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Commercial Retirement FOFs in China: Investment and Persistence Performance Analysis

Yundan Guo [1,†] and Li Shen [2,*,†]

1 School of Business, China University of Political Science and Law, Beijing 102299, China; yundanguo@cupl.edu.cn
2 Beijing Institute of Remote Sensing, Beijing 100101, China
* Correspondence: shenli@bjirs.org.cn
† These authors contributed equally to this work.

Abstract: The number and size of China's commercial retirement Fund of Funds (FOFs) have exploded since 2018, reflecting a dearth of Chinese retirement products and widespread retirement anxiety among individual investors. Therefore, the performance of retirement FOFs continues to garner widespread interest from academia and society. This study evaluates the performance and sustainability of the investment strategies employed by China's retirement FOFs using standard relative and absolute measures. The Sharpe ratio, Treynor ratio, and Jensen's alpha are used as performance measurement standards, and the sustainability of performance is evaluated using the performance dichotomy, cross-sectional regression, and Spearman rank correlation coefficient methods. Target-risk FOFs for retirement are categorized into four groups: conservative, stable, balanced, and aggressive, with each group assuming progressively greater levels of risk. In evaluating fund performance, it was determined that the aggressive and stable groups of funds generated greater excess returns (as indicated by the inflation-adjusted Sharpe ratio). Additionally, the stable group of funds generated greater investment returns than the other groups (as all statistically significant alpha values for Jensen were positive). When evaluating the sustainability of fund performance, it was determined that the stable and balanced group funds exhibited the least sustainable performance. During the economic recession caused by the COVID-19 pandemic between 2020 and 2021, there were multiple fund performance ranking reversals (with significantly negative cross-sectional regression coefficients and Spearman coefficients). In the second half of 2022, the fund's performance exhibited signs of sustainability (as indicated by significant performance dichotomy test values and positively significant Spearman coefficients). Still, this trend did not persist into 2023. Summarizing the different performance indicator results reveals that the stable group is the most worthwhile fund group to purchase among the four groups. Also, given that the historical performance of a signal fund is not sustainable, the investors should diversify their investments in this group and try to obtain the average return of the stable strategy to achieve the goal of supplementing retirement.

Keywords: commercial retirement funds; fund of funds; fund performance; performance persistence; China

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1. Introduction

As the Chinese population ages, the issue of retirement funds has gradually come into focus. The formerly marginally adequate retirement insurance is now inadequate to meet the expanding retirement needs of an aging population. This situation inadvertently reveals a deficiency in Chinese retirement products and highlights the need to develop individual investor fund products. The Ministry of Finance of the People's Republic of China recently released data on pension adjustments for 2023, revealing that 14 provinces face a retirement fund deficit totaling a staggering 244,044 billion yuan. In the coming years, China's retirement fund deficit is projected to reach 8–10 trillion yuan and may continue to grow [1].

Early in April 2018, five departments, including the Ministry of Finance of the People's Republic of China, State Taxation Administration, Ministry of Human Resources and Social Security of the People's Republic of China, China Banking and Insurance Regulatory Commission, and China Securities Regulatory made a commission. The commission issued the *Notice on Launching the Pilot Program of Individual Tax-Deferred Commercial Retirement Insurance* to address the retirement fund gap. Fund of Fund (FOF) is a fund that invests only in other investment funds and indirectly holds securities such as stocks and bonds. FOF has a lower risk than direct funds and is suitable as a long-term financial instrument for investment. The introduction of retirement FOFs into the market was authorized on 1 May of the same year. Currently, domestic retirement FOFs are growing ever larger. This policy clarified that publicly offered funds for retirement provisions are legal investment vehicles and specified that the FOF is the principal product. Retirement FOFs can adjust their investment portfolios and alter their investment strategies at appropriate times [2], thereby lowering the investment threshold, mitigating market risk [3], satisfying the requirements typically associated with retirement investments [4], and delivering stable, long-term returns to investors [5].

Retirement FOFs will enhance China's pension security system in three ways: First, they will reduce pressure on the first pillar and encourage the development of a pension system with multiple tiers. In China, the first pillar of the pension system is social security pensions [1,6], the second pillar is corporate annuities, and retirement FOFs [7], as the emerging third pillar is tasked with the development of a multilayered pension security system. Long ago, the public mutual fund industry, which is distinguished by its well-designed systems [8,9], stringent industry supervision [10,11], and vast investment experience [12,13], made substantial contributions to the preservation and growth of the value of social security funds [14,15] and corporate annuities [16,17]. With the introduction of retirement-focused mutual funds [18], public fund managers will leverage their professional expertise to contribute diversified retirement products to the third pillar of the pension system [19], thereby enhancing the long-term value preservation and growth of individual retirement investments [20]. Serving individual retirement investment is also a higher-level manifestation of the social responsibility of a fund company [21]. Second, retirement FOFs will spur the transformation and improvement of residents' wealth structures [22]. Many Chinese citizens still lack an understanding of retirement savings and investment, with family financial assets heavily reliant on bank deposits, stocks, or real estate. However, the emergence of retirement-focused funds is expected to prompt a shift in family financial management practices [23]. Retirement FOFs, with their dual characteristics of financial investment and retirement focus, and their mature asset allocation strategies, selective investment models, and mid-to-long-term stable risk-return characteristics, are anticipated to reshape the retirement fund investment structure of Chinese households. The optimization of wealth allocation will significantly reduce investors' retirement risk. Thirdly, retirement FOFs will encourage the growth of the elderly finance industry. Implementing retirement FOFs will effectively fill the product void in China's aged finance market, catering to the diverse retirement investment needs of investors with varying risk profiles and retirement maturities. This contributes to improving the social pension security system and facilitating financial circulation and capital "infusion" for the long-term growth of the senior finance industry.

Retirement FOFs have amassed a substantial amount of capital for stock market investment, making them an appropriate investment vehicle for the elderly and potentially yielding additional wealth for their retirement years [24]. Currently, two types of retirement FOF products are available in China: target-risk funds and target-date funds.

A retirement target-date fund is a fund whose asset allocation ratio is dynamically adjusted based on the retirement age or a specified target date. It seeks to achieve stable returns over the long term by diversifying investment risks [25]. In order to reduce portfolio risk as investors approach their retirement age or target date, the fund's investment strategy gradually becomes more conservative [26]. This includes decreasing the proportion of equities and increasing the proportion of bonds [27]. Equity assets include stocks, equity funds, and mixed funds [28]. In the current industry, mixed funds have a minimum equity asset allocation ratio of more than 50% over the last four quarters. Government bonds, corporate bonds, commercial bills, and bank drafts are examples of non-equity assets [29]. By establishing a sloping curve, the retirement target-date fund scientifically reduces investment risks annually in response to changes in risk tolerance caused by the accumulation of human capital and wealth at different ages [30]. It promotes a long-term investment philosophy emphasizing investing in equity assets, indirectly distributing economic development dividends [31]. At various stages, the retirement target-date fund will display the following product characteristics: equity-heavy portfolio—balanced portfolio—bond-heavy portfolio [32].

The target-risk retirement fund significantly differs from the target-date fund, as it determines the proportion of equity to non-equity assets based on a specific risk preference rather than the target date's proximity. This gives investors a high-risk tolerance choice [33,34]. The advantages of a target-risk retirement fund over a target-date fund are:

More flexible asset allocation. Typically, the retirement target-risk fund determines the benchmark allocation ratio of equity and non-equity assets based on market changes and risk preferences to adapt to changes in the market environment and improve return performance. Conservative, constant, balanced, and aggressive are typical risk levels for target-risk fund products. From cautious to aggressive, the level of risk gradually increases [35]. Investors who desire stability and "a calm heartbeat" can select conservative or steady funds with relatively low returns. They can select balanced or aggressive funds if they desire high returns and can tolerate short-term volatility.

