

# Are We Becoming Greener?

## Life-time Experiences and Responsible Investment\*

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October 20, 2022

### Abstract

How important are pro-social concerns for individual investment decisions? What shapes pro-social attitudes across investors and over time? We investigate how life-time experiences affect the demand for responsible assets by exploiting account-level data from the Shanghai Stock Exchange. We show that some experiences, notably growing up in periods with good market returns and being exposed to a natural disaster, have large and persistent effects on investors' demand. We highlight how economic and non-economic experiences affect investors' intrinsic preferences for responsible assets, and how those preferences can change during investors' trading life.

**Keywords:** Pro-social attitudes, responsible investment, experience effects.

**JEL codes:** G11; G41; G51.

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\*We thank Matteo Bobba, Hector Calvo-Pardo, Lina Xie, David Zerbib, Yifei Zhang and seminar participants at CREST, EDHEC, NEOMA, Paris Risk Forum, TSE, and Wuhan University, for insightful comments. Milo Bianchi acknowledges funding from the 111 Project (B18033), FDIR Research Initiative, and ANR (ANR-17-EURE-0010 grant). We have no material interest that relates to the research described in the paper.

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# 1 Introduction

How important are pro-social concerns for individual investment decisions? What shapes pro-social attitudes across investors and over time? We investigate these questions in the context of investors' demand for ESG assets.<sup>1</sup> While responsible investment continues to grow, a fundamental question is whether the trends observed in many countries can be simply explained by standard economic factors, say how investors evaluate ESG assets in terms of risk and returns, or whether they are also driven by pro-social concerns, whereby some investors attach an intrinsic value to ESG investment.

In several recent asset pricing models, investors are assumed to account for both monetary and non-monetary dimensions in their portfolios, where the non-monetary component depends directly on their holdings of ESG assets.<sup>2</sup> Under this perspective, how important is the weight that investors attach to this non-monetary component? Which factors can induce substantial variations in pro-social attitudes across investors? How do these attitudes evolve over time? These aspects are key to understanding what drives the evolution of ESG investment trends, which display significant variations both across investors and over time. More broadly, these questions allow to shed light on what determines investors' pro-social preferences.

We explore the role that life-time experiences may have in shaping investors' preferences and ESG investment. Several experimental studies in economics and in psychology, reviewed in more details below, document how life-time experiences affect on pro-social preferences and behaviors. At the same time, a growing literature in finance shows how economic experiences, such as growing up during periods of recession or high inflation, affects financial decisions later in life (Malmendier (2021)). Building on this logic, we consider the effects of a broad set of economic and non-economic experiences. For example, does growing up in good times 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?

We focus our analysis on 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.<sup>3</sup> The extent to which Chinese firms and investors are

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<sup>1</sup>ESG assets refer to assets with explicit considerations for Environmental, Social, and Governance dimensions. We use the terms ESG, responsible or sustainable investment interchangeably.

<sup>2</sup>See e.g. Pástor et al. (2020), Baker et al. (2020), Zerbib (2020), Goldstein et al. (2021), Pedersen et al. (2021), Avramov, Cheng, Lioui and Tarelli (2021), Avramov, Lioui, Liu and Tarelli (2021).

<sup>3</sup>A recent survey by SynTao Green Finance (2019) 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

truly sensitive to sustainable investment is likely to have a first order impact at a global scale. The effects we highlight are, in our view, even more remarkable in a setting in which individual investors represent the dominant share of stock market participants and at the same time the central government has such strong influence on economic activities (Jiang and Kim (2020)).

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. It allows to 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. Our results support the view that investors' demand is affected by their intrinsic preferences for ESG stocks, not just by their expectations about ESG stock returns. We uncover important variations not across and within investors, thereby speaking to the dynamic nature of investors' attitudes and to the role that these experiences have in shaping investors' pro-social preferences over time.

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 analysis of the text used 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.<sup>4</sup>

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. Previous studies have shown that the policy leads to a significant increase in pollution in cities just north relative to those just south of the river.<sup>5</sup> Using the same regression discontinuity design as in those studies, we show that investors living just north of the river display a significantly larger demand for ESG stocks, indicating 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 et al. (2014) show that individuals who grow up in their financial performance.

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<sup>4</sup>We consider various alternative measures, and show the robustness of our findings, as we proceed with the analysis.

<sup>5</sup>See Chen et al. (2013), Ebenstein et al. (2017), and Li et al. (2019).

rice-growing areas have significantly more pro-social attitudes (measured with a series of psychological tests) 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 restricting their analysis to individuals living around the Yangtze River, which separates the wheat-growing north from the rice-growing south. Adopting a similar design, we show that investors living in rice-growing cities have significantly larger exposure to ESG stocks than those in wheat-growing cities, supporting the view that pro-social attitudes can be an important determinant of ESG demand.

The core of our analysis generalizes these arguments along several dimensions. First, rather than restricting to investors who live close to the Huai and the Yangtze rivers, we now consider the entire population of investors. Second, we explore the effects of a broader set of economic and non-economic experiences. Third, while the previous results may be confounded by local effects, we now consider specifications with *individual* fixed effects. This allows us to exploit much tighter sources of variation and at the same time to analyze how the same investor may change her behaviors over time in response to life experiences. As stressed, these dynamics are key for understanding the observed trends in ESG investing.

We build on the seminal method developed by Malmendier and Nagel (2011) to estimate how life-time experiences affect financial decisions. The method allows to jointly estimate two key parameters. The first, denoted by  $\lambda$ , 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  $\lambda$  is positive (negative), experiences in the recent past would matter more (less) than those in the more distant past. These patterns underlie the dynamics of investors' attitudes. A large and negative  $\lambda$  would imply that only early experiences matter, and recent shocks would not contribute much to changes in investors' attitudes towards ESG stocks. Conversely, a large and positive  $\lambda$  would imply that recent shocks can have a significant impact on investors' attitudes, implying possibly considerable variations in ESG demand over time.

The second key parameter is  $\beta$ , 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 of the variation in ESG demand can be attributed to accumulated life experiences.

We adapt Malmendier and Nagel (2011)'s approach to account for the panel structure of our data, which allows to provide estimates both across and within investors. We observe significant variations in ESG demand and, at first glance, both within- and between-investors

variations appear equally important.<sup>6</sup> A key question is how much life-time experiences can account for such heterogeneity. We start with economic experiences (GDP growth, stock market returns, and own portfolio returns) so as to investigate whether experiencing favorable economic conditions increases the weight investors attach to ESG criteria. We then turn to non-economic experiences that are directly related to the ESG dimensions: pollution, natural disasters, and corporate scandals in the city or province where the investor lives. We focus on shocks occurred after the investor has started trading.

Our main findings can be summarized as follows. First, with the exception of natural disasters, the estimated  $\lambda$  are positive; that is, recent experiences tend to matter more.<sup>7</sup> This suggests that, even for the same investor, the propensity to invest in ESG stocks can evolve considerably over her trading life in response to accumulated experiences. At the same time, these effects are persistent, particularly so for economic experience, whose estimated  $\lambda$  is closer to zero

A second key finding is that living through favorable economic conditions, in particular in terms of stock market returns, positively affects ESG investing. This suggests that pro-social attitudes may increase with economic prosperity. Some non-economic experiences are also important to explain the propensity to invest in ESG stocks, and in particular how ESG demand of a given investor evolves over time.

According to our estimates, the largest experience effects are driven by investors' own portfolio returns in specifications without investor fixed effects and by natural disasters once we add fixed effects. The magnitudes are similar: a one standard deviation increase in experienced portfolio returns or natural disasters is associated to an increase of about 13.7% in ESG demand. These effects are large, in relation to the effects of demographic variables. In 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 to understand the magnitude of our experience effects is their persistence over time.

These findings indicate 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.

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<sup>6</sup>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%.

<sup>7</sup>For natural disasters, the estimated  $\lambda$  is negative and close to zero, implying that these shocks tend to be very persistent.

We provide additional evidence to support the view that our effects are driven by investors' preferences along non-monetary dimensions, rather than by their expectations about financial returns. First, motivated by the evidence that experienced returns may directly impact return expectations (Malmendier and Nagel (2011)), we investigate whether experienced ESG and non-ESG stock returns affect investors' demand. We find no significant effect.

Second, we document significantly different trading patterns between ESG and non-ESG stocks, even for the same investor at the same point in time. Investors are less sensitive to financial performance when trading ESG stocks: they exhibit a lower disposition effect and less trend-chasing behaviors. At the same time, they react to non-financial performance: they are more likely to buy (sell) a stock upon inclusion (exclusion) in an ESG index. Overall, they trade their ESG stocks less frequently. These results are consistent with the view that ESG investing is at least partly driven by investors' non-monetary concerns.

We conclude our analysis by discussing alternative mechanisms and check the robustness of our results. First, we show that our results are not driven by supply-side effects, whereby investors 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. Second, we show that our effects are not explained by investors' exposure to government policies intended to promote a sustainable economy. Third, we show that our patterns cannot be described as some general preference for large-cap stocks or for index investing. Finally, we show that our results are robust when employing alternative measures of ESG exposure and exploiting the stock's ESG rating.<sup>8</sup>

Our results provide a clear motivation to the growing literature, mentioned above, featuring investors with heterogeneous and possibly time-varying preferences towards ESG stocks. Along these lines, Pástor et al. (2020) show that unexpected shocks to investors' preferences for green assets can create a wedge between expected and realized returns. Pástor et al. (2021) empirically show that aggregate shocks to climate concerns, as proxied by media coverage, significantly impact the returns of green assets. Avramov, Lioui, Liu and Tarelli (2021) study the equilibrium implications of (exogenous) shocks to ESG preferences. Bansal et al. (2022) show that green assets outperform brown assets in good times, consistent with the view that investors attach a larger weight to ESG investment in good times. Our findings provide systematic evidence that life-time experiences are an important determinant of those shocks, at the investor level.

We contribute 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

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<sup>8</sup>As we discuss below, ESG ratings have become available only very recently in China, which limits their use for our purposes.

to explain investment in socially responsible projects (Barber et al. (2021), Bauer et al. (2021), Bonnefon et al. (2019), Brodback et al. (2019)). Similar evidence also appears in survey data (see e.g. Beal and Goyen (1998), Nilsson (2008) and in studies combining experimental, survey and administrative data (Riedl and Smeets (2017)). We complement these studies by focusing on how attitudes towards responsible investment may change over time in response to life-time experiences. This also contributes to the broader literature on the determinants of pro-social preferences (see e.g. DellaVigna (2009) and List et al. (2009) for reviews).

On the role of personal experiences, Choi et al. (2020) show that retail investors (measured as residuals from institutional investors' holdings) sell carbon-intensive firms when the local temperature is abnormally high. Dyck et al. (2019) show that institutional investors based in countries with stronger environmental norms have a larger impact on firms' environmental performance. Huynh et al. (2021) show that fund managers reduce their holdings of more polluting firms when exposed to larger pollution in their local areas. Jo et al. (2022) show that green funds experience inflows in high pollution days. We build on this logic and provide a comprehensive investigation on how personal experiences affect ESG investing, looking directly at individual investors' holdings and stressing how these experiences may have persistent effects. More broadly, our findings provide novel evidence to the growing literature on experience effects in financial decisions (see e.g. Cronqvist et al. (2015) on their effects on portfolio choices, and Malmendier (2021) for an overview), showing how economic and non-economic experiences may impact investors' preferences and stressing within-investor dynamics.

Finally, our analysis of ESG trading patterns builds on studies focusing on fund managers' behaviors.<sup>9</sup> We instead analyze individual 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.<sup>10</sup>

## 2 Conceptual Framework

As mentioned, a recent asset pricing literature studies markets in which some investors exhibit a preference for ESG assets. In particular, their utility (or a log transformation thereof) can be

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<sup>9</sup>These include Starks et al. (2017), who show that ESG fund managers have longer horizon; Cao et al. (2019), who show that socially responsible institutions are less likely to trade on mispricing signals when these go against their ESG preferences; Gantchev et al. (2019), who show that an increase in firms' ESG risk leads ESG-driven institutional investors to divest and firms to respond.

