The Surprising Performance of Green Retail Investors: A New (Behavioral) Channel

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ABSTRACT

Contrary to the prevailing wisdom that green investors willingly accept lower returns for sustainable investment, our analysis of account-level data from a major Indian bank indicates the opposite. We find that investors with a higher proportion of green stocks in their portfolios achieve superior risk-adjusted portfolio returns. To explain this surprising observation, we hypothesize—and empirically verify—that green investments may help investors mitigate detrimental behavioral bias, such as the disposition effect and under-diversification. Alternative mechanisms related to stock selection ability, aggregate demand shocks, and risk mitigation fail to explain green performance. Instead, tests utilizing abnormal temperatures as exogenous shocks support a causal interpretation of our findings. These results suggest a novel behavioral channel for fully understanding the implications of green preferences.

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I. Introduction

The past two decades have witnessed a trend toward environmental considerations in financial markets and related green investments. This trend comes with a significant social cost: investors may need to sacrifice financial performance to achieve such nonpecuniary goals. Indeed, a trade-off between nonpecuniary environmental, social, and governance (ESG) preferences and expected returns is a common assumption in recent theoretical models (e.g., Pástor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021) and has been observed among institutional investors, such as mutual funds and private equity funds (e.g., Gantchev, Giannetti, and Li 2024; Barber, Morse, and Yasuda, 2022).[1] Whether retail investors also face a similar tradeoff remains elusive due to the lack of individual trading data.[2] Yet, this question has profound normative implications: if all types of green investors receive lower expected returns, it could cast doubt on the participation incentives of investors and the efficacy of green investments in the long run.

This paper aims to fill this gap by exploring account-level retail investor trading data from a major, albeit anonymous, Indian bank. We document a surprising observation: a higher proportion of green stocks in investors' portfolios[3]—which we refer to as *GreenShare* and interpret as a revealed and holding-implied green preference—is associated with superior risk-adjusted portfolio returns. We further uncover a novel mechanism: nonpecuniary green preference may *indirectly* benefit investors by mitigating the behavioral biases that typically harm returns. Such indirect

[1] Although there is still mixed evidence about fund returns, nonpecuniary preferences at least do not seem to improve returns (e.g., Bialkowski and Starks, 2016; Gibson, et al, 2020), except for temporary demand shocks (Pástor, Stambaugh, and Taylor, 2022). Hence, the empirical literature is largely consistent with the theoretical notion that the nonpecuniary preferences constrain the return optimization process, which cannot generate an investment strategy to outperform unconstrained optimization (e.g., Geczy, Stambaugh, and Levin 2021).

[2] The only exception is Moss, Naughton, and Wang (2024), who use the individual security positions from *Robinhood Markets* to demonstrate the irrelevance of corporate ESG news to retail investors' buy and sell decisions. However, the testing period of the study (from June 2018 to December 2019) is limited. Other studies often measure the nonpecuniary retail demand from mutual fund flows (e.g., Bialkowski and Starks, 2016; Hartzmark and Sussman 2019), the residual ownership of stocks (e.g., Choi, Gao, and Jiang 2020), and survey responses (e.g., Riedl and Smeets, 2017; Bauer, Ruof, and Smeets 2021; Giglio et al 2023) but lack individual trading information to provide an explicit answer.

[3] We adopt the green stock classification of Choi, Gao, and Jiang (2020).

benefits appear to outweigh the direct and adverse impact of green preference on returns in our sample, resulting in a positive relationship between green preference and return.

We articulate our analysis in several steps. Our main testing period spans from 2012 to 2019. To set the stage, we first cross-validate the interpretation of *GreenShare* with investors' consumption carbon footprint. The Indian bank provides both brokerage and banking services, enabling us to calculate the *GreenShare* for all retail accounts (our main sample) and also track the consumption and carbon footprint for the subsample of investors who also use the credit and debit card services of the bank.[4] The latter subsample allows us to categorize investors/consumers into three groups based on their *GreenShare* each month. We observe that those in the top tercile (i.e., with a high *GreenShare*) also exhibit lower carbon footprint, suggesting that the green investments made by these retail investors are likely driven by the same preferences that affect their consumption choices. This consistency is also observed in Brunen and Laubach (2022), which supports the interpretation of *GreenShare* as revealed and holding-implied green preference.

We next move on to examine the baseline relationship between *GreenShare* and the risk-adjusted portfolio returns of investors in our main sample. Our risk adjustment accounts for both the traditional five factors (Fama and French, 2015) and momentum, and also introduces a new value-weighted green-minus-brown (GMB) factor to capture the price impact of green stocks—which we refer to as a GMB-enhanced Fama-French seven-factor model. We observe that the investment returns of retail investors are positively related to *GreenShare*. A one-standard-deviation increase in *GreenShare* is associated with 0.92% higher annualized risk-adjusted returns. This positive relation contrasts with the typical negative relationship observed between ESG-related nonpecuniary preferences and fund performance among institutional investors (e.g., Gantchev, Giannetti, and Li 2024; Barber, Morse, and Yasuda, 2022).

To explain this surprising finding, we hypothesize and empirically examine whether green preference could potentially influence a range of behavioral biases. Economically speaking, a

[4] As detailed in later sections, the carbon footprint is calculated as the monthly transaction value-weighted average CO_2 emission in Kg per Lakh (100,000 INR) of spending. A caveat here is that we can only match retail investors to consumptions for less than a quarter of the whole sample. As a result, we interpret this analysis as a diagnostic assessment rather than a formal test.

nonpecuniary green preference may help reduce common mistakes related to the disposition effect and under-diversification—both of which are known to harm investor welfare. To see how the disposition effect could be potentially affected, we notice that investors having a nonpecuniary green preference could be less sensitive to short-term performance, *ceteris paribus*. This feature is consistent with findings that socially responsible mutual funds often exhibit a lower flow-performance sensitivity (see, among others, Bollen, 2007; Bialkowski and Starks, 2016; Pástor and Vorsatz, 2020). For direct investment, this feature implies that green investors may be less prone to the tendency of selling winners too soon—namely, the disposition effect.

Moreover, as the Indian government and the private sector have begun to intensively promote environmental goals[5], investors may incorporate such goals into their investments by reaching out to buy more green stocks. Additionally, Heeb et al. (2023) suggest that investors' willingness to pay is correlated with the level of positive emotions they experience when choosing sustainable investments. In our context, this effect implies that green investors could derive more nonpecuniary satisfaction from buying more green stocks. Both motivations may lead green investors to diversify their portfolios with green stocks.

Green preference may also intensify the local bias, as it is reasonable for green investors to start with local firms when seeking green stocks for investment. Indeed, even professional fund managers are not immune to home bias when investing in high-carbon firms (e.g., Bolton, Eskildsen, and Kacperczyk 2024). However, the impact of this bias on returns is ambiguous. Investing in local stocks might enhance returns if investors possess a relative information advantage regarding these stocks. Conversely, returns could be negatively affected if familiarity—rather than information—is the main reason for their purchase (see, among others, Ivkovic and Weisbenner 2005; Massa and Simonov 2006; Van Nieuwerburgh, and Veldkamp 2009).

Our empirical findings confirm that *GreenShare* can significantly mitigate the disposition effect and under-diversification while amplifying the local bias. In multivariate regression analyses,

[5] For instance, the National Clean Energy Fund (NCEF) was created to finance innovations in clean energy technologies, and the National Investment and Infrastructure Fund (NIIF) was established in 2015 to address the long-term financing needs of India's infrastructure for decarbonization (Chandra, et al., 2020).

a one-standard-deviation increase in *GreenShare* is associated with 2.82% lower disposition effect and 2.13% lower under-diversification (when scaled by the standard deviation of the respective behavioral bias). Meanwhile, we also observe that a one-standard-deviation increase in *GreenShare* is associated with a 4.67% increase in local bias.

On the performance side, we observe that the risk-adjusted portfolio returns of retail investors are negatively associated with the disposition effect and under-diversification, while the local bias has an insignificant influence. Consequently, the negative relationship between *GreenShare* and the first two biases implies that green preference can indirectly benefit investors by mitigating common behavioral mistakes. Collectively, therefore, these results provide initial evidence that nonpecuniary green preference could play a pivotal role in indirectly affecting returns through behavioral biases.

A caveat here is that the above results do not imply causality. Indeed, existing studies provide several important reasons why investments in green and sustainable stocks may affect returns, including the selection ability of investors, the impact of aggregate demand shocks on green stocks, and the use of green stocks for risk mitigation purposes. Below we first show that these alternative channels fail to account for our observations. We then provide an identification test to validate the behavioral channel.

The first alternative mechanism is that investors may consider sustainability as an indicator of future performance (Amel-Zadeh and Serafeim, 2017). Indeed, survey studies, including those by Giglio et al. (2023) for retail investors and Krueger, Sautner, and Starks (2020) for institutional investors, indicate that a significant portion of investors believe that higher ESG investments could yield greater returns. In other words, green investors may invest in green stocks in anticipation of better performance. If their anticipation is indeed correct, it becomes a type of selection ability. In this case, we can observe the outperformance of green investors.

To address this alternative mechanism, we explicitly examine the stock selection ability of green investors. In particular, we follow Jones, Shi, Zhang, and Zhang (2024) to test whether investors' direction of trading—proxied by their order imbalance[6]—can help predict stock returns. Our results suggest that retail investors in our sample do not exhibit a significant selection ability in general. Moreover, the greenest group of investors performs worse than the brownest group of investors, especially in predicting the returns of green stocks. These observations suggest that the performance of green investors is unlikely due to their ability to use the green features of individual stocks to properly predict their returns.

Second, demand shocks are known to boost realized stock returns (e.g., Pástor, Stambaugh, and Taylor, 2022). If the aggregate demand is high for green stocks, green investors may benefit from riding on the price impact of aggregate demand. However, this channel is unlikely to explain the green performance we observe because we have already used the GMB factor to control for such price impacts. Nonetheless, we further scrutinize this channel by asking whether the aggregate demand of our retail investors helps predict out-of-sample GMB-adjusted green stock returns. We find insignificant predicting power, suggesting that riding-on-aggregate demand is unlikely the main driving force for the observed green performance.

The third alternative explanation is that green stocks may provide a risk mitigation tool. Gibson et al., (2020) observe that responsible investing does not enhance the portfolio returns of institutional investors but acts more as a risk mitigation tool. Several studies in the corporate literature show that corporate sustainability limits downside risk (see, e.g., Edmans, 2011; Lins, Servaes, and Tamayo, 2017; and Albuquerque, Koskinen, and Zhang, 2019). We explore this alternative explanation by examining whether investors use green investments as a risk mitigation tool and, secondly, whether such investments enhance alpha generation. Our results show that *GreenShare* is not positively associated with either the portfolio's exposure to systematic risk or idiosyncratic risk. Furthermore, the mitigation does not lead to improved performance.

Thus far, we show that known alternative mechanisms fail to explain our main findings. Although there could be other non-environmentally related omitted variables, a parsimonious interpretation of the above results is that our findings may indicate a new behavioral channel. To

[6] Order imbalance is defined as their buying orders minus selling orders scaled by the summation of buying and selling orders. We use the realized purchase and selling of stocks to construct this measure.

further establish this channel, we note that heatwaves have become an increasingly pressing climate issue in South Asia, especially around the Indo-Gangetic Plain.[7] The literature has long recognized that exposure to abnormally hot temperatures can heighten people's awareness of climate-related issues and inspire corresponding actions (e.g., Akerlof et al. 2013; Myers et al. 2013; Zaval et al. 2014; Choi, Gao, and Jiang 2020; Di Giuli, Garel, Michaely, and Romec, 2024). For instance, Di Giuli, Garel, Michaely, and Romec (2024) document that fund managers exposed to abnormally hot temperatures are more likely to support climate proposals. In our context, heatwaves may amplify the environmental consciousness and green preferences of at least a subset of investors (inclusion restrictions). On the other hand, the abnormally hot temperatures brought about by heatwaves are difficult to predict and are plausibly exogenous to non-environmental considerations (exclusion restrictions). Therefore, heatwaves provide ideal testing grounds to identify the potential influence of investors' green preferences.

Our identification strategy hinges on the assumption that an abnormal heatwave may strengthen the green preference of some but not all investors. Consider two groups of investors, identical in every respect before experiencing a heat wave. For the first group (the treated group), the heatwave boosts environmental consciousness, leading them to derive more nonpecuniary utility from green investments. As a result, they start purchasing more eco-friendly stocks, thereby increasing the *GreenShare* of their portfolio. In contrast, the second group of investors (the control group) remains largely unaffected in their portfolio choices. Given that the heatwave brings a plausibly exogenous variation to treated investors' green preference, comparing the within-portfolio changes in performance and behavioral bias between treated and control investors provides the desired estimate of the impact of enhanced green preference.[8]

To implement this strategy, we utilize the Propensity Score Matching-Difference in Differences (PSM-DiD) approach following Fang, Tian, and Tice (2014). We first identify heatwaves by abnormal temperature, using the methodology established by Choi, Gao, and Jiang (2020) and Di

[7] See https://www.economist.com/asia/2023/04/02/global-warming-is-killing-indians-and-pakistanis.
[8] The same logic also applies to a control group of investors whose green preference is negatively affected by the heatwave. Empirically, using unchanged or negatively affected investors as the control group does not affect our results.

Giuli, Garel, Michaely, and Romec (2024). For each identified heatwave, investors are categorized into quintiles based on the variation in their *GreenShare* before and after the event. Investors in the top quintile, who exhibit the largest increase in *GreenShare*, are designated as the treated group because their green preferences are the most affected by the heatwave. We then apply the PSM process to match each treated investor with a control investor from the bottom quintile who has identical characteristics prior to experiencing the heatwave.

The above process allows us to form two groups of PSM-matched investors for conducting DiD analysis over a period spanning six months before to six months after the heatwave. To avoid potential contamination of the DiD estimates, as documented in recent studies (e.g., Gormley and Matsa 2011; Cengiz, Dube, Lindner, and Zipperer 2019; Baker, Larcker, and Wang 2022), we also construct panel data within the treatment window for each shock and carefully select a clean control group of investors who have not been treated.[9]

Our main PSM-DiD results concerning performance and behavioral biases are twofold. First, compared to the control group, treated investors have achieved significantly better performance after the heatwave. Indeed, the annualized risk-adjusted returns of the treated investors increased by 3.00% in the post-heat period. This observation aligns with our baseline results, which suggest that a higher green preference is typically associated with better performance. The distinction here is that, in this DiD analysis, the heightened preference of the treated investors is triggered by abnormal heatwaves.

Second, the treated group's under-diversification and disposition effect are significantly lower in the post-heat period. When we regress the under-diversification bias on the interaction between the treated dummy and the post-wave dummy variable, we observe a reduction effect amounting to a 1.49% standard deviation of the bias. As for the question of how diversification is achieved, we observe that investors in the treated group buy more green stocks than the number of brown stocks they sell after the shock, giving rise to a net increase in the number of stocks in their

[9] In our main test, we select investors in the control group without replacement to make sure that a control investor cannot be used for multiple treated investors. For the treated investors, we include only the first time for an investor to be included in the top-quintile *GreenShare* changes, and exclude them in subsequent temperature shocks. We report our results using other specification in the Online Appendix.

portfolio. In other words, although investors may sell some brown stocks to finance the purchase of green ones, the latter purchase outnumbers the former and thus enhances diversification.

As for the disposition effect, we estimate the tendency of retail investors to sell stocks with capital gains, especially green stocks. To avoid a higher-order quadruple interaction, we estimate this disposition tendency separately for treated and control investors based on the triple interaction between the capital gains of a stock, the dummy indicator for green stocks, and the post-wave dummy. We observe that the post-wave tendency for selling winning stocks and particularly that for selling winning green stocks are significantly lower for treated investors. In contrast, both tendencies remain unchanged for the control group, suggesting that the treated group exhibits a reduced disposition effect in dealing with green stocks.[10]

Collectively, our analysis of heatwaves suggests that heightened environmental consciousness and nonpecuniary green preferences could causally reduce the two leading performance-destroying biases: the disposition effect and under-diversification. This behavioral channel indirectly benefits investors by improving their performance. These observations mitigate the concern of endogeneity and lend support to a causal interpretation of how the behavioral channel for green preferences can indirectly influence returns.

Our results speak to several strands of literature. Economic theories have long investigated nonpecuniary preferences. A common assumption is that investors willingly accept lower returns for their nonpecuniary preferences (e.g., Andreoni, 1989, 1990; Fama and French, 2007; Hart and Zingales, 2017; Niehaus, 2014; Chowdhry, Davies, and Waters, 2019; Pástor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; Geczy, Stambaugh, and Levin, 2021; Lo and Zhang, 2023). This tradeoff applies to green investment: when investors have a nonpecuniary green preference in addition to the traditional preference that facilitates return maximization, the former necessarily constrains the return optimization process—and constrained optimization cannot generate an investment strategy to outperform an unconstrained optimization.

