Mutual Fund Performance in China: Empirical Evidence on Regulation and Sustainable Investing

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Abstract

This thesis examines mutual fund performance in the Chinese market, with a focus on regulatory influences and ESG practices. Chapter one introduces the motivation and overview of this thesis. Motivated by CSRC issuing the "Notice on Regulating the Development of Target Pension Securities Investment Funds (Trial)" in 2018, Chapter Two examines the impact of regulatory requirements—including fund family size, lock-in periods, and manager experience—on the performance of pension funds, specifically target date funds (TDFs) and target risk funds (TRFs). The results indicate that such regulations generally improve the performance of TDFs and TRFs, while providing little to no benefit for standard mutual funds. Mechanism tests reveal that TDFs & TRFs achieve greater flow stability, contributing to their outperformance. However, managing these regulated funds may inadvertently reduce the performance of other non-TDF and non-TRF funds within the same family, likely due to higher compliance costs and strategic considerations. These findings highlight the dual benefits and costs of regulation and underscore important policy implications for regulators, fund issuers, and investors, particularly in retirement savings contexts.

This thesis not only examines the regulatory requirements for pension funds but also extends the analysis to ESG investment regulation. In 2018, CSRC revised the "Code of Corporate Governance for Listed Companies", mandating ESG disclosure for listed companies. The improvement in ESG reporting provides mutual funds with greater access to relevant information, thereby facilitating the integration of ESG factors into investment strategies. Chapter Three explores the relationship between ESG investing and fund behavior using over 40,000 quarterly observations from more than 3,000 Chinese mutual funds. This chapter documents a significant negative association between ESG investing and style drift, which is stronger during periods of heightened economic policy uncertainty, elevated investor sentiment,

and non-COVID-19 conditions. ESG commitments are also linked to key fund metrics such as tracking error, risk-adjusted return, and fund flow. The results support the argument that fostering long-term alignment between fund managers and investors through ESG commitments not only promotes sustainability but also helps reduce excessive risk-taking.

Chapter Four builds on the findings of Chapter Three explores the role of ESG profile diversity (ESGPD)—which measures the diversity of stock-level ESG profiles within a fund's holdings—in explaining window dressing. This is the first study that develops this measurement and investigates its relationship with window dressing. The main results show that a one-unit increase in ESGPD is associated with 10.64 units increase in window dressing, with the effect varying across fund, manager, and market conditions. Robustness checks confirm these results using alternative measures of window dressing and ESGPD, and by employing fixed effects. This chapter provides practical implications for fund managers and investors, enhancing transparency and understanding of factors driving window dressing. Overall, this thesis demonstrates that regulatory requirements and ESG practices play crucial roles in shaping fund performance in China's mutual fund market.

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This thesis is dedicated to my family and loved ones, whose guidance, care, and support have made this journey possible.

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List of Abbreviations

Abbreviation	Full Term
ASD	Active Style Drift
ATT	Average Treatment Effect
BHRG	Backward Holding Return Gap
BOISE	Basic Old-Age Insurance System for Employees
BPIURR	Basic Pension Insurance for Urban and Rural Residents
CAPM	Capital Asset Pricing Model
CMA	Conservative Minus Aggressive
CSMAR	China Stock Market and Accounting Research
CSRC	China Securities Regulatory Commission
DB	Defined Benefit
DC	Defined Contribution
DiD	Difference-in-Difference
e.g.	For example
EPU	Economic Policy Uncertainty
ESG	Environmental, Social, and Governance
ESGPD	ESG Profile Diversity
FOFs	Fund of Funds
HML	High Minus Low
i.e.	That is
MSCI	Morgan Stanley Capital International
PAYG	Pay-as-you-go
PRI	Principles for Responsible Investment
PSD	Passive Style Drift
PSM	Propensity Score Matching
RBSA	Return-based Style Analysis
RMW	Robust Minus Weak
SDS	Style Drift Score

SEC	Securities and Exchange Commission
SML	Small Minus Large
SNSI	Sino-Securities Index
SPIVA	S&P Indices versus Active
SRI	Socially Responsible Investing
SSE	Shanghai Stock Exchange-
SZSE	Shenzhen Stock Exchange
TDFs	Target Date Funds
TNA	Total Net Assets
TRFs	Target Risk Funds
U.K.	United Kingdom
U.S.	United States
WHO	World Health Organization

Chapter One: Introduction

This chapter presents the motivation and objectives of the thesis, provides a brief overview of the following chapters, and outlines the overall structure of the thesis.

1.1 Motivation and objectives

In China, mutual funds have experienced rapid growth and have become a major investment vehicle for individual investors. The number of mutual funds rose from 308 in 2006 to 10,174 in 2023, while total net assets expanded from RMB 1 trillion to RMB 27.6 trillion. With this remarkable development and growing public attention, it is increasingly important to gain a deeper understanding of the Chinese mutual fund industry. This study focuses on new insights regarding regulations and requirements related to mutual funds.

Chapter Two focus on pension fund regulation, motived by the "Notice on Regulating the Development of Target Pension Securities Investment Funds (Trial)", issued by the China Securities Regulatory Commission (CSRC) in 2018. Target date funds (TDFs) and target risk funds (TRFs), as the main components of target pension funds, not only serve as saving vehicles for investors but also constitute a crucial part of the third pillar of the Chinese pension system. However, empirical evidence regarding the impact of these regulatory requirements on its performance remains limited. Chapter Two provides valuable insights for household retirement planning particularly facing the challenges arising from population aging.

China faces one of the world's most severe demographic challenges (United Nations, 2022). According to the National Bureau of Statistics, the population aged 65 and above reached 210.35 million in 2022, accounting for 14.9% of the total population. These demographic shifts suggest that the burden of retirement savings will increasingly fall on individual households. At present, China's retirement savings system follows the World Bank's well-known three-pillar model.[1] However, as pointed out by the "China Aging

[1] In 1994, the World Bank introduced the well-known three-pillar retirement saving system to guide institutional and household practices. The first pillar relies on a basic public pension (mandatory and state-provided) designed to provide a basic level of income for all retirees, ensuring that no one falls into poverty in old age. It emphasizes the importance of universal coverage and adequacy, funded primarily through general taxation or payroll contributions. The second pillar consists of occupational or mandatory private savings schemes, often linked to employment. These schemes can be publicly or privately managed and are intended to supplement the basic pension, thereby improving retirement income adequacy. Pillar three, voluntary private savings, encourages individuals to save through private retirement accounts, tax incentives, and other financial products, giving them

Research Report 2022", the first pillar of pensions accounts for as much as 70% of total retirement savings. Such heavy dependence on the first pillar, unsurprisingly, has led to a substantial pension gap amid the rapid growth of the aging population discussed above. Strengthening the third pillar of retirement savings has therefore become an urgent policy priority. In response, CSRC issued the pension fund regulation in 2018, establishing a regulatory framework for TDFs & TRFs.

TDFs automatically adjust their investment mix according to investors' life cycles, while TRFs maintain a constant risk level consistent with investors' risk tolerance. Previous studies provide mixed evidence on their effectiveness (Elton et al., 2015; Elton et al., 2016; Balduzzi and Reuter, 2019). In China, the urgent need to promote private retirement savings and the introduction of stricter regulations raise an important research question for this chapter: Do these regulatory requirements truly enhance the performance of TDFs & TRFs? Chapter Two investigates this issue and evaluates the policy's role in improving retirement fund outcomes.

Despite pension fund regulations, Chapter Three examines ESG investing regulations, motivated by the "Code of Corporate Governance for Listed Companies" issued by CSRC in 2018, which mandates ESG disclosure for listed companies and encourages ESG integrated investing. Globally, Environmental, Social, and Governance (ESG) assets reached USD 30.3 trillion by the end of 2022 and are projected to exceed USD 50 trillion by 2025. However, whether ESG integrated investing improves fund performance remains debated. Some studies find that strong ESG performance provides material information about firm fundamentals, leading to higher returns and reduced risks (Edmans, 2011; Nagy et al., 2015; Bae et al., 2020; Steen et al., 2020), while others argue that ethical investing may involve financial trade-offs (Bollen, 2007).

more control over their retirement planning.

Empirical evidence on ESG investing in China remains limited due to the historical absence of fund-level ESG data. This gap has narrowed since the 2018 revision of the "Code of Corporate Governance for Listed Companies", which mandated ESG disclosures for listed companies and improved data availability (Yuan, 2024). Building on this development, Chapter Three examines the relationship between funds' ESG investing and style drift—defined as the deviation of a fund from its stated investment style (diBartolomeo and Witkowski, 1997; Cumming et al., 2009). Style drift may misalign portfolios with investors' risk–return expectations, undermining confidence and market stability.

Nevertheless, examining only the fund-level ESG score may be insufficient. Fund managers can achieve high ESG exposure through two distinct paths: intentional and unintentional. Purpose-driven managers may deliberately incorporate ESG principles into their investment strategies to promote long-term sustainability, enhance ethical decision-making, and mitigate regulatory or reputational risks (Hoepner et al., 2024). These managers actively select high-ESG assets to align with their objectives. In contrast, non-ESG-oriented managers may hold high-ESG assets unintentionally due to factors such as financial characteristics or industry exposure, resulting in portfolios that appear ESG-friendly by coincidence. Since high ESG exposure can arise from both intentional and unintentional factors, relying solely on average ESG scores is insufficient. Therefore, it is crucial to have a deeper investigation into fund holdings' ESG profile. Chapter Four constructs an indicator, ESGPD, to capture the degree of variability in individual assets' ESG scores within a fund and examines its effectiveness in detecting fund window dressing behavior.

Overall, this thesis aims to provide a comprehensive understanding of mutual fund performance in China from both regulatory requirements and sustainable investing perspectives, emphasizing the impact of regulation. By examining personal pension funds and ESG-related investment behavior, the thesis seeks to offer empirical evidence that contributes

to fund performance evaluation, policy effectiveness, and investor decision-making. The following section outlines an overall review of the thesis.

1.2 Overview of Chapter Two

Chapter Two examines how regulatory requirements influence the performance of TDFs & TRFs. The findings show that regulatory requirements on fund family size, lock-in periods, and manager experience significantly enhance pension fund performance. These structural features encourage long-term investment discipline among households and improve their self-funded retirement outcomes.

The analysis covers all TDFs & TRFs introduced since 2018, together with all open-end standard mutual funds with available data from 2004 to 2022 for comparison. Baseline results indicate that TDFs & TRFs with larger fund families, longer lock-in periods, and more experienced managers generally outperform in terms of returns and net inflows. In contrast, for standard mutual funds not subject to such requirements, only fund family size shows a weak positive effect on returns, while lock-in periods and manager experience tend to negatively affect fund flows. These findings suggest that stricter regulations are effective for pension funds but may not benefit traditional mutual funds.

Additionally, Chapter Two identifies the relative importance of these factors. For TDFs & TRFs, fund returns are mainly driven by manager experience, followed by lock-in period and family size. In terms of fund flows, lock-in period plays the most significant role, reflecting its influence on redemption constraints. Furthermore, adjusted R-squared values indicate that fund family size, lock-in period, and manager experience have greater explanatory power for TDFs & TRFs compared with standard mutual funds, emphasizing their particular relevance for pension fund selection. To assess the robustness of the results, log-likelihood ratio tests are performed, providing additional evidence supporting the validity of the full model.

Further analysis shows that TDFs & TRFs outperform mutual funds after accounting for regulatory requirements (i.e., fund family size, lock-in periods, and manager experience). This finding is further confirmed by additional regression analyses incorporating interaction terms. To explore the underlying mechanisms, Chapter Two finds no evidence of superior fund selection ability. TDFs & TRFs tend to invest in affiliated sub-funds within the same family, which generally have weaker past performance and higher expense ratios—indicating potential agency issues. However, the stability of fund flows resulting from mandatory lock-ins significantly contributes to improved returns, confirming the positive impact of these regulatory features. Moreover, non-TDFs & TRFs managed by the same issuers do not appear to benefit from these policies; instead, they may face higher costs and lower flexibility. Finally, robustness checks confirm the consistency of the main results.

Chapter Two contributes to literature in several ways. First, it provides new evidence on China's third pillar of retirement savings, where TDFs & TRFs serve as the first formal vehicles for voluntary pension investment. The findings confirm their effectiveness in improving household investment outcomes and reinforce their policy importance. Second, the study identifies the key drivers of fund performance—fund family size, lock-in period, and manager experience—offering practical insights for investors. Third, the comparison with standard mutual funds underscores the distinct objectives and characteristics of pension funds. Finally, it highlights potential spillover effects within fund families and agency concerns arising from affiliated sub-fund selection, offering implications for policymakers and regulators.

1.3 Overview of Chapter Three

Chapter Three focuses on the influence of ESG investing in mutual funds' style drift. The analysis covers 40,084 fund-quarter observations from 3,112 mutual funds over 2018–2022, starting from the year ESG disclosure data became available after CSRC reforms. The results

show a robust negative relationship between ESG investing and style drift. By fostering long-term alignment between fund managers and investors, ESG commitments not only enhance sustainability but also curb excessive risk-taking.

Further analysis shows that the effect of ESG on style drift varies across different time periods, during which market conditions, investor attention, and preferences may change significantly. First, the effect is stronger during periods of heightened economic policy uncertainty (EPU). During such times, funds have greater incentives to reduce policy-induced information asymmetry and rebuild trust with stakeholders (Qureshi et al., 2023). Second, this chapter finds a stronger impact when investor sentiment is high. High investor sentiment may encourage fund managers to incorporate ESG investing into their strategies to enhance visibility and reputation (Cheong et al., 2017), thereby strengthening its influence on style drift. Third, the effect is more pronounced during non-COVID-19 periods. The findings support this argument by showing that when ESG was perceived as a "luxury" in the pre-pandemic period, its influence on style drift was stronger. However, as ESG became a "necessity" during the pandemic, its impact diminished, likely because investors and fund managers were already prioritizing ESG considerations regardless of external pressures.

Moreover, this chapter finds that higher controversy scores (indicating fewer negative ESG events) are the primary drivers of lower style drift, reflecting advanced risk management capabilities that help maintain consistency in investment style. Additionally, higher investment concentration amplifies the ESG effect, as more concentrated funds tend to be more sensitive to ESG considerations. Finally, robustness checks confirm the consistency of the baseline result.

This chapter contributes in two ways. First, it advances understanding of factors mitigating style drift, a critical but underexplored aspect of mutual fund behavior. In China's emerging market, characterized by a weak institutional environment, less experienced retail investors, and rapid growth, identifying factors that reduce style drift is important for investor

protection and market stability. Second, it adds to the literature on whether socially responsible investing adds value at the fund level. While prior research focused on firm- and market-level ESG effects, little attention has been given to fund-level strategy consistency. The findings show that higher ESG ratings correlate with lower style drift and more stable investment approaches, highlighting the spillover impact of CSRC's 2018 ESG disclosure reforms.

Overall, the study provides practical implications for investors, fund managers, and policymakers. Minimizing style drift promotes market stability, protects investors, and supports the development of sustainable investment practices. The results are also relevant beyond China, offering insights for other markets where ESG integrated investing, regulatory frameworks, and investor behavior may face similar challenges.

1.4 Overview of Chapter Four

Chapter Four investigates the role of ESG profile diversity (ESGPD) in explaining window dressing among Chinese mutual funds. The analysis uses 32,227 semi-annual observations from 3,302 funds over 2009–2022, based on ESG scores from the Sino-Securities Index (SNSI). Multivariate regressions show a robust positive relationship between ESGPD and window dressing: a one-percentage-point increase in ESGPD is associated with an average 10.64% increase in window dressing. The results indicate that managers of higher ESGPD funds face pressure to deliver strong short-term results and are thus more likely to adjust holdings before reporting. Meanwhile, the diversity of ESG stocks provides additional flexibility for window dressing, making it harder to detect and amplifying such behavior.

This chapter extends the analysis by examining how ESGPD's impact on window dressing varies across fund characteristics. Compared with non-ESG funds, ESG funds face greater pressure to maintain strong ESG reputations (Ramchander, 2012). Their diversification across ESG rankings may therefore reflect genuine portfolio diversification rather than strategic

manipulation. Consequently, ESG funds have lower incentives to engage in window dressing, as their strategies are inherently aligned with ESG objectives. The empirical results provide evidence supporting this view. Moreover, the effect of ESGPD on window dressing is stronger among large funds, which possess greater flexibility, reputational demands, and portfolio complexity (Luo, 2024). The relationship is also more pronounced among low-ranked funds than high-ranked ones, as lower-ranked funds may diversify holdings to attract heterogeneous investors, leading to higher ESG profile diversity and a greater tendency toward window dressing.

This analysis further explores how ESGPD influences window dressing across fund manager characteristics. Funds with lower gender diversity exhibit stronger ESGPD effects, consistent with prior evidence that less diverse teams are more prone to overconfidence and risk-taking (Huang and Kisgen, 2013; Chen et al., 2016). Similarly, the effect is greater among funds managed by older managers, who are better able to adjust portfolio holdings strategically in response to ESG considerations. In addition, ESGPD's impact is stronger for funds managed by multiple managers than single ones, as team management can introduce coordination challenges and interpersonal competition (Sah and Stiglitz, 1988; Adams et al., 2018), resulting in riskier and more diversified ESG portfolios.

Finally, the findings assess the time-series dynamics of ESGPD's influence on window dressing under varying market conditions. The effect intensifies during periods of high economic policy uncertainty, when fund managers face greater forecasting difficulties and may adjust ESG goals to maintain investor confidence (Kammoun and Essaddam, 2024). It is also stronger during economic expansion, as managers broaden ESG holdings to signal stability and attract investors. Consistent with Massa and Yadav (2015), the results indicate that high investor sentiment amplifies the effect of ESGPD, as managers respond to increased investor attention to sustainability by diversifying into a wider range of ESG stocks, thereby heightening

window dressing behavior.

This chapter contributes in two ways. First, it provides the first analysis of window dressing in Chinese mutual funds, leveraging ESGPD as a novel determinant. The Chinese context—with semi-annual disclosure and rapid market growth—offers a unique setting to study managerial incentives. Second, ESGPD offers a practical tool for investors and policymakers to detect window dressing and improve decision-making. Given the limited financial literacy of many Chinese investors, ESGPD helps identify funds that may manipulate holdings to appear more attractive, mitigating potential investor losses.

1.5 Research outputs

Chapter Two: Encouraging retirement savings – the role of Chinese pension funds

- Published in the Journal of International Financial Markets, Institutions and Money.
- Presented at the 2024 Academy of Financial Services Conference (online).
- Presented at the 2024 Massey Sustainable Finance Conference, Auckland, New Zealand.

Chapter Three: Stability through sustainability – the role of ESG in curbing fund style drift

- Presented at the 2024 AFS Australia–New Zealand Chapter Personal Finance and Investment Symposium, Brisbane, Australia.
- Accepted for presentation at the 2025 Massey Sustainable Finance Conference, Nanjing, China.
- Presented at the 2025 New Zealand Finance Meeting, Queenstown, New Zealand.
- Presented at the 2026 New Zealand Finance Colloquium, Auckland, New Zealand.

1.6 Structure of the thesis

This thesis examines mutual fund performance in China from the dual perspectives of regulatory requirements and sustainable investing, emphasizing the importance of regulation. Chapter one introduces the motivation and objectives of study. Chapter Two investigates the impact of regulatory requirements on pension fund performance. Chapter Three focuses on the effect of ESG investing on style drift, while Chapter Four examines how ESG profile diversity influences window dressing. Chapter five concludes the thesis by summarizing the main findings, discussing their implications, addressing limitations, and outlining directions for future research. The reference list is provided at the end of the thesis.

Chapter Two: Encouraging retirement savings – the role of Chinese pension funds

This chapter first investigates the impact of regulatory requirements on pension fund performance in the Chinese market. Section 2.1 describes the introduction. Section 2.2 outlines the institutional background, related literature and hypotheses. Section 2.3 presents the data and methodology. In Section 2.4, the main results are described. In Section 2.5 and Section 2.6, further analysis and robustness checks are shown. Finally, the conclusion is shown in Section 2.7.

Abstract

This chapter explore the impact of regulatory requirements—specifically, fund family size, lock-in periods, and manager experience—on the performance of pension funds, including target date funds (TDFs) and target risk funds (TRFs) in China. The findings reveal that these regulations generally enhance fund performance. However, these same restrictions appear to have little to no benefit for standard mutual funds. In the mechanism test, it finds that TDFs & TRFs are associated with greater flow stability, contributing to their outperformance over standard mutual funds. Moreover, managing TDFs & TRFs may inadvertently dampen the performance of non-TDFs and non-TRFs managed by the same fund family, potentially due to increased compliance and disclosure costs as well as fund family strategic considerations. The results show that the regulatory requirements imposed on TDFs & TRFs are associated with both benefits and costs, suggesting the critical importance of recognizing the distinct policy implications for regulators, fund issuers, and investors, particularly in the context of retirement savings.

Keywords: Target date fund; Target risk fund; Pension fund; Mutual fund; Fund performance; Fund flow; Retirement saving

JEL: G11; G18; J32

2.1 Introduction

The most striking demographic change over the past 30 years has been the rapid pace of the global population aging (Powell, 2010).[2] The physical effects of aging, coupled with the higher likelihood that the aged population possess mismatched skills in the labor market, contribute to a reduced capacity among the elderly to generate private income compared to younger individuals (Banister et al., 2012). At the same time, the demographic distribution has shifted dramatically. Since 2020, there have been more people over the age of 60 than children under the age of 5. This shift not only suggests less familial support for the elderly but also signals potential reduction in government retirement benefits due to a shrinking taxpaying population but an increasing aging population.

In particular, China faces the most acute demographic challenge compared to other regions of the world in the pace of aging (United Nations, 2022). From the National Bureau of Statistics of China, the population aged 65 and above reached 210.35 million, accounting for 14.9% of the total population in 2022. Projections suggest this share will rise to 22% by 2040.[3] Compounding this trend, the natural population growth rate of China has fallen to -0.60‰ in 2022. These demographic shifts imply that the burden of retirement savings will increasingly fall on individual households. Traditionally, guided by the proverb "Bring up children for one's old age," Chinese families relied on children for elder support. However, the historical family planning policies, modern cultural changes and smaller family sizes have weakened this expectation (Chou, 2011; Niu et al., 2020). Additionally, despite rapid economic growth, rural areas remain less developed. These demographic shifts could have an even greater impact on

[2] The natural growth rate of the global population ranged from 1.79% to 0.82% between 1980 and 2021, and the United Nations forecast the population growth rate will drop to negative in 2086 (United Nations, 2022). The World Health Organization (WHO) predicts that the proportion of persons aged 60 and older will roughly double between 2015 and 2050, increasing from 12% to 22%, and the population aged 60 and above will reach 2.1 billion in 2050.

[3] We source the statistics from American Enterprise Institute, more details can be found on the website: https://aei.org/.

rural residents, who face limited pension options, low incomes, meager savings, and a historically greater dependence on family support (Cai et al., 2012).

The retirement saving system in China follows the World Bank's popular three-pillar model. Currently, basic pension insurance constitutes the first pillar and uses the pay-as-you-go (PAYG) model. It is regulated by the Chinese government and encompasses the Basic Old-Age Insurance System for Employees (BOISE) and Basic Pension Insurance for Urban and Rural Residents (BPIURR). The second pillar involves supplementary pension insurance, which consists of enterprise annuities and occupational annuities. The third pillar consists of commercial pensions and private pension funds. However, the composition of the three pillars is unbalanced in China. Wang et al. (2014) point out that China relies almost solely on public pensions to alleviate poverty among the elderly. The "China Aging Research Report 2022" indicates that the first pillar of pensions accounted for as much as 70% of the total retirement savings. Such a heavy reliance on the first pillar, not surprisingly, leaves a significant pension gap with the substantial surge in the aging population as discussed above. In 2020, RMB 50 billion was injected for the first time to fill the gap in basic pension insurance.[4] More importantly, this problem will only further exacerbate with the current demographic trend. The need to solidify the second and third pillars of retirement saving is urgent in China.

As a significant step toward promoting the third pillar of retirement savings in response to an aging population, the China Securities Regulatory Commission (CSRC) issued the "Notice on Regulating the Development of Target Pension Securities Investment Funds (Trial)" in February 2018. This policy established the regulatory framework for target pension funds, including TDFs & TRFs, significantly advancing China's voluntary personal pension system. To build consumer confidence, the policy introduced strict requirements regarding fund family

[4] For more details, refer to the "Report on the execution of the central and local budgets for 2020 and on the draft central and local budgets for 2021", which was issued by the Ministry of Finance on 13 May 2021.

size, lock-in periods, and manager experience on TDFs & TRFs. These regulatory standards distinguish TDFs & TRFs from standard mutual funds in China.

From an international perspective, TDFs & TRFs in China differ from those in the U.S. Although TDFs & TRFs have been widely used in 401(k) plans and individual retirement accounts in the U.S., these products are relatively new in China. Designed for retirement savings, TDFs automatically adjust their investment mix to reflect varied investment risk profiles over investor life cycles based on a specific target retirement date. Differently, TRFs focus on maintaining a consistent level of risk that aligns with an investor's risk tolerance, regardless of time horizon. Previous research finds mixed evidence regarding the efficiency of these specific retirement-saving tools (Elton et al., 2015; Elton et al., 2016; Balduzzi and Reuter, 2019). In the Chinese context, the urgent need to encourage private retirement savings, combined with the first-time introduction of TDFs & TRFs, and the strict and specific regulatory requirements for TDF & TRF issuers, motivate the key research question of this study. That is, do the stricter regulatory requirements on TDFs & TRFs enhance the performance of these funds? The investigation ultimately sheds light on the policy effectiveness in addressing the adequacy of household retirement savings.

It is also worth noting that mutual funds have become a major investment vehicle for Chinese households. Between 2008 and 2020, the net asset value of China's mutual funds grew impressively from RMB 1.87 trillion to RMB 20.01 trillion (You et al., 2023). The number of mutual funds surged from 409 to 7,238 during the same period. While pension funds are still relatively new in China, there is no doubt that it will expand rapidly by borrowing experience from other developed markets. For example, nearly half of the assets in U.S. mutual funds originate from pension fund accounts, defined contribution retirement plan accounts, and individual retirement accounts.[5] Therefore, investigating (pension) fund performance in China,

[5] See the "2024 Investment Company Fact Book" for further details.

the third largest capital market by market capitalization, could have important implications for global financial markets and household well-being.

Our study includes all TDFs & TRFs introduced since 2018. To highlight whether the newly introduced TDFs & TRFs provide advantage over existing general saving means, we also include all open-end mutual funds that have data for our research covering 2004-2022 period. First, we examine whether the regulatory requirements on fund family size, lock-in period, and manager experience contribute to better fund performance of TDFs & TRFs, measured by fund returns and fund net inflows. In general, our results show supportive evidence that TDFs & TRFs with a bigger fund family size, a longer lock-in period, and a more experienced fund manager outperform. Next, as a comparison, we run the same analysis for standard mutual funds (which are not subject to the stricter requirements). The evidence is mixed as previously documented in the literature (Massa, 2003; Ding and Wermers, 2012). We find that only fund family size has a small positive effect on mutual fund returns, while lock-in period and manager experience generally exhibit a negative relationship with fund flows. Taken together, while the results support the efficiency of the stricter regulatory requirements on TDFs & TRFs which specifically serve the investment goal of retirement saving, imposing the same requirements on standard mutual funds may have an adverse impact (Khorana et al., 2005).

Additionally, we test the relative importance of fund family size, lock-in period and manager experience to identify key drivers to different fund performance outcomes and provide guidance for investors' fund selection. Based on adjusted R-squared improvements of competing models, we find the most important drivers for TDFs & TRFs returns are manager experience, lock-in period and fund family size in order. For fund flows of TDFs & TRFs, lock-in period ranks ahead of fund family size and manager experience. It may not be surprising as lock-in period would significantly influence investors' ability to withdraw from funds. When

we perform the same analysis for standard mutual funds, the results are different. The most important drivers of standard mutual fund returns and flows are lock-in-period and fund family size. Interestingly, the experience of fund managers consistently ranks as a lower priority. Moreover, the explanatory power of fund family size, lock-in period and manager experience, as indicated by adjusted R-squared, are consistently higher for TDFs & TRFs than standard mutual funds, highlighting their importance to pension fund selection in particular. To ensure robustness, log-likelihood ratio tests are conducted, providing additional evidence to the overall credibility of the full model.

The initial finding that TDFs & TRFs outperform mutual funds after accounting for regulatory requirements (i.e., on fund family size, lock-in periods, and manager experience) is further confirmed in the additional regression analyses including interaction terms. In the further analysis, we explore the plausible mechanisms contributing to this outperformance. Specifically, we investigate whether this outperformance is due to better genuine skills in sub-fund selection among fund managers (i.e., selection of higher-quality sub-funds) or stronger mechanical flow stability under mandatory lock-ins. Our first mechanism test rules out the proposition of superior selection skills. In particular, we find that TDFs & TRFs are more likely to select sub-funds with weaker past performance. They also tend to include affiliated sub-funds from the same fund family, which exhibit relatively weaker past performance and higher expense ratios. This latter finding is consistent with Pool et al. (2016) and Chan et al (2017), and points to the existence of agency problems in fund selection. Our second mechanism test documents supportive evidence. We find that stronger fund flow stability induced by mandatory lock-ins indeed increases the return performance among TDFs & TRFs, as compared to non-TDFs and non-TRFs.

The contrasting influence of fund family size, lock-in period and manager experience on pension funds and standard mutual funds motivates us to carry out further investigation at

the fund issuer level. Specifically, we examine whether standard mutual funds managed by a TDF & TRF issuer outperform their counterparts that do not issue TDFs or TRFs. We propose two possible impacts: on the one hand, investors could view those issuing companies[6] that have successfully obtained licenses to establish TDFs & TRFs as more reliable and reputable (Gaspar et al., 2006; Bessler et al., 2016). On the other hand, TDF & TRF issuing companies need to meet stricter rules on transparency, disclosure and experience, increasing the risk of sharing private information with other funds, incurring higher regulatory and compliance costs, and hence losing competitive edges (Parida and Teo, 2018). Our results suggest that investors do not seem to favor TDF & TRF issuers. Non-TDFs & TRFs (i.e., standard mutual funds) operated under TDF & TRF issuers do not seem to benefit by meeting the additional regulatory and compliance requirements. Rather, issuing TDFs & TRFs could be a sign of higher costs, lower flexibility, and not profit-oriented for the issuers, which in turn lowers the overall performance of those non-TDFs & TRFs managed by the same issuers. To supplement the analysis, we extend our inquiry to examine the fund performance of fund issuers who meet the TDF & TRF issuance requirements (i.e., fund company size exceeds RMB 20 billion) but choose not to issue TDFs & TRFs. The results show that these fund companies exhibit better performance compared to those fund companies issuing TDFs & TRFs, further supporting the potential negative impact of becoming a TDF & TRF issuer. The results reveal several interesting implications. While the strict regulatory requirements offer benefits to TDFs & TRFs, they may simultaneously impose costs on the issuing companies and other funds managed by the same issuing companies. Our findings suggest that fund issuers should carefully evaluate the benefits and costs of issuing TDFs & TRFs. Similarly, household investors should take into account the potential impact when selecting investment funds.

