How Do Investors React to ESG-related Information? Evidence from Mutual Fund Investors in China

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February 2024

Abstract

We examine how mutual fund investors react to various ESG-related information by leveraging the staggered releases of ESG modules from a dominant financial data platform in China. We present causal evidence that superior flows to high-ESG mutual funds appeared after the platform provided aggregated fund-level ESG rating signals and concentrated at the top 2.5% funds with the AAA rating. The additional flows toward high-ESG funds are irrelevant to their historical ESG performance, and are more pronounced when these funds have lower alternative ESG ratings, higher rating uncertainty, and lower returns. These findings shed light on the behavior of investors, suggesting that they exhibit unsophisticated, inattentive, and non-pecuniary tendencies when making sustainable investments.

Keywords: Mutual Funds; ESG; Investor Behavior; Fund Flows; Sustainability

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1 Introduction

Sustainable investment has experienced significant growth in recent years, with projections indicating that ESG investment will surpass $50 trillion and account for over one-third of global total assets under management by 2025, according to Bloomberg Intelligence. While it is widely recognized that market-wide investors value the environmental, social, and governance (ESG) principle (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Bauer et al., 2021; Baker et al., 2022), the specific manner in which they process ESG-related information during real decision-making remains largely unknown within the existing literature. For example, when faced with a multitude of divergent and complex ESG information (Chatterji et al., 2016; Berg et al., 2022; Christensen et al., 2022), which information holds the most influence over investment decisions for mutual fund investors? Do they tend to rely on easily obtainable aggregated information when making sustainable investments?

The answer to this question remains open and unclear. Given the strong demand from ESG investors for ESG-related information disclosure and activism to promote the exercises of corporate socially responsibility (Krueger et al., 2020; Azar et al., 2021; Ceccarelli et al., 2022; Ilhan et al., 2023), one might naturally hypothesize that ESG investors would display greater sophistication and engagement in gathering, analyzing, and authenticating ESG information. However, an alternative hypothesis suggests that investors may process ESG information in a naive and inattentive manner, relying solely on easily observable signals, similar to how they chase performance and allocate capital across conventional funds (Jegadeesh and Mangipudi, 2021; Ben-David et al., 2022).

In this study, we examine how mutual fund investors process ESG information by leveraging the exogenous staggered reforms of WIND, a dominant financial information platform in China[1]. The platform introduced ESG-related information in different stages and at various levels to its clients. In June 2021, WIND first published its own ESG rating and developed a

[1]WIND serves 90% of China's financial institutions in China (Liu et al., 2019).

specialized ESG module that allowed investors to screen stocks' ESG performance in detail [2]. In July 2022, WIND expanded its ESG module to the mutual fund level by aggregating the stock-level WIND ESG scores of fund holdings. With this module (as shown in Figure 1), platform users could conveniently access scores, rankings, and ESG ratings for the entire mutual fund universe. The ESG scores were classified into different categories based on the funds' ranking, with 2.5%, 10%, 22.5%, 30%, 22.5%, 10%, and 2.5% of funds rated AAA (Best ESG), AA, A, BBB, BB, B, and CCC (Worst ESG) respectively.

We uncover two key findings through this novel experiment. First, the platform's information aggregation significantly influenced flows to funds with the highest ESG ratings, suggesting that socially responsible investors tend to rely on simple and salient signals in their investment decisions (Ben-David et al., 2022). Second, the inflows were concentrated primarily in the top 2.5% of funds with the highest sustainability, indicating that the pursuit of top ESG performance parallels the behavior of investors chasing funds with extreme rankings in financial returns (Sirri and Tufano, 1998; Hartzmark, 2015).

Our empirical analysis starts from pooled regressions using data from different periods when varying levels of ESG-related information were displayed. In the final stage where aggregated fund-level ESG ratings were available, funds with AAA ratings attracted an additional 7% of net flows per quarter, even after controlling for factors such as fund performance, size, age, expense ratio, turnover ratio, family size, and factor loadings. This 7% increase is equivalent to approximately 20% of the standard deviation of fund flows and amounts to over 84 million RMB, considering the average total net assets of funds. These results indicate that investors in China place value on sustainability. However, during periods when only stock-level ESG ratings were provided, we did not observe a positive relationship between top ESG performance and abnormal fund flows. This suggests that investors may not possess the sophistication required to calculate fund-level ESG performance on their own. Additionally, we found that the average fund's ESG score, as well as AA or A ESG ratings, were not signifi-

[2]See https://baijiahao.baidu.com/s?id=1703765497953686739 for more information

cantly associated with fund flows. This implies a sharp convexity in the relationship between ESG and fund flows since the abnormal inflows were concentrated in the top 2.5% of funds with AAA ESG ratings. These findings align with evidence that investors often focus on discrete and extreme outcomes when making investment decisions (Hartzmark, 2015; Feenberg et al., 2017).

To address potential endogeneity concerns and establish causality, we employ both a diff-in-diff (DID) analysis and a regression discontinuity (RD) design in our study. We leverage an exogenous change that affected the availability and visibility of aggregated fund-level ESG performance. In our analysis, we treat the top 2.5% of funds with AAA ESG ratings as the treatment group, while the remaining funds served as the control group. Prior to the launch of fund-level ratings, both groups of funds received similar levels of flows. However, after the launch, the funds rated highest in sustainability experienced a substantial increase of 8% in net inflows per quarter. Moreover, when comparing these AAA-rated funds with a group of matching funds that shared similar characteristics such as size, age, expense ratio, and factor loadings, the abnormal inflow increased to 14% per quarter. In contrast, we find no significant changes in flow differences between funds with other ESG ratings (e.g., AA, A, BB, B, and CCC) and funds with medium ESG performance (e.g., BBB rating) following the shock. Additionally, we do not find the publication of stock-level ESG ratings had substantial effects on the flow of funds with different sustainability.

In our regression discontinuity (RD) design, we concentrate on funds whose ESG scores were close to the cutoff points determining different ESG ratings. We observe a sharp and robust discontinuity in fund flows for funds near the breakpoints for AAA and AA ratings during the period when WIND displayed aggregated fund-level sustainability information. Specifically, there was a significant increase of 23% in net inflows per quarter for funds that were just above the cutoff points compared to those just below the cutoff points. We conduct placebo tests to further validate our findings by examining whether similar discontinuities appeared for cutoffs of other ESG ratings and during periods when the platform only displayed stock-level ratings. The results of the placebo tests do not show any significant discontinuity, indicating that the observed discontinuity in fund flows near the breakpoints for AAA and AA ratings is not a random occurrence but likely driven by the salience of aggregated fund-level ESG ratings. Collectively, these results provide strong support for the idea that investors selectively chase funds with top sustainability if aggregated fund-level ESG ratings are prominently displayed.

One notable advantage of our setting compared with Hartzmark and Sussman (2019) is that funds in our sample are not anonymous and can be linked with publicly available holding data. As ESG ratings from different agencies are usually with huge disagreements and uncertainty (Chatterji et al., 2016; Berg et al., 2022), the holding data allow us to calculate fund-level ESG ratings from alternative sources and examine whether socially-concerned investors regard this potential disagreement as an important factor in their investment. Utilizing the fund holding data, we compute the measures of aggregated fund-level ESG performance from alternative rating agencies and ESG rating uncertainty follow Avramov et al. (2022). Unlike the inflows to funds with top WIND ESG rating, top 2.5% funds with alternative ESG rating do not occur superior inflow. Furthermore, in assessing whether the abnormal inflows to the WIND AAA rating fund vary with these disagreement measures, we surprisingly find that flows are more pronounced in funds with low alternative ratings and high rating uncertainty. These results suggest that investors only focused on the aggregate rating provided by the platform and largely ignored the more detailed sustainability information with calculating requirements.

We also conduct additional analysis to examine the impacts of aggregated but less influential ESG-related information on fund sustainability. Specifically, we investigated the effects of historical ESG ratings of funds and carbon globes based on the aggregate carbon footprints of fund portfolios. Our analysis reveal that these historical records of fund sustainability and carbon footprints did not have a significant influence on fund flows when controlling for the most recent ESG rating. This finding suggests that investors tend to behave in a relatively naive manner when processing ESG-related information. They appear to be more distinctly responsive to the simple and salient ESG rating rather than considering the historical performance of funds or carbon footprints. This finding further reinforces the idea that investors prioritize the overall ESG rating as a primary factor in their investment decisions, while other detailed aspects of ESG-related information have limited impact on fund flows.

We investigate the motives behind ESG chasing as a final piece of empirical analysis. We focused on two key reasons driving the demand for ESG investment: non-pecuniary preferences and beliefs regarding the potential financial benefits associated with sustainability (Riedl and Smeets, 2017; Starks, 2023). To differentiate between these two motivations, we assess how financial performance affects the flows to funds with high sustainability. We find that when the performance of AAA-rated funds falls below the sample median, there is a significant increase of 22% in abnormal flows to these funds. However, when AAA-rated funds have above-median performance, the abnormal flows was only insignificant 5%. This result suggests that investors in our sample hold non-pecuniary preferences and are willing to accept lower financial returns for the sake of sustainability (Białkowski and Starks, 2016; Starks et al., 2017).

Our paper mainly contributes to the growing literature utilizing the flow of ESG mutual funds to infer the preference and decision-making process of socially responsible investors[3]. Hartzmark and Sussman (2019) qualitatively and causally conclude that investors value sustainability because the publishing of ESG Rating on MorningStar attracted additional flows to high ESG Funds. Baker et al. (2022) estimate investors are willing to pay 20 basis points on average per annum for funds with ESG mandate. However, how flows to socially responsible funds are affected by financial and non-financial ESG information are mixed and largely unknown[4]. The focus of our paper is to comprehensively examine the influences of different types of ESG-related information on fund flows. Our results reflect the unsophisticated, inat-

[3]In stock-level, past research finds superior stock returns for stock in sin industries, with high carbon emission, and with lower environmental ratings (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2021; Pástor et al., 2022). Cao et al. (2023) document that socially responsible institutions react less to quantitative mispricing signals.

[4]For the consideration of fund financial performance, some evidence stands for ethical money are more patient and less related to past performance (Renneboog et al., 2011; Białkowski and Starks, 2016), while some other research provides evidence on larger sensitivity of cash flows into ESG funds on positive past returns (Bollen, 2007; Li et al., 2023a).

tentive, and even mindless manner of ESG investors, which brings a deeper understanding of the decision-making for ESG investment.

Our paper more generally relates to the research on the behavior of mutual fund investors. Prior studies document that mutual fund investors mainly follow salient and easy-to-process performance signals[5], and flows to mutual funds tend to be concentrated in the very top funds[6]. Our paper finds that investors only rely on the most observable ESG ratings and chase funds with the top 2.5% highest sustainability, which extends the literature by providing supportive evidence in the context of ESG investment. Our results highlight the role of financial intermediary (platform) as they provide information templates to investors, which is consistent with prior findings that mutual fund investors are likely to be affected by marketing activities (Christoffersen et al., 2013; Roussanov et al., 2021) and cosmetic effects (Cooper et al., 2005; Solomon et al., 2014). Last, with the importance and influence of China's economy significantly improved in recent decades, a growing literature focus on understanding the investor behavior in China's capital market (Xiong and Yu, 2011; Li et al., 2023b; Jones et al., 2023, etc.). Our paper is among the first to causally study the expansion of ESG investment in China and reveals that investors in China hold non-pecuniary preferences.

The paper proceeds as follows. Section 2 provides the institutional background about how ESG information is stagger released on the largest financial platform. Section 3.1 describes our data and summary statistics. We describe the details of empirical methodology and results in Section 4. Section 5 presents additional analysis and robustness checks. Section 6 concludes.

[5] MorningStar ratings are believed to have the strongest independent influence on mutual fund flows (Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2021; Ben-David et al., 2022). Moreover, investors behave as if they are only concerned about market risk, but are largely unaware of other factors(Barber et al., 2016). Ben-David et al. (2022) find that using any of the factor models does not improve flow prediction relative to unadjusted fund returns.

