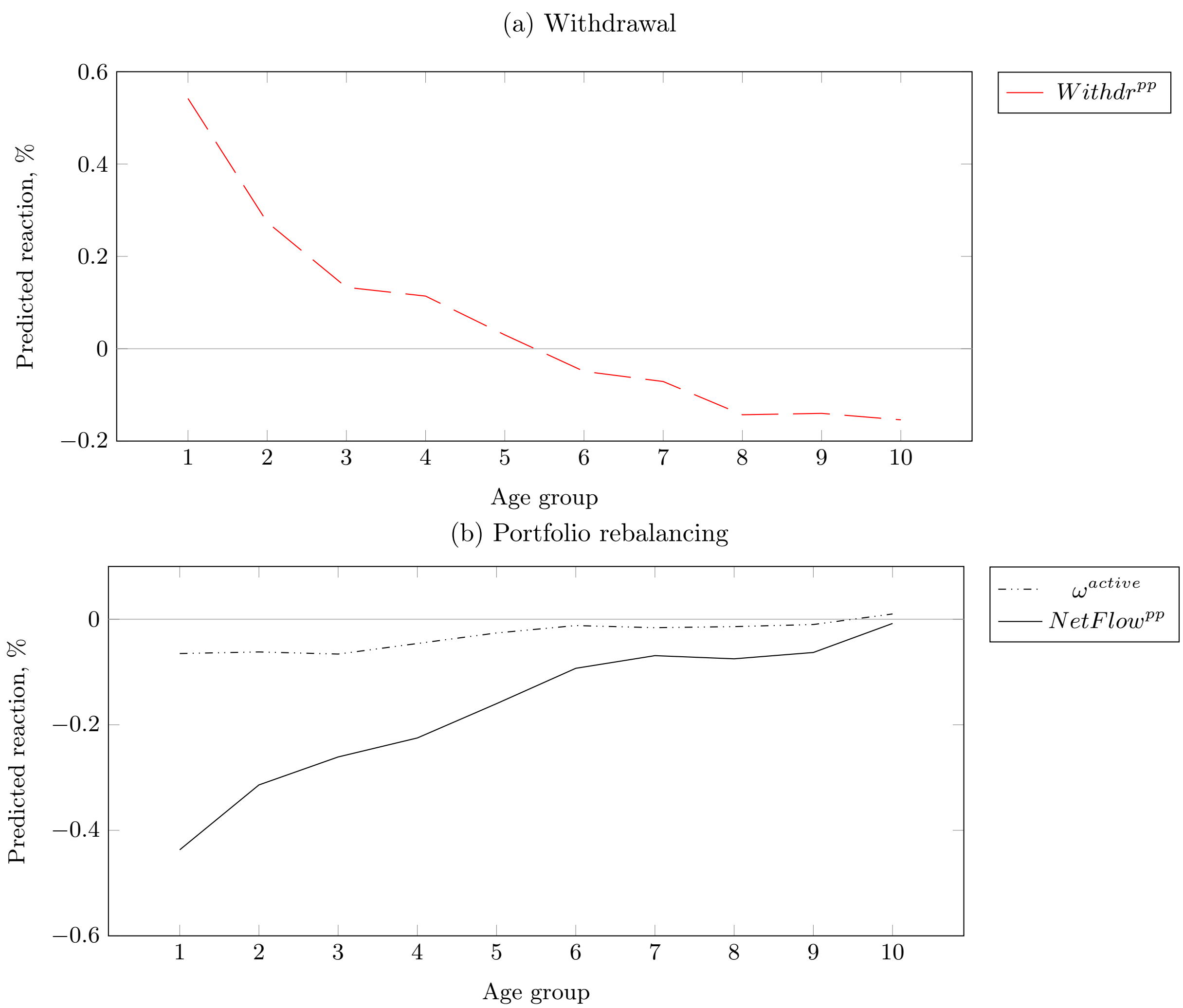


Figure 8: Effect of interest rate changes on investor behavior by age groups

Figure 8 shows the result from regressions of investor behaviour proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The change in interest rate is change in 1-month SHIBOR at the beginning of each month. Each line reflects the values of coefficient for interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and age dummies.

Appendix 1: Derivation of Hypothesis 1

To simplify the notation, we first define

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

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

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

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, i.e.

