Mutual Fund Investments in Retail Banking: Do Low Interest Rates Matter?

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Abstract

Using proprietary account-level data from a commercial bank in China, we find significant reaching-for-yield phenomenon among mutual fund retail investors. It is manifested by lower interest rates that induce (1) higher returns of mutual fund portfolios though active rebalancing, (2) greater inflows into mutual fund products, particularly from structured deposit products, and (3) increased weighted-average risk rating of mutual fund portfolios. Interestingly, we find that the adoption of an APP technology, which allows investors to view products more easily, amplify such reaching-for-yield behavior. In particular, young, male, and lower-income investors exhibit stronger reaching-for-yield tendency. We find consistent evidence to support a backward-looking reference-dependent preference as we detect significant bunching of mutual fund holding at the initial investment level, yet only in a low interest environment. Moreover, investors who purchased mutual fund products at higher historical prices exhibit a stronger reaching-for-yield behavior. Last, we explore an interest rate shock that further supports a causal interpretation of our findings.

Key words: Reach for yield, mutual funds, mobile investing, reference-dependent preference

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1. Introduction

Right after the 2008 global financial crisis, central banks around the world have set interest rate benchmarks to historically low levels for a prolonged period of time. Such low interest rate environments in general tend to benefit borrowers at the expense of lenders and savers in the capital market, while investors tend to increase their appetite for risk taking due to the limited benchmark returns (i.e., reaching-for-yield, hereafter, RFY). In existing studies, there has been ample RFY evidence toward the institutional investors and the role of agency problem between fund managers and investors in creating the RFY phenomena.[1] Nevertheless, there is limited research for retail investors due to data accessibility (see experimental evidence in Lian, Ma, and Wang, 2019). In addition, it is entirely unclear whether researchers can extrapolate incentives that drive institutional investors' RFY behavior to retail investors' if the latter manage financial assets on their own. In this paper, we empirically examine the RFY behavior among retail investors in China's mutual fund industry. In particular, we employ a novel proprietary data set from a commercial bank in China (hereafter, the bank), which includes 4,203 customers' mutual fund transactions at the account level from July 2017 to June 2018.

China's mutual fund industry provides a suitable setting for our study. First, China's mutual fund industry has been growing at an incredibly fast pace and has become a sizable industry. For example, the number of mutual funds grew almost a hundredfold over the past two decades, from 46 in 2001 to 4395 in 2017, implying an annual growth rate over 40% (Jiang, 2020). In 2018, its asset under management reached 12.9 trillion RMB without the support of any pension flows and exceeded China's GDP of that year (i.e., 12.3 trillion RMB).[2] Since China's financial markets lack diversity in investment vehicles, mutual funds provide an important investment venue for investors in China. Second, retail investors play a dominant role in China's financial markets. Retail investors hold

[1] E.g., Choi, and Kronlund (2018) on mutual funds, Di Marggio, and Kacperczyk (2017) on money market funds, Becker, and Ivashina (2015) on insurance companies, etc.

2 See more details at https://www.euromoney.com/Media/documents/euromoney/pdf/CHINA-AND-THE-WORLD-The-future-of-Asset-Management_em.pdf

58 percent of the stock market, according to Jia, Wang, and Xiong (2015), and account for 80 percent of trading volume (Carpenter and Whitelaw, 2017). In particular, since the 2015 Chinese stock market crash, a steady yet substantial growth in the mutual fund industry has mainly been driven by the increasing participation of retail investors. By the end of 2019, the number of stock market participants increased by 9.04% to 160 million since the end of 2018. Among them, approximately 44.8% are retail investors who invest in public offerings of mutual funds while the statistic was 26.7% a year ago. Therefore, understanding retail investors' behavior in China's mutual fund markets is also of great importance in studying China's financial markets.

We combine three sets of account-level data: (1) transactions and holdings of mutual fund products and demand deposit, accompanied with information on their prices and interest costs, (2) investors' demographic information, and (3) investors' digital footprints on the bank's official APP and WeChat public account. We define an investor's portfolio as assets under their mutual fund investment account and demand deposit account. Following the approach in Choi and Kronlund (2018), we decompose the change in monthly portfolio returns into three sources and focus on the active RFY component (i.e., the return change mainly due to active rebalance of the portfolio by investors). We supplement our analysis with other non-return-based measures to reflect investors' RFY behavior. These measures include net flows into mutual fund products, structured deposit products and term deposit products,[3] buy and sell transactions of mutual fund products, and portfolio risk.

By applying a first-difference regression approach on our panel data set, we find a substantial RFY phenomenon among retail investors in China, as reflected by a non-negligible effect via active investment. Specifically, one percent reduction in the yield of one-year government bond is associated with an increase of 2.3 basis points in the active

[3] We have only flow information rather than price and interest rate information of structured deposit products and term deposit products. Therefore, we do not include them in the calculation of portfolio returns and use only flow data for supplemental analysis.

RFY component. However, when zooming into the specific risk category of mutual fund products, we find that the RFY behavior is neither universal nor monotonic across product risk levels. The RFY phenomenon concentrates on the products with intermediate risk levels of R3 and R4, rather than R2 or R5.[4] One percent decline in yields results in an increase of 1.1 basis points and an increase of 1.3 basis points in the active RFY component of products with risk levels of R3 and R4, respectively. For products with risk levels of R2 and R5, we observe insignificant results, indicating that retail investors in China refrain from gambling with products of the highest risk level.

We also find strong and robust results of active RFY behavior from other non-return-based measures. Specifically, we find significant net inflows into mutual fund products and net outflows from structural deposit products as the yield of the one-year government bond goes down. Structured deposit products are subject to mandatory deposit insurance and principal-protected, thus enjoying lower returns and low risk (i.e., R2). Our finding suggests that investors search for returns in mutual funds by offloading less risky products. However, they do not downsize savings in the forms of demand deposits and term deposits when searching for higher yields. Regarding transactions, we find an increase in the buy frequency and a decrease in the sell frequency of mutual fund products when the yield decreases. In particular, the scale of buying is five times that of selling. In addition, we find that investors increase value-weighted portfolio risk by 0.468 percent (based on the risk classification employed by the bank with a two to five scale) when the yield shrinks by one percent, suggesting that RFY behavior is associated with greater risk taking.

[4] The bank evaluates risk (from a two to five scale) based on the risk of principal and the proportion invested in risky assets, such as stocks, foreign exchange, etc. For mutual fund products, in general, classification of two represents extremely low risk products like money market funds and classification of five are those purely or mostly focus on stock markets, while the classification of three and four are those investing in bond markets or a mixed combination of bonds and stock markets.

In light of the fast development of financial technology (hereafter Fintech) that assists participants in financial assets management, we, next, examine its impact on investors' RFY behavior. We take as an exogenous event of the introduction of a new WeChat public account by the bank in January 2018, after which investors can view financial products directly via this public account embedded in WeChat. As a widely used APP in China, WeChat integrates social communication, content sharing, mini-apps, mobile payment, and many other functions into one platform. The Launch of an official public account on WeChat presumably provides investors with easier access to a swath of financial product information. We explore a prominent feature of digital footprints embedded in the data. We identify naive investors as those who have never used the bank's mobile banking APP, which was introduced earlier than the WeChat public account, to view financial products before January 2018, and sophisticated investors as those who have used the mobile banking APP to view financial products at least once before January 2018. While naive investors may just begin to take advantage of accessing information via their WeChat accounts, sophisticated investors may have already used mobile phones for acquiring investment-related information. The key insight, therefore, is that the introduction of the WeChat public account would provide naive investors with a greater reduction in the information acquisition cost than their sophisticated counterparts.

By using a difference-in-differences regression approach that involves interaction with changes in yield, we show that, upon the introduction of the public account, a decline in one-year government bond yield causes naive investors to view mutual fund products more frequently than sophisticated investors do. Consistently, we find that naive investors exhibit a stronger RFY tendency than sophisticated investors do, reflected in the active return component. These results are robust to a propensity matching approach based on age, gender, income, and mutual fund holding. Therefore, our findings suggest that technological innovations that lower the information acquisition cost could amplify RFY tendency.

