Are We Becoming Greener? Life-time Experiences and Responsible Investment*

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Abstract

We study the determinants and the patterns of ESG investing by exploiting account-level data from the Shanghai Stock Exchange, which provide detailed information on individual investors' characteristics and trading over time. We show that investors' pro-social attitudes affect ESG demand and that these attitudes are shaped by economic and non-economic life-time experiences, such as growing up in a region with more pro-social values, being exposed to an increased level of pollution or to a natural disaster. Recent experiences tend to matter more, and non-economic experiences are particularly important to explain how investors change their attitudes during their trading life. We also show that investors display distinct trading patterns between their ESG and non-ESG stocks, which helps explaining stock market dynamics.

Keywords: Responsible investment, experience effects, pro-social attitudes, ESG trading.

JEL codes: G11; G41; G51.

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1 Introduction

Responsible investment continues to grow.[1] The aggregate trends observed in many countries cannot be simply explained by the entry of new investors with larger appetite for ESG assets; incumbent investors are also changing their strategies toward an increased ESG demand. In addition, as we document in details below, the observed trends are highly heterogeneous across investors. The reasons behind those trends, and behind their heterogeneity across investors, can be many. One possibility is that some investors increasingly perceive ESG assets as attractive along some financial dimensions (say, how these stocks perform in crisis times). Another possible reason is that, beyond any financial motivation, some investors are increasingly attentive to ESG criteria.

If one wishes to entertain that at least part of the above-mentioned dynamics are driven by investors' pro-social concerns, the next question is what determines those concerns. In particular, which factors can induce substantial variations in investors' attitudes, how persistent these changes are, and how much they can explain the observed dynamics in investors' demand. These aspects seem key to understand the determinants, and possibly give a sense of the evolution, of ESG investment trends.

We address these questions in the context of ESG investing in China, which is an important setting in many ways. First, while ESG criteria have been introduced only recently in China, they are attracting an increasing attention across investors.[2] The extent to which Chinese firms and investors are truly sensitive to impact investment is likely to have first order effects at a global scale.

In addition, China offers the opportunity to address our questions in a unique way. We have access to complete trading records from the Shanghai Stock Exchange (SSE) between 2011 and 2019. A distinctive feature of these data is that all orders can be associated to the investor who has initiated them, thereby providing an exhaustive picture of the investor's stock trading over time. Moreover, for each individual investor, we can obtain information about her gender, age, education, place of birth and of residence.

This information is key for our analysis. We first study the determinants of individual demand for ESG stocks over time, and relate this demand not only to demographic and portfolio characteristics, but also to life-time experiences along both economic and non-economic dimensions. For example, in the spirit of Malmendier and Nagel (2011), does growing up in good market conditions affect investors' demand for ESG stocks? Is this demand affected by the exposure to environmental shocks, say an increase in pollution or a natural disaster?

[1] Global Impact Investing Network's 2020 annual report indicates that the amount of capital invested in socially responsible funds globally has grown by 12% per year between 2015 and 2019. Morningstar estimates that assets in sustainable funds have reached USD 1 trillion in June 2020.

[2] A recent survey of SynTao Green, China's first ESG rater, reports that 93% of Chinese individual investors consider ESG dimensions in their decisions, and 34% of them are willing to invest in ESG stocks even if that may harm their financial performance.

Answers to these questions can shed light on how attitudes towards ESG stocks are formed and how they evolve over time. Our estimates allow us to uncover important variations not only across investors, but also within investors, thereby speaking to the dynamic nature of investors' attitudes. These aspects are central to our understanding of the impact of ESG investing on firms and ultimately on the real economy.

In the second part of our analysis, we investigate whether investors display distinct trading behaviors on ESG stocks. Do investors have a longer horizon on ESG stocks? Do they react differently to the financial performance of these stocks? Are they sensitive to non-financial performance? Since as mentioned our data provide a complete record of an investor's trades on the exchange over time, we can compare the trading behaviors of the same investor across ESG and non-ESG stocks. Understanding these behaviors can help assessing the impact of ESG investing on market dynamics.

We start by providing reduced-form evidence that life-time experiences matter for ESG investing, highlighting the role of pro-social dimensions. We classify stock indices as ESG or non-ESG based on the keywords they use in the index description, and define a stock as ESG if it belongs to an ESG index. Our main measure of an investor's ESG exposure is the value of ESG stocks over the total value of her portfolio.[3]

We first exploit a discontinuity induced by the so-called Huai River policy, which provides heavily subsidized coal for indoor heating to residents to the north, and not to the south, of the Huai River. The policy has been shown to lead to a significant increase in pollution in cities just north relative to those just south of the river (Chen, Ebenstein, Greenstone and Li (2013), Ebenstein, Fan, Greenstone, He and Zhou (2017), Li, Massa, Zhang and Zhang (2019)). Using the same regression discontinuity design, we show that investors living just north of the river display a significantly larger demand for ESG stocks, suggesting that exposure to pollution can impact ESG investing.

We shed further light on the role of pro-social attitudes by considering the so-called Rice-Theory of cultural differences. Talhelm, Zhang, Oishi, Shimin, Duan, Lan and Kitayama (2014) show that individuals who grow up in rice-growing areas have significantly more pro-social attitudes than those in wheat-growing areas, which can be explained by the fact that growing rice requires much more public investment (for irrigation) and social interactions (for sharing labor). They identify this pattern by comparing provinces just around the Yangtze River, which separates the wheat-growing north from the rice-growing south. Adopting a similar design, we show that investors growing up in rice-growing cities have significantly larger demand for ESG stocks than those in wheat-growing cities, suggesting that pro-social attitudes can play an important role.

The core of our analysis generalizes these arguments in three dimensions. First, we consider the entire population of investors; second, we explore the effects of various economic and non-economic experiences; third, we analyze whether and how the same investor may change her behaviors over time in response to life experiences. As stressed, these dynamics are potentially important to understand the observed trends in ESG investing.

[3]We consider various alternative measures, and show the robustness of our findings, as we proceed with the analysis.

We build on the seminal method developed by Malmendier and Nagel (2011) to estimate how life-time experiences affect financial decisions, which they first used to document how growing up in a recession affects risk-taking later in life. The method allows to jointly estimate two key parameters. The first, denoted by λ, describes how for a given investor at a given point in time the accumulated experience, say of pollution, depends on the history of experienced pollution. If the estimated λ is positive, experiences in the recent past would matter more than those in the more distant past; a negative λ instead would imply that experiences early in life matter more.

These patterns underlie the determinants and the dynamics of investors' attitudes. If the estimated λ turned out to be large and negative, for example, we would conclude that only early experiences matter, and recent experiences would not contribute to changes in investors' attitudes towards ESG stocks. Conversely, a large and positive λ would imply that recent shocks can have a large impact on investors' attitudes, implying possibly considerable variations in ESG demand over time.

The second key parameter is β, which estimates how the investor's accumulated experience affects her demand for ESG stocks. This parameter is important to get a sense of how much the variation in ESG demand, both across and within investors, can be attributed to different life-time experiences.

We repeat the same procedure for various experience measures. We consider both economic experiences (GDP growth, stock market returns, own portfolio returns) and non-economic experiences (pollution, natural disasters, corporate scandals). We adapt Malmendier and Nagel (2011)'s approach to account for some specificities of our setting. First, exploiting the panel structure of our data, we provide estimates both across and within investors. Our data display an important level of variation in ESG demand and, at first glance, both within- and between-investors variations appear important.[4] A key question for our exercises is how much life-time experiences can account for such heterogeneity.

Second, we focus mostly on local experiences, say the level of pollution in the city of residence, as opposed to nation-wide experiences. Third, we focus on experiences occurring since the investor has entered the stock market.[5]

Our main findings can be summarized as follows. First, both economic and non-economic life-experiences affect the propensity to invest in ESG stocks. Living through favorable stock market conditions, for example, positively affects ESG investing. At the same time, living in polluted areas or being exposed to corporate scandals also increases ESG demand. In terms of magnitude, the largest effects are driven by investors' own portfolio returns in specifications without fixed effects and by experienced natural disasters once we add investor fixed effects. A one standard deviation increase in one of those experience measures is associated to an increase of about 13.7% in ESG demand. The magnitude is large, especially in relation to the effects of demographic variables. In

[4]While on average investors increase their ESG demand by 3% over our sample period, the standard deviation of this increase is 37%. The corresponding within-investor standard deviation is 28%, the between-investor standard deviation is 24%.

[5]For many of our variables, the time-series is not available in earlier periods. As we discuss, however, this does not seem a major limitation.

terms of demographics, the largest effect is driven by being female, which is associated to an increase in ESG demand of about 1.3%. As we will discuss, an important dimension that explains the magnitude of the effects of experiences is their persistence over time.

Second, with the exception of natural disaster, the estimated λ are positive; that is, recent experiences tend to matter more. This suggests that even for the same investor the propensity to invest in ESG stocks can evolve considerably over her trading life, possibly in response to accumulated experiences. Third, economic experiences tend to be more persistent; that is, in absolute value, the corresponding λ is closer to zero. Non-economic experiences, instead, tend to have more volatile effects on the demand for ESG stocks. Fourth, economic experiences seem more important to explain between-investors variations in ESG investing, while non-economic experiences seem to matter more for within-investor differences, determining how ESG demand evolves over time for a given investor.

These findings support the view that pro-social attitudes are an important determinant of ESG investing and shed light on how these attitudes evolve as investors are exposed to various life experiences. As we show, these experiences affect ESG demand over and beyond any time-invariant investor characteristic and any attitude that the investor may have acquired before entering the stock market. These effects can provide a motivation for recent asset pricing models featuring investors with heterogeneous preferences towards ESG stocks.[6]

We then consider investors' trading patterns and document significant differences in the ways ESG and non-ESG stocks are traded, even for the same investor at the same point in time. First, investors trade ESG stocks less frequently and, as a result, investors with larger ESG exposure exhibit lower turnover and churn ratios in their portfolios. This is consistent with the view that investors have longer horizons on ESG stocks. Moreover, investors are less sensitive to ESG stocks' financial performance. In particular, they exhibit a lower disposition effect and less trend-chasing behaviors when trading ESG stocks relative to non-ESG stocks in their portfolios. At the same time, investors do react to non-financial performance, and they are more likely to buy (sell) a stock upon inclusion (exclusion) in an ESG index.

These findings can be related to different asset pricing dynamics of ESG vs. non-ESG stocks. They can explain why ESG stocks have lower turnover rates, as we document below. They are also consistent with models in which investors are heterogeneous in their sensitivity to financial and ESG dimensions, and they react differently to signals along those dimensions (as in Landier and Lovo (2020), Goldstein et al. (2021)). While in Goldstein et al. (2021) the resulting trading volumes can be larger or smaller for ESG investors, our finding that overall these investors trade less provides an indication of which effect dominates in our data. In addition, we show that the same investor can react differently even across ESG and non-ESG stocks in her portfolio.

We conclude our analysis by discussing alternative explanations and by checking the robustness of our results. First, we show that our results are not driven by changes

[6]See e.g. Pástor, Stambaugh and Taylor (2020), Baker, Hollifield and Osambela (2020), Goldstein, Kopytov, Shen and Xiang (2021).

coming from the firms' side. These supply effects may occur if investors display home bias and thus are more likely to invest in local stocks, and, at the same time, firms located in areas exposed say to a natural disaster are more likely to adopt ESG standards. We show however that our results are unchanged once we control for the share of ESG stocks in the province where the investor lives, and we observe no interaction between home bias and ESG investing.

Second, we show that our patterns cannot be described as some general form of index investing. As placebo tests, we construct alternative measures of demand for index stocks based on popular SSE capitalization-based indices. We show that investors' behaviors are very different between ESG stocks and stocks included in capitalization-based indices.

Finally, we show that our results are robust when employing alternative measures of ESG exposure, accounting for the possibility that a stock is included in several ESG indices or exploiting the stock's ESG rating.[7]

This paper contributes to the literature on the determinants and on the patterns of ESG investing. A series of recent experimental studies have neatly shown the importance of pro-social preferences, documenting that subjects are willing to forego monetary returns in order to invest in socially responsible projects (Barber, Morse and Yasuda (2021). Bauer, Ruof and Smeets (2021), Bonnefon, Landier, Sastry and Thesmar (2019), Brodback, Guenster and Pouget (2019)). We complement these studies by focusing on how investment behaviors may change over time, especially in response to life-time experiences.

On the role of personal experiences, Choi, Gao and Jiang (2020) show that retail investors (measured as residuals from institutional investors holdings) sell carbon-intensive firms when the local temperature is abnormally high. Dyck, Lins, Roth and Wagner (2019) show that institutional investors based in countries with stronger environmental norms have a larger impact on firms' environmental performance. Huynh, Li and Xia (2021) show that fund managers reduce their holdings of more polluting firms when exposed to larger pollution in their local areas. We build on this logic and provide a comprehensive investigation on how personal experiences affect ESG investing, looking directly at individual investors' holdings. More broadly, our findings provide novel evidence to the growing literature on experience effects in financial decisions (see Malmendier (2021) for a review), showing the importance of non-economic experiences and stressing within-investor dynamics.