More efficient risk control mechanisms. The retirement target-risk fund typically uses widely accepted methods to define portfolio risk (such as volatility) and adopts more efficient and scientific risk control mechanisms, such as "Value at Risk" (VaR) and "Expected Loss" methods [36], to ensure the fund operates effectively and avoid investment risks to the greatest extent possible [37].

The retirement target-risk fund continues aggressive asset allocation after retirement. After the specified retirement date, the target-date fund for retirement only invests in low-risk bonds and other non-equity assets. Unaffected by the retirement date, the target-risk retirement fund makes risky investments based on a predetermined risk level [38]. The retirement target-risk fund aims to provide investors with long-term, stable returns and typically allocates assets flexibly based on the market environment and its risk control mechanisms.

In light of the retirement target-risk fund's more flexible asset allocation method, more efficient risk control mechanism, and continued aggressive asset allocation after retirement [25], we selected it to represent China's emerging commercial retirement model for analysis.

As of 31 March 2023, the Personal Retirement Fund Directory published by the China Securities Regulatory Commission listed 143 retirement FOFs, including 55 retirement target-date funds and 88 retirement target-risk funds. There was one conservative retirement fund, sixty-three steady retirement funds, twenty-one balanced retirement funds with equity assets, and three aggressive retirement funds. From the fund companies' perspective, the 143 retirement FOFs originate from 45 mutual fund companies, as shown in Table 1.

In addition, the policy of deferred tax incentives for personal retirements cannot be disregarded. Initially, personal retirements are exempt from tax during the payment phase, meaning that each individual has an annual tax exemption limit of 12,000 yuan after participating in personal retirements. Participants can freely determine their annual participation level based on their financial circumstances. Participants can declare tax incentives at the time of withholding and prepayment in the current year or when settling and paying in the following year. Second, commercial banks deduct and pay taxes on personal pensions based on a separate 3% tax rate during the receiving phase. Currently, the lowest tax rate bracket is 3%, so taxpayers with a marginal tax rate of 3% or higher, i.e., individuals with salaries and wages greater than 5000 to 8000 yuan, will experience a tax reduction.

Table 1. Number of retirement FOFs of the mutual fund companies.

Fund Company	Number of Funds
China Asset Management Co., Ltd. (Beijing, China)	9
China Southern Asset Management Co., Ltd. (Shenzhen, China)	8
China Universal Asset Management Co., Ltd. (Shanghai, China)	8
E Fund Management Co., Ltd. (Guangzhou, China)	7
Harvest Fund Management Co., Ltd. (Shanghai, China)	7
GF Fund Management Co., Ltd. (Guangzhou, China)	6
Hua An Fund Management Co., Ltd. (Shanghai, China)	6
Yinhua Fund Management Co., Ltd. (Shenzhen, China)	7
Wanjia Asset Management Co., Ltd. (Shanghai, China)	4
Penghua Fund Management Co., Ltd. (Shenzhen, China)	4
Tianhong Asset Management Co., Ltd. (Tianjin, China)	4

Given China's status as the country with the oldest population and the greatest pressure on retirement, the purpose of this article is to examine the efficiency and quality of asset management of retirement FOFs in the context of various retirement investment strategies and to determine whether this type of fund can alleviate the retirement difficulties of China's enormous population. Even though China's commercial retirement target funds only began in 2018, the scale and number of funds have immediately shown exponential growth, indicating a huge demand for commercial retirement funds in the Chinese market. However, the market may be unable to judge the efficacy of various retirement funds, indicating a trend of blind investment.

Therefore, this study makes multiple contributions to the existing literature.

(1) To our knowledge, this is one of the few previous attempts to quantify the performance of Chinese retirement FOFs and the first quantitative analysis of the performance of different strategies in Chinese retirement target-risk funds.
(2) This study attempts to calculate the absolute performance indicators of retirement FOF investment strategies based on the Sharpe ratio, Treynor ratio, and Jensen's alpha model. Additionally, this work assesses the performance of the four groups of target-risk retirement FOFs over the past five years.
(3) This study conducts a sustainability analysis of the performance of Chinese retirement FOFs for the first time. Specifically, it calculates the sustainability indicators of the fund performance using the performance dichotomy, cross-sectional regression, and Spearman rank correlation coefficient methods. The sustainability indicators show the reversal of fund performance rankings of stable balanced fund groups during the economic recession caused by the COVID-19 pandemic between 2020 and 2021.

The remainder of this paper is organized as follows. Section 2 discusses the research background of retirement fund FOF returns and performance issues. Section 3 describes a research method based on relative, absolute, and sustainable performance indicators. This method investigates the strategies and data characteristics of retirement fund FOFs. Section 4 reports the comparative results of various investment strategies of Chinese retirement fund FOFs. Sections 5 and 6 present discussion and conclusions for scientists, asset managers, and especially the large number of individual investors.

2. Literature Review and Hypotheses

Analysis of retirement funds in the literature focuses primarily on two aspects: factors affecting fund performance and the role of retirement funds in green development. In recent years, many publications have conducted in-depth analyses of retirement funds in various countries regarding the factors influencing their performance.

Ammann and Zingg [39] investigated the relationship between pension fund governance and performance. Specifically, they used the Swiss Retirement Fund Governance Index (SPGI) as a standard measure of the governance quality of Swiss pension funds. Additionally, they employed the OLS regressions model to examine the relationship between pension fund governance and investment performance. Their findings indicate a positive relationship between retirement fund governance and investment performance. However, the index is unlikely to cover all important aspects of pension fund governance. Thus, pension fund governance should not only be aimed at increasing value creation and performance.

Zhang [40] investigated the optimal investment problem that managers of defined contribution retirement funds face when inflation risks exist. They assumed that representative members of the DC retirement plan contribute a fixed portion of their salary to the retirement fund within the period [0, T]. During this period, continuous investments are made in risk-free bonds, index bonds, and stocks with contributions to retirement plans. The objective is to maximize the expected utility of the fund's final value. The Martingale method is used to prevent the presence of positive endowment effects by solving this investment problem.

Pennacchi and Rastad [41] focused on a public pension fund's portfolio allocation relative to a benchmark portfolio, which best hedges the fund's liability risks between 2000 and 2009. The authors averaged a sample of 125 state pension plans, including eight different asset allocations, various tracking error volatilities, funding ratios (the market value of assets divided by the actuarial value of liabilities), and return on investment. Investment returns estimate the product of the weights assigned to its asset classes and the returns received by each asset class. They discovered agency behavior in pension fund management firms. When investment performance falls short of expectations, the fund selects portfolios with greater risk. However, the representative taxpayer faces taxation risk not just from the municipality's pension under-funding, but also from other deficits/surpluses that may arise from the government's other activities.

Thomas et al. [42] added new empirical evidence by testing whether volatility diminishes as PF increases their stock investments. The authors used panel data from 34 OECD countries from 2000 to 2010 and estimated the random effects panel model and the Prais–Winsten regression with panel-corrected standard errors and autoregressive errors. The estimates indicate a significant negative correlation between the proportion of retirement fund assets invested in stocks and the volatility of stock markets on OECD markets. The economic explanation of such a negative link between pension funds and market volatility will likely be manifold. They leave the analysis of the role of such large firms as marginal investors and their preference for low-yield/less risky dividend stocks.

Kompa and Witkowska [43] analyzed the efficiency of the private pension funds operating in Poland during 1999–2013 and compared their performance to the efficiency of constructed benchmarks. The authors employed the Sharpe and Treynor ratios and compared the performance of the pension funds to a benchmark constructed to illustrate changes in the composition of pension fund portfolios. This research revealed that the performance of pension funds was better than the constructed benchmarks, regardless of the general situation in the capital market. It proves that a diversified portfolio protects pensioners' interests better than portfolios with limited financial instruments.