While the previous finding suggests heterogeneity along Fintech adoption, we further study retail investors' RFY behavior along other dimensions. We find that RFY is stronger among young, male investors as well as investors with a lower income. Younger investors are in earlier stages of life cycle and thus more likely in pursuit of wealth than older investors. Regarding the gender difference, it is well documented that males are more risk tolerant and thus may have stronger incentive to gamble in low interest environments. Also, the male is considered as the main income earner under the traditional Chinese culture and thus more likely to be subject to a wealth pursuit pressure (Wei, Zhang, and Liu, 2017). Lastly, investors with a lower income could be more eager to gamble and thus more likely to exhibit RFY behavior.

We believe that our results are consistent with a reference-dependent preference explanation rather than a belief-based channel. In particular, we investigate the role of backward-looking reference points in affecting RFY behavior. First, we use various historical purchasing price measures to proxy for reference levels. We find that investors with higher historical purchasing costs display stronger RFY behavior. Second, we look at months when investors have sell transactions and compare portfolio holding in these months to the initial investment level. We detect significant discontinuity of holding at the initial investment level and bunching right to the initial investment level in a low interest environment. In contrast, in a high interest environment, we do not detect discontinuity at the initial investment level, suggesting that investors are more reluctant to liquidate mutual fund investment with a loss when interest rate is low. Our findings are consistent with a reference-dependent preference explanation that underlies RFY behavior (Kahneman and Tversky, 1979, 1991; Koszegi and Rabin, 2006).

Last, there could be an identification challenge in our context due to either omitted variable bias or reverse causality. To address the endogeneity concern, we explore a low interest rate shock initiated by the central bank in China (the People's Bank of China), which is unlikely caused by retail investors' RFY incentive in the mutual fund markets. We focus on a sudden jump of 10 basis points in the repo rate in January 2018. We find that the active component of portfolio returns dropped significantly when the repo rate shifted up, indicating RFY behavior.

Our paper makes the following contributions. First, our paper complements the literature on searching for high-yield securities by various types of institutional investors. Banks, mutual funds, money market funds, insurance companies, and pension funds invest in riskier assets when interest rates are low (e.g., Maddaloni and Peydró, 2011; Jiménez, Ongena, Peydró, and Saurina, 2014; Chodorow-Reich, 2014; Hanson and Stein, 2015; Choi and Kronlund, 2016; Di Maggio and Kacperczyk, 2017; Andonov, Bauer, and Cremers, 2017). While this strand of literature offers insights on RFY behavior based on institutional frictions (e.g., agency problems and financial intermediaries' funding conditions), such frictions can hardly be applied directly to understanding individual investors who manage their own portfolios. Our paper complements this literature by showing that individual investors also exhibit RFY behavior in mutual fund investments due to a reference-dependent preference.

Relatedly, our paper supplements recent experimental studies that explore RFY behavior among individual investment decisions (Lian, Ma, and Wang, 2019; Lian and Ma, 2018). Lian et al. (2019) document the existence of RFY behavior among retail investors using a lab experiment. While an experimental approach presents obvious advantages in addressing challenges that arise from isolating changes in the risk-free rate from risks of assets and measuring investors' beliefs about returns and risks, it is hard to fully square with investment decisions under real investment environments in terms of investment horizon, investment at stake, and asset diversity. By exploiting observational data of retail investors in the mutual fund industry, we show that RFY behavior in a real investment setting where investor demographics, mutual fund risk levels, investment technology, and reference points are found to be relevant in shaping RFY behavior.

Second, our paper contributes to the literature that study reference-based preferences (Tversky and Kahneman, 1979; Koszegi and Rabin, 2006). Our findings are in the same spirit as the literature that investigate reference-dependent preference in the settings of labor supply, job search, and household consumption decisions (e.g., Farber, 2005, 2008; Koszegi and Rabin, 2007, 2009; Crawford and Meng, 2011; and DellaVigna et al., 2017, among others). By showing such a preference for mutual fund investors, we also enrich the applications of prospect theory in the behavioral finance literature (e.g., disposition effect in Odean (1998) and Barberis and Xiong (2012), equity premium puzzle in Benartzi and Thaler (1995), and narrow framing of stock returns in Barberis, Mukherjee, and Wang (2016)).

Finally, our paper contributes to the literature that study Fintech adoption and economic behaviors (Higgins, 2020; Xu et al., 2020; Hong et al., 2020), among which digitalization plays a crucial role in these changes (Berg et al., 2020; Agarwal et al., 2020). We show that Fintech adoption in a form of easy access to financial products via the bank's WeChat public account, is associated with greater RFY intensity. Our findings suggest that Fintech adoption could either amplify investors' behavioral tendency. Our findings, thus, caution that the wide rollout of Fintech may amplify risk-taking of retail investors in the financial system. Therefore, for retail investor-dominated markets, the design and implementation of monetary policy should consider these effects.

Our paper is organized as follows. Section 2 describes data sources and explains variable construction. We illustrate our empirical methodology in Section 3 and empirical findings in Section 4. Section 5 concludes the paper.

2. Data and Variable Construction

Our data set for this paper contains three sets of account-level data, which we obtain from a commercial bank in China. The first data set contains transactions and holdings of mutual funds (MF) and demand deposits (DD). These products' prices and interest rates are also provided to compute portfolio returns. The second data set contains demographic information of investors' profiles. The third data set contains digital footprints on the bank's official mobile banking APP and its WeChat public account. Our data set consists of a randomly selected sample of 4,203 customers, each of whom has executed at least one transaction in mutual fund investment and demand deposits between June 2017 and June 2018. While we do not observe an individual's universal financial investment with one bank account, we try to mitigate concerns by obtaining monthly flow data of other types of financial products invested by our sample investors under the same bank, including structured deposits (SD) and term deposit (TMD) products.[5]

We construct the weighted portfolio returns for customer i in month t, $Ret_{i,t} = \sum_j w_{j,i,t} y_{j,t}$, where j denotes either any mutual fund or demand deposit products invested by customers. Moreover, we decompose the change in returns *ΔRet* into three sources, among which the first term is the *active* RFY component *(ΔRet_active)*, the second term is the passive component (*ΔRet_passive)*, and the third is an interaction between the two *(*Choi and Kronlund, 2018). While the active component reflects changes in return due to account rebalancing, the passive component manifests changes in return from holding the same assets over the period.

$$\Delta Ret_{i,t} = \sum_j \Delta\left(w_{j,i,t} y_{j,t}\right) = \underbrace{\sum_j \Delta w_{j,i,t} y_{j,t}}_{\Delta Ret\_active} + \underbrace{\sum_j w_{j,i,t} \Delta y_{j,t}}_{\Delta Ret\_passive} + \sum_j \Delta w_{j,i,t} \Delta y_{j,t}$$

To capture RFY behavior, we focus on the active component, ΔRet_active, throughout our empirical analysis. Our main analysis is based on an investor' portfolio that includes both mutual fund investment and demand deposits, as noted earlier. We also calculate ΔRet_active based on an investor' portfolio that includes only mutual fund investment for robustness.

To further understand the variations in active RFY behavior across different risk groups of mutual fund products, we calculate *ΔRet_active* for each risk group of mutual

[5] We do not have price and interest rate information of these two types of products. Therefore, we do not include them in the calculation of portfolio returns and use only flow data for supplemental analysis.

fund products to obtain *ΔRet_active_R2*, *ΔRet_active_R3*, *ΔRet_active_R4*, and *ΔRet_active_R5*, where two indicates the lowest risk classification and five the highest as noted in footnote 2. Note that it is mandatory for commercial banks in China to disclose the risk classification of financial products sold to investors.

To reflect more directly the investment choices of investors and overall risk taking, we supplement our main RFY variable with other non-return-based measures, namely, net flows into mutual funds, structured deposits, term deposits and demand deposits, trading frequencies of buy and sell transactions, and value-weighted average of portfolio risk based on risk ratings from a two to five scale as explained above. Table 1 displays the descriptive statistics. We find that investors, on average, obtain an active RFY return of 0.1 basis points monthly and 3.021 weighted portfolio risk classification. Monthly net flow is 97.272 thousands RMB for mutual fund products and 9.650 thousands RMB for demand deposits. Monthly trading frequency is 0.172, and 0.141 comes from buy transactions. We also find that 53.1% investors are below 45 years old, 46.4% have an income level of more than 150 thousands RMB, and 42% are male investors.