Related insights on ESG trading patterns have been derived by looking at fund managers. Starks, Venkat and Zhu (2017) show that ESG fund managers have longer horizons and derive a series of implications on the associated trading behaviors. Cao, Titman, Zhan and Zhang (2019) show that socially responsible institutions are less likely to trade on mispricing signals when these go against their ESG preferences, thereby increasing return predictability. Gantchev, Giannetti and Li (2019) show that an increase in firms' ESG risk, due, for example, to the release of a corporate scandal, leads ESG-driven institutional investors to divest and firms to respond. We instead analyze individual

[7] As we discuss below, however, ESG ratings have become available only very recently in China, which limits their use for our purposes.

investors, which represent the dominant share in the Chinese market under study and which allows us to focus directly on the determinants of investors' preferences.

2 Data

2.1 Investors

We obtain account level data from the Shanghai Stock Exchange (SSE), recording all orders, trades and prices on all the securities traded on the exchange from January 2011 to October 2019. We extract a random sample of 1‰ of investors with an active account as of October 2019, which corresponds to 104,921 accounts, out of which 103,110 belong to individual investors. We exclude investors who trade less than twice or hold less than 100 shares over the entire sample.[8] We are left with 99,592 investors, who collectively trade 1,501 stocks. We aggregate our trading data at the monthly level, which gives 4,758,050 investor-month and 15,603,015 investor-stock-month observations.

As mentioned, a key feature of our data is that each trading order can be associated to a unique investor. While data are anonymized so that investors' identity cannot be tracked, the trading identifier allows to obtain several demographic characteristics, including date and place of birth, gender, and education. We also observe when the trading account was opened and which trading desk is used to send orders, which we use to identify where the investor currently lives.[9] This information is key to construct for each investor our measures of life-time experiences in terms of GDP growth, stock market returns, pollution, natural disasters, and corporate scandals. We provide more details of these measures in the corresponding analysis.

Our data provide a rich but partial account of investors' overall portfolio. First, we do not observe indirect stock holdings through equity or hybrid funds. However, in our context, most investors in the stock market only hold stocks directly. According to the China Household Finance Survey, in 2017, about 17% of investors who hold stocks also hold some fund (including bond and money market funds) and for these investors direct stock holdings account for 62.3% of their entire portfolio. Second, our investors may also trade stocks in a second exchange in China, the Shenzhen Stock Exchange. Stocks in China are listed in either one or the other market, and the SSE tends to include stocks with larger capitalization. As we will see, the majority of ESG stocks are traded in the SSE.

2.2 Stocks and ESG Classification

We obtain information about stocks' characteristics from the China Stock Market & Accounting Research Database (CSMAR), including their market capitalization, market

[8] This is the smallest trading unit in the SSE.

[9] We match the branch of each trading desk with that of the security firm and then obtain its address. As we do not observe investors' city of residence before age 18, we assume it corresponds to their birth city. Assuming instead it corresponds to the city where they live would not change our results, 81.2% of our investors live in their birth city.

and book values, daily and monthly returns, turnover and dividend yield ratios.

We obtain information on the composition and returns of the various stock indices from Wind, the leading financial data provider in China. We are particularly interested in defining ESG indices. We manually search the keywords corresponding to “ESG”, “green”, “environment”, “sustainable”, “social”, “responsibility”, or “corporate governance” in the index database constructed by Wind. We focus on indices that include at least one stock traded in the SSE and that are released before October 2019, which gives us 24 ESG indices, as listed in Table 1, covering a total of 686 stocks out of 1,501 stocks over our sample.[10] In our main analysis, we define a stock as ESG if it belongs to one ESG index; accordingly, 35% of our stocks are defined as ESG. As mentioned, the majority of these stocks are traded in the SSE.[11] We consider alternative measures in robustness checks.

In Table 3, we report some descriptive evidence on the difference between ESG and non-ESG stocks in our sample. For each variable, we compute the difference from the month-level average, and then take the mean across the various ESG or non-ESG stocks across all observations. We report the corresponding averages in columns 1 and 2. In column 3, we report the difference between the means, controlling for time fixed effect. We observe that ESG stocks are statistically different from non-ESG stocks in various dimensions: they tend to have larger market capitalization, lower volatility and turnover ratio. In magnitude, these differences are often small (say, relative to the respective standard deviation) with the exception of market capitalization. We also notice that in terms of returns ESG stocks are not statistically different from non-ESG stocks.[12] All these variables are included as controls in our next analysis

2.3 Demographics and ESG investing

We explore the relation between demographic characteristics and ESG investing by estimating the following equation:

$$y_{i,t} = \alpha + \beta X_{i,t} + \gamma Z_{i,t-1} + \phi_t + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is a measure of investor i's demand for ESG stocks at month t, $X_{i,t}$ is a vector of demographic characteristics including gender, years of education, trading experience, age, and $Z_{i,t-1}$ are portfolio characteristics including past returns and various risk measures (beta, exposure to the size and to the book-to-market factors), computed at month $t-1$, and ϕ_t are time fixed effects. In our main analysis, we measure investor i's ESG demand by the value of ESG stocks, i.e., of stocks that belong to an ESG index, over the total value of the portfolio. We consider alternative measures in robustness checks.

[10]The first index related to one ESG dimension, the CNI Corporate Governance Index, was released in December 2005 and it included 50 stocks. The first ESG Index, the CSI ECPI ESG China 40 Index, was released in September 2010 and included 40 stocks.

[11]At the beginning of our sample, stocks traded in the SSE account for 82.7% of the market value of all ESG stocks; at the end of our sample, they account for 67.3%.

[12]The same is true if we regress returns on ESG status and control for various measures of risk.

In column 1 of Table 4, we observe that females, more educated, and more experienced investors exhibit stronger exposure to ESG stocks. The relation with age is U-shaped, with investors in their mid-40s displaying the minimal exposure.

These patterns suggest that pro-social attitudes may be relevant. Several studies in psychology and neuro-science have documented gender differences in pro-social behaviors (e.g. Diekman and Clar (2015), Espinosa and Kovářík (2015)). Junkus and Berry (2010) survey US investors and show that the typical socially responsible investor is female, younger, less wealthy, and better educated than the rest of the investors.

We add portfolio characteristics in column 2, and we observe that the effects of demographic characteristics are unchanged. In magnitude, the stronger impacts (controlling for the corresponding standard deviations) are driven by female and education, with a one standard deviation increase in those variables being associated to a 0.6% larger proportion of ESG stocks.[13] Overall, however, these effects are quite small, as compared for example to the standard deviation of ESG proportion (equal to 43).

Since our panel is unbalanced, we repeat the same analysis but collapsing our data in a cross-section. Define $\overline{y}_t$ as the average $y_{i,t}$ over all investors at time t, for each investor we define $\overline{y}_i$ as the average of the difference $y_{i,t} - \overline{y}_t$. We repeat the same procedure for all variables in $X_{i,t}$ and $Z_{i,t-1}$ and consider the following specification:

$$\overline{y}_i = \alpha + \beta\overline{X}_i + \gamma\overline{Z}_{i,t-1} + \varepsilon_i. \qquad (2)$$

Our cross-sectional results are reported in columns 3 and 4 and they confirm the panel estimates in columns 1 and 2. In magnitude, results are slightly larger (also in relation to a lower average ESG proportion).

3 Pollution, Social Preferences and ESG Investing

In this section, we build on existing studies that exploit plausibly exogenous sources of variation to the level of pollution and to social norms across Chinese cities. We use these variations to provide reduced-form evidence that pollution and social norms significantly affect investors' demand for ESG stocks.

3.1 Coal Heating and ESG Investing

An interesting source of discontinuity is given by the so-called Huai River Policy. Instituted in the 1950s, the policy provides free or heavily subsidized coal for indoor heating to cities north of the Huai river, but not to those to the south. Comparing cities just north to those just south of the river, Chen et al. (2013) document significantly higher levels of pollution in the north of the river, which has been shown to have large effects

[13]The average effect of age given the estimated coefficients on age (_b[age]) and age-squared (_b[age2]) and the average age (equal to 48.61), can be computed as _b[age] + 2_b[age2]*48.61. Multiplying this coefficient by the standard deviation of age, we obtain an effect of 0.575 in column 1 and of 0.484 in column 2.

on life expectancy (Ebenstein et al. (2017)), cognitive abilities and investment biases (Li et al. (2019)).

As mentioned, we wish to investigate the hypothesis that increased levels of ESG investing are at least in part driven by an increased awareness of environmental and other societal issues, which may respond to life-time experiences. From this perspective, the Huai River Policy provides a useful discontinuity to explore the relation between exposure to pollution and ESG investing.

We report our results in Table 5, which shows that ESG investing is significantly larger in more polluted cities, those just north of the Huai river, than in less polluted cities, those just south of the river. The effect is robust across various specifications, and in fact it becomes even stronger as we consider smaller neighborhoods around the river. Comparing investors located within 3 degrees of latitude around the river, those exposed to more pollution display a 2.5% larger ESG investment than those exposed to less pollution.

3.2 Rice, Wheat, and ESG Investing

In a famous study, Talhelm et al. (2014) document significant differences in social preferences between Chinese cities traditionally devoted to growing rice and those devoted to growing wheat. They compare cities in provinces around the Yangtze River, which divides China between the north areas mostly growing wheat and the south areas mostly growing rice. They report a series of psychological tests showing that rice-growing cities display less individualistic and more collectivist ways of reasoning.[14] They argue that these differences are driven by the fact that, relative to wheat, growing rice requires much larger amount of water, hence the need to develop a common infrastructure for irrigation, and of labor, hence the need to exchange labor force with the neighbors.

Motivated by this evidence, we adopt the same methodology and investigate whether investors growing in cities with a larger tradition of growing rice, relative to wheat, display different patterns of ESG investing. We restrict to provinces around the Yangtze River and correlate our measure of ESG exposure at the investor level with the ratio of rice farmlands at the city level.[15] We report our results in Table 6, which shows that ESG investing is significantly larger in rice-growing cities. In columns 1 and 2, we consider 65 cities in the five provinces crossed by the Yangtze river (Sichuan, Chongqing, Hubei, Anhui, and Jiangsu) as in Talhelm et al. (2014).

These borders partly overlap with the Huai river policy described in the previous subsection. The Huai river is north of the Yangtze river, and 16 of the cities considered in columns 1 and 2 lie north of the Huai river, thereby having coal heating (hence, according our previous analysis, a larger ESG demand) and at the same time being more likely to grow wheat (hence, according the previous result, a lower ESG demand). In order to isolate the rice-wheat effect, we omit those 16 cities in columns 3 and 4, and

[14] They address possible reverse causality concerns by using measures of the province's suitability to grow rice as instrument.

[15] As in Talhelm et al. (2014), we use official statistics from 1996 and 2005 to construct the Rice Ratio at the city level. Chongqing is divided into four parts according to the 2005 statistics.

we show that indeed results are even stronger in this sub-sample. According to these estimates, investors living in a rice-growing city display a 3.2% larger exposure to ESG stocks than those living in a wheat-growing city.

Together with the evidence reported in Talhelm et al. (2014), this suggests that pro-social preferences, possibly driven by traditional agricultural practices, are potentially important determinants of ESG investing.[16] This evidence motivates us to investigate more generally whether ESG investing is affected by life-time experiences, both in terms of economic and of non-economic dimensions, as we discuss next.

4 Life-Time Experiences and ESG Investing

The above results provide suggestive evidence that ESG investing can be affected by life-time experiences, such as living in a city with more pollution or more pro-social attitudes. We now wish to generalize the above logic in three important ways. First, we extend the analysis to the entire population of investors. Second, we consider more systematically the potential effects of various economic and non-economic experiences. Third, we shed light on the potential dynamics of these effects, considering whether and how investors can change their behaviors over time in response to life experiences.

4.1 Methodology

The analysis builds on the seminal method developed in Malmendier and Nagel (2011). Consider a given dimension of life-time experience, say exposure to pollution. We define the accumulated exposure to pollution by investor i at time t, $A_{i,t}$, as

$$\begin{aligned} A_{i,t}(\lambda) &= \sum_{k=1}^{T_{i,t}-1} w_{i,t} E_{i,t-k}, \\ &\quad \text{with } w_{i,t}(k,\lambda) = \frac{(T_{i,t}-k)^{\lambda}}{\sum_{k=1}^{T_{i,t}-1}(T_{i,t}-k)^{\lambda}}, \end{aligned} \tag{3}$$

where $T_{i,t}$ is the trading experience of investor i at time t and $E_{i,t}$ is the level of pollution experienced by investor i at time t. We then analyze how accumulated pollution affects the investor's propensity to invest in ESG stocks $y_{i,t}$ in the following model:

$$y_{i,t} = \alpha_i + \beta A_{i,t}(\lambda) + \gamma X_{i,t} + \phi_t + \varepsilon_{i,t}, \tag{4}$$

where $X_{i,t}$ is as above a vector of investor and portfolio characteristics, and α_i and ϕ_t are respectively investor and time fixed effects. This method can be applied in the same way to the other dimensions of life-time experience mentioned above (stock market returns, natural disasters, etc.) and it allows to jointly estimate two key parameters. First, in

[16]While we cannot directly distinguish the role preferences and beliefs in these regressions, we notice that our results in Tables 5 and 6 are unchanged when controlling for past returns of ESG and non-ESG stocks, which may affect investors' beliefs. We report these results in the Online Appendix.

equation (2), we estimate λ, which measures how the vector of past experiences $E_{i,t-k}$ contributes to the accumulated experience $A_{i,t}$ and so whether and how much experiences in the recent past matter relative to those in the distant past. A positive λ for example would imply that the recent past matters more, and the larger is lambda the more past experiences are discounted; a negative λ instead, would indicate that early experiences matter more. A second key parameter, estimated in equation (3), is β, which measures the impact of the accumulated experience of a given variable, $A_{i,t}$, on the outcome of interest, $y_{i,t}$.