[10] Interestingly, we still observe an increased post-heatwave local bias among the treated investors. Interestingly, additional results show that this local bias effect is prominent only for the purchase of green stocks. For brown stocks, the effect becomes less significant. Since local bias does not affect portfolio returns, we only report this observation for future research.

We contribute by demonstrating that this tradeoff is no longer valid when investors are also susceptible to the tyranny of behavioral biases. In this case, green preference can indirectly contribute to performance by curbing the potential damage attributed to behavioral biases.

More broadly speaking, Starks (2023) points out that investors face the choice between financial *value* and *values* that take into account ESG (environmental, social, and governance), SRI (socially or sustainably responsible investing), and CSR (corporate social responsibility) types of considerations. Our analysis suggests that if *values* also include behavioral preferences and beliefs, then the interplay among different types of *values* may significantly affect the tradeoff between *value* and *values*. This extension lays out a conceptual framework to understand the behavioral channel of green investments. Although our analysis focuses on a sample of Indian retail investors, it is reasonable to believe that this "behavioral channel" could be general among retail and even other types of investors.

We also contribute to the burgeoning literature on how environmental considerations affect the investment decisions of investors. Among institutional investors, mutual fund managers striving to achieve better MorningStar sustainability ratings experienced poor performance (Gantchev, Giannetti, and Li, 2024), while Venture Capital funds with impact objectives earn lower returns (Barber, Morse, and Yasuda, 2022). On the retail investor side, Bialkowski and Starks (2016) and Hartzmark and Sussman (2019) utilize mutual fund flows to examine how retail investors respond to the sustainability of fund investments. Choi, Gao, and Jiang (2020) infer aggregate retail holdings from the residual of institutional ownership. Several recent studies also use surveys (e.g., Riedl and Smeets 2017; Bauer, Ruof, and Smeets 2021; Giglio et al., 2023) or conduct experiments (e.g., Heeb et al., 2023) to measure nonpecuniary preferences and the resulting willingness to pay. For instance, Riedl and Smeets (2017) show that socially responsible investors expect to earn lower returns on socially responsible investment (SRI) funds than on conventional funds and are willing to pay higher management fees. Moss, Naughton, and Wang (2024) report that individual investors using Robinhood Markets as their broker do not respond to corporate ESG news. We extend these studies by leveraging new account-level trading data and proposing a novel behavioral channel to understand the pivotal role of nonpecuniary green preferences.

The remainder of the paper is organized as follows. Section II presents our variables and summary statistics. Section III reports the baseline relation between a retail investor's green preference and his or her portfolio performance and develops our behavioral channels. Section IV presents endogeneity tests, and Section V examines alternative explanations. Finally, Section VI concludes.

II. Data and Variable Construction

We now describe the sources of our data and the construction of our main variables.

A. Sample and Data Sources

We use several data sources in our analysis to uncover the impact of green preference on retail investors' trading performance, and the underlying behavioral channel. Our datasets include account-level stock trading data as well as investor demographic data from a major bank in India, stock price and firm characteristics data from the Prowess Database[11] maintained by the Centre for Monitoring Indian Economy (CMIE), and historical temperature data retrieved from Open-Meteo Weather API.

Account-Level Trading Data: The main data we use for retail investors' trading behavior and performance relies on the proprietary daily account-level stock transaction data from a major bank in India. The bank is one of the constituents of the NIFTY 50 Index, which covers the 50 largest companies listed in the National Stock Exchange of India (NSE). The bank provides multiple banking and financial services to corporates and retail customers across the country, and our data is from the brokerage services in its retail banking business. Our final sample of historical trading records of 40,339 unique investors spans 8 years from Jan 2012 to Dec 2019. We limited our

[11] Prowess is the standard database employed by researchers studying Indian equity markets. See, e.g., Khanna and Palepu (2000); Goldberg et al. (2010); Balasubramaniam et al. (2023); Bau and Matray (2023); Fisman et al. (2023).

analysis to transactions involving stocks listed on the NSE[12]. Investors have transaction records on 1,746 stocks in our sample.

For each account, the trading history data allows us to uncover the date, direction, number of shares purchased or sold, and the execution price. The trading data is merged with the stock pricing data from Prowess and is aggregated into monthly portfolio-level for the analysis of performance following Barber and Odean (2000). We retain only securities that are common shares of domestic stocks and exclude trading activities related to ETFs and foreign stocks, as none of the ETFs in our sample have an explicit ESG orientation. Besides, we remove investor-stocks that have positions opened before 2012. The accompanying investor demographic data contains information about his or her unique identifier, current age, gender, concurrent Postal Index Number (PIN Code), income group[13], account open date, and the Credit Information Bureau India Limited (CIBIL) score[14]. We manually check the demographic data and drop potential accounts owned by institutions. Figure 3 shows the geographic locations of the investors and NSE-listed firms covered in our data. Unsurprisingly, companies in our sample are located mostly in big cities in India, like New Delhi, Mumbai, Kolkata, etc. There is no significant location concentration of green or brown firms. As for investors, they are distributed rather evenly across the whole country.

Consumption Carbon Footprint Data: To validate our portfolio-based measure of green awareness, we combine the bank account transaction data from the bank with transaction carbon footprint data from Connect Earth to calculate investors' carbon footprint in their daily lives. Connect Earth provides country-specific carbon footprint data for each merchant category code (MCC). The bank account transaction data provides records of transaction amounts categorized in MCCs, covering both online and offline transactions.

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[12] The National Stock Exchange of India has taken the spot of the Stock Exchange of Hong Kong as the seventh largest stock exchange in terms of market cap in 2023: https://www.ft.com/content/f263bf84-c3e3-4a0e-b2c6-749e3cc172a0

[13] Investors are split into 9 income groups in the data under the Indian numbering system: < 1 Lakh, 1 – 5 Lakh, 5 – 10 Lakh, 10 – 15 Lakh, 15 – 20 Lakh, 20 – 25 Lakh, 25 – 50 Lakh, 50 Lakh – 1 Crore, and > 1 Crore. One Lakh represents 100,000 Indian Rupee, while one Crore means 10,000,000 Indian Rupee. We recode the income group into the lower bound number in Lakh for each income group in our later analysis.

[14] A CIBIL score is a three-digit numeric summary that determines an individual's creditworthiness. Ranging from 300 to 900, the CIBIL score is provided by the Credit Information Bureau (India) Ltd., a credit rating agency which is authorized by the Reserve Bank of India (RBI).

Identifying Green and Brown Stocks: We classify firms as "green" or "brown" based on their industry classifications, following Choi, Gao, and Jiang (2020), which in turn uses the definition of the Intergovernmental Panel on Climate Change (IPCC) to classify five sectors as sources of high emissions – Energy; Transport; Buildings; Industry (such as chemicals and metals); and Agriculture, Forestry, and Other Land Use. Then, following Krey et al. (2014), each sector is classified into sub-categories each of which is hand-matched with industry names provided by Datastream. We use the industry classifications provided in the Prowess database to hand match to Datastream industries to classify each firm (via its industry classification) as green or brown based on the Choi, Gao, and Jiang (2020) list.

Identifying Extreme Heat Waves in India: We identify the causal effect of green preference on alleviating investors' trading behavioral biases thus enhancing portfolio performance by exploiting the exogenous abnormal temperature in India. We retrieve historical daily temperature data for each county in India and define months as extreme heat waves following Choi, Gao, and Jiang (2020). We will discuss our specifications in more detail in Section IV. The basic idea is to identify the months with abnormal average daily temperature of more than 3 degrees Celsius, after adjustment for the average temperature in the past 10 years as well as the seasonal average temperature for the month in that specific month. Figure 4 illustrates the geographic distribution and intra-year time-series distribution of identified months of heat waves. In our sample period of 2012 to 2019, the abnormally hot weather mainly happens in the northern part of India. From the perspective of time, most of the extreme heat arrives in summer[15].

B. Main Variables

Revealed Green Preference and Performance: We first describe our measure of investors' green preference. For each investor-month observation pair, we construct a proxy for green preference

[15] Warm winter, as well as the extreme heat in other seasons should not be ignored, as they also draw great attention to climate change from the public. See, e.g., https://timesofindia.indiatimes.com/city/pune/december-2015-was-indias-hottest-ever-in-114-years/articleshow/50464747.cms

$GreenShare_{i,t}$, which is the average proportion of green stocks in terms of holding value in the past 12 months. More formally,

$$GreenShare_{i,t} = \frac{1}{12}\sum_{h=1}^{12}\frac{\sum_{s\in S_{i,t-h}}\mathbb{I}\{s\in S_{i,t-h,Green}\}\times HV_{i,s,t-h}}{\sum_{s\in S_{i,t-h}}HV_{i,s,t-h}},$$

where $HV_{i,s,t}$ is investor i's holding value of stock s at month t. $S_{i,t}$ and $S_{i,t,Green}$ denote the set of all stocks and green stocks in investor i's portfolio. The twelve-month estimation horizon is chosen to add more credibility as a proxy for preference and alleviate the concern that our baseline results of a positive relationship between portfolio performance and green preference is due to the contemporaneous greenium. Unavoidably, the way we construct $GreenShare_{i,t}$ is less credible when an investor only holds one stock. Thus, we limit our analysis to the group of investors who have traded no less than 5 stocks in the whole sample period and focus on the variation of $GreenShare_{i,t}$ within the domain excluding zero and one.

In addition to raw return and net return adjusted for transaction cost, we calculate the factor-adjusted alpha of the portfolio for each investor-month observation and present the main results from portfolio alphas. To be more specific, we estimate the alpha of each stock through a 60-month rolling window regression on the Fama-French 5 factor (Fama and French, 2015), momentum factor (Carhart, 1997), and the value-weight green-minus-brown portfolio return from our sample. Then, the portfolio-level alpha is calculated as the holding-value-weighted alpha of all the holding stocks. The benefit of focusing on portfolio alphas is two-fold: (1) The portfolio alpha captures the trading skills (biases) more clearly. Consistent with our premise that retail investors are strongly subject to behavioral biases to begin with, we find that the portfolio alpha is negative on average in our sample. (2) Controlling for the potential green-minus-brown (GMB) factor further mitigates the concern about the effect of greenium. We use the NIFTY 500 index as the market factor, and the three-month government bill yield as the risk-free rate. Both data are retrieved from Datastream.

The data for the remaining factors are downloaded from Global Factor Data (Jensen, Kelly, and Pedersen, 2023)[16].

Behavioral Biases: We now describe the measurement of the behavioral biases that we focus on in our analysis. Specifically, we investigate the impact of green preference on disposition effects, under-diversification, and local bias. In Section III, we formally develop our hypothesis on the behavioral channel through which the green preference helps retail investors earn higher returns from their investments and explain the reason behind our choices of behavioral biases.

Disposition Effect: First, we hypothesize that the non-pecuniary utility derived from green investment (Heeb et al., 2023) helps investors reduce dispositional behaviors due to monetary gain and loss (Shefrin and Statman, 1985; Odean, 1998; Baberis and Xiong, 2012). To measure the level of disposition effect each investor is subject to, we span the transaction data into a holding sample containing all investor-stock-day pairs (Ben-David and Hirshleifer, 2012; Sui and Wang, 2023). We use the value-weighted average purchase price for the cases of multiple purchases and flag the days of sales including partial sales. Then, we estimate the disposition effect through the following model,

$$Sell_{i,s,t} = \alpha + \beta_i Gain_{i,s,t-1} + \varepsilon_{i,s,t},$$

where the subscripts i, s, and t denote investor i, stock s, and day t, respectively. $Sell_{i,s,t}$ is a dummy variable that equals 1 if the investor i sells stock s, either fully or partially, on day t and 0 otherwise. $Gain_{i,s,t-1}$ is a dummy variable indicating whether the investor experiences a gain for that stock in the previous day. The coefficient β_i, multiplied by 100, is our measure of the disposition effect.

Under-diversification: The second behavioral channel we explore is under-diversification. Here we conjecture that greener investors expand their search set for green stocks, hence diversify better. We count the number of stocks in each investor's monthly holding to represent how well

[16] We thank the authors for maintaining a comprehensive global factor dataset and making is easily accessible on: https://jkpfactors.com/

the portfolio is diversified. Since we tend to construct a measure of the bias of under-diversification, we take the negative value of the natural logarithm of the stock number as our proxy.

Local Bias: Thirdly, we investigate the interaction between investors' green preference and the tendency to hold local stocks (Ivkovic and Weisbenner, 2005; Massa and Simonov, 2006). Unlike the carbon home bias, demonstrated by institutional investors (Bolton, Eskildsen, and Kacperczyk, 2024), we hypothesize that retail investors think of carbon emissions in a naïve way and over-weight green stocks near them. Through the *pgeocode* Python package, we retrieve the coordinates information from the PIN Code in our dataset for each investor or firm and calculate the distance (in kilometers) between two locations. Following Sui and Wang (2023), we construct our primary measure of local bias as the benchmark-adjusted distance between an investor's location and the locations of the firms within his or her portfolio. The benchmark distance is the market-capitalization-weighted average distance (in kilometers) between an investor and all listed companies. Similarly, the portfolio distance is the holding-value-weighted average distance between this investor and all companies held in the portfolio. More formally, our measure for local bias is calculated as follows,

$$Local\ Bias\ = \ln\left(\frac{1+Benchmark\ Distance}{1+Portfolio\ Distance}\right).$$

We add 1 to the distances because there are cases in which all stocks held in the portfolio share the same PIN Code as the investor. Although the measure is already adjusted by the benchmark distance, it still generically covariates with the location of the investor in our sample, due to the geographic concentration of firms. For instance, the conceptual upper bound of the local bias for an investor in New Delhi is $\ln\left(1 + Benchmark\ Distance\right)$, while this is not the case for investors living in small cities without listed companies nearby. To alleviate this caveat, we control PIN Code fixed effects when analyzing with local biases.

Control Variables: In addition to the main variables, we also construct a list of control variables to describe the characteristics of retail investors. They can be classified into two groups: variables about portfolio characteristics and those about demographic information.

Portfolio Characteristics: At the portfolio level, we include the natural logarithm of the total portfolio holding value in the previous month (Log(HV)), and the portfolio turnover in the previous month (Turnonver) following Barber and Odean (2000).

In addition, we also include the portfolio-level measures of lottery preference and salience thinking. As the later sections explain, we do not expect these two variables to serve as the economic channel for green preference to affect performance. Nevertheless, since they are also well-documented behavioral biases, we include them as control variables that may potentially affect retail investors' trading activities. They are calculated as the value-weighted average of stock characteristics as specified below.

We estimate idiosyncratic volatility and idiosyncratic skewness following Kumar (2009) and Harvey and Siddique (2000), then classify stocks in the lowest 50th stock price percentile, the highest 50th idiosyncratic volatility percentile, and the highest 50th idiosyncratic skewness percentile as lottery stocks and define the value proportion of lottery stocks in the portfolio as our measure of lottery preference. As for salience, we first calculate the stock-level salience following Cosemans and Frehen (2021). Then, we use the value-weighted average salience level from purchased stocks in the last month as our measure of investors' salience thinking.

Demographic Controls: We control for the income group (Income) an investor belongs to, the natural logarithm of the age of the investor in a year (Log(Age)), the natural logarithm of the number of months since the open date of the account (Log(Account Age)), and the natural logarithm of the Credit Information Bureau India Limited (CIBIL) score assigned by the central bank of India (Credit Score).

In many empirical specifications, we include the PIN Code fixed effects, the job classification fixed effects, and the education level fixed effects. We refer to the joint implication of these fixed effects as *demographic fixed effects* when there is no confusion.

C. Summary Statistics

Table 1 presents summary statistics aggregated at the investor level for our sample. The upper panel describes the average monthly portfolio performance and the average *GreenShare* of the

40,339 investors. Consistent with the retail investor literature (Barber and Odean, 2013), retail investors in our sample perform poorly, achieving an average (median) monthly return of –0.716% (–0.242%), although the NIFTY 500 Index almost surged trifold in our sample period. The numbers become –1.022% on average and –0.627% if we consider the factor-adjusted α. The distribution of performance is left skewed, indicating that the majority on average lose money from his or her equity investment. In terms of allocation between green and brown stocks, there is considerable cross-sectional variation across investors. The average monthly position in green stocks by an average investor is around 61%, while the standard deviation of *GreenShare* is over 27%, implying that retail investors practice green investment in a diverging way.

The middle panel illustrates the trading behaviors of the investors in our sample. The average disposition effect measure is 1.11 for the 28,918 investors with a reasonable estimation of the disposition effect, indicating a tendency to sell the winner stocks. In terms of diversification, most of the investors hold fewer than 10 stocks in their portfolios. As for the local bias, the sample average (median) is 0.383 (0.181). Note that a positive number for local bias implies that the portfolio distance is smaller than the benchmark market portfolio distance. That is to say, investors tend to buy stocks close to themselves, consistent with the literature.