[6] Asymmetric flow-performance relationship posits that investors allocate disproportional more to funds that performed very well (Sirri and Tufano, 1998; Huang et al., 2007). Akbas and Genc (2020) and Clifford et al. (2021) find that fund investors are more like to be affected by those extreme states of past returns.

2 Institutional Background

The mutual fund industry has grown rapidly in the past decade. As of June 2023, the Chinese domestic market hosts 144 fund management companies that collectively manage 10,980 mutual funds, including 9,648 open-end funds and 1,332 closed-end funds, with the total net asset value amassing to 27.69 trillion yuan[7]. According to the Investment Company Institute (ICI), the scale of China's regulated open-end assets ranked first in Asia and fourth worldwide. In line with the global trend, the ESG principle is getting popular in China's capital market. As of June 2023, 101 asset management companies have signed up with UN-PRI. In the mutual fund industry, close to 500 mutual funds incorporate related ESG principles[8].

As the dominant financial data service platform in China, WIND holds approximately 50% market share among domestic institutions, reaching over 90% of financial companies and more than 60% of foreign institutional investors. To meet the growing demand for ESG analysis by investors, WIND has released two ESG-related modules in their platform in June 2021 and July 2022.

In June 2021, WIND launched a detailed ESG database for all of China's A-Shares listed companies, with records dating back to the first quarter of 2018. By leveraging corporate disclosures, governmental announcements, and internet-based public sentiment, WIND consistently updates daily scores across environmental, social, governance, controversy, and management practice dimensions, which are then aggregated into an overarching ESG score and rating. Moreover, WIND also furnishes third-party ESG data for individual stocks, encompassing SSI ESG Rating, FTSE Russell ESG Ratings, as well as ESG Ratings by SynTao Green Finance and SusallWave FIN-ESG Rating. Investors are empowered to independently compute a fund's third-party ESG data by cross-referencing these third-party stock ratings with the fund's disclosed portfolio holdings.

[7] For more detail, please see https://www.amac.org.cn/sjtj/tjbg/gmjj/202311/P020231126433659593839.pdf

[8] For more detail, please see https://mp.weixin.qq.com/s/z14ZwhGjryIfVLTbAKwv5g.

In July 2022, WIND pioneered the launch of the Mutual Fund ESG database by drawing on granular ESG data for individual stocks coupled with fund-holding information. The mutual fund rating module is updated semi-annually, with records dating back to the first half year in 2018. This database offers investors a convenient approach to screen ESG ratings and scores for a corpus of over 9,000 funds with a total market capitalization exceeding 9 trillion RMB. As illustrated in Figure 1[9], In the F9 deep data analysis interface offered by WIND, the 'Fund ESG Analysis' section delineates comprehensive ESG metrics for mutual funds. From top left to top right in Panel A of Figure 1, the interface sequentially displays the fund's current 'ESG Rating', 'Fund ESG Rating Distribution', 'Trends in ESG Rating', 'Key Scores Comparison', and 'Fund Carbon Footprint Rating'. By scrolling down the page, one encounters the 'Sector Breakdown' and 'YoY Change in Scores' information as shown in Panel B of Figure 1. These various ESG-related information give investors an opportunity to easily evaluate the performance of funds.

—Insert Figure 1 about here—

WIND calculates the fund's ESG score by analyzing holding data and the corresponding ESG evaluations of each constituent asset. Subsequent to the fund's semi-annual report, WIND computes funds' comprehensive ESG scores as the value-weighted average ESG score of their portfolio holdings, adjusting the weight of each holding by excluding assets like non-A-shares and bonds that are not covered by WIND's ESG rating system[10]. WIND then positions the funds within a ranking system across all rated funds and assigns ESG ratings accordingly. The top 2.5% of funds are rated 'AAA', indicating an exceptionally high degree of sophistication and risk management with negligible ESG risk. Following 10%, 22.5%, 30%, 22.5%, 10%, and 2.5% of funds are rated AA, A, BBB, BB, B, and CCC, respectively. The deadlines for the re-

[9]Figure 1 takes the Harvest Return Selected Equity Fund (code: 008958.OF) with report date 2023-06-30 as an example, upon accessing the interface, one immediately encounters two data categories: 'Wind ESG Overview' and 'Fund ESG Feature Summary', as shown in Panel A.

[10]Funds with equity assets comprising less than 60% of the total portfolio are deleted from the ranking process.

lease of China Mutual Fund's semi-annual report are August 31st and March 31st respectively. WIND synchronizes the release of ESG scores and ratings with these regulatory dates[11].

These phased releases of the stock-level ESG module and the fund-level ESG module present a unique setting for quasi-natural experiments to examine how investors react to various ESG-related information. As depicted in Figure 2, WIND's disclosure timeline can be segmented into three stages. The first stage, spanning from 2018Q2 to 2021Q2, is characterized by the absence of ESG data provision for both stocks and funds. Although a standardized WIND ESG dataset is not established at this stage, the concept of sustainable investing has already gained traction in the capital markets[12]. WIND retrospectively provides ESG ratings and scores for stocks and funds during this period. This stage was marked by the presence of sustainability concepts and non-standardized data without a unified ESG evaluation framework or publicly available ratings. In the second stage, from 2021Q3 to 2023Q1, WIND supplied daily updated ESG scores and ratings for China A-Shares listed companies but had yet to aggregate at the fund level. With fund holdings disclosed semi-annually, it was possible to aggregate individual stock ESG data to approximate fund ESG scores during this period, albeit with high data retrieval costs and sophisticated data processing requirements. In the third stage, from 2023Q1 onwards, WIND introduced semi-annually updated Mutual Fund ESG data, providing various fund-level ESG information as displayed in Figure 1. This stage is distinguished by the harmonization and public transparency of ESG ratings for both funds and stocks.

—Insert Figure 2 about here—

[11] Hence, our data methodology incorporates a lag structure to preemptively obviate forward-looking bias.

[12] 1,779 China A-share listed companies had already disclosed their social responsibility reports in 2018, and the first mutual fund incorporating ESG factors into its investment strategy, Tianhong Low Carbon Economy Fund (code: 350002.OF), has already established in 2005.

3 Data

3.1 Fund Universe

We rely on the China Stock Market Accounting Research (CSMAR) database and the WIND platform to reach a fund-quarter sample of diversified domestic equity funds for our empirical analysis. We derive fund performance, basic characteristics, and financial ratios from the CSMAR mutual fund database. Because the funds' total net assets (TNA) are quarterly disclosed in China, we establish the panel with quarterly intervals. From the WIND platform, we collect both fund-level and stock-level ESG information, for which stock-level raters consist of WIND, SSI, FTSE Russell, SynTao Green, and SusallWave. We acquire 41,731 fund class-biannual observations with non-missing fund ESG score and ESG rating for 7,932 unique fund classes[13]. Besides, we acquire Carhart (1997)'s four-factor series of China's stock market from the CSMAR factor database.

We rely on the following procedure to get a sample of diversified domestic equity funds. From the entire fund universe on the CSMAR survivor unbiased mutual fund database, we first eliminate close-end funds, ETFs, FOFs, index funds, structure funds, listed open-end funds, umbrella funds, short financing funds, and QDII funds. Secondly, we remove funds whose names contain keywords related to Hong Kong and other foreign markets, to avoid including global funds in our sample. Third, we drop funds with TNA less than 1 million RMB. Fourth, to have a list of diversified equity funds, we require funds to allocate over 60% on equity and their single concentrated industry to invest less than 50% of total assets in the sample period[14]. Fifth, we use main fund codes to merge between CSMAR and WIND datasets and drop observations with missing fund flows, ESG ratings, and other key information. After the screening process above, 2,333 unique funds remained in our sample.

[13]We confirm that all classes within a fund share the exactly same rating and successfully replicate the ESG ratings based on the ESG score according to the claimed ranking methodology of the platform.

[14]Industry of stocks are classified based on ShenWan HongYuan Securities's 2021 industry classification standard. See `https://www.swsresearch.com/institute_sw` for more information

3.2 Variable Definition

The measure of our key dependent variable, net fund flow (*NetFlow*), is defined as the difference between TNA growth and fund return (Sirri and Tufano, 1998; Hartzmark and Sussman, 2019; Ben-David et al., 2022, etc.), given by:

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

Where $TNA_{i,t}$ is the total net assets at the end of quarter t for fund i. $Return_{i,t}$ is the cumulative monthly return of fund i during quarter t, calculated by funds' accumulative NAV. For funds with multiple classes, we value-weight returns across share classes using the previous quarter's TNA of each share class. To eliminate the noise of $NetFlow$, we further standardized it to $RankFlow \in \{0, 1\}$ by the rank of flow among all funds. The fund with the highest $NetFlow$ is assigned the value of 1.

We measure the ESG performance of funds from various aspects. We not only use ESG_Rating, ESG_Score directly acquired from the WIND platform, but also compute the average ESG score (ESG_Alter) and rating uncertainty ($ESG\_Uncertain$) from alternative rating agency by stock holdings of fund following Avramov et al. (2022). We provide detailed variable definitions in Table 1. We use the most recently public-known fund ESG performance to mitigate the disclosure gap. WIND platform publishes fund ESG ratings semi-annually, typically at the end of the following quarter when all mutual funds disclose their complete stock portfolio. Particularly, the ratings based on the semi-annual reports and annual reports are used since the fourth quarter, and second quarter of the next year, respectively.

—Insert Table 1 about here—

Following prior literature, we construct several control variables related to fund performance and other fund characteristics. Following Bollen (2007) and Barber et al. (2016), we use Carhart (1997)'s four-factor alpha to measure the risk-adjusted performance (*Alpha*) and loading of fund on market, size, value, and momentum factors (*BetaMkt*, *BetaSMB*, *BetaHML*, and *BetaUMD*)[15]. Aside from the absolute performance, we compute the percentile ranking of alpha (*AlphaRank*) as the relative performance measure (Chevalier and Ellison, 1997; Ivković and Weisbenner, 2009). We also include the past 1-year cumulative fund return (*RetPast1Y*) following Hartzmark and Sussman (2019), because investors may evaluate fund performance with a longer horizon. Following Chen et al. (2004) and Kacperczyk et al. (2005), we further control for fund characteristics including fund size, fund family size, fund age, expense ratio, and turnover ratio. The fund size (*Size*) is the logarithm of the combined TNA across all share classes in the fund. The fund family size (*FamilySize*) is the logarithm of the combined TNA across all funds in the fund family. The fund age (*Age*) is the age of the oldest share class in the fund. The expense ratio (*ExpRatio*) is the annual management fee over the funds average net asset for the past 1 year. The turnover ratio (*TurnRatio*) is the average of stock buying and selling value over the past 1 year over the funds average net asset. To eliminate extreme values, we winsorize net flow at 2.5% and 97.5% levels and all other continuous variables at 1% and 99% levels.

3.3 Sample Overview

Table 2 reports the summary statistics for our sample which contains 26,442 fund-quarter observations from 2018Q4 to 2023Q1[16].

—Insert Table 2 about here—

In the sample period, the net flow of funds has a mean of 3% and a median of -3%, suggesting a flat-tail distribution and money flows to a small proportion of funds. Mechanically,

[15] To do so, we estimate rolling betas using data from the previous 36 months, requiring a minimum of 18 monthly observations.

[16] The sample begins at 2018Q4 because we assume the back-filled data WIND platform provides for 2018H1 could be publicly known in 2018Q4.

the median fund has a percentile ranking of flow close to 0.5 and receives a BBB rating. The average quarterly gross return and Carhart's four-factor alpha are 3.0% and 0.4%, respectively, which is in line with prior literature(Wang et al., 2023). The average fund size and family size are 381.6 million RMB and 28.4 billion RMB respectively. Funds in our sample are relatively young, with average and median ages of 6.3 and 5.3 years. On average, the expense ratio is at 1.41% per annum. The annual turnover ratio of funds in our sample reaches 4.19 times, which means that the average holding period of their stock portfolio is merely 1 quarter. This could explain the fact that the ESG ratings of a fund are not stable across different periods. As shown in Table B.1, about 50% of funds with AAA rating receive a rating of AA and below in the next period. Funds in our sample exhibit a large variation in factor loadings. For instance, the minimum *BetaSMB* is -0.93 while the maximum is 0.92, indicating funds in our sample could belong to different size categories.