Apart from the specific focus on ESG investing, our model differs from Malmendier and Nagel (2011)'s original paper as we have a panel of individuals. This allows to control not only for time and cohort fixed effects, as in Malmendier and Nagel (2011), but also for individual fixed effects. We can compare the effects of the cross-sectional variation (say, of larger experienced returns relative to other investors) with the effects of the within-investor variation (say, an increase in experienced returns relative to the investor's own average).

Both sources of variations are potentially important in our setting. For our main dependent variable ESG proportion, the within-investor standard deviation is about 32% while the between-investor standard deviation is about 28%. As comparison, the corresponding within-month standard deviation is about 42% while the between-month standard deviation is about 3%.[17]

A second distinctive feature is that for many of our variables we focus on local experiences, say the level of pollution in the city of residence, as opposed to nation-wide experiences. We can also compare the effects of stock market returns (as in Malmendier and Nagel (2011)) to those of individual stock returns. At the same time, for many of these variables (as we detail below) the available time series cannot be constructed for the entire life of investors and we concentrate on the time period after which the investor has started her trading activity, rather than the birth date as in Malmendier and Nagel (2011).[18]

We estimate the non-linear model in (3)-(4) with an iterative procedure similar to Malmendier and Nagel (2011), which we adapt as we have both time and investor fixed effects. We fix the value of λ and estimate equation (4) with OLS, we repeat the same procedure with several possible values of λ from a set with fine enough grids and wide enough coverage, we then select the value of λ that gives the smallest sum of squared residuals and use it as the starting point for a non-linear estimation of equation (4) using least-squares method. We estimate the standard errors of λ by bootstrapping the residuals with re-sampling for 100 times; we obtain the standard errors of β by estimating equation (4) with OLS given the estimated λ.

[17]In order to compute the within-investor standard deviation, we consider for any given investor the standard deviation of ESG proportion over time, and then take the average across investors. In order to compute the between-investor standard deviation, we consider for any given month the mean of ESG proportion across investor, and then compute its standard deviation over time. We compute within-month and between-month standard deviation in a similar way.

[18]Most of our time series are not available in earlier years. This however does not seem key for our results; as we will see, recent experiences tend to receive larger weights.

From a methodological viewpoint, the only modification relative to Malmendier and Nagel (2011) is the addition of individual fixed effects. In the Online Appendix B, we provide the details of how we implement our estimation method in order to account for the large number of fixed effects.

Interpreting Magnitudes

In the next regressions, we compare the estimated λ and β in various specifications. In order to facilitate the interpretation of the implied magnitudes, we introduce two variables. First, we consider an investor with the median trading experience, i.e. 13 years, and define $\hat{k}(\lambda)$ as the number of most recent periods, over the total number of trading periods, that account for 50% of her accumulated experience.[19] When $\lambda = 0$, $\hat{k}(\lambda) = 50\%$, implying that the 50% most recent years account for 50% of the accumulated experience and so all periods receive the same weight. In general, $\hat{k}(\lambda)$ decreases in λ, and it gives a measure of how much recent experience are overvalued (when $\lambda > 0$) or undervalued (when $\lambda < 0$) relative to distant experiences.

In order to interpret the implied magnitudes of our effects on ESG demand, we suppose that an investor is exposed to a one standard deviation increase of a give experience dimension (say, pollution), and define $\hat{\delta}(\lambda, \beta)$ as the associated change in ESG demand that would be observed over the next 13 years.[20] This measure depends on λ, which tells how much a shock received in a given period persists in the subsequent periods, and on β, which tells how much the accumulated experience affects ESG demand.

4.2 Economic Experiences

We start by investigating whether investors' propensity to invest in ESG stocks are affected by economic experiences, such as GDP growth rates and stock market returns at the macro level, and by own portfolio returns.

GDP Growth

Our first experience measure is the GDP growth rate in the province where the investor lives.[21] We obtain province-level annual GDP growth rates from WIND. Over our sample, the average GDP growth rate is 10.5% and its standard deviation is 2.9%.

In column 1 of Table 7, we observe our cross-sectional estimates, showing that λ is around 0.15. This means that recent experiences of GDP growth matters more, but λ remains small; that is, past experiences are quite persistent. When adding individual fixed effects, in column 2, showing an estimated λ around 1.2. As we see in column 1, $\hat{k}(\lambda) = 46\%$ when $\lambda = 0.15$, implying that the 46% most recent years account for 50% of the accumulated experience. As our median investor has about 13 years of trading

[19] While for simplicity of exposition we focus on the investor with the median trading experience, in general this ratio depends also on the investor's trading experience $T_{i,t}$. As we show in the Online Appendix, however, the ratio varies minimally with $T_{i,t}$.

[20] Of course, the 13 years horizon is just one possible reference, the investor may remain in the market for longer or exit earlier. We show how $\hat{\delta}(\lambda, \beta)$ changes with the trading horizon in the Online Appendix.

[21] Provinces are the highest-level administrative divisions, mainland China is divided into 31 such divisions.

experience, the GDP growth experienced in the past 6 years has the same weight as that in the previous 7 years. A λ equal to 1.2, instead, implies that $\hat{k}(\lambda) = 28\%$ and so the most recent 3.6 years matter as much as the earlier 9.4 years.

The effect of experienced GDP growth on ESG demand is sizeable. We observe in column 1 that $\hat{\delta}(\lambda, \beta)$=6.5%, meaning that for our median investor a one standard deviation increase in GDP growth experienced in her first trading period would translate into a 6.5% increase in ESG exposure in the next 13 years. Once we include individual fixed effects, the estimated increase is 1.2%.[22]

Stock Market Returns

We consider the effect of experienced stock market returns, which we compute as the value-weighted monthly return (with reinvested dividends) in the Shanghai Stock Exchange. In our sample, the average monthly return is 0.7% and its standard deviation is 7.3%.

In column 3 of Table 7, we observe a cross-sectional estimate of λ of 1.6, implying a $\hat{k}(\lambda) = 24\%$. This specification is similar to the one by Malmendier and Nagel (2011), and so is our estimated λ, despite that our dependent variable relates to ESG investing while Malmendier and Nagel (2011) focus on stock market participation. Once we add individual fixed effects (column 4), the estimated λ drops to 0.2 (we cannot reject that the estimated λ is different from zero), which shows that the within-investor effect of experienced stock market returns is very persistent.[23]

In terms of magnitude, one standard deviation increase in market returns is associated to a 2.5% increase in ESG demand, as estimated by $\hat{\delta}(\lambda, \beta)$. Once we include individual fixed effect, the estimated impact is 8.7%.[24]

Own Portfolio Returns

A key distinctive feature of our data is that we observe monthly returns at the investor level and we can then explore their effects on ESG demand. We observe an average return of -1.5% and a standard deviation of 13.1% in our sample period.[25]

In column 5 of Table 7, we observe an estimated λ around 0.9, which implies a $\hat{k}(\lambda) = 30\%$, and an estimated β around 47 in cross-sectional regressions. This implies that a one standard deviation increase in own returns is associated to a 13% increase in the proportion of ESG stocks. Once we add individual fixed effects, the estimated λ is around 1.3 ($\hat{k}(\lambda) = 44\%$), and the corresponding increase in ESG proportion is 1.2%.[26]

[22] A one standard deviation increase in GDP growth rates (equal to 0.029) translates into an accumulated increase of 0.086 in the following 13 years when $\lambda = 0.146$ as in column (1) and of 0.051 when $\lambda = 1.171$ as in column (2). Multiplying the accumulated impact with corresponding β, we obtain $\hat{\delta}(\lambda, \beta)$.

[23] Recall that when $\lambda = 0$ all realizations matter in the same way irrespective of whether they have occurred in the recent or in the distant past.

[24] A one standard deviation increase in market returns (equal to 0.073) corresponds to an accumulated impact of 0.113 when $\lambda = 1.572$ and of 0.310 when $\lambda = 0.193$.

[25] See Jones, Shi, Zhang and Zhang (2021) for a comprehensive study of the return patterns of retail investors in the Chinese stock market.

[26] A one standard deviation increase in individual returns (equal to 0.131) translates into an accumulated impact of 0.275 when $\lambda = 0.917$ and 0.220 when $\lambda = 1.343$.

4.3 Non-Economic Experiences

We now consider the effects of non-economic experiences, such as a major natural disaster, a corporate scandal, or an increase in pollution in the city of residence.

Pollution

We measure pollution at the monthly level by the Air Quality Index (AQI) in the city where the investor lives, obtained from CSMAR. [27] The AQI measure, scaled by 100, has an average of 0.8 and a standard deviation of 0.27 in our sample.

In column 1 of Table 8, we observe an estimated λ of 6.9 (that is, a $\hat{k}(\lambda) = 8\%$), while once controlling for individual fixed effects the λ drops to 1.9 (that is, a $\hat{k}(\lambda) = 21\%$). In both cases, the estimates are larger than those for GDP growth and stock returns, implying that experienced pollution has less persistent effects.

The estimated beta is around 1.2 in the cross-section and 2.6 with individual fixed effects, the latter implies that a one standard deviation increase in accumulated pollution is associated to a 1% larger ESG proportion.[28]

Natural Disasters

As a second measure of experience with environmental issues, we look at natural disasters occurring at the yearly level in the province where the investor lives. We obtain the information about natural disasters from the Geo-referenced Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters, a research unit of the University of Louvain. We use the number of deaths over the population as the measure of severity of the disaster. In our sample, the measure is reported in basis points and has an average of 0.01 and standard deviation of 0.33.

In columns 3 and 4, we observe that the estimated λ is negative, even more so with individual fixed effects, which implies that earlier experiences (i.e., those occurring right after the investor has started trading) receive larger weights. The implied $\hat{k}(\lambda)$ are equal to 58% and 71%, respectively. In terms of effects on ESG demand, our estimates imply that a one standard deviation increase in natural disasters is associated to a 2.6% larger ESG proportion, or an increase of 9% once we include individual fixed effects.[29]

Corporate Scandals

We investigate whether experiences of corporate scandals, as measure of poor corporate governance, affect the propensity to invest in ESG stocks. We obtain the records of firms' financial misconducts at the monthly level from the China Listed Firms Research Series published by CSMAR. Since this information is available only for listed firms,

[27] The official definition of AQI has changed in 2013. As robustness check, we we use the PM 2.5 measure from NASA Socioeconomic Data and Applications Center (van Donkelaar, Martin, Brauer, Hsu, Kahn, Levy, Lyapustin, Sayer and Winker (2018)), and we obtain very similar results in terms of statistical and economic significance.

[28] A one standard deviation increase in AQI (equal to 0.270) translates into an accumulated impact of 0.272 when $\lambda = 6.941$ and 0.380 when $\lambda = 1.867$.

[29] A one standard deviation increase in the ratio of deaths over the population (equal to 0.03 basis points) translates into an accumulated impact of 0.159 when $\lambda = -0.268$ and of 0.155 when $\lambda = -0.622$.

we define the measure as the number of scandals over the number of listed firms in the province where the investor lives.[30] In our sample, the variable has a mean of 0.008 and standard of deviation of 0.014.

The effects of corporate scandals also appear less persistent than those of economic variables in Table 7, the implied $\hat{k}(\lambda)$ is around 15% in both columns. In terms of magnitude, our estimates imply that a one standard deviation increase in accumulated scandals is associated to a 1.9% larger ESG proportion, or 0.7% when controlling for individual fixed effects.[31]

4.4 Taking Stock

The above analysis has revealed a rich set of findings, and we can summarize the main patterns as follows. First, both economic and non-economic life-experiences affect the propensity to invest in ESG stocks. Living through favorable stock market conditions, for example, positively affects ESG investing. At the same time, living in polluted areas or being exposed to corporate scandals also increases ESG investing.

Second, with the exception of natural disasters, the estimated λ's are positive, meaning that investors react more to more recent experiences. If the estimated λ were negative, early experiences would matter and investment patterns would not respond much to recent shocks. A positive λ instead suggests that even for the same investor the propensity to invest in ESG can evolve considerably over her trading life, possibly in response to accumulated experiences.

Third, economic experiences tend to be more persistent; that is, in absolute value, the estimated λ are closer to zero. Non-economic experiences, instead, tend to have more volatile effects on the demand for ESG stocks.

In order to better compare the relative magnitudes of these effects, in terms of estimated β, we construct for each factor the accumulated $A_{i,t}$, based on the corresponding λ estimated in the previous regressions, and then consider how they jointly explain the exposure to ESG stocks.

Our results are in Table 9, where in order to ease the comparison on top of point estimates and t-values, we report in brackets the corresponding $\hat{\delta}(\lambda, \beta)$. We first consider the effects of economic factors without individual fixed effects and we show in column 1 that own portfolio returns have the largest effect (equal to 13%) on ESG proportion. Once we add individual fixed effects, in column 2, we observe that the largest effect is driven by experienced market returns (equal to 8.4%).

In columns 3 and 4, we repeat the same analysis with non-economic factors. We observe that both with and without individual fixed effects, experienced natural disasters have the largest impact (the effect is 12.2% and 2.7%, respectively).

In columns 5 and 6, we add both economic and non-economic factors, and we observe that without individual fixed effects, the largest effect (equal to 13.6%) is given by

[30] We define the ratio at the province level rather than at the city level since 75% of listed firms are located in the capital or in the second largest city of the province.