[Insert Table 1 here]

3. Methodology

We regress the change in returns that are attributable to changes in active portfolio weights, ΔRet_active, on the change in one-year government bond yield. We adopt a first-difference regression specification below, where subscript i denotes account-level observations and subscript t denotes month.

$$\Delta Y_{i,t} = \beta \Delta Yield_t + Control_t + Time\ trend + \varepsilon_{i,t}. \quad (1)$$

The dependent variable $\Delta Y_{i,t}$ denotes respectively $\Delta Ret_{i,t}$, $\Delta Ret\_active_{i,t}$, $\Delta Ret\_active\_R2_{i,t}$, $\Delta Ret\_active\_R3_{i,t}$, $\Delta Ret\_active\_R4_{i,t}$, and $\Delta Ret\_active\_R5_{i,t}$. The key independent variable of interest is $\Delta Yield_t$, which measures the change in the yield of the one-year government bond from the previous month. In addition, we include control variables of *GDP Growth* and *Inflation* to control for macroeconomic conditions, and time trend (different for each investor).[6] Standard errors are clustered at the investor level.

4. Empirical Analysis

4.1 Baseline Results

Table 2 reports the results of the baseline regression model in Equation (1). In column (1), we observe a negative coefficient estimate and it is statistically significant at the 1% level. The coefficient estimate of $\Delta Yield$ is -0.023, indicating that a one percent decline in yield, on average, leads to an increase of 2.3 basis points in active returns. From columns (2) to (5), we find that RFY is neither universal nor monotonic. We observe that the active components of return increments are generated by mutual fund products of moderate risk levels with risk classifications of R3 and R4 rather than R1 and R5. One percent decline in yields results in an increase of 1.1 basis points and an increase of 1.3 basis points in the active RFY component of products with risk levels of R3 and R4, respectively. For products with risk levels of R2 and R5, we observe insignificant results with magnitudes close to zero. This result implies that in search for a higher yield, retail investors refrain from investing in the safest category of mutual funds, such as money market funds, and the most risky category of mutual funds, such as pure equity funds. Instead, they focus on mutual funds that invest in bond markets or a mixed combination of bond and stock markets. While it may look counter-intuitive that investors also become more interested in bond markets in a lower interest rate environment, we note that retail investors may hold a diverse set of portfolios that consist of assets with even lower yields than bond mutual funds. We will show in Section 4.1.2 that as the yield of one-year government

[6] Since we use the first-difference model as our main regression specification, the investors' observable and unobservable time-invariant characteristics are differenced out. Therefore, we do not control for investor fixed effects.

bond declines, investors liquidate structured products that are safer than bond mutual funds in search for a higher yield.

[Insert Table 2 here]

Figure 1 presents a graphical display of empirical observations of Table 2. Panel A of Figure 1 shows a negative empirical correlation between changes in one-year government bond yield and active RFY return. Empirical results of different risk groups are also shown graphically in Panel B of Figure 1, in which variations in active RFY return are more sensitive to yield changes for mutual fund products with risk levels of three and four than for risk levels of two and five.

[Insert Figure 1 here]

4.1.1 Transaction-based Measures

Apart from examining return-based measures of active RFY behavior, we utilize other non-return-based measures to reinforce our findings, including net flow, trading frequency and portfolio risk to reflect active portfolio management and risk taking.

Table 3 reports the results using the baseline regression model in Equation (1). In column (1), we observe significant net inflows into mutual fund products. Specifically, we find that a one percent decline in the one-year government yield leads to a 189 thousands RMB net inflow into mutual fund products. This finding suggests that in searching for yield, investors do transfer money to risky mutual fund products.

[Insert Table 3 here]

Second, we examine trading frequencies and portfolio risk. $Buy_{i,t}$ and $Sell_{i,t}$ are the frequency of buy and sell transactions of mutual fund products. Results in columns (2) and (3) show that retail investors tend to buy more frequently and sell less frequently mutual fund products as the yield declines. $Risk_{i,t}$ is value weighted average risk based on mutual fund assets' risk classification from a two to five scale. In column (4), we find that the portfolio risk increases significantly following a decrease in the yield: a one percent decline in the one-year government bond yield leads to a 0.565 percent increase in risk classification.

Overall, our results in this section indicate that investors exhibit a tendency to increase the holdings of riskier assets in their portfolios.

4.1.2 *Flows Across Product Accounts*

From last subsection, we showed that an increased interest rate indeed induces a larger net flow into mutual fund products, consistent with our reaching-for-yield story. The next question to be answered is where the fund flow comes from and why. In this subsection, we investigate fund flows across different products.

First, as noted in Section 2, we do not observe an individual's universal financial investment with one bank account. One might concern that mutual fund investments under one bank account do not reflect overall RFY tendency. We try to mitigate concerns related to this issue by obtaining monthly flow data of other types of financial products invested by our sample investors under this bank. Specifically, we examine four net flow measures to capture investors' active portfolio management, namely, *Netflow* $MF_{i,t}$, *Netflow* $DD_{i,t}$, *Netflow* $SD_{i,t}$, and *Netflow* $TMD_{i,t}$, which are net flows to mutual funds, demand deposits, structured deposits, and term deposits, respectively.

The correlations between fund flows and interest rate fluctuations across different products are displayed in Figure 2. It shows a strong negative correlation between net flows of mutual fund products and change in yields in Panel A, while a positive correlation between net flows of structured deposits products and yield changes in Panel B. We do not detect any noticeable patterns for term deposit or demand deposit products. Consistent with our RFY hypothesis, it indicates that when the yield declines, investors rebalance their portfolio partially by pulling out funds from structured deposit products, which in general are less risky than mutual fund products, and switching into riskier mutual fund products.

[Insert Figure 2 here]

The pattern is visualized more clearly in Figure 3. The scatter plot of account-level monthly observations of net flows of mutual fund products and structured products shows a clear negative correlation, with observations scattering along the $-45°$ line. In high interest environments, funds tend to flow from mutual fund products into structured products, while an opposite pattern is observed when the interest rate is low.

[Insert Figure 3 here]

Regression results are further presented in Table 4. Consistently, we find that, as the yield declines, the net flows into mutual fund products possibly comes from the net flows out of structured deposits. Specifically, a one percent decline in the one-year government yield leads to a 76 thousands RMB net outflow from structured products. In contrast, there are not much flow changes in term deposits and demand deposits, though positive. Structured deposits are less risky than mutual funds but riskier than term deposits and demand deposits. One possible interpretation is due to mental account in the sense that investors may not treat term deposits and demand deposits as sources of investments.[7] Thus, when adjusting or rebalancing their portfolios to chase for a higher yield, they tend to transfer funds from structured deposits (seen as "lower risk investments") to mutual funds (seen as "higher risk investments").

[Insert Table 4 here]

4.1.3 Focusing on Only Mutual Fund Products

[7] For example, term deposits usually are not quite liquid given their feature about fixed terms. Demand deposits, on the other hand, may serve mainly as cash needs and thus may not be treated as a way of investment.

From examining net flows and trading frequencies, we observe that investors shift their assets to mutual funds products, the riskier asset category, rather than to demand deposit products. In this subsection, we further restrict our portfolio construction to investments in only mutual fund products. Table 5 reports the empirical results.

Focusing on mutual fund products only, we find comparable results as those in Table 2. Panel A shows that retail investors retain a strong pursuit for higher yields following a decline in the one-year yield of government bonds. A one percent decline in yield, on average, leads to an increase of 1.1 basis points in active RFY returns. Similarly, RFY behavior mainly comes from the two medium risk levels of R3 and R4.

[Insert Table 5 here]

4.2 Fintech Adoption and Reaching-for-yield Behavior

In this section, we explore a prominent feature of the digital footprints embedded in the data and examine how Fintech adoption affects RFY behavior across investors.

We take the introduction of a new WeChat public account by the bank in January 2018 as an exogenous event. This public account allows investors to view information of all financial products provided by the bank on it. As one of the most popularly used APP in China, WeChat is an instant messaging, social media, and mobile payment APP developed by Tencent. It can also integrate mini-apps and many other functions into its platform. Launching bank's public account on WeChat presumably provides its clients with easier access to a swath of financial products' information and minimize the learning cost.