Finally, the bottom panel summarizes each account's portfolio and demographic characteristics. Since we removed the accounts that trade fewer than 5 stocks in the observed period to ensure we have a valid interpretation as green preference from our proxy *GreenShare*, the remaining investors are wealthy ones. However, the selection bias is less concerning, as the performance and trading behaviors shown in the first two panels are similar to retail investors represented in past literature. The median portfolio size is 232 Lakh (23,200,000 Indian Rupee). The average (median) monthly portfolio turnover is 20.873% (9.675%). The range of investor age varies from 20s to 60s. As for the trading experience inferred from the account age as of Dec 2019, most accounts were opened before 2018, providing a trading history of more than 1 year.

D. Validation with Consumption Data

Table 2 presents how investors distribute their consumption at different levels of carbon footprint. This test is conducted based on the subsample of retail investors who also use the credit card and debit card services of the bank. The carbon footprint is calculated as the monthly transaction value-weighted average CO_2 emission in Kg per Lakh (100,000 INR) of spending. We classify the consumption carbon footprint into four groups, which represent four equal-length intervals from zero-emission to the highest level of emissions (711.64 Kg CO_2 emission/Lakh). Similarly, investors are grouped into three groups based on $GreenShare$ in each month, which represents three equal-length intervals from 0% to 100%.

In line with Brunen and Laubach (2022), we find that individuals exhibit consistent sustainability preferences in consumption and investment.[17] For instance, 80.65% (74.68%) of the time the greenest (brownest) group of investors consume with the least carbon footprint in a month, while the numbers are 2.05% (2.11%) for the most carbon-intensive consumption. These observations suggest that the green investments made by retail investors in our sample are likely driven by the same preferences that affect their consumption choices, which also support the narrative of interpreting *GreenShare* as revealed and holding-implied green preference.

One caveat of the above results is that we can only match retail investors to consumptions for less than a quarter of the whole sample. In other words, many retail investors in our sample either use different banks for their banking activities or do not use a bank at all. Since we cannot quantify the conditions and particularly the considerations behind bank selection choices, which might result in a selection bias, we treat the above results as a diagnostic assessment rather than a formal test. Our later analysis will focus on the whole sample of retail investors to ensure generality.

[17] Famulok, Kormanyos, and Worring (2023) document that people may use green investments as carbon offsets for their consumption with a heavy carbon footprint when investigating the data from a large German bank. Hence, investments may also deviate from consumption. However, since this inconsistency is not observed in our sample, it is not a concern for our analysis.

III. Baseline Results

In this section, we investigate the general link between an investor's green preference and his or her portfolio performance. We show that there is a robust positive relationship between performance and green preference. Next, we start exploring our hypothesized behavioral channel by first verifying that behavioral biases in trading are hazardous to performance, then illustrating the negative association between biases and green preference.

A. Green Preference and Portfolio Performance

We first explore the general link between an investor's green preference and his or her portfolio performance by visualizing the average portfolio performance for investors with different levels of green preference. More explicitly, we sort investors into quartiles based on their $GreenShare$ each month and create value-weighted portfolios for top and bottom quartile investors. We then calculate the return difference between the portfolio of top-quartile investors and that of the bottom-quartile investors. We finally plot the cumulative return difference between top and bottom quartile investors, either with or without risk adjustment based on GMB-enhanced Fama-French seven-factor model.

Figure 1 plots the results. We observe a consistent outperformance of top-quartile investors relative to bottom-quartile investors over the sample period from 2013 to 2019. In particular, when the returns are risk-adjusted, the resulting cumulative performance difference remains positive over the entire sample period and achieves a 54% alpha by the end of the period. Hence, unlike the prevailing view that investors sacrifice financial performance to earn the non-pecuniary utility from impact investing (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Barber, Morese, and Yasuda, 2021; Bauer, Ruof, and Smeets, 2021), we find that the greener investors outperform their browner counterparts.

To formally test the positive relationship, we begin with a monthly portfolio-level analysis that links the factor-adjusted portfolio alpha $\alpha_{FF6+GMB}$ to our proxy of green preference $GreenShare$ and a set of control variables in the following specification:

$$\alpha_{FF6+GMB}^{i,t} = \alpha + \beta \times GreenShare_{i,t} + \gamma \times \text{Controls} + \varepsilon_{i,t}, \tag{1}$$

where $\alpha_{FF6+GMB}^{i,t}$ is the holding value-weighted portfolio performance based on the GMB-enhanced Fama-French seven-factor model for investor i at month t[18], $GreenShare_{i,t}$ denotes investor i's average proportion of investment in green stocks in the past 12 months prior to month t, which is our proxy for investors' green preference, and the vector Controls stacks a group of portfolio characteristics including *Log(HV)*, the natural logarithm of the total portfolio holding value in the previous month, *Turnonver*, the portfolio turnover in the previous month following Barber and Odean (2000), *Income*, the income group an investor belongs to, *Log(Age)*, the natural logarithm of the age of the investor in the year, *Log(Account Age)*, the natural logarithm of the number of months since the open date of the account, and *Credit Score*, the natural logarithm of the Credit Information Bureau India Limited (CIBIL) score assigned by the central bank of India. We also control for demographic fixed effects, which include the PIN Code fixed effects, the job classification fixed effects, and the education level fixed effects.

We start with the panel specification, as it offers more flexibility in controlling for fixed effects with different levels of granularity. These baseline results are reported in Models (1) to (3) of Table 3. All specifications include year-month fixed effects, though different models control for different sets of account characteristics or investor fixed effects. In all specifications, we find a significantly positive relationship between the portfolio alpha and our proxy for green preference. The economic magnitude of the effect is also sizable. For instance, in Model (3), a one-standard-deviation increase in *GreenShare* is associated with 0.91% higher annualized risk-adjusted returns.[19]

Lastly, Model (4) reports the results of the Fama-MacBeth specification, which aims to validate the cross-sectional variation of retail investors' portfolio performance associated with *GreenShare*. The relationship between the portfolio alpha and *GreenShare* remains significantly positive.

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[18] The portfolio alpha is calculated as the holding-value-weighted stock alphas. For each stock in a given month, we estimate factor betas using a 60-month rolling window regression before the month. We then calculate the stock alpha as the realized excess return of the stock in the month minus the risk premium generated by the production between betas and realized factor returns in the same month.

[19] The economic magnitude is estimated as $(1 + 0.243\% \times 0.312)^{12} - 1 = 0.91\%$, where 0.243 is the coefficient of the regression and 0.312 is the standard deviation of *GreenShare*.

Among the control variables, we observe that Income, Age, and Account Age are all positively related to performance. Hence, wealthier and more experienced investors typically achieve better returns. In contrast, turnover is negatively associated with performance, because overtrade is hazardous to performance. All these observations are consistent with the literature (e.g., Odean 1998; Barber and Odean 2000).

Collectively, we observe that retail investors' revealed green preference is positively associated with performance. This positive relationship contrasts with what we observe from institutional investors: the literature typically reports a negative relationship between ESG-related nonpecuniary preferences and fund performance observed for institutional investors (e.g., Gantchev, Giannetti, and Li 2024; Barber, Morse, and Yasuda, 2022). To explain this difference, we next move on to explore the behavioral channel.

B. Green Preference and Behavioral Biases

Compared with institutional investors, retail investors are subject to more behavioral biases in trading and thus usually underperform the market (Barber and Odean, 2013; Hirshleifer, 2015). These biases are often hazardous to the portfolio performance and, hence could be robust predictors of the cross-sectional performances of retail investors. The non-pecuniary utility and good emotions derived from green investing (Heeb et al., 2023) could systematically alternate the utility function and cognitive demand in trading. Therefore, we hypothesize that green preference helps investors mitigate harmful behavioral biases in trading, which leads to outperformance. More specifically, we hypothesize that green preference mitigates the disposition effects when trading green stocks, mitigates under diversification, and makes investors focus more on the local stocks, in which they might have some information advantages.

Firstly, we hypothesize that green investors are less subject to the disposition effect when trading green stocks. The intuition is that green investors hold green stocks because of their green taste and earn non-pecuniary utility from it, thus they react less to the financial gain or loss from these assets. In unreported tests, we estimate the disposition effect separately for green stocks and brown stocks in the full sample period. The average difference between the disposition effect on brown stocks and the disposition effect on green stocks within each investor is 0.236 with t-statistics of 6.197. The economic magnitude of this difference is also significant, as the average disposition effect on all stocks is 1.115 in our sample. Because of this within portfolio variation of the disposition effect, we expect to see a lower level of disposition effect in greener investors.

Secondly, we hypothesize that investors would diversify better with the presence of green preference. As suggested by Heeb et al. (2023), investors care about the relative impact rather than the absolute impact. Therefore, in the process of transition from a brown investor to a green investor, he or she would gain more non-pecuniary utility and positive emotion from holding a larger number of green stocks rather than concentrating on a few green firms with a high absolute impact. As a result, even though the green preference could induce divestment in brown stocks, a positive link between green preference and diversification is expected.

Finally, we hypothesize that green preference could amplify investors' tendency to hold green stocks near where they live. The intuition is that retail investors could think of carbon emissions in a naïve way that only the negative externality is independent across locations. We verify this idea by first calculating the difference between the local bias measure for the green stocks and that for the brown stocks within each investor's portfolio holdings. The average difference is 0.139 with the t-statistics of 85.806. Note that, since our local bias measure is time-varying, this reveals that this naïve thinking is highly persistent over time and across investors. Ivkovic and Weisbenner (2005) and Massa and Simonov (2006) document that retail investors achieve better returns from investing in local stocks due to information advantage. Thus, we expect that the local bias channel could also lead to the outperformance of greener investors. This pattern highlights the significant difference between retail investors, as Bolton, Eskildsen, and Kacperczyk (2024) document institutions' carbon home bias due to network as well as political concerns.

We formally test these relationships in the following panel specifications:

$$Bias_{i,t} = \alpha + \beta \times GreenShare_{i,t} + \gamma \times \text{Controls} + \varepsilon_{i,t}, \quad (2)$$

where $GreenShare_{i,t}$ denotes investor i's average proportion of investment in green stocks in the past 12 months prior to month t, which is our proxy for investors' green preference, and $Bias_{i,t}$

denotes the biases for investor i at month t. All the portfolio characteristics, account-level demographic characteristics, PIN Code fixed effects, occupation fixed effects, education level fixed effects, and year-month fixed effects that are included in regression (1) are controlled. In addition, the two non-hypothesized behavioral biases are included as controls in the analysis of hypothesized biases.

We report the results in Table 4, with Models (1) to (3) separately examining the disposition effects (DISP), under-diversification (UDIV), and local bias (LOCB). For easy interpretation and comparison (across biases), we standardize each bias measure by its sample standard deviation. For the same reason, GreenShare is also standardized into z-scores. The first two models report significantly negative coefficients, suggesting that *GreenShare* is negatively associated with the disposition effect and under-diversification. Model (3) reports a significantly positive coefficient, indicating that *GreenShare* reduces the distance between invested stocks and the location of investors (i.e., more local bias). Economically, a one-standard-deviation higher *GreenShare* is associated with a 2.82% standard-deviation decrease in the disposition effect, a 2.13% standard-deviation decrease in under-diversification, and a 4.67% standard-deviation increase in local bias.[20] These effects are consistent with the narratives that green preference affects particular types of behavioral bias as hypothesized above.

Next, we explore the relationship between an investor's green preference and a synchronized index of behavioral biases that consolidates all three types of biases as hypothesized and tested above. To construct the synchronized index, we first flip the sign of local bias to make the direction of *GreenShare* consistent across these biases. For every month, we then rank investors based on each of the behavioral biases and scale the rank into a [-0.5, 0.5] interval, with the most biased investor ranked as 0.5. Our synchronized bias index, labeled *BIAS3*, is calculated as the average rank of an investor across all three types of biases.

[20] Note that the number of observations for Models (1) and (3) is smaller than that of Model (2) because not all investor-month observations have valid sales or PIN Code.

Model (4) reports a significantly negative relationship between *GreenShare* and the *BIAS3* index. There, a one-standard-deviation increase in $GreenShare$ is associated with a 10.4%-standard-deviation decrease in *BIAS3.*

In addition to the three biases listed above, we also consider two well-documented heuristics: lottery preference and salience thinking. Ex ante, we do not expect green preference to constrain these two biases. Green preference appears independent of lottery bias. Although the salience of environmental conditions may affect retail investors' green tastes (e.g., Fisman et al., 2023), green preference may not be powerful enough to affect the way how salience affects thinking based on salience theory (Bordalo, Gennaioli, and Shleifer 2012; 2013; 2020). Consistent with these considerations, unreported tests show insignificant relationships between *GreenShare* and these two heuristics.

A reverse question is whether the non-significance of lottery preference and salience thinking could potentially dilute the overall level of biases (i.e., the BIAS3 index). To address this concern, we create another bias index BIAS5 to synthesize all five leading biases including lottery preference and salience. The construction of BIAS5 follows the same procedures as BIAS3. The result is reported in Model (5). We observe that the negative relationship between $GreenShare$ and the synchronized bias index remains highly significant.

C. Behavioral Biases and Portfolio Performance

To complete the economic picture, we last verify whether our hypothesized behavioral biases affect portfolio returns in our sample based on the following specification:

$$\alpha_{FF6+GMB}^{i,t} = \alpha + \beta \times Bias_{i,t} + \gamma \times \text{Controls} + \varepsilon_{i,t}, \quad (3)$$

where $\alpha_{FF6+GMB}^{i,t}$ is the 7-factor adjusted alpha for investor i's holding value-weighted portfolio at month t, and $Bias_{i,t}$ denotes the biases for investor i at month t. We standardize bias measures for easy cross-comparison and use the same set of control variables as in Section III.A and Section III.B. In addition, the two non-hypothesized behavioral biases are included as controls in the analysis of hypothesized biases.

The results are tabulated in Table 5. Models (1) to (3) present results for the three individual biases, whereas Model (4) explores their joint explanatory power. Consistent with the literature, we find that the disposition effect is a robust predictor of retail investors' portfolio performance. A one-standard-deviation increase in the disposition effect is associated with an over 0.540% decrease in monthly portfolio alpha in both the individual and joint models. As for under-diversification, if an investor diversifies one standard deviation more, then the joint model suggests a 0.071% increase in his or her monthly portfolio alpha. However, we do not find any significant correlation between local bias and portfolio alpha.

Finally, Models (5) and (6) investigate the link between the portfolio performance and the two synchronized bias indices, BIAS3 and BIAS5. We observe that synchronized behavioral bias indices explain retail investors' portfolio performance very well. Since both indices range from -0.5 (the least biased) to 0.5 (the most biased), we can easily interpret the regression coefficient as the performance difference generated by the most and least biased investors. Based on this interpretation, Models (5) and (6) report that the least biased investors could earn, respectively, 0.852% and 1.394% higher monthly portfolio alphas than the most biased ones. Such performance difference is highly significant in economic terms.

D. A Graphic Demonstration of the Behavioral Channel

Thus far, we have explored the three-way relationship between *GreenShare*, portfolio performance, and behavioral bias. It helps to demonstrate these results graphically to provide more intuitions. To achieve this goal, we first divide investors in our sample into 10 decile groups according to their average *GreenShar*, with each decile representing an equal-sized interval on the level of *GreenShare.* Figure 2 plots in Panel A and Panel B the relationship between *GreenShare* and return and that between *GreenShare* and 7-factor adjusted portfolio alphas. We observe a general upward-sloping pattern in both cases, consistent with a positive relationship between *GreenShare* and portfolio performance.

Next, Panel C provides a graphic illustration of the relationship between *GreenShare* and behavioral bias, proxied by the synchronized *BIAS3* index. We observe a general negative relationship between the two variables, consistent with a suppressing effect of *GreenShare* on behavioral bias. Interestingly, the negative relation is also V-shaped. In other words, although *GreenShare* and *BIAS3* are negatively correlated in general, their relationship appears negative (positive) when *GreenShare* is below (above) a threshold of approximately 65%.

It is perhaps not surprising to observe this V-shaped relationship. When the portfolio is initially brown, an increase in *GreenShare* is very effective in reducing biases. For instance, inducing investors to add one green stock to a portfolio with one brown stock implies a huge diversification benefit. However, when the *GreenShare* goes above a high threshold, many green stocks have already been included in the portfolio. As a result, the diversification benefit of adding one more green stock diminishes. Similarly, an increase in green preference may reduce an investor's sensitivity to returns to a certain degree—but not indefinitely. In both cases, we expect the benefits of *GreenShare* to dimmish when above a certain threshold.