[31] A one standard deviation increase in scandals (equal to 0.014) translates into an accumulated impact of 0.018 in both columns.

experienced portfolio returns, and with individual fixed effects the largest effect (equal to 13.7%) is given by experienced natural disasters.

Overall, non-economic experiences seem to matter more for within-investor differences in ESG investing, while economic experiences seem more important to explain between-investors variations.

5 ESG Trading Patterns

In this section, we analyze whether investors display distinct trading patterns between ESG and non-ESG stocks. Importantly, we can compare the behaviors of the same investor across the various stocks in her portfolio. We first look at how turnover and churn ratios, which we interpret as measures of investor's horizon (as in Starks et al. (2017)), are affected by ESG investing. We then look at how investors react differently to past returns of ESG and non-ESG stocks, both in their decision to keep or sell a stock and in their decision to buy a stock for the first time. Finally, we compare investors' reaction to returns and to changes in the ESG status.

5.1 Investment Horizon

We investigate whether investors with larger ESG investing have longer investment horizons, as measured by lower turnover and churn ratios of their portfolios. Both ratios measure how frequently an investor changes the stock positions in her portfolio; the churn ratio excludes changes that are driven by stock price volatility. More specifically, the turnover ratio for investor i in month t is computed as follows:

$$TurnoverRatio_{i,t} = \frac{\sum_{j \in J} |(N_{i,j,t}P_{j,t} - N_{i,j,t-1}P_{j,t-1})|}{\sum_{j \in J} N_{i,j,t-1}P_{j,t-1}}, \tag{5}$$

where $N_{i,j,t}$ denotes the shares of stock j held by investor i in month t, and $P_{j,t}$ denotes the price of stock j at the end of month t and J is the set of stocks. Following Gaspar, Massa and Matos (2005) and Starks et al. (2017), the corresponding churn ratio is computed as follows:

$$ChurnRatio_{i,t} = \frac{\sum_{j \in J} |N_{i,j,t}P_{j,t} - N_{i,j,t-1}P_{j,t-1} - N_{i,j,t-1}\Delta P_{j,t}|}{\sum_{j \in J}(N_{i,j,t}P_{j,t} + N_{i,j,t-1}P_{j,t-1})/2}, \tag{6}$$

where $\Delta P_{j,t} = P_{j,t} - P_{j,t-1}$.

We report our results in Table 10. We observe that a standard deviation increase in ESG proportion (equal to 43) is associated to a 0.7 lower turnover ratio, which is a 5% decrease relative to the average of 13, and to a 4.5 lower churn ratio, which is a 15% decrease relative to the average of 30. Once we include individual fixed effects, our estimates are still statistically significant and about half in magnitudes.

Since we observe all trades of the same investor at a given point in time, we can investigate more directly whether the investor displays different trading patterns for ESG vs. non-ESG stocks. We start by looking at the number of trades, we then distinguish between buy and sell transactions. In Table 11, we observe that within their own portfolio investors tend to trade ESG stocks less frequently. Specifically, ESG stock has 0.04 lower trades per month, relative to an average of 1.07. The effects are similar for buy and sell transactions. Notice these results are estimated with investor*month fixed effects, hence controlling for any shock that may impact a given investor at a given point in time.

5.2 Reactions to Financial Performance

We then look at the propensity to sell, conditional on holding, as a function of whether the stock price has increased or decreased relative to the purchase price. In Table 12, the dependent variable is a dummy equal to one if investor i sells stock j at time t, conditional on holding stock j at $t-1$, and to zero if the investor holds the stock at time t. $Winner$ is a dummy equal to one if the stock price at time t exceeds the price that the investor has paid for the stock, and equal to zero otherwise.[32]

We show that investors are more likely to sell winning stocks and to hold losing stocks, consistent with the well-known disposition effect. Our estimates in column 1 show that winners are 7.7% more likely to be sold than losers, where the average probability of selling is 15%. In column 2, we observe that investors are less likely to reduce their holdings of ESG stocks. Interestingly, investors display a lower disposition effect for ESG stocks. In our most restrictive specification in column 4, which controls for investor*month and stock*month fixed effects, non-ESG winners are about 7.4% more likely to be sold than non-ESG losers, while ESG winners are about 5.9% more likely to be sold than ESG losers. Notice that in these specifications we are comparing the selling behavior of a given investor at a given point in time across the various stocks that she holds, while controlling for any shock that may occur to a given stock and to a given investor at a given point in time.

The same result also holds if instead of the $Sell$ dummy we consider the fraction of selling, $-\Delta H_{i,j,t}/H_{i,j,t-1}$, where $H_{i,j,t}$ denotes investor's i holdings of stock j at time t and $\Delta H_{i,j,t}= H_{i,j,t} - H_{i,j,t-1}$ (column 5). This is the first instance in which we show that the same investor, at the same point in time, exhibits lower sensitivity to financial performance for ESG stocks relative to non-ESG stocks.

We then consider how past stock returns affect investors' probability of buying the stock. In Table 13, the dependent variable is a dummy equal to one if the investor increases her holdings of stock j at time t (i.e.,$\Delta H_{i,j,t} > 0$), and equal to zero otherwise, conditional on holding stock j at time t or at time $t-1$ (i.e., conditional on $H_{i,j,t} > 0$ or $H_{i,j,t-1} > 0$). The dummy $HighReturn$ is equal to one if in month $t-1$ stock j had returns larger than the median return of all stocks in $t-1$. We observe in columns 3 and 4 that investors are more likely to buy stocks after good performance, consistent

[32] Our data record the price paid even if the investor has bought the stock before our sample period.

with well-documented trend chasing behaviors.[33] Interestingly, this tendency is less pronounced for ESG stocks. In our most restrictive specification in column 6, which controls for investor*month and stock fixed effects, non-ESG High Return stocks are 0.5% more likely to be bought (relative to an average of 16%), while the effect of High Return is 0.3% for ESG stocks.

These results are consistent with our previous findings, showing that the same investor, at the same point in time, tends to be less sensitive to financial performance for a stock labeled as ESG relative to a non-ESG stock.

5.3 Reactions to ESG Dimensions

We investigate whether a change in ESG status of a given stock affects investors' propensity to trade the stock. As we have shown in Table 9, investors are less likely to sell ESG stocks, even controlling for stock fixed effects and so exploiting within-stock variations in ESG status. To make this analysis more precise, we now restrict our sample around events of ESG status change, considering in particular a 12-month window before and after the event. In our sample, 491 of the 1,501 stocks experience a change in ESG status (431 stocks experience an inclusion and 258 stocks experience an exclusion).

We replicate the above analysis and consider investors' propensity to sell a stock and the change in holdings. We observe in Table 14 that the inclusion in ESG index is associated to 1.4% lower propensity to sell (relative to an average of 19%) and to a 1.3% lower decrease in holdings (relative to an average of 10%).

6 Alternative Explanations and Robustness

We consider alternative explanations for our findings, in particular whether our effects could be driven by changes in firms' (as opposed to investors') attitudes towards ESG criteria, and whether investors display similar behaviors with stocks that belong to any index. We then discuss the robustness of our findings when employing alternative measures of ESG demand. We discuss our results in the text, we report the corresponding tables in the Online Appendix.

6.1 Supply-side Explanations

An alternative explanation of our results may posit that firms in a given region respond say to a natural disaster by changing their behaviors and become more compliant to ESG factors. If in addition investors are more likely to buy local stocks (a form of home bias), this would induce a positive correlation between ESG investment and natural disasters even absent any change in investors' attitude toward ESG stocks.

In order to account for this alternative explanation, we construct the ratio of ESG stocks over the total number of stocks in each province. Indeed, investors in our sample display a form of home bias, they are about 4% more likely to invest in a firm located

[33]See, for example, Griffin, Harris and Topaloglu (2003) and Greenwood and Nagel (2009).

in their province. We observe however no interaction between home bias and ESG investing. First, our main results on experience effects are unchanged once we control for the proportion of ESG stocks in the province where the investor lives. Second, we observe no correlation between home bias and ESG demand; that is, investor display no significantly different demand for local stocks depending on whether or not they are ESG-stocks.

6.2 Placebo tests

As mentioned in Section 2, ESG are somewhat different than non-ESG stocks along various dimensions, and in particular they tend to have larger market capitalization. This makes them more likely to belong to size-based indices; moreover, the mere fact of belonging to an index may induce different behaviors on the part of the investors.

In order to address these concerns, we consider whether the determinants and the dynamics of Index-investing are similar to those of ESG-investing. We consider indices based on market capitalization, which are most visible to investors, and among those we focus on the SSE 380 Index, which is most similar to our ESG definition in terms of number of stocks.[34] The proportion of stocks belonging to the SSE 380 Index is about 25% (as compared to 35% of ESG stocks). As of October 2019, about half of the stocks in the SSE 380 Index also belong to one ESG Index. The median market capitalization of ESG stocks is 13.8bn, for 380 stocks it is 8.7bn.[35]

We first notice that, in terms of demographics, investors with larger exposure to the SSE 380 Index (computed by the value of SSE 380 stocks over the total value of their portfolio) tend to be male, lower educated and middle-aged. These patterns are significantly different from those highlighted in Table 3 on ESG investing. We then show how life-time experiences affect Index investing. With the exception of experienced corporate scandals, our life-time experience have negative or no significant impact on index investing.[36] Again, these patterns are very different than those determining ESG investing.

We also observe that investors with larger proportion of SSE 380 stocks have larger (not lower) churn ratio, they display larger (not lower) disposition effect on those stocks, and their selling propensity is not affected by the inclusion or exclusion of the stock in the SSE 380 Index. Overall, these estimates confirm that the patterns uncovered in our main analysis are specific to ESG-investing, not of any index investing.

[34] These indices are constructed based on market capitalization and excluding firms with non-complying corporate conducts. The SSE 180 Index includes the largest 180 stocks, the SSE 380 Index includes stocks ranked between 181st and 561st. Using the SSE 180 Index gives similar results if one considers stocks that are not ESG.

[35] The median market capitalization for SSE 180 stocks is 39.4bn.

[36] The effect of corporate scandals can be explained by the fact that firms subject to a scandal are excluded from the SSE 380 index.

6.3 Robustness

Our main definition of ESG stock is based on the inclusion in one ESG index. The definition is simple, and does not distinguish between stocks which are compatible with ESG standard but have different performances along the ESG dimensions. We consider the robustness of our findings when using finer classifications of ESG stocks.

First, for each stock, we consider the number of ESG indices that contain the stocks. This gives a more continuous measure of ESG, and allows to exploit marginal changes due to the stock's inclusion or exclusion from any ESG index. We observe very similar results, also in terms of magnitude, to our baseline analysis, both regarding experience effects and regarding trading patterns.

Second, we consider stocks' ESG ratings. These ratings appeared very recently in China, and covered only a small set of the SSE stocks.[37] In April 2019, however, Sino-Securities Index Co.Ltd. has started to produce ratings on all stocks in the Chinese market. While the release of these ratings is outside our sample period, Sino-Securities has issued them also retrospectively based on public information available at the time. Ratings take the form CCC-AAA, and we classify ESG stocks as highly rated if they are rated AA or above, which gives 40% of highly rated stocks in our sample. This proportion is similar to that of ESG stocks in the baseline analysis.

We repeat the same analysis as above. We observe that life-time experiences have a similar effect as in our baseline analysis with the exception of natural disasters (whose estimated λ is similar but β is not significant). We observe that trading patterns too are similar to our baseline analysis.[38] These estimates show that the patterns uncovered above are robust when we employ alternative definitions of stocks' ESG status.

7 Conclusion

We have shown that both economic and non-economic life-time experiences affect investors' demand for ESG stocks, inducing significant differences both across investors and for the same investor over time. We have also shown that investors display distinct trading patterns for ESG and non-ESG stocks.

We view these results as a first step, further analysis is needed to better understand the determinants of investors' demand. We still observe large unexplained heterogeneity, which calls for exploring the role of other experiences (possibly at an even more micro level), as well as the potential heterogeneity of experience effects across investors.[39] Another important next step would be trying to quantify the effect of these investment patterns at the macro level, to make their asset pricing implications more explicit. We view these as interesting areas for future research.

[37] The first ESG rating firm (SynTao Green) appeared in China in 2015 and it covered 271 (out of 2800) listed firms.

[38] In this table, we do not consider the effects of a change in rating, since these are not observed by the investors at the time of trading.

[39] D'Acunto, Malmendier and Weber (2021) show how inflation experiences may affect women and men differently.

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Tables

Table 1: ESG Index List

This table lists the ESG indices used in the analysis. *Number of Stocks* is the number of stocks listed in the Shanghai Stock Exchange that appear at least once in the index during our sample period.