Chovancová and Hudcovsky [44] quantified the Return-risk profile of Slovak pension funds by applying the time-weighted rate of return method. They found that Index funds, as passive types of pension funds, increased the value of the entrusted share index or several indexes. Other types of pension funds recorded lower but more stable returns. Aging populations have diminished the capacity of governments to continue retirement systems and provide sufficient retirement income. Additionally, increasing the number of retirees and retirement years poses a solvency risk for such retirement plans. However, the history of Slovak pension funds is too short, so they cannot develop all the analysis methods.

Bradley et al. [45] sampled the stock holdings of U.S. state pension funds and discovered local preferences and biases for politically connected stocks. They cluster standard errors at the pension fund level to address concerns of serial correlation in the error terms within pension funds. Then, they adopted weighted least squares models throughout their paper. They also presented results estimated using unweighted ordinary least squares (OLS) models with the bootstrapping approach. Their research indicates that political bias negatively affects the performance of funds, which can be costly for taxpayers and retirees.

Garon [46] examined the policy of funding public retirements when the government cannot. They used a simple regression model to explain why funding pensions may help governments to commit. Additionally, they assumed that the funding structure of the pension plan is difficult to change in the short run, whereas the contribution rates can be more easily adjusted. For simplicity, they assumed that the funding structure of the pension plan is difficult to change in the short run, whereas the contribution rates can be more easily adjusted. Hence, the authors proposed a plan where the optimal nonlinear retirement will not be abandoned by succeeding governments because a commitment mechanism provides the retirement funds. However, a new set of political risks can emerge since funded assets can be perceived as an inelastic tax base by predatory and short-sighted governments.

Shen et al. [1] analyzed the stock market investment performance of the China Social Security Fund Council-mandated social security fund. This article uses the Fama–French and Carhart four-factor model to measure the risk-adjusted China's National Social Security Fund (CNSSF) portfolio returns. This strategy aligns with empirical researchers who believe this model can explain asset returns. This article further investigates the link between the alumni network of fund managers and the investment performance of social security funds using panel data regressions. It was discovered that private information and alum networks among fund managers contribute to the China National Social Security Fund's investment performance and that there are principal-agent issues in entrusted investment.

Gonzalez et al. [47] determined the degree of deviation from the typical behavior of retirement funds and whether retirement funds utilize investment opportunities with patience. They introduced two measures—Active Share Performance Factor and Duration—to investigate the effects of activity and patience on pension fund equity performance, respectively. To capture the effects of the activity and patience of pension funds on their performance, they run predictive panel regression models for each measure separately. Their analysis focused on the cross-sectional and the time-series changes in the pension funds' performance. They concluded that when high activity is combined with long-term holdings, the performance of retirement funds tends to improve based on a sample of Dutch pension funds. Nevertheless, future research must examine the activity–patience relationship in different institutional settings.

Van Dalen and Henkens [48] investigated whether participants' trust in their pension funds is affected by their funding ratio based on a survey of Dutch retirement fund participants conducted in October 2021. Their model controlled the following individual variables: age, gender, partner status, highest attained educational level divided into three broad categories, and estimated net household wealth with answer categories covering seven intervals. Their methodology analyzed the central research questions as instrumental variables (IV) ordered probit regression analysis. Instrumental variables are used to correct for the potential endogeneity of the funding ratio. The authors concluded that there is a positive correlation between the funding ratio of their retirement funds and the participants' level of trust. Large retirement fund buffers are indicative of a high level of trust. However, the current study is cross-sectional, so they cannot analyze how specific individuals change their perception of trust over time when financial health changes remain unknown.

Retirement funds play a significant role in promoting the creation of environmentally friendly projects. In addition to financial performance, retirement funds are concerned with environmental protection, social responsibility, and corporate governance, which is consistent with the essence of Environmental, Social, and Corporate Governance (ESG) principles [49]. Note that the retirement funds include their durability characteristics [50]. The target-risk funds analyzed in this paper do not terminate at retirement age and have an investment cycle of 30 to 40 years, corresponding to the ESG-focused, long-term sustainable development of the target companies [17]. The longer the time horizon, the greater the risk-bearing capacity of retirement accounts [51]. In the United States, pension funds typically invest in ESG. According to data from 2020, 54% of ESG investments originated from the public sector, with retirement funds accounting for a significant portion [52]. Additionally, the EU actively supports ESG investments. In 2020, 89% of retirement institutions will incorporate ESG factors, a significant increase from the previous year's percentage of 55% [53].

Croce et al. [54] investigated ongoing international initiatives to assist and encourage pension fund support to finance green growth projects. It is drafted to inform current OECD work on engaging the private sector in financing green growth. This paper described various financing mechanisms and suggested roles for governments and retirement fund regulatory and oversight agencies to support investment in this field. The paper concludes that governments have a role to play in ensuring that attractive opportunities and instruments are available to pension funds and institutional investors to tap into this source of capital. Furthermore, economic transformation and green growth opportunities can be constrained or enabled by the existing infrastructure of an economy.

Marti-Ballester [55] examined the financial performance achieved by pension funds that invest in one of the sectors related to sustainable investment goals. In order to examine pension fund financial performance, they employed the unconditional Carhart model. Additionally, they compare the financial performance between pension fund categories by adopting the Student's t-parametric test for the independent samples, assuming equal or unequal variances that depend on the results of the Levene test. This performance was evaluated under environmental or ethical criteria. From January 2007 to December 2018, the Carhart, Bollen, and Busse models were applied to a sample of 1546 commercialized retirement funds worldwide. The results indicated that retirement funds invested in specific sectors tied to sustainable development goals outperformed both the market and traditional retirement funds.

Taghizadeh-Hesary and Yoshino [56] argued that, given obstacles such as a lack of long-term financing, low rates of return, diverse risks, and the limited capacity of market participants, it is essential to provide viable solutions to close the green financing gap. These solutions could include enhancing the role of public and non-bank financial institutions in long-term green investments. They could also include implementing green credit guarantee programs to mitigate credit risk, establishing community-based trust funds, and addressing green investment risks through financial and policy de-risking measures. Using the spillover effects on green energy projects would increase the rate of return of green projects.

By reviewing the existing literature, it is evident that the investment performance of pension funds has been a research focus in recent years and become mainstream. Effective methods, such as Sharpe, Treynor's ratio, regression analysis between pension funds, specific market indices, and other methods, have been utilized.

Compared to developed country markets, China's commercial pension capital market started relatively late, and retirement FOFs only started listing in 2018. On the one hand, due to the huge market demand for retirement fund products, most domestic scholars focus on designing retirement fund products. On the other hand, previous studies [39,41,42] have evaluated the performance of commercial retirement fund investment strategies, focusing either on a single retirement fund or all the available retirement funds in a country. This overemphasizes the personal abilities and alumni networks of fund managers in retirement funds, while the differences in investment strategies among retirement funds have been severely neglected.

Therefore, this paper investigates the market performance of commercial retirement FOF funds, which has not been investigated yet. This article conducts a detailed and in-depth study of this issue.

For confirmative research, we present the following hypothesis:

Hypothesis 1 (H1). *Not all performance measures among the existing ones in international investment practice lead to the same ranking result for evaluating retirement FOFs in China.*

Current research in developed markets investigates fund performance and is often based on regression models for calculating the Jensen ratio.

Existing works show that retirement funds can continuously and stably obtain excess returns over a long period. To validate that in China's retirement FOFs, we present the second hypothesis:

Hypothesis 2 (H2). *The performances of China's retirement FOFs in the same strategy group are sustainable for the observation period (2019–2023).*

The sustainability analysis is widely conducted using effective methods, such as performance dichotomy cross-sectional regression.