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

From equation (36), the sign of Γ is also the sign of $\partial\alpha/\partial r$ so we can re-write the previous result as

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

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

Appendix 2: Summary Statistics for Age and Wealth Groups

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

Table A1: Age Distribution of Investors

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

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

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

Table A2: Wealth Distribution of Investors

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

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

Appendix 3: Descriptive statistics for gains and loses

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

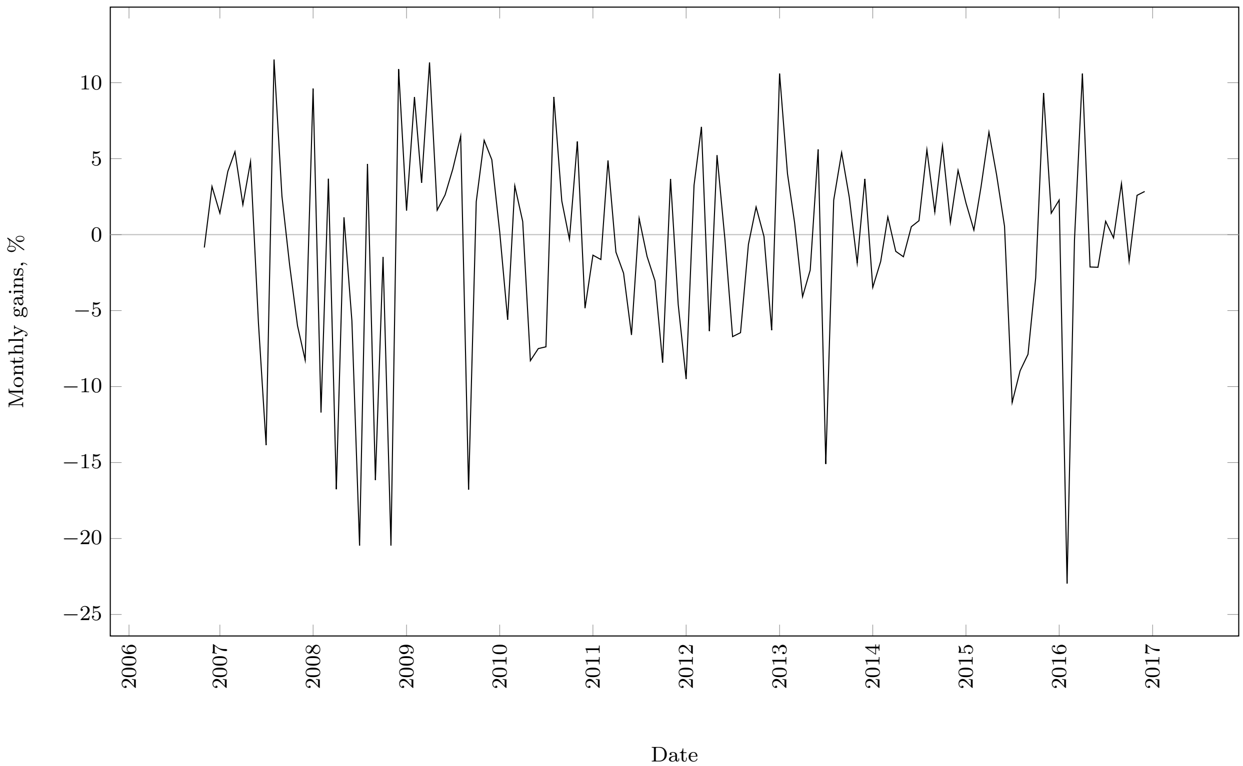


Figure A1: Average monthly account gains and losses

Appendix 4: Baseline regressions for risky share

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

Δr_t	-0.0979***		-0.117***	
	(0.00252)		(0.00451)	
ε_t^r		-0.140***		-0.156***
		(0.00258)		(0.00460)
$\log \Delta W^p$	-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 (equation (11)). The specification in columns 2 and 4 is $\Delta\omega_{j,t+1} = \alpha + \beta\Delta r_t + \gamma X_{jt} + u_{j,t+1}$ (where Δr_t is the change in interest rate), while columns 3 and 5 report results for $\Delta\omega_{j,t+1} = \alpha + \beta\varepsilon_t^r + \gamma X_{jt} + u_{j,t+1}$ for columns 3, 5 and 7 (where ε_t^r is residual from the AR(1) interest rate model). $\log \Delta W^p$ represents the passive change in wealth, and all specifications include dummies for 10 different age groups. The first two regressions include account-level fixed effects while the other two include fixed effects for age. Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$.

