Convenience at a Cost: The Paradox of Internet-Based Fund Distribution Channels and Investment Returns

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Abstract:

With the rapid advancement of digital technology and financial technology (FinTech), independent internet fund distribution channels have emerged as a transformative force in China's mutual fund industry. These platforms offer ordinary investors lower costs and greater convenience, reshaping traditional investment practices. However, whether such innovations genuinely improve investor returns remains uncertain. Based on transaction data from investors simultaneously holding public mutual funds across both internet and traditional channels, this study investigates the impact of internet fund sales channels on investor behavior and performance. The findings reveal that lower transaction costs and higher convenience encourage frequent trading among investors with irrational tendencies, leading to market misjudgments and ultimately diminished returns. In contrast, rational investors exhibit no significant differences in returns across the two channels, indicating that performance disparities primarily stem from irrational behaviors. This pattern holds consistently across various wealth levels, genders, and age groups. The study further validates that moderate transaction costs can act as a friction mechanism to curb excessive trading behavior, thereby enhancing overall investment performance. These findings underscore the need for a cautious approach in reducing transaction costs during FinTech development to balance convenience with investor protection.

Keywords: Fund Distribution, Chinese Fund Market, Overtrading.

Introduction

The rapid advancement of digital and information technologies is profoundly transforming lifestyles and economic activity patterns. Fintech, in particular, is reshaping the financial services industry while posing new challenges and considerations for traditional financial theories. In the mutual fund industry, this transformation has been especially pronounced. Since 2012, when the China Securities Regulatory Commission (CSRC) allowed fund sales institutions to operate through third-party e-commerce platforms, internet-based independent fund distribution channels have experienced explosive growth (Rao et al., 2017). Leading platforms such as Ant Financial and Tiantian Fund had already covered nearly all public mutual fund products in the Chinese market by 2015 (Hong et al., 2024; Minghui et al., 2015) . By the end of 2018, over 34% of non-family mutual fund sales were completed through internet distribution channels (Jia & Winseck, 2018).

The technological transformation of the fund industry has provided ordinary investors with more convenient and cost-effective ways to purchase funds, enabling broader access to the benefits of inclusive finance (Hong et al., 2024; You et al., 2023). However, whether the convenience and low costs offered by internet distribution channels have genuinely helped fund investors achieve higher returns remains a topic worthy of further exploration. Existing research suggests that internet distribution channels may influence investor behavior and fund performance through various mechanisms (Bollaert et al., 2021; Cen, 2024).

First, lower transaction costs may encourage more trading activity, but this does not necessarily translate into better investment outcomes (Edelen et al., 2013; Frazzini et al., 2018). In fact, frequent trading can lead to behavioral biases such as overconfidence or the disposition effect, which may harm investors' long-term returns (G. Chen et al., 2007; Chu et al., 2012). Second, while the rich information and analytical tools provided by internet platforms can help investors make more informed decisions, they may also result in information overload, making it difficult for investors to identify truly valuable insights (Bernales et al., 2022; Guo et al., 2023). The choice of fund distribution channels also impacts investor returns. Direct channels allow investors to select funds independently, potentially reducing investment costs, but they require a certain level of research capability from the investor (Bullard et al., 2008). In contrast, indirect channels—such as those involving brokers or financial advisors—offer professional advice but often charge higher fees, which can erode net returns (Del Guercio et al., 2010).

This study aims to explore how internet distribution channels influence the investment behavior and performance of individual mutual fund investors. To achieve this, a simplified theoretical model is constructed based on the assumption of investors' bounded rationality, analyzing the impact of differences in transaction costs on investment returns. The model suggests that the lower transaction costs associated with internet distribution channels may encourage investors to trade more frequently. However, when investors misjudge market trends, this increased trading activity can exacerbate investment errors, ultimately leading to poorer returns. In contrast, higher transaction costs can act as a barrier to impulsive trading decisions, curbing excessive trading behavior. While higher fees directly reduce returns, they may improve overall investment performance for investors with cognitive biases by limiting erroneous trades. This perspective aligns with Odean's (1999) findings on investor behavioral biases related to overtrading.

The empirical data in this study supports the theoretical analysis outlined above. By examining transaction records from a subset of individual investor accounts at a mutual fund company between 2020 and 2022, several key findings emerge. The low costs and convenience offered by internet distribution channels significantly increase trading frequency among individual investors. When investors misjudge market trends, the combined impact of excessive trading costs and losses from erroneous trades results in lower overall fund returns on internet distribution channels compared to traditional channels. Further analysis reveals that investors with irrational expectations trade more frequently on internet distribution platforms. As the degree of their irrationality increases, the performance gap between traditional channels and internet distribution channels widens. In contrast, for rational investors, there is no significant difference in returns between the two channels. These findings remain robust across various measures of trading performance, proxies for investor irrationality, and demographic subgroups such as wealth levels, gender, and age. The results validate the predictions of the theoretical model and underscore the complex influence of internet distribution channels on investor behavior and investment outcomes.

This study demonstrates that the reduction in transaction costs through internet distribution channels has a negative impact on irrational investors. Therefore, on one hand, there is an urgent need to enhance investor education to mitigate irrational behaviors in investment, helping investors better understand the market and their own decision-making processes. On the other hand, in the development of financial technology, it is crucial to cautiously reduce transaction costs, as a moderate friction mechanism can serve as an effective means to curb excessive trading, thereby protecting investor interests.

A substantial body of academic research has focused on the impact of fintech on the economy. For instance, Chen and Hall et al. analyzed the significant profits and technological barriers created by innovation from the perspective of financial institutions, using patent revenues as a lens (Chen et al., 2019; Hall, 2015). Liu et al. examined the disruption caused by fintech to traditional banking loan businesses through changes in banks' liability structures (Z. Liu et al., 2024). Other studies, such as those by Li and Zhang, demonstrated that digital finance effectively expands corporate financing channels and fosters innovation (H. Liu & Li, 2023; Zhang et al., 2024).

From the investor's perspective, research has also highlighted the transformative effects of fintech. For example, Banerjee et al. found that using robo-advisors helps investors diversify risk and correct cognitive biases in their investment decisions (Back et al., 2022; Banerjee et al., 2024). Overall, the emergence of internet-based distribution channels has increased individual investors' risk tolerance and encouraged them to pursue products with strong short-term performance (Lussier, 2019; Reis & Pinho, 2021). Wang further uncovered that improved trading efficiency driven by fintech can amplify short-term profit-seeking behaviors, increasing herding effects in markets and potentially destabilizing them (Wang, 2024; Peng, 2024).