Tonks [57] analyzed the performance persistence of individual fund management houses appointed as fund managers of segregated occupational pension funds. Specifically, the author measured the fund manager performance as the average abnormal returns on the funds under management, where the abnormal returns for each pension fund are computed from an asset pricing model. Alternative asset pricing models are the single factor Capital Asset Pricing Model, the Fama–French three-factor model, and a four-factor model with a momentum factor. The results from a large sample of occupation pension funds suggested active fund management of pension funds.

Meier and Rombouts [58] proposed a new holdings-based measure of style rotation to investigate the relation between performance persistence and style changes. They first establish the performance dichotomy that divides the top and bottom performing U.S. domestic equity mutual funds. The average style rotation measure of top and bottom is significantly larger for funds with average performance in the past, such as the size and book-to-market deciles of Fama–French or the momentum in Carhart. The authors highlight that top- and bottom-performing decile portfolios, sorted on past one-year returns and risk-adjusted excess performance from a 4-factor model, are subject to a higher degree of style rotation than middle deciles.

Vidal-García et al. [59] examined the short-term persistence in the performance of equity mutual funds around the world between 1990 and 2013. Using a large survivorship bias-free sample of 35 countries, they rank countries by abnormal return and estimate each country's performance for the following quarter. Their evidence is robust to many performance models (stock selection, market timing, and mixed strategies). Additionally, they employed a performance dichotomy methodology based on contingency tables. They used several statistical tests, i.e., repeat winner, odds ratio, and Chi-square, to estimate the significance of the results. They tested the results using Carhart's methodology, demonstrating that the post-ranking performance difference between the top and bottom countries is substantially smaller.

Wermers [60] studied the persistence in performance of mutual funds over the 1975 to 1994 period with a new database to determine whether mutual funds have a strong persistence. Their evaluation relied on the Characteristic Selectivity Measure, the Characteristic Timing Measure, the Average Style Measure, execution costs, the Carhart Measure, and the Ferson-Schadt Measure. They found that the stocks winning funds purchase in response to persistent flows have returns that beat their size, book-to-market, and momentum benchmarks by two to three percent per year over four years. Cross-sectional regressions indicate that these abnormal returns are strongly related to fund inflows, but not to the past performance of the funds. Additionally, the authors demonstrate that mutual fund net returns are strongly predictable and present evidence highlighting consumer flows' role in performance persistence patterns.

3. Materials and Methods

3.1. Performance Measurement Methods

This paper has identified the advantages and risks of the methodology and research findings. The original rate of return is calculated as the logarithm of the monthly return rate, which measures the fund's profitability [61].

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t is the net rate of return of the investment fund in the t-th month, P_t is the net value of the investment fund unit in the t-th month, and P_{t-1} is the net value of the investment fund unit in the $(t-1)$-th month.

In order to ensure comparability of net returns under dynamics, it may be necessary to account for inflation, given its growing significance in recent years. The actual original return is therefore adjusted to [61]

$$RR_t = \frac{R_t - i_t}{1 + i_t} \tag{2}$$

where RR_t is the actual original return rate of the investment fund in month t, and i_t is the inflation rate in month t.

The profitability analysis should consider more than the risk of a single fund portfolio. Specifically, for a given fund group, two funds with the same actual return rate but vastly different risk levels may exist, one with a high-risk profile and the other with a low-risk profile. Therefore, based solely on the initial rate of return, it is impossible to determine which funds are of higher quality and which asset allocation managers are more effective [62,63].

Therefore, in the subsequent stage, the fund performance indicators are calculated, specifically the rate of return and investment risk, which are currently two sets of measurement standards:

(1) Relative indicators, indicating the investment performance of the fund and its managers relative to other funds, are either above average (high) or below average (low) [62]. Related indicators include the classic Sharpe ratio and Treynor ratio.

(2) The absolute single-factor and multi-factor indicators, Jensen's alpha and its modifications, not only compare the performance of a given fund to that of other funds or indexes but also determine whether the fund's managers have achieved positive (greater than zero) or negative (less than zero) risk-adjusted returns [62].

The Sharpe ratio (excess return information ratio) in relative indicators is calculated by dividing a group of funds' excess return (as a premium for investment risk) by the standard deviation of the group's return [62]:

$$S1_{pt} = \frac{R_{pt} - R_{ft}}{\sigma_{pt}} \tag{3}$$

where $S1_{pt}$ represents the Sharpe ratio of a group of investment funds p in the t-th month, R_{pt} stands for the return rate of the same group in the same month, R_{ft} is the risk-free return rate in month t, and σ_{pt} represents the standard deviation of the return rate of the group of investment funds p in month t.

The Sharpe ratio is a simple way to measure the performance of investment funds because it is easy to understand how it works. We also change the inflation rate in the Sharpe ratio to show how the value of money changes:

$$S2_{pt} = \frac{R_{pt} - i_t}{\sigma_{pt}} \tag{4}$$

where $S2_{pt}$ is the inflation-adjusted Sharpe ratio of a group of investment funds p in the t-th month.

The Treynor ratio illustrates the relationship between the excess return of a group of funds and their beta indicator [62]:

$$T_{pt} = \frac{R_{pt} - R_{ft}}{\beta_{pt}} \tag{5}$$

where T_{pt} represents the Treynor ratio of a group of investment funds p in the t-th month, while β_{pt} denotes the beta index of the same group of investment funds p during the same t-th month.

The Sharpe ratio considers the fund's total standard deviation-based risk. The Treynor ratio only considers a portion of the risk, namely the systematic risk of the fund as measured by beta. The primary argument for using this ratio is that the return rate of the fund (particularly actively managed funds) is highly dependent on the fluctuations of the financial market. Therefore, the fund's risk should reflect market risk.

Jensen's alpha (intercept a) enables measuring the average return increment attributable to the manager's stock selection ability [14,64]. Similar to Pavlova and de Boyrie [65], we calculate the risk-adjusted excess return performance of each group of equally weighted retirement funds using four different factor models: (1) the Capital Asset Pricing Model (CAPM), (2) the Fama and French [36] three-factor model (FF3), (3) Carhart [30], and (4) the Fama and French [66] five-factor model (FF5):

$$\begin{cases} R_t - R_{ft} = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \varepsilon_t \\ R_t - R_{ft} = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \gamma_1(SMB_t) + \gamma_2(HML_t) + \varepsilon_t \\ R_t - R_{ft} = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \gamma_1(SMB_t) + \gamma_2(HML_t) + \gamma_3(WML_t) + \varepsilon_t \\ R_t - R_{ft} = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \gamma_1(SMB_t) + \gamma_2(HML_t) + \gamma_3(RMW_t) + \gamma_4(CMA_t) + \varepsilon_t \end{cases} \tag{6}$$

where R_t represents an equally weighted monthly return of a group of investment funds in month t, $R_{mt} - R_{ft}$ represents the market's excess monthly return, R_{ft} is the monthly risk-free interest rate and SMB_t and HML_t represent the size and value factors, respectively. WML_t represents the momentum factor, and RMW_t and CMA_t represent the profitability and investment factors (i.e., the difference in returns between portfolios of stocks with high and low profitability and companies with low and high stock prices).

Similar to Leite and Cortez [67], the risk-free interest rate for funds investing in the China region is the yield on 10-year government bonds. Market risk refers to the unpredictability brought on by shifts in the market's direction. Since retirement FOFs primarily invest in blue-chip stocks, the CSI 300 index was chosen to represent the market return rate. The CSI 300 index comprises 300 large-cap and liquid securities from the Shanghai and Shenzhen markets.