We then divide our data into two sub-samples, naive investors who have never used the bank's mobile banking APP, which was introduced by the bank earlier than the WeChat account, to view financial products before January 2018, and sophisticated investors who have used the APP to view financial products at least once before January 2018. The key insight is that, compared with sophisticated investors who have already been used to information acquisition via mobile device before, the introduction of the new WeChat technology would provide naive investors with more reduction in the information acquisition cost.

$$\Delta Y_{i,t} = \beta_1 \Delta Yield_t + \beta_2 After \times Treat_i \times \Delta Yield_t + \beta_3 After \times \Delta Yield_t + \beta_4 Treat_i \times \Delta Yield_t + \beta_5 After \times Treat_i + \beta_6 After + Control_t + Time\ trend + \varepsilon_{i,t} \quad (2)$$

We modify the baseline regression and adopt a difference-in-differences (DiD) regression interacted with yield changes in Equation (2), where *After* is a dummy variable that indicates the period after January 2018, and *Treat* is an indicator of the aforementioned group of naive investors. Apart from examining *ΔRet_active* as the dependent variable, we also examine *Product view*, which is the total frequency of viewing mutual fund products on WeChat. Other control variables are all defined the same as in Equation (1). β_2 is the main estimate of interest. Table 6 provides the empirical results.

[Insert Table 6 here]

In columns (1) and (2), we find that the coefficients on $After \times Treat \times \Delta Yield_t$ are negative and statistically significant at the five percent level. Specifically, after the the WeChat public account was introduced, a one percent decline in one-year government yield leads to naïve investors to view mutual fund products via the bank's WeChat public account 1.2 times more than sophisticated investors. In addition, we find that naive investors exhibit stronger RFY behavior in terms of active portfolio returns after the introduction of the public account: a one percent decline in the yield leads to naïve investors to obtain six basis points higher than sophisticated investors in terms of active RFY returns. Overall, our results suggest that technological innovations that potentially lowers the information acquisition cost could spur RFY tendency. In unreported tests, we also find that a one percent decline in one-year government yield leads to naïve investors to use the bank's WeChat public account 3.9 times more than sophisticated investors.

One potential concern is that sophisticated investors, who have used mobile technology to acquire investment related information, may own special traits/characteristics that are substantially different from naïve investors, which confounds with the treatment effect of the introduction of the public account. In other words, our findings could suggest either that Fintech adoption amplifies investors' behavioral tendency or that it sifts out investors with such a tendency. We conduct two tests to validate our empirical strategy.

First, one key identification assumption of DiD analysis is parallel trends: naïve and sophisticated investors would continue the same trends in the absence of the treatment shock. We conduct the pre-trend test and the results are reported in Appendix Table 1. Overall, we do not observe any significant differences in changes in product views and active RFY returns prior to the introduction of the WeChat public account between naïve and sophisticated investors. This finding suggests that the effect of the introduction of the WeChat public account is unlikely to be driven by pre-existing differences between the two groups of investors.

Second, to further isolate the treatment effect from selection, we conduct propensity score matching based on investors' age, gender, income and mutual fund investment holding based on a one-to-two matching.[9] The results are shown in columns (3) and (4). Overall, the pattern is consistent with the results from unmatched sample. Once the WeChat public account was introduced, a one percent decline in one-year government bond yield leads to naïve investors to view mutual fund products via the bank's WeChat public account 1.2 times more than sophisticated investors do. In addition, we find that naive investors exhibit stronger RFY behavior in terms of portfolio returns: a one percent

[9] Since the sample of sophisticated investors is about twice as large as naïve investors, we apply a one-to-two matching to maintain the comparability. The comparability of investor characteristics between the treatment and control groups for unmatched and matched samples is shown in Appendix Figure 1. In addition, though not reported, one-to-one matching demonstrates a similar result.

decline in one-year government bond yield leads to naïve investors to obtain 5.2 basis points higher than sophisticated investors in terms of active RFY returns.

Our findings, therefore, suggest that Fintech adoption that potentially reduces information acquisition costs could amplify investors' RFY tendency.

4.3 Heterogeneity

In this section, we study the heterogeneity in retail investors' active searching for risky products with higher yields along several dimensions. Aspects that we take into consideration include backward-looking reference points, demographic characteristics, and interest rate environments.

4.3.1 Reference-dependent Preference

The prospect theory gives rise to the possibility that RFY behavior is attributable to a reference-based preference. Another possible explanation for our previous findings is a belief channel. Yield fluctuations could be caused by changes in investors' belief about the asset market, giving rise to the concern of reverse causality. Or, investors may update their beliefs about assets' returns and risks as the interest environment changes, which is unrelated to a preference-based explanation. To differentiate the reference-based preference explanation from the belief channel, we rely on unique predictions of the reference-based preference theory and find strong evidence that lends support to backward-looking reference points, which can be either the status quo or an average of recent outcomes (see DellaVigna, 2018 for a review).

We first explore historical purchase prices as a potential proxy for an investor's reference level. We conjecture that investors who purchased mutual fund products a high price in the past should have a greater RFY tendency and be more sensitive to an interest rate decline. A typical belief-based channel should be more influenced by information in the future and less likely to be influenced by historical prices. To test this hypothesis, we first compute (1) the average price of all historical month-end prices, (2) the initial purchase price, (3) price in the previous month end, and (4) the highest historical price of a mutual fund product in an investor's portfolio. We then calculate the average price for each of the four prices across all mutual fund products held by the investor. We further divide our sample into two subsamples above and below the median of each of the four prices constructed above. We then run the baseline regression as in Equation (1) and report our findings in Table 7.

[Insert Table 7 here]

We find that while the coefficient estimates in the low-price categories remain uniformly insignificant, the coefficient estimates in the high-price categories are all statistically and economically significant. For example, column (4) shows that when initial purchase price is used as the reference level, a one percent decline in yield, on average, leads to an increase of roughly 4.2 basis points in active RFY returns. We attribute these findings to the reference-based preference that underlies the RFY behavior.

[Insert Figure 4 here]

Second, we conjecture that investors with RFY tendency should be more reluctant to sell assets at a loss (i.e., compared to initial investment levels) in a low interest rate environment than in a high interest rate environment due to loss aversion. A typical belief-based channel should not exhibit such discontinuity at the initial investment levels and variations in the discontinuity across different interest rate environments. To test this, we look at months when investors have sell transactions in Figure 4. We compare mutual fund holdings in these months to the initial investment levels. We detect significant discontinuity of mutual fund holdings at the initial investment level and bunching right to the initial investment levels in a low interest environment. The estimated coefficient of discontinuity is 3.85 with the P-value of 0.001. In contrast, in a high interest environment, we do not detect discontinuity at the initial investment levels. The estimated coefficient is 0.78 with the P-value of 0.44. Our findings suggest that investors are more reluctant to liquidate mutual fund investment with a loss when interest rate is low, consistent with a reference-based preference explanation.

4.3.2 *An Interest Rate Shock: Implications from Different Interest Rate Environments*

In the previous sections, we provide analysis to show that a belief channel cannot explain our findings. To further address the concerns of omitted variables or reverse causality, we explore an interest rate shock initiated by the People's Bank of China (PBOC), the central bank of China. PBOC raised the seven-day and 28-day reverse repurchase rates by five basis points in December 14, 2017 and 63-day reverse repurchase rate by five basis points in January 16, 2018. The market regarded these moves by the PBOC "a bit unexpected", and the PBOC explained their moves largely as responses to the tightening in monetary policies around the globe, especially in the US.[10] Thus, we consider the change in the interest rate environment before and after January 2018 as exogenous to investors' trading activities in the mutual fund markets in China.

We split our sample into pre- and post-January 2018 and conduct analysis based on Equation (1) for three months and five-months before and after January 2018, respectively. The results can be found from columns (1) to (4) in Table 8. Comparing investors' RFY behavior before and after the shock, we find that the sensitivity of active RFY returns to changes in the one-year government bond yield drops by four basis points in three months and two basis points in five months after the PBOC's moves.

In addition, we divide our sample based on the level of one-year government bond yield into higher or lower than the median level of the sample. We conjecture that RFY behavior should be more pronounced if investors already face a low interest environment. We present the findings in columns (5) and (6) in Table 8. Indeed, we find that the

[10] For more details, please refere to http://finance.sina.com.cn/money/bond/market/2017-12-15/doc-ifyptfcn0561748.shtml and https://news.ifeng.com/c/7fZzapsAuft.

coefficient estimate of the low interest rate period is negative and statistically significant. On contrary, the coefficient estimate of the high interest rate period is insignificant and much smaller in magnitude. The results show that RFY behavior is stronger when interest rates are low. Taken together, our findings of the heterogeneity in retail investors' active searching for risky products are consistent with a reference-dependent preference.