Index Code	Index Release Date	Index English Name	Number of Stocks
000970.CSI	September 17, 2010	CSI ECPI ESG China 40 Index	74
000846.CSI	October 16, 2012	CSI CAITONG ECPI ESG China 100 Index	122
931088.CSI	December 10, 2018	CSI 180 ESG Index	171
931148.CSI	February 27, 2019	CSI ECPI ESG 80 index	65
931168.CSI	June 27, 2019	CSI CUFE SH-SZ 100 ESG leading index	64
000977.CSI	January 21, 2011	CSI China Mainland Low Carbon Economy Index	56
H11113.CSI	February 16, 2011	China Low Carbon Index	31
H50031.SH	August 26, 2013	SSE Urbanization Green Cities Index	81
H30139.CSI	August 26, 2013	CSI Urbanization Green Cities Index	67
399556.SZ	June 6, 2014	CCTV Ecology	35
950081.CSI	October 8, 2015	SSE 180 Carbon Efficient Index	294
930956.CSI	May 26, 2017	CSI Green Investing Index	42
931037.CSI	January 4, 2018	CSI 300 Green Leading Stock Index	112
931150.CSI	January 31, 2019	CSI Green Industry Quality Index	53
000048.SH	August 5, 2009	SSE Responsibility Index	181
399369.SZ	November 4, 2009	CNI-CBN-AEGON-INDUSTRIAL CSR	118
399550.SZ	June 6, 2012	CCTV 50 Index	43
CN2550.CNI	June 6, 2012	CCTV 50 Total Return Index	43
399555.SZ	June 6, 2013	CCTV 50 CSR	51
930982.CSI	June 14, 2017	CSI Poverty Alleviation Development Index	20
399322.SZ	December 12, 2005	CNI Corp. Governance	102
000019.SH	January 2, 2008	SSE Corp. Governance Index	394
000021.SH	September 10, 2008	SSE 180 Governance Index	205
399554.SZ	June 6, 2013	CCTV 50 Governance	28

Table 2: Summary Statistics

This table reports summary statistics of the main variables used in the analysis.

Summary Statistics at the Investor-Month Level								
Variable	Obs	Mean	Std. Dev	Min	p25	p50	p75	Max
ESG Demand	4,758,050	57.41	42.81	0.00	0.00	70.57	100.00	100.00
Value Weighted NumIndex	4,758,050	1.938	2.282	0.000	0.000	1.000	3.000	18.000
High ESG Rated Prop	4,235,932	48.68	42.79	0.00	0.00	47.80	100.00	100.00
Female	4,758,050	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Education (Years)	4,758,050	13.22	2.82	9.00	12.00	12.00	15.00	21.00
Age (Years)	4,758,050	48.61	12.77	18.00	40.00	48.00	57.00	98.00
Trading Experience (Months)	4,758,050	143.64	85.20	0.00	58.00	162.00	214.00	338.00
Investor Monthly Return	4,661,245	-0.01	0.13	-0.62	-0.06	-0.01	0.04	0.98
Churn Ratio(%)	4,758,050	30.36	61.95	0.00	0.00	0.00	20.32	200.00
Turnover Ratio(%)	4,758,050	13.43	23.33	0.00	2.44	6.13	13.14	150.99
Ln(Size)	4,758,050	10.16	1.76	2.77	8.98	10.16	11.33	22.14
Portfolio Beta	4,758,050	1.05	0.85	-104.08	0.79	1.04	1.31	116.51
Portfolio Beta for Size	4,758,050	-0.00	2.95	-265.52	-0.69	0.06	0.72	633.87
Portfolio Beta for B-M	4,758,050	0.35	3.29	-279.99	-0.27	0.28	0.87	957.02
Summary Statistics at the Investor-Stock-Month Level								
Sell Dummy	11,664,531	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Sell Prop	11,664,531	0.09	0.42	-1.86	0.00	0.00	0.00	1.00
Winner	11,664,531	0.34	0.47	0.00	0.00	0.00	1.00	1.00
Cumulative Return	11,664,531	-0.07	0.50	-5.78	-0.32	-0.10	0.07	44.07
Buy Dummy	12,726,544	0.16	0.37	0.00	0.00	0.00	0.00	1.00
High Return Past-Month	12,726,544	0.50	0.50	0.00	0.00	1.00	1.00	1.00
Number of Trades	15,603,015	1.07	2.37	0.00	0.00	0.00	1.00	46.00
Number of Buys	15,603,015	0.56	1.30	0.00	0.00	0.00	1.00	23.00
Number of Sells	15,603,015	0.50	1.20	0.00	0.00	0.00	1.00	23.00
Summary Statistics at the Stock-Month Level								
ESG	119,691	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Monthly Return (%)	119,691	0.80	13.87	-80.40	-6.53	-0.35	6.67	456.31
Ln(Market Cap)	119,691	8.97	1.13	6.21	8.17	8.78	9.57	14.59
Return Volatility	119,691	0.03	0.01	0.00	0.02	0.02	0.03	0.43
Stock Turnover Ratio	119,691	1510.40	1611.73	1.47	506.54	975.99	1903.09	27850.68
Market-to-Book Ratio	119,691	10.68	129.97	0.26	1.74	2.73	4.56	9890.99
Dividend Yield Ratio	119,691	1.03	1.44	0.00	0.00	0.57	1.44	36.21
Beta (Mkt Return)	119,691	1.02	1.29	-104.08	0.70	1.03	1.36	116.51
Beta (Size)	119,691	0.62	3.92	-279.99	-0.12	0.57	1.26	957.02
Beta (Value)	119,691	-0.16	3.98	-265.52	-1.04	-0.11	0.74	633.87

Table 3: ESG stocks and non-ESG stocks

This table compares the differences between ESG and non-ESG stocks. For each variable, we report its mean for non-ESG stocks (column 1) and ESG stocks (column 2). In column (3) we report the difference between the means, controlling for time fixed effects. Standard deviations are reported in the parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Non-ESG	ESG	ESG - Non-ESG
Monthly Return(%)	0.862	0.679	-0.387
	(14.85)	(11.88)	(13.87)
Ln(Cap)	8.570	9.698	1.120***
	(0.83)	(1.23)	(1.13)
Return Volatility	0.027	0.023	-0.003***
	(0.01)	(0.01)	(0.01)
Turnover Ratio	1659.305	1237.294	-463.498***
	(1707.66)	(1377.82)	(1611.73)
Market to Book	14.610	3.468	-11.471***
	(152.71)	(70.87)	(129.97)
Dividend Yield Ratio	0.764	1.516	0.770***
	(1.19)	(1.71)	(1.44)
Beta (Mkt Return)	1.002	1.059	0.054***
	(1.48)	(0.83)	(1.29)
Beta (Size)	0.767	0.342	-0.420***
	(4.36)	(2.94)	(3.92)
Beta (Value)	-0.209	-0.077	0.133***
	(4.24)	(3.46)	(3.98)
Number of Observations	77,459	42,232	119,691

Table 4: ESG investment and Demographic Characteristics

This table estimates the relation between investors' demographic characteristics and their demand for ESG stocks. The dependent variable is the value of ESG stocks over the total value of the portfolio. In columns (3) and (4), each variable is first demeaned at the monthly level and then collapsed at the investor level. The smaller sample size in columns (2) and (4) is due to missing investment return from the previous month. Portfolio controls include beta relative to the market, size and book-to-market factors. Standard errors are two-way clustered at the investor and time levels in columns (1) and (2). T-values are in parenthesis. *Coeff. * Std. Dev.* are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ESG Demand			
Method:	Panel		Cross Sectional	
Female	1.370***	1.230***	1.708***	0.900***
	(5.74)	(5.35)	(8.14)	(4.75)
	[0.685]	[0.615]	[0.849]	[0.448]
Education	0.241***	0.236***	0.227***	0.178***
	(5.49)	(5.54)	(5.93)	(5.18)
	[0.682]	[0.667]	[0.635]	[0.499]
Trading Experience	0.008***	0.006***	0.017***	0.006***
	(4.03)	(3.18)	(11.88)	(4.88)
	[0.689]	[0.514]	[1.534]	[0.569]
Age	-0.087	-0.074	-0.144***	-0.056
	(-1.46)	(-1.28)	(-3.02)	(-1.29)
	[-1.115]	[-0.946]	[-1.900]	[-0.736]
Age^2	0.001**	0.001**	0.002***	0.001
	(2.37)	(2.08)	(4.02)	(1.64)
	[1.783]	[1.512]	[2.459]	[0.911]
Investment Return		7.035**		22.873***
		(2.41)		(16.96)
		[0.915]		[1.633]
Constant	53.189***	57.344***	-2.213***	-1.058***
	(34.38)	(32.55)	(-19.27)	(-10.20)
Portfolio Controls	No	Yes	No	Yes
Month FE	Yes	Yes	No	No
Observation	4,758,034	4,661,244	97,755	93,903
R^2	0.007	0.041	0.004	0.185

Table 5: The Huai River Policy and ESG Investment

This table estimates the relation between the Huai River policy and ESG investment. *Coal Heating* is a dummy variable equal to 1 if the city has centralized coal heating (north of the Huai river) and to 0 if the city has no central heating (south of the Huai river). The dependent variable in column (1) is the Air Quality Index, and in columns (2)-(4) it is ESG demand. In columns (1) to (3), we include investors living in cities located within 10 degrees latitude from the Huai river; in columns (4) and (5), we consider a latitude distance of 5 degrees, and in columns (6) and (7), we consider 3 degrees. Portfolio controls include portfolio size, beta relative to the market, size and book-to-market factors. Standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	AQI	ESG Demand					
Latitude to Huai River:		10 degree		5 degree		3 degree	
Coal Heating	14.917***	1.577***	1.421***	1.703***	1.747***	2.518***	2.520***
	(15.97)	(6.64)	(6.23)	(5.83)	(6.27)	(6.80)	(7.08)
Female			1.245***		1.060***		1.023***
			(5.22)		(3.79)		(2.91)
Education			0.251***		0.254***		0.244***
			(5.77)		(4.96)		(3.89)
Trading Experience			0.009***		0.006***		0.005**
			(4.87)		(2.80)		(2.07)
Age			0.048***		0.063***		0.065***
			(4.22)		(4.65)		(3.90)
Constant	76.131***	56.189***	52.385***	55.543***	51.383***	55.030***	50.646***
	(153.91)	(336.54)	(41.36)	(272.07)	(36.43)	(219.74)	(31.61)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	3,542,586	4,004,854	4,004,854	2,776,613	2,776,613	1,763,402	1,763,402
R^2	0.401	0.006	0.040	0.006	0.039	0.007	0.040

Table 6: ESG investment in Rice and Wheat Areas

This table estimates how ESG investment differs between investors living in a rice-growing cities and those living in wheat-growing cities, restricting to provinces around the Yangtze river. *Rice Ratio* is the ratio of rice over total (wheat plus rice) farmlands at the city where the investor lives. In columns (1) and (2), we consider 65 cities in five provinces (Sichuan, Chongqing, Hubei, Anhui, and Jiangsu) as in Talhelm et al. (2014). In column (3) and (4), we omit 16 cities with coal heating (north of the Huai River). Portfolio controls include portfolio size, beta relative to the market, size and book-to-market factors. The standard errors are clustered at the time level. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ESG Demand			
Sample:	Close to Yangtze River		Close to Yangtze River and No Heating	
Rice Ratio	3.714***	2.633**	4.724***	3.165*
	(2.88)	(2.15)	(2.78)	(1.93)
Female		0.749*		0.589
		(1.66)		(1.05)
Education		0.147*		0.081
		(1.84)		(0.80)
Trading Experience		0.007**		0.007*
		(2.24)		(1.80)
Age		0.061***		0.072***
		(2.79)		(2.66)
Constant	53.701***	52.451***	52.871***	52.054***
	(62.18)	(24.26)	(43.69)	(19.83)
Portfolio Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observation	1,012,727	1,012,727	628,818	628,818
R^2	0.006	0.045	0.007	0.041

Table 7: ESG Investment and Life-time Experiences: Economic Factors

This table estimates the relation between life-time economic experiences and ESG investing. The dependent variable is the value of ESG stocks over the total value of the portfolio. The experience measures are based on annual GDP growth rates at the province level in columns (1) and (2), monthly stock market returns in the SSE in columns (3) and (4), and monthly individual portfolio returns in columns (5) and (6). $\hat{k}(\lambda)$ is the number of most recent periods, over total number of trading periods, that account for 50% of the accumulated experience for the investor with the median trading experience. $\hat{\delta}(\lambda, \beta)$ is the cumulative impact of a one standard deviation increase in the experience variable over a 13 years horizon. Demographic controls include gender, education, trading experience and age. Portfolio controls include beta relative to the market, size and book-to-market factors. Standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	ESG Demand					
Experience Measure:	GDP Growth		MKT Ret		Inv Ret	
λ	0.146***	1.171***	1.572***	0.193	0.917***	1.343***
	(6.36)	(4.75)	(3.63)	(1.46)	(6.96)	(7.06)
β	76.308***	24.388*	22.102***	28.084***	47.590***	5.593***
	(9.91)	(1.76)	(3.38)	(4.22)	(9.26)	(2.70)
$\hat{k}(\lambda)$	46.0%	28.4%	23.7%	44.2%	30.4%	25.7%
$\hat{\delta}(\lambda, \beta)$	6.530	1.246	2.494	8.713	13.076	1.233
Demographic Controls	Yes	No	Yes	No	Yes	No
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,690,573	4,687,208	4,691,196	4,687,829	4,385,542	4,383,081
R^2	0.041	0.459	0.040	0.459	0.043	0.481