The SMB factor, which represents the excess return of size risk, indicates that smaller companies typically have smaller scales and are relatively unstable, so they are exposed to greater risks and require greater returns as compensation [68]. To calculate the SMB factor, all stocks in the China Securities Index (CSI) 300 index are sorted by market value and equally divided into three groups: large market value stocks (the largest 1/3 of all stocks by market value), medium market value stocks, and small market value stocks (the smallest 1/3 of all stocks by market value). If the average expected return rate of small market value stocks is r_S and the expected return rate of large market value stocks is r_B, then $SMB = r_S - r_B$.

The book-to-market (B/M) ratio is the book value divided by the market value. The B/M ratio risk describes a company's additional financial distress risk, indicating that its market valuation is below its own. These companies are typically not very successful in terms of sales or profitability, necessitating higher returns than low B/M companies.

The HML factor characterizes the excess return on the B/M ratio risk [69]. The method of calculating HML is as follows: first, all the stocks in the CSI 300 index are sorted by

B/M, and then they are divided into three equal parts: the first part consists of high B/M stocks (the top $1/3$ of all stocks by B/M), the second part consists of low B/M stocks and the third part consists of low B/M stocks (the smallest $1/3$ of all stocks by market value). If the average expected return rate of high B/M stocks is r_H and the average expected return rate of low B/M stocks is r_L, then $HML = r_H - r_L$.

Profitability risk refers to the fact that, in general, industries with a high rate of profitability are associated with greater risks. RMW is calculated using the return on equity (ROE) as the profitability metric. Like SMB and HML, the calculation method divides the CSI 300 stock pool into three parts and then calculates the difference in expected returns between high- and low-profitability stocks.

The reinvestment rate can be used to determine the level of investment [17]. We believe companies with lower investment rates are more prone to risk, so investors demand higher returns from them and vice versa. In their article on the five-factor model, Fama and French provide a method for calculating the reinvestment ratio: using the annual growth rate of total assets to calculate the reinvestment rate. CMA is comparable to SMB, HML, and RMW in terms of computing the excess return brought about by investment-level risk.

3.2. Sustainability Analysis Methods

According to the definition of performance persistence, if a fund's performance is persistent, i.e., its past performance can predict its future performance, investors can obtain investment returns by purchasing funds with good historical performance [70]. This has reference significance for investors' decision-making.

Both parametric and non-parametric methods can be utilized to examine the persistence of fund performance [30,71]. Commonly employed in both theoretical and empirical research [72], performance dichotomy, cross-sectional regression, and the Spearman rank correlation coefficient test are utilized extensively in this paper. In particular tests, samples must be separated into ranking and evaluation periods. The specific introductions are as follows [73]:

When using the performance dichotomy method to investigate fund performance persistence, a standard number must first be established [74]. This could be the average, mode, or another standard. Funds that outperform this benchmark are referred to as "winners" (abbreviated as W), while those that fall short are referred to as "losers" (abbreviated as L). Combining the performance of funds during the ranking and evaluation periods yields four forms: "WW, WL, LL, LW". As shown in Table 2, this is demonstrated as a two-dimensional matrix. (Whereas WW indicates that the fund's performance is excellent in both the ranking period and the evaluation period, indicating that performance is sustainable, LL indicates that the fund's performance is poor in both the comparison period and the test period, both of which indicate fund performance persistence.)

Table 2. Marks under the dichotomy of fund performance.

Sorting/Evaluation Period	Winner	Loser
Winner	WW	WL
Loser	LW	LL

Brown and Goetzmann [75] calculated the ratio of the product of WW, LL and the product of WL, LW:

$$CPR = \frac{WW \times LL}{WL \times LW} \tag{7}$$

and a Z-statistic is constructed, and its calculation formula is

$$Z = \frac{\ln(CPR)}{\sigma_{\ln(CPR)}} \tag{8}$$

$$\sigma_{\ln(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}} \tag{9}$$

Suppose a fund's performance does not persist. In that case, the value of CPR is 1, and Z follows a standard normal distribution, so the Z-statistic can be used to determine whether the performance persistence is statistically significant. Brown and Goetzmann [75] examined the overall performance persistence of WW and LL, whereas Malkiel [16] examines the persistence of fund performance that outperforms the benchmark, i.e., WW.

Cross-sectional regression is a method for determining whether a fund's performance can be sustained by the coefficient obtained by regressing the evaluation period's performance on the ranking period's performance [76]. This indicator reflects the fund's predictability, which is a major concern for academics [77]. Suppose there is performance persistence in the fund. In that case, funds that performed well in the previous period will continue to perform well in the future, and the fund's future performance can be predicted based on its historical performance.

Bollen et al. [75] proposed the following cross-sectional regression model:

$$Perf_{p,t} = \alpha + \beta(Perf_{p,t-1}) + \varepsilon_{p,t} \tag{10}$$

where t represents the evaluation period, $t-1$ represents the ranking period, the dependent variable is the portfolio's performance in period t, and the explanatory variable is its performance in period $t-1$. Performance can be measured using absolute return, excess return, or other metrics. If the coefficient β is positive, the fund's performance can be sustained.

There are various methods for measuring fund performance and testing persistence. Different measurement indicators and test methods used to analyze the same period and sample of funds may produce different results [78].

The Spearman rank correlation coefficient method is a non-parametric test that does not require fund performance to be normal and is less affected by outliers [79]. It tests the correlation of fund performance rankings over two consecutive periods and accurately measures the strength of performance persistence, which is more in line with real-world performance persistence testing needs. The specific method is to rank the performance of sample funds, assign values ranging from 1 to n to performance ranging from high to low (n representing the number of FOFs), then calculate using its formula and run significance tests. The following is the formula:

$$\Sigma d_i^2 = \sum_{i=1}^{n} [r(x_i) - r(y_i)]^2 \tag{11}$$

$$\rho = 1 - \frac{6\Sigma d_i^2}{n(n^2-1)} \tag{12}$$

where $r(x_i)$ and $r(x_i)$ are the fund performance rankings in the ranking period and evaluation period, n is the number of sample funds, and ρ represents the Spearman rank correlation coefficient. Generally speaking, its value ranges from $[-1, 1]$. When $\rho > 0$, it represents a positive correlation in performance, that is, performance is sustainable, and the higher the correlation, the stronger the performance persistence; $\rho = 1$ represents complete persistence; when $\rho < 0$, it represents a negative correlation in performance, i.e., performance reversal; $\rho = -1$ represents complete reversal.

3.3. Data Source

A sample of 102 target-risk retirement funds was used in this study. The observation period is March 2019–June 2023. The rate of return is calculated at monthly intervals for the funds. These funds are classified according to their risk levels, which range from conservative, stable, and balanced to aggressive (Table 3). Due to their short release time, 24 funds surveyed in this paper have not yet been included in the China Securities Regulatory Commission's retirement fund list. Our database is sourced from the JoinQuant quantitative investment platform (https://www.joinquant.com), accessed on 11 August 2023. All the 102 retirement funds used by this work can be found by searching for the retirement FOFs on JoinQuant.

Table 3. Sample of retirement FOFs in China.

Target Risk Retirement Profile	Number of FOFs
Conservative	1
Stable	68
Balanced	30
Aggressive	3

4. Results

4.1. Investment Performance Results

The calculation of fund profitability (Table 4) shows that the monthly average raw returns of the aggressive and stable fund groups investing in Chinese market assets are the highest during 2019–2023, while the conservative fund group has the lowest profitability. Due to larger fluctuations, the balanced group had a lower monthly average return than the stable group.

Table 4. Profitability of retirement FOFs in China (2019–2023).

Group of Funds	Raw Rate of Return			Real Rate of Return		
	Mean	Max/Min	SD	Mean	Max/Min	SD
Conservative	0.000191	0.003030/−0.002638	0.000001	0.000032	0.002872/−0.002796	0.000001
Stable	0.000211	0.006561/−0.003915	0.000004	0.000053	0.006403/−0.004074	0.000004
Balanced	0.000107	0.009296/−0.008761	0.000015	−0.000052	0.009138/−0.008920	0.000015
Aggressive	0.000301	0.011484/0.010366	0.000024	0.000142	0.011325 /−0.010525	0.000024

Source: Derived from our own calculations.