[6] In our paper, the term "issuing companies" refers to fund management companies, which are interchangeably described as "fund companies" or "fund families." In China, mutual funds are both issued and managed by these fund management companies.

Furthermore, we perform a series of robustness checks, including using placebo tests to address potential endogeneity, examining the separate effect of fund family size, lock-in period, and manager experience on fund performance, and employing alternative measures of fund family size and fund performance. All results remain highly consistent.

We contribute to existing literature in the following ways. First, our research adds to the limited evidence related to retirement savings, in particular, the third pillar of savings, in China. Prior to the introduction of TDFs & TRFs, there were no formal government-initiated third pillar retirement saving mechanisms in China. It is vital to understand the effectiveness of the policy for all stakeholders. TDFs & TRFs have been widely discussed and studied in Western countries where the market is more developed and mature (Elton et al., 2015; Elton et al., 2016; Balduzzi and Reuter, 2019), but scarcely examined in the Chinese market. China differs from Western countries with its unique demographical, cultural and regulatory considerations, presenting different opportunities and challenges for its own TDFs & TRFs. Ultimately, a pension system is doomed to fail if it does not benefit household welfare. Our results demonstrate that regulatory requirements on fund family size, lock-in periods and manager experience enhance the performance of TDFs & TRFs, suggesting that these design features promote long-term investment discipline among household investors and ultimately improve their self-funded retirement savings and welfare. Furthermore, our comparative analysis between pension and non-pension funds shows that TDFs & TRFs consistently outperform, thereby strengthening the case for their role in improving household investor outcomes. This evidence has important implications for policymaking. We convey a positive signal to the government regarding the effectiveness of TDFs & TRFs as the key component in the third pillar of the Chinese pension system. Our findings also highlight the need for better public awareness and education about the importance of pension funds as part of individuals' retirement planning.

Second, we observe that the regulatory requirements on fund family size, lock-in period, and fund manager experience, improve the fund returns and net flows of TDFs & TRFs. The findings provide evidence on key drivers of TDFs & TRFs performance, their relative importance, and hence the selection guidelines for investors. These findings provide an international lesson for other countries facing similar aging challenges by suggesting the incorporation of private pension funds into their pension systems: private pension funds are effective in alleviating demographic pressures, improving retirement income adequacy and reducing long-term fiscal burdens on public pension schemes.

Third, we find the regulatory requirements do not equally improve the returns of standard mutual funds and even reduce the net flows of mutual funds. We attribute these differences to the distinct investment objectives and characteristics of the pension funds. Since TDFs & TRFs are inherently long-term oriented pension funds, it is important to distinguish TDFs & TRFs from other mutual funds. While requirements on fund family size, lock-in period, and fund manager experience could protect long-term investment safety and preserve capital for pension funds, they could lead to liquidity constraints, regulatory and disclosure costs for standard mutual funds. It is therefore important for regulators and policymakers to recognize both the benefits and costs associated with the offering of TDFs & TRFs, and work towards a more balanced regulatory framework to encourage the participation of fund issuers, protect investors' interests and ensure the long-term sustainability of the pension system.

Fourth, we identify several issues with TDFs & TRFs in China that require attentions from policymaker. Specifically, our results indicate a negative spillover to non-TDFs & TRFs within the same fund family, as well as a tendency for fund families to include affiliated sub-funds that have weaker past performance in TDFs & TRFs. These findings highlight the potential unintended consequences that require policymakers' attention. To maintain the benefits of TDFs & TRFs while reducing their costs, regulators could consider additional regulatory

measures, such as limiting the inclusion of affiliated funds to mitigate agency problems, strengthening disclosure requirements and regulatory scrutiny, and adopting more rigorous performance benchmarks. Providing clearer guidelines to investors can also help reduce uncertainty and facilitate investors making more informed decisions when choosing the appropriate investment funds.

The remainder of the paper is structured as follows. Section 2.2 outlines the institutional background, related literature and hypotheses. Section 2.3 presents the data and methodology. In Section 2.4, the main results are described. In Section 2.5 and Section 2.6, further analysis and robustness checks are shown. Finally, the conclusion is shown in Section 2.7.

2.2 Institutional background, related literature and hypotheses

2.2.1 International lessons for China's pension reform

From a global perspective, many households under-save for retirement, prompting policymakers to experiment with mechanisms to bolster personal retirement savings (Cribb and Emmerson, 2016). Personal pension funds have emerged as a key vehicle, and cross-country evidence now provides concrete guidance on how such funds should be structured to maximise household welfare. Rather than merely documenting practices abroad, these experiences provide important lessons for China's pension reform, particularly on how Chinese TDFs & TRFs should be introduced, designed and regulated in a meaningful way that truly improve household wealth.

The most notable example, the U.S. 401(k) system, illustrates how regulatory architecture can shape outcomes. Introduced in the early 1980s, this defined contribution (DC) plan grew to hold more than USD 12.5 trillion[7] by 2023, overtaking the combined assets of public and

[7] Moreover, the "Pension Protection Act of 2006" permitted the use of TDFs as default investment vehicles in employer-sponsored retirement plans, thereby establishing them as a key component of many 401(k) (Parker et

private defined-benefit plans (Curtis et al., 2025). Empirical work shows that 401(k) can match or outperform traditional defined benefit (DB) plans in sustaining retirement income (Samwick and Skinner, 2004). Equally important, reforms such as fee disclosure requirements lowered plan costs and improved investment choices, even if participants' cost comprehension remained imperfect (Badoer et al., 2020). Research on fund menu design finds that affiliated funds are often favored and underperforming proprietary funds are rarely removed (Pool et al., 2016).

This highlights a fundamental institutional feature: in the U.S., plan sponsors enjoy wide menu design flexibility, but are constrained ex post by fiduciary duties and litigation risk. By contrast, China takes a more prescriptive approach, TDFs & TRFs are subject to ex-ante regulatory restrictions on sub-fund eligibility, glide-path structure, and lock-in periods. These rules reduce discretion for fund issuers and limit agency problems but also constrain product innovation. Together, these insights demonstrate how disclosure mandates, fiduciary safeguards, and limits on affiliated products can strengthen investor protection and long-term household outcomes, offering direct guidance for the regulatory design of Chinese pension products.

Other advanced economies reinforce the point that institutional architecture matters for household welfare. Australia's compulsory superannuation, the first mandatory private scheme in the English-speaking world, significantly increased household wealth and reliance on self-funded retirement income (Connolly, 2007; Kingston and Thorp, 2019). The U.K.'s automatic-enrolment policy required employers to default workers into pension plans, sharply boosting participation and contributions (Cribb and Emmerson, 2016). Germany's Riester pension adopted a voluntary but heavily subsidised approach; although subsidies encouraged take-up, product complexity dampened participation (Börsch-Supan et al., 2012). Collectively, these cases show that regulatory levers—mandatory contributions, tax incentives, automatic

al., 2022).

enrolment, and subsidies—can foster long-term savings discipline and enhance household financial autonomy.

These international lessons are particularly relevant for China, which faces not only the shared challenge of population aging but also demographic dynamics shaped uniquely by its past family planning policies. The One-Child Policy, introduced in 1979, initially succeeded in curbing rapid population growth and improving population quality (Cao et al., 2015). However, after more than three decades, its negative consequences have become increasingly apparent. The natural population growth rate has steadily declined, falling from 16.61‰ in 1987 to -0.60‰ in 2022. Attempts to reverse this trend through the Universal Two-Child Policy in 2015 and the Three-Child Policy in 2021 brought only a brief uptick in 2016, followed by continued decline. Unlike other aging societies, China's demographic transition is occurring with unprecedented speed and scale. The shrinking share of young workers not only intensifies labor shortages but also heightens the economic burden of supporting a growing elderly population. To indicate, the old-age dependency ratio—the proportion of people aged 65 and over relative to the working-age population—is projected to surge from 19.7% in 2020 to 50% by 2050, according to the "China Aging Research Report 2022".

In response to the aging challenge, China has widely implemented a three-pillar pension system since the 1990s. Pensions serve as a critical source of post-retirement income, helping to ensure the elderly's financial security and resource accessibility (Lu and Shelley, 2021). However, significant gaps in pension coverage have emerged, as noted in the introduction. To strengthen the third pillar of retirement savings, the government introduced TDFs & TRFs in 2018. Further reinforcing this effort, the State Council issued the "Opinions on Promoting the Development of Personal Pensions" on April 8, 2022. Since then, personal pension accounts have experienced rapid growth, with the number of accounts exceeding 50 million by the end of 2023.

Complementing pension reforms, China also announced in 2024 a gradual increase in the statutory retirement age. Under the new plan, the retirement age for male employees will be raised from 60 to 63, and for female workers and cadres (such as teachers, healthcare professionals, and administrators) from 50/55 to 55/58 over the next 15 years, following a voluntary and flexible approach. As Bidewell et al. (2006) argue, delaying retirement can enhance individual savings and superannuation funds, provide greater monetary rewards, and improve retirement preparedness.

Nevertheless, despite these policy efforts, the profound demographic shifts mean that the responsibility for retirement savings is increasingly shifting to individual households (Lusardi and Mitchell, 2011). Retirement planning is a long-term process critical for ensuring a smooth transition into old age and maintaining quality of life (Yeung, 2013). Pension funds, in particular, provide an effective financial instrument for individuals to accumulate retirement savings and help narrow the emerging pension gap (Bongini and Cucinelli, 2019).

This study represents one of the first empirical investigations into the effectiveness of China's newly implemented third-pillar retirement policies. By focusing on the performance of TDFs & TRFs under strict regulatory frameworks, it provides critical early evidence on whether these measures are achieving their intended goals of enhancing retirement security amid an accelerating demographic transition.

2.2.2 Target pension funds

Unlike in other countries, a comprehensive target pension fund system in China only began following the implementation of the trial policy for target pension securities investment funds in 2018. Shortly thereafter, fourteen target pension funds—categorized into two types,

TDFs & TRFs, and structured as fund of funds (FOFs)[8]—became available to investors on August 6, 2018.

Considering the decline in human capital as individuals age, TDFs provide dynamic exposure to stocks, bonds, and other asset classes by gradually reducing equity allocations and increasing fixed-income holdings as the target retirement date nears (Elton et al., 2015; Levy and Levy, 2021; Parker et al., 2023). Each TDF specifies a maturity date (e.g., the China AMC Pension Goal Date 2040), so investors can select a fund aligned with their intended retirement age. This built-in glide path ensures that portfolio risk automatically decreases over time, suiting households that prefer a default mechanism to match changing risk capacity across the life cycle.

By contrast, TRFs are structured around a stable risk profile rather than a retirement date. They maintain a constant mix of equities, bonds, and other assets, classified as conservative, moderate, or aggressive, so that investors retain full control over their long-term risk exposure (Elton et al., 2016). Aggressive TRFs, for example, allocate a higher share of equities and lower-rated bonds, while conservative ones emphasize fixed income.

Regarding their lock-in period, we also observe significant difference between TDFs & TRFs. Based on our summary statistics, the minimum holding period is 41.25 months for TDFs and 21.92 months for TRFs. The longer lock-in period of TDFs reflects their distinct glide-path design, which encourages long-term holding aligned with the retirement year.

Together, these products offer complementary solutions for Chinese households with varying appetites for investment risk and degrees of engagement in retirement planning (Elton et al., 2016): TDFs for those seeking an age-based, automatically de-risking strategy, and TRFs for those who wish to lock in a desired risk level throughout the investment horizon.

[8] FOFs do not invest directly in stocks and bonds, but rather in equity funds, bond funds, and money market funds.

The number of TDFs & TRFs in China grew from virtually non-existent to 143 and 207[9], respectively, from 2018 to 2022. As relatively new financial instruments, TDFs & TRFs have yet to be thoroughly explored in the Chinese market. TDFs & TRFs in China are subject to more stringent requirements regarding the scale of their fund family size, lock-in period, and manager experience. Specifically, according to the trial policy, fund families must maintain an average mutual fund management scale (excluding money market funds) of at least RMB 20 billion over the past three years; with a lock-in period of no less than one year; and with more experienced managers compared to other funds.[10] Additionally, sub-funds included in TDFs & TRFs must also meet quality criteria: they must have a minimum operating history of two years, and their average net assets over the last two quarters must be at least RMB 200 million. Fund names must include "Pension Goal", and disclosure obligations are more stringent than for conventional funds. Fund companies need to first meet these regulatory requirements and then obtain approval from the China Securities Regulatory Commission before they can list their funds on the market. These conditions are mandated by regulation, and not left to fund-family discretion.[11]

Given their status as lifecycle investment funds, TDFs & TRFs represent a significant segment of the mutual fund industry (Lewis, 2008). It is crucial to investigate their performance in China, especially considering the rapid growth of the country's mutual fund market.

[9] We acknowledge that the sample size of TDFs & TRFs in this study is relatively small, as this remains a relatively new area of research. Nevertheless, our analysis provides valuable initial insights, and we hope that future studies will extend these findings using larger samples and broader coverage when more data is available.
[10] Specially, according to the trial regulation, fund managers are expected to give priority to appointing investment research personnel who meet the following qualifications for managing target funds: (i) at least five years of experience in securities investment, securities research and analysis, or securities investment fund research, evaluation, or analysis within the financial industry, including a minimum of two years in securities investment; or (ii) at least five years of experience in asset allocation for pension funds or insurance funds.
[11] The regulatory framework for target pension funds is set by the central government and applies uniformly across the country. As such, all TDFs & TRFs are national-level funds governed by the same set of rules, and there is currently no sub-national heterogeneity in their regulation or availability.

2.2.3 Hypothesis development

In this study, we examine how the three regulatory requirements, as reflected in the mandatory setup rules regarding fund size, lock-in periods, manager experience, imposed on TDFs & TRFs affect their fund performance. The results aim to provide evidence on the effectiveness of such regulations in promoting retirement savings within the current Chinese pension system.

According to the trial regulation of target pension funds, fund families must maintain an average mutual fund management scale (excluding money market funds) of at least RMB 20 billion over the past three years. Generally, a fund company manages a collection of funds, commonly referred to as a "fund family" (Nanda et al., 2004). A fund family is responsible for managing and marketing funds of different scales, and it is also associated with a high level of rigor and complexity in the decision-making process (Gaspar et al., 2006). Many empirical studies confirm the inherent advantages of fund family size on fund performance (Chen et al., 2004; Pollet and Wilson, 2008; Bhojraj et al., 2012). Chen et al. (2004) explain that a larger fund family size captures the economies of scale associated with marketing efforts aimed at enhancing fund performance in the market. Meanwhile, compared to small-fund families, larger-fund families tend to invest heavily in their research departments, purchase proprietary research, gain access to management at conferences, and enjoy resource advantages, which in turn improve their fund performance (Bhojraj et al., 2012). Sirri and Tufano (1998) also reveal that fund visibility and brand awareness are enhanced with larger fund family sizes. In addition, larger fund family size tends to generate increased investor popularity, leading to a higher influx of fund flows from investors (Sirri and Tufano, 1998; Chen et al., 2004; Benson et al., 2008). Based on the above evidence in the existing literature, we propose our H1a and H1b as below:

H1a: A larger fund family size positively affects the fund returns of TDFs & TRFs.

H1b: A larger fund family size positively affects the fund flows of TDFs & TRFs.

Lock-in period refers to the minimum holding period for which investors hold with no withdrawal (Ayayi, 2005). Aragon (2007) and Aiken et al. (2021) discern that hedge funds with lock-in periods improve their performance by reducing liquidity risk and increasing management flexibility. Cumming et al. (2015) find that hedge funds with longer lock-in periods offer fund managers greater discretion in managing risk levels. In particular, a longer lock-in period provides managers with greater freedom to implement their investment strategies (Agarwal et al., 2009), including controlling fund portfolios, adjusting asset allocations, and making strategic investment decisions, without worrying about investors' redemption demands. In addition to the managerial perspective, a longer lock-in period also helps investors navigate market cycles and benefit from the compounding of long-term investments. TDFs & TRFs not only require a lock-in period but also have long-term investment goals, encouraging investors to hold their investments for the long term and pursue stable asset growth.

According to the "Notice on Regulating the Development of Target Pension Securities Investment Funds (Trial)", the lock-in period for TDFs & TRFs could be 12 months and longer. When the lock-in period is at least 1, 3, or 5 years, the fund's total allocation to risky assets (such as stocks, equity funds, hybrid funds, and commodity funds) must not exceed 30%, 60%, and 80%, respectively. This structure reflects the general practice in fund management that a longer investment horizon justifies higher exposure to risk. Notably, all funds in our sample are open-end. After the initial lock-in period expires, investors can either stay invested or redeem their shares. However, as new investors continuously enter the fund, a portion of the total assets remains effectively "locked" at all times. Given the short history of TDFs & TRFs in China, combined with the rapid growth of the fund sector and an aging population, we anticipate that the proportion of "locked" assets remain substantial compared to the volume of

redemptions. Based on the above discussion, we propose our H2a and H2b as follows:

H2a: Funds with a longer lock-in period are associated with a higher level of fund return of TDFs & TRFs.

H2b: Funds with a longer lock-in period are associated with a higher level of fund flow of TDFs & TRFs.

The trial regulation also requires more experienced fund managers for managing target pension funds, i.e., (i) at least five years of experience in securities investment, securities research and analysis, or securities investment fund research, evaluation, or analysis within the financial industry, including a minimum of two years in securities investment; or (ii) at least five years of experience in asset allocation for pension funds or insurance funds. Several studies have observed that fund managers with greater experience, longer tenure, older age, and early career stares during recession tend to generate excess returns compared to their counterparts, holding other factors constant (Golec, 1996; Clare, 2017; Chen et al., 2021a; Clare et al., 2022). Experienced fund managers not only possess superior skills, as observed by Ding and Wermers (2012) in their study of domestic U.S. equity funds, but also help fund teams accumulate stock analysis expertise and build strong connections with sell-side analysts and corporate CEOs. Moreover, fund managers often gather private information (e.g., stock valuations) to enhance performance when they have favorable relationships with CEOs, particularly if they share the same alma mater (Cohen et al., 2008). Based on the above, we propose the following hypotheses, H3a and H3b:

H3a: Fund managers who are of greater experience are associated with a higher level of fund return of TDFs & TRFs.

H3b: Fund managers who are of greater experience are associated with a higher level of fund flow of TDFs & TRFs.

Our hypotheses therefore focus on whether the regulatory requirements imposed on TDFs

& TRFs—fund family size, lock-in periods, and managerial experience—and going beyond these minimum thresholds, influence fund outcomes. As a contrast, we also test whether the same characteristics affect the outcomes of standard mutual funds. Unlike TDFs & TRFs, conventional mutual funds face no such lower limits: lock-in periods are typically absent, manager experience is unconstrained, and family size can be well below the regulatory threshold applied to pension funds. Because TDFs & TRFs were only introduced after these rules came into effect, every fund in this category necessarily satisfies the requirements, while mutual funds remain unaffected. Consequently, the mechanisms through which these characteristics operate for TDFs & TRFs differ from those for mutual funds. Our empirical setting is explicitly designed to capture this regulatory distinction.

2.3 Data and methodology

2.3.1 Sample and data

We start with all fund data available from the WIND and the China Stock Market and Accounting Research (CSMAR) databases. We classify TDFs & TRFs from FOFs based on WIND identification. The remaining funds are standard mutual funds. To ensure sample representativeness, we cross-check the data between the WIND and CSMAR databases. Our final sample comprises 9,276 open-end funds from 2004 to 2022, with a total of 167,084 fund-quarter observations. Following standard practice in the existing literature, we winsorize all continuous variables at the 1st and 99th percentiles to mitigate the effect of outliers.

2.3.2 Measuring fund return and fund flow

Fund return and fund flow are the key outcome variables of interest in our study. Our main fund return measure is the Fama-French three-factor alpha, which includes market risk,

size and book-to-market value in the model (Fama and French, 1993; Yan, 2008; Rao et al., 2020). The regression model is below:

$$r_{i,t} - r_{f,t} = a_i + \beta_{1,i} \times \left(r_{m,t} - r_{f,t}\right) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the return of fund *i* at month *t*, and $r_{m,t}$ represents the return of the corresponding Shanghai Stock Exchange-Shenzhen Stock Exchange (SSE-SZSE) index returns. The risk-free rate $r_{f,t}$ is the monthly interest rate of the official one-year term deposit (Chen et al., 2018). $r_{m,t} - r_{f,t}$ is the excess return of funds. SMB_t (small minus big) is the average return on the small-capitalization stock portfolio minus the average return on the large-capitalization stock portfolio. HML_t(high minus low) is the average return on a high book-to-market stock portfolio minus the average return on a low book-to-market stock portfolio. To calculate quarterly alpha (a_i), we use a rolling window of 24 months to obtain monthly fund returns, and then aggregate them into quarterly returns (Amihud and Goyenko, 2013).

Following Sirri and Tufano (1998), Goldstein et al. (2017), and Fong et al. (2018), we estimate net fund flows by considering the difference in total net assets of each fund between two consecutive quarters, taking into account the corresponding fund return. The fund flow $Flow_{i,t}$ for fund *i* in quarter *t* is defined as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Return_{i,t})}{TNA_{i,t-1}} \quad (2)$$

where $TNA_{i,t}$ is the total net asset value of fund *i* at the end of quarter *t*, and $Return_{i,t}$ is the rate of return of fund *i* during quarter *t*.

2.3.3 Baseline model

Our baseline model estimation is as follows:

$$Y_{c,i,t} = a_i + \beta_1 FundFamilySize_{i,t} + \beta_2 LockInPeriod_{i,t} + \beta_3 Experience_{i,t} + Controls + \theta' FundTypeFE + \psi' QuarterFE + \varepsilon_{i,t} \quad (3)$$

where $Y_{c,i,t}$ represents either quarterly Fama-French three-factor return or quarterly fund flow. To test our main hypotheses, our main explanatory variables are *FundFamilySize*, *LockInPeriod*, and *Experience*. *FundFamilySize* represents the natural logarithm of the total assets under management of the fund's family (Yan, 2008; Bai et al., 2019), *LockInPeriod* represents the minimum holding period required by the fund, and *Experience* denotes the fund managers' experience in the fund management industry measured in number of years (Bai et al., 2019; Chen et al., 2021b; Huang et al., 2021). *Controls* include the following: *FundSize* captures the natural logarithm of the total net assets of the fund (Chen et al., 2004; Yan, 2008), *FundAge* is the number of years since the fund was established (Chen et al., 2004; Yan, 2008), *ExpenseRatio* (%) is calculated as the ratio of a fund's management fee and custodian fee to the total net assets of funds (Yan, 2008), *Gender* takes the value of one if the fund management team includes at least one male manager, and zero otherwise, and *Degree* measures the highest education attainment of a fund management team (*Degree* ranges from 1 to 4 for no tertiary qualification, Undergraduate, Master and MBA/EMBA, and Doctorate, respectively). In our regression, fund type[12] and quarter fixed effects are included throughout to control for omitted variable bias (Sensoy, 2009; Hartzmark and Sussman, 2019). Robust standard errors apply in all regressions. For further details on variable definitions, please refer to Appendix 2.1.

[12] In our sample, fund type is classified into Investment Style, Aggressive Growth, Stable Growth, Growth, Value, Robust Value-added, Capital Guaranteed & Value Added, Appreciation, Balance, Income, and Index funds. The data is obtained from CSMAR.

2.4 Main results

2.4.1 Descriptive analysis

Table 2.1 presents the summary statistics of our main variables for the full sample in Panel A1[13], TDFs & TRFs in Panel A2, and mutual funds in Panel A3. The average quarterly risk-adjusted returns (Fama-French three-factor alpha) for all funds, TDFs & TRFs, and mutual funds are 0.37%, 0.44%, and 0.37%, respectively. It indicates that on a risk-adjusted basis, TDFs & TRFs in general outperform the full universe of funds by more than 0.07% on average. Additionally, the variation in risk-adjusted return is smaller for TDFs & TRFs, with a standard deviation of the alpha being 0.0128, while the corresponding number is 0.0272 for the full sample.

In terms of fund flow, the average fund flows for all funds, TDFs & TRFs, and mutual funds are 0.0896, 0.0990, and 0.0896, indicating the popularity of TDFs & TRFs compared to other funds. Regarding our main explanatory variables, the average fund family size (natural log of the AUM) for the TDFs & TRFs and mutual funds is similar, being 26.78 and 25.63 in order. Additionally, the median value of lock-in period is 0 for mutual funds compared to 36 months for TDFs & TRFs. This aligns our expectations due to the compulsory lock-in period of the latter. Consistent with the regulatory requirements, fund managers of TDFs & TRFs are more experienced; on average, they have 11.4 years of experience in fund management, compared to 10.1 years for mutual funds. Moreover, we find that TDFs & TRFs, on average, have similar fund sizes to other funds, but a lower expense ratio. TDFs & TRFs are also generally younger.

[13] Full sample includes all funds (i.e., TDFs, TRFs and mutual funds).

Table 2. 1. Descriptive analysis

Panels (A1–A3) and (B1-B3) of Table 2.1 report summary statistics and the parametric correlations of the main variables, respectively. Our sample spans from 2004 to 2022. Appendix 2.1 provides more details on variable definitions. *, **, and *** indicate levels of statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A1: All funds						
Variables	N	Mean	Sd	Min	Max	Median
ThreeFactorAlpha	167,084	0.0037***	0.0272	-0.0874	0.0963	0.0022
FundFlow	158,031	0.0896***	0.8146	-0.7859	6.3937	-0.0212
FundFamilySize	167,084	25.6394***	1.5125	21.1333	28.0839	25.7420
LockInPeriod	167,084	0.6817***	4.1961	0	60	0
Experience	149,183	10.0794***	3.9231	2	22	10
FundAge	167,084	4.0141***	3.5543	0	16	3
FundSize	167,084	19.9387***	1.7736	14.6344	23.4756	20.0593
ExpenseRatio	167,084	1.1641***	0.5682	0.2000	2.0500	1.1500
Gender	155,131	0.8301***	0.3756	0	1	1
Degree	155,131	3.1066***	0.4092	1	4	3
Panel A2: TDFs & TRFs						
Variables	N	Mean	Sd	Min	Max	Median
ThreeFactorAlpha	1,504	0.0044***	0.0128	-0.0874	0.0661	0.0044
FundFlow	1,334	0.0990***	0.6541	-0.7859	6.3937	0.0065
FundFamilySize	1,504	26.7767***	0.8593	23.8939	28.0839	27.0057
LockInPeriod	1,504	30.9574***	15.8448	12	60	36
Experience	1,147	11.3697***	3.3359	2	22	11
FundAge	1,504	1.5080***	1.0547	0	4	1
FundSize	1,504	19.0312***	1.4699	15.4281	23.4756	19.2019
ExpenseRatio	1,504	0.9183***	0.1707	0.4000	1.2000	0.9500
Gender	1,372	0.7762***	0.4169	0	1	1
Degree	1,372	3.1618***	0.4007	2	4	3
Panel A3: Mutual funds						
Variables	N	Mean	Sd	Min	Max	Median
ThreeFactorAlpha	165,580	0.0037***	0.0273	-0.0874	0.0963	0.0022
FundFlow	156,697	0.0896***	0.8158	-0.7859	6.3937	-0.0217
FundFamilySize	165,580	25.6291***	1.5133	21.1333	28.0839	25.7199
LockInPeriod	165,580	0.4067***	2.6621	0	36	0
Experience	148,036	10.0694***	3.9256	2	22	10
FundAge	165,580	4.0368***	3.5610	0	16	3
FundSize	165,580	19.9470***	1.7740	14.6344	23.4756	20.0661
ExpenseRatio	165,580	1.1664***	0.5700	0.2000	2.0500	1.2000
Gender	153,759	0.8305***	0.3752	0	1	1
Degree	153,759	3.1061***	0.4093	1	4	3

Panel B1: All funds

	ThreeFactorAlpha	FundFlow	FundFamilySize	LockInPeriod	Experience	FundAge	FundSize	ExpenseRatio	Gender	Degree
ThreeFactorAlpha	1									
FundFlow	0.0516***	1								
FundFamilySize	0.0750***	0.0003	1							
LockInPeriod	-0.0068***	-0.0102***	0.0887***	1						
Experience	0.0222***	-0.0099***	0.1763***	0.0700***	1					
FundAge	0.0094***	-0.0303***	0.0768***	-0.1267***	0.1166***	1				
FundSize	-0.0004	0.0573***	0.2081***	-0.0159***	0.0015	0.1162***	1			
ExpenseRatio	0.0547***	-0.0687***	-0.1813***	-0.0089***	-0.0309***	0.2214***	0.0104***	1		
Gender	0.0060**	-0.0062**	-0.0326***	-0.0083***	-0.0513***	0.0115***	0.0112***	0.1749***	1	
Degree	-0.0025	-0.0041	-0.0311***	0.0096***	-0.0415***	-0.0028	-0.0234***	0.0717***	0.0970***	1

Panel B2: TDFs & TRFs

	ThreeFactorAlpha	FundFlow	FundFamilySize	LockInPeriod	Experience	FundAge	FundSize	ExpenseRatio	Gender	Degree
ThreeFactorAlpha	1									
FundFlow	0.0092	1								
FundFamilySize	0.1558***	0.0441	1							
LockInPeriod	0.1351***	0.0676**	0.1339***	1						
Experience	0.0920***	0.0317	0.0447	0.0924***	1					
FundAge	0.1702***	0.0161	0.2193***	0.0292	0.0500*	1				
FundSize	0.1034***	-0.0144	0.0343	-0.3614***	-0.0545*	0.2206***	1			
ExpenseRatio	0.0920***	0.0384	0.0827***	0.5012***	-0.0882***	0.1388***	-0.1647***	1		
Gender	0.0082	0.0263	0.0799***	0.0615**	0.0425	0.0891***	0.0469*	0.0907***	1	
Degree	-0.0995***	-0.0528*	-0.0360	-0.0109	-0.0700**	-0.0010	-0.0207	-0.1205***	-0.0058	1

Panel B3: Mutual funds

	ThreeFactorAlpha	FundFlow	FundFamilySize	LockInPeriod	Experience	FundAge	FundSize	ExpenseRatio	Gender	Degree
ThreeFactorAlpha	1									
FundFlow	0.0518***	1								
FundFamilySize	0.0749***	0.0000	1							
LockInPeriod	-0.0168***	-0.0206***	0.0585***	1						
Experience	0.0219***	-0.0102***	0.1752***	0.0745***	1					
FundAge	0.0094***	-0.0304***	0.0818***	-0.1282***	0.1189***	1				
FundSize	-0.0007	0.0578***	0.2132***	0.0442***	0.0032	0.1132***	1			
ExpenseRatio	0.0548***	-0.0690***	-0.1794***	0.0227***	-0.0298***	0.2194***	0.0088***	1		
Gender	0.0061**	-0.0065**	-0.0324***	-0.0018	-0.0518***	0.0104***	0.0103***	0.1752***	1	
Degree	-0.0022	-0.0038	-0.0321***	0.0018	-0.0418***	-0.0020	-0.0228***	0.0729***	0.0982***	1

Furthermore, in Table 2.1, Panels B1-B3, we present the parametric correlation matrix of the variables for all funds, TDFs & TRFs, and mutual funds. These correlations provide preliminary support for our main hypotheses. For TDFs & TRFs, we find the relationships between the three-factor alpha and each fund family size, lock-in period, experience are all positive. Additionally, we observe a significant positive correlation between lock-in period and fund flow. Moreover, as reported in Table 2.1, Panels B1–B3, the covariates exhibit low pairwise correlations, suggesting the absence of substantial linear relationships among them. The correlations between three-factor alpha and fund flow with the control variables also align with our predictions in general, lending support to the choice of our model.