With diminishing benefits, the negative impact of green preference as a constraint on stock selection may become important. For instance, too high a concentration in green stocks reduces portfolio diversification. This helps explain why bias slightly increases with very high *GreenShare*. As a result, portfolio performance may also diminish or slightly revert when *GreenShare* is too high. This is exactly what we observe from Panels A and B of Figure 2. For instance, Panel B suggests that portfolio alphas increase when *GreenShare* is approximately below 75%. Above this threshold, a further increase in *GreenShare* reduces performance.

Interestingly, Panel D reports that the relationship between bias and performance is consistently negative without reverting. Hence, it is plausible that the reverting impact of *GreenShare* on performance could be related to the reverting effects of *GreenShare* in constraining behavioral biases. Of course, the *GreenShare* thresholds to trigger the reverting pattern differ across the two cases, suggesting that there could still be missing effects not included in our analysis. Nonetheless, the joint occurrence of the reverting effects (esp when *GreenShare* is high) suggests that behavioral bias may provide a heuristic to even explain the reverting performance of high *GreenShare*.

In sum, Figure 2 summarizes our baseline analysis concerning the three-way relationship between *GreenShare*, portfolio performance, and behavioral bias. While these results are consistent with our working hypothesis that green preference may affect performance through the channel of behavioral biases, there could be alternative explanations underpinning the observed performance-preference relationship. Hence we move on to explore these alternatives.

V. Alternative Explanations

There are several possible explanations for the positive correlation between an investor's green preference and his or her portfolio performance. We first scrutinize these alternative explanations in this section. To the extent that these alternative explanations fail to account for our observations, we will also provide an endogeneity test based on abnormal heatwaves in later sections.

A. Stock Selection

The first alternative explanation is that investors may consider sustainability as a signal of future performance (Amel-Zadeh and Serafeim, 2017). Indeed, survey studies show that material subsets of retail investors (e.g., Giglio et al., 2023) and institutional investors (e.g., Krueger, Sautner, and Starks, 2020) may believe that higher ESG investments will lead to larger returns. In our context, some retail investors may invest in green stocks in anticipation of better performance. If their anticipation is correct, we observe the outperformance of green investors. This alternative explanation resamples a *stock-picking* ability associated with green awareness.

To test this alternative explanation, we build on the setting of Jones, Shi, Zhang, and Zhang (2024) to examine whether the trading activity of investors, especially green investors, can predict the cross-section of future stock returns, especially green stock returns. First, we investigate the return predictability from the order imbalance of all investors, green investors, and brown investors. The order imbalance (OIB) of a group of investors is defined as follows:

$$OIB_{i,d,G} = \frac{\sum_{j \in G} BuyVol_{i,d,j} - \sum_{j \in G} SellVol_{i,d,j}}{\sum_{j \in G} BuyVol_{i,d,j} + \sum_{j \in G} SellVol_{i,d,j}},$$

where subscript i indicates the specific stock, d indicates the day of calculation, and G indicates the group of investors, i.e., green investors, brown investors, or all investors. An investor is defined as a green investor when he or she is in the top tercile of the average $GreenShare$ across the whole sample period, while investors in the bottom tercile is defined as brown investors. In addition, $BuyVol_{i,d,j}$ and $SellVol_{i,d,j}$ are the buying volume and selling volume of stock i on day d by investor j, respectively. Then, we explore whether the trading activity of retail investors can predict future stock returns through the following Fama and MacBeth (1973) regression:

$$Ret_{i,d,h} = \alpha_{h,G} + \beta_{h,G} OIB_{i,d-1,G} + \gamma' Controls_{i,d-1} + \varepsilon_{i,d,h}, \tag{5}$$

where $Ret_{i,d,h}$ is t stock i's h horizon ahead return on day d and $OIB_{i,d-1,G}$ is the previous day's order imbalance of investor group G. More specifically, we investigate three horizons: one day ahead, one week ahead, and one month ahead, to evaluate the trading activity of retail investors in our sample. The control variables include the previous day's return, Ret(-1), the previous week's return, Ret(-6,-2), the previous month's return Ret(-27,-7), as well as the log market cap (Size), earnings-to-price ration (EP), and turnover rate (Turnover) in the last month.

The regression results are presented in Panel A of Table 6. Model (1) conducts the daily predictivity analysis using the entire sample of investors. The regression coefficient $\beta_{h,G}$ can be interpreted as the average stock selection ability in this case. We observe an insignificant coefficient, suggesting that, on average, investors do not have the proper selection ability such that their trading can predict future returns.

Could green investors do better? To address this issue, Model (2) and Model (3) apply the above analysis to, respectively, green investors (i.e., investors within the top tercile of average *GreenShare*) and brown investors (i.e., those from within the bottom tercile of average *GreenShare*). Interestingly, order flows from green investors negatively predict future stock returns, though the effect is only marginally significant in statistics. This "negative selection", even only marginally significant, is at odds with the notion that selection ability could potentially explain the superior portfolio performance of green investors.

One possibility is that green investors may predict stock returns at a longer horizon. To address this possibility, Models (4) to (6) and Models (7) to (9) examine longer-horizon selection ability by extending the predicting horizon to one week and one month. However, these tests fail to detect any positive predicting power of investors' trading orders.

Another alternative is that maybe green investors are good at selecting green stocks rather than all stocks. To test this alternative, we divide stocks into green stocks and brown stocks to sharpen our test on green awareness-associated stock picking ability. More specifically, we run the following regression:

$$Ret_{i,d,h} = \alpha_{h,G} + \beta^1_{h,G} OIB_{i,d-1,G} + \beta^2_{h,G} Green_i + \beta^3_{h,G} OIB_{i,d-1,G} \times Green_i + \gamma' Controls_{i,d-1} + \varepsilon_{i,d}, \tag{6}$$

where $Ret_{i,d,h}$ is t stock i's h horizon ahead return on day d, $OIB_{i,d-1,G}$ is the previous day order imbalance of investor group G, and $Green_i$ takes the value of 1 when stock i is a green stock and 0 otherwise. The coefficient $\beta^3_{h,G}$ indicates whether investors demonstrate green awareness-associated stock-picking ability.

The results are tabulated in Panel B. Across all groups of investors and all forecasting horizons, no positive or significant $\beta^3_{h,G}$ is observed. If anything, order flows from green investors more negatively predict future stock returns of green stocks. Collectively, these results suggest that selection ability is unlikely to explain the superior portfolio performance of green investors.

B. Riding on Demand Shocks

Secondly, even when retail investors face a general tradeoff between nonpecuniary preferences and expected returns, a temporary demand shock may nonetheless improve their realized returns (Pástor, Stambaugh, and Taylor, 2022), if they are able to correctly ride on the waves of demand shocks. This riding-on-demand alternative explanation can also be interpreted as a type of *timing* ability associated with green awareness. It resembles the traditional market timing, except that in our setting the timing variable is aggregate demand shocks rather than aggregate market returns.

To investigate the role of aggregate demand shocks, we replace $OIB_{i,d-1,G}$ in Equation (5) and (6) with $ADS_{i,d-1}$, the previous day's aggregate demand of all retail investors in our sample[21]. The aggregate demand shock $ADS_{i,d}$ is defined as

$$ADS_{i,d} = \frac{\sum BuyVol_{i,d,j} - \sum SellVol_{i,d,j}}{ShrOut_{i,d}},$$

where $ShrOut_{i,d}$ is the number of shares outstanding of stock i on day d. We then ask whether ADS can properly predict future factor-adjusted stock returns. If aggregate demand fails to predict such abnormal returns, then our GMB-enhanced Fama-French seven-factor model sufficiently explains the price impact of demand shocks, leaving no room for a riding-on-demand strategy to generate risk-adjusted green performance as observed in our previous tests.

We report the results in Table 7, where Models (1) and (2), Models (3) and (4), and Models (5) and (6) tabulate the results for the predicting power of ADS on alphas that are one day, one week, and one month ahead. In general, no positive relationship between the aggregate demand shock and the future stock alphas is observed. Neither do we find any predicting power when we interact ADS with an indicator of green stocks. In this case, riding on demand will not allow an investor to generate any superior return.

Between this and the previous tests, we conclude that the alternative explanations associated with stock selection and riding-on-demand shocks fail to provide plausible explanations for our previous findings.

C. Risk Mitigation Motives

Another explanation is that green stocks may provide a risk mitigation tool. Gibson et al., (2020) observe that responsible investing does not enhance the portfolio returns of institutional investors but acts more as a risk mitigation tool. Several studies in the corporate literature show that

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[21] Our construction measures the aggregate demand shock from a representative group of retail investors. Retail trades have a large impact in India stock market. According to a report by GAA advisory (https://www.igaa.in/wp-content/uploads/2021/02/Retail-Investors-in-India.pdf), retail turnover was 49% of total turnover of equity cash market in July 2020. Therefore, we believe the aggregate demand shock can be a plausible proxy for the aggregate demand shock of the whole market.

corporate sustainability limits downside risk (see, e.g., Edmans, 2011; Lins, Servaes, and Tamayo, 2017; and Albuquerque, Koskinen, and Zhang, 2019). By doing so, greener investors are also likely to gain better performance as a result of better risk management.

To explore this alternative explanation, we ask two interconnected questions: (1) Do investors use green investments as a tool of risk mitigation? (2) If so, does the mitigation effect enhance the alpha generation? We use two risk proxies to address these issues. We first proxy for the systematic risk of an investor by her holding value-weighted average of stock market beta, estimated from a 60-month rolling window CAPM regression. Our proxy for idiosyncratic risk is the holding value-weighted average idiosyncratic volatility (Ivol), following Ang, Hodrick, Xing, and Zhang (2006). It is worth noting that, by construction, this proxy for idiosyncratic risk is independent of the diversification benefit that we have examined before.

To investigate the first question, we conduct the following regression:

$$Risk_{i,t} = \alpha + \rho \times \mathrm{GreenShare}_{\mathrm{i,t}} + \gamma \times \mathrm{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where we use $Risk_{i,t}$ refer to the risk proxies. The control variables include the time-varying portfolio characteristics, including Log(HV) and Turnover, Investor fixed effects, and Year-Month fixed effects. A negative coefficient ρ suggests a risk-mitigating usage of green investments as risk mitigation because a higher value *GreenShare* leads to a lower level of risk.

The results are reported in Table 8. Models (1) and Model (2) tabulate the relationship between *GreenShare* and systematic risk, proxied by the market beta, and that between *GreenShare* and idiosyncratic risk, proxied by Ivol. We observe a significantly negative coefficient for systematic risk (Beta) and *GreenShare*, suggesting that green investments could indeed reduce the systematic risk of investors. For instance, green stocks may have lower market beta than brown ones. In contrast, the coefficient for idiosyncratic risk is insignificant, suggesting no particular relation between idiosyncratic risk and *GreenShare*. Our previous tests show that *GreenShare* enhances diversification. The current test further suggests that green investors do not significantly change stock-level idiosyncratic volatility. In other words, while *GreenShare* is associated with buying more green stocks, which enhances diversification, the newly purchased stocks tend to have similar stock-level idiosyncratic volatility as existing stocks in the portfolio.

Although our results suggest that investors may use green investments as a tool to mitigate systematic risk, this observation does not imply that doing so will allow investors to achieve better performance. Indeed, systematic risk exposure should not affect performance when all systematic risk factors are adjusted. To further verify this notion, we investigate whether investors can derive any performance benefit from doing so through the following regression:

$$\alpha_{FF6+GMB}^{i,t} = \alpha + \rho_1 \times \text{GreenShare}_{\text{i,t}} + \rho_2 \times Risk_{i,t} + \rho_3 \times \text{GreenShare}_{\text{i,t}} \times Risk_{i,t} + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where we use Beta as the risk proxy in Model (3), Ivol in Model (4), and include both risks in Model (5). We also include the same set of controls. The coefficient ρ_3 represents the performance enhancement from risk mitigation via green investments.

We do not observe a positive impact on performance of reduced market risk. Hence, even though green investments are associated with lower market risk, this risk mitigation effect cannot explain the performance associated with green investments. In contrast, a higher (lower) level of idiosyncratic risk is associated with a lower (higher) influence of GreenShare on alpha. However, since GreenShare is not associated with lower idiosyncratic risk as mentioned above, investors do not seem to utilize this property to benefit from enhanced performance.

Collectively, although we find evidence that green investments mitigate risk, our results fail to support risk mitigation as a channel for green investments to achieve superior performance.

IV. Endogeneity Test: Extreme Heat as a Shock

Thus far, we show that the three most important alternative mechanisms fail to explain our main findings. Although there could be other non-environmentally related omitted variables, a parsimonious interpretation of the above results is that our findings may indicate a new behavioral channel. This section provides direct evidence to mitigate the remaining endogeneity concerns.

A. Extreme Heat in India

To mitigate the concern of endogeneity, we built on a long-recognized observation of the literature that exposure to abnormally hot temperatures can heighten people's awareness of climate-related issues and inspire corresponding actions (e.g., Akerlof et al. 2013; Myers et al. 2013; Zaval et al. 2014; Choi, Gao, and Jiang 2020; Di Giuli, Garel, Michaely, and Romec, 2024). Choi, Gao, and Jiang (2020) suggest that abnormally hot temperatures draw investors' attention to global warming. Di Giuli, Garel, Michaely, and Romec (2024) document that fund managers exposed to abnormally hot temperatures are more likely to support climate proposals. These studies suggest that heatwave shocks could introduce a plausible source of exogenous variation in affecting investors' green preferences.

The above literature provides an important heuristic to our analysis, because heatwaves become a significant climate concern in South Asia, particularly in the vicinity of the Indo-Gangetic Plain. According to the National Crime Records Bureau of India (NCRB), annual heatwave-related fatalities over the past decade have varied from several hundred to around two thousand, which triggered a systematic government policy response in 2018 to enhance early warning systems for impending heatwaves.[22] Since the main sample period of our analysis (2012 to 2019) precedes the implementation of policy response, the occurrence of heat waves during our sample period is more surprising to investors due to its less predictable nature. Economically speaking, this means that we can build on the above literature to employ heatwave shocks to mitigate the concern of endogeneity in our setup, particularly because the abnormally hot temperatures brought about by heatwaves are difficult to predict and are thus plausibly exogenous to non-environmental considerations (exclusion restrictions).

To systematically identify extremely hot weather in our sample period, we obtain the daily historical temperature data at the district level in India via the Open-Meteo Weather API. The Open-Meteo Weather API is an open-source weather API and offers free access for non-commercial use. It partners with national weather services to bring open data with high resolution,

[22] See NCRB's annual report (https://ncrb.gov.in/accidental-deaths-suicides-in-india-adsi.html) for detailed statistics. In response, the India Meteorological Department (IMD) launched the Atmosphere & Climate Research-Modelling Observing Systems & Services (ACROSS) scheme in 2018 to enhance early warning systems for impending heatwaves (https://pib.gov.in/PressReleasePage.aspx?PRID=1943214), with an annual budget ranging from 18 to 25 million USD. Since our sample period, spanning from January 2012 to December 2019, does not coincide with the implementation of the ACROSS scheme, the occurrence of heat waves during our sample period is more surprising to investors due to its less predictable nature.

ranging from 1 to 11 kilometers. The Historical Weather API is based on reanalysis datasets and uses a combination of weather station, aircraft, buoy, radar, and satellite observations to create a comprehensive record of past weather conditions.

We then adopt Choi, Gao, and Jiang's (2020) approach to calculate abnormal temperatures as a proxy for heat waves. This approach offers two key advantages in our context. First, it identifies warm winters in addition to hot summers. This is helpful because both events may raise awareness about global warming and can influence green preferences. Second, it raises the threshold for subsequent heatwaves following identified ones. This feature ensures that each heatwave presents new information to affect investors' green preferences.

More explicitly, we calculate the monthly temperature as the average daily temperature within that month, then decompose the monthly temperature into three parts: the predictable component, the seasonal component, and the abnormal part. Formally, we define

$$Temperature_{d,t} = Aver\_Temp_{d,t} + Mon\_Temp_{d,t} + Ab\_Temp_{d,t},$$

where $Aver\_Temp_{d,t}$ is the average monthly local temperature in district d over the 120 months prior to t; $Mon\_Temp_{d,t}$ is the average deviation of this month's temperature from the average, and the remainder $Ab\_Temp_{d,t}$ is the measure of abnormal temperature. Next, we classify district-month pairs with $Ab\_Temp_{d,t}$ larger than 3 degrees Celsius as extreme heat pairs. The extreme heat events identified account for less than 0.2% of all observations.

After identifying the district-month pairs with extreme heat, we aggregate consecutive extremely hot months to form an aggregate extreme heat shock. Our subsequent analysis focuses on the top eight extreme heat shocks across the entire country because they are among the most salient climate events in the country and are widely reported and discussed by national and international media outlets. As a result, we expect these shocks to exert a prevailing impact on retail investors. Empirically, we define a heatwave (shock) period as the identified months plus one month before and one month after.[23] The additional months aim to minimize the impact of the

[23] Details regarding the start month, end month, and corresponding media coverage are provided in Table A.1 in the Online Appendix.

warming-up process and the contemporaneous market movements (Choi, Gao, and Jiang, 2020). We then use three months before and three months after the shock period to identify the impact of these extreme temperature shocks on investors.