[Insert Table 8 here]

Overall, our findings in this section lend further support to a causal interpretation of our results. Combined with the findings in Section 4.3.2, we believe that reference-based preference drives investors' RFY behavior.

4.3.3 Demographic Characteristics

In this section, we explore the heterogeneity in RFY behavior across investors with various demographic characteristics. We divide the demographic information into two groups in three ways: (1) below versus above 45 years old, (2) male versus female, and (3) rich who have an income level above 150 thousand RMB versus poor who have an income level below 150 thousand RMB. We present the empirical findings in Table 9.

[Insert Table 9 here]

The demographic study suggests that young investors reach for yield more actively than old investors do, that male investors reach for yield more actively than female investors do, and that low income investors reach for yield more actively than high income ones do. The difference is especially patent in the division based on gender and age. Magnitudes of coefficients on $\Delta Yield_t$ for the young and male (-0.019 and -0.02) are almost double those for the old and female investors (-0.01 and -0.011), respectively. This could be because young investors are in earlier stages of life cycle than older investors and thus more likely in pursuit of greater wealth. Also, males are typically more risk-tolerant than the females. Besides, a male is considered as the main income earner under the traditional Chinese culture and thus more likely to be subject to a wealth pursuit pressure. For investors with relatively low income, they could be more likely to feel compelled to yield chasing and become rich. Our findings in this subsection, therefore, are not inconsistent with a reference-based preference that underlies RFY behavior.

5. Conclusion

While many existing studies have documented that institutional investors chase yield through various channels in mutual fund investments, especially when interest rates are low, we find that retail investors also possess preference for higher yields of mutual fund investments.

We utilize a novel transaction-level data set that contains retail investors' mutual fund investments, demographic information and their digital footprints on the bank's mobile banking APP and WeChat public account. We show that the RFY phenomenon exists among retail investors in China where retail investors dominate the market. We also find that the change in interest rate leads to an obvious increase in investors' risk taking, and according to the data the risk preference seems to concentrate on products with intermediate risk levels. Importantly, we find large net fund inflows to mutual funds from structured deposits as interest rate declines, while no significant net flows in saving accounts associated with demand deposits or term deposits. Investors also buy more frequently and sell less frequently as interest rate declines.

As to further investigate investors' personal traits, RFY behavior is stronger among young, less-wealthy and male investors. The effect is also more pronounced among investors who purchased mutual fund products at higher prices. In times of low interest rates, we find stronger effect of loss aversion. Our findings are consistent with a reference-dependent preference explanation that underlies RFY behavior.

In addition, by taking advantage of the digital footprints of product views by retail investors, we demonstrate that the new technology adoption that lowers the information acquisition cost could spur RFY tendency. These findings suggest that Fintech adoption could either amplify investors' behavioral tendency.

Overall, our results suggest that monetary policy affects retail investors' decision on portfolio choice, wealth allocation and risk preference by influencing the asset returns. An expansionary monetary policy may incentivize retail investors to rebalance individual wealth to riskier mutual fund products, potentially adding to the aggregate risk of the market. Our findings also caution that the wide rollout of Fintech that simplifies financial investment of retail investors may amplify such a risk. Therefore, for retail investor-dominated markets, the design and implementation of monetary policy should take these possible effects into consideration.

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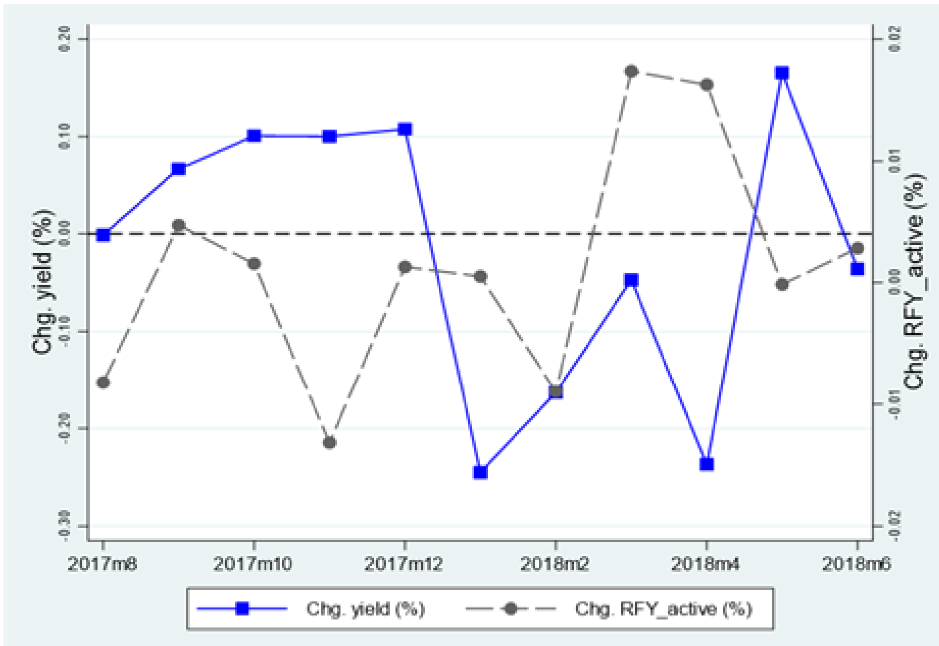
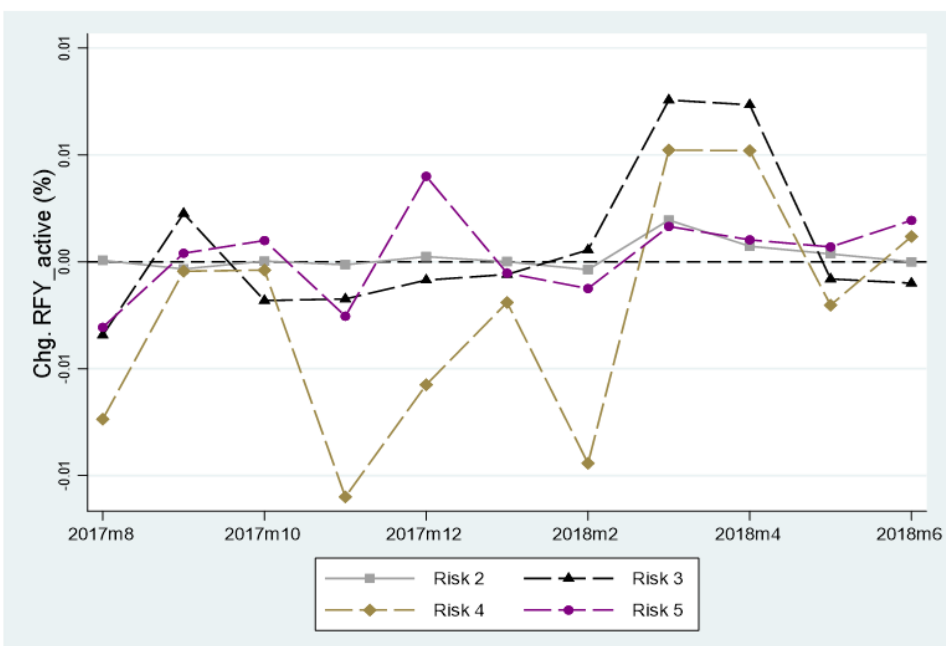
Figure 1. Changes in interest rates and active reaching-for-yield activities

The figures show the negative correlation between changes in yields and reaching-for-yield activities. The left axis shows the change in the yield of one-year government bond. The right axis shows the change in active RFY returns from August 2017 to June 2018. Panel A shows the correlation between changes in one-year government bond yield and active RFY return. Panel B shows the correlation for different risk groups.