2.4.2 The impact of the determinants in different fund groups

In this section, we employ formal regression analysis to examine how the key explanatory variables relate to fund performance in terms of return and attracting net inflows.[14] First, we perform the analysis within each fund group: TDFs & TRFs as our main interest, and standard mutual funds for comparison.

2.4.2.1 Baseline results-fund return

We run Equation (3) using fund Fama-French three-factor alpha as the outcome variable. The results are shown in Table 2.2.

We observe a positive and significant relationship between fund family size and fund returns for TDFs & TRFs and mutual funds. The coefficient of fund family size for TDFs & TRFs is 0.0009, which means that one unit increase in fund family size results in a 0.09% improvement in these funds' quarterly returns. The findings validate our hypothesis that funds with larger fund family sizes posses

[14] All performance measures in this study are based on net returns (after fees), reflecting the actual returns received by investors and providing a measure with greater economic relevance. These returns are net of management, custody, and other applicable fees. They also allow fair comparisons between funds. Moreover, in China, there is no systematic distinction between fees for pension and non-pension products in our dataset, meaning that any fee differences are unlikely to drive the observed performance patterns.

inherent advantages that contribute to superior fund returns (Chen et al., 2004; Pollet and Wilson, 2008; Bhojraj et al., 2012).

Furthermore, we find a positive association between lock-in period and fund returns for TDFs & TRFs. Every time the lock-in period extends by one month, the return increases by 0.02%. As discussed earlier, a longer lock-in period allows managers to exercise greater control over the fund portfolios, asset allocation, and strategic investment decisions, which is particularly important for long-term investment objectives such as retirement savings. Better alignment between fund investment decisions and its objectives ultimately improves fund returns. Conversely, we observe a negative relationship between lock-in period and fund returns for mutual funds. Since lock-in periods are not required for mutual funds due to their varied investment objectives, a longer lock-in period, which restricts investors' ability to move away from poor-performing funds, may result in less market competition, lower peer pressure among funds, and poorer returns. The finding highlights the importance of aligning regulatory focus with the investment objectives of funds.

Additionally, we find mixed results for manager experience. On the one hand, our analysis reveals that more experienced managers generate higher returns for TDFs & TRFs. One year increase in the manager experience raises the return by 0.02%. This aligns with previous findings that fund managers' skills and access to private information grow with their experience, significantly enhancing fund performance (Golec, 1996; Clare et al., 2022). However, on the other hand, the results reveal a negative relationship between manager experience and fund returns for mutual funds. The mixed relationship is consistent with the argument posed by Chevalier and Ellison (1999) that manager experience could relate to fund returns in both ways because younger managers (typically less experienced) might do better since they work harder to advance their career, but worse because of a lack of experience. In our context, for TDFs & TRFs which focus on a more defined long-term investment goal, we do find the regulatory requirement on manager experience benefits investors.

Table 2. 2. Baseline results

This table reports our baseline results examining the effect of regulatory requirements (fund family size, lock-in period, and manager experience) on fund performance from 2004 to 2022. We divide the sample into two groups: TDFs & TRFs and mutual funds. The dependent variables are measured by Fama-French three-factor alpha and fund flow in columns (1)-(2) and (3)-(4), respectively. We include fund family size, lock-in period, and manager experience as our main explanatory variables. Control variables include fund size, fund age, expense ratio, and managers' gender and degree. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Three-factor alpha		Fund flow	
	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds
	(1)	(2)	(3)	(4)
FundFamilySize	0.0009**	0.0004***	-0.0077	-0.0213***
	(0.03)	(0.00)	(0.79)	(0.00)
LockInPeriod	0.0002***	-0.0004***	0.0041***	-0.0086***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.0002**	-0.0001***	0.0033	-0.0020***
	(0.01)	(0.00)	(0.69)	(0.00)
FundSize	0.0008***	0.0006***	-0.0003	0.0376***
	(0.00)	(0.00)	(0.98)	(0.00)
FundAge	0.0038***	-0.0003***	-0.0141	-0.0068***
	(0.00)	(0.00)	(0.71)	(0.00)
ExpenseRatio	-0.0082***	0.0045***	-0.0475	-0.1052***
	(0.00)	(0.00)	(0.69)	(0.00)
Gender	-0.0026***	0.0003**	0.0734*	0.0140**
	(0.00)	(0.05)	(0.09)	(0.02)
Degree	-0.0028***	0.00003	-0.1059***	0.0061
	(0.00)	(0.86)	(0.00)	(0.26)
Constant	-0.0285**	-0.0310***	0.4978	-0.2371***
	(0.02)	(0.00)	(0.58)	(0.00)
Observations	1,147	148,036	1,022	140,246
Adjusted R-squared	0.3370	0.0896	0.0124	0.0210
Fund type fixed effects	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES

To summarize, we find the regulatory requirements imposed on TDFs & TRFs benefit their fund returns, although other than fund family size, lock-in period and fund manager experience do not equally improve returns of mutual funds. The results also highlight the importance of distinguishing TDFs & TRFs from other mutual funds due to their significantly different investment objectives.

2.4.2.2 Baseline results-fund flow

Next, we run Equation (3) using fund flows as the outcome variable. The results are presented in columns (3) and (4) of Table 2.2. We observe that lock-in period significantly affects fund flows

for TDFs & TRFs. A one-unit increase in lock-in period will improve fund flow of TDFs & TRFs by 0.41%. However, we do not find evidence supporting the impact of fund family size and experience on attracting fund flows for TDFs & TRFs. Designed as long-term retirement-oriented products, TDFs & TRFs focus on life-cycle asset allocation rather than short-term returns, which reduces investors' motivation to direct additional flows based on fund family size. Additionally, when investors choose TDFs & TRFs, they do not necessarily prefer those managed by managers with a longer experience, possibly due to the compulsory high threshold of experience mandated on all TDFs & TRFs already. Incremental manager experience beyond this point does not necessarily generate significant differences in terms of fund flows.

Interestingly, the results on fund flows of mutual funds are in stark contrast. As column (4) of Table 2.2 shows, bigger fund families, longer lock-in periods and more experienced fund managers result in net fund outflows for all standard mutual funds. Funds with a longer lock-in period could be less attractive to investors due to the reduced flexibility (Simon, 2011), and more experienced fund managers may not outperform (Chevalier and Ellison, 1999) resulting in decreased fund flows. On fund family size, our results are consistent with Brown and Wu (2016) who find that larger funds with longer histories attract, on average, less capital as a percentage of their asset size, regardless of fund performance. This is consistent with their model, in which the positive drift in fund size comes from the convex relationship between the estimated aggregate skill and equilibrium size. As the uncertainty in aggregate skill decreases over time, the drift becomes weaker. Similar to the results on fund returns, our findings agree with the previous literature that different fund and fund manager characteristics may relate to fund flow in mixed ways. Therefore, nuanced analyses by fund objective and nature, like ours, are necessary.

2.4.3 Relative importance of the explanatory variables

Our analysis above indicates that the regulatory restrictions imposed on TDFs & TRFs all seem

to affect their fund outcomes positively. Next, we investigate which explanatory variable shows the strongest predictive power. To assess the relative importance of the additional regulatory requirements on fund risk-adjusted returns (fund flow), we carry out formal model selection by evaluating the relative importance in model adjusted R^2 (Zhang et al., 2018).

In our first model, we only look at the impact of the basic fund characteristics on fund three-factor alpha and fund flow, which includes *FundSize*, *FundAge*, *ExpenseRatio*, *Gender*, and *Degree.* Subsequently, our second, third, and fourth models gradually add *FundFamilySize, LockInPeriod, and Experience* into the model. Finally, the fifth model tests the combined effect of *FundFamilySize*, *LockInPeriod*, and *Experience.* We run five models and display each model's adjusted R^2 in Panel A1 of Table 2.3. Columns (1) and (2) show the results for three-factor alpha, while columns (3) and (4) present the results for fund flow.

Additionally, Panel A2 in Table 2.3 exhibits the incremental change in adjusted R^2 compared to the baseline regression when considering the outcome variables of three-factor alpha and fund flow, separately. As shown in the first column of Panel B in Table 2.3, when fund family size, lock-in period and manager experience are all included in the model to explain the risk-adjusted returns, adjusted R^2 improvement increases the most, by 25.33% for TDFs & TRFs compared to the baseline model without these variables. It is noteworthy that the impact of the three factors on TDF & TRF returns is much greater than that on mutual funds. It highlights the significance of the regulatory requirements on pension funds, while the returns of mutual funds could be subject to a more complicated set of determinants. Moreover, when we include the three main explanatory factors only one at a time, for TDFs & TRFs, the most important factors that determine returns are experience, fund family size, and lock-in period in order, as indicated by the average adjusted R^2 improvement increases of 9.22%, 4.18%, and 4.05% respectively.

Table 2. 3. Relative importance of the explanatory variables

We compare the adjusted R^2 and log-likelihood of the regression model to calculate the relative importance of regulatory requirements on fund performance. The baseline model includes only control variables: fund age, fund size, expense ratio, and managers' gender and degree. The explanatory variables—fund family size, lock-in period, and experience—are added separately and simultaneously to the model. Panel A1 reports the adjusted R^2 of each regression, and Panel A2 shows the increment in adjusted R^2 for each regression from the baseline model. Panel B1 presents the log-likelihood values of each regression model, and Panel B2 reports the log-likelihood ratio for each regression relative to the baseline model (only controls). *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Three-factor alpha		Fund flow	
	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds
	(1)	(2)	(3)	(4)
Panel A1: Adjusted R^2				
Control Variables (base)	0.2581	0.0898	0.0078	0.0198
+ FundFamilySize	0.2689	0.0902	0.0087	0.0209
+ LockInPeriod	0.2798	0.0913	0.0118	0.0204
+ Experience	0.2937	0.0877	0.0089	0.0194
+FundFamilySize+ LockInPeriod+ Experience	0.337	0.0896	0.0124	0.021
Panel A2: Adjusted R^2 improvement				
+ FundFamilySize	4.18%	0.45%	11.54%	5.56%
+ LockInPeriod	4.05%	1.67%	51.28%	3.03%
+ Experience	9.22%	-2.34%	14.10%	-2.02%
+FundFamilySize+ LockInPeriod+ Experience	25.33%	-0.22%	58.97%	6.06%
Panel B1: Log-likelihood				
Control Variables (base)	3619.04	330526.7	-1059.59	-170144
+ FundFamilySize	3626.23	330554	-1059.56	-170064
+ LockInPeriod	3657.79	330658.7	-1056.49	-170100
+ Experience	3625.94	330557.7	-1059.16	-170134
+FundFamilySize+ LockInPeriod+ Experience	3663.18	330717	-1056.33	-170016
Panel B2: Log-likelihood ratio				
+ FundFamilySize	14.39***	54.46***	0.05	159.54***
+ LockInPeriod	77.50***	263.82***	6.21**	87.98***
+ Experience	13.80***	61.94***	0.85	20.41***
+FundFamilySize+ LockInPeriod+ Experience	88.28***	380.59***	6.53*	256.58***

Furthermore, in the third and fourth columns of Table 2.3, using the same variables to predict fund flow, we consistently find lock-in period ranks as the most important determinant for TDFs & TRFs. Next, fund family size and manager experience are of similar importance. Further, for both TDFs & TRFs and mutual funds, combining the three main explanatory variables results in a much bigger incremental impact on fund flows (adjusted R^2 improvement of 58.97% and 6.06%) compared to fund returns (adjusted R^2 improvement of 25.33% and -0.22%). That is, imposing these regulatory requirements results in a greater increment in fund flows measured in percentage terms. Note that however, overall, the adjusted R^2 values are higher for fund returns than for fund flows. Finally, to

ensure the reliability of the findings, we further calculate the log-likelihood ratio of the competing models (Barron and Ni, 2013) and present the results in Panels B1-B2 of Table 2.3, overall, the findings remain highly consistent with the adjusted R^2 analysis.

2.5 Further analysis

2.5.1 TDFs & TRFs versus mutual funds

In the analysis above, we focus on how the regulatory requirements influence fund performance metrics differently in separate fund groups. In this section, we turn to investigating the differences across the fund groups. It allows us to formally examine whether TDFs & TRFs outperform mutual funds after controlling for the key determinants according to the regulatory requirements.

We introduce a new dummy variable, *TDFTRF*, which takes the value of one for TDFs & TRFs and zero for mutual funds. We include the dummy variable in our baseline regressions for risk-adjusted returns and fund flow and present the results in columns (1) and (3) of Table 2.4. To further examine the incremental impact of regulatory requirements on the performance of TDFs & TRFs relative to mutual funds, we include three interaction terms between dummy variable *TDFTRF* and *FundFamilySize*, *LockInPeriod* and *Experience* respectively in regression, results are reported in column (2) and column (4).

The results show that TDFs & TRFs outperform mutual funds in general. In columns (1) and (3), the coefficients of *TDFTRF* are 0.0072 and 0.1788 for three-factor alpha and fund flow respectively, both highly significant. These findings indicate that TDFs & TRFs perform better than mutual funds in terms of both fund risk-adjusted returns and fund flows. Moreover, the test of interactions terms in columns (2) and (4) shows that how regulatory requirements shape the relative performance of TDFs & TRFs. The results indicate that larger family size, longer lock-in periods, and greater managerial experience all contribute more positively to the returns of TDFs & TRFs than to those of mutual funds, and that longer lock-in periods also contribute more positively to the flows of TDFs & TRFs than to

those of mutual funds. The results lend support to the effectiveness of the regulatory requirements on TDFs & TRFs in particular. The additional regulatory requirements seem to differentiate TDFs & TRFs from mutual funds (which are not designed for the long-term retirement saving objective), reflected in creating higher returns and attracting more savings (i.e., fund flows) for investors.

Table 2. 4. TDFs & TRFs versus mutual funds

This table investigates whether TDFs & TRFs outperform mutual funds after controlling regulatory requirements during the period 2004-2022. The dependent variables are measured by Fama-French three-factor alpha and fund flow in columns (1)-(2) and (3)-(4), respectively. A dummy variable, *TDFTRF*, takes the value of one if the observation is for TDFs & TRFs and zero if it is for mutual funds. We then add *TDFTRF* to the baseline model and include the same set of control variables as in the baseline model in columns (1) and (3). Next, we include the interaction terms between *TDFTRF* and *FundFamilySize*, *LockInPeriod* and *Experience* in regression to better understand the effect of regulatory requirements on TRFs & TDFs. The results of these interaction regressions are reported in columns (2) and (4). Control variables include fund size, fund age, expense ratio, and managers' gender and degree. We also control fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Three-factor alpha		Fund flow	
	(1)	(2)	(3)	(4)
FundFamilySize	0.0004***	0.0004***	-0.0211***	-0.0213***
	(0.00)	(0.00)	(0.00)	(0.00)
FundFamilySize×TDFTRF		0.0007*		0.0255
		(0.09)		(0.36)
LockInPeriod	-0.0003***	-0.0004***	-0.0052***	-0.0087***
	(0.00)	(0.00)	(0.00)	(0.00)
LockInPeriod×TDFTRF		0.0006***		0.0133***
		(0.00)		(0.00)
Experience	-0.0001***	-0.0001***	-0.0020***	-0.0020***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience×TDFTRF		0.0004***		0.0076
		(0.00)		(0.36)
FundSize	0.0006***	0.0006***	0.0368***	0.0375***
	(0.00)	(0.00)	(0.00)	(0.00)
FundAge	-0.0002***	-0.0003***	-0.0065***	-0.0068***
	(0.00)	(0.00)	(0.00)	(0.00)
ExpenseRatio	0.0046***	0.0045***	-0.1044***	-0.1051***
	(0.00)	(0.00)	(0.00)	(0.00)
Gender	0.0003*	0.0003*	0.0143**	0.0144**
	(0.06)	(0.06)	(0.02)	(0.02)
Degree	-0.000005	0.000009	0.0050	0.0053
	(0.97)	(0.96)	(0.36)	(0.33)
TDFTRF	0.0072***	-0.0295***	0.1788***	-0.9068
	(0.00)	(0.01)	(0.00)	(0.23)
Constant	-0.0305***	-0.0309***	-0.2239***	-0.2319***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	149,183	149,183	141,268	141,268
Adjusted R-squared	0.0891	0.0898	0.0205	0.0208
Fund Type fixed effects	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES

2.5.2 Why TDFs & TRFs outperform mutual funds

In this section, we propose two plausible mechanisms through which TDFs & TRFs may outperform mutual funds. The first concerns whether TDFs & TRFs have better selection skills in selecting high-performing sub-funds for their portfolios (Pool et al., 2016; Chan et al., 2017). The second concerns whether the outperformance is due to stronger flow stability induced by mandatory lock-ins.

2.5.2.1 Sub-fund selection

As discussed previously, TDFs & TRFs are structured as FOFs, with various constituent funds (sub-funds). The outperformance of TDFs & TRFs could be due to fund managers' superior skills in selecting high-performing sub-funds. To test this proposition, we examine what characteristics make sub-funds more likely to be selected using a probit model as follows:

$$Constituent\ Fund_{i,t} = \beta_0 + \beta_1 ThreeFactorAlpha_{i,t-1} + \beta_2 FundFlow_{i,t-1} + \beta_3 ExpenseRatio_{i,t-1} + Controls + \theta' FundTypeFE + \psi' QuarterFE + \varepsilon_{i,t-1} \quad (4)$$

where *Constituent Fund* equals one if a fund is selected as a sub-fund for TDFs & TRFs at quarter t, and zero otherwise. Independent variables include one quarter lagged values of Fama–French three-factor alpha, fund flow, and expense ratio. Control variables include fund size, turnover ratio, fund family size, and fund age. Fund type and quarter fixed effects are included.

In Panel A of Table 2.5, we report Probit regression results on the likelihood of a fund being selected as a TDF or TRF constituent, conditional on lagged characteristics. Results show that sub-funds being selected to TDFs & TRFs exhibit inferior return performance and lower expense ratio, evidence contradicts the argument of superior sub-fund selection skills.

Additionally, Pool et al. (2016) demonstrate that 401(k) plan sponsors who design their investment menus tend to prefer in-house funds, despite their inferior performance. Similarly, Chan

et al. (2017) observe that U.S. fund families often include affiliated sub-funds in TDFs that have exhibited weaker past performance or higher expense ratios, raising concerns about potential conflicts of interest. Motivated by this literature, we further supplement our analysis above, by examining whether such favoritism towards affiliated funds exists in the sub-fund selection in the Chinese context.

Table 2. 5. Sub-fund selection

This table estimates the sub-fund selection within TDFs & TRFs. In Panel A, we investigate the likelihood of a fund is selected as a TDF or TRF constituent. The dependent variable, *Constituent*, equals one if a fund is selected as a sub-fund for TDFs or TRFs. and zero otherwise. In Panel B1, we display the yearly frequency of affiliated versus non-affiliated sub-funds being selected into TDFs & TRFs by year. Affiliated sub-funds are sub-funds of TDFs and TRFs from the same fund family, while non-affiliated sub-funds are from other families. Furthermore, Panel B2 tests for the factors that influence affiliated sub-funds are selected by a TDF & TRF. Here, the dependent variable, *Affiliated*, equals one for affiliated sub-funds and zero for non-affiliated sub-funds. In both regressions, independent variables include one quarter lagged value of Fama–French three-factor alpha, fund flow, expense ratio, fund size, turnover ratio, fund family size, and fund age. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Panel A: Probit model of the likelihood of a fund is selected as a TDF or TRF constituent	
Variables	Constituent fund
	(1)
L.ThreeFactorAlpha	-1.7463**
	(0.02)
L.FundFlow	0.0133
	(0.66)
L.ExpenseRatio	-0.2777***
	(0.00)
L.FundSize	0.1513***
	(0.00)
L.TurnoverRatio	0.00004
	(0.15)
L.FundFamilySize	-0.0068
	(0.76)
L.FundAge	0.0066
	(0.33)
Constant	-3.0035***
	(0.00)
Observations	5,544
Pseudo R-squared	0.319
Fund type fixed effects	YES
Quarter fixed effects	YES

Panel B1: Affiliated vs. non-affiliated sub-funds								
	Affiliated sub-funds	Non-affiliated sub-funds	Affiliated sub-funds	Non-affiliated sub-funds	Affiliated sub-funds	Non-affiliated sub-funds	Affiliated sub-funds	Non-affiliated sub-funds
Year	Past return		Past fund flow		Past expense ratio		Number of observations	
2018	-0.0046	-0.0115	-0.0794	0.1098	0.8500	0.8750	14	30
2019	0.0041	0.0049	0.1308	0.3363	1.1358	1.0034	248	304
2020	0.0120	0.0144	0.1947	0.2892	1.1605	1.1228	531	569
2021	0.0191	0.0212	0.1429	0.2564	1.1479	1.0287	556	795
2022	0.0108	0.0149	0.1055	0.1923	0.9514	0.9568	476	870

Panel B2: Probit model of the likelihood of an affiliated sub-fund is selected in a TDF or TRF	
Variables	Affiliated sub-fund
	(1)
L.ThreeFactorAlpha	-5.2733***
	(0.00)
L.FundFlow	-0.0254
	(0.59)
L.ExpenseRatio	0.1472*
	(0.07)
L.FundSize	-0.3106***
	(0.00)
L.TurnoverRatio	0.0001
	(0.38)
L.FundFamilySize	0.3568***
	(0.00)
L.FundAge	0.0200**
	(0.05)
Constant	-3.2162***
	(0.00)
Observations	2,083
Pseudo R-squared	0.127
Fund type fixed effects	YES
Quarter fixed effects	YES

Table 2.5 Panel B1 illustrates the yearly frequency of affiliated (in-house) versus non-affiliated sub-funds being selected into TDFs & TRFs by year. Overall, affiliated sub-funds account for a smaller proportion of TDFs & TRFs than non-affiliated sub-funds. However, affiliated sub-funds that are selected into TDFs & TRFs tend to have weaker past returns, lower fund flows and higher expense ratio compared to non-affiliated sub-funds, characteristics consistent with agency problems documented by Pool et al. (2016) and Chan et al. (2017). The regression results in Panel B2 corroborate this preliminary finding. In this new model, the dependent variable *Affiliated*, equals one

for affiliated sub-funds of TDFs & TRFs, and zero for non-affiliated sub-funds of TDFs & TRFs at quarter *t*. Our results show that affiliated sub-funds exhibit lower return performance and higher expense ratios, suggesting fund family's favoritism towards adding poor-performing affiliated funds to TDFs & TRFs. The findings lend additional support to rule out superior fund selection skills as an explanation of the outperformance of TDFs & TRFs.

2.5.2.2 Flow stability

In this section, we consider an alternative mechanism: TDFs & TRFs may benefit from more stable fund flows compared with mutual funds due to their mandatory lock-in requirements. To test this hypothesis, we introduce a new variable, *FundFlowStability*, which captures the stability of a fund's quarterly flows, and examine whether it correlates with the performance of TDFs & TRFs. *FundFlowStability* is defined as the negative of the standard deviation of a fund's quarterly fund flows over the past four quarters following Rakowski (2010), so that higher values indicate greater stability. We also include an interaction term, *FundFlowStability* × *TDFTRF*, along with standard control variables. This framework allows us to assess whether flow stability of TDFs & TRFs contributes more positively to performance, compared to other mutual funds.

$$\begin{aligned} ThreeFactorAlpha_{i,t} &= a_i + \beta_1 FundFlowStability_{i,t-1} + \beta_2 TDFTRF_{i,t} \\ &+ \beta_3 FundFlowStability_{i,t-1} \times TDFTRF_{i,t} + \theta' FundTypeFE + \psi' QuarterFE \\ &+ \varepsilon_{i,t} \end{aligned} \tag{5}$$

The results are presented in Table 2.6. The interaction term is positive and significant, indicating that compared to standard mutual funds, fund flow stability contributes positively to the performance of TDFs & TRFs. In other words, these findings support the view that fund flow stability, as a result of mandatory lock-in periods, is likely the driver of the outperformance of TDFs & TRFs.

Table 2. 6. Flow stability

This table examines whether TDFs & TRFs may benefit from more stable fund flows compared with mutual funds due to their mandatory lock-in requirements. The dependent variable is the Fama–French three-factor alpha, which measures fund risk-adjusted returns. We introduce a new variable, *FundFlowStability*, capturing the stability of a fund's quarterly flows and investigating whether it correlates with the performance of TDFs and TRFs. We also include an interaction term, *FundFlowStability* × *TDFTRF* in the model. Control variables include fund size, fund age, expense ratio, and managers' gender and degree. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Three-factor alpha
	(1)
L.FundFlowStability	-0.0041***
	(0.00)
L.FundFlowStability×TDFTRF	0.0045*
	(0.05)
TDFTRF	0.0059***
	(0.00)
FundFamilySize	0.0006***
	(0.00)
LockInPeriod	-0.0002***
	(0.00)
Experience	-0.0001***
	(0.00)
FundSize	0.0009***
	(0.00)
FundAge	-0.0005***
	(0.00)
ExpenseRatio	0.0069***
	(0.00)
Gender	0.0003
	(0.12)
Degree	0.0001
	(0.67)
Constant	-0.0293***
	(0.00)
Observations	125,503
Adjusted R-squared	0.1431
Fund type fixed effects	YES
Quarter fixed effects	YES

2.5.3 Survival analysis on ongoing constituent funds

In this section, we further extend our mechanism analysis by performing survival analysis to assess TDF & TRF sub-funds' likelihood of remaining in the portfolio (Chan et al., 2017). This analysis allows us to identify characteristics of sub-funds which are more likely to be replaced, providing insights for ongoing discipline.

Following Cox (1972), we use the proportional hazards model to investigate the survival

probability of TDFs & TRFs' sub-funds. The central focus is the hazard function, $h(t)$, which can be interpreted as the conditional probability that a constituent fund is terminated from a TDF or TRF at time t. *T* denotes the duration a sub-fund remains within a TDF or TRF, the hazard function can be defined as follows:

$$h(t) = \lim_{\delta \to 0^+} \left(\frac{Pr[t \ll T < t + \delta | T \gg t|}{\delta} \right) \tag{6}$$

The hazard function is specified as:

$$h(t, z; \beta, h_0) = e^{z'\beta} h_0(t) \tag{7}$$

where *t* is measured in calendar quarters, and *z* is a vector of explanatory variables that may influence how long a sub-fund remains in a TDF or TRF. We can also express equation (7) as the following model:

$$\begin{aligned} log\ h(t, z; \beta, h_0) \\ &= \beta_1 Avg\_ExpenseRatio_i^{constituent\ fund} \\ &+ \beta_2 Avg\_ThreeFactorAlpha_i^{constituent\ fund} + \beta_3 Avg\_FundAge_i^{constituent\ fund} \\ &+ Controls + log\ h_0(t) \end{aligned} \tag{8}$$

where *Avg_ExpenseRatio* denotes the average expense ratio of constituent fund *i* during its holding period within a TDF or TRF, while *Avg_ThreeFactorAlpha* represents its Fama–French three-factor alpha over the same period. *Avg_FundAge* measures the average age of fund *i* throughout its holding period. In addition, we include the average fund inflows and turnover ratios of each constituent fund, along with other control variables.

As shown in Table 2.7, we find that both *Avg_ExpenseRatio* and *Avg_FundFlow* are positively

and significantly related to fund survival probabilities, suggesting that sub-funds with higher expenses and larger inflows are more likely to be replaced, while fund performance (*Avg_ThreeFactorAlpha)* and fund age (*Avg_FundAge)* are statistically insignificant. The results are consistent with our findings in the mechanism analysis that sub-fund superior performance is unlikely to be related to its inclusion in TDFs & TRFs.

Table 2. 7. Survival test on ongoing constituent funds

This table examines the factors influencing whether constituent funds of TDFs & TRFs remain in the portfolio during 2018–2022. We employ a proportional hazards model, with the dependent variable defined as the hazard rate. A higher hazard rate indicates a lower probability of survival. Independent variables include the constituent funds' average expense ratio, three-factor alpha, fund age, fund flow, and turnover ratio. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Hazard rate
	(1)
Avg_ExpenseRatio	0.3645*
	(0.07)
Avg_ThreeFactorAlpha	-0.2070
	(0.96)
Avg_FundAge	-0.0298
	(0.24)
Avg_FundFlow	0.5148**
	(0.04)
Avg_Turnover	-0.0001
	(0.79)
Observations	246
Pseudo R-squared	0.00745
Log Likelihood	-685.65518
Prob > Chi-squared	0.0672

2.5.4 TDF & TRF issuers versus other issuers

Prior literature widely documents that funds under the same issuing firm share information and fund management expertise, leading to a positive cross-fund correlation (Gaspar et al., 2006; Bessler et al., 2016). Alternatively, another strand of literature argues that funds under the same management compete for resources so a negative correlation in fund returns is observed (Kempf and Ruenzi, 2008). In our context, on the one hand, investors could view those issuing companies that successfully obtain

licenses to operate in the growing TDF & TRF sector as more reliable and reputable, especially in the early stage of the industry. On the other hand, however, when a fund company needs to meet stricter rules surrounding transparency, disclosure and experience to obtain its license to enter the TDF & TRF fund industry, it may also be exposed to the risk of sharing private information with other funds, and higher regulatory and compliance costs, hence losing competitive edges (Parida and Teo, 2018).

We therefore extend our analysis to compare whether funds under TDF & TRF issuing companies outperform their counterparts that do not issue TDFs or TRFs. There is no a priori reason based on the arguments above. We construct a dummy variable, namely *TDFTRFCOMPANY*. This variable takes a value of one for funds whose issuers also manage a TDF & TRF concurrently, and zero otherwise. We then run the baseline regressions with *TDFTRFCOMPANY* added to the model. The results are in Table 2.8.

As indicated by the first column, the coefficient of *TDFTRFCOMPANY* is negative and significant. It suggests that overall, funds under the management of TDF & TRF issuers underperform funds from non-TDF & TRF issuers. This aligns with the argument that higher compliance and regulatory costs could set constraints that prevent managers from allocating resources to maximize returns. For example, funds from TDF & TRF issuers may attract more investors and regulatory attention, but they are also more followed and "copycat" by industry peers, leading to a negative impact on fund returns. Moreover, fund managers may carry over their conservative practices when managing TDFs & TRFs, which could extend to those non-TDFs & TRFs managed within the same fund company, resulting in underinvestment.

Moreover, in terms of fund flow, we do not observe a significant difference between funds from TDF & TRF issuers and non-issuers, as indicated by the insignificant sign of *TDFTRFCOMPANY*. That is, investors do not seem to favor TDF & TRF issuers for their ability and effort to obtain a TDF & TRF issuers' license. Our results suggest that non-TDFs & TRFs operated under TDF & TRF issuers do not seem to benefit by meeting the additional regulatory and compliance costs. Rather,

issuing TDF & TRF could be a sign of higher costs, lower flexibility, and not profit-oriented.