Table 8: ESG Investment and Life-time Experiences: Non-Economic Factors

This table estimates the relation between life-time non-economic experiences and ESG investing. The dependent variable is the value of ESG stocks over the total value of the portfolio. The experience measures are based on monthly Air Quality Index at the city level in columns (1) and (2), annual occurrence of natural disasters at the province level in columns (3) and (4), and monthly occurrence of corporate scandals at the province level in columns (5) and (6). $\hat{k}(\lambda)$ is the number of most recent periods, over the total number of trading periods, that account for 50% of the accumulated experience for the investor with the median trading experience. $\hat{\delta}(\lambda, \beta)$ is the cumulative impact of a one standard deviation increase in the experience variable over a 13 years horizon. Demographic controls include gender, education, trading experience and age. Portfolio controls include beta relative to the market, size and book-to-market factors, past returns. Standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	ESG Demand					
Experience Variable:	AQI		Natural Disaster		Corp. Scandals	
λ	6.941***	1.867***	-0.268***	-0.622***	3.012***	3.246***
	(22.71)	(3.23)	(-4.43)	(-7.31)	(24.70)	(5.56)
β	1.174**	2.567***	20.617***	58.476***	116.832***	43.531**
	(2.25)	(3.07)	(2.91)	(2.69)	(3.19)	(2.35)
$\hat{k}(\lambda)$	8.4%	20.9%	58.4%	70.8%	15.9%	15.1%
$\hat{\delta}(\lambda, \beta)$	0.319	0.976	2.553	9.097	1.857	0.676
Demographic Controls	Yes	No	Yes	No	Yes	No
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,408,035	4,404,590	4,603,570	4,600,518	4,667,376	4,664,222
R^2	0.040	0.464	0.040	0.462	0.040	0.460

Table 9: ESG Investment and Life-Time Experiences: A Comparison

This table estimates the effects of economic and non-economic experiences on ESG investing. The dependent variable is the value of ESG stocks over the total value of the portfolio. For each experience measure, we use the λ estimated in the previous regressions to compute the accumulated experience. We report in brackets the $\hat{\delta}(\lambda, \beta)$ of the associated variable, that is the cumulative impact of a one standard deviation increase in the experience variable over a 13 years horizon. Demographic controls include gender, education, trading experience and age. Portfolio controls include beta relative to the market, size and book-to-market factors. Standard errors are two-way clustered at the investor and time level. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	ESG Demand					
GDP Growth	74.753***	28.158*			68.249***	29.616*
	(9.23)	(1.89)			(7.72)	(1.82)
	[6.397]	[1.439]			[5.840]	[1.514]
Market Return	-2.324	26.949***			0.021	25.371***
	(-0.35)	(3.26)			(0.00)	(2.71)
	[-0.262]	[8.361]			[0.002]	[7.871]
Investor Return	47.221***	5.295**			49.492***	5.851***
	(9.08)	(2.55)			(9.72)	(2.79)
	[12.974]	[1.167]			[13.598]	[1.290]
AQI			1.284**	2.410***	0.942*	2.372**
			(2.40)	(2.78)	(1.70)	(2.48)
			[0.343]	[0.901]	[0.252]	[0.887]
Natural Disaster			18.066**	65.032**	6.762	72.572**
			(2.27)	(2.56)	(0.80)	(2.62)
			[2.709]	[12.248]	[1.014]	[13.668]
Corporate Scandal			120.762***	51.323**	149.493***	72.075***
			(3.20)	(2.60)	(4.32)	(3.53)
			[2.172]	[0.902]	[2.689]	[1.267]
Demographic Controls	Yes	No	Yes	No	Yes	No
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,384,959	4,382,500	4,305,701	4,302,721	4,056,576	4,054,170
R^2	0.043	0.481	0.040	0.468	0.044	0.489

Table 10: ESG Investment and Investor Horizon

This table estimates the relation between ESG stock holding and investment horizon. In columns (1) and (2), the dependent variable is the monthly turnover ratio of the investor's portfolio. In columns (3) and (4), the dependent variable is the monthly churn ratio of the investor's portfolio. ESG Demand is the value of ESG stocks over the total value of the portfolio. Standard errors are two-way clustered at the investor and time level. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable	Turnover Ratio		Churn Ratio	
ESG Demand	-0.017***	-0.006***	-0.102***	-0.049***
	(-9.17)	(-4.76)	(-14.35)	(-9.42)
Female	-1.262***		-7.304***	
	(-15.13)		(-25.65)	
Education	0.094***		0.135***	
	(7.29)		(3.55)	
Age	0.012***		-0.104***	
	(3.69)		(-6.70)	
Trading Experience	-0.003***		-0.050***	
	(-4.23)		(-16.91)	
Investment Return	0.146	3.438*	-144.467***	-103.313***
	(0.09)	(1.78)	(-14.07)	(-13.61)
Portfolio Beta	0.935***	0.480***	2.069***	0.588**
	(6.39)	(6.12)	(4.30)	(2.24)
Portolio Beta for Size	0.383***	0.179***	1.056***	0.343***
	(6.21)	(5.68)	(4.37)	(2.85)
Portolio Beta for B-M	-0.462***	-0.217***	-1.143***	-0.316***
	(-7.32)	(-5.81)	(-5.74)	(-2.88)
Constant	12.814***	13.537***	42.372***	27.466***
	(36.78)	(111.67)	(27.49)	(66.97)
Investor FE	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
Observation	4,661,245	4,658,227	4,661,245	4,658,227
R^2	0.042	0.178	0.182	0.430

Table 11: Trading Frequency on ESG and non-ESG Stocks

This table compares the investor's trading frequency on ESG stocks vs. non-ESG stocks in her portfolio. The dependent variable is the log number of trades in columns (1), buy trades in columns (2), and sell trades in columns (3). The sample is conditional on holding the stock at the end of the month or on having traded the stock during the month. Number of trades is the total number of trades (buy or sell) that an investor has conducted on a stock in the month. ESG Stock is a dummy equal to 1 for ESG-stocks and to 0 for non-ESG stocks. Standard errors are two-way clustered at the investor and time level. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	Trades Num	Buy Num	Sell Num
ESG Stock	-0.044***	-0.024***	-0.020***
	(-5.20)	(-5.10)	(-4.92)
Ln(Stock Turnover)	0.126***	0.073***	0.053***
	(23.04)	(25.07)	(19.68)
Return Volatility	6.949***	4.050***	2.900***
	(16.19)	(17.69)	(13.69)
Ln(Market Cap)	0.217***	0.139***	0.078***
	(27.48)	(30.16)	(22.21)
Market-to-Book Ratio	0.000*	0.000*	0.000
	(1.73)	(1.95)	(1.50)
Dividend Yield	0.004*	0.000	0.004***
	(1.69)	(0.00)	(3.33)
Constant	-2.010***	-1.356***	-0.654***
	(-24.04)	(-28.35)	(-17.14)
Stock FE	Yes	Yes	Yes
Investor-by-Month FE	Yes	Yes	Yes
Observation	13,358,092	13,358,092	13,358,092
R^2	0.602	0.550	0.587

Table 12: Disposition Effect on ESG and non-ESG Stocks

This table estimates whether investors' tendency to sell winners and keep losers differs between ESG and non-ESG stocks. In columns (1-4), the dependent variable is a dummy equal to one if the investor sells the stock at time t, and zero if the investor keeps the stock. In column (5), the dependent variable is $-\Delta Holdings_{i,j,t}/Holdings_{i,j,t-1}$, conditional on $Holdings_{i,j,t-1} > 0$. Winner is a dummy equal to 1 if the stock is trading at a larger price than what the investors has paid, and zero otherwise. ESG Stock is a dummy equal to 1 for ESG-stocks and to 0 for non-ESG stocks. Standard errors are clustered at the stock level. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Sell Dummy				$-\frac{\Delta Holdings_{i,j,t}}{Holdings_{i,j,t-1}}$
Winner	0.076***		0.089***	0.074***	0.092***
	(39.65)		(55.51)	(55.55)	(59.60)
ESG Stock		-0.006***	0.004***		
		(-4.89)	(4.51)		
ESG Stock * Winner			-0.021***	-0.015***	-0.021***
			(-8.33)	(-7.72)	(-9.68)
Ln(Stock Turnover)	0.004***	0.010***	0.005***		
	(3.98)	(12.21)	(4.95)		
Return Volatility	0.687***	0.798***	0.657***		
	(7.70)	(9.39)	(7.58)		
Ln(Market Cap)	-0.002***	0.001**	-0.001**		
	(-4.17)	(2.40)	(-2.53)		
Market-to-Book Ratio	-0.000***	0.000	-0.000***		
	(-3.00)	(0.15)	(-3.30)		
Dividend Yield	0.002***	0.004***	0.002***		
	(4.91)	(8.25)	(5.63)		
Constant	0.098***	0.050***	0.086***	0.131***	0.051***
	(12.84)	(6.96)	(12.37)	(326.70)	(115.89)
Investor-by-Month FE	Yes	Yes	Yes	Yes	Yes
Stock-by-Month FE	No	No	No	Yes	Yes
Observation	9,454,072	9,454,072	9,454,072	9,503,091	9,503,091
R^2	0.591	0.585	0.591	0.623	0.473

Table 13: Trend Chasing on ESG and non-ESG Stocks

This table estimates whether investors' tendency to buy stocks after positive returns differs between ESG and non-ESG stocks. The dependent variable is a dummy equal to one if the investor buys the stock, conditional holding the stock in the previous or in the current month, and to zero if she keeps or sells the stock. High Return Past-Month is a dummy equal to 1 if the return of the stock is higher than the median market return in that month. ESG Stock is a dummy equal to 1 for ESG-stocks and to 0 for non-ESG stocks. Standard errors are clustered at the stock level. T-values are reported in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			Buy Dummy			
ESG Stock	-0.004***	-0.002			-0.002**	-0.000
	(-4.04)	(-1.08)			(-2.22)	(-0.20)
High Return Past-Month			0.004***	0.003***	0.006***	0.005***
			(6.31)	(4.58)	(7.66)	(6.13)
ESG Stock * High Return Past-Month					-0.003***	-0.003***
					(-2.98)	(-2.65)
Ln(Stock Turnover)	0.017***	0.019***	0.016***	0.018***	0.017***	0.018***
	(17.55)	(21.31)	(17.29)	(21.13)	(17.49)	(21.14)
Return Volatility	1.406***	0.976***	1.394***	0.953***	1.366***	0.947***
	(20.18)	(14.85)	(19.78)	(14.31)	(19.30)	(14.23)
Ln(Market Cap)	0.008***	0.040***	0.007***	0.040***	0.008***	0.040***
	(13.09)	(24.39)	(12.10)	(24.22)	(12.93)	(24.27)
Market-to-Book Ratio	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(6.50)	(5.93)	(6.94)	(6.25)	(6.60)	(6.17)
Dividend Yield	-0.001	-0.003***	-0.001*	-0.003***	-0.001*	-0.003***
	(-1.52)	(-5.64)	(-1.83)	(-5.67)	(-1.72)	(-5.67)
Constant	-0.063***	-0.382***	-0.056***	-0.379***	-0.063***	-0.380***
	(-6.41)	(-23.60)	(-5.78)	(-23.39)	(-6.43)	(-23.57)
Investor-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes	No	Yes
Observation	10,549,036	10,549,036	10,549,036	10,549,036	10,549,036	10,549,036
R^2	0.440	0.442	0.440	0.442	0.440	0.442

Table 14: Investors' Reaction to Changes in ESG Status

This table estimates the relation between changes ESG status and investors' tendency to sell the stock. In columns (1-2), the dependent variable is a dummy equal to one if the investor sells the stock and to zero if she keeps or buys the stock. In columns (3), the dependent variable is $-\Delta Holdings_{i,j,t}/Holdings_{i,j,t-1}$. ESG Stock is a dummy equal to 1 for ESG-stocks and to 0 for non-ESG stocks. We consider an event-window of twelve month before and after the changes in status. Standard errors are clustered at the stock level. T-values are reported in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	Sell Dummy		$-\frac{\Delta Holdings_{i,j,t}}{Holdings_{i,j,t-1}}$
ESG Stock	-0.016***	-0.013***	-0.012***
	(-4.58)	(-4.76)	(-4.04)
Ln(Stock Turnover)		0.047***	0.027***
		(11.32)	(6.32)
Return Volatility		1.140***	0.983***
		(3.97)	(3.19)
Ln(Market Cap)		0.034***	0.002
		(3.55)	(0.20)
Market-to-Book Ratio		-0.000***	-0.000***
		(-3.56)	(-3.38)
Dividend Yield		0.000	0.003*
		(0.09)	(1.88)
Investment Return		0.016***	0.012***
		(3.08)	(3.00)
Constant	0.196***	-0.488***	-0.124
	(108.33)	(-5.42)	(-1.49)
Stock-Event FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Observation	1,391,080	1,391,080	1,391,080
R^2	0.106	0.114	0.047

Online Appendix

A Additional Results

Table A1: Home Bias and ESG Investing

In Panel A, we report the estimates of β as in Tables 7 and 8 once we control for *ESG Stock Proportion*, which is the value proportion of ESG stocks over the total capitalization of listed stocks in the province where the investor lives. Panel B shows the correlation between ESG investment and home bias. In columns (1) to (4), the dependent variable *Home Bias* is the difference between the ratio (in percentage) of the market value of local stocks (i.e. located in the province where the investor lives) over the total portfolio value and the ratio of the market capitalization of local stocks over the total market capitalization. In columns (5) and (6), the dependent variable *Home* is a dummy that is equal to one if the stock is a local stock, and to 0 otherwise. Demographic controls include gender, education, trading experience and age. Portfolio controls include beta relative to the market, size and book-to-market factors. Stock controls include logarithm value of stock turnover ratio, return volatility, logarithm value of market capitalization, the market-to-book ratio, and the dividend yield. In Panel A, the standard errors are two-way clustered at the investor and time levels. In Panel B, the standard errors clustered at the stock level. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for ESG Supply