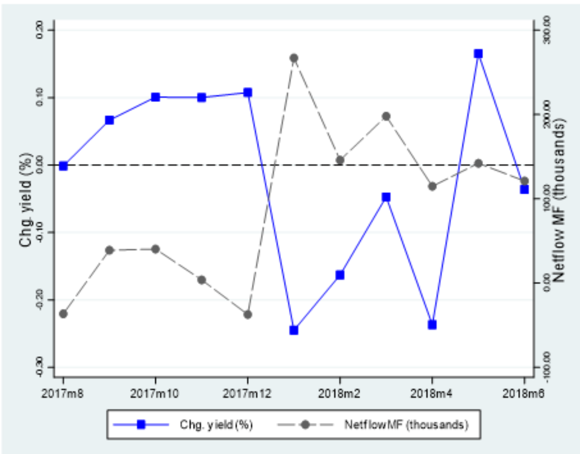
Panel A. Active RFY



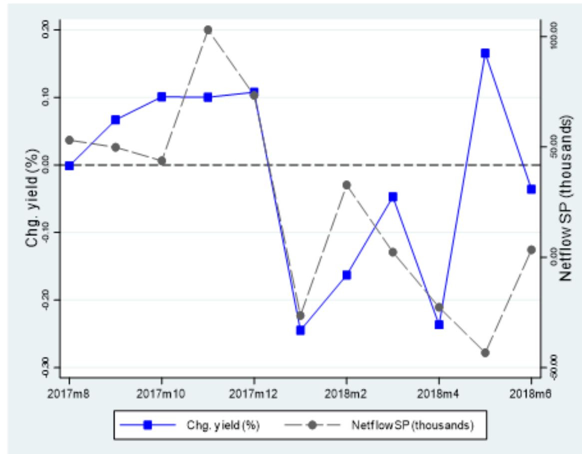
Panel B: Active RFY by risk

Figure 2. Changes in interest rates and net fund flows by products

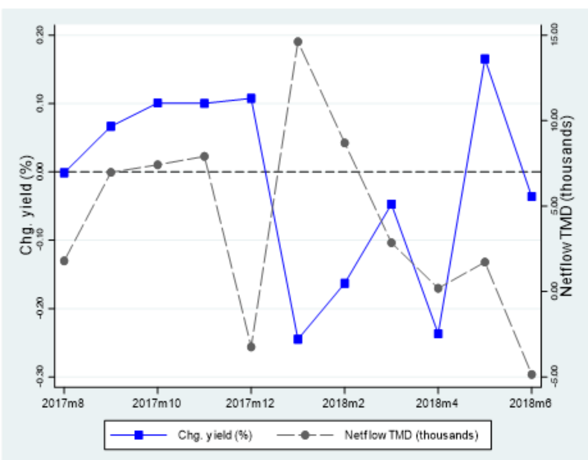
Panels A-D show the correlation between changes in the one-year government bond yield and net flows of mutual funds, structured deposits, term deposits, and demand deposits from August 2017 to June 2018, respectively. The left axis shows the change in the one-year government bond yield. The right axis shows the changes in net flows of each financial product in thousands.



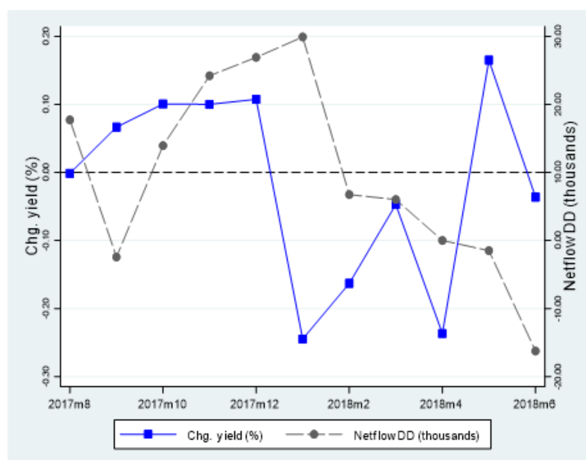
Panel A. Mutual funds



Panel B. Structured deposits



Panel C. Term deposits



Panel D. Demand deposits

Figure 3. Correlations between net flows of mutual funds and structured deposits in different interest rate environments

The shows the scatter plots of net flows of mutual fund products and structured deposit products in different interest environments from August 2017 to June 2018. The horizontal axis presents the net flow of mutual fund products in thousands. The vertical axis shows the net flows of structured deposit products in thousands. Blue dots represent observations in high interest environments (higher than the sample median) while red dots represent those in low interest environments (lower than the sample median).

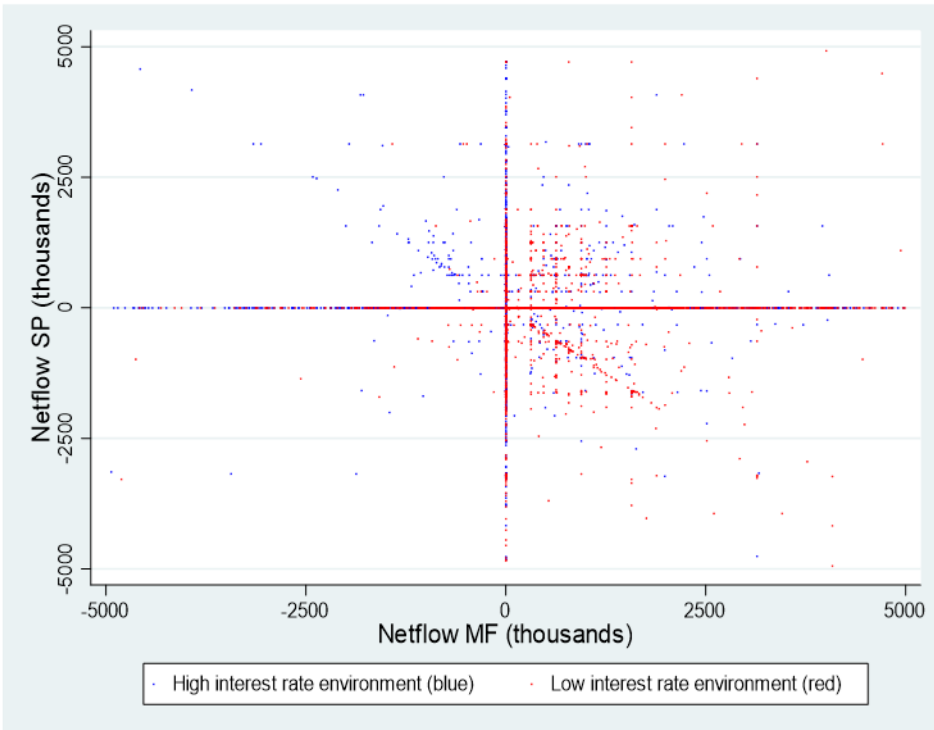
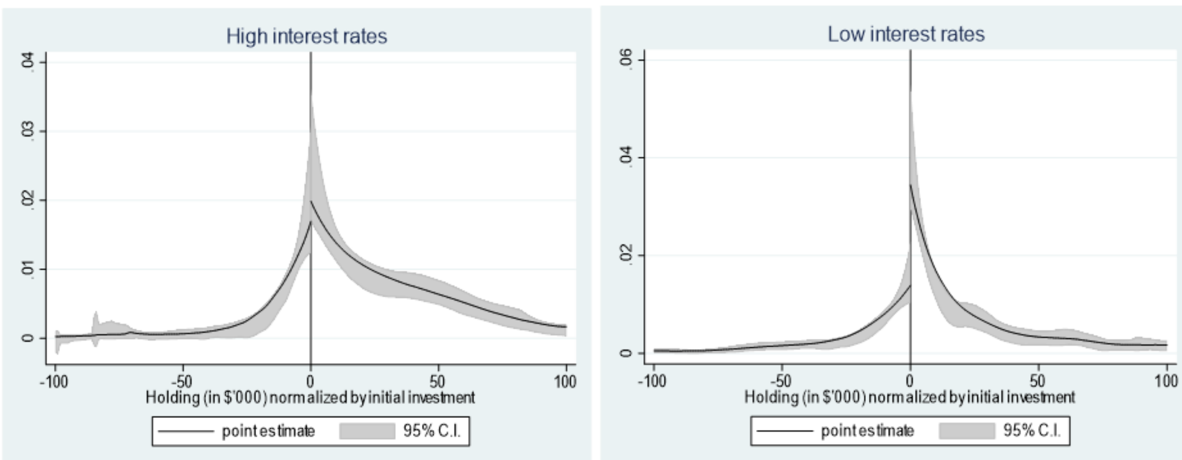


Figure 4. Detecting bunching in different interest rate environments

Panel A shows the bunching detection in high interest rate environments (higher than sample median). Holdings of mutual fund products on the horizontal axis are normalized by initial investment in thousands. We keep months when investors have sell transactions of mutual fund products. The vertical axis presents the density. The 95% confidence interval is shaded in grey. Panel B shows the bunching detection in low interest environments (lower than sample median) with similar setting.