Investing in all types of retirement fund strategies in the Chinese market is profitable (based on average raw returns), and the impact of the inflation process has reduced the highest monthly average real raw returns to 1/6 of what they were.

In the following study stage, we calculated the excess returns over risk-free asset returns and examined the risks of the four groups of retirement FOFs (see Table 5). In the Sharpe ratio $S2$, the return on investment of the balanced group of funds is negative, indicating that other strategies provide higher returns than the risk-free return. The conservative group of funds had the highest Sharpe ratio $S1$ value, but after excluding the risk-free return rate, the aggressive group had the highest Sharpe ratio $S2$.

Table 5. Retirement fund performance (the Sharpe ratio) in China (2019–2023).

Group of Funds	$S1$	$S2$
Conservative	1.334414	0.150742
Stable	0.894079	0.243671
Balanced	0.223208	−0.219352
Aggressive	0.501502	1.180334

Source: Derived from our own calculations.

To calculate the risk-adjusted excess alpha returns of our various groups of equally weighted portfolio strategy funds, we use different factor models in the following research phase: (1) CAPM, (2) Fama–French [36] three-factor model (FF3), (3) Carhart [30], and (4) Fama–French [66] five-factor model (FF5). According to the findings, only eight of the sixteen Jensen's alphas calculated have statistical significance. Three of the four corresponding fund groups' calculation results contain statistically significant regression results (Table 6).

Table 6. Performance (regression models) of retirement FOFs in China.

Group of Funds	CAPM α	FF3 α	Carhart α	FF5 α
Conservative	−0.000052 ** (−2.51124)	0.000039 (1.62644)	0.000029 (1.19065)	0.000023 (0.87409)
Stable	−0.000007 (−0.60506)	0.000149 *** (4.23554)	0.000134 *** (3.86865)	0.000134 *** (3.81152)
Balanced	−0.000075 ** (−2.28039)	−0.000061 * (−1.705256)	−0.000065 * (−1.72416)	−0.000071 * (−1.8358)
Aggressive	0.000028 (−0.330856)	0.000063 (−1.150316)	0.000048 (−0.84328)	0.000028 (−0.36556)

Source: Derived from our own calculations. Asterisks denote statistically significant coefficients, with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively. Following the methodology of Newey and West [80], these significance levels are based on errors adjusted for heteroskedasticity and autocorrelation. Parentheses encircle t-statistics.

The alpha values in Table 6 are the constant term in the regressions in Equation (6). The beta values in Table 7 are the regression coefficients of the dependent variable $R_{mt} - R_{ft}$. The independent variable is $R_t - R_{ft}$. The alpha values calculated by Jensen for all aggressive strategies lack statistical significance. All regression models are deemed appropriate for application to conservative, balanced, and aggressive retirement funds. The alpha value assigned by Jensen to balanced funds is significant across almost all models. The statistical significance of Jensen's alpha derived from the Carhart model is the highest among the four investment strategies.

In studies of investment strategies employing Jensen's alpha, funds of the same type consistently exhibit all positive or negative characteristics. All statistically significant fund values are either entirely positive or entirely negative. Both conservative and balanced fund groups tend to be less efficient: the risk-free investment return strategy lessens the profitability of conservative fund groups, while balanced fund groups may offer the greatest investment diversification for various issuers' assets. In contrast, the stable and aggressive fund groups exhibit positive Jensen's alphas for all statistically significant values, validating the efficacy of this active investing strategy. The large number of funds in this category (68 funds) is further evidence that the market favors this investment strategy.

Regarding how well assets are managed, the Jensen alpha values with statistical significance have given similar results to the Sharpe ratio $S2$. The Sharpe ratio is figured out by comparing the fund's return rate to the index's return rate. However, the results of Jensen's alpha show that this ratio cannot be used to compare all investment strategy groups used by retirement funds because there are too many statistically insignificant values. Compared to Jensen's alpha, the value of the beta indicator (which we assume shows the market risk of the investment) is statistically significant for all regression models that were built (Table 7).

Table 7. Market risk of retirement FOFs in China.

Group of Funds	CAPM β	FF3 β	Carhart β	FF5 β
Conservative	0.107138 * (11.261057)	0.111705 *** (12.480113)	0.107337 *** (11.485393)	0.108713 *** (11.498843)
Stable	0.186368 *** (12.633088)	0.194378 *** (14.345977)	0.188839 *** (13.289868)	0.191438 *** (13.181232)
Balanced	0.415318 *** (21.833794)	0.416405 *** (21.55218)	0.415662 *** (20.30878)	0.420344 *** (20.17739)
Aggressive	0.548228 *** (28.056229)	0.550234 *** (27.786409)	0.543566 *** (26.08879)	0.550436 *** (26.261346)

Source: Derived from our own calculations. Asterisks denote statistically significant coefficients, with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively. These significance levels are calculated using errors adjusted for heteroskedasticity and autocorrelation, as Newey and West [80] described. T-statistics are enclosed in parentheses.

The β indicator peaks (greater than 0.55) in aggressive funds and then declines in balanced, stable, and conservative funds, reaching its lowest value (less than 0.11) in conservative funds. The β indicator emphasizes that aggressive funds comprise equity assets. The proportion of equity assets in balanced and stable funds decreases, while conservative funds comprise bonds and cash.

The Treynor ratio is used to evaluate the performance of investment strategies using the beta coefficient (β value) (Table 8). The conservative and stable groups of investment funds have achieved the most effective investment returns based on this measurement standard. Calculating the Sharpe ratio $S1$ yielded similar results.

Table 8. Retirement fund performance (Treynor ratio) in China (2019–2023).

Group of Funds	$T1$	$T2$	$T3$	$T4$
Conservative	0.145498	0.139550	0.145229	0.143390
Stable	0.092631	0.088814	0.091419	0.090178
Balanced	0.020878	0.0208238	0.020861	0.020628
Aggressive	0.045026	0.0448627	0.045413	0.044846

Source: Derived from our own calculations. $T1$—β from the CAPM model is used for calculation; $T2$—β from the FF3 model is used for calculation; $T3$—β from the Carhart model is used for calculation; $T4$—β from the FF5 model is used for calculation.

Since Treynor's measure is based on the difference between the return rate of the fund group and the index return rate, the indicator of the balanced group of funds is small, indicating that some asset management firms of balanced and aggressive groups are inefficient.

4.2. Sustainability Analysis Results

This study utilized the Cross Product Ratio (CPR) test, the Z-statistics test, and the χ^2 independence test to analyze the sustainability of the performance of the retirement FOFs [73]. The conservative group has one fund, and the aggressive group has three funds. The small number of funds may out 'Nan' in the sustainability analysis. So, the sustainability analysis is only applied to the stable and balanced groups.

The previous theoretical section introduced the CPR and Z-statistics tests. Here, the χ^2 independence test is briefly explained. The primary purpose of the χ^2 independence test is to determine whether the performance of the ranking and evaluation periods are independent. If the two are independent, the performance cannot be sustained, and vice versa. The formulas for its calculations are as follows:

$$\begin{cases} \chi^2 = & (WW - D_1)^2/D_1 + (WL - D_2)^2/D_2 + (LW - D_3)^2/D_3 \\ & +(LL - D_4)^2/D_4 \\ D_1 = & (WW + WL) \times (WW + LW)/n \\ D_2 = & (WW + WL) \times (WL + LL)/n \\ D_3 = & (LW + LL) \times (WW + LW)/n \\ D_4 = & (LW + LL) \times (WL + LL)/n \\ n = & WW + LL + LW + WL \end{cases} \tag{13}$$

where WW, LL, LW, and WL are the frequencies corresponding to performance, and if $\chi^2 > \chi^2_\alpha$ (where α is the significance level), it indicates that the fund performance is sustainable (Table 9).