4 Empirical Results

In this section, we investigate the relationship between fund ESG performance and fund flow in detail. We first establish the association using pooled OLS regression in subsection 4.1. In subsection 4.2, we conduct a difference-in-differences analysis to examine the causal impacts of the releases of ESG-related modules by WIND. Subsection 4.3 provides the methodology and results of our regression discontinuity design to assess the influence of coarse ESG ratings.

4.1 Baseline Results

We start with a simple pooled ordinary least squares (OLS) regression to examine the impacts of ESG performance on fund flow. The specification is as follows:

$$Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} + \text{Controls} + v_t + \epsilon_{i,t} \tag{2}$$

where $Flow_{i,t+1}$ the flow of fund i in quarter $t+1$, which we specifically use the $NetFlow$ and $RankFlow$ in different specifications. $ESG\_AAA_{i,t}$ indicates if fund i has an AAA ESG rating in quarter t. We consider other publicly observable ESG performance measures in alternative specifications. For the vector of control variables, we first control for the percentile ranking of four-factor alpha in both quarter $t+1$ and t, as the fund flow could be affected by both contemporaneous and prior performance (Chevalier and Ellison, 1997)[17]. We also include the past 1-year cumulative fund return, because investors may evaluate fund performance with a longer horizon (Barber et al., 2016; Hartzmark and Sussman, 2019). We also include a set of fund characteristics, such as fund size(in logs), family size (in logs), fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. We include year-quarter dummies v_t to control for time-specific fixed effects that are common to all funds. We cluster the standard errors by fund in our main specifications.

Table 3 reports the regression results based on Equation 2 in different stages. The first stage is from 2018Q4 to 2021Q1 when all ESG-related data are back-filled so investors cannot actually evaluate the fund's ESG performance. In this period, as shown in column (1) and column (4) of Table 3, the coefficients of the ESG AAA rating indicator are reasonably insignificantly different from 0. However, as shown in column (2) and column (5), these coefficients are still insignificant, even though the WIND platform has already provided stock-level ESG scores to investors in the period from 2021Q2 to 2022Q2. The lack of reaction to funds with top sustainability in this stage could arise from either inattention to stock-level ratings or the inability to perform score aggregation. Compared to the pre-period shown Hartzmark and Sussman (2019) when Sustainalytics has not been takeover by MorningStar so its stock-level ratings are unpopular among investors, the stock-level ESG evaluation in our setting is conducted by the WIND platform itself. Given the leading place of the WIND platform and market-wide attention to the ESG concept after the carbon commitment in 2020Q3 in China, these preliminary results are

[17] Because we measure fund flows in quarter frequency and assume inflows and outflows only happen at the quarter end, controlling for the contemporaneous return ranking is important to mitigate the influences of those intra-quarter fund flows, especially related to concerns about the potential relationship between fund ESG and return performance.

likely to suggest that the inability of information aggregation is an important reason that high ESG funds do not generate extra flow in this period.

—Insert Table 3 about here—

Column (3) and column (6) of Table 3 estimate the impacts of ESG ratings on fund flow in the last stage when the WIND platform directly provides fund-level ESG ratings to investors. The coefficient of *ESG_AAA* is 0.07 in column (3), which is statistically positive and suggests that funds with the highest sustainability rating on average attract an additional 7% net flows per quarter compared with all other funds. This increase is equivalent to approximately 20% of the standard deviation of fund flows and over 84 million RMB considering the average TNA of funds. In column (6) where we use the standardized percentage ranking as the dependent variable, the estimated coefficient is 9%, which remains to be statistically and economically significant. These results provide evidence that investors in China indeed value ESG performance when fund-level ESG information is easily observable, consistent with the previous findings based on global investors (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Bauer et al., 2021; Baker et al., 2022, etc.). As for control variables, we find that fund flows positively respond to all return performance variables in all stages (Berk and Green, 2004). Consistent with Chen et al. (2004), the fund flow is positively associated ed with fund family size and negatively associated with fund size. The coefficients of turnover ratio and different factor loading vary across periods, which could be explained by money flows to different styles under different market conditions (Barberis and Shleifer, 2003; Cooper et al., 2005).

Aside from the triple-A ESG rating indicator, we further include other rating dummies in Panel A of Table 4. As shown in column (3) and column (6) of Table 4, in the stage that fund ESG rating has been launched, the coefficients of *ESG_AAA* remain significant and hold similar magnitude compared with the counterparts in Table 3. However, we find that other relatively high ESG ratings (e.g., *ESG_AA* and *ESG_A*) are insignificant, suggesting that their flows are similar to the omitted group which are BBB funds with medium rating. In panel B of Table 4, we additionally include the average fund ESG score as a measure of sustainability. While the estimated effects of triple-A funds hold unchanged, the coefficients of *ESG Score* are close to 0 in both stage 2 and stage 3. Combined together, these results reflect that China's investors only chasing the best-rated funds in their ESG investment. These findings further suggest that the pursuit of top ESG performance parallels the behavior of the pursuit of top returns, supporting that investors focus on discrete and extreme outcomes when making investment decisions (Sirri and Tufano, 1998; Hartzmark, 2015; Feenberg et al., 2017).

—Insert Table 4 about here—

4.2 Difference-in-difference Analysis

Our identification strategy exploits two ESG rating modules launched by the WIND Platform, for which Section 2 introduces the background in detail. In June 2021, WIND launched an ESG module giving ESG scores to all China A-Shares listing stocks. In July 2022, as the second step, WIND launched another ESG rating module for mutual funds by simply value-weighting the ESG score of individual stocks. Leveraging these novel events, we conduct a difference-in-difference (DID) analysis with the following specifications:

$$Flow_{i,t+1} = \alpha + \beta_1 Post_t \times ESG\_AAA_{i,t} + \beta_2 ESG\_AAA_{i,t} + \text{Controls} + v_t + \epsilon_{i,t} \tag{3}$$

where we add the interaction term between a treat dummy $ESG\_AAA_{i,t}$ and time dummy $Post_t$ to Equation 2. $ESG\_AAA_{i,t}$ indicates if the fund i has an AAA ESG rating in quarter t. When we assess the impacts of the stock-level ESG module, $Post_t$ equals one if quarter t is after 2021Q2. As for assessing the fund-level ESG rating release, $Post_t$ instead indicates whether quarter t is after 2022Q3.

We start the DID analysis by examining the influences of releasing stock-level ESG ratings on fund flow. We regard this round of release as a shock to decrease the cost of evaluating the sustainability performance of funds. If socially responsible investors are sophisticated in calculation and willing to spend time processing stock-level ESG information, we should expect funds with higher aggregated sustainability to experience abnormal flow after the stock-level ESG module is introduced. However, as shown in Table B.2, compared with other funds, the flow of funds with high aggregated ESG rating do not increase after the shock. This result suggests that only providing stock-level ESG information is not enough to attract flow for funds with high sustainability.

We then focus on analyzing the impacts of releasing fund-level ESG ratings. Table 5 shows the regression results based on Equation 3. As shown in columns (1) and (3) of Table 5, the coefficient of *ESG_AAA* is not significantly different from zero, indicating AAA funds receive similar flows compared with other funds prior to the launch of fund-level ESG model. The coefficient of the interaction term in columns (1) and (3), are both statistically significant above 0. The funds with triple-A ratings experienced a substantial increase of 8% in net inflows per quarter and an increase of 12% in percentage ranking compared to the other funds. Compared with the prior stage, the mutual fund ESG model directly provided a salient aggregated ESG rating signal for investors. Our finding suggests that this practice demonstrates a triggering role in attracting money flows to sustainable funds.

—Insert Table 5 about here—

In columns (2) and (4) of Table 5. We include other dummies indicating whether have an AA, A, BB, B, or CCC rating. Therefore, we test whether flow differences between other ratings and BBB rating funds changed after WIND released the mutual fund ESG module. Though the coefficients of $ESG\_AAA \times Post$ remain positively significant, we find no significant changes in flow differences between funds with other ESG ratings and funds with medium ESG performance. This result is consistent with our finding in Table 3, that investors in China only chase the top 2.5% of funds with the best ESG performance after the mutual fund ESG module appears.

One may be concerned that the fund flow responded to the ESG performance even before WIND launched the mutual fund ESG rating module. If so, our regression results may not reflect the impact of the exogenous reduction of ESG information processing costs due to module release. We test the parallel trend assumption by regressing the fund flow on a vector of interaction terms between *ESG_AAA* and quarter dummies, with 2022Q3 as the omitted period. Figure 3 depicts the estimated coefficients of the interaction terms against the corresponding benchmark period. We find that the differences between the flow of AAA-rated funds and other funds are not significantly different from zero in the pre-period. After the launch of the mutual fund ESG module, however, the coefficients become significantly positive in 2022Q4. The above results support the parallel trend assumption that the shock on accessibility of fund-level ESG information shifts the flow to high sustainability funds.

—Insert Figure 3 about here—

In our baseline DID analysis, we utilize the AAA fund as the treatment group and all other funds as the control group. To address the potential concern that funds in the treatment group are distinct in omitted characteristics, we further adopt a matching approach to estimate the DID effect rather than using the entire fund population. In particular, for each AAA fund in the treatment group, we select close funds in the control group sharing similar fund size, age, expense ratio, and factor loading following Bollen (2007) and Białkowski and Starks (2016). We describe the detail matching procedure in Section A.1. As shown in Panel A of Table B.3, the balance test confirms that the matched group exhibits similar fund characteristics with the AAA funds. Compared with this matching group, the abnormal inflow of AAA funds after the launch of the mutual fund ESG module increased to remarkably 14% per quarter, which is larger than the counterpart of 8% in Table 5.

4.3 Regression Discontinuity Approach

To further alleviate the concern that funds with different ESG scores are not comparable along other dimensions, we apply a regression discontinuity (RD) approach exploiting the cutoffs determining the ESG rating of funds. According to the rating methodology of WIND, the ESG rating of a fund is decided by the relative ranking of its aggregated ESG score among the entire fund universe. By focusing on a narrow bandwidth where similar mutual funds receive different ratings on either side of the cutoffs, we could causally identify the impact of different coarse fund ESG ratings on fund flows.

In Figure 4, we illustratively explore the association between fund flows, fund percentile rankings, and fund ESG rating. To do so, we divide funds into 200 groups based on their quarter ranking of ESG Score and estimate the residual flow by regressing fund flow on control variables in Equation 2 and year-quarter fixed effects. Panel A of Figure 4 displays the average residual flow by the group from 1 through 200 after regression in the period WIND launched the mutual fund ESG module. The dashed vertical lines indicate the cutoffs to determine the ESG rating of funds. We find that, though there is no apparent relationship between the bin's ESG score and fund flow, the group whose ESG performance is merely above the cutoff of AAA rating gets a striking 19% of residual flow on average. Panel B of Figure 4 repeats the analysis in the pre-release period, and the abnormally high inflow above the AAA rating cutoff disappears. These results suggest investors are responding to the fund ESG attribute, especially for funds labeled with top ESG performance.

—Insert Figure 4 about here—

We formally test the influence of ESG rating on fund flow by RD approach after the launch of the fund-level ESG module in Table 6. Exploiting the net flow after removing the year-quarter fixed effects as the dependent variable and the distance between fund ESG score and the actual cutoffs deciding AAA and AA rating as the explanatory variable, we follow Calonico et al. (2014) and Calonico et al. (2019) to estimate the discontinuities around the cutoffs. Table 6 reports both conventional and bias-corrected RD estimates based on Calonico et al. (2014) with various bandwidth selection and standard-error clusters, all results consistently suggest that the discontinuity of fund flow exists at the cutoff of AAA ESG rating[18]. The coefficient based on the simplest specification in column (1) of Table 6 is 0.24, suggesting 24% abnormal net inflows per quarter for funds that were just above the cutoff points compared to those just below the cutoff points.