<sup>10</sup>Individual investors represent about 98% of the investors in the SSE. In terms of market capitalization, their aggregate holdings are about 1.3 times larger than those of institutional investors by the end of 2019.

written as a linear combination between a monetary and a non-monetary component:

$$U(W, X) = f(W) + \mu g(X), \quad (1)$$

where  $W$  is the investor's wealth, which depends on her global portfolio choice,  $X$  denotes her ESG holdings, and  $\mu$  is a measure of the intensity of pro-social concerns. All these terms may potentially vary by investor and over time.<sup>11</sup> Under this perspective, our next analysis investigates how life-time experiences affect the weight  $\mu$ , and how they can generate both across and within investor variations in  $\mu$ .

We first consider economic experiences; that is, experienced GDP growth, stock market returns, and own portfolio returns. A large literature in psychology has investigated how living through unfavorable economic conditions affect pro-social (and other) preferences (see e.g. Wu et al. (2020) for a recent meta-study). In economic models, prosociality tends to be viewed as a normal good, whose demand increases with economic prosperity (Bénabou and Tirole (2006)). This view is supported by some experimental work (such as Andreoni et al. (2021) and Bartling et al. (2021)), but the evidence is still scarce. Our analysis does not focus on investors' wealth *per se* but rather investigates how growing up in a richer environment may affect investors' demand, and how this effect may vary even for a given investor over time.

This approach builds on the literature showing how life-time economic experiences affect financial decisions. Much of this literature builds on Malmendier and Nagel (2011), who show that growing up in a recession has persistent effects on stock market participation and risk taking (Malmendier (2021) provides an extensive review). These experiences have been shown to affect preferences also in other domains. Individual preferences for redistribution, for example, vary with experienced economic downturns and inequality (Giuliano and Spilimbergo (2014), Roth and Wohlfart (2018)). Following this logic, we investigate whether, even at a given point in time, investors who have lived through favorable economic conditions tend to attach a larger weight to ESG investment. This allows us to highlight the extent to which ESG preferences tends to be stronger in more economically developed countries or regions, thereby speaking to the above mentioned literature on whether prosociality can be viewed as a normal good and, more generally, to global and individual variations in preferences (Falk et al. (2018)).

We then consider non-economic experiences, including the exposure to increased pollution,

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<sup>11</sup>For example, in Pedersen et al. (2021),  $f(W)$  is a standard mean-variance function of terminal wealth and  $g(X)$  is the average ESG score in the investor's portfolio. Similarly, Pástor et al. (2020) assume that investor  $i$  has CARA utility  $V_i(W_i, X_i) = -\exp[-A_i W_i - b'_i X_i]$ , where  $A_i$  is the agent's risk aversion,  $W_i$  is terminal wealth, and  $b'_i$  denotes the non-monetary benefits the agent derives from her stock holdings  $X_i$ . A similar formalization is adopted in Zerbib (2020), Goldstein et al. (2021), Avramov, Cheng, Lioui and Tarelli (2021) and Avramov, Lioui, Liu and Tarelli (2021). A more general specification of utility including monetary and non-monetary components is developed in List et al. (2009).



to natural disasters or to corporate scandals. Several studies in psychology show that having experienced a natural disaster affects pro-social preferences and behaviors (Cassar et al. (2017), Oishi et al. (2017), Chantarat et al. (2019), Maki et al. (2019), Vardy and Atkinson (2019)), and that these effects can be long-lasting (Solnit (2010), Becchetti et al. (2017)). Experimental studies have shown that natural disasters and other non-economic experiences also affect preferences towards risk and time (see Ertac (2020) for a review).

The effects of exposure to pollution and to corporate scandals on pro-social attitudes have been less investigated. Pollution has been shown to affect a broad range of behaviors (see Lu (2020) for a review), including pro-environmental behaviors (Ming et al. (2022)) and the trading of local stocks (Wu et al. (2018)). Corporate scandals have been shown to affect investors' trust and consequently their stock market participation (Giannetti and Wang (2016)) and reliance on financial advisors (Gurun et al. (2018)). To our knowledge, none of these papers looks at the effects on investors' pro-social preferences and on the composition of their portfolios.

At a broader level, our analysis aims at highlighting some possibly central determinants of pro-social preferences. A large economics literature, reviewed e.g. in DellaVigna (2009) and List et al. (2009), has provided substantial evidence on how these preferences affect economic decisions. At the same time, however, much less is known on their determinants.<sup>12</sup>

## 3 Data

### 3.1 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 the 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.<sup>13</sup> We are left with 99,592 individual investors, who collectively trade 1,501 stocks. Individual investors submit their orders online or over the phone, without any intermediation from an advisor. 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

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<sup>12</sup>Exceptions include Cappelen et al. (2020) and Kosse et al. (2020), who point at the role of early childhood education.

<sup>13</sup>This is the smallest trading unit in the SSE.

trading identifier allows to obtain several demographic characteristics, including date and place of birth, gender, education, and the date at which the trading account was opened. For our next analysis of experience effects, it is important to identify where the investor currently lives. We obtain this information by observing the trading desk used to send orders, which allows to identify the place of residence in a precise way.<sup>14</sup> There are 8078 different trading desks in our sample, corresponding to about 260 trading desks per province and 11.8 trading desks per city.

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.<sup>15</sup> We provide more details of these measures in the corresponding analysis.

While our data do not allow to observe the investors' overall financial portfolio, they typically cover a substantial fraction of equity investment. According to the 2017 China Household Finance Survey, for investors who hold some stock, direct stock holdings represent on average 38.5% of the total financial wealth.

Our data does not allow to observe indirect stock holdings through funds. However, in our context, most investors in the stock market only hold stocks directly. According to the China Household Finance Survey, in 2017, only 17% of investors who hold stocks also hold some fund and even for these investors direct stock holdings is the most important part of their portfolio.<sup>16</sup>

Finally, we do not observe the trades that our investors may do on the Shenzhen Stock Exchange (SZSE). Stocks in China are listed either in Shanghai or in Shenzhen. As we will see, the majority of ESG stocks are traded in Shanghai.

### 3.2 Stocks and ESG Classification

In order to measure ESG demand at the investor level, we start by defining ESG indices. We exploit the information on the various stock indices from Wind, the leading financial data provider in China. We search the keywords corresponding to “ESG”, “green”, “environment”, “sustainable”, “social”, “responsibility”, or “corporate governance” in the index description, and manually check their consistency. We define an index as ESG if its description includes one such keyword. 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, covering a total of 686 stocks out of 1,501 stocks over our sample.<sup>17</sup>

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<sup>14</sup>Each trading desk can be matched with the corresponding security firm and then with the corresponding address.

<sup>15</sup>We use the city of residence in our main analysis, using the birth city would not affect our results, 81.2% of our investors live in their birth city.

<sup>16</sup>For these investors, the value of direct stock holdings is 1.6-times larger than the value of their holdings in equity, hybrid, bond and money market funds.

<sup>17</sup>No ESG index was discontinued during our sample period. See Table A1 in Online Appendix A for more details.

As mentioned, the development of ESG investing in China has started a few years later than in Western markets. Chinese practitioners often explicitly state that they adopt very similar methods as in foreign markets to construct ESG indices. The boundaries between the various dimensions of ESG are loose. It is common to observe in the index description terms related to social factors even if the index title only refers to environmental issues, for example. Similarly, removal from say a governance index can occur even if the firm misbehaves along environmental dimensions. We refer to Online Appendix A for some examples along those lines and for further details about ESG indexing in China.

In our main analysis, we say that a given stock  $j$  at a given point in time  $t$  is an ESG stock if  $j$  belongs to one ESG index at  $t$ . On average, in our sample, 35% of our stocks are defined as ESG. As mentioned, the majority of these stocks are traded in the SSE.<sup>18</sup> We consider alternative definitions of ESG stock in robustness checks.

Comparing ESG and non-ESG stocks, we notice 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, 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.<sup>19</sup> All these variables are included as controls in our next analysis.

### 3.3 Demographics and ESG investing

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

$$y_{i,t} = \alpha + \beta X_{i,t} + \gamma Z_{i,t-1} + \phi_t + \varepsilon_{i,t}, \quad (2)$$

where  $y_{i,t}$  measures 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, computed at month  $t - 1$ , and  $\phi_t$  are time fixed effects. In our main analysis, we measure investor  $i$ 's ESG demand by the value of ESG stocks over the total value of the portfolio. We consider alternative measures in robustness checks.

In column 1 of Table 2, 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.

<sup>18</sup>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%.

<sup>19</sup>The corresponding estimates are reported in Table A2 in Online Appendix A.

These patterns are consistent with previous studies based on survey evidence. Junkus and Berry (2010) show that the typical socially responsible investor in the U.S. is female, younger, less wealthy, and better educated than the rest of the investors.<sup>20</sup> These patterns also suggest that pro-social attitudes may be relevant, in line with several studies in economics, psychology and neuro-science on gender differences in pro-social behaviors (e.g. Diekmann and Clar (2015), Espinosa and Kovářík (2015), Falk et al. (2018)).

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. 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  $\bar{y}_t$  as the average  $y_{i,t}$  over all investors at time  $t$ , for each investor we define  $\bar{y}_i$  as the average of the difference  $y_{i,t} - \bar{y}_t$ . We repeat the same procedure for all variables in  $X_{i,t}$  and  $Z_{i,t-1}$  and consider the following specification:

$$\bar{y}_i = \alpha + \beta \bar{X}_i + \gamma \bar{Z}_{i,t-1} + \varepsilon_i. \quad (3)$$

Our cross-sectional results are reported in columns 3 and 4 and they confirm the panel estimates in columns 1 and 2. In relative terms, estimated effects are slightly larger.

Overall, these results confirm previous findings on the relation between demographic characteristics and responsible investment, and point at the potential role of pro-social attitudes. Our main interest, in the next analysis, is to investigate how these attitudes can be shaped by investors' life-time experiences.

## 4 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.

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<sup>20</sup>These traits are also important to explain green consumption, see e.g. Diamantopoulos et al. (2003) for a review

## 4.1 Coal Heating and ESG Investing

An interesting source of variation 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 on life expectancy (Ebenstein et al. (2017)), cognitive abilities, and investment biases (Li et al. (2019)).

From our perspective, the Huai River Policy provides a useful discontinuity to explore how the individual exposure to pollution may affect the demand for ESG stocks, since for example it would affect the investor's awareness of environmental issues.

We report our results in Table 3. In column 1, we consider a reduced-form specification relating coal heating at the city level and ESG demand, restricting to cities within 5 degrees of latitude from the Huai river.<sup>21</sup> In columns 2-3, we use the Huai river policy as instrument for pollution at the city level (measured by the Air Quality Index obtained from CSMAR), again restricting to cities just around the river. We consider various controls at the individual and at the city level (the ratio of ESG stocks over the total number of stocks, GDP growth). In columns 4-6, we repeat the same analysis by restricting to cities within 3.6 degrees of latitude from the Huai river, which correspond to the optimal bandwidth in our setting according to Calonico et al. (2014). For this specification, we also perform standard tests to assess the validity of our RDD.<sup>22</sup>

Our estimates show that investors living in more polluted cities, those just north of the Huai river, have a significantly larger ESG demand than investors living in less polluted cities 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. The addition of controls does not significantly change our estimates. According to our estimates in column 6, comparing investors located within 3.6 degrees of latitude around the river, a standard deviation increase in AQI (equal to 0.270) induced by the Huai river policy is associated to an increase in ESG demand by 5.3%.

This analysis suggests that exposure to pollution may be important to understand investors' demand for ESG stocks. The underlying assumption is that the Huai river policy affects this demand only through the induced increase in pollution. Even if our analysis considers only cities

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<sup>21</sup>Li et al. (2019) consider cities within 10, 5 and 3 degrees from the Huai river.

<sup>22</sup>The results of these tests are reported in Online Appendix B. They show very small or non-significant differences in demographic and local characteristics between cities just north and just south of the river, and no apparent discontinuities in the distribution of investors around the river.

close to the river (and in fact our results are stronger as we consider smaller neighborhood around the river), this exclusion restriction is not directly testable. One may wonder how much of these effects can be driven by (unobserved) local characteristics other than pollution. In the next section, we will develop an empirical strategy able to account for fixed effects not only at the local but also at the individual level.

## 4.2 Rice, Wheat, and ESG Investing

We now explore more directly the relation between pro-social attitudes 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 consider 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.<sup>23</sup> They argue that these differences are driven by the fact that, relative to growing 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 up 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. We report our results in Table 4, 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).<sup>24</sup> We show that investors living in a rice-growing city display a 2.6% larger exposure to ESG stocks than those living in a wheat-growing city.