Panel A. High interest rate environments

Panel B. Low interest rate environments

Table 1. Descriptive statistics

This table reports the descriptive statistics of 46,116 investor-month observations (mean, standard deviation, median, minimum, and maximum) for changes in return variables in Panel A, changes in net flows of various products, mutual fund trading frequencies, and portfolio risk in Panel B, changes in the frequency of viewing financial products on the bank's WeChat public account in Panel C, investors' demographic information in Panel D, and macro variables in Panel E.

Variables	mean	sd	p50	min	max
Panel A: Returns					
ΔRet_active	0.001%	0.002	0.000%	-5.624%	13.773%
ΔRet_active_R2	0.000%	0.000	0.000%	-1.105%	1.212%
ΔRet_active_R3	0.001%	0.001	0.000%	-2.356%	2.791%
ΔRet_active_R4	-0.003%	0.001	0.000%	-5.875%	3.611%
ΔRet_active_R5	0.000%	0.001	0.000%	-4.630%	13.497%
Panel B: Flow, trading frequency, and risk					
ΔNetflow MF (thousands)	6.090	639.290	0.000	-2,600.927	2,897.863
ΔNetflow DD (thousands)	0.735	499.881	0.000	-1,884.000	1,884.000
ΔNetflow SD (thousands)	-0.852	485.182	0.000	-2,277.624	2,371.485
ΔNetflow TMD (thousands)	-0.703	7.672	0.000	-73.756	9.420
ΔTrading freq._buy	0.007	0.683	0.000	-7.000	8.000
ΔTrading freq._sell	0.000	0.320	0.000	-12.000	12.000
ΔWeighted risk	-0.031	0.307	0.000	-4.604	4.517
Panel C: Product views on bank's WeChat public account					
ΔProduct view	0.030	3.379	0.000	-188.000	188.000
Panel D: Demographics					
Young (<46)	0.531	0.499	1.000	0.000	1.000
Rich (>150 thousands RMB)	0.464	0.499	0.000	0.000	1.000
Male	0.427	0.495	0.000	0.000	1.000
Panel E: Macro variables					
Yield	3.404%	0.002	3.383%	3.066%	3.758%
ΔYield	-0.017%	0.001	-0.001%	-0.245%	0.165%
chn_gdp	1.591	0.100	1.500	1.500	1.700
cpi_index	1.891	0.353	1.800	1.500	2.900

Table 2. Return-based measures and reaching-for-yield behavior

This table presents the results for the baseline regression model (1) with return-based dependent variables. The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *p < 0.1; **p < 0.05; ***p < 0.01.

Dep. Var.:	ΔRet_active	ΔRet_active_R2	ΔRet_active_R3	ΔRet_active_R4	ΔRet_active_R5
	(1)	(2)	(3)	(4)	(5)
ΔYield	-0.023***	0.000	-0.011***	-0.013***	0.002
	(0.006)	(0.001)	(0.002)	(0.004)	(0.003)
chn_gdp	0.014*	-0.001	0.003	0.014**	-0.002
	(0.008)	(0.001)	(0.003)	(0.006)	(0.004)
cpi_index	-0.005	0.000	0.001	-0.003	0.000
	(0.003)	0.000	(0.001)	(0.003)	(0.001)
Trend	Y	Y	Y	Y	Y
R-squared	0.0006	0.0001	0.0007	0.0006	0.0001
N	46116	46116	46116	46116	46116

Table 3. Non-return-based measures and reaching-for-yield behavior

This table presents the results for the baseline regression model (1) with non-return-based dependent variables. The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See the appendix for variable definitions. *p < 0.1; **p < 0.05; ***p < 0.01.

Dep var:	ΔNetflow MF	ΔBuy	ΔSell	ΔRisk
	(1)	(2)	(3)	(4)
ΔYield	-1.89e+04***	-16.682***	2.992**	-0.565**
	(2387.984)	(2.586)	(1.292)	(0.229)
chn_gdp	-3.75e+04***	-50.012***	-3.390***	-0.531**
	(2486.406)	(2.700)	(1.040)	(0.250)
cpi_index	-1.66e+04***	-19.493***	-0.533	-0.103
	(1370.071)	(1.451)	(0.528)	(0.127)
Trend	Y	Y	Y	Y
R-squared	0.0090	0.0112	0.0003	0.0003
N	46116	46116	46116	46116

Table 4. Flow measures and reaching-for-yield behavior across products

This table presents the results for the baseline regression model (1) with changes in net flow measures as dependent variables across different products, including mutual fund products (MF), structured deposits (SD), term deposits (TMD), and demand deposits (DD). The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See the appendix for variable definitions. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Dep var:	ΔNetflow SD	ΔNetflow TMD	ΔNetflow DD
	(1)	(2)	(3)
ΔYield	7554.275***	8.634	1721.422
	(1655.995)	(24.471)	(1907.420)
chn_gdp	9212.608***	-0.035	-8167.343***
	(1797.960)	(32.592)	(1772.758)
cpi_index	6092.571***	-18.093	-2578.450***
	(842.889)	(11.052)	(899.396)
Trend	Y	Y	Y
R-squared	0.0019	0.0005	0.0005
N	46116	46116	46116

Table 5. RFY behavior on only mutual fund products

This table presents the results for the baseline regression model (1) with return-based dependent variables by restricting our portfolio construction to investments in only mutual fund products. We calculate *ΔRet_active* within each risk group of mutual fund products to obtain *ΔRet_active_R2*, *ΔRet_active_R3*, *ΔRet_active_R4*, and *ΔRet_active_R5*, where 2 indicates lowest risk classification and 5 highest. The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *p < 0.1; **p < 0.05; ***p < 0.01.

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	ΔRet_active	ΔRet_active_R2	ΔRet_active_R3	ΔRet_active_R4	ΔRet_active_R5
ΔYield	-0.012***	0.001*	-0.004***	-0.009***	-0.000
	(0.002)	(0.000)	(0.001)	(0.002)	(0.002)
chn_gdp	-0.010***	-0.001*	-0.006***	-0.004	0.001
	(0.003)	(0.000)	(0.001)	(0.003)	(0.002)
cpi_index	-0.003*	0.000	0.001	-0.002	-0.002**
	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)
Trend	Y	Y	Y	Y	Y
R-squared	0.0007	0.0002	0.0007	0.0005	0.0002
N	46116	46116	46116	46116	46116

Table 6. Adoption of mobile investment and reaching-for-yield behavior

This table presents the results for the adoption of Wechat public account on reaching-for-yield behavior. The treatment dummy *Treat* is defined as one if the investor had never had any digital footprints using mobile banking before January 2018 when the bank's WeChat public account was introduced. *After* is a dummy variable with value of one if the sample observation is after January 2018 and zero otherwise. The independent variable of interest is the triple interaction term of *After×Treat×ΔYield*. Control variables include changes in GDP and inflation index. Columns (1) and (2) present results of WeChat View and reaching-for-yield behavior with unmatched sample. Columns (3) and (4) show respective results with a matched sample using one-to-two matching. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

	(1)	(2)	(3)	(4)
Dep. Var.:	ΔProduct view	ΔRet_active	ΔProduct view	ΔRet_active
	Unmatched		1-2 matched	
ΔYield	-6.659***	-0.021***	-6.141***	-0.015
	(2.179)	(0.007)	(2.055)	(0.014)
After	-0.336***	-0.000**	-0.383***	-0.000*
	(0.050)	(0.000)	(0.072)	(0.000)
After×ΔYield	-3.026	0.002	2.851	-0.006
	(26.852)	(0.013)	(39.150)	(0.022)
Treat×ΔYield	-0.917**	0.010	-0.966***	0.004
	(0.376)	(0.010)	(0.359)	(0.016)
After×Treat	-0.387***	0.000***	-0.339***	0.000***
	(0.105)	(0.000)	(0.118)	(0.000)
After×Treat×ΔYield	-118.169**	-0.060**	-123.623*	-0.052*
	(56.904)	(0.024)	(63.649)	(0.030)
Controls	Y	Y	Y	Y
Trend	Y	Y	Y	Y
R-squared	0.012	0.004	0.012	0.003
N	46116	46116	53633	53633