Behavioral finance scholars frequently attribute overtrading phenomena to overconfidence theory. Studies consistently show that investors with higher trading frequencies tend to achieve poorer investment performance—a pattern validated across multiple global markets (Barber & Odean, 2000; Odean, 1999).

Building upon existing literature and research, this paper makes two primary contributions. First, it deepens the understanding of fintech's economic impact, particularly in the asset management industry. Unlike prior studies that focus on fintech's influence on credit markets (e.g., Chen et al., 2019; Hall, 2015), this paper examines its effects on the wealth management sector. Specifically, it diverges from Hong (2024) and others by directly analyzing how sales channels influence the behavior of mutual fund investors and their welfare outcomes. This approach sheds light on the potential negative consequences of fintech, emphasizing that cost reductions driven by technological advancements do not necessarily lead to welfare improvements. This insight aligns with Laibson's (1997) argument that excessive liquidity from financial innovation can weaken market constraints on irrational investors, thereby amplifying such behaviors and potentially reducing overall welfare. Second, from a broader perspective, the findings suggest that in imperfect markets, moderate transaction costs may actually promote healthier market development. This conclusion echoes Tobin’s (1978) assertion that friction in financial markets can serve as a stabilizing mechanism(Tobin, 1978). Additionally, this paper underscores the critical importance of investor education from both welfare and investment return perspectives. Educating investors can mitigate cognitive biases and enhance their decision-making processes, ultimately improving investment outcomes and fostering more rational market participation.

Secondly, this paper contributes to the literature on excessive trading by offering new insights. Unlike Odean's studies (2000; 1999), which focus on stock market trading, this research examines mutual fund trading behavior among individual investors across different distribution channels. Typically, while stock trades can immediately impact stock prices, mutual fund transactions have little to no immediate effect on net asset value (NAV). This distinction allows for a more precise measurement of the costs associated with poor decision-making due to frequent trading. By comparing investor behavior across different sales channels, this study provides a clearer understanding of how fintech influences investment decisions. Specifically, it analyzes the performance of investors who trade funds through multiple channels, effectively mitigating endogeneity concerns. Empirical results show that, unlike Barber and Odean's (2000) findings—where trading frequency does not affect returns when transaction costs are excluded—the study reveals that more frequent fund trading correlates with lower investment returns even without factoring in transaction costs. This suggests that frequent trading increases the likelihood of irrational decisions, leading to diminished returns. The divergence from Barber and Odean's (2000) results may stem from the focus of this study on the timing abilities of mutual fund investors. Unlike stock investments, where individual investors may have some timing advantages, mutual funds are typically managed by professionals with superior investment expertise. Since fund managers have already optimized portfolio allocations, additional timing efforts by fund investors are often unnecessary and may even be detrimental. This highlights the potential harm caused by excessive trading in mutual funds and underscores the importance of understanding investor behavior within this context.

Theory Model and Hypothesis

This study seeks to demonstrate, through the construction of a theoretical model, that the reduced transaction costs enabled by internet-based distribution channels do not necessarily lead to improved investment returns. In the proposed model, investors with irrational expectations are more likely to misjudge market conditions. Under a low-cost trading environment, such investors tend to engage in more frequent trading, which ultimately results in poorer investment performance. Conversely, higher transaction costs create a greater barrier to trading decisions. While these costs directly reduce net returns, they also lower trading frequency, which can effectively mitigate excessive trading behavior and improve overall investment outcomes.

Investors with bounded rationality

This study assumes a market with only two types of assets: a risk-free asset and a mutual fund. The price of the risk-free asset is assumed to remain constant at 1, with a risk-free interest rate of 0. The price of fund at time t, denoted as V_t is assumed to follow the following process:

$$V_t = V_{t-1}\left(r_t + 1\right) = V_{t-1}\left(1 + \rho_t + \epsilon_t\right),\ \epsilon_t \sim N\left(0, \sigma^2\right) \tag{1}$$

In formula (1), r_t represents the return per period, σ^2 corresponds to the volatility of returns, and ρ_t, which varies over time, represents the expected return. This study assumes that investors are price takers and can observe ρ_t, but only rational investors can correctly interpret it as the expected return. Irrational investors, on the other hand, believe that $r_t = \hat{\rho}_t + \epsilon_t$, where $\hat{\rho}_t = \rho_t + \tilde{\epsilon}_t$. ϵ_t is a random error term independent of other random variables, with its distribution function denoted as $F(\cdot)$ and its density function as $f(\cdot)$.

To simplify, assume that the subscription and redemption fees for mutual funds are uniformly set at a rate of λ. For investors, the purchase or redemption price of the fund can be expressed as $V_t(1 \pm \lambda)$. To streamline the model for subsequent analysis, this study considers initial transaction costs but assumes no transaction costs thereafter. Investors can trade 0 or 1 unit of the fund in each period, and they may borrow or lend at a risk-free rate to purchase funds. However, short selling is not allowed, and the fund holdings at the beginning of each period must remain non-zero.

At the outset, investors hold an initial amount of mutual funds s_0 and risk-free assets b_0. The total wealth of an investor at time t, denoted as W_t, can be expressed as $W_t = \left(F_t - \lambda\right)s_t + b_t$. Investors make trading decisions based on their assessment of future price trends to maximize their next-period total wealth. Assuming investors are risk-neutral and their utility function reflects this preference, let the trading volume at time t be ΔS_t. The optimization problem for maximizing investor wealth can then be formulated as:

$$\max_{\Delta s_t \in \{0, \pm 1\}} E\left[W_{t+1} \mid \hat{\rho}_t\right] = \max_{\Delta s_t \in \{0, \pm 1\}} [b_t + s_t F_t + F_t[(s_t + \Delta s_t)\rho_t - |\Delta s_t| \lambda]] \tag{2}$$

The risk-free asset b_t, the fund's holding quantity S_t, the fund's net asset value per unit F_t, the fund's true expected return ρ_t, and the transaction cost λ are all known values or variables when investors make decisions for the $t+1$ period.

Differences Between Channels

This study focuses on the differences between traditional channels and internet distribution channels, primarily in terms of subscription and redemption fees. Specifically, internet distribution channels are characterized by lower fees. This paper assumes that the transaction cost for internet distribution channels is $\lambda = 0$, while for traditional channels, the transaction cost is $\lambda > 0$. In practice, internet distribution channels are also simpler to operate and involve lower time costs compared to traditional channels, which further reduces the associated transaction costs. The model incorporates these costs into λ for unified consideration.