—Insert Table 5 about here—

We conduct similar tests to look at whether the discontinuity only appears in the cutoff of extreme AAA ratings during the period WIND provides the fund-level ESG module. As shown in column (1) of Table B.5, funds whose ESG performance near the AAA cutoff have similar flows in the period WIND only provide the stock-level ESG ratings. In column (2) to column (5) of Table B.5, we estimate the discontinuity for other rating cutoffs and find that all coefficients are insignificant, indicating investors ignore other rating cutoffs. This series of placebo tests suggests that the observed discontinuity in fund flows near the breakpoints for AAA and AA ratings is not a random occurrence. Compared with MorningStar giving 20% of funds with five globes on sustainability, AAA ESG funds in WIND only account for 2.5%, therefore our finding suggests that mutual fund investors are even more aggressive and conspicuous in terms of paying attention to the extreme and discrete coarse ESG ratings compare with Hartzmark and Sussman (2019).

5 Further Analysis

In Section 4, we collectively document that investors select funds with high-ESG performance only if the simple fund-level ESG performance signals are well externally prepared and they

[18]Table B.4 alternatively use the percentile ranking of flow as the dependent variable. Results are robust.

only chase funds with extreme ESG ratings. In this section, we provide further evidence to bring a deeper understanding of how mutual fund investors process ESG-related information among sustainable investments.

5.1 Ratings from Other Agencies

Given that ESG ratings are widely-document inconsistent across different rating agencies(Chatterji et al., 2016; Berg et al., 2022), we start to look at whether investors are sophisticated engough to evaluate fund ESG performance with alternative rating sources. To do so, we retrieved stock ESG information from Sino-Securities, FTSE, SusallWave, and SynTao Green Finance from WIND's in-depth stock data. Employing WIND's methodology for scoring fund ESG, we constructed fund ESG scores from these four independent rating agencies. This represents a significant advantage over Hartzmark and Sussman (2019) approach since WIND's stock codes are standardized, allowing investors theoretically to construct fund ESG scores from other independent rating agencies using the same method[19]. We average the fund ESG scores from these four agencies to derive the *ESG_Score_Alter* indicator, representing a composite fund ESG score from the other four institutions. To explore the potential trend of investment preference for high ESG performers as rated by alternative agencies, we followed WIND's fund rating scoring conversion mechanism. We assigned an AAA rating to funds whose *ESG_Score_Alter* was in the top 2.5%, denoted as *ESG_AAA_Alter*.

We examined whether mutual fund investors integrate ESG data from alternative rating agencies into their decision-making process in Table 7. Columns (1) and (3) of Table 7 present the relationship between placebo top rating indicator from other independent agencies and the fund flows, with the WIND AAA-rating indicator controlled. It can be observed that the coefficients of *ESG_AAA_Alter* are all insignificant, indicating that investors do not respond to

[19]Specifically, we converted individual stock ESG data from the four independent agencies into uniform ESG scores according to the rating-to-score conversion mechanism detailed in the Appendix A.2. Then, by combining each fund's semi-annual stock holdings, we calculated the independent agencies' fund ESG score using methodology of WIND mentioned in Section 2.

top ESG performance computed from other rating agencies. This indifference may stem from the less accessible nature of these ratings compared to WIND's direct ratings. Columns (2) and (4) of Table 7 extend the examination to the impact of mean ESG scores from alternative agencies on fund flows. It is evident that investors still do not react to *ESG_Score_Alter*. The lack of investor response to other ratings reflects an unsophisticated manner of investors, whereby investors choose to ignore important ESG-related information that requires self-calculation.

—Insert Table 7 about here—

As the market's ESG evaluation standards could be extremely inconsistent, we continue to investigate those extreme cases when funds that receiving AAA-ESG rating by WIND are of great disagreement with the evaluations from other rating agencies. We designate *LowESG_Alter* to indicate if a fund ranks in the bottom quintile using ESG rating from other four agencies. In Panel A of Table 8, we estimate the coefficients term of the interaction between *LowESG_Alter* and WIND's *ESG_AAA* ratings. Consistent with our findings in Table 7, the fund flows are not responsive to low ESG performance evaluated by other rating agencies. Furthermore, as the interaction between *LowESG_Alter* and WIND's *ESG_AAA* ratings are positively significant, suggesting flows are more positive to WIND AAA funds even if other agency give them extremely low ratings.

In Panel B of Table 7, we further calculate the fund ESG rating uncertainty incorporating WIND and the other four major rating agencies. We define the ESG rating uncertainty index for the five major rating agencies using the method proposed by Avramov et al. (2022)[20]. The indicator *HighUncertainty* flags funds within the highest quintile as measured by this uncertainty index. The positively significant interaction terms result from columns (2) and (4) indicate that fund flows are more positive towards WIND AAA-rating funds, even if these fund amid high

[20]We calculate the pairwise rating uncertainty for each fund as the sample standard deviation of the ranks assigned by the two agencies in each pairing. These pairwise standard deviations are then averaged to derive a comprehensive uncertainty index for each fund.

rating uncertainty.

—Insert Table 8 about here—

In this subsection, we explore whether investors pay enough attention to ESG ratings provided by other companies. Our findings suggest that investors largely disregard ratings from other agencies, even in situation that ratings from different sources are of great disagreement. These evidence supports the hypothesis of naivety and inattention of mutual fund investors, and posits concerns about the abilities of investors to select funds with real good ESG performance.

5.2 Other Observable ESG-related Information

As shown in Figure 1, the mutual ESG analysis module in WIND not only displays the ESG rating in the top left but also allows investors to conveniently check the historical ESG rating of funds in the top middle and the carbon footprint rating in the top right. We investigate whether investors pay attention to the observable ESG-related information in this subsection.

Table 9 reports the relationship between historical fund ESG rating and fund flows after WIND launched its ESG ratings. In the column (1) and (2) of Table 9, we gradually add the historical ESG rating. Though there is a statistically significant 6% abnormal in-flow to funds receiving AAA ratings in the current period, funds receiving similar ratings in past quarters do not experience statistically abnormal in-flow. To consider the longer rating history and ratings other than AAA, we construct the indicator *GoodHist*, which equals to one if the fund has average historical rating ranks in the bottom quintile. The estimation coefficient between *GoodHist* and *ESG_AAA* are not significantly different from 0, suggesting that investors cannot differentiate AAA rating funds that have worse ESG records and occasionally go green. However, as shown in Table B.1, ESG ratings of a fund are not stable across different periods, meaning that the historical ESG performance is important to tease out funds persistently keep the ESG principle.

—Insert Table 9 about here—

We examine the relationship between carbon footprint rating and fund flows in Table B.6. Again, we do not find investors allocate their assets based on the carbon rating of funds during our sample period. These results suggest that investors narrow their attention to the most recent ESG ratings but not to other observable signals such as historical ESG performance and the carbon footprint rating of the funds.

5.3 Flow-performance Sensitivity

Investors may invest in high-ESG funds because of non-pecuniary preferences and beliefs regarding the potential financial benefits associated with sustainability (Riedl and Smeets, 2017; Starks, 2023). To further investigate the motive behind flows to funds with top ESG ratings, we examine the sensitivity of flow to different return performances with the following specifications:

$$\begin{aligned} Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} \times LowAlpha_{i,t} + \beta_2 ESG\_AAA_{i,t} \times HighAlpha_{i,t,} \\ + \beta_3 LowAlpha_{i,t} + \beta_4 HighAlpha_{i,t} + \text{Controls} + v_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

where we add interaction term between $ESG\_AAA_{i,t}$ and performance dummies $LowAlpha_{i,t}$ and $HighAlpha_{i,t}$. $LowAlpha_{i,t}$ takes the value of 1 if the fund i have a below-median performance in quarter t. $HighAlpha_{i,t}$ takes the value of 1 if it performs above the median in quarter t.

The results in Table 10 indicate that when the performance of AAA-rated funds falls below the sample median, there is a statistically significant increase of 22% in abnormal flows to these funds. However, when AAA-rated funds have above-median performance, the abnormal flows are 5% but not statistically significant. Similarly, the performance of AAA-rated funds affects the rank of flow in a consistent fashion. The performance of AAA-rated funds falls below the sample median resulting in an increase of 32% in percentage ranking compared to the other funds. The results suggest that investors are willing to accept lower financial returns for sustainability (Białkowski and Starks, 2016; Starks et al., 2017).

—Insert Table 10 about here—

6 Conclusion

In this paper, we provide causal evidence on how mutual fund investors respond to different ESG-related information by leveraging the staggered releases of two ESG analysis modules from WIND, a leading and dominant financial data service provider in China. Our findings shed light on several key aspects of investor behavior in the context of ESG investment.

Firstly, we find that the presence of a salient aggregated fund-level signal is crucial in attracting additional flows to funds with high-ESG performance by comparing fund flows in three stageswithout ESG information, with indirect stock-level ESG information, and with direct fund-level ESG informationsupports this observation. Secondly, we observe that the additional flows concentrate solely on funds with top 2.5% performance, indicating that investors pay conspicuous attention to extreme and discrete coarse rating outcomes. Thirdly, our analysis reveals that mutual fund investors tend to rely on the most salient rating signal while disregarding other easily observable ESG-related information such as historical ESG performance and carbon footprint ratings of funds. Furthermore, utilizing the stock holding of funds, we find that flows towards high-ESG funds are unexpectedly more pronounced when these funds have lower ESG performance by alternative rating agencies and higher rating uncertainty. Lastly, we examine the flow-performance sensitivity to gauge the motives behind investing in high-ESG funds. We find stronger flows to high-ESG funds when these funds exhibit relatively low returns, indicating that investors in our sample have non-pecuniary incentives.

Overall, our findings collectively reflect that investors often exhibit naive and inattentive behavior when it comes to ESG investment. These findings have important implications. Firstly, the disclosure of ESG-related information should be carefully designed and monitored, taking into account investor behavioral patterns. Secondly, the role of financial data platforms as key information intermediaries in influencing decision-making on sustainable investments warrants further investigation. Lastly, increasing efforts in investor education may yield significant benefits for the long-term development of ESG investment in China's capital market.