B. The PSM-DiD Analysis

The setup of heatwave shocks allows us to adopt a difference-in-difference (DiD) approach and use the within-investor changes in revealed green preference and related trading activities to obtain our desired estimates. To achieve this goal, we further construct the treatment group and the control group through propensity score matching following Fang, Tian, and Tice (2014).

Specifically, for each extreme heat shock sample, we sort investors into quintiles based on the *change* of *GreenShare* after the shock, which is measured as the difference in the average monthly portfolio weights in green stocks between the pre- and post-shock periods. We then use the propensity score estimated from a Probit model to match each investor in the top quintile (the treated group) with one investor in the bottom quintile (the control group).[24] We require each investor to have a full observation during the shock period, and since our shocks happen in sequence, we exclude the previously treated investors from subsequent shocks. This request helps to avoid potential contamination of the DiD estimates, as documented in recent studies (e.g., Gormley and Matsa 2011; Cengiz, Dube, Lindner, and Zipperer 2019; Baker, Larcker, and Wang 2022). In total, the matched sample consists of 12,514 investors across all shock periods.

The effectiveness of our matching process can be demonstrated via a commonly used metric for classification job in the machine learning literature: the receiver operating characteristic (ROC) curve (Bradley, 1997).[25] Figure 5 provides such curves. Specifically, Panels A and B plot the ROC

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[24] The matching is based on a Probit model and a list of characteristics, including *GreenShare*, performance, behavioral bias measures, and all the control variables in the estimation of Equations (2) and (3) from the pre-shock periods. We retain the pair with the smallest difference in propensity scores when multiple matching occurs.

[25] A receiver operating characteristic (ROC) curve, is a graphical plot that illustrates the performance of a binary classifier model at varying threshold values. Each point on the curve represents the (false positive rate, true positive rate) coordinate of a given threshold. The area under the curve (AUC) score calculate the area under the ROC curve. A perfect classifier has an AUC score of 1 and a random guess results in an AUC score of 0.5. For some recent application of ROC curve in finance, please refer to Iyer, Khwaja, Lottmer, and Shue (2016) and Berg, Burg, Gombović, and Puri (2020), who investigate the discrimination issue in FinTech lending.

curves of the Probit model fitted before and after the matching. The before-match area under the curve (AUC) score is 0.762, suggesting that the quintile positions of investors can be predicted by their characteristics. However, after the match, the AUC score drops to 0.554, indicating that investor characteristics can no longer be used to predict quintile positions. In other words, treated investors now exhibit indistinguishable characteristics compared to matched investors in the control group. Combined, these observations suggest that the matching process is proper for our intended DiD analysis.

With the matched sample, we estimate how extreme temperature shocks affect the performance and biases of treated investors when compared to the control group in the following PSM-DiD specification:

$$Y_{i,t} = \alpha + \rho \times Treated_i \times Post_t + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}, \qquad (4)$$

where $Y_{i,t}$ refers to portfolio performance ($\alpha_{FF6+GMB}$), under-diversification ($\text{UDIV}_{i,t}$), and local bias ($\text{LOCB}_{i,t}$) for investor i in the month t, $Treated_i$ is a dummy variable that takes a value of one if investor i is from the treated group and zero otherwise, $Post_t$ is a dummy variable that takes a value of one if the month t is in the post-shock period and zero otherwise, and. We control all the investor-month level control variables as presented in regression (1), (2), and (3), including the portfolio characteristics and non-hypothesized behavioral biases, and we also include the investor fixed effects δ_i and year-month fixed effects θ_t, to capture the cross-sectional variation of the within-investor transition.

The results are reported in Table 9. Model (1) presents the results of portfolio performance adjusted by the GMB-enhanced Fama-French seven-factor model. Models (2) and (3) tabulate the relative change in under-diversification and local bias. We observe that increases in green awareness significantly enhance portfolio performance, reduce the under-diversification bias, and lessen the distance between the investor and his or her holding firms, as the interaction term $\text{Treated}_i \times \text{Post}_t$ is significant in the corresponding direction. As for economic magnitude, the first column suggests a 0.25% monthly outperformance of the treated group.

Figure 6 plots the dynamic treatment effects. Note that we extended the post-shock period by two more months to demonstrate the potential variations of post-heatwave effects. Panel A depicts the dynamic treatment effects of the GMB-enhanced Fama-French seven-factor alpha. Panel B and Panel C plot those for the two behavioral biases: under-diversification and local bias. All panels support the parallel trend assumption. As for the post-shock treatment effects, we observe a significant reduction in portfolio under-diversification increase and a significant increase in local bias at least up to four months after the shock. Portfolio performance significantly increases in the post-shock period, especially between the second and fourth months. All these observations are consistent with a behavioral channel as hypothesized before.

As for the disposition effect, we provide suggestive evidence of the change in the disposition effect on green stocks in the subsample of the treatment and the control groups. We extract the investor-stock-day holding data for the shock sample and analyze stocks held by investors in the pre-shock periods. For the subsample of the treated group and the control group, we construct three dummy variables: $Gain_{i,s,t}$, $Green_s$, and $Post_t$, and their interactions. The dummy $Gain_{i,s,t}$ takes the value of one if investor i's holding on stock s is in gain on day $t-1$, and zero otherwise. The dummy indicator $Green_s$ takes the value of one for green stocks, and zero otherwise. The dummy $Post_t$ still refers to the post-shock period.

We then use the triple interaction across the three variables, namely $Green_s \times Gain_{i,s,t} \times Post_t$, to measure how extreme temperature shocks affect the disposition tendency for investors to sell winning green stocks. To avoid a higher-order quadruple interaction, we estimate this disposition tendency separately for the treated and control investors.

The results are tabulated in Table 10. Models (1) and (2) report the triple interaction results of, respectively, the investors in the treated and control group. We observe that extreme temperature shocks significantly reduce treated investors' tendency to sell green stocks and their tendency to sell winning green stocks. The first tendency is consistent with their increases in realized green preference. The second tendency indicates that their disposition effect gets significantly attenuated after the shocks. In contrast, both tendencies remain unchanged for the control group, confirming that the treated group also exhibits a reduced disposition effect relative to the control group.

As a robustness check, we further zoom into the subsample of investors that have positive *GreenShare* changes. The goal of this test is to examine whether the identified treatment effects only reflect the difference between investors that are the most sensitive to temperature shocks (i.e., quintile-one vs. quintile-five investors), or whether it implies a general and incremental effect that can be detected even among the subgroup of investors who are positively affected by these shocks. To achieve this goal, we sort these investors into terciles and apply the PSM-DiD process to investors in the top (treated) and bottom (control) terciles. All other analyses are similarly conducted. We present corresponding results in our Online Appendix (i.e., Figure A.1, Figure A.2, Table A.2, and Table A.3). Our results remain highly robust, suggesting that our PSM-DiD test identifies a general treatment effect across different groups of investors. In addition, we tabulate our main results by only using never-treated investors as control, to show that our results are robust to different specifications. This would further exclude any investor who get treated in subsequent heatwaves from being selected as control investors in previous waves. We present our in our Online Appendix (i.e., Figure A.3, Figure A.4, Table A.4, and Table A.5).

In summary, by exploiting extreme heatwaves in India as an exogenous shock to investors' green awareness, we provide causal evidence that green awareness helps mitigate investors' behavioral biases in trading and leads to better portfolio performance. More specifically, investors with growing green awareness demonstrate a lower level of under-diversification, a lower level of disposition effect in trading green stocks, and a higher level of local bias. Additionally, we confirm that the impact on trading behaviors persists after the increase in green preference, validating our hypothesized behavioral channels.

D. Additional Analysis

We lastly provide several additional analyses using the extreme heat shock periods constructed above to shed light on the economics of our proposed behavioral channel. Specifically, we provide further evidence on how treated investors diversify their portfolios and adjust their portfolio risk.

To complement our DiD analysis on portfolio performance, we also use the same DiD framework to explore the return dynamics of green and brown stocks around extreme heatwaves.

We first ask how investors achieve better diversification based on the following PSM-DiD specification:

$$Num_{i,t} = \alpha + \rho \times \text{Treated}_i \times \text{Post}_t + \delta_i + \theta_t + \varepsilon_{i,t},$$

where $Num_{i,t}$ refers to the number of green stocks in the portfolio. To compare the purchasing behavior of investors on green stocks to that of brown stocks, we also replace the number of green stocks with the number of brown stocks.

Table 11 reports the estimated results, with Models (1) and (2) employing the numbers of green and brown stocks as the dependent variable. The DiD analysis reveals that treated investors significantly increase the number of green stocks in their portfolios after the shock. The DiD coefficient is 0.773, suggesting that treated investors on average add less than one new green stocks. At the same time, the DiD coefficient becomes negative (-0.439) for brown stocks, suggesting that investors also sell the entire holding of some brown stocks.

It is worth noting that adding a new stock and selling the entire holding in an existing stock implies a trading motivation distinct from traditional portfolio rebalancing (Odean, 1998). These activities are likely due to enhanced green preference. It is also important to notice that treated investors do not sell one brown stock to buy one green stock. The coefficient difference implies that investors buy more green stocks than the number of brown ones they sell. It is this net effect that enhances the portfolio diversification of treated investors.

The net increase in the number of stocks implies that investors might use new capital to buy green stocks. Model (3) investigates this possibility by exploring portfolio value (i.e., the natural log of the portfolio holding value) in the same DiD setup. We observe a significant increase in portfolio value, confirming that treated investors finance the purchase of new green stocks through both the selling of brown stocks and new capital.

Although enhanced diversification enhances performance, could treated investors also benefit from the potential price change in green stocks associated with the temperature shocks? To examine this source of return, we regress stock returns on the interaction between Post and the dummy indicator for Green stocks in Model (4). We observe a significantly negative coefficient, suggesting that green stocks on average experience price drops in the post-shock period. This negative price change is consistent with the literature. Choi, Gao, and Jiang (2020) document that stock prices overreact to extreme temperature shocks in the short run. Our observation captures the reversal part, confirming that the relative performance gain of treated investors does not come from the price impact of green stocks.

VI. Conclusion

In this paper, we propose and empirically test a novel behavioral channel for nonpecuniary green preferences to shape investor welfare. Utilizing a proprietary dataset from a major Indian bank, we find that green investments help investors mitigate behavioral bias, such as the disposition effect and under-diversification. Since these behavioral biases harm the investment returns of retail investors, the behavioral channel enables green awareness to indirectly help these investors in enhancing returns. This effect contradicts the prevailing wisdom that green investors willingly accept lower returns for sustainable investment.

Further tests exploiting extreme heatwaves as an exogenous shock on investors' green awareness suggest that the behavioral channel is plausibly causal. Investors who increase green awareness exhibit significantly higher portfolio returns, a lower level of disposition effect in green stock, and a lower level of under-diversification. We also rule out a list of alternative explanations of the positive green performance related to investors' selection ability, total demand, and risk mitigation effects.

Our results have important normative implications regarding how environmental considerations affect the investment decisions of investors. The positive green-performance relationship observed among retail investors not only demonstrates the bright side of green investments for an important group of investors. It may also point out a potential direction for the financial market to mobilize capital needed for the green transition. Our results call for more research on the broader influence of green preference and related investments.

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Table 1 Summary Statistics

This table presents summary statistics of the 40,339 investors in our data from 2012 to 2019 used in this paper at investor level. The upper panel presents the average monthly portfolio performance, measured by raw return and alpha adjusted for Fama-French 5 factors plus Carhart's momentum factor and green-minus-brown (GMB) factor, as well as the monthly average of our green preference proxy *GreenShare*. The middle panel describes the level of disposition effect, diversification, and local bias for each individual investor. The panel at the bottom includes portfolio characteristics and investor's demographic characteristics. The monthly average holding value is presented in Lakh (100,000 INR), and the monthly portfolio turnover is constructed following Barber and Odean (2000).

	N	Mean	Std dev	10%	25%	Median	75%	90%
Performance and $GreenShare$								
Raw Return (%)	40339	-0.716	2.901	-3.788	-1.751	-0.242	0.707	1.412
$\alpha_{FF6+GMB}$ (%)	40339	-1.022	2.541	-3.57	-1.749	-0.627	0.086	0.857
Average $GreenShare$ (%)	40339	61.051	27.046	20.569	41.99	64.152	83.39	95.852
Behavioral Biases								
Disposition Effect	28918	1.117	3.5	-0.125	0.023	0.239	1.097	3.371
Average # of Stocks	40339	6.853	7.054	2.059	3.2	5	8.035	13.233
Average Local Bias	36947	0.383	0.802	-0.292	-0.107	0.181	0.614	1.257
Portfolio and Investor Characteristics								
Average Holding Value	40339	1112.41	11541.64	22.615	72.442	232.969	713.823	2007.524
Average Turnover (%)	40339	20.873	30.872	3.222	5.286	9.675	20.494	50
Total # of Stocks Traded	40339	12.293	11.036	5	6	9	14	23
Investor Age (in year)	40339	41.329	11.196	29	33	39	47	57
Account Age (in month)	40339	66.969	50.812	17	27	53	93	152
Credit Score	40339	665.889	326.963	0	723	828	857	876

Table 2 GreenShare and Carbon Footprint in Consumption

This table reports the investors' distribution of consumption at different levels of carbon footprint. The carbon footprint is calculated as the monthly transaction value weighted average CO_2 emission in Kg per Lakh (100,000 INR) of spending. We classify the consumption carbon footprint into four groups, which represents four equal length intervals from zero emission to the highest level of emissions (711.64 Kg CO_2 emission/Lakh). Similarly, investors are grouped into three groups based on GreenShare in each month,. which represents three equal length intervals from 0% to 100%. All numbers are presented in percentage.

	Consumption Carbon Footprint				
GreenShare	Q1	Q2	Q3	Q4	Total
[0.00%, 33.33%)	74.68	16.81	6.41	2.11	100
[33.33%, 66.67%)	74.80	18.67	4.02	2.51	100
[66.67%, 100%]	80.65	12.40	4.90	2.05	100

Table 3 Green Preference and Portfolio Performance

This table reports the baseline results on the relationship between an investor's portfolio performance and his or her green preference estimated from

$$\alpha_{FF6+GMB}^{i,t} = \alpha + \beta \times GreenShare_{i,t} + \gamma \times \text{Controls} + \varepsilon_{i,t},$$

where $\alpha_{FF6+GMB}^{i,t}$ is the holding value-weighted portfolio alpha adjusted for the Fama-French 5 factors, Carhart's momentum factor, and the value-weighted Green-Minus-Brown factor for investor i at month t, $GreenShare_{i,t}$ denotes investor i's average proportion of investment in green stocks in the past 12 months prior to month t, which is our proxy for investors' green preference, and the vector Controls stacks a group of portfolio and account characteristics. We include year-month fixed effects in all panel regression specifications and control for investor fixed effects and account characteristics interchangeably. The first three columns report the results from panel regression, and the last column reports the results from Fama-MacBeth regression. The sample period is from Jan 2013 to Dec 2019. Standard errors are clustered at the investor level for the panel regression and are adjusted for autocorrelation following Newey and West (1987). The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$\alpha_{FF6+GMB}$ (%)			
	Panel OLS			Fama-MacBeth
	(1)	(2)	(3)	(4)
GreenShare	0.275***	0.249***	0.243***	0.384**
	(7.614)	(6.938)	(2.951)	(2.206)
Log(HV)		0.0625***	-0.657***	0.0959***
		(10.48)	(-26.87)	(4.248)
Turnover		-0.698***	-0.324***	-0.614***
		(-10.62)	(-4.840)	(-3.673)
Income	0.0654***	0.0488***		0.0536***
	(7.236)	(5.430)		(6.076)
Log(Age)	0.327***	0.233***		0.230***
	(7.713)	(5.544)		(4.174)
Log(Account Age)	0.195***	0.170***		0.172***
	(11.43)	(10.06)		(3.300)
Credit Score	-0.128***	-0.0956***		-0.125***
	(-4.551)	(-3.425)		(-4.514)
Intercept	-2.060***	-2.847***	10.89***	-3.533***
	(-8.218)	(-10.79)	(25.19)	(-6.939)
Demographic FE	Y	Y	N	N
Investor FE	N	N	Y	N
Year-Month FE	Y	Y	Y	N
Observations	809,327	809,327	819,878	818,118
R-squared	0.090	0.091	0.136	0.017