Table 9. Results of the annual performance persistence test for retirement funds (2019–2023).

Sorting Period	Evaluation Period	Stable Group Retirement FOFs					Balanced Group Retirement FOFs				
		n	WW, WL, LW, LL	CPR	Z-Stat	χ^2	n	WW, WL, LW, LL	CPR	Z-Stat	χ^2
2019Q2	2020Q2	17	4,4,4,5	1.25	0.22894	0.052469	3	0,1,1,1	0	Nan	0.75
2019Q3	2020Q3	19	5,3,6,5	1.388889	0.346274	0.120222	6	1,0,4,1	Inf	Nan	0.24
2019Q4	2020Q4	24	6,4,7,7	1.5	0.483801	0.234965	10	4,0,2,4	Inf	Nan	4.444444 **
2020Q1	2021Q1	24	5,7,7,5	0.510204	−0.81266	0.666667	12	2,3,4,3	0.5	−0.58236	0.342857
2020Q2	2021Q2	32	7,6,10,9	1.05	0.067619	0.004573	16	4,2,4,6	3	1.017117	1.066667
2020Q3	2021Q3	32	7,9,10,6	0.466667	−1.05625	1.129412	20	1,7,9,3	0.047619	−2.41651	7.5 ***
2020Q4	2021Q4	35	7,9,9,10	0.864198	−0.21402	0.045825	21	5,5,7,4	0.571429	−0.62848	0.397727
2021Q1	2022Q1	36	9,8,11,8	0.818182	−0.29847	0.089164	21	6,4,5,6	1.8	0.66412	0.444298
2021Q2	2022Q2	38	8,11,9,10	0.808081	−0.32610	0.106443	23	5,6,5,7	1.166667	0.183005	0.033508
2021Q3	2022Q3	50	14,7,12,17	2.833333	1.744397	3.120395 *	23	9,2,3,9	13.5	2.533272	7.425103 ***
2021Q4	2022Q4	59	17,11,16,15	1.448864	0.702089	0.494424	27	10,3,6,8	4.444444	1.751861	3.240135 *
2022Q1	2023Q1	64	13,20,18,13	0.469444	−1.48475	2.230979	27	6,7,7,7	0.857143	−0.19980	0.039941
2022Q2	2023Q2	68	18,15,13,22	2.030769	1.432384	2.073746	30	5,10,9,6	0.333333	−1.44532	2.142857

Source: Derived from our own calculations. Asterisks denote statistically significant coefficients, with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively.

The annual performance persistence is poor, as only five of the three tests have passed. Only in the third quarter of 2021 did the fund performance of the stable group funds demonstrate notable consistency. Balanced group funds maintained their performance throughout the second half of 2022. This indicates a degree of performance consistency during the recovery phase of the COVID-19 pandemic in the second half of 2022, following the volatility in the capital markets caused by the COVID-19 pandemic in 2020. Nonetheless, performance persistence deteriorated once more in the first half of 2023.

Using the Sharpe ratio to measure fund performance, the specific practice of cross-sectional regression continues to adhere to the above period division. The least squares method is used to cross-sectionally regress the performance of the sample funds during the evaluation period against the sorting period. The model of regression is as follows:

$$Y_i = \alpha + \beta X_i + \varepsilon \qquad (i = 1, 2, 3, \ldots, T) \tag{14}$$

where Y_i represents the Sharpe ratio of the fund in the i-th evaluation period, X_i represents the Sharpe ratio of the fund in the i-th sorting period, and ε is a random disturbance term. The regression coefficients of each inspection period, as well as the corresponding t-values, p-values, and R^2, are organized as shown in Table 10.

Table 10. Annual cross-sectional regression results of retirement fund performance (2019–2023).

Sorting Period	Evaluation Period	Stable Group Retirement FOFs						Balanced Group Retirement FOFs					
		n	α	β	t-Value	p-Value	R^2	n	α	β	t-Value	p-Value	R^2
2019Q2	2020Q2	17	2.034476	−0.19517	−1.86432	0.081966	0.188123	3	2.269673	−0.10181	−0.558610	0.675688	0.237829
2019Q3	2020Q3	19	0.875825	0.047438	0.641888	0.529507	0.023663	6	0.987652	0.059393	1.082529	0.339914	0.226585
2019Q4	2020Q4	24	1.531951	−0.04564	−0.45892	0.650796	0.009482	10	0.866569	0.461071	2.516572	0.036000	0.441853
2020Q1	2021Q1	24	−0.15274	0.222627	2.221260	0.036937	0.183188	12	−0.25928	−0.02040	−1.00403	0.339042	0.091576
2020Q2	2021Q2	32	1.101438	0.138783	4.027999	0.000354	0.350997	16	1.059668	0.030597	0.814626	0.428927	0.045256
2020Q3	2021Q3	32	0.159018	−0.13594	−0.77547	0.444133	0.019651	20	0.085460	−0.26935	−1.75026	0.097099	0.145438
2020Q4	2021Q4	34	0.925304	−0.16306	−0.548212	0.587357	0.009304	21	0.664321	−0.05817	−0.28878	0.775875	0.004372
2021Q1	2022Q1	36	−1.53459	0.157707	1.396467	0.171625	0.054245	21	−1.60186	−0.28194	−1.31574	0.203918	0.083506
2021Q2	2022Q2	38	−0.57455	0.215341	2.173634	0.033325	0.066804	23	0.476719	−0.04362	−0.24815	0.806428	0.002924
2021Q3	2022Q3	49	−1.41235	0.044749	0.750896	0.456458	0.011854	23	−1.61933	0.589653	3.618547	0.001611	0.384054
2021Q4	2022Q4	59	−0.65669	0.092267	0.998836	0.322095	0.017202	27	−0.35550	0.342112	2.713407	0.011883	0.227503
2022Q1	2023Q1	64	0.552334	−0.14991	−1.22686	0.224512	0.023702	27	0.732410	0.030741	0.186458	0.853590	0.001389
2022Q2	2023Q2	68	0.625490	0.041993	0.426741	0.672109	0.005033	30	−0.56325	−0.14625	−0.90238	0.374550	0.028260

Source: Derived from our own calculations.

The end-of-year cross-sectional regression has a generally average effect on fitting. The retirement stable group FOFs passed the 5% confidence level test in the first half of 2021 and the second quarter of 2022, while the balanced group FOFs passed the test in the fourth quarter of 2020 and the second half of 2022. All values under the 5% confidence level are positive, indicating consistency in the fund's performance over the respective periods.

The results of the cross-sectional regression test and the contingency table method test are dissimilar and do not accurately represent the market situation during the period of market volatility. This could be associated with the sample data. The data we use are the risk-adjusted performance indicator—Sharpe ratio $S1$, which has smaller fluctuations after introducing risk factors compared to traditional return rate indicators [81]; therefore, the more robust data are also more stable when fitting and cannot reflect the possibility of a performance reversal during periods of market volatility.

Given that the conclusion of this comparative study is not of comparative significance and that the above two methods can only test whether performance persistence exists, rather than quantifying and comparing the annual performance persistence strength, this study continues to use the Spearman rank correlation coefficient method for testing.

In the previous theoretical section, the Spearman rank correlation coefficient was introduced. This article uses the previous method to divide the sample period into sorting and evaluation periods, as well as the Sharpe ratio $S1$ as the fund performance measure indicator and calculates the Spearman rank correlation coefficient with the year as the time interval for persistence testing (Table 11).