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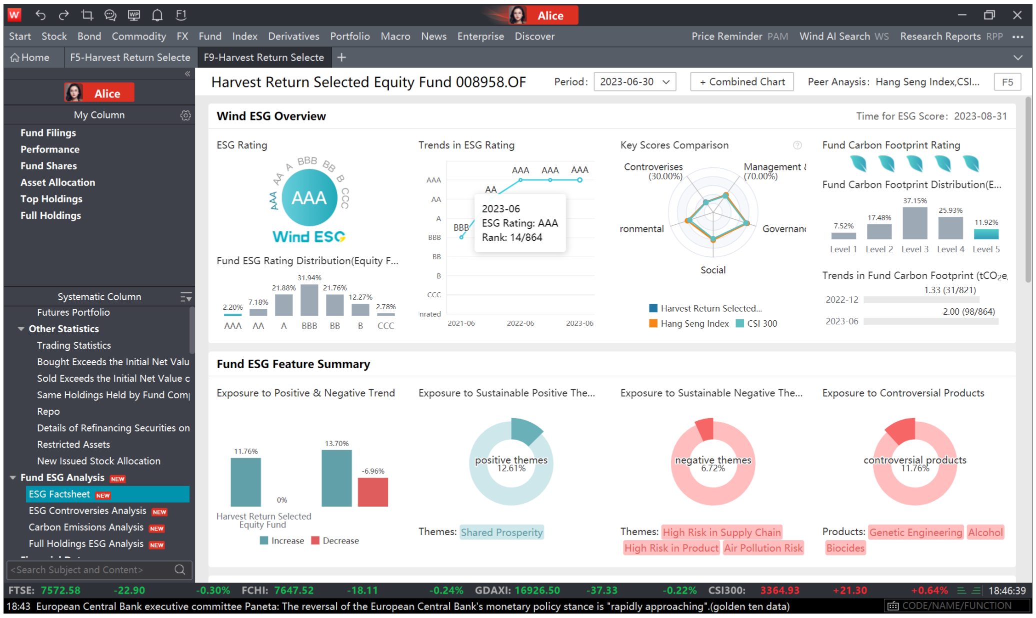
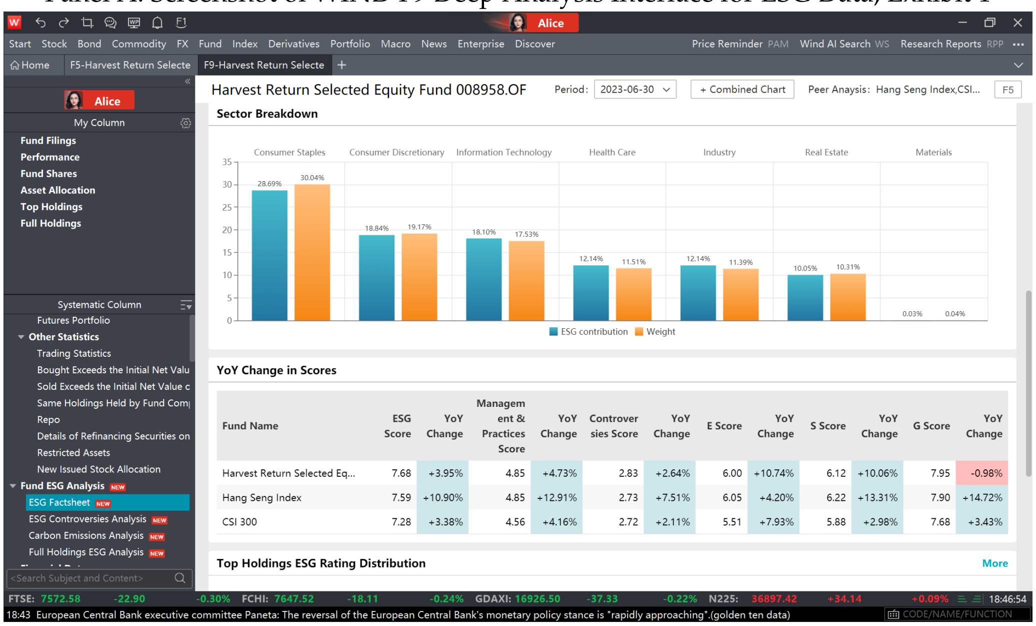


Panel A: Screenshot of WIND F9 Deep Analysis Interface for ESG Data, Exhibit 1



Fund Name	ESG Score	YoY Change	Management & Practices Score	YoY Change	Controversies Score	YoY Change	E Score	YoY Change	S Score	YoY Change	G Score	YoY Change
Harvest Return Selected Eq...	7.68	+3.95%	4.85	+4.73%	2.83	+2.64%	6.00	+10.74%	6.12	+10.06%	7.95	-0.98%
Hang Seng Index	7.59	+10.90%	4.85	+12.91%	2.73	+7.51%	6.05	+4.20%	6.22	+13.31%	7.90	+14.72%
CSI 300	7.28	+3.38%	4.56	+4.16%	2.72	+2.11%	5.51	+7.93%	5.88	+2.98%	7.68	+3.43%

Panel B: Screenshot of WIND F9 Deep Analysis Interface for ESG Data, Exhibit 2

Figure 1: **WIND Fund ESG Data Interface.** This figure illustrates the ESG Factsheet interface of the Fund ESG Analysis in the WIND Financial Terminal. Panel A displays the data a user encounters upon entry, which predominantly comprises the fund's ESG Ratings and Carbon Ratings for the current and preceding five periods. Panel B presents the subsequent interface, revealed through a downward scroll, that delineates the fund's ESG Score and its constituent ESG component scores.

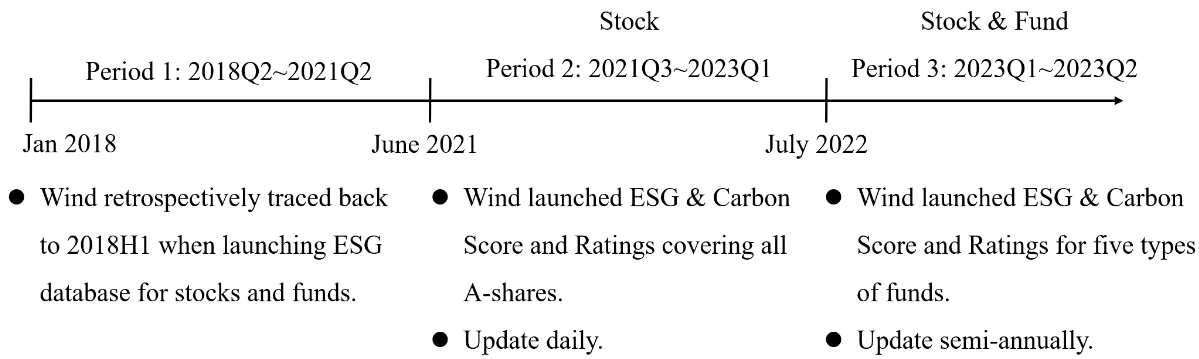
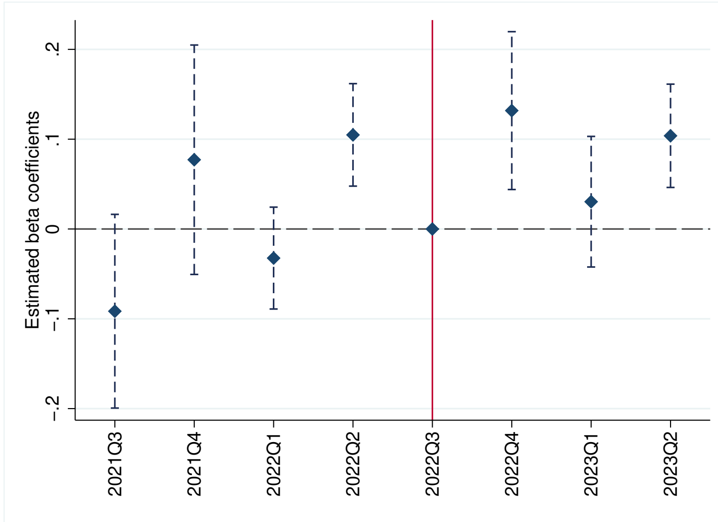
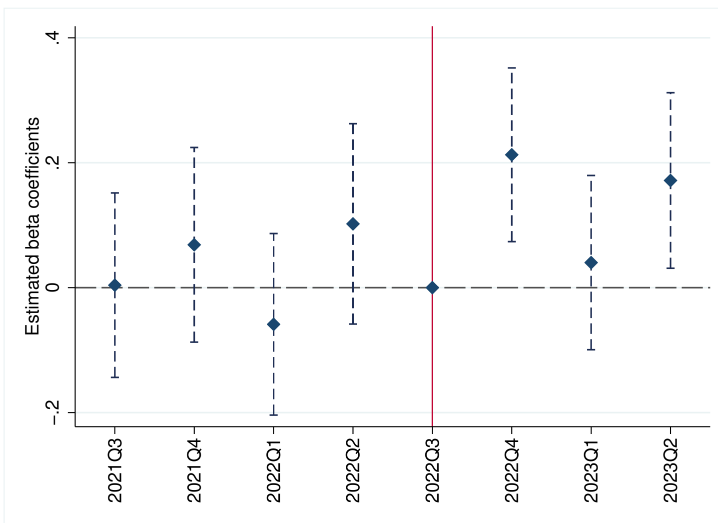


Figure 2: **Timeline of Launching ESG Module on WIND.** This figure provides a timeline based on the release of ESG data for stocks and funds by WIND. WIND began issuing ESG ratings and scores for stocks and mutual funds in June 2021 and July 2022 respectively, with both sets of data retrospectively extended back to 2018. This historical extension has demarcated three distinct phases. The first period only have retrospective ESG data for individual stocks and funds. The second period introduces real-time ESG data for China A-Shares and Hong Kong listed companies but not for funds. And the third period introduces real-time ESG data for both stocks and funds.

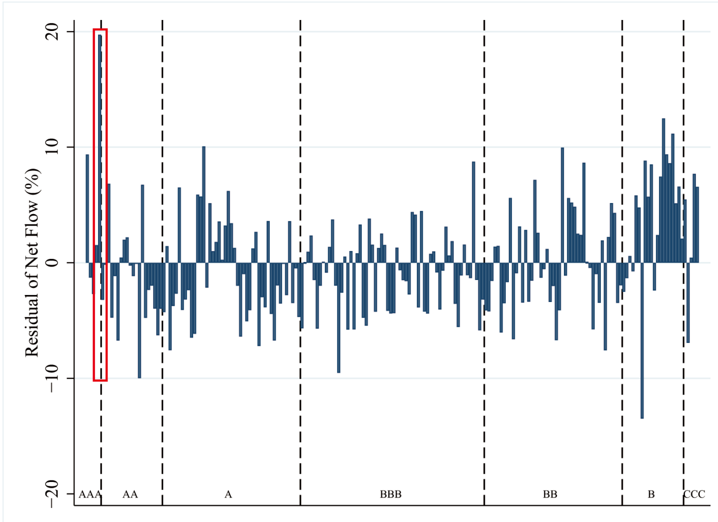


Panel A: Net flow

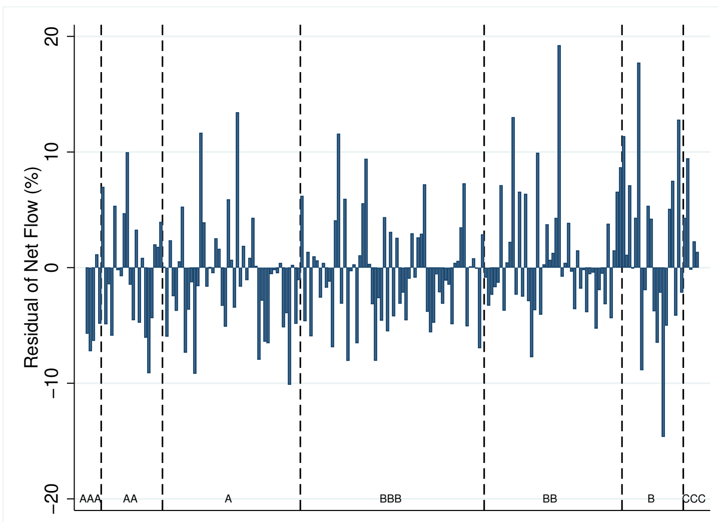


Panel B: Rank of net flow

Figure 3: **Pre-Launch Trend Analysis of WIND ESG Ratings.** This figure illustrates the regression coefficients from an event study, focusing on the interaction between year-quarter dummies and the AAA ESG rating dummy variable. Our specification is given by: $Flow_{i,t+1} = \alpha + \sum_\tau \beta_\tau I^{t=\tau} ESG\_AAA_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. The dependent variable $Flow_{i,t+1}$ is the net flow in the in panel A and the rank of net flow in panel B. Control variables include the rank of alpha in quarter $t+1$ and t, the past one-year cumulative return, fund size, fund age, expense ratio, turnover ratio, loadings on market, size, value, and momentum factors. Time fixed effects are controlled. The dashed lines represent the 90% confidence interval based on standard errors clustered at the fund level.