Table 7. Historical purchasing price and reaching-for-yield behavior

This table presents the results for the study of reaching-for-yield behavior across historical purchasing prices. We first compute (1) the average price of all historical monthly prices, (2) the initial purchase price, (3) the most recent price, and (4) the highest historical price of a mutual fund product in an investor's portfolio. We then calculate the average price for each of the four prices across all mutual fund products held by the investor. We further divide our sample into two subsamples based on the median of each of the four prices constructed above and run the baseline regression as in Equation (1). The dependent variable is active RFY return. The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.: ΔRet_active	Average Price		Initial Price		Latest Price		Highest Price	
	Low	High	Low	High	Low	High	Low	High
ΔYield	-0.001	-0.042***	-0.001	-0.043***	-0.003	-0.041***	-0.002	-0.042***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.0004	0.0012	0.0005	0.0012	0.0005	0.0011	0.0005	0.0011
N	21577	24539	21971	24145	21857	24259	21850	24266

Table 8. Different interest rate environments

This table presents the results for the study of various interest rate environments. In columns (1) to (4), we examine an interest rate shock. We focus on sudden jumps of the reverse repo rate in January 2018. We divide our sample period into three months before and after January 2018 in columns (1) and (2), and into five months before and after January 2018 in columns (3) and (4). In columns (5) and (6), we divide our sample based on the level of one-year government bond yield into higher or lower than the median level of the sample. The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *p < 0.1; **p < 0.05; ***p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: ΔRet_active	Before repo	After repo	Before repo	After repo	Low yield	High yield
	Six-month window		Ten-month window		Full sample	
ΔYield	-0.067***	0.027	-0.042***	-0.022***	-0.043***	-0.002
	(0.015)	(0.021)	(0.008)	(0.007)	(0.010)	(0.011)
Controls	Y	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y	Y
R-squared	0.0041	0.0041	0.0024	0.0029	0.0040	0.0004
N	12574	12593	20945	20999	20999	25117

Table 9. Demographic characteristics and reaching-for-yield behavior

This table presents the results for the study of reaching-for-yield behavior across investors with various demographic characteristics. We divide the demographic information into two groups in three ways: (1) below versus. above 45 years, (2) male versus female, and (3) rich who have an income level above 150 thousand RMB versus poor who have an income level below 150 thousand RMB. The dependent variable is active RFY return. The independent variable of interest is *ΔYield*. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: ΔRet_active	Young	Old	Male	Female	Rich	Poor
ΔYield	-0.031***	-0.014**	-0.028***	-0.020***	-0.023**	-0.024***
	(0.010)	(0.007)	(0.011)	(0.007)	(0.010)	(0.007)
Controls	Y	Y	Y	Y	Y	Y
Trend	Y	Y	Y	Y	Y	Y
R-squared	0.0007	0.0004	0.0012	0.0008	0.0005	0.0009
N	24498	21618	19494	26162	21196	24491

Figure A.1. comparability of unmatched versus matched sample

The figure shows the comparability of unmatched versus matched sample of naïve versus sophisticated investors. The variables used for the one-to-two propensity score matching include age, gender, income and investment volume in mutual fund products. The horizontal axis is standardized percentage bias across covariates. After matching, sample comparability improves across all four variables used.

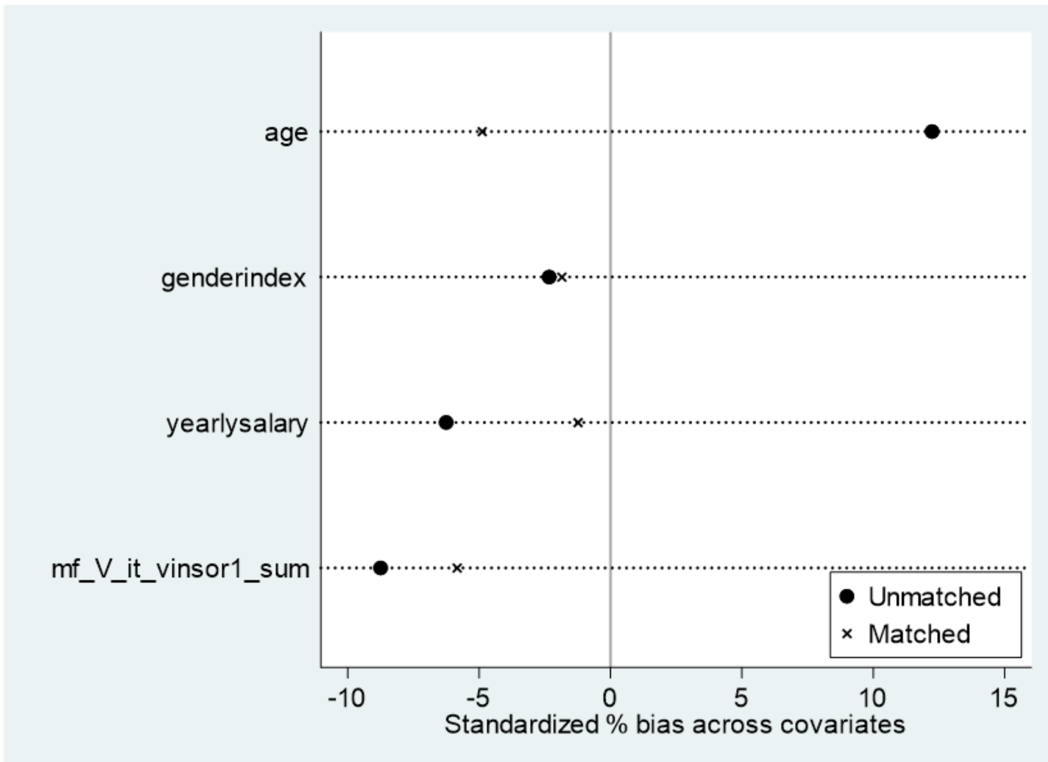


Table A.1. Pre-trend test

This table presents the results for the study of several facts related to reaching-for-yield behavior. Panel D presents the results for the regression with changes in return due to active reaching-for-yield behavior and weighted risk being the dependent variables. The independent variable of interest is ΔYield. Control variables include changes in GDP and inflation index. Robust standard errors are clustered at the account level and reported in parentheses. See appendix for variable definitions. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

	(1)	(2)
Dep. Var.:	ΔProduct view	ΔRet_active
1.pre3#1.treat_wechat#c.chgir_1y	-1.236	-0.015
	(1.737)	(0.021)
1.pre2#1.treat_wechat#c.chgir_1y	4.601	0.041
	(3.504)	(0.032)
1.pre1#1.treat_wechat#c.chgir_1y	2.438	-0.057
	(2.596)	(0.035)
1.after#1.treat_wechat#c.chgir_1y	-119.257**	-0.064***
	(56.915)	(0.025)
1.pre3#1.treat_wechat	-0.019**	0.000
	(0.009)	(0.000)
1.pre2#1.treat_wechat	-0.017**	-0.000*
	(0.007)	(0.000)
1.pre1#1.treat_wechat	-0.015**	-0.000
	(0.007)	(0.000)
1.after#1.treat_wechat	-0.396***	0.000***
	(0.107)	(0.000)
1.pre3#c.chgir_1y	0.156	0.013
	(0.311)	(0.012)
1.pre2#c.chgir_1y	3.121*	0.040**
	(1.768)	(0.017)
1.pre1#c.chgir_1y	-3.294	-0.039

	(2.991)	(0.028)
1.after#c.chgir_1y	-1.032	0.041
	(1.865)	(0.030)
1.treat_wechat#c.chgir_1y	-0.015***	-0.000***
	(0.006)	(0.000)
chgir_1y	-3.368	0.003
	(26.856)	(0.013)
1.pre3	0.004*	-0.000
	(0.002)	(0.000)
1.pre2	-0.008**	0.000
	(0.003)	(0.000)
1.pre1	-0.009**	-0.000
	(0.004)	(0.000)
1.after	-0.338***	-0.000**
	(0.050)	(0.000)
Controls	Y	Y
Trend	Y	Y
R-squared	0.012	0.004
N	46116	46116