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. Hence, they have coal heating and at the same time they are more likely to grow wheat. In order to isolate the rice effect, we omit those 16 cities in columns 3 and 4, and we show that indeed results are even stronger in this sub-sample. According to these estimates, investors in rice-growing cities display a 3.2% larger ESG demand relative to those

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<sup>23</sup>They address possible reverse causality concerns by using measures of the province's suitability to grow rice as instrument.

<sup>24</sup>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.

in wheat-growing cities.

Together with the evidence reported in Talhelm et al. (2014), this suggests that pro-social preferences, as driven by traditional agricultural practices, are potentially important determinants of ESG investing.<sup>25</sup> As for the Huai river policy, these results cannot directly rule out that local characteristics other than pro-social preferences affect ESG demand. In the next analysis, we investigate more generally whether ESG investing is affected by life-time experiences, both in terms of economic and of non-economic dimensions, while at the same time exploiting even more specific sources of variation.

## 5 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 several 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 further rule out local effects and consider specifications with *individual* fixed effects. This allows to focus on a much tighter source of variation and at the same time to shed light on the dynamics of our effects, considering whether and how investors change their behaviors over time in response to life experiences.

### 5.1 Methodology

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

$$A_{i,t}(\lambda) = \sum_{k=1}^{T_{i,t}-1} w_{i,t} E_{i,t-k}, \quad (4)$$

$$\text{with } w_{i,t}(k, \lambda) = \frac{(T_{i,t} - k)^\lambda}{\sum_{k=1}^{T_{i,t}-1} (T_{i,t} - k)^\lambda},$$

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  $t$ . Even if we observe investors' orders only from 2011, we know the date at which the investor has opened the trading account at the SSE and so we can compute the trading experience  $T_{i,t}$ . We then analyze how accumulated pollution affects the

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<sup>25</sup>While we cannot directly distinguish the role of preferences and beliefs in these regressions, we notice that our results in Tables 3 and 4 are unchanged when controlling for past returns of ESG and non-ESG stocks, which may affect investors' beliefs. We report these results in Online Appendix B.

investor's demand for ESG stocks  $y_{i,t}$  in the following model:

$$y_{i,t} = \alpha_i + \beta A_{i,t}(\lambda) + \gamma X_{i,t} + \eta Z_{i,t-1} + \phi_t + \varepsilon_{i,t}, \quad (5)$$

where  $X_{i,t}$  and  $Z_{i,t-1}$  are as above vectors of investor and portfolio characteristics, while  $\alpha_i$  and  $\phi_t$  are respectively investor and time fixed effects. This method can be applied in the same way to the other dimensions of life-time experience (stock market returns, natural disasters, etc.) and it allows to jointly estimate two key parameters. First, in equation (3), we estimate  $\lambda$ , which measures how the vector of past experiences  $E_{i,t-k}$  contributes to the accumulated experience  $A_{i,t}$  and so how much experiences in the recent past matter relative to those in the distant past. A positive  $\lambda$  would imply that the recent past matters more, and the larger is  $\lambda$ , the more past experiences are discounted; a negative  $\lambda$  instead, would indicate that early experiences matter more. A second key parameter, estimated in equation (4), is  $\beta$ , which measures the impact of the accumulated experience of a given variable,  $A_{i,t}$ , on ESG demand  $y_{i,t}$ .

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. The within-investor standard deviation of ESG demand is about 32% and the between-investor standard deviation is about 28%.<sup>26</sup>

Our model differs from Malmendier and Nagel (2011) in two additional ways. First, 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 also compare the effects of stock market returns to those of individual portfolio returns. Second, for many of these variables the available time series cannot be constructed for the entire life of investors and we concentrate on the time period after the investor's first trading date, rather than the birth date as in Malmendier and Nagel (2011).<sup>27</sup> Accordingly, our investor fixed effects absorb any experience that may have influenced investors before their first trading date.

We estimate the non-linear model in (3)-(4) with a standard iterative procedure. We fix

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<sup>26</sup>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.

<sup>27</sup>When long-enough time series are available, we check the robustness of our results using the birth date as starting point, and find no significant differences in the estimated  $\lambda$ .



the value of  $\lambda$  and estimate equation (4) with OLS, we repeat the same procedure with several possible values of  $\lambda$  from a set with fine enough grids and wide enough coverage. We then select the value of  $\lambda$  that gives the smallest sum of squared residuals and use it as the starting point for a non-linear estimation of equation (4) using the least-squares method. We estimate the standard errors of  $\lambda$  by bootstrapping the residuals with re-sampling for 100 times; we obtain the standard errors of  $\beta$  by estimating equation (4) with OLS given the estimated  $\lambda$ . The only modification here relative to Malmendier and Nagel (2011) is the addition of individual fixed effects on top of time fixed effects. In Online Appendix C, 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  $\lambda$  and  $\beta$  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.<sup>28</sup> When  $\lambda = 0$ ,  $\hat{k}(\lambda) = 50\%$ , implying that all periods receive the same weight. In general,  $\hat{k}(\lambda)$  decreases in  $\lambda$ , 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 life experiences on ESG demand, we suppose that an investor is exposed to a one standard deviation increase of a given 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.<sup>29</sup> This measure depends on  $\lambda$ , which tells how much a shock received in a given period persists in the subsequent periods, and on  $\beta$ , which tells how much the accumulated experience affects ESG demand.

## 5.2 Economic Experiences

We start by investigating whether investors' propensity to invest in ESG stocks is affected by economic experiences, such as GDP growth rates and stock market returns at the macro level, and by own portfolio returns. This allows us to investigate if experiencing favorable economic conditions increases the weight investors attach to ESG criteria.

<sup>28</sup>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 Online Appendix B, however, the ratio varies minimally with  $T_{i,t}$ .

<sup>29</sup>To improve comparability, we consider the same standard deviation in specifications with and without individual fixed effect. 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 Online Appendix B.

## GDP Growth

Our first experience measure is the GDP growth rate in the province where the investor lives.<sup>30</sup> 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 5, we observe an estimated  $\lambda$  around 0.15. This means that recent experiences of GDP growth matters slightly more, but  $\lambda$  remains small; that is, past experiences are persistent. 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 experience, the GDP growth experienced in the past 6 years has the same weight as that in the previous 7 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.

When adding individual fixed effects, in column 2, we obtain an estimated  $\lambda$  around 1.2, which implies that  $\hat{k}(\lambda) = 28\%$  and so the most recent 3.6 years matter as much as the earlier 9.4 years. The estimated increase in ESG demand is equal to 1.2%.<sup>31</sup>

Since for GDP growth the available time series starts in 1952, we can check the robustness of our findings when using the investor's experienced GDP growth since the birth date, rather than the first trading date. We report our results in Table B3 in Online Appendix B, showing a very similar estimate of  $\lambda$  as those in Table 5.<sup>32</sup>

## 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 5, we observe an estimate of  $\lambda$  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  $\lambda$ , 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  $\lambda$  drops to 0.2 (we cannot reject that the estimated  $\lambda$  is equal to zero), which

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<sup>30</sup>Provinces are the highest-level administrative divisions, mainland China is divided into 31 such divisions.

<sup>31</sup>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 the corresponding  $\beta$ , we obtain  $\hat{\delta}(\lambda, \beta)$ .

<sup>32</sup>The estimated  $\beta$  with investor fixed effects is significantly larger than our baseline estimate, possibly due to the fact that the longer time-series allows for larger within-investor variations.

shows that the within-investor effect of experienced stock market returns is very persistent.<sup>33</sup>

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%.<sup>34</sup>

### 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.<sup>35</sup>

In column 5 of Table 5, we observe an estimated  $\lambda$  around 0.9, which implies a  $\hat{k}(\lambda) = 30\%$ , and an estimated  $\beta$  around 47. 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  $\lambda$  is around 1.3 ( $\hat{k}(\lambda) = 44\%$ ), and the corresponding increase in ESG proportion is 1.2%.<sup>36</sup>

## 5.3 Non-Economic Experiences

We now consider the effects of non-economic experiences, an in particular of major natural disasters, corporate scandals, and shocks to pollution in the city of residence. Of course, many non-economic experiences may in principle affect investors' attitudes towards ESG stocks. Our focus on these three experiences is dictated, first, by their direct relation to the ESG factors and, second, by the availability of a sufficiently long time-series measuring these variables at the local level. Our analysis has no intent to be comprehensive, our main goal is to show that *some* non-economic experiences can have a significant impact on ESG demand.

### Pollution

We measure pollution by the Air Quality Index (AQI) in the city where the investor lives, obtained from CSMAR.<sup>37</sup> We obtain daily pollution levels and take their average at the monthly level. The AQI measure, scaled by 100, has an average of 0.8 and a standard deviation of 0.27 in our sample.

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<sup>33</sup>A mentioned,  $\lambda = 0$  implies that all realizations matter in the same way irrespective of whether they have occurred in the recent or in the distant past.

<sup>34</sup>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  $\lambda = 0.193$ .

<sup>35</sup>See Jones et al. (2021) for a comprehensive study of the return patterns of retail investors in the Chinese stock market and An et al. (2021) for an analysis of their implications for wealth inequality.

<sup>36</sup>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  $\lambda = 1.343$ .

<sup>37</sup>The official definition of AQI has changed in 2013. As robustness check, we use the PM 2.5 measure from NASA Socioeconomic Data and Applications Center (van Donkelaar et al. (2018)), and we obtain very similar results in terms of statistical and economic significance.

In column 1 of Table 6, we observe an estimated  $\lambda$  of 6.9 (that is,  $\hat{k}(\lambda) = 8\%$ ), while once controlling for individual fixed effects the  $\lambda$  drops to 1.9 (that is,  $\hat{k}(\lambda) = 21\%$ ). 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 without 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.<sup>38</sup>

### Natural Disasters

As a second measure of experience with environmental issues, we look at natural disasters occurring in a given year in the province where the investor lives. We obtain the information 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 0.033.

In columns 3 and 4, we observe that the estimated  $\lambda$  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.<sup>39</sup>

Our measure of natural disasters is available since 1950; hence, we can check our estimates when using the investor's experienced natural disasters since the birth date, rather than the first trading date. We report our results in Table B3 in Online Appendix B. Results are consistent with those in Table 5; in particular, the estimated  $\lambda$  is still negative and it becomes not significantly different from zero once we add individual fixed effects. This confirms the view that the effects of experienced natural disasters is large and very persistent.<sup>40</sup>

### 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

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<sup>38</sup>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  $\lambda = 1.867$ .

<sup>39</sup>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  $\lambda = -0.622$ .

<sup>40</sup>As already noticed in the case of GDP growth, the estimated  $\beta$  with investor fixed effects is significantly larger using the longer time series.

CSMAR. Since this information is available only for listed firms, we consider the number of scandals over the number of listed firms in the province where the investor lives.<sup>41</sup> 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 5, 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.<sup>42</sup>

## 5.4 Taking Stock

The above analysis has revealed a rich set of findings. We summarize the main patterns as follows. First, with the exception of natural disasters, the estimated  $\lambda$  are positive, meaning that investors react more to more recent experiences.<sup>43</sup> If the estimated  $\lambda$  were large and negative, only early experiences would matter and investment patterns would not respond much to recent shocks. A positive  $\lambda$  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.

Second, both economic and non-economic 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. 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.

Third, the implied magnitudes are large. In order to better compare their relative magnitudes, we construct for each factor the accumulated  $A_{i,t}$ , based on the corresponding  $\lambda$  estimated in the previous regressions, and then consider how they jointly explain the exposure to ESG stocks.

Our results are in Table 7, 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 demand. Once we add individual fixed effects, in column 2, we observe that the largest effect is driven by experienced market returns

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<sup>41</sup>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.

<sup>42</sup>A one standard deviation increase in scandals (equal to 0.014) translates into an accumulated impact of 0.018 in both columns.

<sup>43</sup>Malmendier (2021) report positive  $\lambda$  estimates in various settings, suggesting a form of "recency bias."

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

As comparison, the largest effect in terms of demographic variables is driven by being female, which is associated to an increase in ESG demand of about 1.3%. Our largest experience effects are about 10 times bigger, and as stressed the key reason is that these experience effects tend to be persistent over time.