Table 4 Green Preference and Behavioral Biases

This table reports the relationship between the level of green preference and the level of behavioral biases estimated from

$$Bias_{i,t} = \alpha + \beta \times GreenShare_{i,t} + \gamma \times \text{Controls} + \varepsilon_{i,t},$$

where $GreenShare_{i,t}$ denotes investor i's average proportion of investment in green stocks in the past 12 months prior to month t, which is our proxy for investors' green preference, and $Bias_{i,t}$ denotes the biases for investor i at month t. We report the results for our hypothesized disposition effects (DISP), under-diversification (UDIV), and local bias (LOCB) channels separately and jointly in the first four columns. All the bias measures are standardized. The fifth and sixth column reports the results for the aggregated 3 biases (BIAS3) and the aggregated 5 biases (BIAS5) including lottery preference and salience thinking. Biases are aggregated as the average cross-sectional rank of biases at each month which is scaled into a [-0.5, 0.5] interval and then standardized. We control for the portfolio characteristics, demographic characteristics, demographic fixed effects, and year-month fixed effects. The sample period is from Jan 2013 to Dec 2019. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	DISP	UDIV	LOCB	BIAS3	BIAS5
Variables	(1)	(2)	(3)	(4)	(5)
GreenShare	-0.0282***	-0.0213***	0.0467***	-0.104***	-0.091***
	(-5.869)	(-4.372)	(7.448)	(-12.87)	(-15.21)
Controls	Y	Y	Y	Y	Y
Demographic FE	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y
Observations	519,811	809,327	738,502	738,502	738,502
R-squared	0.354	0.426	0.491	0.318	0.464

Table 5 Behavioral Biases and Portfolio Performance

This table reports the relationship between the level of behavioral biases and portfolio performance estimated from

$$\alpha_{FF6+GMB}^{i,t} = \alpha + \beta \times Bias_{i,t} + \gamma \times \text{Controls} + \varepsilon_{i,t},$$

where $\alpha_{FF6+GMB}^{i,t}$ is the holding value-weighted portfolio alpha adjusted for the Fama-French 5 factors, Carhart's momentum factor, and the value-weighted Green-Minus-Brown factor for investor i at month t, and $Bias_{i,t}$ denotes the biases for investor i at month t. We report the results for our hypothesized disposition effects (DISP), under-diversification (UDIV), and local bias (LOCB) channels separately and jointly in the first four columns. All the bias measures are standardized. The fifth and sixth column reports the results for the aggregated 3 biases (BIAS3) and the aggregated 5 biases (BIAS5) including lottery preference and salience thinking. Biases are aggregated as the average cross-sectional rank of biases at each month which is scaled into a [-0.5, 0.5] interval. We control for the portfolio characteristics, demographic characteristics, demographic fixed effects, and year-month fixed effects. The sample period is from Jan 2013 to Dec 2019. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$\alpha_{FF6+GMB}$ (%)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
DISP	-0.547***			-0.540***		
	(-25.74)			(-24.36)		
UDIV		-0.119***		-0.0711***		
		(-10.32)		(-4.339)		
LOCB			-0.0171	-0.0196		
			(-1.216)	(-1.073)		
BIAS3					-0.852***	
					(-19.56)	
BIAS5						-1.394***
						(-22.73)
Controls	Y	Y	Y	Y	Y	Y
Demographic FE	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y
Observations	710,943	1,081,088	984,105	648,871	1,081,088	1,081,088
R-squared	0.093	0.087	0.087	0.094	0.087	0.088

Table 6 Predicting Stock Returns Using Order Imbalances

This table reports whether trading activity by different groups of investors can predict the cross section of future stock returns, following the specificastion of Jones, Shi, Zhang, and Zhang (2024). Panel A presents the predictability of all stocks. The results are estimated from the following Fama and MacBeth (1973) regression: $Ret_{i,d,h} = \alpha_{h,G} + \beta_{h,G} OIB_{i,d-1,G} + \gamma' Controls_{i,d-1} + \varepsilon_{i,d}$, where $Ret_{i,d,h}$ is the one day, one week, or one month ahead stock i's return and $OIB_{i,d-1,G}$ is the previous day order imbalance of investor group G. Panel B highlights the predictability on green stocks. Specifically, the results are estimated from the following regression: $Ret_{i,d,h} = \alpha_{h,G} + \beta^1_{h,G} OIB_{i,d-1,G} + \beta^2_{h,G} Green_i + \beta^3_{h,G} OIB_{i,d-1,G} \times Green_i + \gamma' Controls_{i,d-1} + \varepsilon_{i,d}$, where $Green_i$ indicates whether stock i is a green stock. The control variables are the previous day's return Ret(-1), previous week return Ret(-6,-2), previous month return Ret(-27,-7), previous month's log market cap (Size), earnings-to-price ration (EP), and turnover rate (Turnover). The Newey and West (1987) adjusted t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	One Day Ahead Return (%)			One Week Ahead Return (%)			One Month Ahead Return (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	All Investors	Green Investors	Brown Investors	All Investors	Green Investors	Brown Investors	All Investors	Green Investors	Brown Investors
Panel A:									
OIB	0.00472	-0.0156*	0.0148	-0.0358**	-0.0793***	0.00140	-0.0182	-0.0809	0.00855
	(0.681)	(-1.921)	(1.032)	(-2.035)	(-3.726)	(0.0486)	(-0.499)	(-1.617)	(0.147)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	489,153	489,153	246,719	487,774	487,774	245,933	481,466	481,466	242,461
R-squared	0.124	0.124	0.201	0.136	0.135	0.207	0.142	0.141	0.211
Panel B:									
OIB	0.525	0.00662	0.140	0.767	-0.0228	0.255*	2.191	0.0167	0.231
	(1.044)	(0.533)	(1.448)	(1.035)	(-0.727)	(1.727)	(1.020)	(0.223)	(1.592)
Green	0.520	0.00317	0.0513	0.840	0.0522	0.143	2.389	0.210	-0.157
	(1.039)	(0.246)	(0.433)	(1.140)	(1.075)	(0.703)	(1.122)	(1.260)	(-0.306)
OIB×Green	-0.537	-0.0297**	-0.0605	-0.849	-0.0834**	-0.112	-2.276	-0.165*	0.387
	(-1.068)	(-2.041)	(-0.509)	(-1.146)	(-2.210)	(-0.551)	(-1.069)	(-1.829)	(0.826)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	489,153	489,153	246,719	487,774	487,774	245,933	481,466	481,466	242,461
R-squared	0.138	0.137	0.226	0.150	0.149	0.234	0.157	0.156	0.237

Table 7 Predicting Stock Alphas Using Aggregate Demand Shocks

This table reports whether the aggregate demand by retail investors can predict the cross section of future stock alphas. Specifically, we replace $OIB_{i,d-1,G}$ in Equation (5) and (6) with $ADS_{i,d-1}$, the previous day's aggregate demand shock. Besides, we also replace $Ret_{i,d,h}$ with $\alpha_{FF6}^{i,d,h}$. The aggregate demand shock $ADS_{i,d}$ is defined as $ADS_{i,d} = \frac{\sum BuyVol_{i,d} - \sum SellVol_{i,d}}{ShrOut_{i,d}}$, where $ShrOut_{i,d}$ is the number of shares outstanding of stock i on day d. The control variables are the previous day's return Ret(-1), previous week return Ret(-6,-2), previous month return Ret(-27,-7), previous month's log market cap (Size), earnings-to-price ration (EP), and turnover rate (Turnover). The Newey and West (1987) adjusted t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	One Day Ahead $\alpha_{FF6+GMB}$ (%)		One Week Ahead $\alpha_{FF6+GMB}$ (%)		One Month Ahead $\alpha_{FF6+GMB}$ (%)	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
ADS	-1.829	13.88	-12.50	-35.72*	-50.04**	-70.26
	(-0.322)	(1.349)	(-1.119)	(-1.798)	(-2.041)	(-1.641)
Green		-0.00638		0.00336		0.0735
		(-0.483)		(0.0715)		(0.522)
ADS×Green		-24.49*		32.13		51.43
		(-1.662)		(1.149)		(0.945)
Controls	Y	Y	Y	Y	Y	Y
Observations	489,056	489,056	487,664	487,664	481,314	481,314
R-squared	0.179	0.195	0.188	0.205	0.185	0.202

Table 8 Do Investor Become Greener to Mitigate Risk?

This table reports the results on investors' risk mitigation motives from green investments. The first two columns report the results on whether investors use green investments as a tool for risk mitigation from the following regression:

$$Risk_{i,t} = \alpha + \rho \times \text{GreenShare}_{\text{i,t}} + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where $Risk_{i,t}$ is the holding weighted portfolio market beta (Beta) in column (1) and holding weighted idiosyncratic volatility (Ivol) in column (2) following Ang, Hodrick, Xing, and Zhang (2006). The last three columns report the results on whether investors can derive performance benefit from the risk mitigation through green investments from the following regression:

$$\alpha_{FF6+GMB}^{i,t} = \alpha + \rho_1 \times \text{GreenShare}_{\text{i,t}} + \rho_2 \times Risk_{i,t} + \rho_3 \times \text{GreenShare}_{\text{i,t}} \times Risk_{i,t} + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}.$$

Both Investor fixed effects and Year-Month fixed effects are included in all regressions. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables	Beta	Ivol	$\alpha_{FF6+GMB}$	$\alpha_{FF6+GMB}$	$\alpha_{FF6+GMB}$
GreenShare	-0.161***	0.000619	0.436**	0.966***	1.021***
	(-14.01)	(1.546)	(2.060)	(6.285)	(4.429)
Beta			-0.961***		-1.017***
			(-8.632)		(-9.058)
GreenShare×Beta			-0.271		-0.150
			(-1.629)		(-0.894)
Ivol				4.214	6.624
				(0.815)	(1.239)
GreenShare×Ivol				-32.24***	-33.98***
				(-4.653)	(-4.829)
Log(HV)	-0.0225***	-0.00103***	-0.572***	-0.563***	-0.586***
	(-6.892)	(-7.845)	(-23.64)	(-23.40)	(-24.62)
Turnover	-0.00741***	0.000448***	-0.314***	-0.304***	-0.312***
	(-3.263)	(3.931)	(-5.095)	(-4.924)	(-5.065)
Intercept	1.713***	0.0376***	10.55***	9.003***	10.71***
	(30.10)	(16.95)	(23.72)	(20.90)	(24.28)
Investor FE	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y
Observations	850,893	850,893	850,893	850,893	850,893
R-squared	0.814	0.721	0.134	0.133	0.134

Table 9 DiD on Extreme Heat Shocks

This table reports the difference-in-difference tests associated with extremely hot temperature shocks. The month is defined as an extremely hot month if that month experiences an abnormal temperature of more than 3 degrees Celsius, following the construction in Choi, Gao, and Jiang (2020). One month before and after the extremely hot month is also considered as the shock period to mitigate the direct effect of hot weather on investors' behaviors. We use the [-3 months, 3 months] around the shock periods as our event window. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in *GreenShare* after the extreme heat shocks following Fang, Tian, and Tice (2014). The treatment effects are estimated from

$$Y_{i,t} = \alpha + \rho \times \text{Treated}_i \times \text{Post}_t + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where $Y_{i,t}$ are $\alpha_{FF6+GMB}^{i,t}$, $\text{UDIV}_{i,t}$, and $\text{LOCB}_{i,t}$, in the column one, two, and three respectively. We control for the portfolio characteristics, the two non-hypothesized biases, i.e., lottery preference and salience thinking, investor fixed effects, and year-month fixed effects in all regressions. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) $\alpha_{FF6+GMB}$ (%)	(2) UDIV	(3) LOCB
Treated×Post	0.247***	-0.0149**	0.0558***
	(2.831)	(-2.111)	(6.649)
Log(HV)	-0.671***	-0.532***	-0.0524***
	(-7.349)	(-48.95)	(-4.313)
Turnover	-0.00501***	-0.00326***	-0.000140
	(-2.683)	(-28.75)	(-0.981)
Lottery Preference	5.743***	-0.0504**	0.0221
	(12.82)	(-2.568)	(0.808)
Salience Thinking	-0.0885**	-0.00656***	-0.00113
	(-2.074)	(-3.824)	(-0.487)
Intercept	10.36***	9.108***	0.879***
	(6.659)	(49.20)	(4.245)
Investor FE	Y	Y	Y
Year-Month FE	Y	Y	Y
Observations	75,053	75,053	75,053
R-squared	0.244	0.944	0.915

Table 10 Extreme Heat Shocks and Disposition Effects

This table reports the dynamics of disposition effects on green and brown stocks for the treated and control groups, before and after the shock of extreme heat. The month is defined as an extremely hot month if that month experiences an abnormal temperature of more than 3 degrees Celsius, following the construction in Choi, Gao, and Jiang (2020). One month before and after the extremely hot month is also considered as the shock period to mitigate the direct effect of hot weather on investors' behaviors. We use the [-3 months, 3 months] around the shock periods as our event window. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in *GreenShare* after the extreme heat shocks following Fang, Tian, and Tice (2014). The effects are estimated from a saturated model with three dummy variables, $Gain_{i,s,t}$, $Green_s$, and $Post_t$, and their interactions. The dummy $Gain_{i,s,t}$ takes the value of 1 if investor i's holding on stock s is in gain on day $t-1$, and 0 otherwise. The dummy $Green_s$ is 1 if stock s is classified as green stocks and 0 otherwise. The dummy $Post_t$ is 1 if day t is after the shock period and 0 otherwise. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Treated	Control
	(1)	(2)
Variables	Sell100	Sell100
Gain	0.150***	0.156***
	(12.21)	(10.97)
Green	0.000594	0.0131**
	(0.109)	(2.338)
Post	-0.0226***	-0.0437***
	(-3.323)	(-6.548)
Green×Gain	0.0275**	0.0459***
	(2.243)	(3.428)
Green×Post	-0.0135**	0.00168
	(-2.090)	(0.245)
Gain×Post	-0.0830***	-0.131***
	(-5.990)	(-8.829)
Green×Gain×Post	-0.0539***	0.0150
	(-3.688)	(0.971)
Intercept	0.0894***	0.0897***
	(14.64)	(15.36)
Observations	5,309,591	5,303,044
R-squared	0.0005	0.001

Table 11 Additional Analysis

This table reports additional analysis on the diversification mechanism and the stock return around the extreme heat events. The left panel presents the dynamics of number of green and brown stocks and the portfolio holding value for the treated and control groups, before and after the shock of extreme heat. The right panel presents the return dynamics of green and brown stocks around the shock of extreme heat. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in *GreenShare* after the extreme heat shocks following Fang, Tian, and Tice (2014). The treatment effects are estimated from

$$Y_{i,t} = \alpha + \rho \times \text{Treated}_i \times \text{Post}_t + \delta_i + \theta_t + \varepsilon_{i,t},$$

where $Y_{i,t}$ are the number of green stocks in the portfolio, the number of brown stocks in the portfolio, and the natural log of the portfolio holding value, in the first three columns The last columns presents the result of stock-level analysis, where the dependent variable is the the $\alpha_{FF6+GMB}$ (%) of the stock and the independent variable is the interaction between green stock indicator and post shock indicator. Standard errors are clustered at the investor/stock level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)		(4)
Variable	# Green Stocks	# Brown Stocks	Log(HV)	Variable	$\alpha_{FF6+GMB}$ (%)
Treated×Post	0.773***	-0.439***	0.111***	Green×Post	-0.949***
	(21.76)	(-15.31)	(10.05)		(-3.588)
Intercept	4.073***	3.523***	17.02***	Intercept	-0.205***
	(458.7)	(491.0)	(6,177)		(-2.686)
Investor FE	Y	Y	Y	Stock FE	Y
Year-Month FE	Y	Y	Y	Year-Month FE	Y
Observations	75,084	75,084	75,053	Observations	77,469
R-squared	0.925	0.923	0.951	R-squared	0.194

Figure 1 The Cumulative Return Difference between Green and Brown Retail Investors

This figure plots the cumulative return difference between green and brown retail investors. We first sort investors into quartiles based on their *GreenShare* each month and then create value-weighted portfolios for top and bottom quartile investors. We then calculate the return difference between the portfolio of top-quartile investors and that of the bottom-quartile investors. Finally, we plot the cumulative return difference between top and bottom quartile investors, as well as the cumulative performance of the return difference (i.e., alphas), when we use the GMB-enhanced Fama-French seven-factor model to adjust the returns.

Figure 2 GreenShare-Bias-Performance Relationships

This figure illustrates the triangular relationship between green preference, behavioral biases, and portfolio performance. Investors are split into 10 groups based on *GreenShare* or the aggregated *BIAS3* index. The *BIAS3* index is calculated as the average cross-sectional rank scaled to [-0.5, 0.5] intervals of 3 behavioral biases in each month: disposition effects, under-diversification, and local bias. Panel A and Panel B illustrate the positive link between green preference and portfolio performance. Panel C shows the negative link between green preference and our hypothesized overall behavioral biases. Panel D verifies the harm of behavioral biases by showing the downward-sloping relation between the level of biases and portfolio performance.