Assume two identical investors, A and B, both holding risk-free assets and trading mutual funds. The key difference is that investor A can only trade through traditional channels, while investor B can only trade through internet-based distribution channels. At the beginning, both investors hold a certain amount of risk-free assets and mutual funds. For investor B, due to the negligible transaction costs in internet-based distribution channels, they will adjust their portfolio with probability 1. This implies that whenever B perceives favorable or unfavorable market movements, they will immediately adjust their portfolio to pursue higher returns or avoid risks. In contrast, for investor A, transaction costs impose constraints on trading behavior. Investor A will only choose to trade when the expected fund returns are sufficiently high or sufficiently low.

From the perspective of trading frequency, investor B, who faces lower transaction costs, exhibits a higher trading frequency. To further verify this phenomenon and provide a benchmark for comparison, this paper introduces a rational investor as a reference. It is assumed that the rational investor will convert their initial holdings of risk-free assets into mutual fund products at the beginning and refrain from any subsequent trading, resulting in a trading frequency of 0.

From the perspective of investment returns, the expected return per transaction for investor A:

$$E[R_A] = \int_{\rho_t+\epsilon_t>\lambda} (\rho_t - \lambda) dF(\epsilon_t) + \int_{\rho_t+\epsilon_t<-\lambda} (-\rho_t - \lambda) dF(\epsilon_t) \tag{3}$$

Similarly, the expected return per transaction for investor B:

$$E[R_B] = \int_{\rho_t+\epsilon_t>0} \rho_t dF(\epsilon_t) + \int_{\rho_t+\epsilon_t<0} (-\rho_t) dF(\epsilon_t) \tag{4}$$

After simplification, the mean expected return per transaction for investor A, denoted as $\overline{ER_A}$, can be calculated:

$$\begin{aligned} \overline{ER_A} &= \rho_t[1 - F(\lambda - \alpha - (1+\beta)\rho_t) - F(-\lambda - \alpha - (1+\beta)\rho_t)] \\ &-\lambda[1 - F(\lambda - \alpha - (1+\beta)\rho_t) + F(-\lambda - \alpha - (1+\beta)\rho_t)] \end{aligned} \tag{5}$$

Similarly, for investor B without transaction costs, the mean expected return per transaction $\overline{ER_B}$ can be calculated:

$$\overline{ER_B} = \rho_t(1 - 2F(-\alpha - (1+\beta)\rho_t)) \tag{6}$$

After performing a second-order expansion on the distribution function $F(\cdot)$, the parameter conditions can be obtained as follows:

$$\phi\left(\frac{-(1+\beta)\rho_t^2}{\sigma_\epsilon^2}+2\right)\left(\frac{(1+\beta)\rho_t}{\sigma_\epsilon}\right)\frac{\lambda}{\sigma_\epsilon}>1 \quad (7)$$

In formula (7), ϕ represents the density function of the standard normal distribution. As long as ρ_t and λ are slightly greater than σ_ϵ, and $1+\beta$ is slightly less than 0, the inequality can hold. Such assumptions are feasible in practical scenarios. Under the same assumptions, $F(\cdot)$ is a concave function around $-(\alpha+(1+\beta)\rho_t)$. When λ is relatively small, the following inequality always holds:

$$\rho_t-\rho_t[F(\lambda-\alpha-(1+\beta)\rho_t)+F(-\lambda-\alpha-(1+\beta)\rho_t)]-[\rho_t-2\rho_t F(-\alpha-(1+\beta)\rho_t)]>0 \quad (8)$$

Under the above conditions, it is easy to verify that the left-hand side of Equation (8) will be greater than $\lambda\left[1-F(\lambda-\alpha-(1+\beta)\rho_t)+F(-\lambda-\alpha-(1+\beta)\rho_t)\right]$, thereby leading to expected return of investor A higher than that of investor B.

Furthermore, under the assumption that $F(\cdot)$ follows a normal distribution, with $\alpha=0$ and $1+\beta<0$, the derivative of $\overline{ER_A}$ with respect to the transaction cost λ can be simplified to:

$$\begin{aligned}&\frac{\partial(\overline{ER_A})}{\partial\lambda}=(\lambda-2\rho_t)f(\lambda-\alpha-(1+\beta)\rho_t)\\&+(\lambda+2\rho_t)f(-\lambda-\alpha-(1+\beta)\rho_t)\\&-\left[F(\lambda-\alpha-(1+\beta)\rho_t)-F(-\lambda-\alpha-(1+\beta)\rho_t)\right]\end{aligned} \quad (9)$$

Clearly, under the condition $\lambda>2\rho_t$, Equation (9) can be greater than 0. Moreover, as the transaction cost λ increases, the actual return paradoxically becomes higher. Specifically, there exists an interval $[x_1,x_2]$ such that $\overline{ER_A}$ is monotonically increasing within this interval, and $\overline{ER_A}>\overline{ER_B}$. Figure 1 illustrates the relationship between $\overline{ER_A}-\overline{ER_B}$ and the transaction cost λ, based on parameters calibrated using actual trading data (referencing Table 2's statistical data, with $\rho_t=0.0291$, $\sigma_\epsilon=0.012$, and $\beta=-1.3$). It can be observed that when transaction costs are close to 0, reducing costs benefits investors. However, when transaction costs exist but are not excessively high, a moderate increase in costs can actually benefit investors. Furthermore, the interval $[x_1,x_2]$ is relatively wide in practical scenarios.

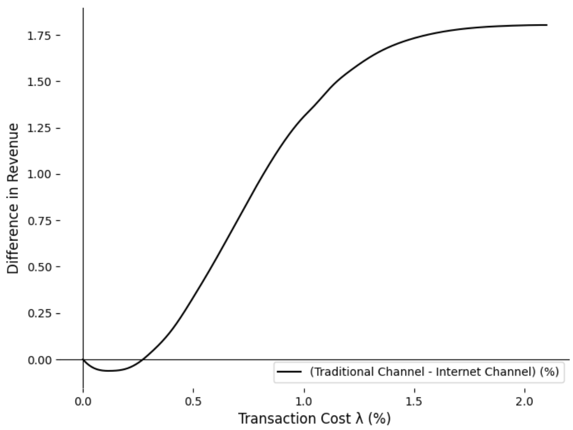

Figure 1: The difference in rate of return between distribution channels varies with changes in transaction costs.