## 6 Preferences and Expectations

As discussed in Section 2, our analysis is centered on how life-time experiences affect pro-social preferences. An alternative mechanism behind our findings is that these experiences affect investors' expectations about the financial returns of ESG stocks. For example, after being exposed to a natural disaster, investors may revise their beliefs about the likelihood of extreme environmental events and increase their ESG demand as they view ESG stocks as providing relatively higher returns when these events occur. While we have no direct way to distinguish whether investors' beliefs or preferences (or both) are affected, we provide some indirect evidence on the importance of those channels in our setting.<sup>44</sup>

### 6.1 Experienced ESG Returns

We first test whether investors' ESG demand is affected by experienced market returns on ESG stocks. To the extent that experienced market returns affect investors' return expectations (as documented e.g. in Malmendier and Nagel (2011)), these estimates shed light on how much our effects are driven by investors' expectations about ESG returns. We can differentiate ESG and non-ESG stocks' returns starting from 2005, when the first ESG-related index was introduced in China (see Table A1). We construct for each investor the time series of experienced ESG stocks returns, as we do with overall stock market returns in the above analysis. In order to differentiate between the two effects, we here consider ESG stocks' returns in excess of market

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<sup>44</sup>See Malmendier (2021) for a general discussion on how experience effects may be interpreted in terms of preferences and beliefs.

returns in a given month.

In Table 8, we report our estimates of  $\lambda$  and  $\beta$  both for excess ESG and for excess non-ESG returns, both with and without fixed effects. We observe that the estimated  $\beta$  is not significantly different from zero in all these specifications. In terms of sign, experienced ESG returns are negatively related to ESG demand, while the relation with non-ESG returns is positive. In terms of magnitude, the effects on ESG demand tend to be small. With fixed effects, the change in ESG demand associated to a standard deviation increase in excess returns (described by the corresponding  $\hat{\delta}(\lambda, \beta)$ ) is less than 1%.

While this evidence is imperfect (due to the shorter time series) and only indirect, it supports a preference-based (rather than a belief-based) explanation of our findings.

## 6.2 Reactions to Financial and non-Financial Information

If investors' objective functions include both a monetary and a non-monetary component, as described say by equation (5), one would expect that investors react both to financial and non-financial information (as e.g. in Landier and Lovo (2020) and Goldstein et al. (2021)) and that the reaction to financial information is lower the larger is the non-monetary weight  $\mu$ . Similar predictions apply for the same investor across the various stocks in her portfolio, implying that the investor would be less sensitive to the financial performance of ESG relative to non-ESG stocks.

Our data allow to compare the behaviors of the same investor across the various stocks in her portfolio, while controlling for any shock that may impact a given investor at a given point in time.

We report a summary of our main results in Table 9.<sup>45</sup> We first consider the investor's propensity to sell as a function of whether the stock price has increased or decreased relative to the purchase price.<sup>46</sup> In column 1, the dependent variable is a dummy equal to one if investor  $i$  sells stock  $j$  at time  $t$ , conditional on holding it 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  $t$  exceeds the price that the investor has paid for the stock, and equal to zero otherwise. We observe that investors are more likely to sell winning stocks and to hold losing stocks, consistent with the well-known disposition effect. Interestingly, investors display a lower disposition effect for ESG stocks. Controlling for both investor\*month and stock\*month fixed effects, we observe that non-ESG winners are about 7.4% more likely to be sold than non-ESG losers (the average probability of

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<sup>45</sup>A more complete set of results with various specifications is available in Online Appendix B, Tables B4-B8. We also include a series of robustness and placebo tests in Tables B17-B19.

<sup>46</sup>Our data record the price paid even if the investor has bought the stock before our sample period.

selling is 15%), while the effect is 1.5% lower for ESG stocks.

We then consider how past stock returns affect investors' propensity to buy. In column 2, the dependent variable is a dummy equal to one if the investor increases her holdings of stock  $j$  at time  $t$ , and equal to zero otherwise, conditional on holding stock  $j$  at time  $t$  or at time  $t - 1$ . The dummy *HighReturn* is equal to one if in month  $t - 1$  stock  $j$  had returns larger than the median return at  $t - 1$ . We observe that investors are more likely to buy stocks after good returns, consistent with well-documented trend chasing behaviors.<sup>47</sup> Interestingly, this tendency is less pronounced for ESG stocks. Controlling for investor\*month and stock fixed effects, *HighReturn* increases the buying probability of non-ESG stocks by 0.5% (relative to an average of 16%), while the effect on ESG stocks is 0.2% lower.

These results suggest that the same investor, at the same point in time, exhibits lower sensitivity to financial performance for ESG stocks relative to non-ESG stocks in her portfolio. These findings provide an explanation to the evidence that ESG fund inflows are less sensitive to past returns relative to traditional funds (Benson and Humphrey (2008), Renneboog et al. (2011)).

We next investigate whether a change in the stock's ESG status affects investors' propensity to trade. We restrict our sample to a 12-month window before and after any change in ESG status. In our sample, 491 of the 1,501 stocks experience a change in ESG status (431 stocks experience an inclusion and 258 stocks experience a removal). Both the inclusion and the removal from the index follow similar rules than in Western markets. We report in Appendix C several examples of firms losing their ESG status as they failed to comply with ESG standards.

In column 3, we observe that the exclusion from an ESG index is associated to a 1.4% higher propensity to sell the stock (relative to an average of 19%). This suggests that investors react to non-financial information.

We next look at investors' portfolio rebalancing. To the extent that shocks to financial performance occur more frequently than shocks to non-financial performance, we would expect investors to trade ESG stocks less frequently. This is consistent with the view that ESG investors tend to have a longer horizon (Starks et al. (2017)). This is also consistent with the evidence that the volatility of fund inflows is lower for ESG than for conventional funds (Bollen (2007)).

In column 4, we consider the number of trades, and observe that within their own portfolio investors indeed tend to trade ESG stocks less frequently. ESG stocks have a 4% lower probability to be traded within a given month, controlling for investor\*month fixed effects.

In columns 5 and 6, we look at investors' turnover and churn ratios, interpreted as in Gaspar

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<sup>47</sup>See, for example, Griffin et al. (2003) and Greenwood and Nagel (2009).



et al. (2005) and Starks et al. (2017) as measures of the investors' horizon.<sup>48</sup> We observe that, even including individual fixed effects, investors who are more exposed to ESG stocks change their stock positions at a significantly lower frequency, suggesting that they have a longer horizon.<sup>49</sup>

Overall, these results clearly show that investors display distinct trading patterns between ESG and non-ESG stocks. While again this evidence is only indirect, it is consistent with the view that ESG investing is at least partly driven by investors' concerns for non-monetary dimensions.

## 7 Alternative Explanations and Robustness

We investigate alternative explanations for our findings and consider whether our effects could be driven by changes in firms' (as opposed to investors') attitudes towards ESG criteria, whether they can be explained by investors' exposure to government policies, and whether investors display similar behaviors with stocks of state-owned enterprises or with stocks that belong to other indices. We also 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 Online Appendix B.

### 7.1 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, as shown in Table B9, investors in our

<sup>48</sup>The turnover ratio for investor  $i$  in month  $t$  is computed as follows:

$$Turnover_{i,t} = \frac{\sum_{j \in J} |(N_{i,j,t}P_{j,t} - N_{i,j,t-1}P_{j,t-1})|}{\sum_{j \in J} N_{i,j,t-1}P_{j,t-1}}, \quad (6)$$

where  $N_{i,j,t}$  denotes the shares of stock  $j$  held by investor  $i$  in month  $t$ ,  $P_{j,t}$  denotes the price of stock  $j$  at the end of month  $t$  and  $J$  is the set of stocks. The churn ratio excludes changes that are driven by stock price volatility and is computed as follows:

$$Churn_{i,t} = \frac{\sum_{j \in J} |N_{i,j,t}P_{j,t} - N_{i,j,t-1}P_{j,t-1} - N_{i,j,t-1}\Delta P_{j,t}|}{\sum_{j \in J} (N_{i,j,t}P_{j,t} + N_{i,j,t-1}P_{j,t-1})/2}, \quad (7)$$

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

<sup>49</sup>A standard deviation increase in ESG proportion (equal to 43) is associated to a 2.5% decrease in turnover ratio, relative to the average of 13, and to a 7.5% decrease in churn ratio, relative to the average of 30.

sample display a form of home bias, they are about 4% more likely to invest in a firm located 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, investors display no significantly different demand for local stocks depending on whether or not they are ESG-stocks.

## 7.2 Government-side Explanations

State-owned enterprises (SOE) represent 56% of the stocks in our sample. Moreover, 45% of SOE stocks are also ESG, according to our classification (as comparison, we have 35% of ESG stocks in the overall sample). While this overlap is intuitive (e.g., both SOE and ESG stocks tend to have a larger capitalization), one may wonder if our effects on ESG demand are instead a proxy for a demand for SOE stocks.

In Table B10, we show that this is not the case. First, we show that our results on ESG demand are basically unchanged if we restrict to non-SOE stocks. Second, we consider non-ESG stocks and we build a measure of SOE demand as the value of SOE stocks over the total value of the portfolio. We show that experience effects are significantly different on SOE demand, confirming the view that the drivers of ESG investing are not the same as those of SOE investing.

Other possibly important factors behind ESG demand are the various policies taken by the Chinese government to promote a sustainable economy (Liu et al. (2021)) and to influence firms' CSR practices (Jiang and Kim (2020)). For our purposes, the key question is whether government policies may directly affect investors' demand, possibly in a way that confounds the experience effects documented above. We measure the intensity of the government's policy on environmental protection in two ways. First, we consider the waste reduction at the province level, defined as one minus the ratio between the amounts of gas, water and solid wastes that are emitted over those that are produced, as in Chen and Chen (2021). Second, we consider the government's investment to control pollution over the total industrial output, following Wang and Li (2021).

We explore how the exposure to those policies affect investors' demand for ESG stocks, along the lines developed in Section 4. We show in Table B11 that experienced environmental regulation does not have a significant impact on ESG demand. Even though a full investigation of how public policies affect investors' demand is beyond our scope, these findings indicate that the experience effects we identify cannot be simply explained by the exposure to government policies.

### 7.3 Placebo Tests

As mentioned in Section 2, ESG stocks are somewhat different from 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. One concern is that the above patterns just reflect some form of preferences for large-cap stocks. Moreover, the mere fact of belonging to an index may induce different investment behaviors.

In order to address these concerns, we consider whether the determinants and the dynamics of large-cap investing are similar to those of ESG-investing. Indices based on market capitalization are most visible to investors, and among those we focus on the SSE 380 Index, which is the most similar to our ESG Index definition.<sup>50</sup> 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 SSE 380 stocks it is 8.7bn.<sup>51</sup>

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 portfolios) tend to be male, lower educated and middle-aged. These patterns are significantly different from those highlighted in Table 2 on ESG investing. We then show how life-time experiences affect Index investing (see Table B12). With the exception of experienced corporate scandals, our life-time experience have negative or no significant impact on index investing.<sup>52</sup> Again, these patterns are very different from those underlying ESG investing.

### 7.4 Robustness

Our main definition of ESG stock is based on the inclusion in one ESG index. We now show the robustness of our findings when using finer classifications of ESG stocks. We also show their robustness when defining ESG demand in terms of relative number, rather than relative value, of ESG stocks.

First, for each stock, we consider the number of ESG indices that contain the stocks. This gives a more continuous measure and it 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 (see Table B13).

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<sup>50</sup>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.

<sup>51</sup>The median market capitalization for SSE 180 stocks is 39.4bn.

<sup>52</sup>The effect of corporate scandals can be explained by the fact that firms subject to a scandal are excluded from the SSE 380 index.

Second, we consider stocks' ESG ratings. These ratings appeared very recently in China, and covered only a small set of the SSE stocks.<sup>53</sup> 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 32% of highly rated stocks in our sample. This proportion is similar to that of ESG stocks in the baseline analysis.<sup>54</sup>

We repeat the same analysis as above. We observe in Table B14 that life-time experiences have a similar effect as in our baseline analysis with the exception of natural disasters (whose estimated  $\lambda$  is similar but  $\beta$  is not significant). These estimates show that the patterns uncovered above are robust when we employ alternative definitions of stocks' ESG status.<sup>55</sup>

Finally, we consider an alternative measure of ESG demand based on the number (rather than the value) of ESG stocks over the total number of stocks in the investor's portfolio. While the relative value of ESG stocks may fluctuate as a result of differential returns of ESG vs. non-ESG stocks, the alternative definition does not depend on these valuation effects. We report our results in Table B16, which are again very similar to our baseline estimates.

## 8 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. Our evidence suggests that these experiences affect investors' intrinsic preferences for ESG stocks.

We view these results as a first step, further analysis is needed to better understand the determinants of ESG 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.<sup>56</sup> Another important next step would be 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.