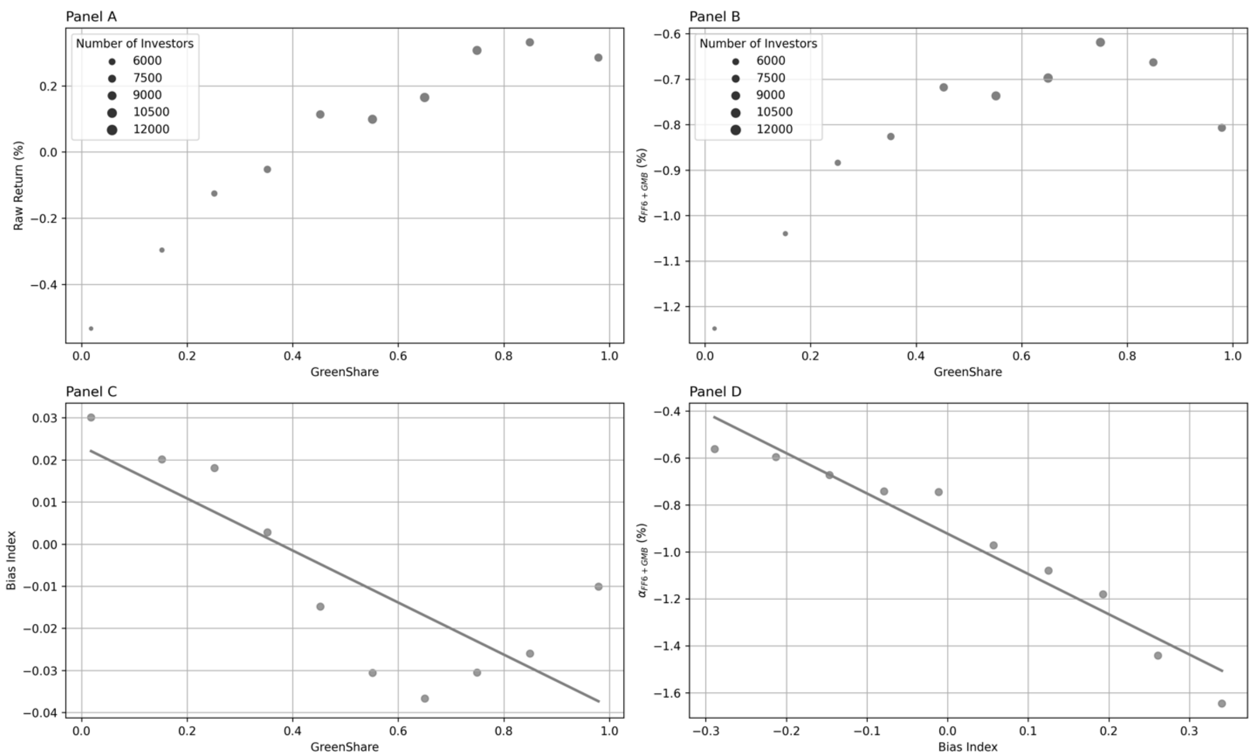


Figure 3 Geographic locations of investors and NSE firms

This figure plots the geographic locations of investors covered in our account-level trading data, and the locations of NSE-listed firms. Each blue point represents the location of one investor inferred from the reported PIN Code. In Panel A, the green points represent the location of firms classified as green. The locations of brown firms are shown in Panel B.

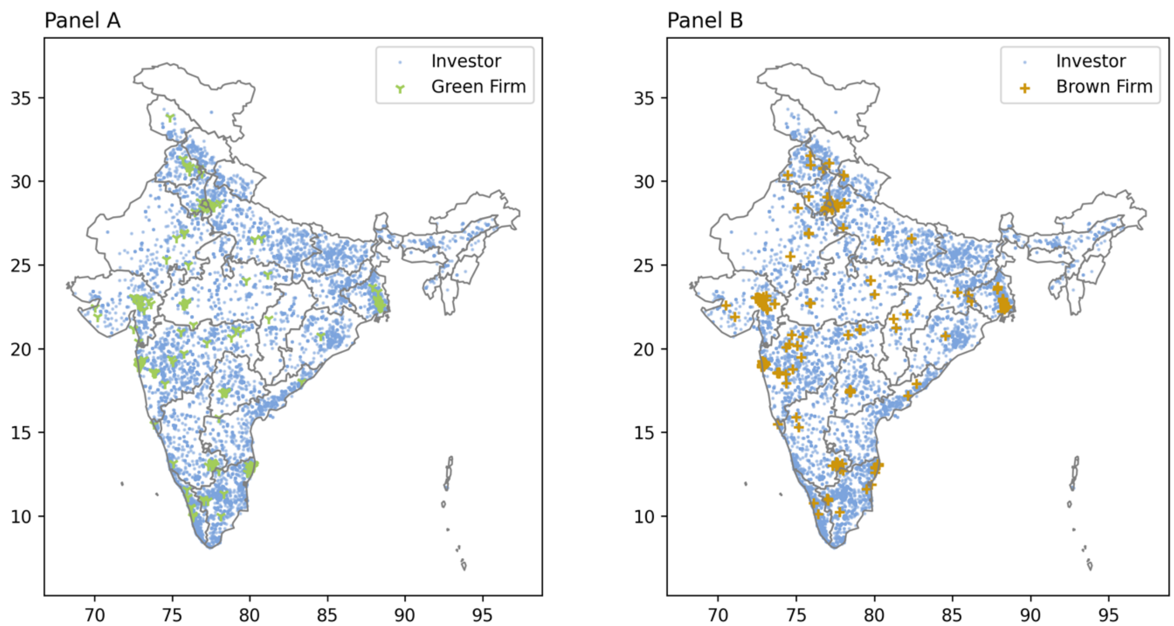


Figure 4 Geographic and intra-year time-series distribution of extreme heat months in India

This figure illustrates the distribution of extreme heat months with at least 3°C abnormal temperature in India from 2012 to 2019. The formal definition of abnormal temperature ($Ab\_Temp_{d,t}$) follows the construction in Choi, Gao, and Jiang (2020):

$$Temperature_{d,t} = Aver\_Temp_{d,t} + Mon\_Temp_{d,t} + Ab\_Temp_{d,t},$$

where $Aver\_Temp_{d,t}$ is the average monthly local temperature in district d over the 120 months prior to t; $Mon\_Temp_{d,t}$ is the average deviation of this month's temperature from the average, and the remainder $Ab\_Temp_{d,t}$ is the measure of abnormal temperature. Panel A shows the geographic distribution, while Panel B illustrates the seasonal distribution.

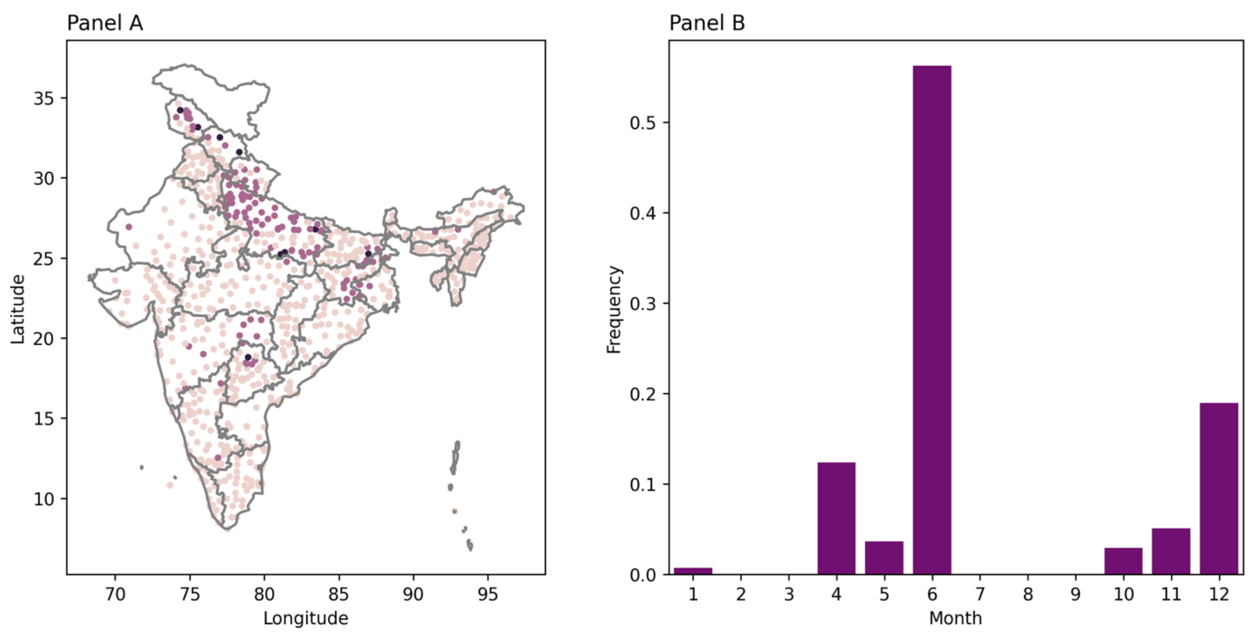


Figure 5 ROC Curve Before and After PSM

This figure illustrates the ROC curve of the Probit model for the pre-matching and matched samples. Panel A shows that, in the original sample, an AUC score of 0.762 is achieved using *GreenShare*, portfolio characteristics, demographic characteristics, and behavioral biases, indicating that these attributes well predict whether the increase of *GreenShare* is in the top or bottom quintile. In Panel B, the AUC score for the matched sample is 0.554, similar to a random guess, showing that almost all the predicting power is exploited through the matching.

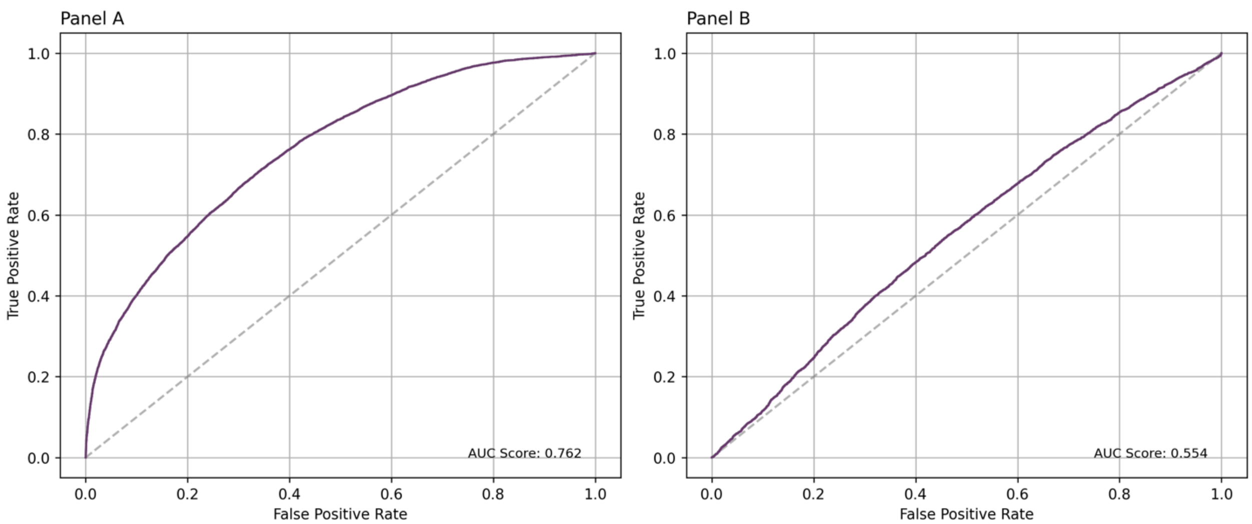
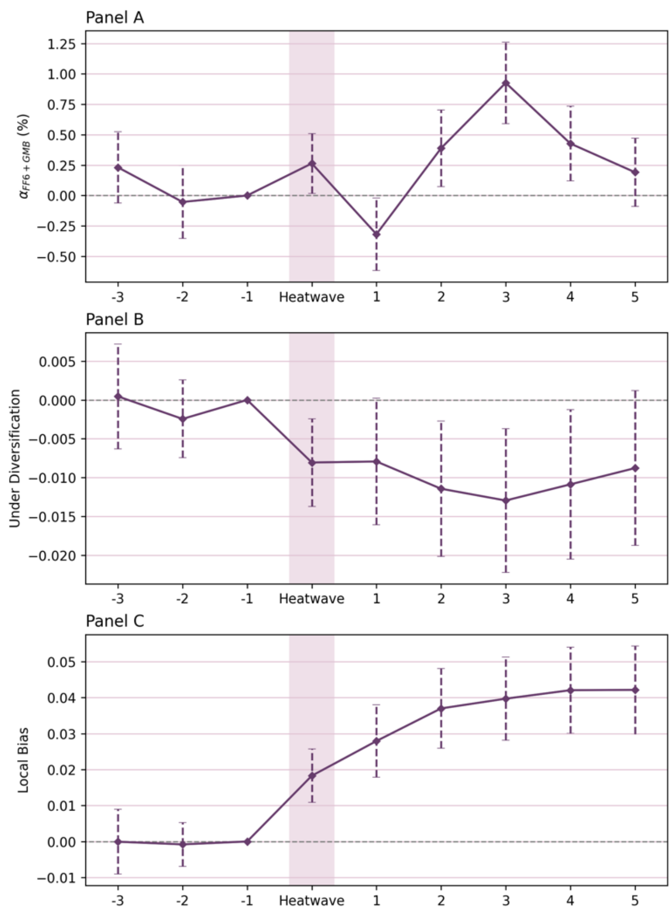


Figure 6 Dynamic Treatment Effects with Extension Period

This figure illustrates the dynamic treatment effects around extremely hot temperature shocks and the lasting effects in extended periods. Panel A shows that investors in the top quintile of *GreenShare* change earn a better return relative to investors in the bottom quintile. Panel B and Panel C show a relative decrease in under-diversification and a relative increase in local bias for investors in the top quintile of *GreenShare* change. The treatment effects last for five months after the shock.



Online Appendix

Figure A.1 ROC Before and After PSM based on Increase in *GreenShare*

This figure illustrates the ROC curve of the Probit model for the pre-matching and matched samples. Panel A shows that, in the original sample, an AUC score of 0.814 is achieved using *GreenShare*, portfolio characteristics, demographic characteristics, and behavioral biases, indicating that these attributes well predict whether the increase of *GreenShare* is in the top or bottom tercile. In Panel B, the AUC score for the matched sample is 0.556, similar to a random guess, showing that almost all the predicting power is exploited through the matching.

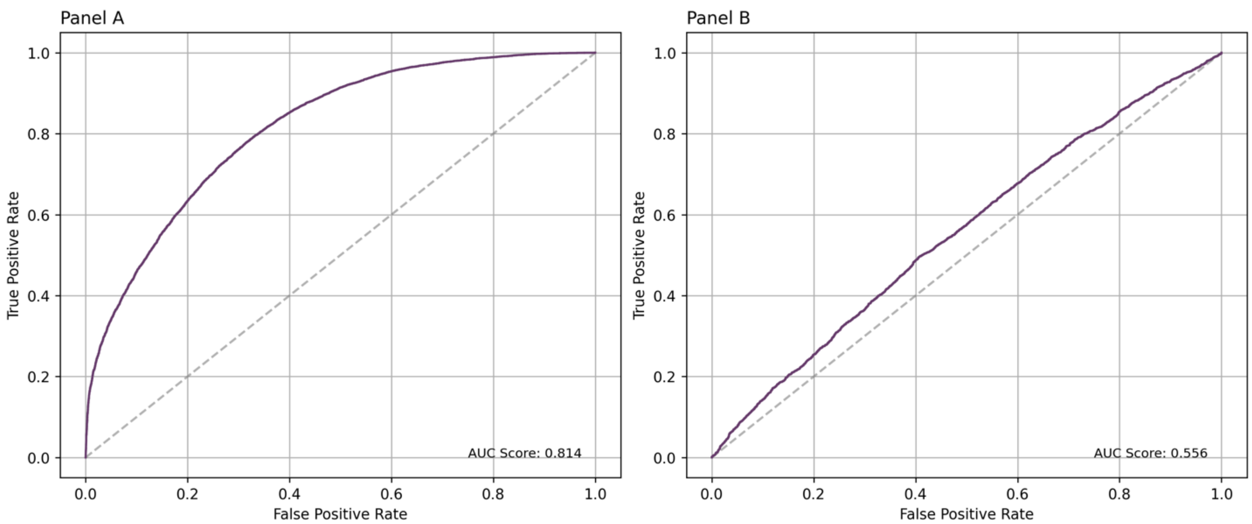


Figure A.2 Dynamic Treatment Effects based on Increase in *GreenShare*

This figure illustrates the dynamic treatment effects around extremely hot temperature shocks and the lasting effects in extended periods. Panel A shows that investors in the top tercile of *GreenShare* increase earn a better return relative to investors in the bottom tercile. Panel B and Panel C show a relative decrease in under-diversification and a relative increase in local bias for investors in the top tercile of *GreenShare* increase. The treatment effects last for five months after the shock.