The above model demonstrates that the low costs associated with internet-based distribution channels lead to abnormally high trading frequencies. In cases of misjudgment, excessive trading can result in poorer investment performance. In other words, for non-rational investors, the differences in returns across channels can largely be attributed to the irrational excessive trading behavior triggered by the low costs and low barriers of internet-based distribution channels.

Research Hypothesis

The analysis of the above model indicates that, in cases of misjudgment by investors, lower transaction costs and more convenient trading channels encourage more frequent trading, increasing the likelihood of trading errors and thereby leading to a decline in investment performance. Based on this, the following testable hypotheses are proposed:

Hypothesis 1: The low transaction costs and convenience of internet-based distribution channels will lead investors to trade more frequently.

Hypothesis 2: When investors misjudge the market, considering both the costs of excessive trading and the losses from erroneous trades, the fund investment returns for investors in internet-based distribution channels will be lower than those in traditional channels.

In the simplified model above, investors' expectations across different channels are assumed to be identical, implying that the probability of errors in expectations is also the same. However, in reality, internet-based distribution channels are prone to information overload and shorter decision-making times. These adverse factors further increase the likelihood of irrational trading behavior on internet-based channels (e.g., higher error rates in trading decisions or poorer timing ability). Such factors further reduce the likelihood of investors achieving high returns through internet-based channels. Based on this analysis, this paper considers trading error rates and poor timing ability as proxies for the degree of irrationality and proposes the following testable hypothesis:

Hypothesis 3: Among groups with higher trading error rates or poorer timing ability, investors exhibit higher turnover rates and larger differences in returns between the two channels.

Data Source & Processing

Preprocessing of Raw Data

The micro-level dataset used in this study is sourced from a public mutual fund company in Shenzhen, China, covering the transaction records of individual clients from 2020 to 2022. The original dataset includes 31 mutual funds, 5,324 investors, and a total of 133,127 complete transaction records. Additionally, the study incorporates other relevant data derived from publicly available Wind and CSMAR financial databases, such as fund dividend information, fund market trends, Wind fund indices, and Fama-French three-factor data.

The transaction data is categorized into two distinct channels based on the type of fund trading institution: internet-based distribution channels and traditional channels. Internet-based distribution channels primarily include platforms such as Ant Financial (Alipay), Tiantian Fund, Teng'an Fund, and Yingmi Fund. Traditional channels mainly consist of direct sales, banks, and brokerage firms.

To better match samples and address endogeneity issues, the study applies the following preprocessing steps to the dataset:

- The daily-frequency data is aggregated into monthly panel data.
- Return data for funds within three months of their establishment is removed.
- Data for users who trade exclusively through a single channel is excluded; only users with transaction records in both channels are retained.
- For individual investors, data on funds traded exclusively through a single channel is removed; only data where a single investor trades the same fund through both channels is retained.

Variable Construction

To address the potential impact of extreme or abnormal values caused by factors such as frequent trading within a month, large-scale subscriptions or redemptions, or zero portfolio value at the beginning or end of certain months, this study calculates two turnover rate indicators. Turnover Rate is the cumulative daily turnover rate, which smooths fluctuations caused by abnormal trading behaviors on a single day, thereby reducing the likelihood of extreme values. This measure is more suitable for assessing overall trading frequency. Adjusted turnover rate (Adj Turnover rate) is defined as the ratio of the absolute sum of monthly transaction amounts to the average portfolio value. This indicator directly reflects the total scale of an investor's monthly transaction amounts relative to their average portfolio level, making it more sensitive in capturing differences in trading behaviors at different points within a month. It is particularly useful for analyzing how timing decisions influence turnover rates.

The measure of excess error rate aims to quantify the incremental error rate caused by frequent trading behaviors. Subsequent data analysis reveals that trading error rates gradually decline over time and stabilize after six months. Therefore, the error rate after six months can be considered an investor's inherent and stable error level, while the error rate after one month is more susceptible to short-term irrational behaviors. For rational investors, the difference between the one-month and six-month error rates is minimal, indicating relatively stable trading behavior. In contrast, for irrational investors, the one-month error rate is significantly higher than the six-month level.

Parameter	Description
Fund Value (Holding Value)	The value of funds held by different investors through various channels is calculated separately, with the calculation time set at the end of the month.
Rate of Return r	The money-weighted rate of return is employed, with each calculation interval spanning one month. To simplify the computation, the modified internal rate of return method is utilized. Here, V_S, V_E represent the portfolio values at the beginning and end of the month, respectively, r denotes the monthly rate of return, N is the total number of transactions made by the investor through a specific channel, C_t signifies the cash flow generated by fund transactions on the $t-th$ day of the month, and w_t is calculated as the number of days from the $t-th$ day to the end of the month divided by the total number of days in the month. $$r=\frac{H_{\text{End}}-H_{\text{Start}}-\sum_{t=1}^{N}C_t}{H_{\text{Start}}+\sum_{t=1}^{N}C_t w_t}$$
Net Rate of Return r' (Excluding Fees)	By analyzing transaction records, the difference between the actual transaction amount and the transaction amount under frictionless conditions can be calculated, which is recorded as the friction cost F_t. By adjusting the aforementioned yield, the monthly yield under frictionless conditions, denoted as r', can be obtained. $$r'=\frac{H_E-H_S-\sum_{t=1}^{N}(C_t-F_t)}{H_S+\sum_{t=1}^{N}w_t(C_t-F_t)}$$
Risk-Adjusted Return (Based on Wind Fund Index)	Based on the Wind Fund Index, the monthly return of the fund can be calculated by subtracting the monthly return of the corresponding type of Wind Fund Index from the fund's monthly return.
Risk-Adjusted Return (Based on Fama-French Three-Factor Model)	Based on the Fama-French three-factor model, utilizing the Fama-French three-factor data from the CSMAR database for the Chinese mainland stock market, the excess returns α of individual investors' overall portfolios across different channels were calculated (Fama & French, 1992).
Transaction Fee Rate	The transaction costs and transaction amounts of the same investor across different channels in the same month are calculated separately. The absolute value of the ratio of these two values is then taken to obtain the transaction fee rate for that month.
Trading Frequency	The number of transactions made by investors through a specific channel (traditional or internet-based) in a given month serves as an indicator to measure the frequency of investor trading activity.
Turnover Ratio	It is defined as the sum of daily turnover rates for the month, where the daily turnover rate is calculated by dividing the total daily trading amount by the arithmetic average of the beginning-of-day and end-of-day holding amounts.
Adjusted Turnover Ratio	The sum of the transaction amounts for the month divided by the average daily holding amount for the month.
Error Rate After n Months	Using the fund's adjusted net asset value at the time of each transaction as the benchmark, compare it with the fund's adjusted net asset value at the end of the nth month after the