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<sup>53</sup>The first ESG rating firm (SynTao Green Finance) appeared in China in 2015 and it covered 271 (out of 2800) listed firms.

<sup>54</sup>The correlation between this measure based on ratings and our baseline ESG Stock dummy is 0.6.

<sup>55</sup>Our results are also robust if we employ stricter definitions of ESG stocks and consider a stock as ESG if it is included in at least three ESG indices. This definition leads to a proportion of ESG stocks equal to 13%, (as compared to 35% in the baseline definition), but this does not significantly change the effects uncovered in our baseline analysis (see Table B15).

<sup>56</sup>D'Acunto et al. (2021) show how inflation experiences may affect differently women and men.

## References

- An, L., Lou, D. and Shi, D. (2021), ‘Wealth Redistribution in Bubbles and Crashes’, *Journal of Monetary Economics*, *forthcoming* .
- Andreoni, J., Nikiforakis, N. and Stoop, J. (2021), ‘Higher socioeconomic status does not predict decreased prosocial behavior in a field experiment’, *Nature communications* **12**(1), 1–8.
- Avramov, D., Cheng, S., Lioui, A. and Tarelli, A. (2021), ‘Sustainable Investing with ESG Rating Uncertainty’, *Journal of Financial Economics*, *forthcoming* .
- Avramov, D., Lioui, A., Liu, Y. and Tarelli, A. (2021), ‘Dynamic ESG Equilibrium’, *Available at SSRN 3935174* .
- Baker, S. D., Hollifield, B. and Osambela, E. (2020), ‘Asset Prices and Portfolios with Externalities’, *Available at SSRN 3344940* .
- Bansal, R., Wu, D. and Yaron, A. (2022), ‘Socially responsible investing in good and bad times’, *Review of Financial Studies* **35**(4), 2067–2099.
- Barber, B. M., Morse, A. and Yasuda, A. (2021), ‘Impact Investing’, *Journal of Financial Economics* **139**(1), 162–185.
- Bartling, B., Valero, V. and Weber, R. A. (2021), ‘The causal effect of income growth on consumer social responsibility’, *Available at SSRN 3249788* .
- Bauer, R., Ruof, T. and Smeets, P. (2021), ‘Get real! Individuals Prefer More Sustainable Investments’, *Review of Financial Studies* **34**(8), 3976–4043.
- Beal, D. and Goyen, M. (1998), “putting your money where your mouth is’ a profile of ethical investors’, *Financial services review* **7**(2), 129–143.
- Becchetti, L., Castriota, S. and Conzo, P. (2017), ‘Disaster, aid, and preferences: The long-run impact of the tsunami on giving in sri lanka’, *World Development* **94**, 157–173.
- Bénabou, R. and Tirole, J. (2006), ‘Incentives and prosocial behavior’, *American economic review* **96**(5), 1652–1678.
- Benson, K. L. and Humphrey, J. E. (2008), ‘Socially responsible investment funds: Investor reaction to current and past returns’, *Journal of Banking & Finance* **32**(9), 1850–1859.
- Bollen, N. P. (2007), ‘Mutual fund attributes and investor behavior’, *Journal of financial and quantitative analysis* **42**(3), 683–708.
- Bonnefon, J.-F., Landier, A., Sastry, P. and Thesmar, D. (2019), ‘Do Investors Care about Corporate Externalities? Experimental Evidence’, *HEC Paris Research Paper No. FIN-2019-1350* .
- Brodback, D., Guenster, N. and Pouget, S. (2019), ‘The Valuation of Corporate Social Responsibility: An Experiment’, *mimeo* .
- Calonico, S., Cattaneo, M. D. and Titiunik, R. (2014), ‘Robust nonparametric confidence intervals for regression-discontinuity designs’, *Econometrica* **82**(6), 2295–2326.

- Cao, J., Titman, S., Zhan, X. and Zhang, W. E. (2019), ‘ESG Preference and Market Efficiency: Evidence from Mispricing and Institutional Trading’, *SSRN Electronic Journal* .
- Cappelen, A., List, J., Samek, A. and Tungodden, B. (2020), ‘The effect of early-childhood education on social preferences’, *Journal of Political Economy* **128**(7), 2739–2758.
- Cassar, A., Healy, A. and Von Kessler, C. (2017), ‘Trust, risk, and time preferences after a natural disaster: experimental evidence from thailand’, *World Development* **94**, 90–105.
- Chantararat, S., Oum, S., Samphantharak, K. and Sann, V. (2019), ‘Natural disasters, preferences, and behaviors: evidence from the 2011 mega flood in cambodia’, *Journal of Asian Economics* **63**, 44–74.
- Chen, X. and Chen, Z. (2021), ‘Can China’s Environmental Regulations Effectively Reduce Pollution Emissions?’, *International Journal of Environmental Research and Public Health* **18**(9), 4658.
- Chen, Y., Ebenstein, A., Greenstone, M. and Li, H. (2013), ‘Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China’s Huai River Policy’, *Proceedings of the National Academy of Sciences* **110**(32), 12936–12941.
- Choi, D., Gao, Z. and Jiang, W. (2020), ‘Attention to Global Warming’, *Review of Financial Studies* **33**(3), 1112–1145.
- Cronqvist, H., Siegel, S. and Yu, F. (2015), ‘Value versus growth investing: Why do different investors have different styles?’, *Journal of Financial Economics* **117**(2), 333–349.
- DellaVigna, S. (2009), ‘Psychology and economics: Evidence from the field’, *Journal of Economic literature* **47**(2), 315–72.
- Diamantopoulos, A., Schlegelmilch, B. B., Sinkovics, R. R. and Bohlen, G. M. (2003), ‘Can socio-demographics still play a role in profiling green consumers? a review of the evidence and an empirical investigation’, *Journal of Business research* **56**(6), 465–480.
- Diekmann, A. B. and Clar, E. K. (2015), ‘Beyond the Damsel in Distress: Gender Differences and Similarities in Enacting Prosocial Behavior’, *The Oxford handbook of prosocial behavior* **12**, 376–391.
- Dyck, A., Lins, K. V., Roth, L. and Wagner, H. F. (2019), ‘Do Institutional Investors Drive Corporate Social Responsibility? International Evidence’, *Journal of Financial Economics* **131**(3), 693–714.
- D’Acunto, F., Malmendier, U. and Weber, M. (2021), ‘Gender Roles Produce Divergent Economic Expectations’, *Proceedings of the National Academy of Sciences* **118**(21).
- Ebenstein, A., Fan, M., Greenstone, M., He, G. and Zhou, M. (2017), ‘New Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China’s Huai River Policy’, *Proceedings of the National Academy of Sciences* **114**(39), 10384–10389.
- Ertac, S. (2020), ‘The formation and malleability of preferences and noncognitive skills’, *Handbook of Labor, Human Resources and Population Economics* pp. 1–27.
- Espinosa, M. P. and Kovářík, J. (2015), ‘Prosocial Behavior and Gender’, *Frontiers in behavioral neuroscience* **9**, 88.
- Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D. and Sunde, U. (2018), ‘Global evidence on economic preferences’, *The Quarterly Journal of Economics* **133**(4), 1645–1692.

- Gantchev, N., Giannetti, M. and Li, R. (2019), ‘Does Money Talk? Market Discipline through Selloffs and Boycotts’, *European Corporate Governance Institute–Finance Working Paper No. 634/2019* .
- Gaspar, J.-M., Massa, M. and Matos, P. (2005), ‘Shareholder Investment Horizons and the Market for Corporate Control’, *Journal of Financial Economics* **76**(1), 135–165.
- Giannetti, M. and Wang, T. Y. (2016), ‘Corporate scandals and household stock market participation’, *The Journal of Finance* **71**(6), 2591–2636.
- Giuliano, P. and Spilimbergo, A. (2014), ‘Growing up in a recession’, *Review of Economic Studies* **81**(2), 787–817.
- Goldstein, I., Kopytov, A., Shen, L. and Xiang, H. (2021), ‘On ESG Investing: Heterogeneous Preferences, Information, and Asset Prices’, *Available at SSRN 3823042* .
- Greenwood, R. and Nagel, S. (2009), ‘Inexperienced Investors and Bubbles’, *Journal of Financial Economics* **93**(2), 239–258.
- Griffin, J. M., Harris, J. H. and Topaloglu, S. (2003), ‘The Dynamics of Institutional and Individual Trading’, *Journal of Finance* **58**(6), 2285–2320.
- Gurun, U. G., Stoffman, N. and Yonker, S. E. (2018), ‘Trust busting: The effect of fraud on investor behavior’, *The Review of Financial Studies* **31**(4), 1341–1376.
- Huynh, T., Li, F. W. and Xia, Y. (2021), ‘Something in the Air: Does Air Pollution Affect Fund Managers’ Carbon Divestment?’, *Available at SSRN 3908963* .
- Jiang, F. and Kim, K. A. (2020), ‘Corporate governance in china: A survey’, *Review of Finance* **24**(4), 733–772.
- Jo, H., Kim, H.-E. and Sim, M. (2022), ‘Environmental preference, air pollution, and fund flows in china’, *Pacific-Basin Finance Journal* **72**, 101723.
- Jones, C. M., Shi, D., Zhang, X. and Zhang, X. (2021), ‘Understanding Retail Investors: Evidence from China’, *Available at SSRN 3628809* .
- Junkus, J. C. and Berry, T. C. (2010), ‘The Demographic Profile of Socially Responsible Investors’, *Managerial Finance* .
- Kosse, F., Deckers, T., Pinger, P., Schildberg-Hörisch, H. and Falk, A. (2020), ‘The formation of prosociality: causal evidence on the role of social environment’, *Journal of Political Economy* **128**(2), 434–467.
- Landier, A. and Lovo, S. (2020), ‘ESG Investing: How to Optimize Impact?’, *HEC Paris Research Paper No. FIN-2020-1363* .
- Li, J. J., Massa, M., Zhang, H. and Zhang, J. (2019), ‘Air Pollution, Behavioral Bias, and the Disposition Effect in China’, *Journal of Financial Economics*, *forthcoming* .
- List, J. A. et al. (2009), ‘Social preferences: Some thoughts from the field’, *Annual Review of Economics* **1**(1), 21–1.
- Liu, B., Wang, T., Zhang, J., Wang, X., Chang, Y., Fang, D., Yang, M. and Sun, X. (2021), ‘Sustained Sustainable Development Actions of China from 1986 to 2020’, *Scientific Reports* **11**(1), 1–10.

- Lu, J. G. (2020), ‘Air pollution: A systematic review of its psychological, economic, and social effects’, *Current opinion in psychology* **32**, 52–65.
- Maki, A., Dwyer, P. C., Blazek, S., Snyder, M., González, R. and Lay, S. (2019), ‘Responding to natural disasters: Examining identity and prosociality in the context of a major earthquake’, *British journal of social psychology* **58**(1), 66–87.
- Malmendier, U. (2021), ‘Experience Effects in Finance: Foundations, Applications, and Future Directions’, *Review of Finance*, *forthcoming* .
- Malmendier, U. and Nagel, S. (2011), ‘Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?’, *Quarterly Journal of Economics* **126**(1), 373–416.
- Ming, Y., Deng, H. and Wu, X. (2022), ‘The negative effect of air pollution on people’s pro-environmental behavior’, *Journal of Business Research* **142**, 72–87.
- Nilsson, J. (2008), ‘Investment with a conscience: Examining the impact of pro-social attitudes and perceived financial performance on socially responsible investment behavior’, *Journal of business ethics* **83**(2), 307–325.
- Oishi, S., Yagi, A., Komiya, A., Kohlbacher, F., Kusumi, T. and Ishii, K. (2017), ‘Does a major earthquake change job preferences and human values?’, *European Journal of Personality* **31**(3), 258–265.
- Pástor, L., Stambaugh, R. F. and Taylor, L. A. (2020), ‘Sustainable Investing in Equilibrium’, *Journal of Financial Economics*, *forthcoming* .
- Pástor, L., Stambaugh, R. F. and Taylor, L. A. (2021), ‘Dissecting Green Returns’, *NBER Working Paper* (w28940).
- Pedersen, L. H., Fitzgibbons, S. and Pomorski, L. (2021), ‘Responsible Investing: The ESG-efficient Frontier’, *Journal of Financial Economics* **142**(2), 572–597.
- Renneboog, L., Ter Horst, J. and Zhang, C. (2011), ‘Is ethical money financially smart? non-financial attributes and money flows of socially responsible investment funds’, *Journal of Financial Intermediation* **20**(4), 562–588.
- Riedl, A. and Smeets, P. (2017), ‘Why do investors hold socially responsible mutual funds?’, *Journal of Finance* **72**(6), 2505–2550.
- Roth, C. and Wohlfart, J. (2018), ‘Experienced inequality and preferences for redistribution’, *Journal of Public Economics* **167**, 251–262.
- Solnit, R. (2010), *A paradise built in hell: The extraordinary communities that arise in disaster*, Penguin.
- Starks, L. T., Venkat, P. and Zhu, Q. (2017), ‘Corporate ESG Profiles and Investor Horizons’, *Available at SSRN 3049943* .
- SynTao Green Finance (2019), ‘China Sustainable Investment Review 2019’, *Available at <http://syntaogf.com/uploads/files/China%20Sustainable%20Investment%20Review%202019.pdf>*.
- Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X. and Kitayama, S. (2014), ‘Large-scale Psychological Differences within China Explained by Rice versus Wheat Agriculture’, *Science* **344**(6184), 603–608.