Table 2. 8. TDF & TRF issuers versus other issuers

This table compares whether funds from TDF &TRF issuing companies outperform their counterparts that do not issue TDFs or TRFs. The dependent variables are measured by Fama-French three-factor alpha and fund flow in columns (1) and (2), respectively. We construct a dummy variable, *TDFTRFCOMPANY*, which equals one for funds whose issuers also manage a TDF or TRF at the same time, and zero otherwise. We then add *TDFTRFCOMPANY* to the baseline regression and include the same set of control variables as in the baseline model. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Three-factor alpha	Fund flow
	(1)	(2)
TDFTRFCOMPANY	-0.0022***	0.0035
	(0.00)	(0.67)
FundFamilySize	0.0008***	-0.0213***
	(0.00)	(0.00)
LockInPeriod	-0.0002***	-0.0024***
	(0.00)	(0.00)
Experience	-0.0001***	-0.0020***
	(0.00)	(0.00)
FundSize	0.0005***	0.0364***
	(0.00)	(0.00)
FundAge	-0.0002***	-0.0063***
	(0.00)	(0.00)
ExpenseRatio	0.0045***	-0.1064***
	(0.00)	(0.00)
Gender	0.0003*	0.0142**
	(0.07)	(0.02)
Degree	0.00002	0.0053
	(0.89)	(0.33)
Constant	-0.0385***	-0.2071***
	(0.00)	(0.00)
Observations	149,183	141,268
Adjusted R-squared	0.0893	0.0203
Fund Type fixed effects	YES	YES
Quarter fixed effects	YES	YES

Furthermore, we employ the propensity score matching (PSM) based difference-in-differences (DiD) test to investigate the impact of issuing TDF & TRF on the overall performance of fund companies. DiD approach is used to test the influence of an exogenous shock that could alter the relationship between firm returns (fund flow) and explanatory variables (Bertrand et al., 2004; Beck et al., 2010).

Specifically, we take the first instance of TDF & TRF issuance in a fund family as a shock and

investigate the impact of such a shock on fund performance metrics. To validate the suitability of utilizing DiD in our specific context, we conduct parallel trend testing as a prerequisite. The outcomes of this test provide confirmation that the treated and control groups within our sample meet the necessary criteria. Specifically, the results demonstrate that in the absence of treatment, the disparity in fund performance between these groups remains constant over time. Subsequently, we proceed to perform the official DiD test using the following model:

$$Y_{i,t} = \alpha + \beta_1 DiD_{i,t} + \beta_2 FundFamilySize_{i,t} + \beta_3 LockInPeriod_{i,t} + \beta_4 Experience_{i,t} + Controls + \theta' FundTypeFE + \psi' QuarterFE + \varepsilon_{i,t} \quad (9)$$

where $DiD_{i,t}$ is a binary variable that takes the value of one for all years following the first-time disclosure of TDF & TRF by fund *i*'s family, and zero otherwise. Our DiD specification resembles Beck et al. (2010). In this setting, $DiD_{i,t}$ captures the differential effect of the main explanatory variables on fund company *i*'s fund performance, specifically in the context of the first-time issuance of TDFs & TRFs by the fund company. All other variables retain the same definitions as the primary model. We report on the ATT of the PSM-DiD on Panel A of Table 2.9. From Panel B, the results demonstrate that the coefficient of $DiD_{i,t}$ is negatively significant indicating disclosure of TDFs & TRFs decreases fund risk-adjusted returns. The results support our findings documented earlier in this section and with endogeneity addressed. We then use a calliper nearest neighbor propensity score matching with a set of control variables, and illustrate results in column (2) of Table 2.9. Similar process is conducted for fund flow in columns (3) and (4), but with insignificant results documented.

Our results imply that TDF & TRF family companies may incur higher costs of producing and distributing holding-related information when issuing TDFs & TRFs for the first time, which in turn deteriorates the overall performance of all funds managed under the same family companies. This result is in line with Shi (2017), who finds a negative relationship between portfolio disclosure and hedge fund performance when observing the policy debate over optimal portfolio disclosure. More

frequent disclosure decreases the performance of mutual funds, especially those holding illiquid assets (Parida and Teo, 2018).

Table 2. 9. PSM-DiD

This table reports our robustness check using PSM-DiD to examine the external shock effect on fund performance from 2004 to 2022. We use the earliest inception date of TDF & TRF within one fund company as a time shock, DiD equals one if the fund's fund company first time issued TDF & TRF, and zero otherwise. We report on the Average Treatment Effect (ATT) of the PSM. In Panel B, columns (1), and (3) are the DiD without considering PSM, and columns (2), and (4) include the results of PSM. We include the same set of control variables as in the baseline model. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regression. The p-value of regression coefficients is reported in parentheses, and *, **, *** indicate the level of statistical significance at 10%, 5%, and 1% respectively. See Appendix 2.1 for more details of variable definition.

Panel A: Average treatment effect on the treated			
Outcome variable	ATT	Standard Errors	T-statistics
Three-factor alpha	-0.0064***	0.0010	-6.35
Fund flow	-0.0434***	0.0340	-1.27

Panel B: PSM-DiD regression results				
Variables	Three-factor alpha		Fund flow	
	(1)	(2)	(3)	(4)
DiD	-0.0022***	-0.0013***	-0.0040	0.0162
	(0.00)	(0.00)	(0.63)	(0.18)
FundFamilySize	0.0008***	0.0012***	-0.0207***	-0.0257***
	(0.00)	(0.00)	(0.00)	(0.00)
LockInPeriod	-0.0002***	-0.0003***	-0.0086***	-0.0081***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience	-0.0001***	-0.00002	-0.0020***	-0.0018**
	(0.00)	(0.47)	(0.00)	(0.04)
FundSize	0.0005***	0.0007***	0.0376***	0.0425***
	(0.00)	(0.00)	(0.00)	(0.00)
FundAge	-0.0002***	-0.0005***	-0.0068***	-0.0055***
	(0.00)	(0.00)	(0.00)	(0.00)
ExpenseRatio	0.0045***	0.0026***	-0.1051***	-0.1159***
	(0.00)	(0.00)	(0.00)	(0.00)
Gender	0.0003*	0.0005*	0.0140**	0.0006
	(0.07)	(0.06)	(0.02)	(0.95)
Degree	0.00003	0.0008***	0.0062	0.0090
	(0.86)	(0.00)	(0.26)	(0.31)
Constant	-0.0390***	-0.0506***	-0.2532***	-0.2231*
	(0.00)	(0.00)	(0.00)	(0.07)
Observations	149,183	62,837	140,246	59,282
Adjusted R-squared	0.0894	0.1083	0.0210	0.0236
PSM	NO	YES	NO	YES
Fund Type fixed effects	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES

Furthermore, to strengthen the robustness of our results, we perform a placebo analysis following Zhou et al. (2023), and report results in Figure 2.1. In this test, the timing of the regulatory shock is randomly assigned across funds, and the pseudo-treatment variable is reconstructed accordingly. We then re-estimate the DiD specification in Equation (9) using these simulated values. If the placebo treatment does not predict fund performance, this would indicate that our baseline findings are unlikely to be driven by random variation. We repeat the randomization 1,000 times and summarize the distribution of coefficients and p-values in Figure 2.1. The average coefficient estimates for the placebo treatment are close to zero and far smaller than those from the actual regression. Moreover, most of the associated p-values are above 0.10, suggesting an absence of statistical significance. Taken together, this evidence reinforces that the identified effect of the shock on fund performance is not a spurious outcome.

2.5.5 Non-TDF & TRF issuers

According to the regulation governing the issuance of TDFs & TRFs, fund companies must meet specific requirements in size, having a total asset of over RMB 20 billion. As a further extension to Section 2.5.4, we are particularly interested in examining why those funds that meet the threshold do not choose to become TDF & TRF issuers. Naturally, bigger funds in general should be more attracted to expansion opportunities, especially when there is a threshold that restricts many others from entering the market. Is it because of the potential negative impact of the additional regulatory and compliance costs?

Figure 2. 1. Placebo test of DiD

Figures 2.1.1–2.1.2 plot the distributions of regression coefficients from placebo tests, where pseudo external shock is randomly assigned to assess their effects on fund performance.

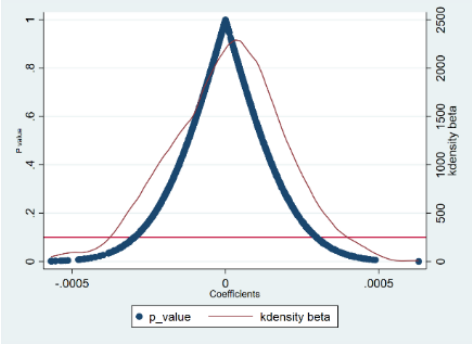

Figure 2.1. 1 External shock effect on fund return

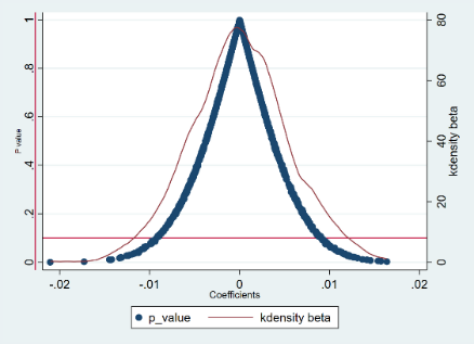

Figure 2.1. 2. External shock effect on fund flow

To investigate this, we introduce a dummy variable called *Over20*. It takes the value of one if the total assets of a fund company exceed RMB 20 billion on average, but the fund company does not issue TDFs & TRFs, and zero if the total assets of a fund company exceed RMB 20 billion and issue TDFs & TRFs. Upon analyzing the results in Table 2.10, our results suggest that fund companies meet the size requirement but do not issue TDFs & TRFs exhibit better performance than those TDF & TRF issuing companies. This finding is consistent with the previous results and further corroborates the implied regulatory and compliance costs with TDF & TRF issuance.

Viewed collectively, results from sections 2.5.4 and 2.5.5 imply that issuing TDFs & TRFs appear to weaken the performance of other funds managed by the same family. We propose several plausible attributes to this finding. First, we argue that the additional compliance and disclosure obligations of managing TDFs & TRFs can inadvertently weaken the performance of non-TDFs & TRFs within the same family. Issuing these pension products raises operational costs, limits managerial flexibility, and diverts attention from profit maximization. Stricter reporting requirements not only add costs but may also erode shareholder returns if external investors reverse-engineer disclosures to infer investment strategies, constraining managers' ability to exploit proprietary research (Wermers, 2001). Resources may therefore be reallocated toward TDFs & TRFs to ensure regulatory compliance, leaving fewer resources for other funds.

Table 2. 10. Non-TDF & TRF issuers

We estimate the effect of non-TDF & TRF issuers on fund performance for the period 2004-2022. We add a dummy variable, *Over20*, which takes the value of one if the fund company's total assets are over RMB 20 billion and it does not issue TDFs or TRFs, and zero if the total assets of a fund company exceed RMB 20 billion and it does issue TDFs or TRFs. We then run the baseline regression after adding *Over20* and include the same set of control variables as in the baseline model. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Variables	Three-factor alpha	Fund flow
	(1)	(2)
Over20	0.0011***	-0.0069
	(0.00)	(0.44)
FundFamilySize	0.0002***	-0.0196***
	(0.01)	(0.00)
LockInPeriod	-0.0002***	-0.0021***
	(0.00)	(0.00)
Experience	-0.0002***	-0.0021***
	(0.00)	(0.00)
FundSize	0.0005***	0.0339***
	(0.00)	(0.00)
FundAge	-0.0002***	-0.0063***
	(0.00)	(0.00)
ExpenseRatio	0.0050***	-0.0989***
	(0.00)	(0.00)
Gender	0.0004**	0.0098
	(0.01)	(0.12)
Degree	0.0002	0.0055
	(0.30)	(0.32)
Constant	-0.0193***	-0.1473
	(0.00)	(0.14)
Observations	134,364	127,540
Adjusted R-squared	0.0830	0.0191
Fund Type fixed effects	YES	YES
Quarter fixed effects	YES	YES

Beyond compliance costs, strategic considerations can further tilt fund families toward prioritizing pension products. Because TDFs & TRFs are new and rapidly expanding in China's financial market, obtaining approval to issue them can enhance a fund company's reputation, strengthen long-term client relationships, foster collaboration with the regulators, and position it for future growth in the pension sector. These incentives make fund families more likely to channel resources and marketing support to TDFs & TRFs once approval is secured. Consistent with the literature on cross-fund subsidization, fund families may transfer performance or resources across member funds to maximize overall revenue (Gaspar et al., 2006; Bhattacharya et al., 2013; Wang, 2024). For example, Gaspar et al. (2006) show that families use IPO allocations or coordinated trading

to benefit strategically important funds, while Wang (2024) documents targeted subsidies and marketing support for star funds. In the Chinese context, pension funds can become the new "star products," receiving preferential treatment through internal performance transfers, research support, or promotional budgets. Such strategic reallocation may further disadvantage non-pension funds managed by the same company, exacerbating the performance drag created by higher compliance and disclosure costs.[15]

2.6 Robustness checks

In this section, we carry out various robustness checks. First, we perform an endogeneity test following the placebo test approach of Zhou et al. (2023). To examine whether the observed effects of fund family size, lock-in period, and manager experience on fund performance could arise by chance, we randomly shuffle these characteristics across funds and then re-estimate the main model (Equation 3) using these pseudo values. We repeat this randomization 1,000 times and plot the estimated coefficients and corresponding p-values in Figures 2.2.1-2.2.6. The resulting average coefficients for fund family size, lock-in period, and manager experience are all near zero and substantially smaller than the baseline estimates. Furthermore, the majority of p-values exceed 0.10, indicating no statistical significance. Collectively, these results confirm that the effects documented in the baseline regressions are unlikely to be due to random variation, hence further safeguard our results against endogeneity.

Additionally, we separately test the effects of *FundFamilySize*, *LockInPeriod* and *Experience* on fund return to test the robustness of our results. As shown in Panel A1 of Table 2.11, when investigating the effects of these three regulatory requirements individually, the coefficients of fund family size, lock-in period, and experience are all positive and statistically significant for TDFs &

[15] A formal analysis using fund-level marketing or investor attention metrics would provide the most rigorous test of this proposition. We acknowledge the limitation that such data are not available for our sample, and note that this offers an interesting avenue for future research.

TRFs. Similar results are also observed in general when we estimate the fund flow of all funds in Panel A2.

Next, instead of assets under management, we utilize the number of funds held by the fund company as an alternative measure of fund family size, namely *NumFund*. The joint effects of *NumFund*, *LockInPeriod*, and *Experience* on three-factor alpha and fund flow are documented in Panel B of Table 2.11, and the results are largely consistent with our main results.

Moreover, previous research points out that Fama-French three factor model may not best capture risk-adjusted returns in a Chinese context (Guo et al., 2017; Wang and Zhu, 2024). To address these concerns, we employ Jensen's alpha (Yan, 2008; Rao et al., 2020) and Fama-French five-factor alpha (Fama and French, 2015) as our alternative measures for fund return. Jensen's alpha measures the risk-adjusted return relative to the Capital Asset Pricing Model (CAPM). The Fama–French five-factor alpha measures the abnormal return after controlling for market risk, size, book-to-market value, profitability, and investment factors. The two regression models are shown below:

$$r_{i,t} - r_{f,t} = a_i + \beta_{1,i} \times \left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t} \tag{10}$$

$$r_{i,t} - r_{f,t} = a_i + \beta_{1,i} \times \left(r_{m,t} - r_{f,t}\right) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t + \beta_{4,i} \times RMW_t + \beta_{5,i} \times CMA_t + \varepsilon_{i,t} \tag{11}$$

where $r_{i,t}$ is the return of fund *i* at month *t*, and $r_{m,t}$ represents the return of the corresponding Shanghai Stock Exchange-Shenzhen Stock Exchange (SSE-SZSE) index returns. The risk-free rate $r_{f,t}$ is the monthly interest rate of the official one-year term deposit (Chen et al., 2018). $r_{m,t} - r_{f,t}$ is the excess return of funds. SMB_t (small minus big) is the average return on small-capitalization portfolios minus the average return on large-capitalization portfolios. HML_t(high minus low) is the average return on high book-to-market portfolios minus the average return on low book-to-market portfolios. RMW_t(robust minus weak) is the average return on robust profitability portfolios minus

the average return on weak profitability portfolios. CMA_t(conservative minus aggressive) is the average return on conservative investment strategies portfolios minus the average return on aggressive investment strategies portfolios. To calculate quarterly alphas, we use a rolling window of 24 months to obtain monthly fund returns, and then aggregate them into quarterly returns (Amihud and Goyenko, 2013). We rerun our main analysis and present the results in columns (1)-(4) of Panel C in Table 2.11. The results are highly consistent with our baseline model results.

Furthermore, we use the net flow[16] as one alternative measure of fund flow (Ivković and Weisbenner, 2009) to provide a warrant for our main analysis. In columns (5)-(6) of Panel C in Table 2.11, we present the results which again remain similar to the main analysis. To ensure a more balanced comparison, we compare the performance of TDFs & TRFs with standard mutual funds after 2018 only, when TDFs & TRFs were first introduced. The results, presented in Panel D, align with our main findings in Table 2.2 and further support our conclusions.

[16]Estimated NetFlow is calculated as follows: $InFlow_{i,t} = New\ Sales_{i,t}/TNA_{i,t}$; $OutFlow_{i,t} = Redeemed\ Cash_{i,t}/TNA_{i,t}$; $NetFlow_{i,t} = InFlow_{i,t}\text{-}OutFlow_{i,t}$. TNA is the total net assets of the fund i in month t. $New\ Sales_{i,t}$ and $Redeemed\ Cash_{i,t}$ are the total number of individual investors' purchases and sales for fund i in month t, respectively.

Figure 2. 2. Placebo test of baseline model

Figures 2.2.1–2.2.6 plot the distributions of regression coefficients from placebo tests, where pseudo fund family size, lock-in period, and manager experience are randomly assigned to funds to assess their effects on performance.

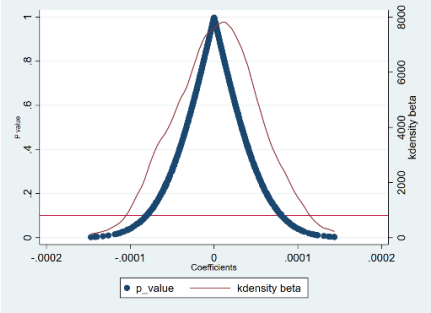

Figure 2.2. 1. Fund family size on fund return

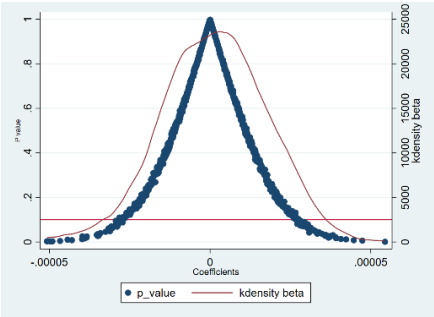

Figure 2.2. 2. Lock-in period on fund return

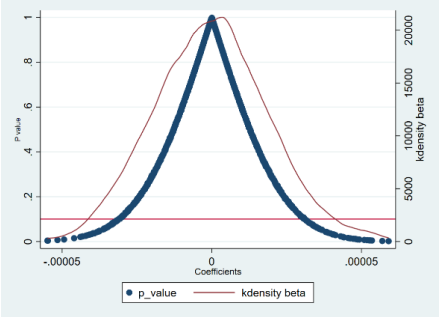

Figure 2.2. 3. Manager experience on fund return

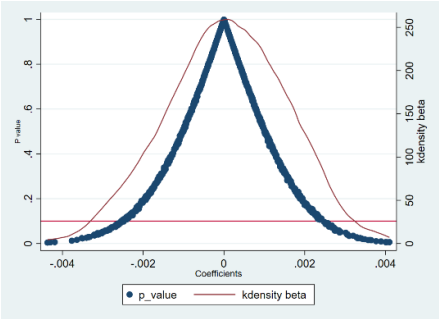

Figure 2.2. 4. Fund family size on fund flow

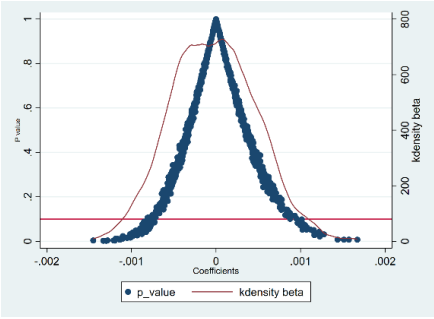

Figure 2.2. 5. Lock-in period on fund flow

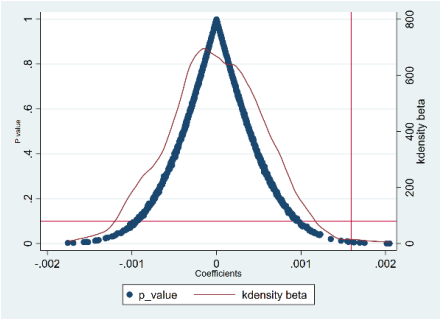

Figure 2.2. 6. Manager experience on fund flow

Table 2. 11. Robustness checks

This table reports our various robustness checks. In Panel A1-A2, we gradually add fund family size, lock-in period, and manager experience to the model in columns (1)-(6) to examine the effect of these factors on fund performance. In Panel B, the number of funds held by the fund company (*NumFund*) is used as an alternative measure of fund family size. We employ Jensen's alpha and Fama-French five-factor alpha as alternative performance measures, and utilize net flow as an alternative metric for fund flow in Panel C. We include the mutual funds sample from 2018 onward, covering the TDFs & TRFs period in Panel D. We include the same set of control variables as in the baseline model. We also control for fund type and quarter fixed effects, and robust standard errors are applied in all regressions. The p-values of regression coefficients are reported in parentheses, and *, **, *** indicate levels of statistical significance at 10%, 5%, and 1%, respectively. See Appendix 2.1 for more details on variable definitions.

Panel A1: The effect of regulatory requirements on fund return						
Variables	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds
	(1)	(2)	(3)	(4)	(5)	(6)
FundFamilySize	0.0016***	0.0004***	0.0014***	0.0004***	0.0014***	0.0004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LockInPeriod			0.0001***	-0.0004***		
			(0.00)	(0.00)		
Experience					0.0003***	-0.0002***
					(0.00)	(0.00)
Observations	1,372	153,759	1,372	153,759	1,147	148,036
Adjusted R-squared	0.2689	0.0902	0.2875	0.0917	0.3017	0.0881
Controls	YES	YES	YES	YES	YES	YES
Fund Type fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES

Panel A2: The effect of regulatory requirements on fund flow						
Variables	TDFs & TRFs	Mutuals funds	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds
	(1)	(2)	(3)	(4)	(5)	(6)
FundFamilySize	0.0332*	-0.0217***	0.0269	-0.0216***	0.0060	-0.0215***
	(0.09)	(0.00)	(0.17)	(0.00)	(0.83)	(0.00)
LockInPeriod			0.0033***	-0.0087***		
			(0.00)	(0.00)		
Experience					0.0060	-0.0022***
					(0.46)	(0.00)
Observations	1,216	145,520	1,216	145,520	1,022	140,246
Adjusted R-squared	0.0087	0.0209	0.0121	0.0215	0.0080	0.0204
Controls	YES	YES	YES	YES	YES	YES
Fund Type fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES

Panel B: Alternative measurement of fund family size				
Variables	Three-factor alpha		Fund flow	
	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds
	(1)	(2)	(3)	(4)
NumFund	0.0011*	0.0004***	-0.0232	-0.0292***
	(0.07)	(0.00)	(0.63)	(0.00)
LockInPeriod	0.0002***	-0.0004***	0.0042***	-0.0087***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.0002**	-0.0001***	0.0033	-0.0020***
	(0.02)	(0.00)	(0.69)	(0.00)
Observations	1,147	148,036	1,022	140,246
Adjusted R-squared	0.3360	0.0893	0.0126	0.0207
Controls	YES	YES	YES	YES
Fund Type fixed effects	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES

Panel C: Alternative measurement of dependent variables						
Variables	Jensen's alpha		Five-factor alpha		Net flow	
	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds	TDFs & TRFs	Mutual funds
	(1)	(2)	(3)	(4)	(5)	(6)
FundFamilySize	0.0016***	0.0004***	0.0006*	0.0004***	0.0068	-0.0055***
	(0.00)	(0.00)	(0.08)	(0.00)	(0.86)	(0.00)
LockInPeriod	0.0003***	-0.0005***	0.0002***	-0.0005***	-0.0036	-0.0147***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)
Experience	0.0002***	-0.0002***	0.0002*	-0.0001***	0.0032	-0.0022***
	(0.01)	(0.00)	(0.09)	(0.00)	(0.62)	(0.00)
Observations	1,147	148,036	1,147	148,036	344	130,326
Adjusted R-squared	0.5712	0.1696	0.2413	0.0730	0.1475	0.0695
Controls	YES	YES	YES	YES	YES	YES
Fund Type fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES

Panel D: Alternative sample: 2018 – 2022		
Variables	Three-factor alpha	Fund flow
	(1)	(2)
FundFamilySize	0.0001**	-0.0186***
	(0.05)	(0.00)
LockInPeriod	-0.0005***	-0.0081***
	(0.00)	(0.00)
Experience	-0.0002***	-0.0023***
	(0.00)	(0.00)
Observations	104,543	99,491
Adjusted R-squared	0.0902	0.0160
Controls	YES	YES
Fund Type fixed effects	YES	YES
Quarter fixed effects	YES	YES

2.7 Conclusion

In this study, we find that extra regulatory requirements imposed on TDFs & TRFs, namely fund family size, lock-in period, and fund manager experience, improve the returns and net flows of these funds significantly. In contrast, we discover these regulatory requirements for TDFs & TRFs have a limited effect on mutual fund returns, and a negative effect on mutual fund flows. Our mechanism test shows that TDFs & TRFs have greater fund flow stability, which contributes to their superior performance over mutual funds. Results from further analyses imply a negative spillover to the performance of other non-pension funds managed under the same fund family, which can be attributed to the extra regulatory disclosure and compliance burden as well as the fund family's strategic reasons.

We supplement the literature on pension funds and give a first glance at the characteristics and performance of TDFs & TRFs in the Chinese market. While prior studies have examined extensively how fund size, flows, and managerial quality influence performance (Chen et al., 2004; Agarwal et al., 2009; Ding and Wermers, 2012), our setting is unique in that these characteristics are mandated by regulation for newly established TDFs & TRFs in China, rather than chosen strategically by fund families. By showing that regulatory thresholds on fund family size, lock-in periods, and managerial experience significantly shape fund outcomes, we demonstrate how regulation itself can serve as an effective channel to enhance retirement saving effectiveness. This not only advances the literature on fund performance by shifting the focus from discretionary characteristics to regulatory design, but also provides timely policy insights for China and other aging economies seeking to strengthen private pension systems.

While our analysis focuses on the national-level effects of regulatory requirements on TDFs & TRFs, we recognize that heterogeneity in investor behavior, occupation, and demographic characteristics may also influence household participation and fund outcomes. At present, such household-level subscription data are not available. This is left as a promising direction for future research to provide deeper insights into how different groups engage with target pension funds.

Appendix 2.1 Variable definition

Variables	Definition
ThreeFactorAlpha	The abnormal returns generated by the Fama-French three-factor model.
FundFlow	The net growth in fund assets beyond reinvested dividends. $$\text{Flow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \times (1 + r_{i,t})}{\text{TNA}_{i,t-1}}$$
FundFamilySize	The natural logarithm of the total assets under management of the fund's family
LockInPeriod	The minimum holding period required by the fund.
Experience	The fund managers' experience in the fund management industry measured in number of years
FundSize	The natural logarithm of the total net assets of the fund.
FundAge	The number of years in which the fund was established.
ExpenseRatio	the ratio of a fund's management fee and custodian fee to the total net assets of funds.
Gender	Takes the value of one if the fund management team includes at least one male manager, and zero otherwise
Degree	The highest education attainment of a fund management team (Degree ranges from 1 to 4 for no tertiary qualification, Undergraduate, Master and MBA/EMBA, and Doctorate, respectively)
TDFTRF	Takes the value of one if the fund is TDFs or TRFs, and zero for mutual funds.
TurnoverRatio	Defined as the greater of total purchases or total sales of securities during the reporting period, divided by the fund's average net assets over the same period.
FundFlowStability	Defined as the negative of the standard deviation of a fund's quarterly fund flows over the past four quarters.
Avg_ExpenseRatio	Represents the average expense ratio of constituent funds during their holding period within TDFs or TRFs.
Avg_ThreeFactorAlpha	Represents the average Fama–French three-factor alpha of constituent funds during their holding period within TDFs or TRFs.
Avg_FundAge	Measures the average age of constituent funds throughout their holding period within TDFs or TRFs.
Avg_FundFlow	Represents the average fund flow of constituent funds during their holding period within TDFs or TRFs.
Avg_Turnover	Represents the average turnover ratio of constituent funds during their holding period within TDFs or TRFs.
TDFTRFCOMPANY	Takes the value of one if the funds' issuers also manage a TDF or TRF at the same time, and zero otherwise.
Over20	Takes the value of one if the fund company's total assets are over RMB 20 billion and it does not issue TDFs or TRFs, and zero if the total assets of a fund company exceed RMB 20 billion and it does issue TDFs or TRFs.
NumFund	The number of funds held by the fund company.
Jensen's alpha	Captures the risk-adjusted return based on the CAPM model.
FiveFactorAlpha	Captures the abnormal return based on the Fama-French five-factor model.
NetFlow	The net monthly fund flow, calculated as the difference between purchases and redemptions by individual investors, scaled by the fund's total net assets.

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Yuruo Feng is responsible for research design, literature review, data collection, methodology, and manuscript writing. All stages of the work are carried out with guidance and support from the supervisory team.

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Chapter Three: Stability through sustainability---the role of ESG in curbing fund style drift

In Chapter Two, the findings indicate that regulatory requirements enhance pension fund performance, particularly in comparison with normal mutual funds. Beyond the pension fund regulation, the CSRC's 2018 mandate required ESG disclosures for listed companies. However, evidence at the fund level remains scarce. Chapter Three examines the impact of ESG investing on mutual fund style drift. Section 3.1 provides the introduction, followed by Section 3.2, which outlines the hypothesis development. Section 3.3 presents the data and methodology, while Section 3.4 reports the main results. Sections 3.5 and 3.6 discuss further analysis and robustness checks, respectively. Finally, Section 3.7 concludes the chapter.

Abstract

Using over 40,000 quarter-fund observations from more than 3,000 Chinese mutual funds, this chapter finds a significant negative relationship between fund ESG investing and style drift. Further analysis shows that the effect is more pronounced during periods with elevated economic policy uncertainty, high investor sentiment, and non-COVID-19 pandemic conditions. ESG investing is also associated with other key fund metrics, including tracking error, risk-adjusted return, and fund flow. By fostering long-term alignment between fund managers and investors, ESG commitments not only promote sustainability but also curb excessive risk-taking. The findings are particularly timely, given the China Securities Regulatory Commission's (CSRC) 2018 mandate requiring ESG disclosures for listed companies. However, evidence at the fund level remains scarce.