	transaction. If the purchase price of the fund is higher than the price after n months or the purchase price is higher than the price after n months, the transaction is deemed a mistake. This method is used to count the number and probability of transaction errors.
Excess Error Rate	It is defined as the difference between the error rate of investors one month after a transaction and the error rate six months after the transaction.
Market Timing Ability	Based on the Treynor-Mazuy Four-Factor Model: $r_p - r_f = \alpha + \beta(r_m - r_f) + \gamma(r_m - r_f)^2 + \epsilon$ r_p denote the monthly return of the investment portfolio, r_f the risk-free rate, and r_m the market portfolio return (measured in this study using the monthly return of the CSI Fund Index). α represents stock-picking ability, indicating whether an investor can achieve excess returns through stock selection after accounting for market factors. β measures the sensitivity of the portfolio to market risk. The coefficient γ serves as an indicator of market timing ability. In this study, γ is calculated using a six-month rolling time window to reflect whether investors can adjust their portfolio's risk exposure based on market trends. A larger γ indicates stronger ability to adjust fund portfolios in response to market movements in a timely manner.

Table 1: Parameter Description

Descriptive Statistics

For the preprocessed monthly-frequency dataset, Table 2 presents the descriptive statistics by channel and conducts t-tests on the mean differences between channels. In terms of trading frequency indicators, the turnover rate and number of transactions in internet-based distribution channels are significantly higher than those in traditional channels. This aligns with the prediction in Hypothesis 1 that lower transaction costs and greater convenience lead to more frequent trading.

From the perspective of transaction costs and returns, the transaction fee rate in traditional channels is 0.321% higher than that in internet-based distribution channels, and the average transaction fee is 17.21$ higher in traditional channels. However, despite the higher transaction costs in traditional channels, their monthly return is 0.138% higher than that of internet-based distribution channels. This further supports the hypothesis that excessive trading and erroneous decision-making negatively impact investment performance.

	Traditional Channel			Internet Channel			Difference Test
Parameters	Count	Mean	Std	Count	Mean	Std	P-Value
Rate of Return	24011	2.967	6.012	21630	2.829	5.781	0.0125
Net Rate of Return	24011	3.081	6.103	21630	2.894	5.834	<0.001
Turnover Ratio	24011	0.294	0.663	21630	0.437	0.752	<0.001
Adj Turnover Ratio	24011	0.253	0.605	21630	0.352	0.704	<0.001
Trading Frequency	24011	0.802	2.03	21630	1.845	3.233	<0.001
Error Rate (1 month)	24011	11.956	27.041	21630	21.254	39.022	<0.001
Error Rate (2 month)	24011	10.223	25.981	21630	18.507	33.872	<0.001
Error Rate (3 month)	24011	9.303	25.131	21630	15.443	30.156	<0.001

Error Rate (4 month)	24011	8.956	23.887	21630	11.237	28.813	<0.001
Error Rate (5 month)	24011	8.851	23.104	21630	9.403	28.101	0.0228
Error Rate (6 month)	24011	8.738	22.623	21630	9.153	26.509	0.0736
Transaction Fee	24011	31.552	261.584	21630	14.338	196.055	<0.001
Transaction Amount	24011	6826.22	47634.08	21630	6224.57	53864.32	0.208
Transaction Fee Rate	7055	0.473	0.508	8132	0.152	0.196	<0.001

Table 2: Descriptive Statistics and Mean Difference Tests of Data from Different Channels

Empirical Analysis

Empirical Methods

This section employs empirical methods, including an interactive fixed effects model, to further test the research hypotheses of this paper. Specifically, the study conducts a regression analysis using investors' trading frequency indicators, incorporating an interaction term between trading channels and transaction fee rates. This aims to investigate whether the low-cost advantage of internet-based mutual fund distribution channels accelerates investors' fund trading activities.

$$\Theta_{i,j,k,n} = \alpha + \beta_1 D_k + \beta_2 C_{i,j,k,n} + \lambda_t \eta_j + \mu_i + \epsilon_{i,j,k,n} \qquad (10)$$

In formula (10), $\Theta_{i,j,k,n}$ represents the turnover rate or number of transactions for investor i in month n when subscribing to or redeeming fund j through channel k. The coefficient β_1 captures the effect of the sales channel on trading behavior, where D_k is a dummy variable equal to 1 for traditional channels and 0 for third-party internet-based distribution channels. The coefficient β_2 reflects the impact of transaction costs on trading behavior, with $C_{i,j,k,n}$ representing the fee rate for subscribing to or redeeming fund j through channel k in month n. The term $\lambda_t \eta_j$ denotes the interaction fixed effects between time and fund, while \$ μ_i represents the individual fixed effects of investors.

If β_1 is significantly negative, it indicates that internet-based channels promote investor trading. If β_2 is significantly negative, it suggests that lower transaction costs encourage trading. If both coefficients are significantly negative, it implies that, in addition to low transaction costs, internet-based channels possess other characteristics that drive investors to trade more frequently (such as portability, social interaction, and information accessibility).

The sample used in this study was preprocessed to include only investors with fund investment records in both channels and required that each investor had trading activity for the same fund across both channels. In the regression analysis, by controlling for individual fixed effects μ_i and the interaction fixed effects between month and fund $\lambda_t \eta_j$, the study effectively eliminates potential endogeneity issues arising from channel selection, enabling a more accurate estimation of the impact of the channel itself on investor behavior. Furthermore, to account for potential heteroscedasticity across individuals and within-group correlation in the standard error estimation, the study employs cluster-robust standard errors at the investor level, enhancing the robustness and reliability of the estimation results.

To further examine whether excessive trading by investors leads to reduced returns, this study conducts an interactive fixed effects regression of investor returns on trading frequency and trading channels:

$$Y_{i,j,k,n} = \alpha + \beta_1 D_k + \beta_2 \Theta_{i,j,k,n} + \lambda_n \eta_j + \mu_i + \epsilon_{i,j,k,n} \tag{11}$$

In formula (11), $Y_{i,j,k,n}$ represents the return rate of investor i in month n when subscribing to or redeeming fund j through channel k. The coefficient β_1 measures the impact of internet-based distribution channels on investor returns. If β_1 is significantly positive, it indicates that traditional channels can improve investor returns compared to internet-based channels; conversely, if it is significantly negative, it suggests that the characteristics of trading behavior in internet-based channels may lead to a decline in returns. Meanwhile, β_2 captures the effect of transaction costs on returns. If β_2 is significantly negative, it implies that an increase in trading frequency or transaction costs reduces investor returns. To further validate the hypothesis, if controlling for the trading frequency variable $\Theta_{i,j,k,n}$ renders β_1 insignificant, it can be inferred that the primary cause of declining returns may stem from excessive irrational trading behavior.