- van Donkelaar, A., Martin, R. V., Brauer, M., Hsu, N. C., Kahn, R. A., Levy, R. C., Lyapustin, A., Sayer, A. M. and Winker, D. M. (2018), ‘Documentation for the Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR, 1998-2016’, *Palisades NY: NASA Socioeconomic Data and Applications Center* .
- Vardy, T. and Atkinson, Q. D. (2019), ‘Property damage and exposure to other people in distress differentially predict prosocial behavior after a natural disaster’, *Psychological Science* **30**(4), 563–575.
- Wang, H. and Li, B. (2021), ‘Environmental Regulations, Capacity Utilization, and High-quality Development of Manufacturing: An Analysis based on Chinese Provincial Panel Data’, *Scientific Reports* **11**(1), 1–13.
- Wu, J., Guo, Z., Gao, X. and Kou, Y. (2020), ‘The relations between early-life stress and risk, time, and prosocial preferences in adulthood: A meta-analytic review’, *Evolution and Human Behavior* **41**(6), 557–572.
- Wu, Q., Hao, Y. and Lu, J. (2018), ‘Air pollution, stock returns, and trading activities in china’, *Pacific-Basin Finance Journal* **51**, 342–365.
- Zerbib, O. D. (2020), ‘A Sustainable Capital Asset Pricing Model (S-CAPM): Evidence from Green Investing and Sin Stock Exclusion’, *Available at SSRN 3455090* .

## Tables

Table 1: Summary Statistics

This table reports the summary statistics. *ESG Demand* is the value of ESG stocks over the total value of the portfolio. *High ESG Rated Prop* is the proportion of stocks that are highly rated in ESG (AA or above) by Sino Securities. *Education* is the number of academic years. *Trading Experience* is the number of months since the start of the investment account. *Investor Monthly Return* is the investment return in the month. *Churn Ratio* and *Turnover Ratio* are defined in Equations (6) and (7). *Ln(Size)* is the market value of the portfolio. *Portfolio Beta*, *Beta for Size*, and *Beta for B-M* are the value weighted beta of the stock for market, size and value factors. *Sell Dummy* is equal to one if the investor sells the stock at time t, and zero if the investor keeps the stock. *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. *Buy Dummy* 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 the previous month. *ESG Stock* is a dummy equal to 1 for ESG-stocks and to 0 for non-ESG stocks. *Number of Trades*, *Number of Buys*, and *Number of Sells* are the number of transactions, buy transactions, and sell transactions. *ESG stock* is a dummy that is one if the stock is included in one ESG index, and to 0 otherwise.

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
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
Winner	11,664,531	0.34	0.47	0.00	0.00	0.00	1.00	1.00
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 Stock	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 2: 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 month levels in columns (1) and (2). T-values are in parenthesis. The product between the estimated coefficient and the standard deviation of the corresponding variable is reported in brackets. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

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

Table 3: The Huai River Policy and ESG Investment

This table estimates the relation between the Huai River policy and ESG investment. The dependent variable is the value of ESG stocks over the total value of the portfolio. *Coal Heating* is a dummy 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). AQI is the level of pollution at the city level, measured by the Air Quality Index. In columns 1-3, we include investors living in cities located within 5 degrees latitude from the Huai river, and in columns 4-6, we consider a latitude distance of 3.6 degrees (optimally chosen following Calonico et al. (2014) ). Columns (1) and (4) report the reduced-form estimates of the effects of *Coal Heating* on ESG demand. In columns 2-3 and 5-6, we report the results of 2SLS regressions in which AQI is instrumented by *Coal Heating*. Controls include variables at the city level (ESG Stock Proportion and GDP growth) and at the portfolio level (portfolio size, beta relative to the market, size and book-to-market factors). Standard errors are two-way clustered at the investor and month 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:	ESG Demand					
Latitude to Huai River:	5 degrees			3.6 degrees		
Coal Heating	1.724*** (5.88)			2.206*** (6.62)		
AQI (predicted)		15.314*** (5.88)	16.013*** (6.62)		18.578*** (6.62)	19.517*** (6.97)
Female			1.092*** (3.90)			1.051*** (3.29)
Education			0.253*** (4.93)			0.235*** (4.07)
Trading Experience			0.006*** (2.84)			0.005** (2.33)
Age			0.063*** (4.63)			0.065*** (4.29)
ESG Stock Proportion			-0.002 (-0.18)			0.011 (0.92)
GDP Growth			4.552** (2.05)			7.927** (2.36)
		First Stage			First Stage	
Coal Heating		0.113*** (14.24)	0.119*** (15.14)		0.119*** (13.50)	0.120*** (14.49)
F-Stat (first stage)		202.854	81.468		182.148	72.904
Controls	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	2,761,442	2,761,442	2,759,990	2,142,706	2,142,706	2,141,623
R <sup>2</sup>	0.006	0.006	0.039	0.007	0.007	0.040

Table 4: ESG Investment in Rice and Wheat Areas

This table estimates how ESG investment differs between investors living in rice-growing cities and those living in wheat-growing cities, restricting to provinces around the Yangtze river. The dependent variable is the value of ESG stocks over the total value of the portfolio. *Rice Ratio* is the ratio of rice over total (wheat plus rice) farmlands in 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 month 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	3.776*** (2.92)	2.279* (1.84)	4.817*** (2.83)	3.073* (1.86)
Female		0.766* (1.69)		0.646 (1.14)
Education		0.138* (1.73)		0.078 (0.77)
Trading Experience		0.007** (2.30)		0.007* (1.81)
Age		0.064*** (2.95)		0.077*** (2.80)
ESG Stock Proportion		0.053*** (2.89)		0.049** (2.20)
GDP Growth		5.781 (1.19)		0.014 (0.00)
Portfolio Controls	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Observation	1,004,924	1,004,924	624,670	624,670
R <sup>2</sup>	0.006	0.045	0.007	0.041

Table 5: 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 month 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:	GDP Growth		MKT Ret		Inv Ret	
$\lambda$	0.146*** (6.36)	1.171*** (4.75)	1.572*** (3.63)	0.193 (1.46)	0.917*** (6.96)	1.343*** (7.06)
$\beta$	76.308*** (9.91)	24.388* (1.76)	22.102*** (3.38)	28.084*** (4.22)	47.590*** (9.26)	5.593*** (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
Observations	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 6: 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 month 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:	AQI		Natural Disasters		Corp. Scandals	
$\lambda$	6.941*** (22.71)	1.867*** (3.23)	-0.268*** (-4.43)	-0.622*** (-7.31)	3.012*** (24.70)	3.246*** (5.56)
$\beta$	1.174** (2.25)	2.567*** (3.07)	20.617*** (2.91)	58.476*** (2.69)	116.832*** (3.19)	43.531** (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
Observations	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 7: 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  $\lambda$  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 month 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*** (9.23) [6.397]	28.158* (1.89) [1.439]			68.249*** (7.72) [5.840]	29.616* (1.82) [1.514]
Market Return	-2.324 (-0.35) [-0.262]	26.949*** (3.26) [8.361]			0.021 (0.00) [0.002]	25.371*** (2.71) [7.871]
Investor Return	47.221*** (9.08) [12.974]	5.295** (2.55) [1.167]			49.492*** (9.72) [13.598]	5.851*** (2.79) [1.290]
AQI			1.284** (2.40) [0.343]	2.410*** (2.78) [0.901]	0.942* (1.70) [0.252]	2.372** (2.48) [0.887]
Natural Disasters			18.066** (2.27) [2.709]	65.032** (2.56) [12.248]	6.762 (0.80) [1.014]	72.572** (2.62) [13.668]
Corporate Scandals			120.762*** (3.20) [2.172]	51.323** (2.60) [0.902]	149.493*** (4.32) [2.689]	72.075*** (3.53) [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
Observations	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 8: ESG Investment and Experienced ESG Stock Returns

This table estimates the relation between ESG investing and the experienced ESG stock returns. The dependent variable is the value of ESG stocks over the total value of the portfolio. The experience measures are based on the value weighted excess return over the market return of ESG stocks in columns (1) and (2), and of non-ESG stocks in columns (3) and (4). 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 month levels. T-values are in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ESG Demand			
Experience:	Excess ESG Stock Return		Excess Non-ESG Stock Return	
$\lambda$	1.234*** (17.56)	0.424 (1.22)	2.156*** (19.02)	2.546*** (7.28)
$\beta$	-76.763 (-1.40)	-30.903 (-1.48)	30.774 (1.38)	14.448 (1.23)
$\hat{k}(\lambda)$	26.682	37.794	19.773	17.810
$\hat{\delta}(\lambda, \beta)$	-2.035	-0.764	1.401	0.614
Demographic Controls	Yes	No	Yes	No
Portfolio Controls	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	4,691,196	4,687,829	4,691,196	4,687,829
$R^2$	0.040	0.459	0.040	0.459

Table 9: Trading Patterns on ESG and non-ESG Stocks

This table compares investors' trading behaviors between ESG stocks and non-ESG stocks in their portfolio. In columns (1) and (3), the dependent variable *Sell* 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 (2), the dependent variable *Buy* 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. In column (4), the dependent variable *TradeNum* is the number of trades. In columns (5) and (6), the dependent variables are the monthly turnover ratio and churn ratio of the investor's portfolio. *ESG Stock* is a dummy equal to 1 for ESG stocks and to 0 for non-ESG stocks. *Winner* is a dummy equal to 1 if the stock is trading at a larger price relative to what the investor has paid, and zero otherwise. *High Return (Past-Month)* is a dummy equal to 1 if the return of the stock is higher than the median market return in the previous month. *ESG Demand* is the value of ESG stocks over the total value of the portfolio. *Stock controls* include the log of stock turnover ratio, return volatility, log of market capitalization, market-to-book ratio, and dividend yield. *Portfolio controls* include portfolio beta relative to the market, size and book-to-market factors. Standard errors are clustered at the stock level in columns (1) and (2), at the stock\*event level in column(3), and two-way clustered at the investor and month levels in columns (4-6). T-values are in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Sell	Buy	Sell	TradeNum	TurnoverRatio	ChurnRatio
ESG Stock		-0.000 (-0.20)	-0.013*** (-4.78)	-0.044*** (-5.20)		
Winner	0.074*** (55.55)					
ESG Stock * Winner	-0.015*** (-7.72)					
High Return		0.005*** (6.13)				
ESG Stock * High Return		-0.003*** (-2.65)				
ESG Demand					-0.006*** (-5.11)	-0.048*** (-9.04)
Fixed Effects	Investor*Month + Stock*Month	Investor*Month + Stock	Stock*Event + Month	Investor*Month + Stock	Investor + Month	Investor + Month
Stock Controls	No	Yes	Yes	Yes	No	No
Portfolio Controls	No	No	No	No	Yes	Yes
Observations	9,503,091	10,549,036	1,391,080	13,358,092	4,754,140	4,754,140
$R^2$	0.623	0.442	0.113	0.602	0.175	0.437

## Online Appendix A: ESG Indices in China

As mentioned, ESG criteria have been introduced only recently in China. 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 in China, the CSI ECPI ESG China 40 Index, was released in 2010 by China Security Index Co. Ltd and included 40 stocks. The first ESG rating firm (SynTao Green) appeared in China only in 2015 and it covered about 10% of the Chinese listed companies. ESG ratings on all stocks in the Chinese market become available from April 2019 (from Sino-Securities Index Co.Ltd).