Keywords: ESG; Style drift; Mutual fund; Fund manager; Economic policy uncertainty

JEL: G11; G23; M14

3.1 Introduction

Socially responsible investing (SRI), which incorporates social, environmental, and ethical considerations into investment decisions, has gained increasing attention from researchers and market participants (Renneboog et al., 2008; Cao et al., 2024). By the end of 2022, global Environmental, Social, and Governance (ESG) investing assets had reached USD 30.3 trillion[17] and are projected to exceed USD 50 trillion[18] by 2025. While this study primarily focuses on ESG investing, terms like "sustainable investing" and "socially responsible investing" are often used interchangeably or in closely related contexts to ours (Maxfield and Wang, 2021).

Despite the growing discussion around ESG in recent years, its effectiveness in enhancing fund performance remains a subject of debate. On the one hand, numerous studies highlight the positive impact of ESG investing on portfolio returns, since ESG performance often provides material information about a firm's fundamentals (Edmans, 2011; Nagy et al., 2015). ESG investing has been linked to higher returns (Steen et al., 2020), increased fund inflows (El Ghoul and Karoui, 2017; Hartzmark and Sussman, 2019), and reduced risk (Bae et al., 2020; Maxfield and Wang, 2021; Zhang et al., 2023), highlighting its potential financial and risk-mitigation benefits. Recently, Huang and Li (2025) investigate the impact of ESG investing on fund managers' incentives and find that ESG fund managers with poor skills can earn higher compensation because of high ESG investment. On the other hand, some studies suggest that ethical investing may entail financial trade-offs. Investors often bear a cost for adhering to ethical principles (Renneboog et al., 2008), and SRI fund flows tend to be less sensitive to returns (Bollen, 2007). In the Australian context, Humphrey and Lee (2011) find no significant return differences between SRI and conventional funds. Moreover, portfolio constraints from excluding sin stocks[19] may limit performance potential (Nofsinger and Varma, 2014).

Existing evidence on the relationship between ESG investing and fund performance

[17] More details are available from: https://www.gsi-alliance.org/.
[18] Source: Bloomberg Intelligence's ESG Midyear Outlook 2021.
[19] Sin stocks include companies involved in alcohol, tobacco, weapons, gambling, and similar industries.

predominantly concentrates on the mature Western markets. However, exploring this topic in the context of China is particularly compelling for two key reasons. First, as the world's largest carbon emitter and a major proponent of the Paris Agreement (Luo et al., 2024), China stands at the crossroads of sustainable development and investment, making it an ideal setting to investigate the role of ESG investing. Second, Chinese mutual fund market has witnessed a rapid surge. The number of mutual funds has increased from 308 in 2006 to 10,174 by 2023. Over the same period, the net fund assets grew remarkably, from RMB 1 trillion to RMB 27.6 trillion. Despite growing global interest, evidence on ESG investing by mutual funds in China remains limited[20], largely due to the historical lack of firm-level ESG data. This gap has begun to close following the 2018 revision of the "Code of Corporate Governance for Listed Companies" by the CSRC, which mandated ESG disclosures for listed companies. As ESG reporting improves, mutual funds have greater access to relevant data, facilitating ESG integrated investing in investment strategies (Yuan, 2024).

In this study, we contribute to this ongoing debate regarding funds' ESG and fund performance from a new perspective, i.e., style drift. Style drift occurs when a fund deviates from its stated investment style (diBartolomeo and Witkowski, 1997; Cumming et al., 2009), exposing investors to a portfolio misaligned with their risk-return profile, disrupting expectations and confidence, and ultimately undermining the fund market function and the financial system stability. Style drift is often a result of mutual funds intentionally misrepresenting their investment strategies to attract more capital and increase fee-based revenue (Brown et al., 1996). Concerns regarding style drift is non-trivial. According to the S&P Indices versus Active (SPIVA) scorecard, approximately half of U.S. equity funds experienced style drift from 2014 to 2023 (S&P Dow Jones Indices, 2023), only 53.97% funds adhere to their investment style mandates.

Concerning the prevalence of style drift, over the past two decades, the determinants of style

[20] Zhang et al. (2023) find a positive relationship between mutual fund ESG performance and reduced downside risk. Wang (2024) demonstrates that funds that commit to strong ESG investing are less vulnerable to risks. Lin et al. (2025) observe that ESG investment styles positively improve fund performance.

drift have been widely discussed in the literature, particularly because of the soaring importance of retail mutual fund markets and consumer protection. Style drift can be influenced by various factors, including agency conflict (Tkac, 2004), poor fund performance, fund manager career concerns (Chevalier and Ellison, 1997; Chan et al., 2002), the pursuit of higher assets under management (Holmes and Faff, 2007), compensation incentives (Kurniawan et al., 2016), and fund active trading (Wermers, 2012). Fund governance mechanisms can also play a role in influencing style drift (Kurniawan et al., 2016). The study also examines managerial characteristics and finds that funds with high managerial ownership tend to drift more.

These findings are largely based on the U.S. market, while research on the determinants of style drift in China remains limited, despite the issue being equally—if not more—important. Chua et al. (2018) report that approximately 67% of open-end equity funds in China deviated from their declared investment styles between 2004 and 2015. China's institutional and cultural landscape differs significantly from that of the U.S., as its regulatory influence, market efficiency, and investor behavior are still undergoing significant development. In mature financial markets like the U.S., strict regulations and active investor oversight exert strong pressure on fund managers to adhere to investment mandates, making style drift often a reputational risk. In contrast, China's relatively less mature market, more flexible regulations, and the dominance of retail investors provide fund managers with greater latitude for style drift.

Moreover, the significant growth of individual investors in China deserves attention. According to the Shanghai Stock Exchange (SSE) Statistics Annual 2018, retail investors dominate the market, accounting for 82% of the SSE trading volume in 2017. By March 2022, the number of individual investors had surpassed 200 million, with the number of fund accounts increasing 17-fold over the past decade.[21] Unlike the U.S., where sophisticated institutional investors dominate the market,

[21] More details can be found in the China Securities Depository and Clearing Corporation Limited: http://www.chinaclear.cn/.

China's market is primarily composed of less experienced retail investors (Jiang et al., 2020). These investors often lack experience and tend to exhibit herding behavior, highlighting the need for transparent fund evaluation based on ESG performance.

The distinct features of the Chinese fund market, coupled with the limited evidence on both ESG investing and style drift, serve as the catalyst for this research. Focusing on the influence of ESG investing on Chinese funds' style drift, we propose that investors and fund managers in high-performing ESG funds share common long-term sustainable investment objectives. Such alignment naturally encourages fund managers to adopt stable and long-term investment strategies, reducing short-term deviations from their stated goals. Moreover, integrating ESG practices into fund management, such as enhanced ESG disclosure and external monitoring, also helps curb excessive risk-taking by fund managers, further mitigating the likelihood of style drift.

Our study analyzes 40,084 fund-quarter observations from 3,112 Chinese mutual funds over the period 2018 to 2022, starting from the year when ESG disclosure data became available following regulatory reforms by the CSRC. We include all open-ended mutual funds with available data from the WIND and CSMAR databases. Using multivariate regression, we find a robust negative relationship between ESG investing and style drift. When examining ESG score upgrades, we observe that an upgrade has a negative effect on style drift.

We extend our analysis in several ways. First, we examine whether the effect of ESG investing on style drift is uniform across different time periods during which market states and investor attention and preference could vary significantly. We find that the impact is particularly strong during periods of heightened economic policy uncertainty (EPU). This result is consistent with Qureshi et al. (2023), who suggest that funds have stronger incentives to leverage to reduce policy-induced information asymmetry and rebuild trust with stakeholders during high EPU periods. Additionally, we find a more pronounced impact when investor sentiment is high. High investor sentiment could incentivize fund managers to integrate ESG investing into their investment strategies to enhance

visibility and reputation (Cheong et al., 2017), hence strengthens its impact on style drift. Moreover, the impact also appears to be stronger during non-COVID-19 periods. In the early stages, ESG was viewed as a "luxury". Over time, it has evolved from a niche concept to a mainstream imperative, with the pandemic accelerating its development. Pástor and Vorsatz (2020) suggest that during the COVID-19 pandemic, investors perceived sustainability as a necessity rather than a luxury, maintaining a strong focus on ESG principles. Our findings support this argument by showing that when ESG was viewed as a "luxury" in the pre-pandemic period, its influence on style drift was more pronounced. However, as ESG became a "necessity" during the pandemic, its impact on style drift diminished, likely because investors and fund managers were already prioritizing ESG considerations regardless of external pressures.

Second, we decompose the composite ESG score into two components: the manager practice score and the controversies score, to identify which aspect of ESG drives style drift. The former comprehensively reflects a fund's long-term ESG fundamentals, while the latter captures the impacts of short-term risk. We find that higher controversies scores (fewer negative ESG events) are the key drivers of a lower style drift, while manager practices have an insignificant effect. Controversies scores reflect the fund company's short-term responsiveness to unexpected negative ESG events, with higher scores indicating more advanced risk management systems. Enhanced risk management capabilities enable fund managers to better preserve investment style consistency and thus mitigate the risk of style drift.

Third, we observe that higher investment concentration strengthens the effect of ESG investing on style drift. Concentrated funds, being riskier and less diversified, are more sensitive to ESG considerations, making their investment strategies more susceptible to ESG-driven adjustments. Finally, we expand our sample in two ways. We firstly include funds that do not disclose their ESG investment strategies. This expands our enquiry from the level of ESG investing to ESG disclosure. We find that funds that first disclose ESG scores are less likely to experience style drift compared to

those that do not. This finding aligns with previous literature suggesting that transparency in ESG practices contributes to more stable and consistent investment strategies (Lian et al., 2023). We also expand the sample period to include data from 2005 to 2022, despite the limited ESG investing data available before 2018. The results hold continuously in the extended period.

In our robustness checks, we use alternative measures of ESG investing and style drift to confirm the robustness of our baseline results. Additionally, we adopt three different measures of fund performance—tracking error, risk-adjusted return, and fund flow—to further examine the impact of ESG investing on related fund performance dimensions. We find ESG investing significantly reduces style drift and tracking error at the cost of lower fund returns and fund flow. Different fixed effects models are also employed to verify the main results. Overall, our findings remain consistent.

We contribute to literature in two ways. First, we enhance the understanding of factors influencing style drift, a critical but underexplored dimension of mutual fund behavior. Chinese fund market is characterized with a weak institutional environment (Cao et al., 2022), less experienced retail investors (Jiang et al., 2020), and unprecedented expansion (Chi et al., 2022; Hope et al., 2023). Understanding factors that mitigate style drift are particularly crucial for consumer empowerment and long-term sustainable market growth. As socially responsible investing gains momentum (Geczy et al., 2021), our findings could guide retail investors toward more informed and ethical financial decisions based on fund ESG commitments. Our results also suggest a new pathway to stabilize the market and ensure order for policymakers.

Second, our results add to the ongoing discussion of whether SRI adds value (Steen et al., 2020) from a mutual fund context. More broadly, while sustainable investing has been extensively studied at firm- and market- levels (Tsang et al., 2023; Hoepner et al., 2024), much less attention has been given to fund level analysis (Zhang et al., 2023). Nevertheless, prior limited research has analyzed the relationship between ESG performance and fund returns, flows, and risk (El Ghoul and Karoui, 2017; Bae et al., 2020; Steen et al., 2020), no study to date has examined whether ESG investing

influences the consistency of a fund's stated investment strategy. Our findings highlight that higher ESG ratings are associated with lower style drift and more stable investment approaches. The results highlight the regulatory spillover effect of the CSRC's 2018 revised code. The increased availability of firm ESG data has enabled mutual funds to incorporate ESG investing more systematically, which subsequently extends to retail investors, reflecting a broader market transition toward ESG-oriented decision-making.

Collectively, our study offers valuable practical implications to minimize investor risk, enhance market stability, and attract capital inflows. Less style drift indicates a more stable investment environment, which in turn promotes the growth of environmental responsibility by providing greater security for both managers and investors in their decision-making. Our findings underscore the importance of promoting clear ESG investment disclosures and addressing style drift to cultivate a more stable and trustworthy financial environment. Beyond China, our insights hold broader relevance for mutual fund management and ESG practices in other markets, where regulatory frameworks, investor behavior, and market maturity may present similar challenges. In February 2025, the European Commission introduced the Omnibus Regulation to significantly reduce sustainability reporting and due diligence requirements for businesses across the European Union. The new regulation, which aims to alleviate the reporting burden of companies, leaves a concern on whether the sustainability goals reduce the economic competitiveness of companies. By emphasizing the role of ESG in curbing style drift and stabilizing the wider financial markets, our study provides timely evidence for regulators and policy makers to re-evaluate the ESG considerations.

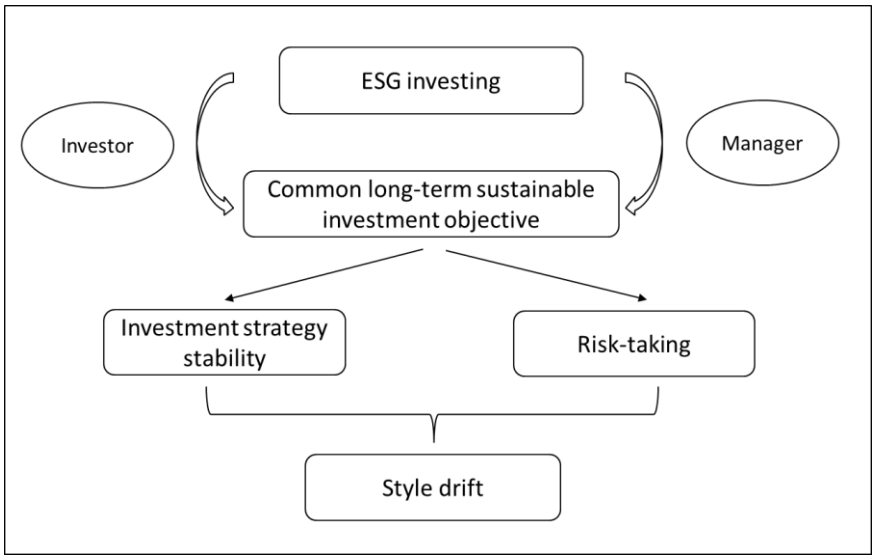
3.2 Hypothesis development

Investors are increasingly drawn to ESG investing for its dual advantages: fostering a long-term mindset and enhancing responsible investment practices (Eccles et al., 2017). Building on these benefits, Starks et al. (2017) find that companies integrating ESG reporting tend to attract more long-

term investors. Stronger ESG performance aligns well with these investors' objectives of long-term sustainability and ethical investing. Similarly, in the fund investing context, investors selecting high-ESG funds are often socially responsible, prioritizing long-term outcomes (Riedl and Smeets, 2017). From the fund manager's perspective, embedding ESG principles enhances ethical decision-making, reduces risky behavior, and mitigates regulatory and reputational risks (Hoepner et al., 2024). ESG-driven funds thus reflect greater managerial accountability and ethical commitment. We thus posit that fund managers engaging in high levels of ESG investing are better aligned with their investors in pursuing long-term sustainable investment goals, which gives rise to two effects that collectively contribute to a reduction in style drift, as conceptualized in Figure 3.1.

Figure 3. 1. Chapter Three process of hypothesis development

The figure summarizes the hypothesis development process based on theoretical and empirical foundations.



First, these common objectives encourage fund managers to adhere more consistently to stable, long-term investment strategies, making short-term deviations from stated goals (i.e., style drift) less likely. He et al. (2022) argues that ESG engagement helps mitigate managerial misconduct—a major driver of corporate fraud—by reinforcing ethical standards and lowering agency costs. As ESG disclosure increases, managers become more aware of their ESG risk exposures, leading to improved

risk management and reduced unethical behavior (Menla Ali et al., 2024). This heightened awareness strengthens corporate governance and decreases the likelihood of investment decisions that diverge from a fund's original objectives.

Second, enhanced ESG investing functions as a safeguard against excessive risk-taking (He et al., 2023), as alignment with common long-term sustainability objectives promotes more prudent decision-making by fund managers. We propose that funds with high ESG performance are often associated with enhanced disclosure, greater transparency, external scrutiny, and a focus on long-term value creation, all of which curb fund managers' excessive risk-taking behavior. Darnall et al. (2022) observe that adherence to ESG principles often entail enhanced disclosure, which strengthens transparency and investor-manager alignment. Raghunandan and Rajgopal (2022) also observe that stronger ESG commitment enhances transparency, noting that even basic ESG disclosures—regardless of content depth—can encourage ethical investing behavior. Moreover, once a fund chooses to disclose its ESG scores, it subjects itself to greater scrutiny from both media and the public (Groza et al., 2011). Such external monitoring pressures managers to maintain ethical and responsible investment practices. Under this scrutiny, fund managers tend to avoid high-risk projects that could jeopardize their reputation or career prospects (Porter and Kramer, 2006) and focus on long-term value creation (Davis and Lescott, 2019).

Based on these insights, we propose that funds with stronger ESG engagement align more closely with the long-term sustainable goals of both managers and investors. This alignment encourages stable, long-term investment strategies, minimizing short-term deviations from objectives. Additionally, improved ESG disclosure and external monitoring help curb excessive risk-taking. Together, these effects lower the likelihood of style drift. Accordingly, we propose the following main hypothesis four:

H4: Funds with higher ESG performance are associated with lower levels of style drift.

3.3 Data and methodology

3.3.1 Sample and data

We collect fund data from the WIND and CSMAR databases, cross-checking the sample for representativeness across the two sources. Our analysis includes all open-end mutual funds with available ESG score data from 2018 to 2022. Most firm-level ESG disclosure data in China began in 2018, when the CSRC revised the "Code of Corporate Governance for Listed Companies" to mandate ESG reporting. The final sample consists of 40,084 observations across 3,112 funds in China. We winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers.

3.3.2 Measuring fund style drift

Our main measure of style drift is calculated following the return-based style analysis (RBSA), introduced by Sharpe (1992), and widely adopted in the literature (Weng and Trück, 2011; Kurniawan et al., 2016). RBSA relies on the role of asset allocation in explaining the variability of portfolio returns. Following Sharpe (1992), we perform style analysis by using quadratic programming which regresses a fund's historical returns on the returns of a set of passively constructed reference portfolios, with each reference portfolio representing an asset class or style. Gallo and Lockwood (1997) highlight that RBSA is advantageous due to its simplicity, discriminatory power, and cost-effectiveness.

Following Sharpe (1992), we run a constrained regression using N asset classes to replicate the historical return pattern of a fund. The model for the constrained regression is specified as follows:

$$r_{i,m} = \sum_{n=1}^{N} w_{i,n} F_{n,m} + \varepsilon_{i,m} \tag{12}$$

where $r_{i,m}$ represents the monthly return of the fund i, $F_{n,m}$ is the monthly return of the style n benchmark index sourced from the Morgan Stanley Capital International (MSCI) style index on

month m, which includes nine different styles; and $w_{i,n}$ denotes the weight of style n. The term $\varepsilon_{i,m}$ represents the error term.

We then employ the quadratic programming algorithm to determine the set of style weights ($w_{i,n}$) that minimizes the tracking error, which is the variance of $\varepsilon_{i,m}$. Since the sum of the weights for the replicated asset classes must equal one, and mutual fund managers are prohibited from shorting, Sharpe (1992) imposes two constraints on the coefficients $w_{i,n}$. The first constraint ensures that the sum of the weights equals one, and the second constraint requires that each weight is non-negative:

$$\sum_{n=1}^{N} w_{i,n} = 1, \ \forall i \tag{13}$$

$$w_{i,n} \geq 0, \forall i \tag{14}$$

Thus, for each fund i and each month m, using a rolling 24-month window, we obtain a set of nine style weights, which characterize the fund's time-varying investment style. Following the approach outlined by Idzorek and Bertsch (2004), we construct a fund-quarter style drift score (SDS), which is the square root of the sum of the variances of w. A low (or high) SDS score indicates a low (or high) degree of style drift.

$$SDS_{i,t} = \sqrt{\sum_{n=1}^{N} var(w_{i,n,m})} \tag{15}$$

3.3.3 Measuring ESG score

The ESG scores in this study come directly from the WIND database, offering a comprehensive view of a fund's sustainable investment capability. These scores capture both the quality of ESG

management within a fund's holdings and its exposure to ESG-related controversies. The overall score consists of two parts: the management & practices score (70%), which reflects how well ESG principles are integrated into corporate strategies, and the controversies score (30%), which assesses exposure to negative ESG events like regulatory violations or scandals.

3.3.4 Baseline model

Our baseline models are presented below:

$$\mathrm{SDS}_{i,t} = a_i + \beta_1 ESGScore_{i,t} + Controls + \theta' FundTypeFE + \psi' QuarterFE + \varepsilon_{i,t} \quad (16)$$

$$\mathrm{SDS}_{i,t} = a_i + \beta_1 Upgrade_{i,t} + Controls + \theta' FundTypeFE + \psi' QuarterFE + \varepsilon_{i,t} \quad (17)$$

where $SDS_{i,t}$ represents fund style drift. We employ two key explanatory variables: *ESGScore* and *Upgrade*. *ESGScore* measures the ESG performance of the fund, serving as an indicator of its alignment with sustainable investment principles. *Upgrade* is a dummy variable that equals one if a fund's ESG score increases compared to the previous year and zero otherwise (Zheng et al., 2023). To account for additional factors influencing fund style drift, we include the following control variables, drawn from Kurniawan et al. (2016). *FundAge* is the number of years since the fund's inception (Chen et al., 2004; Yan, 2008), *FundSize* is the natural logarithm of the fund's total net assets (Chen et al., 2004; Yan, 2008), *FundFamilyAge* is the number of years since the fund family's establishment (Yan, 2008; Bai et al., 2019), *FundFamilySize* is the total assets under management by the fund family (Massa, 2003; Chen et al., 2004), *ExpenseRatio* (%) is the ratio of the fund's management and custodian fees to its total net assets (Yan, 2008), *Turnover* is defined as the greater of total purchases or total sales of securities during the reporting period, divided by the fund's average net assets over the same period. It captures the impact of managerial investment activities on the degree of style drift (Kurniawan et al., 2016). *Single* is a dummy variable that equals one if the fund

is managed by a single manager, and zero if it is managed by a team (Kurniawan et al., 2016). To mitigate potential omitted variable bias, our regression models incorporate fund type and quarter fixed effects, in line with Sensoy (2009) and Hartzmark and Sussman (2019). We use robust standard errors in all regressions. Appendix 3.1 provides a detailed explanation of all variable definitions.

3.4 Main results

3.4.1 Descriptive analysis

The summary statistics of the main variables are presented in Panel A of Table 3.1. The average quarterly style drift score (%) is 5.024, ranging from a minimum of 0 to a maximum of 32.56. Regarding the key explanatory variables, the average *ESGScore* for the full sample is 6.464, with a range from 5.710 to 7.359. This indicates that most of the funds in the sample maintain a mid-level ESG performance. In addition, 71.4% of funds experienced an upgrade in ESG score compared to the previous year.

Panel B of Table 3.1 provides the parametric correlation matrix for the main variables in the full sample. We observe a negative correlation between *ESGScore* and *SDS*, lending preliminary support to our main hypothesis that funds with better ESG performance are less likely to experience style drift. Additionally, *SDS* exhibits a negative correlation with *Upgrade*, further supporting our key hypothesis. Moreover, the correlations between *SDS* and the control variables generally align with our expectations, providing justification for the selection of our baseline model.

3.4.2 Univariate test of fund characteristics by ESG score

In Table 3.2, we present the univariate test results examining the differences in characteristics between funds with low and high ESG scores, following Kurniawan et al. (2016). We divide the sample into three tertiles based on *ESGScore*. We find significant differences in several fund characteristics between the top and bottom groups. Specifically, funds with higher *ESGScore* exhibit

lower levels of style drift. The findings suggest that by incorporating ESG practices, fund managers better align their strategies with long-term sustainability goals, promoting accountability and ethical decision-making. As a result, their funds are less likely to deviate from the stated investment strategies (Edmans, 2011; Nagy et al., 2015). In terms of the control variables, the trends observed across *ESGScore* terciles are consistent with previous literature, with all low-minus-high differences being statistically significant. These findings reinforce the appropriateness of the model.

Table 3. 1. Descriptive analysis

This table presents the summary statistics in Panel A and the parametric correlation matrix of the main variables in Panel B. The sample period spans from 2018 to 2022. Appendix 3.1 provides more detailed variable definitions. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary Statistics						
Variables	N	Mean	Min	Median	Max	STD
	(1)	(2)	(3)	(4)	(5)	(6)
SDS (%)	40,095	5.024	0	3.342	32.56	5.611
ESGScore	40,095	6.464	5.710	6.454	7.359	0.333
Upgrade	28,763	0.714	0	1	1	0.452
FundAge	40,095	6.365	2	5	17	3.795
FundSize	40,095	19.71	14.79	19.80	23.54	1.692
FundFamilyAge	40,095	16.56	4	17	24	4.770
FundFamilySize	40,095	25.92	21.52	26.17	28.08	1.425
ExpenseRatio (%)	40,095	1.430	0.200	1.750	2.100	0.456
Turnover	40,095	3.437	0.102	1.810	59.12	6.812
Single	40,095	0.734	0	1	1	0.442

3.4.3 Baseline results

We run regression models (16), (17) and (18) to examine the impact of *ESGScore* and *Upgrade* on style drift, respectively. First, *ESGScore* is negatively related to style drift, with a coefficient of -0.4167. This finding supports the view that stronger ESG commitment contributes to more consistent and stable investment strategies (Bae et al., 2020; Maxfield and Wang, 2021). *Upgrade* is negatively associated with style drift, with a coefficient of -0.3277. ESG upgrade may signal a more disciplined approach to investment management, reducing the tendency of funds deviating from their intended style. Both results align with our hypotheses.

Panel B: Parametric correlation										
	SDS	ESGScore	Upgrade	FundAge	FundSize	FundFamilyAge	FundFamilysSize	ExpenseRatio	Turnover	Single
SDS	1									
ESGScore	-0.0591***	1								
Upgrade	0.00190	0.3915***	1							
FundAge	-0.0366***	0.0693***	0.0239***	1						
FundSize	0.00330	0.0500***	0.0371***	0.3111***	1					
FundFamilyAge	-0.0246***	0.1447***	0.0314***	0.2330***	0.2532***	1				
FundFamilySize	-0.0114**	0.1375***	0.0365***	0.0563***	0.3611***	0.5777***	1			
ExpenseRatio	-0.0429***	-0.1360***	-0.0704***	0.1750***	0.1265***	-0.0670***	-0.1654***	1		
Turnover	-0.0146***	0.0358***	0.00860	-0.0461***	-0.1141***	0.0172***	0.0111**	-0.1366***	1	
Single	0.0134***	-0.0329***	0.00550	0.0454***	-0.0692***	-0.1101***	-0.1259***	-0.0097*	-0.00600	1

Overall, these results underscore the importance of ESG investing in explaining style drift. Funds with higher ESG scores tend to demonstrate lower levels of style drift. Two possible reasons may explain the results. First, strong commitment to ESG investing fosters alignment between fund managers and investors in pursuing long-term sustainability objectives. This alignment not only reinforces investment discipline but also reduces the likelihood of abrupt style shifts, for (unethical) purposes of fund managers (Hoepner et al., 2024). Second, enhanced ESG investing acts as a safeguard against excessive risk-taking by fund managers, as adherence to ESG principles often entails enhanced disclosure (Darnall et al., 2022), greater transparency (Raghunandan and Rajgopal, 2022), external scrutiny (Porter and Kramer, 2006; Groza et al., 2011), and a focus on long-term value creation (Davis and Lescott, 2019). Together, these factors contribute to greater investment strategy stability, mitigate potential risks, and ultimately reduce the occurrence of style drift, enhancing both investor confidence and market integrity.

Table 3. 2. Univariate analysis

This table presents our univariate analysis of the main variables from 2018 to 2022. Appendix 3.1 provides more detailed variable definitions. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	ESGScore				
	Tertile1	Tertile2	Tertile3	Difference (1-3)	t-Value
SDS	5.521	4.674	4.876	9.125***	5.521
FundAge	6.034	6.455	6.605	-12.338***	6.034
FundSize	19.640	19.640	19.860	-10.751***	19.640
FundFamilyAge	15.850	16.400	17.420	-27.463***	15.850
FundFamilySize	25.760	25.820	26.190	-25.415***	25.760
ExpenseRatio	1.495	1.450	1.346	26.803***	1.495
Turnover	3.273	3.268	3.769	-5.810***	3.273
Single	0.743	0.748	0.711	5.851***	0.743

Table 3. 3. Baseline results

This table reports the main regression outcomes assessing the influence of *ESGScore*, and *Upgrade* on fund style drift for the period from 2018 to 2022. *ESGScore* reflects a fund's ESG investing, indicating how well it aligns with sustainable investment practices. *Upgrade* is a dummy variable equals to one if a fund's ESG rating rises relative to the previous year, and zero otherwise. Control variables include fund age, fund size, fund family age, fund family size, expense ratio, turnover, and single manager. We also control fund type and quarter fixed effects, with robust standard errors applied in all regressions. The p-values of the regression coefficients are reported in parentheses, and *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 3.1 for more detailed variable definitions.

	SDS	
Variables	(1)	(2)
ESGScore	-0.4167***	
	(0.00)	
Upgrade		-0.3277***
		(0.00)
FundAge	-0.0331***	0.0190**
	(0.00)	(0.04)
FundSize	0.0521***	0.0912***
	(0.00)	(0.00)
FundFamilyAge	-0.0043	-0.0037
	(0.54)	(0.63)
FundFamilySize	0.0102	-0.0095
	(0.68)	(0.72)
ExpenseRatio	-0.8946***	-1.2462***
	(0.00)	(0.00)
Turnover	-0.0170***	-0.0258***
	(0.00)	(0.00)
Single	0.0543	0.0915
	(0.38)	(0.17)
Constant	13.4750***	2.3485***
	(0.00)	(0.00)
Observations	40,095	28,763
Adjusted R-squared	0.1338	0.0738
Fund type fixed effects	YES	YES
Quarter fixed effects	YES	YES

3.5 Further analysis

Building on the baseline results, Section 3.5 conducts a series of supplementary analyses to further examine whether the relationship between ESG investing and fund style drift varies across different market conditions, ESG dimensions, fund characteristics, and disclosure environments.

3.5.1 Different market states

While the baseline results establish an overall relationship between ESG investing and style drift, this effect may vary across different economic and market environments. Market conditions such as economic policy uncertainty and investor sentiment could influence fund managers' behavior and constraints. Therefore, we first examine whether the ESG–style drift relationship differs across various market states. Specifically, we analyze market states with different levels of economic policy uncertainty and investor sentiment. We also examine the highly volatile COVID-19 pandemic periods separately.