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

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

	ω^a		$NetFlow^{pp}$		$Withdr^{pp}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δr	-0.0293***		-0.107***		0.0206***	
	(0.00159)		(0.00324)		(0.00282)	
ε_t^r		-0.104***		-0.358***		0.302***
		(0.00167)		(0.00343)		(0.00306)
$\log \Delta W^p$	-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; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Appendix 6: Institutional details and descriptive statistics for mortgages in China

In China, mortgages are exclusively adjustable rate mortgages (ARMs). 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 second-hand 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 get an insight about home ownership and mortgage utilization, we use the data from The China Family Panel Studies (CFPS). It is an annual longitudinal survey conducted by Peking University. It collects comprehensive longitudinal data on individuals and families in China, with a particular focus on both economic and non-economic wellbeing.

Column (2) of Table A5 shows that the percentage of households that own a house in China was high and relatively stable over the period, with an overall 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 the column (3) of Table A5, 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.

It is also important to note that the percentage of stock owners with a mortgage (column (4)) is moderate and has not shown significant growth, remaining 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.

Table A5: Mortgage ownership in China in 2010-2016, CFPS

year	Owners, %	Mortgage, %	
		All	Stock-holders
(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%

The table A5 presents data from the China Family Panel Studies on home ownership and mortgage in China from 2010 to 2016. The second column indicates the percentage of households that own a house in China for each year. The third column shows the percentage of all households that have a mortgage. The last column provides the percentage of stock owners with a mortgage..

Appendix 7: 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 SSE (Shanghai Stock Exchange) 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 logarithm of market excess returns, calculated by subtracting the 1-month SHIBOR from either the SSE Index or CSMAR value-weighted index in current month (month t), and $\log SHIBOR^{3m}_{t-1}$ is the logarithm of the 3-month SHIBOR in the previous month (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 A6 below. 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 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 equation (37) and $\hat{\sigma}_e$ is the standard deviation of the residuals from the following regression

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

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 includes periods of dramatic market movements ("bubbles and crashes"). Therefore, we also repeat the previous regression for the more "stable" period (January 2009 to December 2014), and we obtain similar results: the estimated $\hat{\beta}$ is -1.62 for the SSE 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.

Table A6: Predictive performance of lagged interest rate

Dev.Var.	(1)	(2)	(3)	(4)
$\log RetX_t$	Full sample	2009-2014	Full sample	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, i.e., the difference between a return for 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 sub-sample spanning January 2009 to December 2014 and excludes boom and bust periods.

Appendix 8: Forecasting regressions in the Chinese stock market

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 previously studied, in the context of the Chinese stock market, by Nie and Yin (2022). The paper argues that an institutional change in 2008 produced a distinct influence on the dividends policy of the Chinese-listed firms and affected the information conveyed by dividends. [41] Motivated by this, they estimate the predictive regression separately for the pre- and post-2008 periods and, consistent with the regime shift hypothesis, they 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 A7. Our full sample period is between 2006 and 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 A8. 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.

[41] 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.

Table A7: 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: $\log RetX_t = \beta_0 + \beta_1 \cdot \log DP_{t-1} + \varepsilon_t$, where $RetX_t$ is market excess return, i.e. 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 ($\log \frac{D_t^{12}}{P_t}$). Both variables are in logarithms. The sample covers the period from 2006 to 2018 at monthly frequency. Column (1) uses the full sample, while Columns (2) and (3) are based on the sub-samples before and after 2009.

Table A8: 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: $\log RetX_t = \beta_0 + \beta_1 \cdot \log RetX_{t-1} + \varepsilon_t$, where $RetX_t$ is market excess return, i.e. a return for aggregate equal-weighted market portfolio with dividends reinvested over risk free return (1-month SHIBOR). The sample covers the period from 2006 to 2018 at monthly frequency. Column (1) uses the full sample, while Column (2) is based on the sub-sample spanning January 2009 to December 2014 and excludes boom and bust periods.