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	ESG Demand					
Experience Measure:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
β	25.233*	27.951***	5.602***	2.415***	62.556***	41.123**
	(1.82)	(4.21)	(2.71)	(2.89)	(2.87)	(2.24)
ESG Stock Proportion	0.026***	0.025***	0.026***	0.021***	0.029***	0.025***
	(3.89)	(3.79)	(3.86)	(3.10)	(4.33)	(3.79)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,687,208	4,687,829	4,383,081	4,404,590	4,600,518	4,664,222
R^2	0.459	0.459	0.481	0.464	0.462	0.460

Panel B: Home Bias and Its Correlation with ESG Investing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Home Bias				Home	
ESG Demand			-0.0023	-0.0015		
			(-1.33)	(-1.01)		
ESG Stock					0.0002	-0.0002
					(0.05)	(-0.06)
Constant	4.6007***	3.5046***	3.4003***	4.6824***	0.0927***	0.0943***
	(42.78)	(5.84)	(5.76)	(48.81)	(4.64)	(4.17)
Demographic Controls	No	Yes	Yes	No	No	No
Portfolio Controls	No	Yes	Yes	Yes	No	No
Stock Controls	No	No	No	No	Yes	Yes
Investor FE	No	No	No	Yes	No	No
Investor-by-Month FE	No	No	No	No	No	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	Yes	Yes
Observation	4,478,982	4,388,418	4,388,418	4,385,904	11,640,914	9,463,305
R^2	-0.000	0.002	0.003	0.527	0.079	0.399

Table A2: Huai River Policy and Rice Planting : Robustness Checks

This table presents robustness checks for the results on the centralized coal heating and rice planting on ESG investing. *ESG Stock Proportion* is the value proportion of ESG stocks over the total capitalization of listed stocks in the province where the investor lives. *Lag ESG Stock Return* is the value weighted return of ESG stocks in the previous month. *Lag Non-ESG Stock Return* is the value weighted return of Non-ESG stocks in the previous month. Demographic controls include gender, education, trading experience and age. Portfolio controls include beta relative to the market, size and book-to-market factors. The standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	ESG Demand							
Main Independent Variable:	Coal Heating				Rice Ratio			
	5 degree to Huai River		3 degree to Huai River		Yangtze River		Yangtze River No Heating	
Heating	1.804***	1.753***	2.520***	2.538***				
	(6.34)	(6.27)	(6.64)	(7.09)				
Rice Ratio					2.343*	2.598**	3.143*	3.137*
					(1.89)	(2.11)	(1.81)	(1.90)
ESG Stock Proportion	0.008		0.000		0.061***		0.051**	
	(0.88)		(0.01)		(3.27)		(2.20)	
Lag ESG Stock Return		-5.713		-5.448		-4.483		-7.039
		(-0.82)		(-0.85)		(-0.59)		(-0.86)
Lag Non-ESG Stock Return		9.457		9.036		9.219		11.090
		(1.61)		(1.60)		(1.46)		(1.61)
Constant	50.896***	51.312***	50.651***	50.493***	49.457***	52.537***	49.115***	52.166***
	(33.14)	(35.52)	(27.84)	(31.25)	(20.78)	(24.33)	(16.76)	(19.78)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Observation	2,752,510	2,752,510	1,747,874	1,747,874	1,004,166	1,004,166	623,603	623,603
R^2	0.039	0.034	0.039	0.034	0.045	0.040	0.041	0.035

Table A3: How $\hat{k}(\lambda)$ and $\hat{\delta}(\lambda,\beta)$ vary with trading experience

This table shows how $\hat{k}(\lambda)$ and $\hat{\delta}(\lambda,\beta)$ vary with trading experience T. $\hat{k}(\lambda)$ is the number of most recent periods, over the total number of trading periods, that account for 50% of the accumulated experience for an investor trading experience equal to T. $\hat{\delta}(\lambda,\beta)$ is the cumulative impact of a one standard deviation increase in the experience variable occurring at the beginning of the trading period for an investor trading experience equal to T.

Experience Measure	λ	β	$\hat{k}(\lambda)$			$\hat{\delta}(\lambda,\beta)$		
			$T=10$	$T=13$	$T=20$	$T=10$	$T=13$	$T=20$
GDP Growth, No Investor FE	0.146	76.308	46.181	46.016	45.838	6.089	6.530	7.232
GDP Growth, Investor FE	1.171	24.388	28.729	28.448	28.050	1.227	1.246	1.269
Market Return, No Investor FE	1.572	22.102	23.727	23.701	23.676	2.494	2.494	2.495
Market Return, Investor FE	0.193	28.084	44.187	44.160	44.132	8.431	8.713	9.059
Individual Return, No Investor FE	0.917	47.590	30.463	30.430	30.399	13.037	13.076	13.113
Individual Return, Investor FE	1.343	25.715	25.687	25.661	5.593	1.232	1.233	1.233
AQI, No Investor FE	6.941	1.174	8.392	8.388	8.377	0.319	0.319	0.319
AQI, Investor FE	1.867	2.567	20.111	20.921	21.319	0.976	0.976	0.976
Natural Disaster, No Investor FE	-0.268	20.617	57.967	58.384	59.004	2.294	2.553	3.019
Natural Disaster, Investor FE	-0.622	58.476	69.645	70.809	72.696	7.891	9.097	11.459
Corporate Scandal, No Investor FE	3.012	116.832	15.936	15.918	15.902	1.857	1.857	1.857
Corporate Scandal, Investor FE	3.246	43.531	15.127	15.110	15.094	0.676	0.676	0.676

Table A4: Determinants of Investment in SSE 380 Stocks

This table reports the results of the placebo tests for the effects of life-time experiences where the ESG indices are replaced by the SSE 380 Index. The dependent variable is the proportion of stocks that are included in the SSE 380 Index in investors' portfolios. The other variables are constructed as in the main text. Portfolio controls include beta relative to the market, size and book-to-market factors. All the standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	SSE380Index Prop					
Experience Measure:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
λ	3.530***	1.242***	3.005***	-0.177	0.184	1.110***
	(5.91)	(6.37)	(9.2)	(-0.2)	(0.32)	(3.21)
β	-1.247	-9.027*	-4.635***	-0.586	19.567	62.636***
	(-0.34)	(-1.98)	(-3.45)	(-0.51)	(1.29)	(3.63)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,687,208	4,687,829	4,383,081	4,404,590	4,600,518	4,664,222
R^2	0.355	0.355	0.374	0.361	0.357	0.356

Table A5: Investing Behaviors in SSE 380 Stocks

This table reports the results of the placebo tests on investing behaviors where the ESG indices are replaced by the SSE 380 Index. The dependent variable is the *Churn Ratio* in column (1), the *Number of Trades* in column (2), the *Sell Dummy* in columns (3) and (5), and the *Buy Dummy* in column (4). *SSE380Index* is a dummy that is equal to 1 if the stock belongs to the SSE 380 Index, and 0 otherwise. Other variables are the same as in previous tables. The sample construction for columns (2) to (5) is the same as column (1) of Table 9, column (4) of Table 10, column (6) of Table 11, and column (2) of Table 12. Portfolio controls include beta relative to the market, size and book-to-market factors. Stock controls include logarithm value of stock turnover ratio, return volatility, logarithm value of market capitalization, the market-to-book ratio, and the dividend yield. The standard errors are clustered at the stock level. T-values are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ChurnRatio	N.O. Trades	Sell Dummy	Buy Dummy	Sell Dummy
SSE380Index Prop	0.019***				
	(5.20)				
SSE380Index		-0.023***		0.001	-0.004
		(-3.92)		(0.74)	(-0.72)
Winner			0.061***		
			(43.56)		
SSE380Index * Winner			0.015***		
			(7.56)		
High Return Past-Month				0.003***	
				(3.47)	
SSE380Index * High Return Past-Month				0.001	
				(0.52)	
Constant	25.285***	-2.005***	0.131***	-0.378***	-0.199***
	(74.02)	(-23.96)	(319.04)	(-23.38)	(-3.15)
Portfolio Controls	Yes	No	No	No	No
Stock Controls	No	Yes	No	Yes	Yes
Investor FE	Yes	No	No	No	No
Investor-by-Month FE	No	Yes	Yes	Yes	No
Stock FE	No	Yes	No	Yes	No
Stock-by-Month FE	No	No	Yes	No	No
Stock-Event FE	No	No	No	No	Yes
Year-Month FE	Yes	No	No	No	Yes
Observation	4,386,428	13,358,092	9,503,091	10,549,036	2,527,364
R^2	0.427	0.602	0.623	0.442	0.119

Table A6: ESG demand and inclusion in several ESG Indices

This table reports the results of estimation for the effects of life-time experience on investors' ESG demand, defined by the intensity of ESG index inclusion. The dependent variable, *Value Weighted NumIndex*, is the value weighted number of ESG indices in which a stock is included. It ranges from 0 to 18, with an average of 2.04 and standard deviation of 2.30. The other variables are constructed as in the main text. Portfolio controls include beta relative to the market, size and book-to-market factors. All the standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Value Weighted NumIndex					
Experience Measure:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
λ	0.631***	0.574***	0.299***	6.042***	-0.095	7.899***
	(7.85)	(4.73)	(4.02)	(6.94)	(-0.24)	(7.65)
β	0.895**	1.100***	0.738***	0.071**	3.767***	1.161*
	(2.43)	(3.41)	(6.86)	(2.24)	(3.88)	(1.78)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,687,208	4,687,829	4,383,081	4,404,590	4,600,518	4,664,222
R^2	0.534	0.534	0.554	0.544	0.536	0.535

Table A7: Investment behaviors and inclusion in several ESG Indices

This table estimates the investment behaviors on ESG stocks, defined by the intensity of ESG index inclusion. The dependent variable is the *Churn Ratio* in column (1), the *Number of Trades* in column (2), the *Sell Dummy* in columns (3) and (5), and the *Buy Dummy* in column (4). *NumIndex* is the number of ESG Indeces that the stock belongs to in a given month, which ranges from 0 to 18. *Value Weighted NumIndex* is the value weighted number of ESG Indeces that the stock belongs to in a given month. Other variables are the same as in previous tables. The sample construction for columns (2) to (5) is the same as column (1) of Table 9, column (4) of Table 10, column (6) of Table 11, and column (2) of Table 12. Portfolio controls include beta relative to the market, size and book-to-market factors. Stock controls include logarithm value of stock turnover ratio, return volatility, logarithm value of market capitalization, the market-to-book ratio, and the dividend yield. The standard errors are clustered at the stock level. T-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ChurnRatio	N.O. Trades	Sell Dummy	Buy Dummy	Sell Dummy
Value Weighted NumIndex	-0.849***				
	(-7.51)				
NumIndex		-0.240***		-0.019*	-0.028
		(-4.68)		(-1.66)	(-1.41)
Winner			0.073***		
			(60.22)		
NumIndex * Winner			-0.088***		
			(-10.15)		
High Return Past-Month				0.004***	
				(5.69)	
NumIndex * High Return Past-Month				-0.017**	
				(-2.35)	
Constant	26.301***	-2.039***	0.131***	-0.385***	-0.435***
	(73.33)	(-23.95)	(349.74)	(-23.70)	(-6.20)
Portfolio Controls	Yes	No	No	No	No
Stock Controls	No	Yes	No	Yes	Yes
Investor FE	Yes	No	No	No	No
Investor-by-Month FE	No	Yes	Yes	Yes	No
Stock FE	No	Yes	No	Yes	No
Stock-by-Month FE	No	No	Yes	No	No
Stock-Event FE	No	No	No	No	Yes
Year-Month FE	Yes	No	No	No	Yes
Observation	4,658,227	13,358,092	9,503,091	10,549,036	4,641,659
R^2	0.430	0.602	0.623	0.442	0.118

Table A8: ESG demand and ESG Rating

This table reports the results of estimation for the effects of life-time experience on investors' ESG demand, defined by ESG rating. The dependent variable, *High ESG Rated Prop* is the proportion of stocks that are highly rated in ESG by Sino Securities (i.e., their rating is AA or above). The other variables are constructed as in the main text. Portfolio controls include beta relative to the market, size and book-to-market factors. All the standard errors are two-way clustered at the investor and time levels. T-values are in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	High ESG Rated Prop					
Experience Measure:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
λ	0.917***	0.107	0.249***	1.054***	-0.455*	3.162***
	(4.09)	(1.27)	(4.13)	(11.36)	(-1.89)	(17.84)
β	89.079***	28.449***	11.505***	2.658***	-2.225	35.788***
	(2.84)	(4.24)	(5.16)	(2.81)	(-0.08)	(2.71)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	4,194,861	4,195,392	3,991,241	3,995,132	4,125,067	4,177,078
R^2	0.412	0.412	0.429	0.418	0.415	0.413

Table A9: Investment behaviors and ESG Ratings

This table estimates the investment behaviors on ESG stocks, defined by ESG ratings. The dependent variable is the *Churn Ratio* in column (1), the *Number of Trades* in column (2), the *Sell Dummy* in columns (3) and (5), and the *Buy Dummy* in column (4). *High ESG Rated* is a dummy that is equal to 1 if the stock is highly rated in ESG by Sino-Securities (i.e., its rating is AA or above), and 0 otherwise. *High ESG Rated Prop* is the proportion of the stocks that are highly rated in ESG in investors' portfolios. Other variables are the same as in previous tables. The sample construction for columns (2) to (4) is the same as column (1) of Table 9, column (4) of Table 10, and column (6) of Table 11. Portfolio controls include beta relative to the market, size and book-to-market factors. Stock controls include logarithm value of stock turnover ratio, return volatility, logarithm value of market capitalization, the market-to-book ratio, and the dividend yield. The standard errors are clustered at the stock level. T-values are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable	ChurnRatio	N.O. Trades	Sell Dummy	Buy Dummy
High ESG Rated Prop	-0.026***			
	(-5.61)			
High ESG Rated		0.002		0.005***
		(0.23)		(3.02)
Winner			0.068***	
			(51.20)	
High ESG Rated * Winner			-0.011***	
			(-5.88)	
High Return Past-Month				0.004***
				(5.00)
High ESG Rated * High Return Past-Month				-0.002*
				(-1.76)
Constant	26.657***	-2.101***	0.135***	-0.376***
	(71.42)	(-23.37)	(346.23)	(-23.98)
Portfolio Controls	Yes	No	No	No
Stock Controls	No	Yes	No	Yes
Investor FE	Yes	No	No	No
Investor-by-Month FE	No	Yes	Yes	Yes
Stock FE	No	No	No	No
Stock-by-Month FE	No	No	Yes	No
Stock-Event FE	No	No	No	No
Year-Month FE	Yes	No	No	No
Observation	4,188,080	11,652,520	8,498,682	9,433,860
R^2	0.440	0.594	0.625	0.445

B Details of the estimation procedure

We present the details for the procedure of the non-linear estimation, which is adapted from Malmendier and Nagel (2011) (hereafter MN) to include investor fixed effects. The estimation is conducted in python. The packages needed in the estimation are: *pandas*, *numpy*, *scipy*, *linearmodels*, *statsmodels*, and *random*. If multiprocessing is used in the computation process, the following packages are also needed: *itertools*, *functools*, and *multiprocessing*.