Given this late development relative to the western markets, the Chinese financial practitioners have widely borrowed from ESG practices in Europe and the US. The construction of ESG indices is based on very similar methods to those in Europe and the US. For example, China Securities Index Co. Ltd., which provides thirteen of our twenty-four ESG indices, explicitly states that they use the ESG rating method from ECPI, a European rater, in three ESG indices in our sample (000970.CSI, 000846.CSI, and 931148.CSI). Another index, 931088.CSI is a result of collaboration with S&P Global Trucost, which is the ESG rating provider of S&P Global. Also, in their ESG rating and ESG database product description, the Sino-Securities Index Co. Ltd. clearly states that they use the methods developed in foreign markets.

As in western markets, Chinese stocks can lose their ESG status (i.e., they can be removed from an ESG index) if they fail to comply with ESG practices. For example, Heilongjiang Interchina Water Treatment Co.,Ltd. (600187.SH) was excluded from the index CSI China Mainland Low Carbon Economy Index (000977.CSI) in December 2015 after being punished for polluting water. Jiangsu Wuzhong Pharmaceutical Development Co., Ltd. (600200.SH) was excluded from SSE Corp. Governance Index (000019.SH) in October 2018 after being detected producing in dangerous workplaces. Jiangxi Hongdu Aviation Industry Co., Ltd. (600316.SH) was excluded from SSE 180 Carbon Efficient Index (950081.CSI) in October 2016 after being detected disclosing misleading information.

Interestingly, the ESG status can also be lost for misbehaviors across the various ESG dimensions. Nanjing Chemical Fibre (600889.SH), for example, was excluded from the SSE Corporate Governance Index (000019.SH) in May 2019 after it got punished for polluting the environment.

Table A1: 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 CUFES 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 A2: ESG and non-ESG Stocks

This table compares the differences between ESG and non-ESG stocks. 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 coefficients of a series of regressions in which each variable is regressed over the ESG stock dummy, controlling for time fixed effects. Standard deviations are reported in the parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively. The information about stock characteristics comes from the China Stock Market & Accounting Research Database (CSMAR).

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

## Online Appendix B: Additional Results

Figure 1: Number of Investors at Different Latitudes to the Huai River  
The vertical axis represents the number of investors, the horizontal axis represents the latitude values.

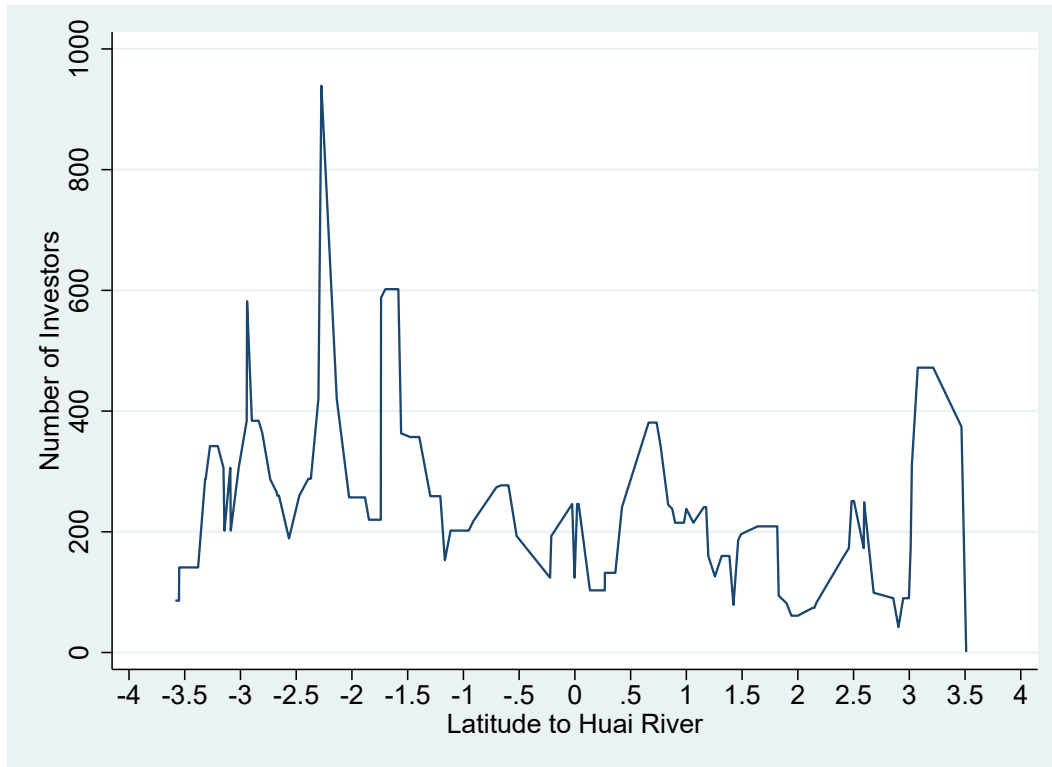


Table B1: Investors to the North and South of the Huai River

This table compares the differences between the characteristics of the investors to the north and south of the Huai River. The sample includes investors that live within 3.6 degree of latitude to the north and south of the Huai River. For each variable, we first take the mean value of the variables at the city level, and then compute mean values across investors that are living in the north or south of the Huai river. We report the corresponding averages in columns 1 and 2. Standard deviations are reported in the parenthesis. In column 3, we report the coefficients of a series of regressions in which each variable is regressed over the coal heating dummy. T-values for coefficients are reported in the parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	North	South	Diff (North-South)
Female	0.448 (0.10)	0.441 (0.14)	0.007 (0.32)
Education	13.622 (0.49)	13.375 (0.94)	0.248* (1.78)
Age	44.877 (4.19)	45.799 (6.32)	-0.922 (-0.93)
Trading Experience	117.431 (31.53)	113.060 (39.07)	4.372 (0.67)
Portfolio Size	2.275 (0.04)	2.274 (0.05)	0.001 (0.11)
Portfolio Beta	1.051 (0.02)	1.051 (0.04)	-0.001 (-0.08)
Portfolio Beta for Size	0.335 (0.17)	0.415 (0.11)	-0.080*** (-3.11)
Portfolio Beta for B-M	-0.000 (0.10)	-0.003 (0.08)	0.003 (0.17)
ESG Stock Proportion	52.497 (13.45)	54.517 (7.81)	-2.020 (-1.01)
GDP Growth	0.075 (0.02)	0.084 (0.03)	-0.010* (-1.97)

Table B2: Trading experience,  $\hat{k}(\lambda)$ , and  $\hat{\delta}(\lambda, \beta)$

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 with 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 and accumulated over  $T$  periods.

Experience	$\lambda$	$\beta$	$\hat{k}(\lambda)$			$\hat{\delta}(\lambda, \beta)$		
			$T = 10$	$T = 13$	$T = 20$	$T = 10$	$T = 13$	$T = 20$
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 B3: ESG Investment and Life-time Experiences: Longer History

This table estimates the relation between ESG investing and life-time experiences starting from the birth year of the investor. 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), and natural disasters in columns (3) and (4). 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 month levels. T-values are in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ESG Demand			
Experience:	GDP Growth		Natural Disaster	
$\lambda$	0.940*** (13.50)	1.062*** (15.58)	-0.577*** (-5.18)	-0.022 (-0.30)
$\beta$	71.731*** (7.54)	67.492** (2.60)	19.284*** (2.65)	374.627*** (3.01)
Demographic Controls	Yes	No	Yes	No
Portfolio Controls	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	4,690,573	4,687,208	4,690,507	4,687,142
$R^2$	0.040	0.459	0.040	0.459

Table B4: 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				$-\frac{\Delta Holdings_{i,j,t}}{Holdings_{i,j,t-1}}$
Winner	0.076*** (39.65)		0.089*** (55.51)	0.074*** (55.55)	0.092*** (59.60)
ESG Stock		-0.006*** (-4.89)	0.004*** (4.51)		
ESG Stock * Winner			-0.021*** (-8.33)	-0.015*** (-7.72)	-0.021*** (-9.68)
Ln(Stock Turnover)	0.004*** (3.98)	0.010*** (12.21)	0.005*** (4.95)		
Return Volatility	0.687*** (7.70)	0.798*** (9.39)	0.657*** (7.58)		
Ln(Market Cap)	-0.002*** (-4.17)	0.001** (2.40)	-0.001** (-2.53)		
Market-to-Book Ratio	-0.000*** (-3.00)	0.000 (0.15)	-0.000*** (-3.30)		
Dividend Yield	0.002*** (4.91)	0.004*** (8.25)	0.002*** (5.63)		
Investor*Month FE	Yes	Yes	Yes	Yes	Yes
Stock*Month FE	No	No	No	Yes	Yes
Observations	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 B5: 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 the previous 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					
ESG Stock	-0.004*** (-4.04)	-0.002 (-1.08)			-0.002** (-2.22)	-0.000 (-0.20)
High Return			0.004*** (6.31)	0.003*** (4.58)	0.006*** (7.66)	0.005*** (6.13)
ESG Stock * High Return					-0.003*** (-2.98)	-0.003*** (-2.65)
Ln(Stock Turnover)	0.017*** (17.55)	0.019*** (21.31)	0.016*** (17.29)	0.018*** (21.13)	0.017*** (17.49)	0.018*** (21.14)
Return Volatility	1.406*** (20.18)	0.976*** (14.85)	1.394*** (19.78)	0.953*** (14.31)	1.366*** (19.30)	0.947*** (14.23)
Ln(Market Cap)	0.008*** (13.09)	0.040*** (24.39)	0.007*** (12.10)	0.040*** (24.22)	0.008*** (12.93)	0.040*** (24.27)
Market-to-Book Ratio	0.001*** (6.50)	0.001*** (5.93)	0.001*** (6.94)	0.001*** (6.25)	0.001*** (6.60)	0.001*** (6.17)
Dividend Yield	-0.001 (-1.52)	-0.003*** (-5.64)	-0.001* (-1.83)	-0.003*** (-5.67)	-0.001* (-1.72)	-0.003*** (-5.67)
Investor*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes	No	Yes
Observations	10,549,036	10,549,036	10,549,036	10,549,036	10,549,036	10,549,036
R <sup>2</sup>	0.440	0.442	0.440	0.442	0.440	0.442

Table B6: 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\*event level. T-values are reported in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	Sell		$-\frac{\Delta Holdings_{i,j,t}}{Holdings_{i,j,t-1}}$
ESG Stock	-0.016*** (-4.58)	-0.013*** (-4.78)	-0.012*** (-4.06)
Stock Turnover		0.047*** (11.54)	0.028*** (6.46)
Return Volatility		1.142*** (4.01)	0.984*** (3.21)
Ln(Market Cap)		0.039*** (4.02)	0.005 (0.56)
Market-to-Book Ratio		-0.000*** (-3.48)	-0.000*** (-3.34)
Dividend Yield		0.000 (0.10)	0.003* (1.89)
Stock*Event FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,391,080	1,391,080	1,391,080
R <sup>2</sup>	0.106	0.113	0.047

Table B7: 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 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 clustered at the investor level. T-values are in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Dependent Variable	TradeNum	BuyNum	SellNum
ESG Stock	-0.044*** (-5.20)	-0.024*** (-5.10)	-0.020*** (-4.92)
Ln(Stock Turnover)	0.126*** (23.04)	0.073*** (25.07)	0.053*** (19.68)
Return Volatility	6.949*** (16.19)	4.050*** (17.69)	2.900*** (13.69)
Ln(Market Cap)	0.217*** (27.48)	0.139*** (30.16)	0.078*** (22.21)
Market-to-Book Ratio	0.000* (1.73)	0.000* (1.95)	0.000 (1.50)
Dividend Yield	0.004* (1.69)	0.000 (0.00)	0.004*** (3.33)
Stock FE	Yes	Yes	Yes
Investor*Month FE	Yes	Yes	Yes
Observations	13,358,092	13,358,092	13,358,092
R <sup>2</sup>	0.602	0.550	0.587