The first analysis, with results reported in columns (1) and (2) of Table 3.4, splits our sample based on funds' exposure to EPU in the same year. We follow the methodology of Baker et al. (2016) and Davis et al. (2019) and use data from the Economic Policy Uncertainty website[22]. Monthly EPU is calculated based on the scaled frequency count of articles related to policy-related economic uncertainty in two major Chinese newspapers: Renmin Daily and Guangming Daily. For our analysis, we define a dummy variable, *EPU*, which equals one if the value of EPU exceeds the median value of the full sample in each year, and zero otherwise.

We find that *ESGScore* has a stronger effect during high-EPU periods. The corresponding coefficients are -0.5726 and -0.3296 for high- and low-EPU periods. During high-EPU periods, companies tend to enhance their social performance to reduce policy-induced information asymmetry and rebuild trust with stakeholders (Qureshi et al., 2023). Our results align with those of Kammoun

[22] More information regarding the data is available from: https://www.policyuncertainty.com/.

and Essaddam (2024), who suggest that economic policy uncertainty increases funds' motivation to pursue ESG objectives, thereby reducing the likelihood of style drift. Our results add to these studies, highlighting ESG investing as a stability mechanism in uncertain periods, during which investors often demand safe-haven assets, fund managers face higher uncertainty in predicting short-term market movements and regulatory oversight typically intensifies.

The second analysis, shown in columns (3) and (4) of Table 3.4, examines the impact of investor sentiment on the relationship between ESG investing and style drift. Barberis et al. (1998) suggest that investor sentiment is higher when investors receive a series of either positive or negative news, leading to overreactions in stock prices due to the representativeness heuristic. Following Baker and Wurgler (2006), we construct a composite sentiment index based on the common variation in six underlying proxies of market sentiment:

$$SENTIMENT_t = -0.241 \times CEFD_t + 0.242 \times TURN_t + 0.253 \times NIPO_t + 0.257 \times RIPO_{t-1} + 0.112 \times SHARE_t - 0.283 \times PDND_{t-1}^{D-ND} \quad (18)$$

where the proxies are as follows: *CEFD* is the closed-end fund discount (the average difference between net asset value and market prices). *TURN* is the market turnover rate, measured by total volume divided by total capital stock. *NIPO* and *RIPO* are the numbers and average first day returns of IPOs, respectively. *SHARE* is the proportion of stock financing relative to stock and bond financing. *PDND* is the natural logarithm of the dividend premium.

We find that the effect of ESG investing on style drift is significantly stronger during high investor sentiment periods. Specifically, during high sentiment periods, the coefficient for *ESGScore* is -0.9633, compared to -0.4058 in low sentiment periods. Our findings support Cheong et al. (2017) and Wang et al. (2024), who emphasize that investor sentiment influences corporate socially responsible performance. Under optimistic market conditions, ESG investing plays a more significant role in stabilizing fund style, likely because investors are more inclined to prioritize sustainability and

long-term goals during periods of heightened confidence. Fund managers are then incentivized to integrate ESG investing into their investment strategies to enhance visibility and reputation, strengthening its impact on style drift.

Table 3. 4. Different market states

This table presents the results of three different market states based on our baseline regression. The first analysis, shown in columns (1) and (2), divides the main sample into funds with higher and lower economic policy uncertainty (EPU) in the same year, with EPU measured using data from Renmin Daily and Guangming Daily. The second analysis, reported in columns (3) and (4), examines funds with higher and lower investor sentiment. Columns (5) and (6) analyze the COVID-19 period (2020–2022) versus the non-COVID-19 period. We include the same set of control variables as in the baseline model. Additionally, we control fund type and quarter fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 3.1 for more detailed variable definitions.

	SDS					
Variables	High EPU	Low EPU	High sentiment	Low sentiment	COVID-19 periods	Non-COVID-19 periods
	(1)	(2)	(3)	(4)	(5)	(6)
ESGScore	-0.5726***	-0.3296***	-0.9633***	-0.4058***	-0.3668***	-0.6231***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	4.4292***	14.2650***	16.1260***	5.5770***	7.9422***	14.0335***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	12,553	27,542	15,246	14,782	26,252	13,843
Adjusted R-squared	0.1015	0.1400	0.1406	0.1019	0.0586	0.2585
Fund type fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES

Finally, in columns (5) and (6) we examine the impact of ESG investing during the COVID-19 pandemic period (2020-2022) compared to the pre-pandemic period. During the COVID-19 period, the world faced significant economic and social fragility (Folger-Laronde et al., 2022). Our results reveal that the coefficient for *ESGScore* is -0.3668 during the COVID-19 period, while it is -0.6231 in the non-COVID-19 period. This suggests that the influence of ESG investing on style drift is stronger in the pre-pandemic period. Originally viewed as a luxury, ESG has evolved from a niche concept to a mainstream imperative. The pandemic accelerated its development, making it a "necessity." As suggested by Pástor and Vorsatz (2020), during the pandemic period, investors view sustainability as a necessity rather than a luxury. Our results are consistent in showing that when ESG investing is valued as a "luxury" during pre-pandemic period, it has stronger influence on style drift,

whereas when ESG investing is valued as a "necessity" during pandemic period, its influence on style drift is weakened.

3.5.2 Different components of ESG score

Having examined the role of external market conditions, we next turn to the internal composition of ESG scores. The composite ESG measure may capture distinct dimensions of fund behavior, which could have heterogeneous effects on style drift. Therefore, we decompose the ESG score into its key components to identify the primary driver of the observed relationship.

In this section, we study the two components of the composite ESG score separately: *ManagerPracticeScore* and *ControversiesScore*, to identify the key factor driving the relationship between ESG investing and style drift. *ManagerPracticeScore* includes more than 400 management and practice indicators across the E, S, and G pillars, capturing long-term ESG fundamental impacts. *ControversiesScore*, reflects short-term ESG risks based on over 1,200 risk labels, measures the ESG-related controversies a company faces during a fiscal year (Dorfleitner et al., 2020), covering news events, regulatory penalties, and lawsuits. The results in Table 3.5 show that *ManagerPracticeScore* has an insignificant positive relationship with style drift. In contrast, the *ControversiesScore* shows a significant negative relationship with style drift at the 1% significant level, with a coefficient of -3.7779. A higher controversies score indicates lower fund controversies (fewer negative ESG events), which measure a fund company's ability to respond to sudden negative events in the short term. Higher controversies scores, signaling more mature risk management mechanisms, demonstrate a negative relationship with style drift as stronger risk management capabilities enhance investment style consistency.

Table 3. 5. Different components of ESG score

This table presents the results of our analysis on the two components of the composite ESG score: *ManagerPracticeScore* and *ControversiesScore*. *ManagerPracticeScore* reflects a fund's long-term ESG practices, while *ControversiesScore* captures the effects of short-term ESG-related risks. Columns (1) and (2) examine their respective impacts on style drift, allowing us to identify which component plays a more significant role in driving the relationship between ESG investing and style drift. We include the same set of control variables as in the baseline model. Additionally, we control fund type and quarter fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 3.1 for more detailed variable definitions.

	SDS	
Variables	(1)	(2)
ManagePracticesScore	0.0245	
	(0.78)	
ControversiesScore		-3.7779***
		(0.00)
FundAge	-0.0337***	-0.0436***
	(0.00)	(0.00)
FundSize	0.0488***	0.0558***
	(0.01)	(0.00)
FundFamilyAge	-0.0042	-0.0035
	(0.55)	(0.62)
FundFamilySize	0.0114	0.0079
	(0.64)	(0.74)
ExpenseRatio	-0.8563***	-0.5103***
	(0.00)	(0.00)
Turnover	-0.0164***	-0.0144***
	(0.00)	(0.00)
Single	0.0482	0.0117
	(0.44)	(0.85)
Constant	10.8059***	21.2734***
	(0.00)	(0.00)
Observations	40,095	40,095
Adjusted R-squared	0.1334	0.1391
Fund type fixed effects	YES	YES
Quarter fixed effects	YES	YES

3.5.3 The effect of investment concentration

Beyond ESG components, fund-specific attributes may also shape the relationship between ESG investing and style drift. In particular, funds with higher investment concentration are more susceptible to idiosyncratic liquidity shocks, as their portfolios are less diversified and more exposed to disruptions affecting individual assets or investors (Kruttli et al., 2017). This lack of diversification reduces their ability to absorb shocks, making them more vulnerable to market instability. They also find that hedge funds with high investment concentration are more likely to experience large liquidity-

driven outflows because these idiosyncratic shocks cannot be diversified away. We are interested in testing whether the level of investment concentration affects the relationship between fund ESG investing and style drift.

Table 3. 6. The effect of investment concentration

This table presents the results of analyzing how investment concentration influences the relationship between ESG investing and style drift. Investment concentration is measured as the weighted average of the top ten holdings in a fund's current portfolio. To capture its moderating effect, we construct an interaction term, *ESGScore* × *InvestmentConcentration*, and examine its impact on style drift. We include the same set of control variables as in the baseline model. Additionally, we control fund type and quarter fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 3.1 for more detailed variable definitions.

	SDS
Variables	(1)
ESGScore	-0.2806***
	(0.01)
InvestmentConcentration	5.0690***
	(0.00)
ESGScore × InvestmentConcentration	-0.7944***
	(0.00)
FundAge	-0.0337***
	(0.00)
FundSize	0.0611***
	(0.00)
FundFamilyAge	-0.0056
	(0.43)
FundFamilySize	0.0100
	(0.68)
ExpenseRatio	-0.8765***
	(0.00)
Turnover	-0.0204***
	(0.00)
Single	0.0742
	(0.23)
Constant	12.4066***
	(0.00)
Observations	39,630
Adjusted R-squared	0.1350
Fund type fixed effects	YES
Quarter fixed effects	YES

We obtain fund concentration data from WIND, investment concentration is calculated as the weighted average of the top ten holdings in the fund, based on the percentage of current assets invested in each stock. Specifically, investment concentration is calculated as:

$$Investment\ Concentration = \sum \frac{Number\ of\ shares\ held}{Total\ tradable\ shares} \times W_i \quad (19)$$

where W_i represents the market value of each individual share divided by the total market value of all individual shares. Next, we construct the interaction term *ESGScore×InvestmentConcentration* to examine the effect of investment concentration.The results are reported in Table 3.6. We observe that higher investment concentration amplifies the effect of ESG investing on style drift. Funds with concentrated portfolios are more prone to style drift, as large positions in specific stocks or sectors can pull them away from their original mandates. Our results suggest an important means to reduce style drift for these more vulnerable funds. ESG investing plays a stronger role in mitigating style drift when these funds lack diversification, as their heightened risk exposure makes them more responsive to ESG-driven adjustments.

3.5.4 The influence of ESG disclosure

Finally, following the analyses across market conditions, ESG dimensions, and fund characteristics, we extend our focus from ESG levels to ESG disclosure practices. While the baseline results emphasize ESG investment intensity, disclosure may independently influence fund behavior by enhancing transparency and reducing information asymmetry.

The introduction of ESG disclosure provides a useful setting to examine this question. In particular, fund-level ESG data became widely available starting in 2018 following the CSRC's regulatory reform, whereas disclosure was largely voluntary prior to this period. Exploiting this institutional change, we examine whether ESG disclosure is associated with fund style drift, beyond the effect of ESG levels. This could extend our understanding of the importance of ESG investing, practiced through different ways, in reducing style drift.

Employing a multi-period difference-in-differences methodology (Bertrand et al., 2004; Beck et al., 2010), we investigate the impact of ESG disclosure on style drift, using the longest possible

sample period from 2005 to 2022 from WIND and CSMAR. The main explanatory variable is a dummy variable, *Disclosure*, which takes the value of one if a fund discloses ESG score for the first time, and zero otherwise.

Table 3. 7. The influence of ESG disclosure

This table extends the analysis to a broader sample covering the period from 2005 to 2022, applying a multi-period difference-in-differences approach to examine how ESG disclosure (rather than ESG levels) influences style drift. The key explanatory variable, *Disclosure*, is a dummy variable equal to one if a fund discloses its ESG score for the first time, and zero otherwise. We include the same set of control variables as in the baseline model. Additionally, we control fund type and quarter fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 3.1 for more detailed variable definitions.

	SDS
Variables	(1)
Disclosure	-1.4366***
	(0.00)
FundAge	-0.0584***
	(0.00)
FundSize	0.1357***
	(0.00)
FundFamilyAge	-0.0090
	(0.12)
FundFamilySize	-0.0595***
	(0.00)
ExpenseRatio	-0.9803***
	(0.00)
Turnover	-0.0111***
	(0.00)
Single	-0.0501
	(0.33)
Constant	11.6370***
	(0.00)
Observations	74,928
Adjusted R-squared	0.2371
Fund type fixed effects	YES
Quarter fixed effects	YES

The results in Table 3.7 show a significant negative relationship between *Disclosure* and style drift, with a coefficient of -1.4366. This indicates that funds that voluntarily disclose ESG score tend to exhibit lower levels of style drift. This finding aligns with previous literature suggesting that transparency in ESG practices contributes to more stable and consistent investment strategies (Lian et al., 2023).

These results highlight the potential benefits of ESG score disclosure in reducing style drift, consistent with prior research on the role of ESG factors in enhancing fund performance and stability (Edmans, 2011; Nagy et al., 2015; Steen et al., 2020). As investors and fund managers increasingly recognize the importance of sustainable investing, those funds with higher ESG scores or more transparent ESG disclosures may be more focused on long-term strategies, thereby reducing the volatility of their investment style over time.

3.6 Robustness checks

In Section 3.6, we conduct several robustness checks to ensure the reliability and validity of our findings.

3.6.1 Alternative measurement of ESG score

Apart from the ESG score, WIND also assigns funds into seven different ESG categories based on ESG scores, which range from AAA, AA, A, BBB, BB, B, to CCC. Therefore, we introduce an alternative fund ESG investing measure, *ESGCategory*, to measure fund ESG performance. Our analysis reveals a significant negative correlation between *ESGCategory* and style drift, as reported in Panel A of Table 3.8. This suggests that higher *ESGCategory* are associated with a lower degree of style drift, highly consistent with our main results.

3.6.2 Alternative measurement of style drift

In this section, we employ two alternative style drift proxies. The first alternative style drift measure, *SDS_CNI*, performs the return-based style analysis by using the CNI Indices[23] which includes six sub-indices to gauge the overall performance of stocks with different risk profiles. The alternative proxy addresses measurement error arising from the underlying benchmarks in capturing style drift.

Furthermore, the second alternative style drift proxy, *SDS_HBSA*, uses holding-based style analysis following Daniel et al. (1997) and Brown et al. (2009). Firstly, all stocks listed on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) are ranked into quintiles based on three dimensions: size, book-to-market ratio, and momentum. For each dimension, stocks falling into the highest (lowest) quintile are assigned a score of five (one). As a result, each of the 125 fractile portfolios receives a style score. In line with previous literature, fund style in *SDS_HBSA* is measured as the sum of the style dimensions, following the formula:

$$SCORE_{i,t} = \sum_{Dj} w_{j,t} \times Characteristics_{j,t}^{D} \tag{20}$$

where $w_{j,t}$ represents the weight of stock *j* in fund *i*, calculated as the market value of stock *j* to the fund's total net asset value (NAV). The style dimensions *D* include stock market capitalization, book-to-market ratio (B/M), and momentum. Market capitalization is measured as the natural logarithm of the stock's market cap, the B/M ratio is calculated as the logarithm of the book equity to market equity, and momentum is calculated as the cumulative return from *(t-11, t)*.

As Wermers (2012) suggests, two sources drive style changes: passive style drift (PSD) and active style drift (ASD). Passive style drift arises from changes in stock characteristics that are not

[23] CNI Indices comprises two distinct style indices: Growth and Value. In our study, the Growth Style Index includes the CNI Large Cap Growth, the CNI Mid-Cap Growth, and the CNI Small Cap Growth. Similarly, the Value Style Index consists of the CNI Large Cap Value, the CNI Mid-Cap Value, and the CNI Small Cap Value.

influenced by the fund manager's decisions, whereas active style drift reflects changes in the fund's holdings as managers add or reduce certain stocks. The two components are measured as follows:

$$PSD_{i,t} = \sum_{Dj} \widehat{w_{j,t}^{D}} \times Characteristics_{j,t}^{D} - w_{j-1,t}^{D} \times Characteristics_{j,t-1}^{D} \quad (21)$$

$$ASD_{i,t} = \sum_{Dj} w_{j,t}^{D} \times Characteristics_{j,t}^{D} - \widehat{w_{j,t}^{D}} \times Characteristics_{j,t}^{D} + w_{k,t}^{D} \quad (22)$$

Thus, style drift is calculated as the difference between the style score at time *t* and time *t-1*, as below:

$$SDS\_HBSA_{i,t} = \sum_{Dj} w_{j,t}^{D} \times Characteristics_{j,t}^{D} - w_{j-1,t}^{D} \times Characteristics_{j,t-1}^{D} \quad (23)$$

In Panel B of Table 3.8, column (1) and column (2) present the results of regressing *SDS_CNI* and *SDS_HBSA* on *ESGScore*. The coefficients are -0.3435 and -1.7593 respectively. These findings, using alternative style drift proxies to reduce issues associated with measurement, support our main hypothesis that higher ESG scores are associated with lower levels of style drift.

3.6.3 The effect of ESG score on fund performance

In this section, we expand our analysis beyond style drift, to examine the impact of ESG investing on other key fund performance matrices: tracking error, Jensen's alpha (risk-adjusted return), and fund flow. The analysis provides a more comprehensive view of how ESG investing shapes mutual fund behavior overall.

Tracking error focuses on performance deviation from its benchmark index as disclosed in fund prospectus, while style drift focuses on a fund's consistency with its declared investment style. It is calculated as the standard deviation of the difference between the fund's returns and the benchmark's returns. A high tracking error indicates that the fund is not closely following its benchmark, suggesting active management. We follow Chua and Tam (2020) to calculate tracking error as the first performance measure.

Additionally, we examine Jensen's alpha. This metric evaluates the risk-adjusted return based on the CAPM model (Yan, 2008; Rao et al., 2020). The regression model for this analysis is presented

below:

$$r_{i,t} - r_{f,t} = a_i + \beta_{1,i} \times \left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t} \tag{24}$$

where $r_{i,t}$ represents the return of fund *i* in month *t*, and $r_{m,t}$ denotes the return of the corresponding SSE and SZSE indices. The risk-free rate $r_{f,t}$ is the monthly interest rate of the official one-year term deposit (Chen et al., 2018). $r_{m,t} - r_{f,t}$ represents the excess return of the funds. To calculate the quarterly Jensen's alpha, we use a rolling 24-month window to compute monthly fund returns, which are then aggregated into quarterly returns (Amihud and Goyenko, 2013).

Finally, we construct net fund flow by considering the difference in total net assets of each fund between two consecutive quarters, adjusted for the corresponding fund return (Sirri and Tufano, 1998; Goldstein et al., 2017). The fund flow, $Flow_{i,t}$, for fund *i* in quarter *t* is defined as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Return_{i,t})}{TNA_{i,t-1}} \tag{25}$$

where $TNA_{i,t}$ is the total net asset value of fund *i* at the end of quarter *t*, and $Return_{i,t}$ is the rate of return of fund *i* during quarter *t*.

As shown in Panel C of Table 3.8, the coefficients of *ESGScore* on tracking error, risk-adjusted return, and fund flow are -0.0005, -0.0028, and -0.0321, respectively. The results suggest that although ESG investing significantly reduces style drift and tracking error, it comes at the cost of lower fund returns and fund flow. Nofsinger and Varma (2014) suggest that responsible investing can constrain portfolio construction by excluding "sin" stocks that might otherwise generate superior returns. In addition, funds with stronger ESG focus may not attract significantly more investors, as Renneboog et al. (2008) argue that adhering to ethical principles often comes at a financial cost. Overall, incorporating ESG investing presents fund managers with a trade-off between financial

growth and style stability. Our findings imply that regulators, investors, and fund managers may need to carefully weigh these priorities when navigating this dilemma. These results contribute to the ongoing debate about the impact of ESG investing on fund outcomes by highlighting that the effects largely depend on the emphasis placed on different objectives.

Table 3. 8. Robustness checks

This table presents the results of several robustness checks. In Panel A, we use *ESGCategory* as an alternative measure for ESG investing and re-estimate the baseline regression. Panel B applies alternative measurements of style drift, including *SDS_CNI* and *SDS_HBSA*. In Panel C, we extend the analysis by examining the impact of ESG investing on fund performance, using metrics such as tracking error, Jensen's alpha (risk-adjusted return), and fund flow, to reassess the baseline model. Panel D controls funds and quarter fixed effects. We include the same set of control variables as in the baseline model. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 3.1 for more detailed variable definitions.

Panel A: Alternative measurement of ESG score	
	SDS
Variables	(1)
ESGCategory	-0.0862***
	(0.00)
Observations	32,695
Adjusted R-squared	0.1138
Controls	YES
Fund type fixed effects	YES
Quarter fixed effects	YES

Panel B: Alternative measurement of style drift		
	SDS_CNI	SDS_HBSA
Variables	(1)	(2)
ESGScore	-0.3435***	-1.7593***
	(0.01)	(0.00)
Observations	40,095	39,644
Adjusted R-squared	0.0846	0.5676
Controls	YES	YES
Fund type fixed effects	YES	YES
Quarter fixed effects	YES	YES

Panel C: The effect of ESG score on fund performance			
	Tracking error	Jensen's alpha	Fund flow
Variables	(1)	(2)	(3)
ESGScore	-0.0005***	-0.0028***	-0.0321**
	(0.00)	(0.00)	(0.01)
Observations	40,071	40,095	40,084
Adjusted R-squared	0.1740	0.2141	0.0326
Controls	YES	YES	YES
Fund type fixed effects	YES	YES	YES
Quarter fixed effects	YES	YES	YES

Panel D: Fund fixed effects	
	SDS
Variables	(1)
ESGScore	-0.8687***
	(0.00)
Observations	40,095
Adjusted R-squared	0.2347
Controls	YES
Fund fixed effects	YES
Quarter fixed effects	YES

3.6.4 Fund fixed effects

Finally, we incorporated fund fixed effects into our model to account for unobserved heterogeneity across individual funds that could influence the relationship between ESG score and style drift. The coefficient for *ESGScore* under the fund fixed effect is -0.8687, as shown in Panel D of Table 3.8, again highly consistent with the main findings.

3.7 Conclusion

In China, the CSRC 2018 mandate requires ESG disclosures for all listed companies, enabling mutual fund managers to integrate ESG factors into their investment strategies. Against this background, we examine the impact of fund's ESG investing on its style drift. Our findings reveal a significant negative relationship between fund ESG performance scores and the style drift. Further

analysis shows that the negative effect of fund ESG performance scores on style drift is more pronounced during periods of elevated economic policy uncertainty, high investor sentiment, and in the non-COVID-19 pandemic period. These results remain robust across various proxies for ESG scores and style drift, as well as when considering fund fixed effects. Our findings suggest that investors and managers from funds with high ESG performance share common long-term sustainable investment objectives, which fosters the stability of fund investment strategy and discourages excessive risk-taking, thereby reducing the likelihood of style drift.

Our results have several important implications. First, the mandatory ESG disclosure requirements in China generate a positive spillover effect from the company level to the fund market. With improved access to ESG information, our results suggest that fund managers are better equipped to integrate ESG factors into their investment strategies, which in turn reduces fund style drift and enhances the overall stability of the fund market. Second, the mandatory disclosure of ESG information enables both institutional investors and retail investors to incorporate ESG considerations into their investment strategies, supporting a broader market transition toward EGS-oriented decision making. Third, our findings contribute timely evidence to the ongoing global debate on socially responsible investment (in particular, the European Commission proposed Omnibus Regulation in 2025 to ease the burden of ESG reporting obligations). Despite ESG investing sometimes associated with inferior performance (e.g., lower returns or fund flows), higher ESG standards are effective in encouraging fund managers to adopt more ethical behaviors and focus on long-term investment goals, ultimately improving financial market stability. In this regard, our findings highlight the value of robust ESG disclosure requirements and sustainable investment practices.

Appendix 3.1 Variable definition

Variables	Definition
SDS	The style drift score of the fund, using return-based style analysis.
ESGscore	It measures the ESG performance of the fund.
Upgrade	A dummy variable that equals one if the fund received an ESG score upgrade in the year prior to the last year, and zero otherwise.
FundAge	The number of years since the fund's inception.
FundSize	The natural logarithm of the fund's total net assets.
FundFamilyAge	The number of years since the fund family's establishment.
FundFamilySize	The total assets under management by the fund family.
ExpenseRatio	The ratio of the fund's management and custodian fees to its total net assets.
Turnover	The greater of total purchases or total sales of securities during the reporting period, divided by the fund's average net assets over the same period.
Single	A dummy variable that equals one if the fund is managed by a single manager, and zero if it is managed by a team.
EPU	A dummy variable that equals one if the value of EPU exceeds the median value of the full sample in each year, and zero otherwise.
Sentiment	A composite sentiment index based on the common variation in six underlying proxies of market sentiment.
ManagerPracticeScore	Includes more than 400 management and practice indicators across the E, S, and G pillars, capturing long-term ESG fundamental impacts.
ControversiesScore	Reflects short-term ESG risks based on over 1,200 risk labels, measures the ESG-related controversies a company faces during a fiscal year.
InvestmentConcentration	Calculated as the weighted average of the top ten holdings in the fund, based on the percentage of current assets invested in each stock.
Disclosure	A dummy variable equal to one if a fund discloses its ESG score for the first time, and zero otherwise.

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Chapter Four: ESG diversification profiling and window dressing – Evidence from China

In Chapter Three, the findings show that ESG integrated investing reduces style drift, aligning with prior evidence that high ESG investing enhances returns, attracts fund inflows, and lowers risk (Tampakoudis et al., 2023; El Ghoul and Karoui, 2017; Bae et al., 2020). However, relying solely on fund-level overall ESG scores may be insufficient, as high ESG exposure can result from either intentional or incidental factors. To investigate this issue further, Chapter Four develops a novel new measure, namely ESG profile diversity (ESGPD), to capture variations in ESG scores across fund holdings and further examines its implications on fund window dressing. Section 4.1 is the introduction for this chapter. Section 4.2 reports literature review and hypothesis development. Section 4.3 describes the data sources and methodology used in the analysis. Sections 4.4 and 4.5 present empirical findings and additional analyses. Section 4.6 discusses the robustness checks, and Section 4.7 concludes the study.

Abstract

This chapter investigates the role of fund holdings' ESG profile diversity (ESGPD) in explaining window dressing among Chinese mutual funds. This study finds a significant positive relationship between ESGPD and window dressing, with an increase of 10.64 units in window dressing for every one-unit increase in a fund's ESGPD. Further analysis demonstrates that ESGPD has a differential impact on window dressing across various fund and manager characteristics, as well as under different market conditions. The robustness of the findings is supported by alternative measures of ESGPD, window dressing, and alternative models. The findings provide valuable implications beyond overall ESG ratings for managers and investors, enhancing their understanding of the factors driving window dressing and promoting greater transparency in fund management practices.

Keywords: ESGPD; Window dressing; ESG; Mutual fund; Fund manager; Fund performance

JEL: G11; G23; M14

4.1 Introduction

Fund voluntary nonfinancial disclosure, particularly on Environmental, Social, and Governance (ESG) performance, has recently drawn growing attention from researchers and market participants (Tsang et al., 2023). Socially responsible investors increasingly favor assets with ESG integrated investing, and fund managers are adopting ESG principles in portfolio construction. By the end of 2022, the Asset Management Association of China reported that 296 mutual funds, which focus on ESG investing, collectively managed over USD 55.5 billion (about RMB 403.7 billion) in assets.[24] Strong ESG performance not only enhances a fund's reputation and brand image but also provides fund management companies with resources that can foster sustainable competitive advantages (Bhandari et al., 2022).

Despite fund managers' stated commitment to ESG principles and the inclusion of ESG-labeled assets in their portfolios, studies to date tend to focus on the aggregate fund ESG ratings (e.g., high ESG investing is associated with superior returns (Tampakoudis et al., 2023), greater fund inflows (El Ghoul and Karoui, 2017), and lower risk (Bae et al., 2020)), without a deeper investigation into fund holdings' ESG profile. Our preliminary analysis reveals an interesting pattern in this regard: managers often simultaneously invest in both high- and low-ESG score assets even for ESG funds.

It seems that examining only the fund-level ESG score may be insufficient. Fund managers can achieve high ESG exposure through two distinct paths: intentional and unintentional. Purpose-driven managers deliberately incorporate ESG principles into their investment strategies to promote long-term sustainability, enhance ethical decision-making, and mitigate regulatory or reputational risks (Hoepner et al., 2024). These managers actively select high-ESG assets to align with their values and objectives. In contrast, non-ESG-oriented managers may hold high-ESG assets unintentionally due to unrelated factors such as financial characteristics or industry exposure, resulting in portfolios that

[24] More details can be found in China's Green Financing Surges to $4.1 Trillion in 2023, Boosting ESG Investments - ESG News.

appear ESG-friendly by coincidence. Therefore, it is crucial to investigate the ESG profiles of fund holding.

To capture the variability of ESG scores among fund holdings, we propose a new measure, namely ESG Profile Diversity (ESGPD). A high ESGPD indicates that a fund holds a broad range of stocks with varying ESG scores, reflecting greater heterogeneity in ESG characteristics within the portfolio. Applying this measure to 3,302 Chinese mutual funds, we find that more than two-thirds mutual funds exhibit ESGPD values above the sample average, indicating considerable diversity in their ESG compositions.

We propose two plausible explanations for why fund managers may favor high ESGPD. First, the mutual fund industry in China faces increasing pressure to align with ESG initiatives (Liu et al., 2023). However, such ESG engagement may not be inherently value-maximizing (e.g., high-ESG stocks are often associated with lower short-term returns, see Stotz, 2022). Chinese funds are hence incentivized to balance ESG standards with financial returns. Fund managers include high ESG stocks to demonstrate their commitment to ESG principles, while simultaneously holding low ESG stocks to maintain financial returns and competitiveness. Second, fund managers may wish to include "something for everyone" through increasing the heterogeneity of stock holdings to meet investors' diverse expectations.

For both motives, we argue it could lead to fund window dressing. Window dressing refers to the practice where fund managers change their portfolio holdings just before the reporting date—typically by selling underperforming assets and retaining or acquiring top-performing ones—to present a more favorable image of the fund's performance (Musto, 1997, 1999; Ng and Wang, 2004; Morey and O'Neal, 2006; Agarwal et al., 2014). This strategy can help managers impress key stakeholders, such as fund sponsors, by temporarily enhancing the fund's reported appearance (Lakonishok et al., 1991). However, it may send misleading signals to investors regarding the manager's actual skill, particularly when poor returns are masked by strategically curated holdings

(Xin et al., 2024). In addition, such behavior can distort the flow of capital by attracting investment into underperforming funds (Kim and Park, 2025).

Understanding the drivers behind window dressing is thus essential for both managers and potential investors aiming to make decisions. ESGPD could positively relate to window dressing. On the one hand, managers of high ESGPD funds are pressured to showcase a good tradeoff between ESG commitment and financial returns, potentially promoting their engagement in window dressing. On the other hand, funds with higher ESG profile diversity may have greater flexibility to engage in window-dressing behavior, as a more heterogeneous portfolio makes such behavior less detectable.