The first step is to do a procedure called "grid-estimations", which estimates model (4) for given a set of tightly spaced grid values of λ. We obtain the λ with the smallest sum of squared residuals, which we call $grid\_optimal\_\lambda$. The second step is the least squared estimation to jointly estimate λ and β, using the $grid\_optimal\_\lambda$ as the initial guess for λ. In this step, we revise the MN procedure so as to have two-way fixed effects at the investor and month levels. In the third step, we bootstrap for 100 times to estimate the standard deviation of λ, where in each time, we reshuffle the residuals and re-estimate λ.

Step 1: Grid-Estimations

A function that calculates the experience measure a ($experience(.)$) and a function for the grid-estimations ($grid\_reg(.)$) are defined first and then they are recalled for the estimations.

Function to Calculate Experience Measures

$experience(\lambda, exp\_data, exp\_measure)$:
  In exp_data: $month] = month + 1$ # experience till one month before now
  In exp_data: keep if $month] > month\_start$
  # experience starts from the beginning month of trading
  $w_{each} = [(month - month\_start)/12]^{\lambda}$
  $w_{cum} = Cumulative\ Sum\ (by\ investor)\ of\ w_{each}$
  $w = w_{each}/w_{cum}$
  $wa = w * exp\_measure$
  $a = Cumulative\ Sum\ (by\ investor)\ of\ wa$
  keep variable $investor, month, a$
  return dataframe$[investor, month, a]$

Note: *experience* is the function for experience measures that are at the monthly frequency. *exp_data* is the data set that includes the investors' experience variables, and the start time of their account. *exp_measure* is the experience variable that is used to construct the experience measures. *month* is the month encoded to integers with 1960m1 to be 0. *month_start* is the first month of the investors' account (encoded as integer). The calculation for experience measures for variables at the annual frequency (GDP growth rates and natural disasters) can be done by replacing the time measure from month to year.

Function to do Grid Estimation

$grid\_reg(\lambda, exp\_data, exp\_measure, dependent\_variable, holding, control\_list\_1, control\_list\_2)$:
    $experience = experience(\lambda, exp\_data, exp\_measure)$ # experience function is recalled
    data = merge *experience* and *holding*, by investor and month
    $time\_fe\_reg$ = PanelOLS(data[*dependent_variable*], data[a + control_list_1], entity_effects=False, time_effects=True, drop_absorbed=True).fit(cov_type='clustered', cluster_time=True)
    $twoway\_fe\_reg$ = PanelOLS(data[*dependent_variable*], data[a + control_list_2], entity_effects=True, time_effects=True, drop_absorbed=True).fit(cov_type='clustered', cluster_time=True)
    return $[\lambda, time\_fe\_reg.params[0], time\_fe\_reg.resid\_ss,$
        $twoway\_fe\_reg.params[0], twoway\_fe\_reg.resid\_ss]$

Note: *holding* is a data set that includes ESG demand measures, demographic characteristics, and portfolio controls. *experience* is the function for experience measures that are at the monthly frequency. *PanelOLS* is the module imported from *linearmodels.panel*.

Procedure for Grid Estimation

$control\_list\_1 = [female, education, trading\_experience, age, beta, beta\_size, beta\_value]$
$control\_list\_2 = [beta, beta\_size, beta\_value]$
$dependent\_variable$ = dependent_variable
$exp\_variable$ = experience_variable
λ_list = list(np.arange(-5, 5, 0.1))
    # In some cases, when boundary is obtained, the range is enlarged to be from -10 to 10
with multiprocessing.Pool(processes=4) as pool:
        $grid\_estimation$ = pool.map(partial($grid\_reg$, $exp\_data, exp\_measure$, $dependent\_variable, holding, control\_list\_1, control\_list\_2$), λ_list)
$grid\_optimal\_\lambda\_time\_fe = \lambda$ when third column of *grid_estimation* is smallest
2 as column number in python
$grid\_optimal\_\lambda\_twoway\_fe = \lambda$ when fifth column of *grid_estimation* is smallest
4 as column number in python

Note: multiprocessing procedure is imported for multiprocessing computation; otherwise, a loop can be used for the estimation for different values of λ. In several cases, the boundary -5 or 4.9 is reached and the range is enlarged.

Step 2: Procedure for Least Square Regression

To include two dimensional fixed effects, two functions are defined to demean the variables and two objective functions are defined for optimization. Then the optimization is done by the *least_squares* module from the package *scipy*.

Demeaning functions

$demean\_time\_fe(data, dependent\_variable, independent\_variable)$:
    $mean\_dv$ = mean *dependent_variable* by month
    $mean\_indv$ = mean *independent_variable* by month
    dependent_variable = *dependent_variable* - *mean_dv*
    independent_variable = *independent_variable* - *mean_indv*
    return *data*[*dependent_variable*], *data*[*independent_variable*]

$demean\_twoway\_fe(data, dependent\_variable, independent\_variable, niter)$:
while $i < niter$:
$mean\_dv$ = mean $dependent\_variable$
$mean\_dv1$ = mean $dependent\_variable$ by month
$mean\_dv2$ = mean $dependent\_variable$ by investor
$mean\_indv$ = mean $independent\_variable$
$mean\_indv1$ = mean $independent\_variable$ by month
$mean\_indv2$ = mean $independent\_variable$ by investor
$dependent\_variable = dependent\_variable - mean\_dv1 - mean\_dv2 + mean\_dv$
$independent\_variable = independent\_variable - mean\_indv1 - mean\_indv2 + mean\_indv$
$i+ = 1$
return $data[dependent\_variable]$, $data[independent\_variable]$

Note: *niter* is the number of times of demeaning in the estimation with two dimensional fixed effects. Eight is used in our analysis, because after seven iterations, the results have already converged.

Objective functions

$res\_time\_fe(x, holding, exp\_data, exp\_measure, dependent\_variable, control\_list)$:
$experience = experience(x[0], exp\_data, exp\_measure)$
$data$ = merge $experience$ and $holding$, by investor and month
$independent\_variable = data[a + control\_list]$
$dependent\_variable, independent\_variable =$
$demean\_time\_fe(data, dependent\_variable, independent\_variable)$
return $independent\_variable$.dot(x[1:]) - $dependent\_variable$

$res\_twoway\_fe(x, holding, exp\_data, exp\_measure, dependent\_variable, control\_list, niter)$:
$experience = experience(x[0], exp\_data, exp\_measure)$
$data$ = merge $experience$ and $holding$, by investor and month
$independent\_variable = data[a + control\_list]$
$dependent\_variable, independent\_variable =$
$demean\_twoway\_fe(data, dependent\_variable, independent\_variable)$
return $independent\_variable$.dot(x[1:]) - $dependent\_variable$

Note: *niter* is the number of times of demeaning in the estimation with two dimensional fixed effects. Eight is used in our analysis, because after seven iterations, the results have converged. *.dot* is the dot product operation between matrices that are before and after it.

Procedure for Least Square Regression with Month Fixed Effects

$experience = experience(grid\_optimal\_\lambda\_time\_fe, exp\_data, exp\_measure)$
$data$ = merge $experience$ and $holding$, by investor and month

reg_time_fe = PanelOLS(data[$dependent\_variable$], data[a + $control\_list\_1$], entity_effects=False, time_effects=True, drop_absorbed=True).fit(cov_type='clustered', cluster_time=True)
$parameters\_0$ = estimated βs
$residual0\_time\_fe$ = residuals
x = [$grid\_optimal\_\lambda\_time\_fe$,] + list($parameters\_0$)
"+" here means to append two lists
$bounds$ = ([$grid\_optimal\_\lambda\_time\_fe$ - 0.5,] + list(-np.ones(len($parameters\_0$))*np.inf),

$[grid\_optimal\_\lambda\_time\_fe$ + 0.5,] + list(np.ones(len($parameters\_0$))*np.inf))
The boundary for λ is limited and that for coefficients are not
Coefficients for Fixed Effects are included
$estimation\_time\_fe = least\_squares(res\_time\_fe, x, bounds = bounds,$
$args = (holding, exp\_data, exp\_measure, dependent\_variable, control\_list))$

Note: *least_squares* is a module for non-linear optimization with the method of minimizing the sum of squared residuals imported from the package *scipy.optimize*. $residual0\_time\_fe$ is the residual in the non-linear least square estimation, which will be used in bootstrapping.

Procedure for Least Square Regression with Investor and Month Fixed Effects

$experience = experience(grid\_optimal\_\lambda\_twoway\_fe, exp\_data, exp\_measure)$
$data$ = merge *experience* and *holding*, by investor and month
reg_twoway_fe = PanelOLS(data[$dependent\_variable$], data[a + $control\_list\_2$], entity_effects=True, time_effects=True, drop_absorbed=True).fit(cov_type='clustered', cluster_time=True)
$parameters\_0$ = estimated βs
$residual0\_twoway\_fe$ = residuals
$x = [grid\_optimal\_\lambda\_time\_fe,$] + list($parameters\_0$)
"+" here means to append two lists
$bounds$ = ([$grid\_optimal\_\lambda\_twoway\_fe$ - 0.5,] + list(-np.ones(len($parameters\_0$))*np.inf),
[$grid\_optimal\_\lambda\_twoway\_fe$ + 0.5,] + list(np.ones(len($parameters\_0$))*np.inf))
The boundary for λ is limited and that for coefficients are not
Coefficients for Fixed Effects are included
$estimation\_twoway\_fe = least\_squares(res\_twoway\_fe, x, bounds = bounds,$
$args = (holding, exp\_data, exp\_measure, dependent\_variable, control\_list, niter))$

Note: *least_squares* is a module for non-linear optimization with the method of minimizing the sum of squared residuals imported from the package *scipy.optimize*. $residual0\_time\_fe$ is the residual in the non-linear least square estimation, which will be used in bootstrapping.

Step 3: Bootstrapping

As the bootstrapping procedure is very time-consuming, parallel computation is highly recommended. We define two functions and then recall the functions in parallel computations. We enlarge the boundaries in minimizing the least square in bootstrapping to [-1 + least-square-estimated λ, 1+ least-square-estimated λ], because the errors are reshuffled and thus the estimated λ can be different from the least-square-estimated λ.

Bootstrapping functions

$boot\_time\_fe(btimes, x, bonds, holding, exp\_data, y$
$exp\_measure, dependent\_variable, residual0\_time\_fe, control\_list)$:
random.shuffle($residual0\_time\_fe$)
$holding[dv] = y + residual0\_time\_fe$
$estimation\_time\_boot = least\_squares(res\_time\_fe, x, bounds = bounds,$
$args = (holding, exp\_data, exp\_measure, dependent\_variable, control\_list))$

$boot\_twoway\_fe(btimes, x, bonds, holding, exp\_data, y,$
$exp\_measure, dependent\_variable, residual0\_twoway\_fe, control\_list, niter)$:

random.shuffle($residual0\_twoway\_fe$)
$holding[dv] = y + residual0\_twoway\_fe$
$estimation\_twoway\_boot = least\_squares(res\_twoway\_fe, x, bounds = bounds,$
$args = (holding, exp\_data, exp\_measure, dependent\_variable, control\_list, niter))$

Procedure for Bootstrapping

$y = holding[dependent\_variable]$
$btimes = list(np.arange(0, 100))$
with multiprocessing.Pool(processes=4) as pool:
$boot\_time\_fe\_out$ = pool.map(partial($boot\_time\_fe(x, bonds, holding, exp\_data, y$
$exp\_measure, dependent\_variable, residual0\_time\_fe, control\_list\_1)$, $btimes$)

with multiprocessing.Pool(processes=4) as pool:
$boot\_twoway\_fe\_out$ = pool.map(partial($boot\_twoway\_fe(x, bonds, holding, exp\_data, y,$
$exp\_measure, dependent\_variable, residual0\_time\_fe, control\_list\_2, niter)$, $btimes$)

Note: The number of *processes* can be chosen according to the computation power of the cpu and the RAM size.