Appendix 9: Wealth effects from regressions with controls for expected returns

In this appendix we repeat the analysis in section 5.1, where 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 Figure A2. 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 engage in more reaching for yield type behavior. 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 more striking that we are still able to uncover this relationship.

The results in Figure A2 reveal a large number of wealth groups that exhibit reverse reaching for yield. Therefore, it may 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 opted for using economically relevant wealth cutoffs. As a result, almost 2/3 (63.92%) of our investors are in the bottom 3 groups. These investors are responsible for reaching for yield at the aggregate level.

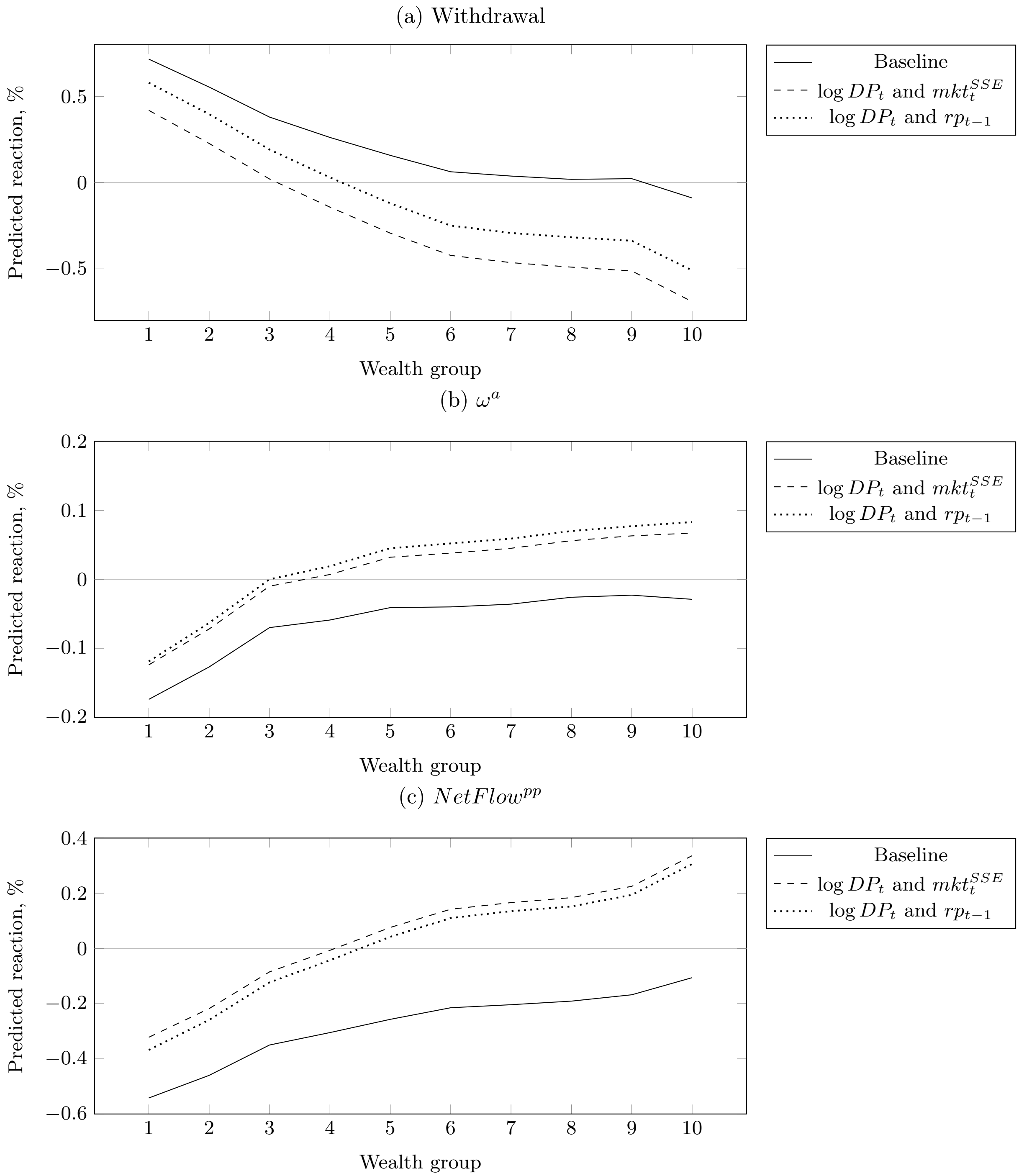


Figure A2: Effect of interest rate changes on investor behavior by wealth groups controlling for past stock market returns