To further exclude the impact of transaction costs on investor behavior, this study also conducts a regression analysis on returns that do not account for transaction costs, denoted as $Y'_{i,j,k,n}$. The aim is to explore another potential reason for the lower returns in internet-based distribution channels, namely trading errors caused by irrational expectations. If the coefficient β_1 is significantly positive and β_2 is significantly negative, it suggests that, beyond transaction cost factors, irrational expectations may also contribute to the decline in returns for the same investor in internet-based distribution channels.

This study uses trading error rates and negative timing ability as proxy variables for the degree of irrationality and employs the following fixed effects regression model to examine whether investors with higher levels of irrationality exhibit higher trading frequencies and whether the return differences between the two channels are more pronounced.

$$Z_{i,n} = \alpha + \beta_1 \theta_{i,n} + \lambda_n + \mu_i + \epsilon_{i,t} \tag{12}$$

The dependent variable $Z_{i,n}$ represents either the turnover rate of investor i in month n or the return difference between the two channels. $\theta_{i,n}$ is a proxy variable for the degree of irrationality, measuring the level of irrational behavior of investor i in month n. Specifically, $\theta_{i,n}$ includes three irrationality indicators: average error rate, excess error rate, and negative timing ability, as well as grouping variables based on these indicators. If an investor's average error rate is above the median, they are defined as a "Type I Irrational Investor," with the variable assigned a value of 1; otherwise, it is 0. If the excess error rate is above the median, they are defined as a "Type II Irrational Investor," with the variable assigned similarly. Likewise, investors with timing ability less than or equal to 0 are defined as "Type III Irrational Investors." If the regression model coefficient β_1 is significantly positive, it indicates that the higher an investor's degree of irrationality, the higher their turnover rate or the greater the return difference between the two channels.

In the heterogeneity analysis, this study constructs a regression model with interaction terms to explore the relationship between the differences in trading frequency and return differences across the two channels among different groups.

$$Z_{i,j,k,n} = \alpha + \beta_1 D_k + \beta_2 D_k G_i + \lambda_t \eta_j + \mu_i + \epsilon_{i,j,k,n} \qquad (13)$$

The dependent variable $Z_{i,j,k,n}$ represents the turnover rate or return of investor i in month n when subscribing to or redeeming fund j through channel k. G_i denotes the grouping variable, with the primary grouping criteria including investor gender, age group, wealth level, trading frequency, and platform information.

Channels, Transaction Costs, and Transaction Frequency

The impact of channels on trading frequency is presented in columns (1), (3), and (5) of Table 3. The regression results indicate that, for the same investor, the monthly turnover rate in traditional channels is 13.5% to 17.3% lower than that in internet-based distribution channels, and the monthly number of transactions is approximately 1.16 fewer in traditional channels compared to internet-based channels. Columns (2), (4), and (6) of Table 3 filter the sample to include only months with actual trading activity and further control for factors affecting transaction fees. In this case, the number of transactions in traditional channels remains significantly lower than in internet-based channels, while the turnover rate becomes insignificant. This suggests that, beyond transaction cost factors, other aspects such as the lower convenience of traditional channels may also contribute to their lower trading frequency compared to internet-based channels.

In summary, this study confirms that traditional channels exhibit lower turnover rates and fewer transactions, while internet-based distribution channels, leveraging their low transaction costs and higher convenience, significantly increase the trading frequency of ordinary investors.

	Transaction Amount	Transaction Amount'	Turnover Ratio	Turnover Ratio'	Adj Turnover Ratio	Adj Turnover Ratio'
	(1)	(2)	(3)	(4)	(5)	(6)
Channel Selection	-0.173***	-0.00764	-0.135***	0.0336	-1.157***	-1.302***
	(0.0105)	(0.0148)	(0.0051)	(0.0264)	(0.0809)	(0.112)
Transaction Fee		-0.0813**		-0.0926***		-0.3721**
		(0.0405)		(0.0218)		(0.132)
Count	45641	14638	45641	14638	45641	14638
R Square	0.293	0.478	0.288	0.472	0.438	0.591

Table 3: Regression of Sales Channels on Transaction Frequency

Note 1: The rates in Column (2), (4), (6) are calculated as monthly transaction fees divided by the transaction amount. If an investor did not conduct any transactions in a given month, the transaction amount would be zero, rendering the rate non-existent. Such samples are excluded from the regression analysis, leading to a significant reduction in the sample size.

Note 2: *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively. The values in parentheses represent cluster-robust standard errors at the investor level. The regressions control for individual fixed effects and time-fund interaction effects, as is the case in the following tables.

Channels, Yield, and Trading Frequency

Columns (3), (5), and (7) of Panel A in Table 4 display the impact of investor trading frequency and purchase channels on mutual fund investment returns (including transaction fees). By comparing Panel A (including transaction fees) with Panel B (excluding transaction fees) in Table 4, it is possible to further estimate the proportion of the decline in returns caused by frequent trading that can be attributed to transaction costs. Overall, the proportion of the decline in total returns attributable to transaction costs, as calculated by the three trading frequency indicators, is similar, ranging from 50% to 70%. Meanwhile, the proportion of the decline in returns caused by erroneous investment decisions accounts for 30% to 50%. This indicates that the higher the trading frequency, the lower the investor's return.