Panel A: After the launch



Panel B: Before the launch

Figure 4: **Fund Flow by Rank of Fund ESG Score.** This figure plots the average residual of fund net flow for 200 bins sorted by the rank of fund ESG Score. The analysis divides the sample into two time periods: panel A for the post-launch phase from 2022Q3 to 2023Q2, and panel B for the pre-launch phase from 2021Q3 to 2022Q2. We estimate the fund residual flow by specification: $Flow_{i,t+1} = \alpha + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. $Flow_{i,t+1}$ is measured by the net flow in quarter $t+1$. Control variables include the rank of alpha in quarter $t+1$ and t, the past one-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, loadings on market, size, value, and momentum factors. Time fixed effects are also controlled.

Table 1: Variable Definitions

Variable	Definition
NetFlow (%)	Percentage difference between quarterly TNA growth and return for fund i in quarter $t+1$, winsorized at 2.5% and 97.5% level for each quarter.
RankFlow	Normalized quarterly fund flow rank for fund i in quarter $t+1$, calculated as the fund's flow rank divided by the total number of funds, presented in decimal form, with the lowest flow ranked as 1 and ties assigned the mean rank.
ESG_Rating	ESG rating classification dummies, with each dummy, for instance, ESG_AAA assigned a value of 1 if the fund is rated AAA by WIND and 0 otherwise. All ESG rating categories are represented except for the BBB grade, which is the regression baseline.
AlphaRank	Calculated as the fund's alpha rank over the total funds with alpha observation in decimal, where fund with lowest alpha in given quarter is ranked 1 and equal observations are assigned the average rank. The value is then winsorized at 1% and 99% level for each quarter.
FAlphaRank	Forward alpha rank, the AlphaRank for fund i advanced by one quarter to $t+1$.
Ret_Past1Y	Cumulative past year return, the product of the current and three preceding quarterly returns for fund i in quarter t.
Size	Logarithm of total net asset for fund i in quarter t.
FamilySize	Logarithm of family aggregate net asset for the fund family of fund i in quarter t.
Age	Number of years fund i has been in the sample prior to quarter t.
ExpRatio	Management fee ratio, the annual management fee (i.e. sum of two reporting period) over the fund's average net asset for the past year (i.e. mean of start- and end-of-period net asset).
TurnRatio	Ratio between stock trading value over the past year (i.e. average of stock buying and selling values) and fund's average net asset (i.e. mean of start- and end-of-period net asset).
BetaMkt	Market exposure estimated by Fama French Carhart four factor (FFC4) model.
BetaSMB	Size factor exposure estimated by Fama French Carhart four factor (FFC4) model.
BetaHML	Value factor exposure estimated by Fama French Carhart four factor (FFC4) model.
BetaUMD	Momentum factor exposure estimated by Fama French Carhart four factor (FFC4) model
HighAlpha	Dummy variable which takes value of 1 if rank of alpha is in the top 50% for the quarter.
LowAlpha	Dummy variable which takes value of 1 if rank of alpha is in the bottom 50% for the quarter .
LowESG_Alter	Bottom Quintile ESG Score Dummy, equal to 1 for funds with average ESG scores in the lowest 20% according to SSI ESG Rating, FTSE Russell ESG Ratings, ESG Rating by SynTao Green and SusallWave FIN-ESG Rating in that given quarter and 0 otherwise.
Rating Uncertainty	Average of rating uncertainty from all rater pairs, following Avramov et al. (2022), where rating uncertainty is calculated as the absolute difference in ESG rating percentile, divide by $\sqrt{2}$, using percentile to preserve comparability across different raters as raters have different sample coverage. Raters included are WIND, SSI, FTSE Russell, SynTao Green and SusallWave.
HighUncertainty	Dummy variable which takes value of 1 if variable Rating Uncertainty is in the highest quintile for that given quarter and 0 otherwise.

Table 2: Summary Statistics

This table reports the summary statistics for our main fund-quarter level variables. Our sample spans between 2018Q1 and 2023Q2. *Net Flow* is measured by the net money flow as a percentage of fund's TNA. *Rank of Flow* is the rank of net flow in given quarter. *ESG Rating* is assigned a value from 1 (rated AAA) to 7 (rated CCC), based on underlying ESG score and predetermined percentage cutoff brackets. *ESG score* is the actual underlying ESG scores by WIND. *Return* is fund's quarterly return. *Alpha* is fund's quarterly alpha estimated by Fama French Carhart 4 factor model in 36-month rolling windows. *Log Size* and *Log FamilySize* is the logarithm of a fund's TNA and the fund family's TNA. *Age* is number of years since inception of the fund. Expense ratio (*expratio*) is annual ratio between management fee and fund's average net asset. Turnover Ratio (*TurnRatio*) is ratio between annual trading volume and fund's average net asset. A fund's betas (*beta_mkt*, *beta_smb*, *beta_hml*, *beta_umd*) are estimated by Fama French Carhart 4 factor model in 36-month rolling windows.

	Mean	S.D.	Min.	P25.	Med.	P75.	Max.
Net Flow, %	0.03	0.36	-0.66	-0.10	-0.03	0.03	4.27
Rank of Flow	0.52	0.29	0.00	0.28	0.53	0.78	1.00
ESG Rating	4.12	1.20	1.00	3.00	4.00	5.00	7.00
ESG score	6.50	0.34	5.29	6.27	6.49	6.73	7.74
Return, %	3.03	11.59	-25.63	-4.38	2.47	9.61	46.71
Alpha, %	0.41	6.53	-20.92	-3.41	0.01	3.73	38.75
Log Size	19.76	1.61	15.27	18.62	19.82	20.92	23.55
Log FamilySize	24.07	1.61	17.83	23.30	24.21	25.27	26.91
Age	6.33	4.08	1.50	3.25	5.25	8.50	19.00
ExpRatio, %	1.41	0.41	0.34	1.29	1.42	1.53	6.77
TurnRatio	4.19	3.55	0.25	1.87	3.18	5.24	24.63
BetaMkt	0.73	0.23	0.07	0.58	0.75	0.89	1.31
BetaSMB	-0.04	0.30	-0.93	-0.22	-0.04	0.15	0.92
BetaHML	-0.43	0.40	-1.57	-0.70	-0.41	-0.16	0.71
BetaUMD	0.20	0.22	-0.44	0.06	0.19	0.34	0.92

Table 3: ESG Rating and Fund Flow: Baseline Results

This table reports the baseline regression results of fund flow on fund ESG rating over three distinct stages: Stage 1 (2018Q4-2021Q1), Stage 2 (2021Q2-2022Q2), and Stage 3 (2022Q3-2023Q1). Our specification is given by: $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_AAA_{i,t}$ indicate whether fund i gets an AAA ESG rating in quarter t. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level and t-statistics are presented in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow			Rank of Flow		
	(1) Stage1	(2) Stage2	(3) Stage3	(4) Stage1	(5) Stage2	(6) Stage3
ESG_AAA	0.03	-0.03	0.07***	-0.03	-0.04	0.09***
	(0.72)	(-1.30)	(2.77)	(-1.21)	(-1.30)	(3.27)
AlphaRank	0.16***	0.18***	0.07***	0.14***	0.18***	0.12***
	(10.06)	(12.43)	(6.42)	(14.95)	(14.36)	(8.18)
FAlphaRank	0.16***	0.22***	0.14***	0.12***	0.15***	0.17***
	(9.78)	(14.08)	(12.50)	(12.16)	(12.21)	(12.57)
Ret_Past1Y	0.30***	0.28***	0.34***	0.23***	0.16***	0.12**
	(9.32)	(7.84)	(6.95)	(11.42)	(6.44)	(2.13)
Size	-0.05***	-0.03***	-0.02***	-0.02***	-0.03***	-0.03***
	(-12.07)	(-10.08)	(-10.24)	(-6.22)	(-9.48)	(-10.65)
FamilySize	0.02***	0.01***	0.01***	0.01***	0.01***	0.02***
	(4.72)	(4.99)	(6.01)	(3.59)	(5.61)	(7.45)
Age	0.01***	0.00	0.00**	0.01***	0.01***	0.01***
	(4.92)	(0.32)	(2.20)	(14.47)	(5.61)	(5.79)
ExpRatio	-0.05***	-0.02*	-0.04***	-0.07***	-0.03***	-0.03**
	(-2.81)	(-1.83)	(-3.20)	(-6.83)	(-4.07)	(-2.10)
TurnRatio	-0.00***	0.00**	0.00***	-0.00**	-0.00	0.00
	(-3.34)	(2.34)	(3.59)	(-2.47)	(-0.52)	(0.28)
BetaMkt	-0.10***	-0.01	0.07***	-0.09***	0.07***	0.09***
	(-4.20)	(-0.33)	(5.03)	(-5.49)	(3.54)	(4.18)
BetaSMB	-0.03	0.04**	0.09***	-0.04***	0.06***	0.11***
	(-1.42)	(2.18)	(7.97)	(-2.69)	(3.60)	(7.55)
BetaHML	0.02	-0.00	-0.01	0.03***	-0.02**	-0.03***
	(1.54)	(-0.23)	(-1.09)	(2.65)	(-2.21)	(-3.05)
BetaUMD	0.06**	-0.03	0.01	0.04**	0.01	-0.03
	(2.16)	(-1.51)	(0.38)	(2.14)	(0.46)	(-1.02)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,757	8,275	6,410	11,757	8,275	6,410
R-squared	0.09	0.13	0.12	0.11	0.09	0.09

Table 4: Various ESG Performance Measures and Fund Flow

This table reports the relationship between fund flow and fund ESG rating. Our specification for Panel A is given by: $Flow_{i,t+1} = \alpha + \sum_s \beta_s ESG\_dummy^s_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$ and $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} + \beta_2 ESG\_Score_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$ for panel B. $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_dummy_{i,t}$ are ESG rating indicators for fund i in quarter t. $ESG\_Score_{i,t}$ represents the fund ESG score for fund i in quarter t. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level and t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

Panel A: Include all ESG ratings

	Net Flow (%)			Rank of Flow		
	(1) Stage1	(2) Stage2	(3) Stage3	(4) Stage1	(5) Stage2	(6) Stage3
ESG_AAA	0.03	-0.03	0.07***	-0.03	-0.04	0.09***
	(0.76)	(-1.05)	(2.85)	(-1.42)	(-1.31)	(3.30)
ESG_AA	-0.02	0.02	0.00	-0.01	0.01	0.01
	(-1.40)	(1.37)	(0.26)	(-1.52)	(0.80)	(0.81)
ESG_A	-0.02*	-0.00	0.01	-0.02**	-0.01	0.00
	(-1.86)	(-0.45)	(1.15)	(-2.35)	(-0.77)	(0.30)
ESG_BB	0.02**	0.02*	-0.00	-0.00	0.00	-0.01
	(2.23)	(1.70)	(-0.18)	(-0.44)	(0.24)	(-0.71)
ESG_B	0.01	0.03	0.03**	0.01	-0.02	0.02
	(0.98)	(1.54)	(2.17)	(0.51)	(-1.25)	(0.97)
ESG_CCC	0.02	0.04*	0.00	-0.00	0.02	-0.01
	(0.65)	(1.65)	(0.18)	(-0.02)	(0.89)	(-0.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,757	8,275	6,410	11,757	8,275	6,410
R-squared	0.09	0.13	0.12	0.11	0.09	0.09

Panel B: Include fund ESG score

	(1) Stage1	(2) Stage2	(3) Stage3	(4) Stage1	(5) Stage2	(6) Stage3
ESG_AAA	0.06	-0.03	0.07***	-0.03	-0.04	0.09***
	(1.63)	(-0.97)	(2.85)	(-1.42)	(-1.42)	(3.04)
ESG Score	-0.06***	-0.01	-0.01	-0.02*	0.01	0.00
	(-3.34)	(-0.89)	(-0.69)	(-1.72)	(0.58)	(0.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,757	8,275	6,410	11,757	8,275	6,410
R-squared	0.09	0.13	0.12	0.11	0.09	0.09