Figure A2 plots the result from regressions of investor behaviour proxies on change in interest rate interacted with wealth group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovations correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of interaction effect of change in SHIBOR and wealth group. All regressions also include the passive change in wealth, wealth dummies and account fixed effects. Regressions additionally control for dividend-price ratio combination with either investor's past return or previous month stock market returns (SSE Index).

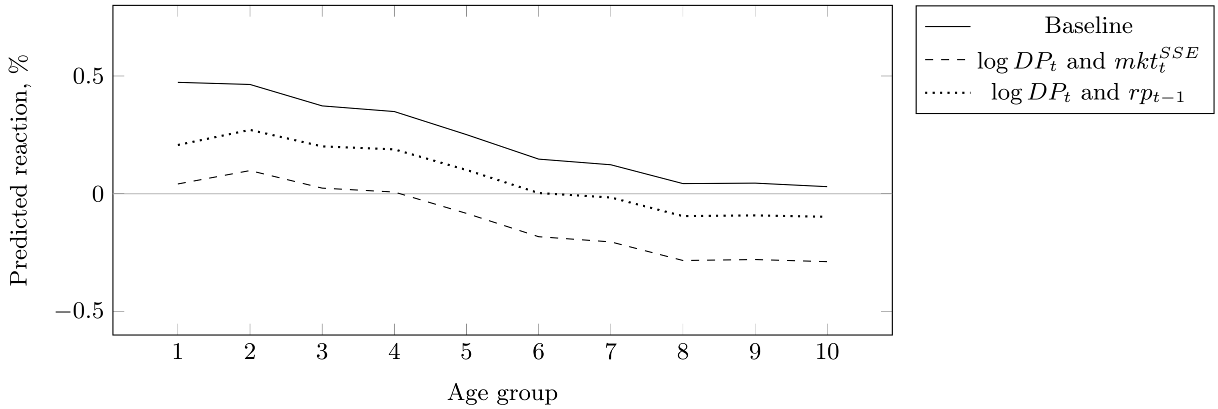
Appendix 10: Age effects from regressions with controls for expected returns

In this appendix we repeat the analysis in section 5.2, where we study heterogeneity in portfolio responses to interest rate changes 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.

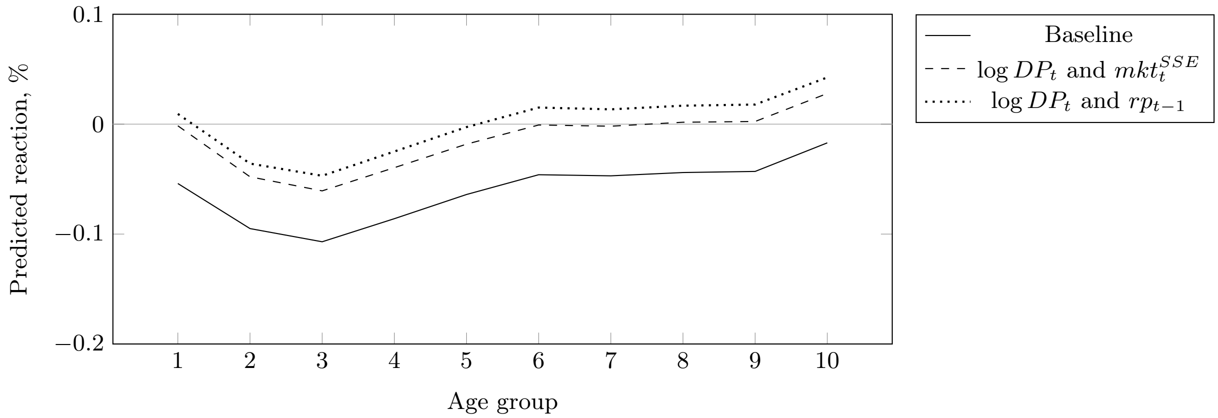
The results are shown in Figure A3 We find the same patterns as in baseline specification: younger agents are more actively reaching for yield.[42] This, again, aligns well with the theory. In terms of the overall magnitude, consistent with the results in section 4.4, the inclusion of additional controls reduces the size of reaching for yield. This also coincides with more cases showing the opposite, namely, reverse reaching for yield.