Specifically, without controlling for trading frequency, the monthly return (including transaction fees) for traditional channels is 0.051% higher than that for internet-based distribution channels (as shown in column (1) of Panel A in Table 4). For returns excluding transaction fees, traditional channels outperform internet-based channels by 0.072% per month. However, after controlling for trading frequency factors (columns (3), (5), and (7) in Panel A), the return differences directly caused by sales channels become statistically and economically insignificant. This suggests that variables related to trading frequency (such as turnover rate or number of transactions) fully explain the impact of sales channels on returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Rate of Return (with Fees) and Trading Frequency							
Channel	0.0510^{**}		-0.0310		-0.0104		0.0232
Selection	(0.0183)		(0.0322)		(0.0315)		(0.0270)
Turnover		-0.467^{***}	-0.472^{***}				
Ratio		(0.0513)	(0.0155)				
Adj Turnover				-0.449^{***}	-0.452^{***}		
Ratio				(0.0602)	(0.0607)		
Transaction						-0.0281^{***}	-0.0276^{***}
Amount						(0.00335)	(0.00351)
Count	45641	45641	45641	45641	45641	45641	45641
R Square	0.892	0.898	0.902	0.870	0.873	0.865	0.868

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: Rate of Return (without Fees) and Trading Frequency							
Channel	0.0720^{***}		0.0603^{***}		0.0559^{**}		0.0673^{***}
Selection	(0.0301)		(0.0117)		(0.0247)		(0.0130)
Turnover		-0.237^{***}	-0.250^{***}				
Ratio		(0.0295)	(0.0577)				
Adj Turnover				-0.143^{***}	-0.150^{***}		
Ratio				(0.0311)	(0.0707)		
Transaction						-0.0178^{***}	-0.0139^{***}
Amount						(0.00407)	(0.00412)

Count	45641	45641	45641	45641	45641	45641	45641
R Square	0.902	0.904	0.912	0.910	0.913	0.907	0.908

Table 4: Regression Results of Yield on Trading Frequency

As part of their portfolio strategy, investors may choose to trade through internet-based distribution channels, potentially to leverage the low costs and convenience of these channels in optimizing the risk-return balance of their overall portfolio. To test this hypothesis, this study analyzes the risk-adjusted returns of investors' asset portfolios held through internet-based and traditional channels. The risk-adjusted returns are measured using excess returns α derived from the Fama-French three-factor model, and the returns from the two channels are compared.

The findings reveal that the risk-adjusted returns of portfolios held through traditional channels are significantly higher than those of portfolios held through internet-based channels. Additionally, frequent trading activity is shown to reduce returns, and trading frequency fully explains the impact of channel choice on returns. This further confirms that the motivation to adjust portfolios cannot adequately explain the observed decline in returns associated with internet-based distribution channels.

The lower returns observed in internet-based distribution channels compared to traditional channels may be influenced by other rational factors, such as budget constraints and information asymmetry. Investors facing budget constraints might redeem funds more frequently to secure cash flow. For convenience and efficiency in fund turnover, they may prioritize redeeming funds purchased through internet-based channels, leading to redemption fees that lower returns in these channels. To test the budget constraint hypothesis, this study divides the sample into groups of investors with varying levels of budget constraints during specific periods. Specifically, if an investor frequently repurchases funds shortly after redemptions, it indicates higher trading frequency and relatively relaxed budget constraints. This subset of investors was selected for a replication study of the regression analysis results from Table 4. The findings show that the investment returns in traditional channels remain significantly higher than those in internet-based distribution channels. This suggests that budget constraints cannot fully explain why the same investor achieves significantly lower returns when using internet-based channels.

Additionally, the sample selection criteria restricted the analysis to investors who had trading activity in both channels (internet-based and traditional) and held positions during the same period. Based on this criterion, the information set relied upon by a single investor for decision-making across different channels is consistent. Therefore, the theory of information asymmetry also struggles to effectively explain the return differences for the same investor across internet-based and traditional channels.

In summary, it can be inferred that internet-based distribution channels, by offering greater convenience and lower transaction costs (as shown in Table 2), significantly increase investors' trading frequency (including turnover rates and the number of transactions, as detailed in Table 3). However, at the same time, the study finds that, regardless of whether transaction fees are considered, higher trading frequency is often inversely correlated with investor returns (see Table 4). This finding differs from the conclusions of Barber and Odean (2000) in their research on stock markets, where trading frequency was found to have an insignificant impact on investment returns when transaction fees were excluded.

Overall, in the context of investor misjudgments, incorporating both the costs of excessive trading and the losses from erroneous trades into a comprehensive evaluation reveals that returns from mutual fund investments made through internet-based distribution channels are lower than those made through traditional channels. This supports Hypothesis 2.

The impact of channels on returns can be divided into two levels: direct and indirect. By controlling for trading frequency, this study further reveals the offsetting effect of the relatively higher fee rates in traditional channels on their overall channel influence, as reflected in the horizontal comparison between Panel A and Panel B of Table 3. Consequently, the coefficient estimates for channel factors in columns (3), (5), and (7) of Panel A in Table 3 are not significant, with values close to zero. However, the indirect impact of channels on returns is both present and significant. As discussed earlier in this paper, channels can indirectly influence final returns by affecting trading frequency (including turnover rates and the number of transactions).

Irrationality, Trading Frequency, and Return Gap

In the subsequent analysis, this study uses trading error rates and negative timing ability as proxy indicators for measuring the level of investor irrationality. A fixed effects regression model, as specified in Equation (12), is employed to examine whether investors with higher levels of irrationality exhibit higher trading frequency and whether their return differences across different channels are more pronounced. Columns (1) to (3) in Panel A of Table 5 reveal a phenomenon: the higher the level of investor irrationality, the higher their turnover rate. Similarly, columns (4) to (6) in Panel A further confirm that irrational investors tend to trade more frequently. Furthermore, columns (1) to (3) in Panel B of Table 5 indicate that as the level of investor irrationality increases, the return differences between channels also widen. Columns (4) to (6) in Panel B further validate that irrational investor exhibit more pronounced return differences across different channels.

The impact of investment channels on returns exhibits significant heterogeneity depending on the level of investor irrationality. Excess error rate is an important indicator reflecting the degree of investor irrationality. This study further uses excess error rate and the average error rate over 1 to 6 months as primary and secondary sorting criteria, respectively, and divides the sample into five groups in ascending order. Based on this grouping, the return differences between traditional investment channels and internet-based channels are calculated for each group, and the significance of these differences is tested.