Table 5: ESG Rating and Fund Flow: Diff-in-diff Analysis

This table reports the regression results for diff-in-diff analysis between fund ESG rating and fund flow in period from 2021Q3 to 2023Q2. Our specification is given by: $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} Post_t + \beta_2 ESG\_AAAi, t + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_AAA_{i,t}$ indicate if fund i gets an AAA ESG rating in quarter t. $Post_t$ indicate if quarter t is after 2022Q3. Column (2) and column (4) include more rating dummies and their interactions with $Post_t$. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow		Rank of Flow	
	(1)	(2)	(3)	(4)
ESG_AAA × *post*	0.08**	0.08**	0.12***	0.12***
	(2.48)	(2.36)	(3.15)	(3.19)
ESG_AAA	-0.03	-0.03	-0.04	-0.04
	(-1.18)	(-1.00)	(-1.19)	(-1.23)
ESG_AA × *post*		-0.03		-0.00
		(-1.48)		(-0.24)
ESG_AA		0.02		0.01
		(1.35)		(0.88)
ESG_A × *post*		0.00		0.01
		(0.44)		(0.44)
ESG_A		-0.00		-0.01
		(-0.41)		(-0.67)
ESG_BB × *post*		-0.01		-0.00
		(-0.67)		(-0.24)
ESG_BB		0.01		-0.00
		(1.28)		(-0.06)
ESG_B × *post*		0.02		0.04**
		(1.08)		(2.16)
ESG_B		0.02		-0.02
		(1.13)		(-1.52)
ESG_CCC × *post*		-0.01		-0.02
		(-0.20)		(-0.57)
ESG_CCC		0.03		0.02
		(1.34)		(0.83)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	14,685	14,685	14,685	14,685
R-squared	0.12	0.12	0.09	0.09

Table 6: ESG Rating and Fund Flow: Regression Discontinuity Design

This table investigates the casual analysis of the effect of ESG ratings on fund flows, employing a regression discountinuity desigh centered on the AAA rating cutoff. The sample period is from 2022Q3 to 2023Q2 after the WIND ESG rating has been launched. The primary explanatory variable is the distance between fund ESG score and the cutoff score for an AAA rating. We select equal bandwidth (different bandwidths) on two sides of the break point in the left (right) panel following the procedure described in Calonico et al. (2014) and Calonico et al. (2019). The first (second) row shows the conventional (bias-corrected) RD estimate based on Calonico et al. (2014). Time fixed effects are controlled. z-statistics are in parentheses and calculated with the clustering variable indicated below. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow (%)					
	Equal Bandwidth			Diff. Bandwidths		
	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	0.24**	0.25***	0.23*	0.23**	0.25***	0.22*
	(2.07)	(4.34)	(1.88)	(2.07)	(3.19)	(1.93)
Bias-corrected	0.29**	0.28***	0.28**	0.27**	0.28***	0.27**
	(2.45)	(4.85)	(2.27)	(2.49)	(3.62)	(2.35)
Observations	6,410	6,410	6,410	6,410	6,410	6,410
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	No	Quarter	Fund	No	Quarter	Fund
Effective obs.	172	127	176	2,127	1,300	2,389
Bandwidth left	0.088	0.069	0.092	0.555	0.435	0.584
Bandwidth right	0.088	0.069	0.092	0.092	0.074	0.096

Table 7: Alternative ESG Ratings and Fund Flow

This table reports the relationship between alternative ESG ratings given by ESG rating agencies other than WIND and fund flows. The sample period is from 2022Q3 to 2023Q2 following the introduction of the WIND ESG ratings. Our specification is given by: $Flow_{i,t+1} = \alpha + \beta_1 ESG\_Alter_{i,t} + \beta_2 ESG\_AAA\_WIND_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. We measure $ESG\_Alter_{i,t}$ by $ESG\_AAA\_Alter_{i,t}$ or $ESG\_Score\_Alter_{i,t}$. The variable $ESG\_Score\_Alter_{i,t}$ represents the mean standardized ESG score, which is derived through a transformation of ESG ratings. These ratings are constructed from the ESG information of stock holdings as aggregated and analyzed by a consortium of rating agencies, including SSI, FTSE Russell, SynTao Green, and SusallWave. $ESG\_AAA\_Alter_{i,t}$ indicates if $ESG\_Score\_Alter_{i,t}$ of fund i is on top 2.5% in quarter t. $ESG\_AAA\_WIND_{i,t}$ indicate if fund i gets an WIND AAA ESG rating in quarter t. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow		Rank of Flow	
	(1)	(2)	(3)	(4)
ESG_AAA_Alter	-0.01		0.01	
	(-0.64)		(0.27)	
ESG_Score_Alter		0.02		0.02
		(1.52)		(1.12)
ESG_AAA_WIND	0.06**	0.06**	0.07**	0.07**
	(2.11)	(2.08)	(2.25)	(2.28)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	6,313	6,313	6,313	6,313
R-squared	0.12	0.12	0.09	0.09

Table 8: ESG Rating Disagreements and Fund Flow

This table reports the relationship between ESG Rating Disagreements and fund flows. The sample period is from 2022Q3 to 2023Q2 following the introduction of the WIND ESG ratings. Our specification in Panel A is given by: $Flow_{i,t+1} = \alpha + \beta_1 LowESG\_Alter_{i,t} + \beta_2 ESG\_AAA_{i,t} LowESG\_Alter_{i,t} + \beta_3 ESG\_AAA_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. Our specification in Panel B of this table is given by: $Flow_{i,t+1} = \alpha + \beta_1 HighUncertainty_{i,t} + \beta_2 ESG\_AAA_{i,t} HighUncertainty_{i,t} + \beta_3 ESG\_AAA_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. Where $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_AAA_{i,t}$ indicate whether fund i gets an AAA ESG rating by WIND in quarter t. $LowESG_{A}lter_{i,t}$ reflects whether the stock holdings of fund i are, on average, relegated to the bottom quintile of ESG scores as determined by Sino-Securities, FTSE Russell, SusallWave, and SynTao Green Finance. Conversely, $HighUncertainty_{i,t}$ denotes whether the stock holdings of fund i are classified within the top quintile of rating uncertainty, according to WIND, Sino-Securities, FTSE, Susallwave, and SynTao Green Finance. The methodology employed to compute rating uncertainty adheres to the approach outlined in Avramov et al. (2022). Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow		Rank of Flow	
	(1)	(2)	(3)	(4)
Panel A: Low alternative ratings				
LowESG_Alter	0.00	0.00	0.00	-0.00
	(0.48)	(0.21)	(0.13)	(-0.25)
ESG_AAA × *LowESG_Alter*		0.07**		0.15***
		(1.97)		(3.25)
ESG_AAA	0.06***	0.03	0.09***	0.03
	(2.69)	(1.33)	(3.22)	(0.97)
Panel B: High rating uncertainty				
HighUncertainty	0.01	0.01	0.01	0.01
	(1.40)	(1.11)	(1.50)	(1.11)
ESG_AAA × *HighUncertainty*		0.08**		0.08**
		(2.07)		(2.07)
ESG_AAA	0.06***	0.01	0.09***	0.01
	(2.69)	(0.80)	(3.14)	(0.80)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	6,410	6,410	6,410	6,410
R-squared	0.12	0.12	0.09	0.12

Table 9: Historical ESG Ratings and Fund Flow

This table reports the relationship between historical fund ESG ratings and fund flows. The sample period is from 2022Q3 to 2023Q2 following the introduction of the WIND ESG ratings. Our specification is given by: $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} + \beta_2 ESG\_AAA_{i,t-1} + \beta 3 ESG\_AAA_{i,t-2} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$ for column (1) column (2), column (4) and column (5), and $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} + \beta_2 GoodHist_{i,t} + \beta_3 ESG\_AAA_{i,t} GoodHist_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$ for column (3) and column (6). $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_AAA_{i,t}$ indicate whether fund i gets an AAA ESG rating in quarter t. $GoodHist_{i,t}$ indicate if fund i on average is ranked in the top quintile of ESG ratings historically ignoring the most recent two ratings. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow			Rank of Flow		
	(1)	(2)	(3)	(4)	(5)	(6)
ESG_AAA	0.06***	0.06***	0.05**	0.08***	0.08***	0.08***
	(2.70)	(2.69)	(2.54)	(3.05)	(3.04)	(2.68)
ESG_AAA_Lag1	0.04	0.03		0.05*	0.05*	
	(1.23)	(1.19)		(1.76)	(1.71)	
ESG_AAA_Lag2		0.02			0.02	
		(0.75)			(0.45)	
GoodHist			0.00			-0.01
			(0.41)			(-0.51)
ESG_AAA × *GoodHist*			0.07			0.02
			(0.97)			(0.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,410	6,410	6,410	6,410	6,410	6,410
R-squared	0.12	0.12	0.12	0.09	0.09	0.09

Table 10: Flow Performance Sensitivity

This table reports the relationship between fund performance and fund flows. Sample period in stage 2, and 3 represent 2021Q3 to 2022Q2, and 2022Q3 to 2023Q2, respectively. Our specification is given by: $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} LowAlpha_{i,t} + \beta_2 ESG\_AAA_{i,t} HighAlpha_{i,t,} + \beta_3 LowAlpha_{i,t} + \beta_4 HighAlpha_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_AAA_{i,t}$ indicate if fund i gets an AAA ESG rating in quarter t. $LowAlpha_{i,t}$ indicate if fund i is in the lower-half performing funds in quarter t. $HighAlpha_{i,t}$ indicate if fund i is in the upper-half performing funds in quarter t. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow (%)		Rank of Flow	
	(1) Stage 2	(2) Stage 3	(3) Stage 2	(4) Stage 3
ESG_AAA × *LowAlpha*	-0.07	0.22**	-0.16	0.32**
	(-0.81)	(1.99)	(-1.18)	(1.99)
ESG_AAA × *HighAlpha*	-0.08	0.05	-0.04	0.04
	(-1.50)	(1.12)	(-0.59)	(0.86)
LowAlpha	0.12***	0.01	0.08***	-0.02
	(4.06)	(0.46)	(2.59)	(-0.45)
HighAlpha	0.16***	0.06***	0.16***	0.09***
	(11.22)	(5.03)	(11.65)	(5.73)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	8,275	6,410	8,275	6,410
R-squared	0.13	0.12	0.09	0.09

A Appendix

A.1 Matching Procedure

Table B.3 replicates Table 5 in a matching sample, where we replace control group from all non-AAA rated funds to funds with similar age, expense ratio, size and beta exposures. To be exact, we require that the control group matching observations compare to the treatment group observation must: (1) the age differences must be less than 3 years; (2) the expense ratio of the control observation must be within one standard deviation of the expense ratio of the treatment group for that quarter; and (3) total distance between the treatment group and their matching control observations ,as calculated in Equation A.1, must be among one of the top three closest to be considered as the matching observation for treatment group. Following Bollen (2007), this procedure ensures that the flow differentiation between treatment group and control group is not caused by those variables consider above. Panel A of this table reports that the fund characteristics between treatment group and control group are not significantly different. Panel B reports the relationship between fund ESG rating and fund flow. Column (1) and column (3) shows the closest match observation measured by total distance as calculated in Equation A.1, whereas, column(2) and column (4) relax the restriction of the closest matching to top three closest matching. Similar results are observed, AAA rated funds face significant in-flow in next quarter. After controlling for the similarity between treatment group and control group, we notice that the magnitude of in-flow doubled from 0.07 to 0.14 for the 1-to-1 matching sample and increase to 0.1 for the 1-to-3 matching sample.

$$Total\_Distance_{i,t} = \sum_k Dist^k_{i,t} \tag{A.1}$$

Where

$$Dist^k_{i,t} = \Big[\frac{k_{treat,t} - k_{control,t}}{SD_{k,t}}\Big]^2 \tag{A.2}$$

for $k \in \{size,\ \beta_{MKT},\ \beta_{HML},\ \beta_{SMB},\ \beta_{MOM}\}$, for each quarter t and SD is the standard deviation of k in given quarter t.