Table B8: 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 month levels. 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	-0.016*** (-8.77)	-0.006*** (-5.11)	-0.111*** (-16.81)	-0.048*** (-9.04)
Female	-1.182*** (-13.43)		-8.573*** (-28.54)	
Education	0.093*** (7.38)		0.110** (2.59)	
Age	0.013*** (4.10)		-0.148*** (-8.06)	
Trading Experience	-0.000 (-0.18)		-0.079*** (-15.14)	
Portfolio Beta	0.920*** (6.41)	0.466*** (6.06)	2.809*** (5.31)	0.977*** (3.64)
Portfolio Beta for Size	0.378*** (6.22)	0.176*** (5.68)	1.317*** (4.60)	0.458*** (3.33)
Portfolio Beta for B-M	-0.455*** (-7.29)	-0.213*** (-5.73)	-1.458*** (-6.72)	-0.461*** (-4.09)
Investor FE	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	4,758,050	4,754,140	4,758,050	4,754,140
R <sup>2</sup>	0.042	0.175	0.177	0.437

Table B9: Home Bias and ESG Investing

In Panel A, we report the estimates of  $\beta$  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:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\beta$	25.233* (1.82)	27.951*** (4.21)	5.602*** (2.71)	2.415*** (2.89)	62.556*** (2.87)	41.123** (2.24)
ESG Stock Proportion	0.026*** (3.89)	0.025*** (3.79)	0.026*** (3.86)	0.021*** (3.10)	0.029*** (4.33)	0.025*** (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
Observations	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 (-1.33)	-0.0015 (-1.01)		
ESG Stock					0.0002 (0.05)	-0.0002 (-0.06)
Constant	4.6007*** (42.78)	3.5046*** (5.84)	3.4003*** (5.76)	4.6824*** (48.81)	0.0927*** (4.64)	0.0943*** (4.17)
Fixed Effects			Month	Month + Investor	Month + Stock	Investor*Month + Stock
Demographic Controls	No	Yes	Yes	No	No	No
Portfolio Controls	No	Yes	Yes	Yes	No	No
Stock Controls	No	No	No	No	Yes	Yes
Observations	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 B10: ESG Investing and SOE Investing

This table reports the results of estimation for the effects of life-time experience on investors' demand for stocks of state-owned enterprises (SOE), and for ESG stocks among non-SOE stocks. In Panel A, the dependent variable, *SOE Demand* is the value proportion of SOE stocks over the non-ESG portfolios. In Panel B, the dependent variable, *ESG Demand* is the value proportion of non-SOE stocks that are included in ESG indices over the non-SOE 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 month levels. T-values are in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: SOE Proportion over Non-ESG Portfolios						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	SOE Demand					
Experience:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	-1.042** (-2.75)	-1.840*** (-16.58)	5.007*** (15.79)	-0.388*** (-5.49)	2.261*** (8.84)	-0.013 (-0.07)
$\beta$	71.448 (0.66)	18.482 (1.49)	-7.539*** (-7.13)	-4.142*** (-2.74)	29.103** (2.46)	-32.473 (-0.96)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,875,608	2,876,148	2,698,342	2,572,898	2,824,395	2,862,791
$R^2$	0.553	0.553	0.578	0.532	0.555	0.554
Panel B: ESG Proportion over Non-SOE Portfolios						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	ESG Demand					
Experience:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	1.158*** (5.26)	0.403 (1.47)	1.500*** (4.87)	7.249*** (14.24)	-0.369*** (-3.58)	4.324*** (11.21)
$\beta$	24.250*** (2.93)	10.735 (1.40)	4.467** (2.21)	2.541*** (2.97)	69.154** (2.09)	40.638** (2.19)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,422,303	2,422,572	2,290,241	2,221,922	2,382,084	2,412,360
$R^2$	0.523	0.537	0.552	0.532	0.539	0.538

Table B11: ESG Investment and Environmental Regulation

This table estimates the relation between ESG investing and investors' experienced environmental regulation intensity. The dependent variable is the value of ESG stocks over the total value of the portfolio. In columns (1) and (2), the experience measure is given by waste reduction at the province level (i.e., one minus the ratio between amounts of gas, water and solid wastes that are emitted and produced), as in Chen and Chen (2021). In columns (3) and (4), it is given by government investment in pollution control over the total industrial output, as in Wang and Li (2021). 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 month levels. T-values are in parenthesis. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	ESG Demand			
Experience:	Waste Reduction		Govt. Envt. Expenditure	
$\lambda$	-2.203*** (-5.71)	1.265*** (3.28)	-1.484*** (-3.85)	0.626 (1.31)
$\beta$	2.845 (1.25)	8.681 (1.50)	3.473 (0.64)	14.604 (0.90)
Demographic Controls	Yes	No	Yes	No
Portfolio Controls	Yes	Yes	Yes	Yes
Investor FE	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,944,455	2,942,694	4,063,939	4,062,001
$R^2$	0.038	0.512	0.039	0.475

Table B12: Determinants of Investment in SSE 380 Stocks

This table reports the results of placebo tests for the effects of life-time experiences on the demand for SSE 380 stocks. The dependent variable is the value of the stocks that are included in the SSE 380 Index over the total value of the investor's portfolio. 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 month 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:	SSE380 Demand					
Experience:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	3.530*** (5.91)	1.242*** (6.37)	3.005*** (9.2)	-0.177 (-0.2)	0.184 (0.32)	1.110*** (3.21)
$\beta$	-1.247 (-0.34)	-9.027* (-1.98)	-4.635*** (-3.45)	-0.586 (-0.51)	19.567 (1.29)	62.636*** (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
Observations	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 B13: Alternative ESG Definition: Number of ESG Indices

This table reports the results of 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 month 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:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	0.631*** (7.85)	0.574*** (4.73)	0.299*** (4.02)	6.042*** (6.94)	-0.095 (-0.24)	7.899*** (7.65)
$\beta$	0.895** (2.43)	1.100*** (3.41)	0.738*** (6.86)	0.071** (2.24)	3.767*** (3.88)	1.161* (1.78)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	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 B14: Alternative ESG Definition: 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 month 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:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	0.917*** (4.09)	0.107 (1.27)	0.249*** (4.13)	1.054*** (11.36)	-0.455* (-1.89)	3.162*** (17.84)
$\beta$	89.079*** (2.84)	28.449*** (4.24)	11.505*** (5.16)	2.658*** (2.81)	-2.225 (-0.08)	35.788*** (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
Observations	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 B15: Alternative ESG Definition: Stricter Definition

This table reports the results of estimation for the effects of life-time experience on investors' ESG demand, defined with stricter standards. The dependent variable, *ESG Demand (strict)* is the proportion of stocks that are included at least three ESG indices. The mean of ESG demand is 13.6% with the stricter definition, with a standard deviation of 31.3%. 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 month 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:	ESG Demand (strict)					
Experience:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	2.435*** (13.76)	0.313*** (3.94)	2.741*** (3.81)	0.753*** (10.32)	-0.255** (-2.31)	2.272*** (16.71)
$\beta$	33.597** (2.36)	26.650*** (5.02)	7.201*** (8.17)	1.500* (1.91)	33.850** (2.59)	23.323** (2.32)
Portfolio Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,475,631	4,476,173	4,190,607	4,205,550	4,393,984	4,454,176
$R^2$	0.492	0.492	0.501	0.512	0.494	0.494

Table B16: Alternative ESG Demand Measure: Number Ratio

This table reports the results of the effects of life-time experiences on investors' ESG demand, defined by the number of ESG stocks over the total number of stocks held by the investor. The measure ranges from 0 to 100, with an average of 57.35 and standard deviation of 40.97. 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 month 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:	ESG Stock Number Proportion					
Experience:	GDP Growth	MKT Ret	Inv Ret	AQI	Natural Disaster	Corp. Scandals
$\lambda$	2.021*** (9.73)	0.386** (2.63)	0.845*** (8.78)	0.873*** (3.13)	-0.518*** (-8.68)	2.241*** (4.55)
$\beta$	6.139 (1.36)	28.972*** (4.55)	7.406*** (3.47)	2.692*** (2.87)	46.268** (2.32)	45.260** (2.19)
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
$R^2$	0.470	0.470	0.494	0.475	0.473	0.471

Table B17: Trading Patterns in SSE 380 Stocks

This table reports the results of the placebo tests on investment behaviors where the ESG indices are replaced by the SSE 380 Index. The dependent variable is the *ChurnRatio* in column (1), the *TradeNum* in column (2), the *Sell* in columns (3) and (5), and the *Buy* 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 and the sample construction are the same as in Table 9. 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. Standard errors are are clustered at the stock level in columns (1) and (2), at the stock\*event level in column(3), and two-way clustered at the investor and month levels in (4) and (5). 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	Sell	Buy	Sell	TradeNum	ChurnRatio
SSE 380 Index		0.001 (0.74)	-0.004 (-0.80)	-0.023*** (-3.92)	
Winner	0.061*** (43.56)				
SSE 380 Index * Winner	0.015*** (7.56)				
High Return		0.003*** (3.47)			
SSE 380 Index * High Return		0.001 (0.52)			
SSE 380 Index Prop					0.023*** (6.49)
Fixed Effects	Investor*Month + Stock*Month	Investor*Month + Stock	Stock*Event + Month	Investor*Month + Stock	Investor + Month
Stock Controls	No	Yes	Yes	Yes	No
Portfolio Controls	No	No	No	No	Yes
Observations	9,503,091	10,549,036	2,527,364	13,358,092	4,476,173
R <sup>2</sup>	0.623	0.442	0.119	0.602	0.428



Table B18: Trading Patterns and Alternative ESG Definition

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 *TradeNum* in column (2), the *Sell* in columns (3) and (5), and the *Buy* in column (4). *NumIndex* is the number of ESG Indices 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 Indices that the stock belongs to in a given month. Other variables and the sample construction are the same as in Table 9. 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. Standard errors are clustered at the stock level in columns (1) and (2), at the stock\*event level in column(3), and two-way clustered at the investor and month levels in columns (4) and (5). T-values are reported in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Sell	Buy	Sell	TradeNum	ChurnRatio
NumIndex		-0.019* (-1.66)	-0.030 (-1.49)	-0.240*** (-4.68)	
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)			
Value Weighted NumIndex					-0.849*** (-7.51)
Fixed Effects	Investor*Month + Stock*Month	Investor*Month + Stock	Stock*Event + Month	Investor*Month + Stock	Investor + Month
Stock Controls	No	Yes	Yes	Yes	No
Portfolio Controls	No	No	No	No	Yes
Observations	9,503,091	10,549,036	4,641,659	13,358,092	4,658,227
$R^2$	0.623	0.442	0.118	0.602	0.430

Table B19: Trading Patterns and ESG Ratings

This table estimates the investment behaviors on ESG stocks, defined by ESG ratings. The dependent variable is the *ChurnRatio* in column (1), the *TradeNum* in column (2), the *Sell* in columns (3) and (5), and the *Buy* 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 and the sample construction are the same as in Table 9. 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. Standard errors are are clustered at the stock level in columns (1) and (2), and two-way clustered at the investor and month levels in columns (3) and (4). T-values are reported in the parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable	Sell	Buy	TradeNum	ChurnRatio
High ESG Rated		0.005*** (3.02)	0.002 (0.23)	
Winner	0.068*** (51.20)			
High ESG Rated * Winner	-0.011*** (-5.88)			
High Return		0.004*** (5.00)		
High ESG Rated * High Return		-0.002* (-1.76)		
High ESG Rated Prop				-0.023*** (-4.77)
Fixed Effects	Investor*Month + Stock*Month	Investor*Month + Stock	Investor*Month + Stock	Investor + Month
Stock Controls	No	Yes	Yes	No
Portfolio Controls	No	No	No	Yes
Observations	8,498,682	9,433,860	11,652,520	4,232,138
R <sup>2</sup>	0.625	0.445	0.594	0.407

## Online Appendix C: 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  $\lambda$ . We obtain the  $\lambda$  with the smallest sum of squared residuals, which we call *grid\_optimal\_λ*. The second step is the least squared estimation to jointly estimate  $\lambda$  and  $\beta$ , using the *grid\_optimal\_λ* as the initial guess for  $\lambda$ . 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  $\lambda$ , where in each time, we reshuffle the residuals and re-estimate  $\lambda$ .

### 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]λ
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  
 $\lambda$ 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),  $\lambda$ 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  $\lambda$ . 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 beta_s
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 lambda 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 beta_s
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 lambda 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  $[-1 + \text{least-square-estimated } \lambda, 1 + \text{least-square-estimated } \lambda]$ , because the errors are reshuffled and thus the estimated  $\lambda$  can be different from the least-square-estimated  $\lambda$ .

---

#### Bootstrapping functions

---

```
boot_time_fe(btmes, 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(btmes, 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]
btmes = 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), btmes)
```

```
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), btmes)
```

---

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

---