As shown in Figure 2, for the more rational investor group (Group 1), the return difference between the two investment channels is nearly zero and not statistically significant. In contrast, for the most irrational investor group (Group 5), the return difference between the two channels reaches 0.857% (equivalent to an annualized simple interest rate of 10.284%) and is significant at the 1% level. For investors in Groups 2, 3, and 4, as the degree of irrational behavior gradually increases, the return difference between the two investment channels also shows a progressively increasing trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Irrational Indicators, Irrational Groups, and Trading Frequency						
			Turnover Rate			
Explanatory Variable	Error Rate in Average	Excess Error Rate	Timing Ability	Irrational Investor 1	Irrational Investor 2	Irrational Investor 3
Regression	1.431***	0.332***	0.0922***	0.559***	0.287***	0.0897***
Parameter	(0.0562)	(0.0402)	(0.0178)	(0.0622)	(0.0413)	(0.0552)

Individual Fixed Effect	Control	Control	Control	Control	Control	Control
Time Fixed Effect	Control	Control	Control	Control	Control	Control
Count	11942	11942	6208	11942	11942	6208
R Square	0.573	0.389	0.410	0.496	0.420	0.381

	(1)	(2)	(3)	(4)	(5)	(6)
Irrational Indicators, Irrational Groups, and differences in Rate of Returns						
Differences in Rate of Returns between different Channels						
Explanatory Variable	Error Rate in Average	Excess Error Rate	Timing Ability	Irrational Investor 1	Irrational Investor 2	Irrational Investor 3
Regression Parameter	0.503** (0.138)	0.580*** (0.167)	0.162** (0.0591)	0.291*** (0.0707)	0.348*** (0.0605)	0.186* (0.0866)
Count	11942	11942	6208	11942	11942	6208
R Square	0.299	0.315	0.303	0.310	0.308	0.286

Table 5: Regression Analysis of Trading Frequency, Channel Return Spread, and Investor Irrationality Indicators

Note: The identification of irrational behavior is based on investors' mutual fund portfolios, which are organized into panel data with individual and time dimensions. In the regression analysis, individual fixed effects and time fixed effects are controlled. Since the timing ability indicator is calculated using a six-month rolling window, this results in a significant reduction in the number of observations in columns (3) and (6) of both Panel A and Panel B.

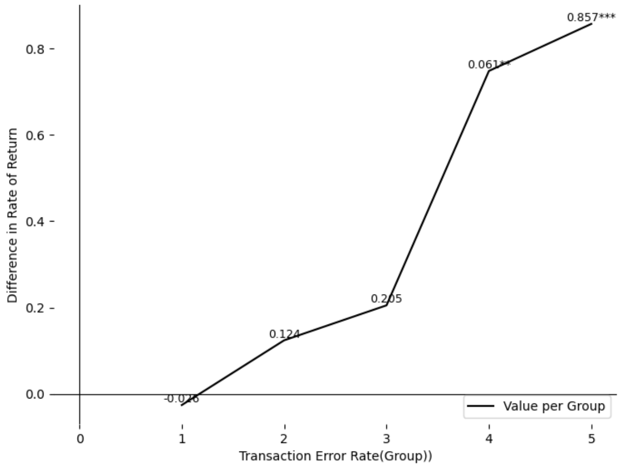

Figure2: The Difference in Return between Traditional Channels and Internet Distribution Channels as a Function of Investor Irrationality

Heterogeneity Analysis

Although the results presented earlier indicate that internet-based channels have a general impact on investor behavior, whether this impact is consistent across different groups requires further investigation. To this end, the sample is divided into five groups based on wealth level, trading frequency, marketing intensity, gender, and age.

Specifically, investors are classified as high-wealth or low-wealth based on the average number of funds held per month, and as high-turnover or low-turnover based on trading frequency. Groups with higher or lower marketing intensity for internet-based channels are distinguished based on the ratio of average monthly fees between traditional and internet-based channels. Additionally, investors are divided into young investors and elder investors using 55 years as the cutoff.

Using these five group classifications, this study employs a regression model with interaction terms (Formula (13)) to conduct heterogeneity tests on the impact of fund trading channels on turnover rates and returns. The detailed results are presented in Table 6. The heterogeneity test results reveal significant differences in the influence of channels across different groups; however, the direction of the impact remains largely consistent. In other words, trading frequency is higher for transactions conducted through internet-based channels, but actual investment returns are relatively lower (or show no significant difference).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
heterogeneity	Wealth Level		Turnover Rate		Marketing Level		Gender(Female)		Age(Above 55)	
	Turnover	Return	Turnover	Return	Turnover	Return	Turnover	Return	Turnover	Return
Channel	-0.180^{***}	0.0311	-0.0526^{***}	-0.0321	-0.0988^{***}	0.0172	-0.178^{***}	0.0224	-0.178^{***}	0.0316
Selection	(0.0337)	(0.0352)	(0.122)	(0.0334)	(0.0157)	(0.0224)	(0.0258)	(0.0295)	(0.0311)	(0.0259)
Channel*	0.0121	0.0267	-0.322^{***}	0.156^{**}	-0.0718^{***}	0.0503	0.0130	0.0433	-0.0265	0.0439
heterogeneity	(0.0126)	(0.0334)	(0.0307)	(0.0556)	(0.0206)	(0.0422)	(0.0177)	(0.0388)	(0.0202)	(0.0335)
Individual Fixed Effect	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Interactive Fixed Effect	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Count	45641	45641	45641	45641	45641	45641	45641	45641	45641	45641
R Square	0.285	0.876	0.295	0.880	0.288	0.892	0.303	0.894	0.290	0.894

Table 6: Regression Result of Heterogeneity Analysis

Conclusion

The rise of internet-based distribution channels has provided investors with more convenient and cost-effective investment options. However, despite the advancements in financial technology, it appears that these developments have not substantially helped many individual investors improve their investment returns. Based on subscription and redemption data from thousands of individual investors who simultaneously use both internet-based and traditional mutual fund distribution channels, this study finds that trading frequency is significantly higher in internet-based channels, yet the returns are relatively lower.

Further analysis reveals that the root cause of this phenomenon lies in the low operational costs and high convenience of internet-based channels, which encourage irrational expectations and excessive trading among investors. Excessive trading not only leads to more frequent errors in decision-making but also increases hidden costs such as fees and taxes. The combined effect of these factors ultimately results in lower returns for mutual fund investments conducted through internet-based channels compared to traditional ones.

The core principle of mutual fund investing is to achieve long-term returns through professional management, a goal that is undermined by frequent trading behaviors. For boundedly rational investors, an excessive focus on reducing transaction costs and enhancing convenience may amplify their irrational behaviors, thereby negatively impacting both social welfare and individual utility. These findings offer critical insights for the mutual fund industry: the development of financial technology should prioritize improving investor outcomes. By optimizing product design and strengthening investor education, the industry can guide investors toward more rational and long-term investment strategies. Only by doing so can financial technology truly fulfill its promise of empowering the financial sector and enhancing its contribution to economic development.

Acknowledge:

We would like to express our gratitude to an anonymous fund company from Shenzhen and Samoyed Cloud Technology from Hong Kong for sharing data with the researchers of this paper to support the achievement of this study. We respect the request of the anonymous fund company and will not disclose its specific name or detailed information. We kindly ask for the readers' understanding and consideration.

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