The majority of existing research on window dressing focuses on the U.S. market, on both its causes and consequences. U.S. mutual funds are typically found to engage in window dressing—adjusting portfolio holdings to appear more attractive to investors—particularly near the end of reporting periods (Lakonishok et al., 1991; Meier and Schaumburg, 2004; Elton et al., 2010). Various incentives have been identified in the literature, e.g., investor behavior (Wang, 2014), managerial demographics (Bai et al., 2019), higher job termination costs (Cici et al., 2021), higher reporting frequency (Xin et al., 2024), and information asymmetry (Kim and Park, 2025). In terms of window dressing consequences, it can negatively affect asset prices (e.g., Ng and Wang, 2004). Outside the U.S., Ortiz et al. (2012) investigate Spanish bond funds and conclude that disclosure timing may influence portfolio decisions, potentially misleading investors. Moreover, Marques et al. (2019) examine Brazilian investment funds and discover that window dressing behavior is more prevalent among funds managed by smaller companies compared to those run by large institutions.

More specifically, socially responsible investment (SRI)-related window dressing is in its early stage[25] and remains a subject of ongoing debate in the Chinese context. Investors typically make

[25] There are three working papers about green window dressing in Western markets. Parise and Rubin (2023) find that fund managers adjust ESG holdings around disclosure dates to temporarily boost ESG exposure, enhancing sustainability ratings and performance. Chen et al. (2024) report that U.S. mutual funds increase holdings in high-ESG stocks before quarter-end, reversing positions shortly after, indicating short-term, performance-driven rebalancing. Similarly, An et al. (2025) observe U.S. actively managed funds significantly increase investments in high-ESG stocks and reduce investments in low-ESG stocks just before quarter-end, quickly reversing these trades at the start of the next quarter.

allocation decisions for the upcoming year toward the end of the current one, during which SRI funds tend to adjust their portfolios toward stocks with higher ESG portfolio score (Kempf and Osthoff, 2008). In contrast, Muñoz et al. (2022) find no evidence that SRI funds artificially enhance their ESG profiles in disclosure reports to attract investor inflows.

Empirical research on window dressing in Chinese mutual fund sector remains scarce, with only two exceptions. Guo (2023) finds evidence of window dressing in the Chinese mutual fund market. Especially, the 10th-largest holdings of mutual funds outperform the 11th-largest holding only before disclosures, with a one standard deviation increase in top 10 returns boosting quarterly inflows by 1.13%. Yu et al. (2023) show that funds with more winning (losing) stocks are more (less) likely to engage in window dressing, primarily through buying recent outperformers and selling underperformers.

In this study, we examine how ESGPD relates to fund window dressing behavior. Our study analyzes 32,227 semi-annual fund observations from 3,302 Chinese mutual funds between 2009 and 2022, beginning in the year when ESG score data became available. Because Chinese mutual funds disclose only their top 10 holdings quarterly and provide full portfolio disclosure semi-annually, we include all open-end mutual funds with semi-annual disclosures available from the WIND and CSMAR databases. Using a multivariate regression model, we find a robust and statistically significant positive relationship between ESGPD and window dressing. This relationship is economically significant, for every one-unit increase in a fund's ESGPD, window dressing rises by 10.64 units.

We extend our analysis by examining how ESGPD's impact on window dressing varies across fund characteristics. First, compared to non-ESG funds, ESG funds face greater pressure to maintain a strong ESG reputation (Ramchander, 2012), their diversification across ESG rankings may primarily reflect genuine portfolio diversification rather than strategic manipulation. As a result, ESG funds should have lower incentives to engage in window-dressing, since their investment strategies

are inherently consistent with ESG objectives. Our results show supportive empirical evidence to this point. Second, we find that the impact of ESGPD on window dressing is stronger among large funds than small funds. Large funds have more flexibility to include diverse stocks, face greater reputational demands and manage more complex portfolios (Luo, 2024), which may incentivize the fund managers to engage more in window dressing. Moreover, we find stronger relation between ESGPD and window dressing among low-ranked funds than high-ranked funds. To attract investor inflows, lower-ranked funds may diversify their stock holdings to appeal to heterogenous investor preferences, resulting in a higher ESG profile diversity and greater propensity for window dressing.

Next, we analyze how ESGPD influences window dressing across different fund manager characteristics. Lower gender diversity within funds is associated with a higher likelihood of overconfident behavior (Huang and Kisgen, 2013; Chen et al., 2016), resulting in investment decisions influenced by personal biases or risk preferences. Consistent with this argument, we find that ESGPD is associated with stronger impact on window dressing among funds with lower gender diversity. Additionally, we observe a stronger relationship between ESGPD and window dressing among older managers. Older managers have greater experience and are better able to make strategic portfolio adjustments aligned with ESG considerations. Moreover, the relation between ESGPD and window dressing also appears to be stronger among funds managed by multiple managers than single managers. Team management can create competition among members, resulting in coordination challenges, interpersonal conflicts, and decision-making delays (Sah and Stiglitz, 1988; Adams et al., 2018). As a result, fund managers often take greater risks by including stocks with varied ESG scores (i.e., higher ESGPD), leading to stronger impact on window dressing activities.

Furthermore, we analyze how the impact of ESGPD on window dressing, evolves over time under different levels of economic policy uncertainty, business cycles, and investor sentiment. Our findings suggest that the effect of ESGPD on window dressing is stronger during periods of high EPU. During high EPU periods, investors tend to pursue safe-haven assets and fund managers encounter

heightened uncertainty in short-term market forecasts. To maintain or attract capital inflows, managers may adjust their ESG goals (Kammoun and Essaddam, 2024), leading to greater diversification of ESG profiles and, consequently, an intensification of window dressing practices. We also show that the influence of ESGPD on window dressing is more pronounced during economic expansions. Under such conditions, fund managers adjust their ESG objectives to signal stability and attract investors, increasing ESG profile diversification. Additionally, consistent with Massa and Yadav (2015), who argue that investor sentiment influences managerial behavior, our findings suggest that during periods of high investor sentiment, investors may pay more attention to sustainability and long-term objectives, which incentivizes fund managers to incorporate a broader mix of ESG stocks. This increased ESG diversification (i.e., higher ESGPD) can potentially amplify window dressing behavior.

For robustness checks, we employ a propensity score matching difference-in-differences (PSM-DiD) approach to evaluate the impact of first time becoming a Principles for Responsible Investment (PRI) signatory on the relationship between ESGPD and window dressing. The first-time signing of the PRI represents an exogenous, institution-level commitment to ESG integrated investing that can influence managers' incentives and disclosure practices. We find a positive and significant coefficient, suggesting that becoming a PRI signatory is associated with an increase in window dressing activities. We also conduct a placebo test to assess potential biases. Alternative measures of window dressing and ESGPD are used to confirm the stability of our results. Furthermore, we examine the impact of ESGPD on various performance metrics, including Fama-French three-factor alpha and fund flow, to assess its influence on fund performance. Finally, fund fixed effects models are employed to validate the main findings. Overall, our results remain consistent across these various robustness checks.

We make two contributions. First, the Chinese mutual fund market remains underexplored in the context of window dressing, and our study addresses this gap by providing the first analysis examining the impact of ESGPD on window dressing. The Chinese mutual fund market presents a

distinct institutional setting for studying portfolio management behavior. Unlike Western markets, Chinese mutual funds are required to disclose their full portfolio holdings only semi-annually, with quarterly disclosures limited to the top ten holdings. This less-frequent reporting schedule offers fund managers a longer adjustment window and greater discretion in managing portfolios between disclosures. Additionally, the Chinese mutual fund industry has undergone rapid growth. The number of mutual funds expanded from 308 in 2006 to 10,174 by 2023, while assets under management increased significantly, rising from RMB 1 trillion to RMB 27.6 trillion over the same period. Exploring the incentives for window dressing in Chinese mutual fund markets is worthwhile.

Second, we propose ESGPD as a novel determinant of window dressing, offering both investors and policymakers a valuable tool for more informed decision-making. Given the inexperience of many Chinese investors, who are more susceptible to being misled by window dressing practices, ESGPD can serve as an important indicator. As Wu and Li (2022) highlight, only 15% of Chinese investors have received comprehensive financial education. This lack of financial literacy, combined with a tendency toward momentum-driven investing, makes them more likely to be influenced by superficial changes in fund portfolios. Our findings suggest that ESGPD can serve as a reliable measure for detecting window dressing, effectively identifying funds that manipulate their portfolios to create a misleadingly favorable impression among uninformed investors.

The remainder of the paper is structured as follows: Section 4.2 reports the literature review and hypothesis development. Section 4.3 describes the data and methodology used in the analysis. Sections 4.4 and 4.5 present main findings and further analyses. Section 4.6 discusses robustness checks, and Section 4.7 concludes this chapter.

4.2 Literature review and hypothesis development

4.2.1 Background

In recent years, individual investors have increasingly participated in China's mutual fund market. According to Liu et al. (2024), this growing trend is evidenced by a sharp rise in mutual fund subscriptions by retail investors. Data from the "Shanghai Stock Exchange (SSE) Statistics Annual Report 2018" show that retail investors accounted for approximately 82% of the SSE's trading volume in 2017. By March 2022, the number of individual investors surpassed 200 million, and the number of fund accounts had grown more than 17 times over the past decade.

Unlike the U.S. capital market—dominated by sophisticated institutional investors—the Chinese mutual fund market primarily caters to relatively unsophisticated retail participants (Jiang et al., 2020). Despite their significant trading presence, numerous studies have pointed out that these individual investors in China often exhibit limited financial literacy and investment experience, which can lead to suboptimal decision-making (Huang et al., 2022). In our context, these investors are most prone to fund manager window dressing due to limited attention and cognitive constraints. They tend to focus on salient and easily observable fund characteristics, such as short-term performance or prominent portfolio features, when evaluating fund managers (Wang, 2014). The backdrop highlights both the importance and relevance to study fund window dressing in Chinese financial markets.

4.2.2 Literature review

Numerous studies have investigated window dressing behavior among mutual funds. Lakonishok et al. (1991) present one of the earliest pieces of evidence, showing that U.S. pension fund managers are more likely to sell underperforming stocks toward the end of reporting periods. Similarly, Meier and Schaumburg (2004) find that portfolio turnover increases in the final days of the quarter, particularly among growth-oriented and poorly performing funds, which are more susceptible

to window dressing practices. Expanding beyond equities, Morey and O'Neal (2006) report that bond funds tend to increase their holdings of government bonds when closer to disclosure time, suggesting a shift toward safer assets to improve perceived fund quality. Elton et al. (2010) contribute further by documenting strong evidence of window dressing around annual report due dates. The impact of window dressing on investor behavior is highlighted by Agarwal et al. (2014), who show that window dressers experience increased investor inflows when performance is good, whereas poorly performing dressers face reduced inflows—implying that window dressing influences capital allocation decisions by investors.

The determinants of window dressing have been widely discussed in recent years. Mutual funds with poor past performance, high expense ratios, and shorter tenure are more likely to engage in window dressing to improve the perceived quality of their portfolios at reporting dates (Lakonishok et al., 1991; Chevalier and Ellison, 1997; Zheng, 1999). In addition, due to limited attention, investors tend to focus on prominent features of a portfolio when evaluating fund managers, which creates incentives for window dressing (Wang, 2014). Bai et al. (2019) observe that younger fund managers are more likely to engage in window dressing, as they are less confident in their past decision-making and seek to hide poorly performing stocks at the end of a reporting period. By window dressing their portfolios, fund managers can improve their standing and job security within the industry, as this strategy can attract new investments and generate higher income. Fund managers may be particularly incentivized to window-dress given the increased job termination costs associated with stronger enforcement of non-compete clauses in recent years (Cici et al., 2021).

Moreover, the Securities and Exchange Commission's (SEC) 2004 mandate requiring mutual funds to report their holdings quarterly resulted in more frequent disclosures. This increased transparency may have unintentionally encouraged fund managers to engage more in window dressing to improve the appearance of their portfolios before each reporting date. Xin et al. (2024) find consistent evidence that more frequent reporting actually exacerbates window dressing,

particularly among funds managed by lower-skilled managers. Furthermore, mutual funds' window dressing often arises from information asymmetry regarding their trading activities, which motivates some fund managers to manipulate their portfolios to attract greater inflows (Kim and Park, 2025).

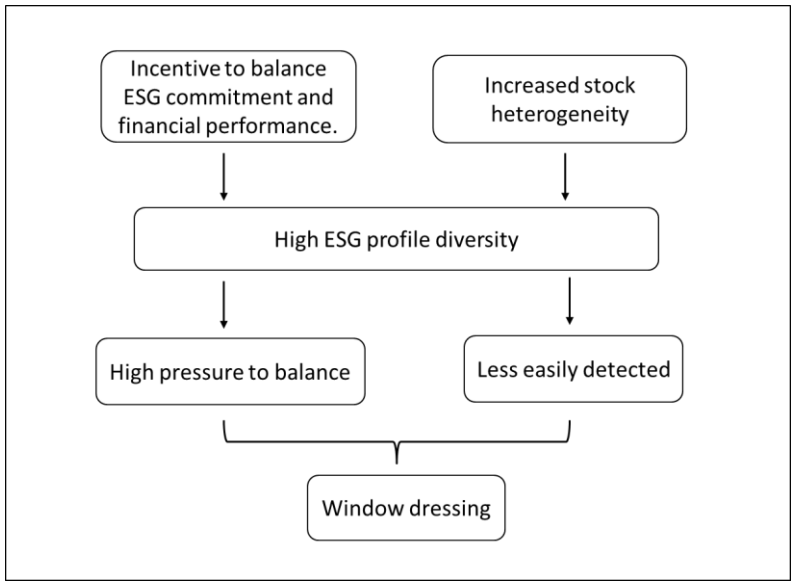
Despite the incentives of window dressing and its benefit for fund managers, several studies have found that window dressing negatively impacts securities' performance (Musto, 1997, 1999; He et al., 2004; Ng and Wang, 2004; Morey and O'Neal, 2006). Xin et al. (2024) observe that under the new rule requiring higher reporting frequency, funds exhibiting higher levels of window dressing tend to experience lower long-term returns, less fund flows, and an increased risk of collapse. Furthermore, from a new perspective, Kim and Park (2025) focus on firm-level window dressing, exploring the relationship between shareholder funds' window dressing and earnings management by investee firms. They find that funds engaging in window dressing are more likely to reduce their holdings in stocks that have experienced negative earnings surprises.

4.2.3 Hypothesis development

We develop our hypothesis from two perspectives. First, fund managers face pressure to align with ESG initiatives (Liu et al., 2023) while balancing ESG commitments with financial performance. However, ESG engagement may not always be value-maximizing (e.g., high-ESG stocks are often associated with lower short-term returns; see Stotz, 2022). Consequently, fund managers are incentivized to balance ESG standards and financial returns by including both high- and low-ESG stocks—holding high-ESG stocks to signal commitment to ESG principles and low-ESG stocks to sustain returns and competitiveness—resulting in higher ESGPD. Managers of high-ESGPD funds therefore face pressure to present a favorable trade-off between ESG commitment and financial performance, making them more likely to adjust holdings prior to reporting periods.

Figure 4. 1. Chapter Four process of hypothesis development

The figure summarizes the hypothesis development process based on theoretical and empirical foundations.



Second, fund managers may aim to include "something for everyone" by increasing portfolio heterogeneity to meet investors' diverse expectations. Those motivated by career concerns and short-term performance pressures tend to take greater risks in volatile markets (Chevalier and Ellison, 1997). Cici et al. (2021) also show that job insecurity encourages risk-taking behavior. Such incentives may lead managers to engage in window dressing to enhance apparent performance and reduce dismissal risk. Greater stock heterogeneity provides flexibility for such activities, as they become less detectable when portfolios contain a wider range of stocks.

Overall, we hypothesize that fund managers are more likely to engage in window dressing when ESGPD is high. On the one hand, managers of high-ESGPD funds face pressure to demonstrate a balance between ESG commitment and financial performance, potentially encouraging window dressing. On the other hand, greater stock heterogeneity provides flexibility for such behavior, as it is less likely to be detected in more diversified portfolios. The rationale for this hypothesis is illustrated in Figure 4.1.

H5: Funds with higher ESG profile diversity are more likely to engage in window dressing behavior, particularly before disclosure dates.

4.3 Data and methodology

4.3.1 Sample and data

We obtain our fund-level data from the WIND and CSMAR databases, cross-checking across both to ensure sample accuracy and inclusiveness. We use the Sino-Securities Index (SNSI) ESG score to capture fund ESG profile, available and widely used in China since 2009. To maintain consistency in our analysis, we exclude funds that invest in foreign stocks, otherwise which could introduce errors in risk-adjusted return calculations due to different foreign market regulations (Yu et al., 2023). Our study includes all open-end mutual funds with semi-annual data from 2009 to 2022, resulting in a final sample of 32,227 observations across 3,302 funds. To minimize the impact of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

4.3.2 Measuring window dressing

We adopt the rank gap approach proposed by Agarwal et al. (2014) as a relative measure of window dressing. This method captures the discrepancy between a fund's actual performance ranking and a ranking based on the proportions of winner and loser stocks disclosed at the end of each semi-annual period.

Specifically, at the end of each fiscal semi-annual period, we classify all domestic stocks listed on the Shanghai and Shenzhen Stock Exchanges into quintiles according to their past period returns, with the first quintile representing the highest-performing stocks and the fifth quintile the lowest. Based on each fund's reported holdings, we then calculate the proportions of its portfolio allocated to the top-quintile ("winners") and bottom-quintile ("losers") stocks.

For each fiscal semi-annual period in which at least 100 funds report holdings, we construct three rankings: (1) by semi-annual fund performance (descending), (2) by the proportion of winners held (descending), and (3) by the proportion of losers held (ascending). In the first ranking, funds are

ordered by semi-annual raw returns in descending order, with those in the top percentile assigned a rank of 1 and those in the bottom percentile a rank of 100. The second and third rankings are constructed analogously. A well-performing fund should rank highly in both performance and the related winner/loser proportions. In contrast, a fund with weak performance but disproportionately high exposure to winners or low exposure to losers may be engaging in window dressing. Figure 4.2 provides a visual illustration of the ranking procedures.

Figure 4. 2. Design of the rank gap method

Rank	Fund performance	Winner proportion	Loser proportion
1	1 (best performance)	1 (highest proportion)	1 (lowest proportion)
2	2	2	2
3	3	3	3
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
98	98	98	98
99	99	99	99
100	100(worst performance)	100(lowest proportion)	100(highest proportion)

Finally, we compute the *Rank Gap* as the difference between a fund's performance rank and the average of its winner and loser ranks:

$$Rank\ Gap = PerformanceRank - \frac{WinnerRank + LoserRank}{2} \tag{26}$$

where *PerformanceRank* is the ranking of fund returns, *WinnerRank* is the ranking based on winner holdings, and *LoserRank* is the ranking based on loser holdings. A larger rank gap indicates a higher likelihood of window dressing.

4.3.3 Measuring ESG profile diversity

We introduce a novel measure, Environment, Social, Governance profile diversity (ESGPD), to assess the diversity of stock-level ESG profiles in a fund's holdings. To construct ESGPD, we first gather firm-level SNSI ESG scores, which are available from 2009 to 2022. SNSI categorizes firms into nine ESG rating categories, ranging from AAA (highest) to C (lowest). Next, for each stock *j* held by a fund *i* in a semiannual period *t*, we calculate its ESG weighting towards a fund's total ESG score as:

$$ESGweighting_{j,t} = ESGscore_{j,t} \times Stock\ holding\ proportion_{j,t} \tag{27}$$

where $ESGscore_{j,t}$ is the SNSI ESG score of stock *j* at time *t*, and $Stock\ holding\ proportion_{j,t}$ is the proportion of stock *j* held by fund *i* at time *t*. For each fund *i*, we compute the sum of all stock-level ESG weightings across all holdings for each semiannual period *t*. We then divide each ESG weighting of stock *j* by this sum to ensure that the total ESG weight for each fund equals one, and obtain $w_{j,t}$. Finally, building on the methodologies of Woerheide and Persson (1992), Ivković et al. (2008), and Fulkerson and Riley (2019), we calculate the Herfindahl–Hirschman ESG index to quantify the concentration of a fund's ESG holdings.

$$HHESG_{i,t} = \sum_{i=1}^{n} (w_{j,t})^2 \tag{28}$$

Finally, we use one minus *HHESG*, to obtain the fund level ESGPD[26]:

$$ESGPD_{i,t} = 1 - HHESG_{i,t}$$

[26] Here is an example to demonstrate the calculation. Suppose a hypothetical fund invests 50% in a stock with an AAA ESG rating and 50% in a stock with a C ESG rating. We then calculate the ESGPD. If AAA corresponds to the score of 96 and C corresponds to the score of 54, the *ESGweighting* are 48 and 27, respectively. Next, we sum them to obtain 48 + 27 = 73. In general, we calculate the *w* by dividing it by the total ESG weights of all holdings in the fund for that period. Based on this, the *w* for each stock is 65.75% and 36.99%. Using these weights, the *HHESG* is calculated as 0.5691, which gives an *ESGPD* of 0.4309. Note that if a hypothetical fund invests 100% in a single stock, the ESGPD would equal 0.

(29)

4.3.4 Baseline model

Our baseline model is presented below:

$$RankGap_{i,t} = a_i + \beta_1 ESGPD_{i,t} + Controls + \theta' FundTypeFE + \psi' SemiyearFE + \varepsilon_{i,t}$$

(30)

where *RankGap* represents the relative measurement of fund window dressing. *ESGPD,* our key explanatory variable, measures the ESG profile diversity of the fund. To account for additional factors affecting fund window dressing, we include the following control variables, drawn from Agarwal et al. (2014) and Bai et al. (2019). *FundAge* is the number of years since the fund's inception (Chen et al., 2004; Yan, 2008), *FundSize* is the natural logarithm of the fund's total net assets (Chen et al., 2004; Yan, 2008), *FundFamilyAge* is the number of years since the fund family's establishment (Yan, 2008; Bai et al., 2019), *FundFamilySize* is the total assets under management by the fund family (Massa, 2003; Chen et al., 2004), *ExpenseRatio* (%) is the ratio of the fund's management and custodian fees to its total net assets (Yan, 2008), *Turnover* is defined as the greater of total purchases or total sales of securities during the reporting period, divided by the fund's average net assets over the same period, which captures the impact of managerial investment activities on window dressing (Kurniawan et al., 2016). *Gender* takes the value of one if the fund management team includes at least one male manager, and zero otherwise. *Experience* reflects the fund managers' experience in the fund management industry measured in number of years (Bai et al., 2019). *Degree* is defined as the highest education attainment of a fund management team (Degree ranges from 1 to 4 for no tertiary qualification, Undergraduate, Master and MBA/EMBA, and Doctorate, respectively). To mitigate potential omitted variable bias, our regression models incorporate fund type[27] and semi-annual fixed

[27] In our sample, funds are classified into Investment Style, Aggressive Growth, Stable Growth, Growth, Value, Robust Value-added, Capital Guaranteed & Value Added, Appreciation, Balance, Income, and Index funds. The data is obtained from CSMAR.

effects, in line with Sensoy (2009) and Hartzmark and Sussman (2019). We use robust standard errors in all regressions. Appendix 4.1 provides a detailed explanation of all variable definitions.

4.4 Main results

4.4.1 Descriptive analysis

Panel A of Table 4.1 presents the summary statistics for the key variables. The average *RankGap* is 1.489, with a median value of 0.500, which suggests that the distribution of *RankGap* is right-skewed. This indicates that, in our sample, while most funds exhibit relatively moderate levels of window dressing, a smaller subset of funds engage in substantially higher window-dressing activities, pushing the mean above the median value. For the main explanatory variable, *ESGPD*, the average and median values are 0.947 and 0.965, respectively, with a range from 0.417 to 0.997, which indicates that most funds hold highly diversified ESG portfolios in our study.

Panel B of Table 4.1 reports the parametric correlation matrix for the main variables in our sample. We first observe a negative and statistically significant unconditional (or raw) correlation between *ESGPD* and *RankGap*. *RankGap* is also negatively associated with fund size, providing initial evidence that larger funds face greater reputational pressure and manage more complex portfolios (Luo, 2024). These factors, in turn, give them stronger incentives and greater flexibility to engage in window dressing. The results on the other correlations also show patterns that are consistent with our hypothesis.

Table 4. 1. Descriptive analysis

This table presents the summary statistics in Panel A and the parametric correlation matrix of the main variables in Panel B. The sample period spans from 2009 to 2022. Appendix 4.1 provides more detailed variable definitions. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary statistics

	N	Mean	SD	Min	Max	Median
Variables	(1)	(2)	(3)	(4)	(5)	(6)
RankGap	32,227	1.489	26.74	-50.50	62	0.500
ESGPD	32,227	0.947	0.0800	0.417	0.997	0.965
FundAge	32,227	6.140	3.596	2	17	5
FundSize	32,227	19.95	1.689	15.16	23.50	20.01
FundFamilyAge	32,227	14.98	4.852	4	24	16
FundFamilySize	32,227	25.59	1.432	21.47	28.05	25.62
ExpenseRatio	32,227	1.390	0.458	0.400	1.750	1.750
Turnover	32,227	3.277	5.402	0.1000	41.63	1.852
Gender	32,227	0.864	0.343	0	1	1
Experience	32,227	9.990	4.058	0	28	10
Degree	32,227	3.123	0.400	2	4	3

Panel B: Parametric correlation											
	RankGap	ESGPD	FundAge	FundSize	FundFamilyAge	FundFamilySize	ExpenseRatio	Turnover	Gender	Experience	Degree
RankGap	1										
ESGPD	-0.035***	1									
FundAge	-0.027***	0.019***	1								
FundSize	-0.081***	0.058***	0.270***	1							
FundFamilyAge	-0.017***	0.035***	0.284***	0.057***	1						
FundFamilySize	-0.046***	0.037***	0.114***	0.215***	0.613***	1					
ExpenseRatio	-0.055***	0.220***	0.176***	0.157***	-0.112***	-0.197***	1				
Turnover	0.062***	-0.272***	-0.065***	-0.175***	0.00400	-0.016***	-0.155***	1			
Gender	-0.019***	0.041***	-0.023***	0.037***	-0.056***	-0.038***	0.104***	-0.018***	1		
Experience	-0.013**	0.00900	0.135***	0.00800	0.234***	0.166***	-0.069***	0.00000	-0.053***	1	
Degree	0.00200	0.040***	-0.016***	0.0000	-0.051***	-0.022***	0.00100	0.00700	0.068***	-0.056***	1

4.4.2 Baseline results

We analyze the relationship between ESGPD and window dressing using model (30) and present the results in Table 4.2. In columns (1), we include fund type fixed effects, and in column (2), we employ fund type and semi-annual fixed effects simultaneously.

Our initial findings show a positive relationship between ESGPD and window dressing when applying fund type fixed effects. Specifically, when we are using the full model with fund type and semi-annual fixed effects in column (2), we observe a sizeable impact that every one-unit increase in ESGPD corresponds to 10.64 units increase in *RankGap*. These results provide strong evidence that funds with greater ESGPD are associated with higher levels of window dressing and support our previous discussion. On the one hand, fund managers face pressure to align with ESG initiatives (Liu et al., 2023) while balancing ESG commitments with financial performance by including both high- and low-ESG stocks—holding high-ESG stocks to signal commitment to ESG principles and low-ESG stocks to sustain returns and competitiveness—resulting in higher ESGPD. Managers of high-ESGPD funds therefore face pressure to present a favorable trade-off between ESG commitment and financial performance, which may encourage window dressing behavior. On the other hand, fund managers may aim to include "something for everyone" by increasing portfolio heterogeneity to meet investors' diverse expectations. Greater stock heterogeneity provides additional flexibility for such practices, as they become harder to detect when portfolios contain a wider variety of stocks.

4.5 Further analysis

4.5.1 Different fund characteristics

In this section, we conduct a series of sub-sample analyses to examine whether and how various fund characteristics influence the relationship between ESGPD and window dressing. Specifically, we focus on ESG funds, fund size, and fund ranking. We propose the following hypothesis:

H6: The relationship between ESGPD and window dressing is influenced by fund characteristics, including ESG theme, fund size, and fund ranking.

Table 4. 2. Baseline results

This table reports the main regression outcomes assessing the influence of *ESGPD* on fund window dressing for the period from 2009 to 2022. The dependent variable is RankGap, which measures the inconsistency between a fund's actual performance ranking and a ranking based on the proportions of winner and loser stocks disclosed at the end of each semi-annual period. The key explanatory variable is *ESGPD,* which reflects ESG profile diversity of the fund. Control variables include fund age, fund size, fund family age, fund family size, expense ratio, turnover, gender, experience, and degree. In columns (1), we include fund type fixed effects, and in column (2), we employ the full model with fund type and semi-annual fixed effects. Robust standard errors applied in all regressions. The p-values of the regression coefficients are reported in parentheses, and *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 4.1 for more detailed variable definitions.

	RankGap	
Variables	Fund type FE	Fund type and semi-annual FE
	(1)	(2)
ESGPD	8.4118***	10.6426***
	(0.00)	(0.00)
FundAge	0.0213	0.1204**
	(0.64)	(0.01)
FundSize	-0.7298***	-0.8522***
	(0.00)	(0.00)
FundFamilyAge	0.1165***	0.1927***
	(0.00)	(0.00)
FundFamilySize	-0.8173***	-0.5577***
	(0.00)	(0.00)
ExpenseRatio	-7.4966***	-8.1570***
	(0.00)	(0.00)
Turnover	0.2538***	0.2685***
	(0.00)	(0.00)
Gender	-0.7744*	-0.9242**
	(0.07)	(0.03)
Experience	-0.1083***	-0.0198
	(0.00)	(0.60)
Degree	0.5540	0.6753*
	(0.13)	(0.06)
Constant	36.7298***	27.2262***
	(0.00)	(0.00)
Observations	32,227	32,227
Adjusted R-squared	0.0304	0.0386
Fund type fixed effects	YES	YES
Semi-annual fixed effects	NO	YES

Our first analysis splits the sample based on whether a fund is classified as an ESG fund, with the results presented in columns (1) and (2) of Table 4.3. ESG fund data is obtained from WIND. We find that ESGPD has a positive and significant effect on window dressing among non-ESG funds, with a corresponding coefficient of 10.2991. We provide the first evidence that ESG funds in China are less involved in window dressing compared to other types of general funds. The first insight can be attributed to the limited sample size of ESG funds. Additionally, ESG funds prioritize social responsibility and face greater pressure to maintain a strong ESG reputation (Ramchander, 2012). Since ESG funds are specifically designed to follow ESG principles, their diversification across ESG rankings primarily reflects genuine portfolio diversification rather than strategic manipulation. Consequently, ESG funds have less incentive to engage in window-dressing activities, as their investment objectives are inherently aligned with ESG goals.