When the Spearman rank correlation coefficient is calculated with the year as the time interval, it is determined that in the 13-time segments, the stable group and balanced group funds exhibit performance reversals in the 4- and 7-time segments, respectively, but they are not statistically significant overall. The performance of the stable group and the balanced group reversed in the second and third quarters of 2020 and 2021, respectively, and the Spearman coefficient of the balanced group funds was statistically significant in the third quarter of 2021, with a Spearman rank correlation coefficient ranging from [−0.5, −0.12867]. By the second half of 2022, the Spearman coefficient has been consistently positive, and the Spearman coefficient of the balanced group funds is statistically significant, with a Spearman rank correlation coefficient ranging between [0.102396, 0.595850]. This shows that the fund's performance reversed due to the impact of the COVID-19 epidemic in 2020 and the capital market volatility and that the fund's performance was sustainable in the second half of 2022 as the economy recovered.

Table 11. Annual Spearman rank correlation coefficient of retirement funds (2019–2023).

Sorting Period	Evaluation Period	Stable Group Retirement FOFs			Balanced Group Retirement FOFs		
		n	Spearman Coefficient	*p*-Value	*n*	Spearman Coefficient	*p*-Value
2019Q2	2020Q2	17	−0.13725	0.599369	3	−0.5	0.666667
2019Q3	2020Q3	19	0.156140	0.523260	6	0.771429	0.072397 *
2019Q4	2020Q4	24	0.016522	0.938923	10	0.6	0.066688 *
2020Q1	2021Q1	24	0.156522	0.465156	12	−0.31469	0.319139
2020Q2	2021Q2	32	0.204912	0.260577	16	0.223529	0.405298
2020Q3	2021Q3	32	−0.12867	0.482797	20	−0.50677	0.022588 ***
2020Q4	2021Q4	34	−0.08449	0.634722	21	0.002597	0.991085
2021Q1	2022Q1	36	0.189704	0.267795	21	−0.13766	0.551801
2021Q2	2022Q2	38	0.152861	0.359550	23	−0.21937	0.314560
2021Q3	2022Q3	49	0.236429	0.101932	23	0.595850	0.002698 ***
2021Q4	2022Q4	59	0.102396	0.440278	27	0.382173	0.049152 **
2022Q1	2023Q1	64	−0.18874	0.135283	27	−0.07265	0.718763
2022Q2	2023Q2	68	0.303890	0.011757 **	30	−0.20623	0.27423

Source: Derived from our own calculations. Asterisks denote statistically significant coefficients, with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively.

Using the contingency table method test, cross-sectional regression, and Spearman rank correlation coefficient, it is clear that the annual performance of the retirement FOFs is not sustainable most of the time. This is especially true in 2019–2020, when it was affected by the COVID-19 epidemic, making fund performance reversibility better. The retirement fund's performance showed strong sustainability in the second half of 2022, influenced by the economic recovery. However, the fund's performance did not continue into 2023.

5. Discussion

This study highlights that different risk strategy retirement FOFs have distinct profit margins and risk exposures, which can be effectively categorized by fund names. The profitability of the conservative group of funds cannot significantly exceed risk-free returns, the efficiency of the stable group of funds is low due to an insufficient stock asset ratio, and the balanced group of funds, being the most diversified type of FOFs, has achieved positive investment returns to fulfill the retirement security function. Additionally, the aggressive group of funds has the highest returns, and its investment efficiency is low due to high-risk exposure.

Using a performance dichotomy, cross-sectional regression, and the Spearman rank correlation coefficient [74,75,79], this study investigates the performance sustainability of stable group FOFs and balanced group FOFs. The sample period for the fund spans from 2019 to 2023, where only brief intervals of performance sustainability pass the significance test, indicating that the performance of China's retirement FOFs is generally unsustainable most of the time. The instability and irregular factors of the Chinese stock market exert a substantial disruptive influence, resulting in substantial changes in the fund's ability to generate excess returns during the pandemic-affected economic recession and recovery phases. Moreover, in conjunction with the efficient market hypothesis, the findings of this study shed some light on the degree of efficiency of the Chinese securities market. During the sample period, China's stock market has reached a weak form of efficiency, as indicated by the unreliability of fund performance as a whole [82]. Consequently, relying heavily on a fund manager's abilities to achieve long-term retirement goals is risky.

6. Conclusions

This study contributes to the existing knowledge in two substantial ways. First, it presents a comprehensive methodology for analyzing the performance of investment strategies employed by Chinese retirement FOFs. Second, to our knowledge, this is the first study to comprehensively evaluate the profitability and performance of various strategies employed by target-risk retirement funds in China. Research into the profitability, performance, and quality of asset management of China's retirement FOFs for the 2019–2023 period showed:

(1) Gross return rates (including inflation) were positive for all retirement FOF investment strategy groups. The highest monthly average real gross return rate was reduced by inflation to one-sixth of its original value.
(2) The performance of funds is contingent upon the modification of the Sharpe ratio. The conservative fund group's investment strategies may appeal to conservative investors because they offer higher returns than risk-free assets (with positive Sharpe ratios $S1$ and $S2$). However, the conservative group of analyzed retirement funds lacks appeal for risk-tolerant investors because their Sharpe ratio $S2$ is lower than those of the stable and aggressive fund groups.
(3) Using Jensen's alpha as an absolute measure of fund performance is limited when comparing all investment strategies used by retirement FOFs (owing to the high number of statistically insignificant values). In investment strategy research based on Jensen's alpha, the positive and negative characteristics of the same type of fund are consistent. The stable funds achieved a positive Jensen's alpha for all statistically significant values, validating the efficacy of this strategy in active investing. The stable fund type was the most abundant, with 68 funds, further confirming the market's preference for this investment strategy. However, the aggressive funds did not achieve statistically significant values of Jensen's alpha, indicating the inefficiency of this indicator. Hence, Hypothesis 1, that not all performance measures among existing ones in international investment practice lead to the same ranking result for evaluating retirement FOFs in China, is verified positively.
(4) A fund's performance based on the conventional Treynor ratio yielded comparable results to those obtained by calculating the Sharpe ratio $S1$. Using this metric, funds with stable and aggressive investment strategies generated the most profitable returns.
(5) The sustainability of the performance of funds from 2019 to 2023 was evaluated using the performance dichotomy, cross-sectional regression, and Spearman rank correlation coefficient methods. The annual performance of retirement FOFs was largely unsustainable, particularly in the 2019-2020 period affected by the COVID-19 pandemic when fund performance reversal was exacerbated. In the second half of 2022, retirement fund performance exhibited remarkable sustainability due to the economic recovery. This sustainability, however, did not extend into 2023. Hence, our Hypothesis 2, that the performances of China's retirement funds in the same strategy group are sustainable for the observation period, is verified negatively.

According to our data analyses, retirement due to their pursuit of long-term investment objectives and their characteristic dual diversification of risk, FOFs may not distinguish themselves from other options during market upswings. Nevertheless, their low volatility and low drawdown could make them potentially useful instruments for diversifying an individual's asset allocation. However, their performance is susceptible to economic downturns and lacks sustainability, requiring investors to decide based on their risk tolerance and return objectives.

Nevertheless, it is important to consider the study's limitations. For instance, the Sharpe ratio for stable and balanced group funds does not have a normal distribution. Investors frequently employ various fund combination strategies to increase their investment returns. To better understand the performance of retirement fund investment strategies, further discussion is required regarding the tax avoidance function of retirement funds, the combination investment of retirement funds and other assets (bonds, mixed funds), the comparative analysis of the profitability and performance of retirement funds in the commercial retirement markets of various countries [38], and the construction of key scores to summarize the profitability and performance. In addition, future work will also consider the limited availability of public data on retirement FOFs, the limitations imposed by the selected research timeline, and the limited number of investment funds available for analysis.

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