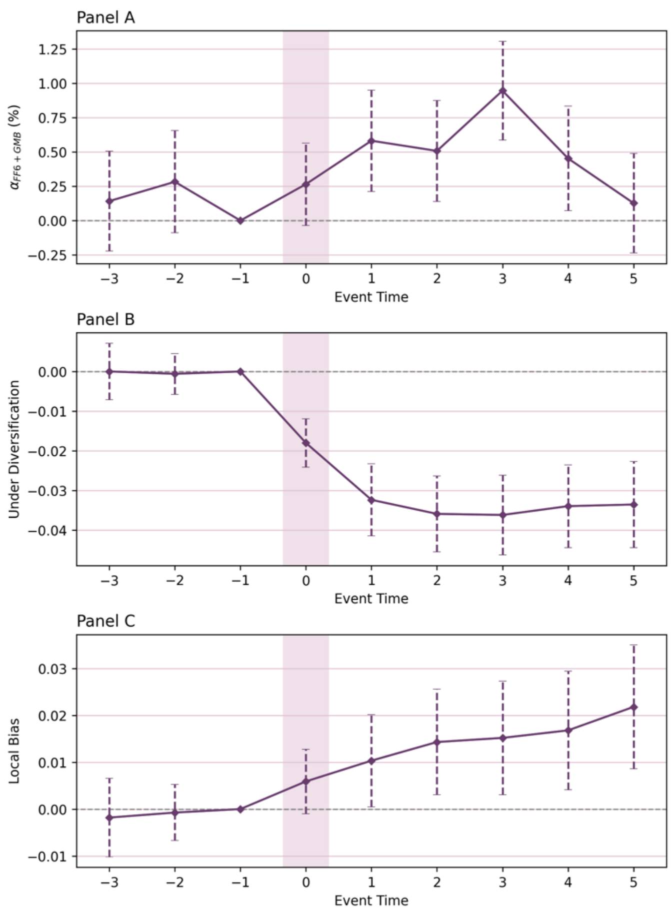


Figure A.3 ROC Before and After PSM with Never-Treated Investors as Control

This figure illustrates the ROC curve of the Probit model for the pre-matching and matched samples. Panel A shows that, in the original sample, an AUC score of 0.771 is achieved using *GreenShare*, portfolio characteristics, demographic characteristics, and behavioral biases, indicating that these attributes well predict whether the increase of *GreenShare* is in the top or bottom tercile. In Panel B, the AUC score for the matched sample is 0.560, similar to a random guess, showing that almost all the predicting power is exploited through the matching.

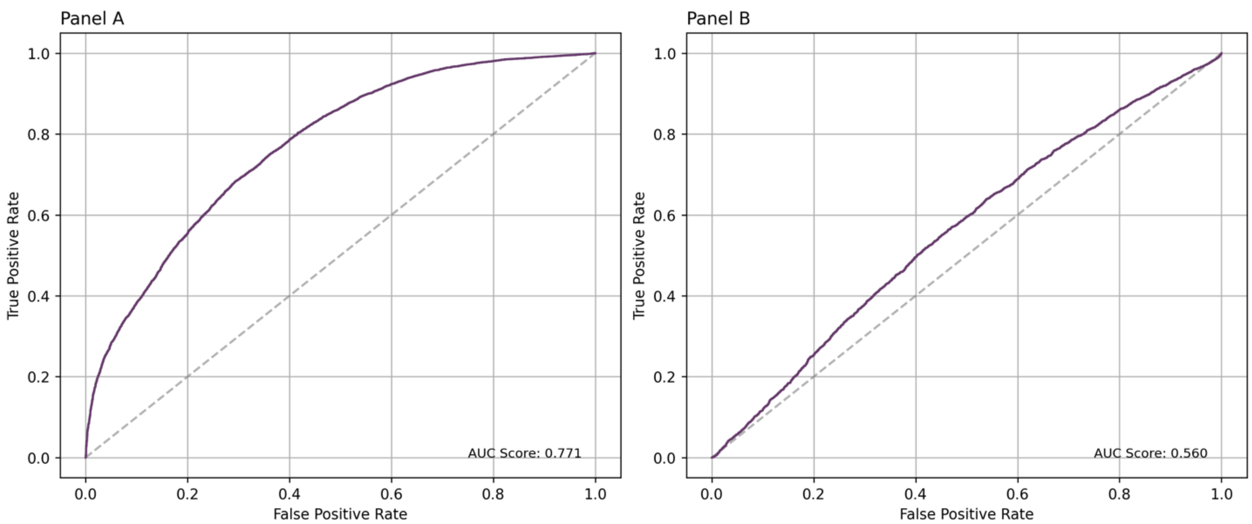


Figure A.4 Dynamic Treatment Effects with Never-Treated Investors as Control

This figure illustrates the dynamic treatment effects around extremely hot temperature shocks and the lasting effects in extended periods. Panel A shows that investors in the top tercile of *GreenShare* increase earn a better return relative to investors in the bottom tercile. Panel B and Panel C show a relative decrease in under-diversification and a relative increase in local bias for investors in the top tercile of *GreenShare* increase. The treatment effects last for five months after the shock.

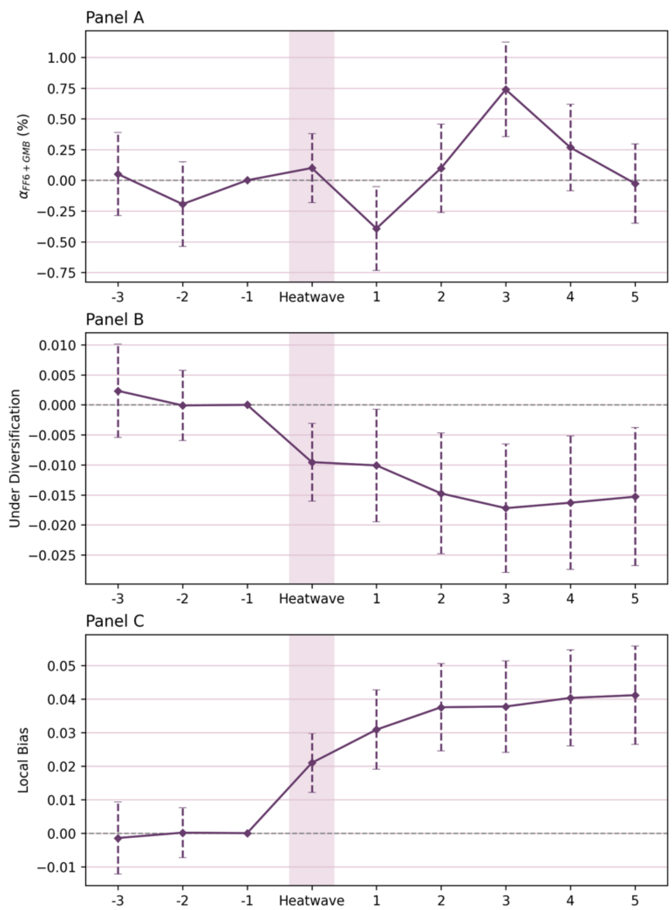


Table A.1 Extreme Heat Shocks

This table reports the start month and end month of our identified extreme heat shocks and corresponding media coverage. The extremely hot months are first identified as district-month pairs with an abnormal temperature larger than 3 degrees Celsius. The formal definition of abnormal temperature ($Ab\_Temp_{d,t}$) follows the construction in Choi, Gao, and Jiang (2020):

$$Temperature_{d,t} = Aver\_Temp_{d,t} + Mon\_Temp_{d,t} + Ab\_Temp_{d,t},$$

where $Aver\_Temp_{d,t}$ is the average monthly local temperature in district d over the 120 months prior to t; $Mon\_Temp_{d,t}$ is the average deviation of this month's temperature from the average, and the remainder $Ab\_Temp_{d,t}$ is the measure of abnormal temperature. Then, each extreme heat shock is obtained by stacking the consecutive extremely hot months. We focus on the aggregate extreme heat shocks, as the extremely hot months identified in the first step are salient climate shocks across the whole country, which are reported in well-known national-level mass media or even international media companies.

Start	End	Media Coverage
2012-05	2012-06	https://www.dw.com/en/dog-days-for-delhis-homeless/a-15988700
2014-04	2014-04	https://www.downtoearth.org.in/news/did-climate-change-trigger-heat-wave-in-india-and-other-nations-in-2014-44224
2015-10	2015-12	https://timesofindia.indiatimes.com/city/pune/december-2015-was-indias-hottest-ever-in-114-years/articleshow/50464747.cms
2016-04	2016-04	https://www.bbc.com/news/world-asia-india-36339523
2016-11	2016-12	https://indianexpress.com/article/cities/delhi/december-2016-was-the-warmest-in-eight-years-delhis-warm-winter-due-to-rain-deficit-4461151
2017-12	2018-01	https://timesofindia.indiatimes.com/city/pune/2017-fourth-hottest-year-ever-in-country/articleshow/62421335.cms
2018-10	2018-10	https://timesofindia.indiatimes.com/city/pune/october-heat-missing-after-almost-a-decade/articleshow/71767787.cms
2019-06	2019-06	https://edition.cnn.com/2019/06/14/india/india-heat-wave-deaths-intl/index.html

Table A.2 PSM-DiD Results based on Increase in *GreenShare*

This table reports the difference-in-difference tests associated with extremely hot temperature shocks. The month is defined as an extremely hot month if that month experiences an abnormal temperature of more than 3 degrees Celsius, following the construction in Choi, Gao, and Jiang (2020). One month before and after the extremely hot month is also considered as the shock period to mitigate the direct effect of hot weather on investors' behaviors. We use the [-3 months, 3 months] around the shock periods as our event window. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in $GreenShare$ after the extreme heat shocks following Fang, Tian, and Tice (2014). The treatment effects are estimated from

$$Y_{i,t} = \alpha + \rho \times \text{Treated}_i \times \text{Post}_t + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where $Y_{i,t}$ is $\alpha^{i,t}_{FF6+GMB}$, $\text{UDIV}_{i,t}$, and $\text{LOCB}_{i,t}$, in the column one, two, and three respectively. We control for the portfolio characteristics, the two non-hypothesized biases, i.e., lottery preference and salience thinking, investor fixed effects, and year-month fixed effects in all regressions. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) $\alpha_{FF6+GMB}$ (%)	(2) UDIV	(3) LOCB
Treated×Post	0.282***	-0.0486***	0.0210***
	(2.903)	(-7.038)	(2.828)
Log(HV)	-1.165***	-0.535***	-0.0422***
	(-8.087)	(-37.35)	(-2.868)
Turnover	-0.00129	-0.00330***	-0.000241
	(-0.478)	(-19.87)	(-1.317)
Lottery Preference	4.847***	-0.0314*	-0.0176
	(9.104)	(-1.805)	(-0.662)
Salience Thinking	-0.204***	-0.00766***	0.000148
	(-3.910)	(-4.177)	(0.0633)
Investor FE	Y	Y	Y
Year-Month FE	Y	Y	Y
Observations	59,487	59,487	59,487
R-squared	0.251	0.962	0.950

Table A.3 Extreme Heat Shocks and Disposition Effects based on Increase in $GreenShare$

This table reports the dynamics of disposition effects on green and brown stocks for the treated and control groups, before and after the shock of extreme heat. The month is defined as an extremely hot month if that month experiences an abnormal temperature of more than 3 degrees Celsius, following the construction in Choi, Gao, and Jiang (2020). One month before and after the extremely hot month is also considered as the shock period to mitigate the direct effect of hot weather on investors' behaviors. We use the [-3 months, 3 months] around the shock periods as our event window. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in *GreenShare* after the extreme heat shocks following Fang, Tian, and Tice (2014). The effects are estimated from a saturated model with three dummy variables, $Gain_{i,s,t}$, $Green_s$, and $Post_t$, and their interactions. The dummy $Gain_{i,s,t}$ takes the value of 1 if investor i's holding on stock s is in gain on day $t-1$, and 0 otherwise. The dummy $Green_s$ is 1 if stock s is classified as green stocks and 0 otherwise. The dummy $Post_t$ is 1 if day t is after the shock period and 0 otherwise. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Treated	Control
	(1)	(2)
Variables	Sell100	Sell100
Gain	0.0870***	0.0592***
	(9.654)	(5.960)
Green	0.00502	-0.00196
	(1.030)	(-0.404)
Post	0.00899	-0.0371***
	(1.351)	(-7.365)
Green×Gain	0.0196*	0.0227**
	(1.924)	(2.154)
Green×Post	-0.0215***	0.00160
	(-3.217)	(0.304)
Gain×Post	-0.0265**	-0.0339***
	(-2.090)	(-3.235)
Green×Gain×Post	-0.0578***	-0.0288**
	(-4.115)	(-2.404)
Intercept	0.0590***	0.0594***
	(12.12)	(12.05)
Observations	4,402,950	4,426,255
R-squared	0.0002	0.0003

Table A.4 PSM-DiD Results with Never-Treated Investors as Control

This table reports the difference-in-difference tests associated with extremely hot temperature shocks. The month is defined as an extremely hot month if that month experiences an abnormal temperature of more than 3 degrees Celsius, following the construction in Choi, Gao, and Jiang (2020). One month before and after the extremely hot month is also considered as the shock period to mitigate the direct effect of hot weather on investors' behaviors. We use the [-3 months, 3 months] around the shock periods as our event window. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in $GreenShare$ after the extreme heat shocks following Fang, Tian, and Tice (2014). The treatment effects are estimated from

$$Y_{i,t} = \alpha + \rho \times \text{Treated}_i \times \text{Post}_t + \gamma \times \text{Controls}_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where $Y_{i,t}$ is $\alpha_{FF6+GMB}^{i,t}$, $\text{UDIV}_{i,t}$, and $\text{LOCB}_{i,t}$, in the column one, two, and three respectively. We control for the portfolio characteristics, the two non-hypothesized biases, i.e., lottery preference and salience thinking, investor fixed effects, and year-month fixed effects in all regressions. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Variables	$\alpha_{FF6+GMB}$ (%)	UDIV	LOCB
Treated×Post	0.167*	-0.0231***	0.0557***
	(1.686)	(-2.813)	(5.670)
Log(HV)	-0.698***	-0.531***	-0.0573***
	(-6.697)	(-42.05)	(-4.148)
Turnover	-0.00547***	-0.00335***	-0.000110
	(-2.604)	(-26.57)	(-0.689)
Lottery Preference	5.809***	-0.0478**	0.00565
	(11.37)	(-2.103)	(0.177)
Salience Thinking	-0.116**	-0.00580***	-0.000233
	(-2.396)	(-2.986)	(-0.0956)
Investor FE	Y	Y	Y
Year-Month FE	Y	Y	Y
Observations	58,066	58,066	58,066
R-squared	0.245	0.941	0.910

Table A.5 Disposition Effects with Never-Treated Investors as Control

This table reports the dynamics of disposition effects on green and brown stocks for the treated and control groups, before and after the shock of extreme heat. The month is defined as an extremely hot month if that month experiences an abnormal temperature of more than 3 degrees Celsius, following the construction in Choi, Gao, and Jiang (2020). One month before and after the extremely hot month is also considered as the shock period to mitigate the direct effect of hot weather on investors' behaviors. We use the [-3 months, 3 months] around the shock periods as our event window. The treated and control groups are constructed using propensity score matching from the investors in the top and bottom terciles of the increase in *GreenShare* after the extreme heat shocks following Fang, Tian, and Tice (2014). The effects are estimated from a saturated model with three dummy variables, $Gain_{i,s,t}$, $Green_s$, and $Post_t$, and their interactions. The dummy $Gain_{i,s,t}$ takes the value of 1 if investor i's holding on stock s is in gain on day $t-1$, and 0 otherwise. The dummy $Green_s$ is 1 if stock s is classified as green stocks and 0 otherwise. The dummy $Post_t$ is 1 if day t is after the shock period and 0 otherwise. Standard errors are clustered at the investor level. The robust t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Treated	Control
	(1)	(2)
Variables	Sell100	Sell100
Gain	0.268***	0.337***
	(11.26)	(10.82)
Green	0.00681	0.0195*
	(0.665)	(1.756)
Post	-0.0372***	-0.0811***
	(-2.884)	(-6.256)
Green×Gain	0.0425*	0.0835***
	(1.787)	(2.930)
Green×Post	-0.0261**	0.00977
	(-2.123)	(0.726)
Gain×Post	-0.149***	-0.277***
	(-5.656)	(-8.490)
Green×Gain×Post	-0.0904***	0.0326
	(-3.198)	(0.989)
Intercept	0.147***	0.162***
	(13.02)	(14.21)
Observations	2,476,631	2,401,506
R-squared	0.001	0.001