The second analysis, presented in columns (3) and (4) of Table 4.3, examines the role of fund size in the relationship between ESGPD and window dressing. We test this by dividing the sample into small and large funds, with large funds defined as those whose assets exceed the 50th percentile in a given year. We find that the effect of ESGPD on window dressing is significantly stronger for larger funds. Specifically, for larger funds, the coefficient of ESGPD is 12.5808, compared to 6.2525 for smaller funds. Larger funds face greater reputational pressure and manage more complex portfolios (Luo, 2024), which gives them stronger incentives and greater flexibility to include a wider variety of stocks to meet diverse investor preferences. These stocks often differ in ESG scores, contributing to higher ESGPD, and resulted in stronger impact on window dressing.

Finally, we analyze the impact of fund performance rankings on the relationship between ESGPD and window dressing, as presented in columns (5) and (6) of Table 4.3. We divide the sample into high- and low-performance ranking funds based on mutual fund 3-year rankings obtained from WIND. These rankings are determined by a comprehensive risk-return evaluation over a three-year period and range from 1 to 5.

Table 4. 3. Different fund characteristics

This table presents the results of three different fund characteristics based on our baseline regression. The first analysis, shown in columns (1) and (2), splits the sample based on whether a fund is classified as an ESG fund. The second analysis, reported in columns (3) and (4), dividing the sample into small and large funds, with large funds defined as those whose assets exceed the 50th percentile in a given year. As presented in columns (5) and (6) of Table 4, we divide the sample into high- and low-ranking funds based on mutual fund 3-year rankings obtained from WIND. We include the same set of control variables as in the baseline model. Additionally, we control fund type and semi-annual fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 4.1 for more detailed variable definitions.

	RankGap					
Variables	ESG funds	Non-ESG funds	Large funds	Small funds	High-ranking	Low-ranking
	(1)	(2)	(3)	(4	(5)	(6)
ESGPD	35.5370	10.2991***	12.5808***	6.2525**	2.6967	15.9041***
	(0.15)	(0.00)	(0.00)	(0.02)	(0.39)	(0.00)
Observations	1,394	30,833	16,110	16,117	13,586	18,641
Adjusted R-squared	0.1989	0.0370	0.0596	0.0359	0.0561	0.0740
Controls	YES	YES	YES	YES	YES	YES
Fund type fixed effects	YES	YES	YES	YES	YES	YES
Semi-annual fixed effects	YES	YES	YES	YES	YES	YES

We find that the effect of ESGPD on window dressing is significantly stronger for low-ranking funds. Specifically, for low-ranking funds, the coefficient of ESGPD is 15.9041, compared to 2.6967 for high-ranking funds. Unlike higher-ranked funds, which tend to follow their investment mandates due to established performance and investor trust (Blake and Morey, 2000), lower-ranked funds face greater pressure to attract investor inflows. They are more inclined to include different types of stocks to satisfy varying investor preferences, which may result in high ESG profile diversity and stronger associated impact on window dressing.

4.5.2 Different fund manager characteristics

Fund managers may face survival or career pressures within their companies, and their individual characteristics could influence the way ESGPD affects their window dressing behavior. We further hypothesize that the impact of ESGPD on window dressing may vary depending on fund

manager characteristics, including gender diversity, manager age, and the presence of multiple managers. And we propose hypothesis as follows:

H7: The relationship between ESGPD and window dressing is influenced by fund manager characteristics, including gender diversity, manager age, and team management.

The first analysis examines the role of gender diversity, as shown in columns (1) and (2) of Table 4.4. Following Calder-Wang and Gompers (2021), we define high gender diversity as having a proportion of female managers above the sample median, and low gender diversity otherwise. Our results reveal that the coefficient for ESGPD is 11.2058 for funds with low gender diversity, and it is statistically significant, suggesting that the relationship between ESGPD and window dressing is stronger in funds with lower gender diversity. Research shows that increased gender diversity improves fund performance and risk management (Barber and Odean, 2000; Bliss and Potter, 2002; Calder-Wang and Gompers, 2021), suggesting that funds with more female managers tend to be more disciplined and less prone to overconfidence. Conversely, funds with lower gender diversity are more likely to exhibit overconfidence (Huang and Kisgen, 2013; Chen et al., 2016), leading to stock selection based on personal biases or risk appetite. This behavior can result in higher ESG profile diversity, which in turn increases window dressing.

Next, in columns (3) and (4) of Table 4.4, we examine the influence of manager age on the relationship between ESGPD and window dressing. We define a manager as older if their age is above the sample median in a given year, and as younger otherwise. Our results show that the coefficient for ESGPD is 23.7878 for the older manager group, compared to 14.7913 for the younger manager group. This suggests that the impact of ESGPD on window dressing is stronger among older managers. More experienced managers are better able to strategically adjust portfolio holdings in response to ESG considerations. In contrast, younger managers, facing higher career risk and a greater likelihood of termination due to poor risk-adjusted returns, may adopt less mature strategies. Consequently,

funds managed by older managers tend to exhibit higher ESGPD, as these managers are more capable of implementing deliberate and considered adjustments.

Lastly, since the risk-taking behavior of team-managed funds differs from that of single-manager funds (Kurniawan et al., 2016), we analyze the effect of having multiple managers versus a single manager in columns (5) and (6) of Table 4.4. Our results show that funds managed by multiple managers are more likely to engage in window dressing compared to those with a single manager. The coefficient for ESGPD is 10.5666 for funds with multiple managers, compared to 10.1531 for single-manager funds. Including multiple managers in a team can lead to competition among members, causing coordination problems, interpersonal conflicts, and delays in decision-making (Sah and Stiglitz, 1988; Adams et al., 2018). Consequently, fund managers are more likely to include stocks with diverse ESG scores in their portfolios to suit their different objectives and needs, which results in higher ESGPD and more window dressing activities.

Table 4. 4. Different fund manager characteristics

This table presents the results of three different fund manager characteristics based on our baseline regression. The first analysis, presented in columns (1) and (2), examines the role of gender diversity. In columns (3) and (4), we explore how manager age influences the relationship between ESGPD and window dressing. Finally, columns (5) and (6) analyze the effect of having multiple managers versus a single manager on this relationship. We include the same set of control variables as in the baseline model. Additionally, we control fund type and semi-annual fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 4.1 for more detailed variable definitions.

	RankGap					
Variables	High gender diversity	Low gender diversity	Old managers	Young managers	Multiple managers	Single managers
	(1)	(2)	(3)	(4	(5)	(6)
ESGPD	9.8753***	11.2058***	23.7878**	14.7913**	10.5666**	10.1531***
	(0.00)	(0.00)	(0.01)	(0.03)	(0.03)	(0.00)
Observations	19,961	12,266	1,988	1,922	7,553	24,674
Adjusted R-squared	0.0361	0.0459	0.0664	0.0347	0.0506	0.0371
Controls	YES	YES	YES	YES	YES	YES
Fund type fixed effects	YES	YES	YES	YES	YES	YES
Semi-annual fixed effects	YES	YES	YES	YES	YES	YES

4.5.3 Different market states

In this section, we conduct several sub-period analyses to examine whether and how different market conditions influence the relationship between a fund's ESGPD and window dressing. Specifically, we investigate the effects of Economic Policy Uncertainty (EPU), business cycle, and investor sentiment on this relationship. We also propose hypothesis as follows:

H8: The relationship between ESGPD and window dressing is influenced by market period, including EPU, business cycle, and investor sentiment.

The first analysis, presented in columns (1) and (2) of Table 4.5, divides our sample based on funds' exposure to EPU during the same year. Following the methodology of Baker et al. (2016) and Davis et al. (2019), we use data from the Economic Policy Uncertainty website. EPU is calculated as the scaled frequency of articles discussing policy-related economic uncertainty in two prominent Chinese newspapers: Renmin Daily and Guangming Daily.

The coefficients for high- and low-EPU periods are both significant, with values of 21.7264 and 5.7421, respectively. Our findings suggest that the effect of ESGPD on window dressing is stronger during periods of high EPU. In such periods, investors often seek safe-haven assets, and fund managers face greater difficulty in predicting short-term market movements. To signal stability and attract investment, managers are more likely to adjust their ESG objectives (Kammoun and Essaddam, 2024), increasing ESG profile diversification and thereby amplifying window dressing behavior.

The second analysis examines the effects across different phases of the business cycle, as presented in columns (3) and (4) of Table 4.5. To construct the business cycle indicator, we follow the methodology of Mariano and Murasawa (2003) and define $Cycle_{GDP}$ as follows:

$$Cycle_{GDP} = \frac{GDP_{current\ quarter} - GDP_{same\ quarter\ last\ year}}{GDP_{same\ quarter\ last\ year}} \times 100\% \tag{31}$$

In our sample, we define high business cycle as when the value of $Cycle_{GDP}$ exceeds the sample median, and low otherwise. Our analysis shows that the influence of ESGPD on window dressing is more pronounced during periods of economic expansion periods. Specifically, the estimated coefficients are 12.12 during expansion periods and 9.0449 during contraction periods. During economic expansions, mutual fund managers face stronger competition and greater investor attention. To attract capital and signal responsible management, they often diversify across ESG stocks, leading to higher ESGPD. This strategy can amplify window dressing, as adjustments may aim more at improving reported ESG metrics than at genuine sustainability.

The third analysis, reported in columns (5) and (6) of Table 4.5, investigates how investor sentiment influences the relationship between ESGPD and window dressing. According to Barberis et al. (1998), investor sentiment tends to intensify when investors are exposed to a sequence of consistent positive or negative information, often leading to exaggerated price reactions due to the representativeness heuristic. Following Baker and Wurgler (2006), we construct a composite investor sentiment index derived from the common components of six widely recognized market sentiment indicators.

$$SENTIMENT_t = -0.241 \times CEFD_t + 0.242 \times TURN_t + 0.253 \times NIPO_t + 0.257 \times RIPO_{t-1} + 0.112 \times SHARE_t - 0.283 \times PDND_{t-1}^{D-ND} \quad (32)$$

We construct the investor sentiment index using six commonly adopted proxies, consistent with Baker and Wurgler (2006). The components include: *CEFD*, the average closed-end fund discount, representing the deviation between a fund's net asset value and its market price; *TURN*, the overall market turnover ratio, calculated as total trading volume divided by total market capitalization; *NIPO* and *RIPO*, representing the number and average first-day returns of IPOs, respectively; *SHARE*, the proportion of equity financing relative to total equity and debt financing; and *PDND*, the natural logarithm of the dividend premium, capturing investors' preference for dividend-paying stocks.

Our findings, presented in columns (5) and (6) of Table 4.5, indicate that the impact of ESGPD on window dressing is significantly strong during periods of high investor sentiment. Specifically, the coefficient for ESGPD is 16.7096 during high-sentiment periods, compared to 14.0559 during low-sentiment periods. These results align with Massa and Yadav (2015), who suggest that investor sentiment shapes fund managers' strategic behaviors. Under optimistic market conditions, ESGPD can amplify window dressing behavior, as investors tend to pay more attention to sustainability and long-term objectives during periods of high confidence. To attract investor capital and enhance perceived fund quality, managers are incentivized to incorporate a broader mix of ESG stocks into their portfolios. This increased diversification across ESG dimensions—reflected in higher ESGPD—provides managers with a tool to improve their visibility and reputation, thereby strengthening the effect of window dressing.

Table 4. 5. Different market states

This table presents results under three different market conditions, based on our baseline regression. columns (1) and (2) analyze funds during periods of high and low economic policy uncertainty (EPU) within the same year, using EPU data from Renmin Daily and Guangming Daily. Columns (3) and 4) examine the effects across different phases of the business cycle. Columns (5) and (6) explore how ESGPD influences window dressing in environments of high versus low investor sentiment. We include the same set of control variables as in the baseline model. Additionally, we control fund type and semi-annual fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 4.1 for more detailed variable definitions.

	RankGap					
Variables	High EPU	Low EPU	High Business cycle	Low Business cycle	High Sentiment	Low Sentiment
	(1)	(2)	(3)	(4	(5)	(6)
ESGPD	21.7264***	5.7421**	12.1200***	9.0449**	16.7096***	14.0559***
	(0.00)	(0.04)	(0.00)	(0.01)	(0.00)	(0.00)
Observations	9,722	22,505	17,971	14,256	5,967	9,552
Adjusted R-squared	0.0249	0.0535	0.0371	0.0426	0.0251	0.0369
Controls	YES	YES	YES	YES	YES	YES
Fund type fixed effects	YES	YES	YES	YES	YES	YES
Semi-annual fixed effects	YES	YES	YES	YES	YES	YES

4.6 Robustness checks

4.6.1 PSM-DiD test

To reinforce the robustness of our primary findings, we implement a propensity score matching combined with difference-in-differences approach, following established methodologies in the literature (Bertrand et al., 2004; Beck et al., 2010). This empirical strategy is designed to assess the effect of an exogenous policy shock on the relationship between ESGPD and window dressing, thereby addressing potential endogeneity concerns.

We exploit funds' first-time adoption of the Principles for Responsible Investment[28] as an exogenous shock that shape mutual fund managers' ESG diversity profile strategies, which in turn affects their window dressing. Parise and Rubin (2023) note that PRI-signatory funds face stronger reputational pressure to maintain an ESG-friendly image, these signatories also have greater incentives to "appear green."

We estimate the DiD effect using the following model specification:

$$RankGap_{i,t} = a_i + \beta_1 DiD_{i,t} + \beta_2 ESGPD_{i,t} + Controls + \theta' FundTypeFE + \psi' SemiyearFE + \varepsilon_{i,t} \quad (33)$$

where $DiD_{i,t}$ equals one for fund management first become the PRI signatories and zero otherwise, following Beck et al. (2010). It captures the differential impact of ESGPD on fund behavior post-policy, particularly regarding the PRI signatories. Panel A of Table 4.6 reports the average treatment effect on the treated group using caliper-based nearest neighbor propensity score matching with a set of control variables. Panel B shows that $DiD_{i,t}$ has a positive and significant coefficient, indicating that the policy led to increased window dressing. This supports our main findings and addresses endogeneity concerns. We further confirm robustness using caliper-based nearest neighbor matching,

[28] We manually collected data on UNPRI signatory fund companies and their signatory dates from the official website: https://www.unpri.org/signatories/signatory-resources/signatory-directory.

as shown in column (2) of Table 4.6.

Table 4. 6. PSM-DiD

This table reports our robustness check using PSM-DiD to examine the external shock effect on fund performance from 2009 to 2022. We treat the first instance of a fund becoming a Principles for Responsible Investment (PRI) signatory as an exogenous shock. The DiD indicator equals 1 in the period when a fund first signs the PRI, and 0 otherwise. In Panel A, we report the average treatment effect on the treated (ATT) of the PSM-DiD methodology. In Panel B, columns (1) present the DiD without considering PSM, and columns (2) include the results of PSM. We include the same set of control variables as in the baseline model. Additionally, we control fund type and semi-annual fixed effects and apply robust standard errors in all regressions. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 4.1 for more detailed variable definitions.

Panel A: Average treatment effect for RankGap			
Matching method	ATT	Standard Errors	T-statistics
Nearest neighbor matching	-2.4206**	1.0701	-2.26

Panel B: PSM-DiD results	RankGap	
Variables	Before PSM	After PSM
	(1)	(2)
DID	-2.7093***	-2.1924*
	(0.01)	(0.07)
ESGPD	10.6406***	-1.0575
	(0.00)	(0.88)
FundAge	0.1192**	0.1213
	(0.01)	(0.35)
FundSize	-0.8530***	-0.6900**
	(0.00)	(0.02)
FundFamilyAge	0.1958***	0.1260
	(0.00)	(0.35)
FundFamilySize	-0.5293***	0.1968
	(0.00)	(0.77)
ExpenseRatio	-8.1665***	-10.3544***
	(0.00)	(0.00)
Turnover	0.2682***	0.1384
	(0.00)	(0.11)
Gender	-0.9290**	0.3504
	(0.03)	(0.75)
Experience	-0.0228	0.1098
	(0.55)	(0.37)
Degree	0.6561*	-0.4675
	(0.07)	(0.67)
Constant	26.6366***	36.0507
	(0.00)	(0.16)
Observations	32,227	3,945
Adjusted R-squared	0.0387	0.0438
Fund type fixed effects	YES	YES
Period fixed effects	YES	YES

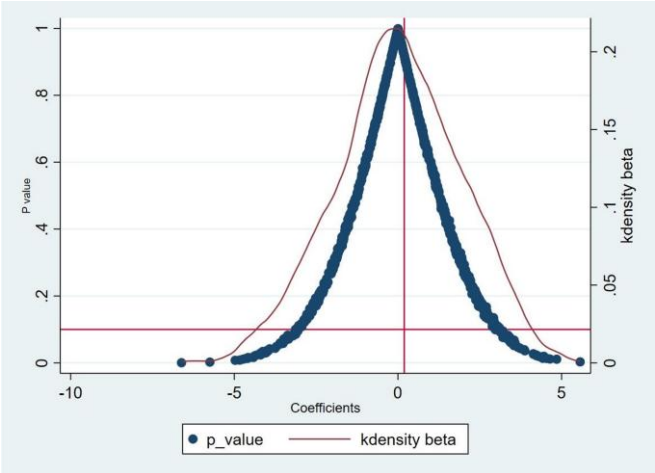
4.6.2 Placebo test

To further address potential endogeneity, we implement a placebo test following Ferrara et al. (2012) and Cai et al. (2016). Specifically, we randomly assign a subset of funds into a pseudo-treatment group and designate a random year as the treatment period. We then re-estimate our baseline regression model using this synthetic dataset. If the observed relationship between ESGPD and window dressing is indeed causal, we should not detect significant coefficient for ESGPD in these placebo tests. This random assignment is repeated 1,000 times to ensure robustness. The distribution of estimated ESGPD coefficients is displayed in Figure 4.3, providing additional validation of our main results.

As illustrated in the placebo test results, the ESGPD coefficients center around a mean of zero, with p-values predominantly exceeding 0.1, indicating a lack of statistical significance in most simulations. This contrasts sharply with our primary findings, where ESGPD consistently exhibits a coefficient of 10.6426, significant at the 1% level. The absence of significant results in the placebo samples, alongside the robust positive association in the actual analysis, reinforces the credibility of our main conclusion and suggests that the observed relationship between ESGPD and window dressing is unlikely to be driven by random chance.

Figure 4. 3. Distribution of regression coefficients (RankGap)

The following figures plot the distribution of regression coefficients for pseudo RankGap, respectively, based on placebo tests.



4.6.3 Alternative measurement of window dressing

Following Agarwal et al. (2014), Solomon et al. (2014), and Xin et al. (2024), we employ an absolute measure—Backward Holding Return Gap (BHRG)—as an alternative indicator of window dressing. This measure is defined as the difference between (a) the semi-annual return of a hypothetical portfolio consisting of a fund's disclosed end-of-period holdings, assumed to have been held throughout the preceding quarter, and (b) the fund's actual return (Kacperczyk et al., 2008):

$$BHRG_{i,t} = Backward\ holding\ return_{i,t} - Actual\ return_{i,t} \tag{34}$$

where $Backward\ holding\ return_{i,t}$ is the sum of the actual return on a fund *i*'s holdings in time *t*, which is weighted by the time the fund held each stock. Aligned with the disclosure frequency in Chinese fund market, our measure *BHRG* based on a semi-annual reporting frequency. We incorporate *BHRG* into our baseline model and obtain similar results in Panel A of Table 4.7, thereby confirming the robustness of our main dependent variable.

4.6.4 Alternative measurement of ESGPD

In Panel B of Table 4.7, we introduce two alternative proxies for ESGPD: $Range_{ESG}$ and SD_{ESG}. $Range_{ESG}$ is defined as the difference between the highest and lowest ESG scores among a fund's holdings in a given period, while SD_{ESG} represents the standard deviation of ESG scores for fund *i* in period *t*. Both variables serve to capture the dispersion of ESG characteristics within a portfolio. The regression results reveal a significant and positive association between these measures and window dressing behavior. Specifically, $Range_{ESG}$ exhibits a coefficient of 0.0036, and SD_{ESG} shows a coefficient of 0.0094. These findings align closely with our primary results, reinforcing the robustness of ESGPD as a valid proxy for detecting window dressing activity.

4.6.5 The impact of ESGPD on fund performance

In this section, we extend our analysis beyond window dressing to explore the influence of ESGPD on additional critical fund performance metrics, including the Fama-French three-factor alpha and fund flows. These analyses offer a more comprehensive understanding of how ESGPD impacts mutual fund behavior as a whole.

The Fama-French three-factor alpha model incorporates market risk, firm size, and book-to-market value as explanatory variables (Fama and French, 1993; Yan, 2008; Rao et al., 2020). The regression specification is as follows:

$$r_{i,t} - r_{f,t} = a_i + \beta_{1,i} \times \left(r_{m,t} - r_{f,t}\right) + \beta_{2,i} \times SMB_t + \beta_{3,i} \times HML_t + \varepsilon_{i,t} \quad (35)$$

where $r_{i,t}$ is the return of fund *i* at month *t*, and $r_{m,t}$ represents the return of the corresponding Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) index returns. The risk-free rate $r_{f,t}$ is the monthly interest rate of the official one-year term deposit (Chen et al., 2018). $r_{m,t} - r_{f,t}$ is the excess return of funds. SMB_i (small minus big) is the average return on the small-capitalization stock portfolio minus the average return on the large-capitalization stock portfolio. HML_t(high minus low) is the average return on a high book-to-market stock portfolio minus the average return on a low book-to-market stock portfolio. To calculate quarterly alpha (a_i), we use a rolling window of 24 months to obtain monthly fund returns and then aggregate them into quarterly returns (Amihud and Goyenko, 2013).

In line with the methodologies of Sirri and Tufano (1998) and Goldstein et al. (2017), we calculate net fund flows by determining the change in the total net assets of each fund between two consecutive quarters, adjusting for the respective fund returns. The net fund flow $Flow_{i,t}$ for fund *i* in quarter *t* is defined as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Return_{i,t})}{TNA_{i,t-1}} \quad (36)$$

where $TNA_{i,t}$ represents the total net asset value of fund *i* at the end of quarter *t*, while $Return_{i,t}$ denotes the rate of return for fund *i* during quarter *t*. As illustrated in Panel C of Table 4.7, the coefficients of ESGPD on fund returns and fund flows are -0.0088 and 0.1348, respectively. Our findings suggest that funds with higher ESGPD tend to experience lower returns, as fund managers are more likely to engage in risk-taking behavior. Risk-taking fund managers increase the likelihood of large negative return shocks, which can trigger fund liquidation and thereby reduce long-term performance and survival (Massa and Patgiri, 2009). Additionally, these managers are also more attuned to investors' diverse expectations, which leads to increased investor flow into such funds.

Table 4. 7. Robustness checks

This table presents the results of several robustness checks. In Panel A, we use *BHRG* as an alternative measure for window dressing and re-estimate baseline regression. Panel B applies alternative measurements of ESGPD, including $Range_{ESG}$ and SD_{ESG}. In Panel C, we extend the analysis by examining the impact of ESG investing on fund performance, using metrics such as Fama-French three alpha and fund flow, to reassess the baseline model. Panel D controls fund and semi-annual fixed effects. We include the same set of control variables as in the baseline model. The regression coefficients are reported with p-values in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See Appendix 4.1 for more detailed variable definitions.

Panel A: Alternative measurement of window dressing	
Variables	BHRG
	(1)
ESGPD	0.1424***
	(0.00)
Observations	32,227
Adjusted R-squared	0.3012
Controls	YES
Fund type fixed effects	YES
Semi-annual fixed effects	YES

Panel B: Alternative measurement of ESGPD		
Variables	RankGap	
	(1)	(2)
$Range_{ESG}$	-1.7703***	
	(0.00)	
SD_{ESG}		-7.2871***
		(0.00)
Observations	32,227	32,006
Adjusted R-squared	0.0581	0.0610
Controls	YES	YES
Fund type fixed effects	YES	YES
Semi-annual fixed effects	YES	YES

Panel C: The impact of ESGPD on fund performance		
Variables	ThreeFactorAlpha	FundFlow
	(1)	(2)
ESGPD	-0.0086***	0.1307***
	(0.00)	(0.00)
Observations	32,227	32,215
Adjusted R-squared	0.2229	0.0296
Controls	YES	YES
Fund type fixed effects	YES	YES
Semi-annual fixed effects	YES	YES

Panel D: Fund fixed effects	
Variables	RankGap
	(1)
ESGPD	20.5385***
	(0.00)
Observations	32,227
Adjusted R-squared	0.0988
Controls	YES
Fund type fixed effects	YES
Semi-annual fixed effects	YES

4.6.6 Fund fixed effects

Finally, we include fund fixed effects in our model to control unobserved heterogeneity across individual funds that may affect the relationship between ESGPD and window dressing. The coefficient for ESGPD with the fund fixed effects is 0.0601, as reported in Panel D of Table 4.7, which remains highly consistent with our main findings.

4.7 Conclusion

In this study, we investigate the relationship between ESGPD and window dressing in mutual funds, providing new insights into how fund managers use ESG considerations for performance manipulation. We find a significant positive relationship between ESGPD and window dressing, with an average increase of 10.64% in window dressing for every one percentage point increase in a fund's ESGPD. Our findings align with the earlier hypothesis that managers of high-ESGPD funds face pressure to achieve appealing short-term performance, leading them to adjust portfolio holdings prior to reporting periods. Moreover, holding a more diverse set of ESG stocks provides these managers with additional flexibility to engage in window dressing, as such practices become harder to detect, thereby intensifying this behavior.

We further explore how ESGPD affects window dressing across different fund characteristics. Our results show that funds with a non-ESG theme, larger sizes, and lower rankings are more likely to increase ESGPD, thereby reducing window dressing. Manager characteristics, also influence ESGPD—lower gender diversity, older managers, and team-managed funds tend to increase ESGPD. The impact of ESGPD varies over time, with its effect on window dressing being stronger during periods of high EPU, economic expansion, and high investor sentiment.

The robustness of our results is supported by alternative measures of ESGPD, window dressing, and fund-level fixed effects. Our study contributes to a deeper understanding of the factors driving

window dressing, promoting greater transparency in fund management practices and providing valuable insights for investors and shareholders.

Moreover, our study makes two important contributions in the context of the Chinese mutual fund market. First, it fills a gap in understanding window dressing in China, where the market is characterized by semi-annual portfolio disclosures and rapid growth, with the number of mutual funds increasing from 308 in 2006 to 10,174 by 2023. Second, we introduce ESGPD as a new determinant for measuring window dressing, offering a valuable tool for investors and policymakers to detect potential manipulation. Given the low financial literacy among Chinese investors, with only 15% receiving comprehensive financial education, ESGPD can help mitigate the risks of misleading fund practices and support more informed decision-making in this rapidly developing market.

Appendix 4.1 Variable definition

Variables	Definition
RankGap	Captures the discrepancy between a fund's actual performance ranking and a ranking based on the proportions of winner and loser stocks disclosed at the end of each semi-annual period.
ESGPD	The ESG profile diversity of fund.
FundAge	The number of years since the fund's inception.
FundSize	The natural logarithm of the fund's total net assets.
FundFamilyAge	The number of years since the fund family's establishment.
FundFamilySize	The total assets under management by the fund family.
ExpenseRatio (%)	The ratio of the fund's management and custodian fees to its total net assets.
Turnover	Defined as the greater of total purchases or total sales of securities during the reporting period, divided by the fund's average net assets over the same period.
Gender	Takes the value of one if the fund management team includes at least one male manager, and zero otherwise.
Experience	The fund managers' experience in the fund management industry measured in number of years.
Degree	The highest education attainment of a fund management team (Degree ranges from 1 to 4 for no tertiary qualification, Undergraduate, Master and MBA/EMBA, and Doctorate, respectively).

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Chapter Five: Conclusion

This chapter summarizes the main findings and implications of the thesis and discusses its limitations and directions for future research.

5.1 Main findings and implications

This thesis examines factors affecting Chinese mutual funds from the perspectives of regulatory requirements and sustainable investing, both highlighting the role of regulation. Chapter Two indicates that the extra regulatory requirements applied to TDFs & TRFs, on fund family size, lock-in period, and manager experience, lead to notable improvements in fund returns and net inflows for retirement funds. In contrast, these requirements have limited or negative effects on ordinary mutual funds, and further analysis reveals potential spillovers within fund families in terms of compliance burdens. These findings highlight the effectiveness of regulatory design in promoting retirement savings and provide valuable insights for policy and investor decision-making.

Chapter Three explores the role of ESG investing in mitigating style drift. The analysis demonstrates a significant negative relationship between fund ESG scores and style drift, which is stronger during periods of high economic policy uncertainty, elevated investor sentiment, and non-COVID-19 pandemic period. The results indicate that investors and managers of high-ESG funds tend to pursue aligned long-term sustainable investment goals, which promote stability in fund strategies and limit excessive risk-taking, thus lowering the risk of style drift. Additionally, the evidence highlights the wider effects of mandatory ESG disclosure, reinforcing sustainable investment practices and contributing to ongoing discussions on socially responsible investing.

Chapter Four extends the analysis by constructing ESGPD to examine the effect of ESG profile diversity on fund window dressing behavior. The empirical results demonstrate that funds with higher ESGPD exhibit greater window dressing. Managers of high-ESGPD funds face pressure to demonstrate a favorable balance between ESG commitments and financial returns, which may encourage window dressing. Moreover, greater stock heterogeneity increases flexibility for such practices, as they are harder to detect in more diversified portfolios. Furthermore, the influence of ESGPD varies across fund and manager characteristics, including fund size, ranking, ESG theme, manager age, gender diversity, and fund management team structure, and is stronger during periods

of high economic policy uncertainty, economic expansions, and elevated investor sentiment. These findings offer new insights into the drivers of window dressing and provide a practical tool for investors and policymakers to detect and mitigate misleading practices.

Taken together, the thesis provides a comprehensive understanding of Chinese mutual fund behavior, demonstrating how regulatory design and ESG integrated investing shape fund performance. The findings contribute to the literature on retirement savings and sustainable investing, inform policy and regulatory discussions, and offer guidance for investors in navigating the rapidly developing Chinese mutual fund market. This study also highlights key considerations for future regulation to enhance both retirement planning and ESG integrated investing.

5.2 Limitation and implications for future research

Despite this thesis's contributions to understanding regulatory requirements and sustainable investing in relation to mutual fund performance in the Chinese market, it faces several limitations and provides implications for future research.

First, this thesis relies solely on data from Chinese mutual funds, which may limit the generalizability of the findings to other markets with different regulatory frameworks, disclosure practices, or investor behaviors. Future researchers are encouraged to extend the analysis to other contexts to enhance cross-market comparability. Second, the sample size of TDFs & TRFs in Chapter Two is relatively small, as this remains a new and emerging area of research. Nevertheless, this analysis provides valuable initial insights, and it is hoped that future studies will extend these findings using larger samples and broader coverage as more data become available. Additionally, when the data is available, in Chapter Two, a formal analysis using fund-level marketing or investor attention metrics would provide a more rigorous test of why non-pension funds managed by the same issuers exhibit weaker performance. Third, in Chapter Three, the fund-level ESG data are only available from 2018 to 2022. Future research could benefit from examining a longer time horizon to capture the

long-term effects and evolution of ESG integrated investing. Fourth, in Chapter Four, the relationship between ESGPD and window dressing shows no significant effect among ESG funds, which may reflect characteristics specific to the Chinese fund market. Future studies could explore other markets to determine whether this phenomenon also exists elsewhere.

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