A.2 Methodology for Converting Stock ESG Rating to Score for Independent Agencies

This section provides a detailed explanation of how to construct corresponding fund ESG scores based on the individual stock ESG ratings from four independent rating agencies. In the in-depth stock information available on WIND, there are ESG data from Sino-Securities, FTSE Russell, SusallWave, and SynTao Green Finance. Except for FTSE, which provides ESG scores, the other three agencies offer ratings. Therefore, we first need to convert individual stock ESG ratings into ESG scores for Sino-Securities, Sustainalytics, and SynTao Green Finance.

Sino-Securities has established a standard for converting its stock ESG scores into ratings[21]: there are nine distinct ratings ranging from AAA to C. A stock with an ESG score of 95 or above is classified as AAA; a score between 90 and 94 is denoted as AA; a score between 85 and 89 is categorized as A; a score between 80 and 84 is identified as BBB; a score between 75 and 79 is labeled as BB; a score between 70 and 74 is given a B rating; a score between 65 and 69 is assigned a CCC rating; a score between 60 and 64 is considered CC; and any score below 60 is rated as C. In accordance with the established rating-to-score conversion criteria, we transform the ratings into individual stock ESG scores for Sino-Securities by employing the median score associated with each rating category.

SynTao Green Finance possesses seven distinct ratings, yet lacks an official document delineating the conversion scale between ratings and scores. Drawing a parallel with the methodology utilized by Sino-Securities, we have arbitrarily established the following conversion scale: a rating of A is equated to a score of 95, $A-$ is translated to 87.5, $B+$ corresponds to 82.5, B is converted to 77.5, $B-$ is set at 72.5, $C+$ is matched with 65, and C is assigned a score of 55.

Sustainalytics features a total of 17 ratings, yet there is no official documentation to define the corresponding scale between ratings and scores. Analogous to the approach employed by China Securities, we delineate the ratings using a 3-point boundary: a AAA rating is assigned a score of 98.5, $AA+$ is translated to 92.5, and AA is given a score of 89.5. This pattern continues in a similar fashion, with a CC rating equating to 47.5 and a C rating corresponding to 44.5.

[21] See https://www.chindices.com/esg-ratings.html for more information

B Table Appendix

Table B.1: Rating Transition Matrix from YH_t to YH_{t+1}

This table reports the transition matrix for two adjacent rating disclosure by WIND. The rating is based on full portfolio holdings released by funds in annual and semi-annual reports. Fund with the top 2.5% ESG score will be rated AAA, the next 10% for AA, next 22.5% for A, next 30% for BBB, next 22.5% for BB, next 10% for B and finally, botoom 2.5% for CCC.

Current	Next YearHalf ESG Rating						
ESG Rating	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*
AAA	32	74	49	36	10	2	2
	15.6%	36.1%	23.9%	17.6%	4.9%	1.0%	1.0%
AA	67	279	325	226	75	16	3
	6.8%	28.2%	32.8%	22.8%	7.6%	1.6%	0.3%
A	40	314	879	837	304	48	14
	1.6%	12.9%	36.1%	34.4%	12.5%	2.0%	0.6%
BBB	24	214	799	2,046	1,046	139	24
	0.6%	5.0%	18.6%	47.7%	24.4%	3.2%	0.6%
BB	8	73	272	987	1,580	451	68
	0.2%	2.1%	7.9%	28.7%	45.9%	13.1%	2.0%
B	5	9	39	168	391	395	74
	0.5%	0.8%	3.6%	15.5%	36.2%	36.5%	6.8%
CCC	1	5	9	31	58	83	92
	0.4%	1.8%	3.2%	11.1%	20.8%	29.7%	33.0%

Table B.2: Diff-in-diff Analysis for the Launch of Stock-level Ratings

This table reports the regression results for diff-in-diff analysis between fund ESG rating and fund flow in period from stage1 to stage2. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow		Rank of Flow	
	(1)	(2)	(3)	(4)
ESG_AAA × *post*	-0.07	-0.07	-0.03	-0.02
	(-1.59)	(-1.44)	(-0.66)	(-0.47)
ESG_AA × *post*		0.03		-0.01
		(1.60)		(-0.31)
ESG_A × *post*		0.01		-0.01
		(0.75)		(-0.67)
ESG_BB × *post*		0.00		0.02**
		(0.01)		(2.03)
ESG_B × *post*		0.02		0.01
		(1.14)		(0.28)
ESG_CCC × *post*		0.03		0.06*
		(0.80)		(1.96)
ESG_AAA	0.03	0.03	-0.02	-0.04*
	(0.75)	(0.79)	(-1.08)	(-1.67)
ESG_AA		-0.02		-0.01
		(-1.36)		(-0.88)
ESG_A		-0.02*		-0.02**
		(-1.74)		(-2.22)
ESG_BB		0.02**		-0.1*
		(2.10)		(-1.65)
ESG_B		0.01		-0.01
		(0.92)		(-0.57)
ESG_CCC		0.02		-0.02
		(0.68)		(-0.88)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	20,032	20,032	20,032	20,032
R-squared	0.10	0.10	0.03	0.03

Table B.3: Diff-in-diff Analysis in Matching Sample

This table replicates Table 5 in the matching sample. Following Bollen (2007), for each AAA fund-quarter observation in our sample, we match it with a non-AAA fund-quarter observation on the basis of fund age, expense ratio, size and beta exposures. Specifically, we require that (1) the age of two fund-quarter observations must less than 3 years apart; (2) the expense ratio of the two fund-quarter observations must within one standard deviation of expense ratio of that quarter for the AAA rated observation; and (3) total distance between the two fund-quarter observations' fund size, beta exposures to market, size, value and momentum factors should be among one of the top three closest. Panel A shows the closeness of the two sample and Panel B reports the result. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

Panel A: Balance Tests

	Treat (N=200)	Match		*Diff.*	
	(1)	(2) 1-to-1	(3) 1-to-3	(1)−(2)	(1)−(3)
Size	19.77	19.79	19.87	-0.02	-0.09
FamilySize	24.35	24.42	24.48	-0.15	-0.13
Age	5.79	5.94	5.87	-0.15	-0.09
ExpRatio	1.35	1.35	1.35	-0.00	-0.01
TurnRatio	2.61	2.99	2.89	-0.39*	-0.28
BetaMkt	0.81	0.81	0.81	-0.00	-0.00
BetaSMB	-0.38	-0.34	-0.33	-0.04	-0.04*
BetaHML	-0.39	-0.39	-0.39	-0.00	0.00
BetaUMD	0.11	0.12	0.12	-0.01	-0.00

Panel B: Regression Results

	Net Flow		Rank of Flow	
	(1) 1-to-1	(2) 1-to-3	(3) 1-to-1	(4) 1-to-3
ESG_AAA $\times$ *post*	0.14**	0.10**	0.11***	0.12***
	(2.14)	(2.09)	(2.05)	(2.62)
ESG_AAA	-0.07	-0.04	-0.05	-0.04
	(-1.36)	(-1.21)	(-1.25)	(-1.17)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	400	800	400	800
R-squared	0.15	0.14	0.18	0.11

Table B.4: RD Design with Alternative Dependent Variable

This table investigates the relationship between fund ESG rating and fund flow around the AAA rating break point using regression discontinuity design for which the dependent variable is the *rank of flow*. The sample period is from 2022Q3 to 2023Q2 after the Wind ESG rating has been launched. The independent variable is the distance between *rank of fund flow* and *predetermined AAA rating break point* (top 2.5%). We select equal bandwidth (different bandwidths) on two sides of the break point in the left (right) panel following the procedure described in Calonico et al. (2014) and Calonico et al. (2019). The first (second) row shows the conventional (bias-corrected) RD estimate based on Calonico et al. (2014). Time fixed effects are controlled. z-statistics are in parentheses and calculated with the clustering variable indicated below. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Dependent Variable: Rank of Flow					
	Equal Bandwidth			Diff. Bandwidths		
	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	0.23***	0.25***	0.23**	0.23***	0.21***	0.22***
	(2.68)	(5.11)	(2.55)	(2.88)	(6.45)	(3.37)
Bias-corrected	0.27***	0.27***	0.27***	0.27***	0.24***	0.26***
	(3.10)	(5.64)	(2.94)	(3.42)	(7.31)	(3.96)
Observations	6410	6410	6410	6410	6410	6410
Cluster	No	Quarter	Fund	No	Quarter	Fund
Effective obs.	217	128	217	1,903	812	2,628
Bandwidth left	0.111	0.070	0.111	0.525	0.337	0.612
Bandwidth right	0.111	0.070	0.111	0.086	0.068	0.084

Table B.5: Placebo Tests for RD Design

This table investigates the relationship between fund ESG rating and fund flow around different ESG rating break point using regression discontinuity design for which the dependent variable is the net flow of fund. The sample period is from 2021Q3 to 2022Q2 in column (1) and from 2022Q3 to 2023Q2 in column (2) to column (5). The independent variable is the distance between fund ESG score and the ESG score for the break point of indicated rating. We select equal bandwidth following the procedure described in Calonico et al. (2014) and Calonico et al. (2019). The first (second) row shows the conventional based on Calonico et al. (2014). Time fixed effects are controlled. z-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow (%)					
	Stage 2	Stage 3				
	(1) AAA	(2) AA	(3) A	(4) BBB	(5) BB	(6) B
Conventional	-0.03	-0.04	0.00	0.02	0.01	-0.06
	(-0.38)	(-1.57)	(0.14)	(1.11)	(0.20)	(-0.79)
Bias-corrected	-0.04	-0.03	0.01	0.02	0.01	-0.10
	(-0.43)	(-1.37)	(0.32)	(1.41)	(0.39)	(-1.24)
Observations	8,275	6,410	6,410	6,410	6,410	6,410
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Effective obs.	107	1,034	2,840	2,895	1,131	224
Bandwidth	0.044	0.154	0.198	0.187	0.125	0.093

Table B.6: Carbon Rating and Fund Flow

This table reports the relationship between portfolio carbon emission and fund flows. The sample period is from 2022Q3 to 2023Q2 after the Wind ESG rating has been launched. Our specification is given by: $Flow_{i,t+1} = \alpha + \beta_1 ESG\_AAA_{i,t} + \beta_2 HighCarbon_{i,t} + \beta 3 LowCarbon_{i,t} + \sum_k \gamma_k Controls^k_{i,t} + v_t + \epsilon_{i,t}$. Column(2) and column(4) include their interactions between $ESG\_AAA_{i,t}$ and $Carbon_{i,t}$. $Flow_{i,t+1}$ is measured by the net (rank of net) flow in the left (right) panel. $ESG\_AAA_{i,t}$ indicate if fund i gets an AAA ESG rating in quarter t. $HighCarbon_{i,t}$ indicate if fund i portfolio carbon emission scaled by fund size is in the top quintile in quarter t. $LowCarbon_{i,t}$ indicate if fund i portfolio carbon emission scaled by fund size is in the bottom quintile in quarter t. Control variables include the rank of alpha in quarter $t+1$ and t, past 1-year cumulative return, fund and family size, fund age, expense ratio, turnover ratio, and loading on market, size, value, and momentum factors. Time fixed effects are controlled. Standard errors are clustered at the fund level. t-statistics are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

	Net Flow (%)		Rank of Flow	
	(1)	(2)	(3)	(4)
ESG_AAA	0.07***	0.08**	0.09***	0.11***
	(2.75)	(2.32)	(3.26)	(3.02)
HighCarbon	0.01	0.01	0.01	0.01
	(1.07)	(1.17)	(0.73)	(0.83)
LowCarbon	0.01	0.01	0.01	0.01
	(1.18)	(1.26)	(0.71)	(0.73)
HighCarbon × *ESG_AAA*		-0.04		-0.05
		(-0.83)		(-0.79)
LowCarbon × *ESG_AAA*		-0.05		-0.02
		(-1.21)		(-0.30)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	6,410	6,410	6,410	6,410
R-squared	0.12	0.12	0.09	0.09