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

(a) Withdrawal



(b) ω^a



(c) $NetFlow^{pp}$

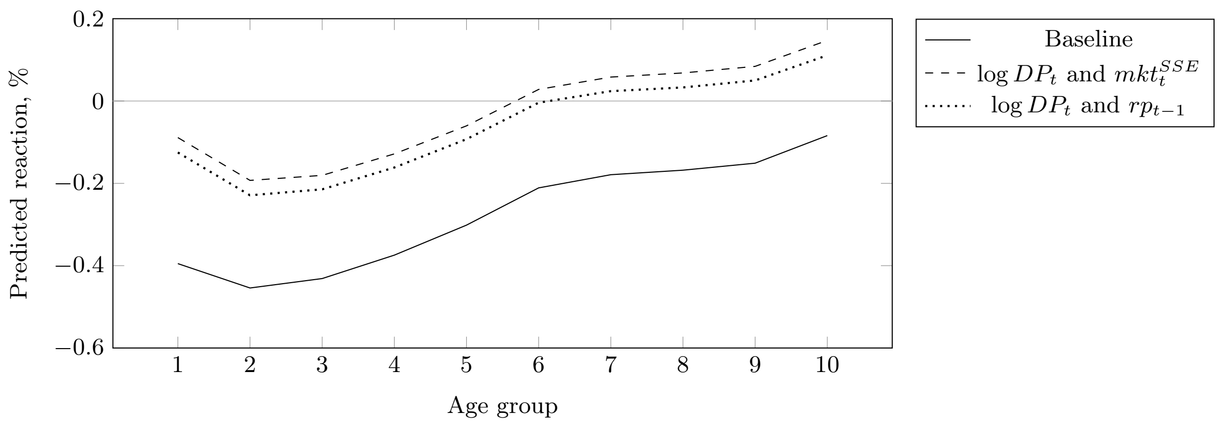


Figure A3: Effect of AR(1) interest rate innovations on investor behavior by age groups controlling for past stock market returns

Figure A3 shows the result from regressions of investor behaviour proxies on change in interest rate interacted with age group dummies. Investor behavior proxies are active change in risky share, net flow into equity and withdrawals (both as share of previous balance). The interest rate innovations correspond to the residuals from an AR(1) process for SHIBOR. Each line reflects the values of coefficient for interaction effect of change in interest rate and age group. All regressions also include the passive change in wealth and wealth dummies. Regressions additionally control for dividend-price ratio combination with either investor's past return or previous month stock market returns (SSE Index).

Appendix 11: Prospect theory channel with controls for expected returns

In this appendix we repeat the analysis in section 5.3, where 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 show in Table A9.[43] We obtain the same patters of reaching for yield as in section 5.3: investors trading at a loss engage in reaching for yield, while those trading at a gain engage in reverse reaching for yield. As in all previous cases, 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 (the ones for withdrawals), while the coefficient on the dividend-yield has the opposite sign, consistent with retail investors behaving as trend-chasers.

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

Table A9: 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)	
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\}$		-0.146***		-0.336***		0.265***
		(0.00209)		(0.00422)		(0.00405)
$\varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\}$		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	116166277	116487592	116232207	116554658	116232207	116554658
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 with additional control for dividend-price ratio and past market returns. 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 $y_{j,t+1} = \alpha + \beta_1 \varepsilon_t^r \times \mathbf{1}\{\text{Gain} < 0\} + \beta_2 \Delta \varepsilon_t^r \times \mathbf{1}\{\text{Gain} > 0\} + u_{j,t+1}$ for columns 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), 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 ($\log \Delta W^p$), account-level fixed effects, dummy variables for 10 different wealth groups, dividend-price ratio ($\log DP_t$) and returns for SSE index (mkt_t^{SSE}). Statistical significance is based on account-clustered SEs for Δr_t and ε_t^r and on time-clustered SEs for $\log \Delta W^p$, mkt_t^{SSE} and $\log DP_t$.