Price of clean air: Evidence from Chinese ESG mutual funds

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Abstract

This study shows that Chinese environmental, social, and governance (ESG) funds act as impact investments and thus sacrifice financial returns in exchange for clean air. During the high air pollution period, the flow-performance relationship of ESG funds becomes weaker, consistent with the notion that ESG investors derive their utility from non-financial considerations. Our willingness-to-pay estimates suggest that investors may accept 1.6%-4.9% lower expected returns for ESG funds to combat air pollution. The ESG funds economically and statistically underperform (4.4%-4.8%) non-ESG funds during the high air pollution period.

JEL classification codes: G11, G23, Q53

Keywords: Air pollution; Environmental, social, and governance (ESG) funds; Mutual fund flows; Fund performance; willingness-to-pay

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I. Introduction

Environmental, social, and governance (ESG) investing, socially responsible investing (SRI), and impact investing are collectively referred to as responsible investments. However, differences exist in whether investors intend to have both financial and social returns (Pastor et al., 2021; Pedersen et al., 2021). The Global Impact Investing Network (GIIN) defines impact investing as investments made to generate positive, measurable social and environmental impacts alongside a financial return. Impact investors are willing to forgo financial returns for non-pecuniary benefits (Barber et al., 2021; Pastor et al., 2021). GIIN's (2020) survey result indicates that two-thirds of investors in impact investing principally target risk-adjusted, market-rate returns, while the remaining one-third target below-market rate.

This paper investigates whether investors are willing to pay for environmental impact. Specifically, we examine how air pollution, one of the most significant environmental threats to human health, attracts ESG and sustainability-conscious investors and subsequently influences the flows and future performance of ESG funds. We conduct this study in the Chinese context because China is one of the most polluted countries globally.[1] As the Chinese central government attempts to improve air quality and meet the social norm, investors are increasingly aware of the importance of aligning financial portfolios with sustainability. This study shows that ESG funds act more closely to impact investment during China's high air pollution periods, where the impact investing market has not yet been fully developed.

Air pollution can be a critical non-financial consideration in investment decision-making. The World Health Organization (WHO, 2018) estimates air pollution causes seven million premature deaths annually. Nonetheless, only a few previous studies directly link air pollution to investor behaviors. For example, Huang et al. (2020) and Li et al. (2021) examine the relationship between air pollution and individual investors' trading behavior and find that air pollution makes investors more susceptible to the disposition effect. However, the above studies do not investigate how air pollution affects the future performance associated with ESG funds or whether high air pollution periods affect the extent of willingness-to-pay (WTP) (Miller et al., 2011; Deschênes et al., 2017; Barber et al., 2021) to sacrifice financial returns for clean air. Many social scientists argue that social norms are critical in sculpting economic

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[1] According to WHO statistics, the average PM2.5 concentration (particles less than 2.5 micrometers in diameter) in 2016 was 51 μg/m^3 in China, over five times higher than WHO air quality guidelines.

behavior and market outcomes and superseding profit motives (e.g., Becker, 1957; Arrow, 1972; Hong and Kacperczyk, 2009). We maintain that the investment community aims to follow social norms when air pollution can seriously affect humans, environments, and capital markets. Thus, reducing air pollution becomes one of the most crucial social norms to protect human life.

To examine the effect of air pollution on investor behaviors, we obtain Chinese ESG equity mutual fund lists identified by SynTao Green Finance (2020). Our base sample consists of 30,225 fund-quarter[2] observations. After conducting a 3:1 nearest neighbor matching, the ESG and conventional matching funds (non-ESG funds) sample have 667 and 1,669 fund-quarter observations. We use China's air quality index (AQI) level obtained from the World Air Quality Index as a proxy for air pollution. During the sample period of 2014-2020, we first construct the AQI measure, which is defined as a quarterly mean value of the PM2.5 index for the ten largest cities in China: Beijing, Chengdu, Chongqing, Guangzhou, Hangzhou, Nanjing, Shanghai, Shenyang, Tianjin, and Wuhan (in alphabetical order). We then identify high (low) air pollution periods based on AQI as AQI is higher (lower) than the median value of the sample period. We assume that AQI affects aggregate investor preference and investment choice to create environmental change nationally, not locally. Although China shows a cross-sectional variation in ambient air pollution (Ito and Zhang, 2020; Li et al., 2021)[3], our identification of high/low air pollution periods is based on the nationwide time-series variation in air pollution.

Our empirical findings are as follows. We first find that the high AQI negatively impacts the flow-return sensitivity, implying that ESG fund investors care less about financial performance than conventional investors. This is consistent with our first hypothesis that high air pollution ESG funds' flows-performance association is lower than the corresponding effect on non-ESG funds. Secondly, although investors are likely to invest in ESG funds during high pollution periods, ESG funds underperform conventional funds following the high air pollution period, supporting our second hypothesis. Lastly, our WTP estimates suggest that ESG investors are willing to pay 1.6%-4.9% for ESG funds for clean air. Based on the ex-post performance estimation, the ESG funds yield 4.4%-4.8% lower risk-adjusted abnormal returns than non-ESG funds during the high air pollution period.

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[2] Since monthly fund total net asset (TNA) data, which is the primary variable to measure fund flows, is not readily available in China, this paper performs main analysis including fund flow measure on a quarterly basis.
[3] Chinese government policy (i.e., the Huai River heating policy) generates geographical variations in air pollution. The increases in coal usage in winter season unintentionally worsen the air quality of cities north of the river.

This study contributes to the existing literature as follows. First, this study relates to the ESG fund literature. Our findings related to the flow-performance relationship are consistent with the notion that ESG investors are likely to derive utility from non-financial considerations (Benson and Humphrey, 2008; Renneboog et al., 2011; El Ghoul and Karoui, 2017; Riedl and Smeets, 2017; Baker et al., 2018; Hartzmark and Sussman, 2019; Pastor et al., 2021). More importantly, this study shows that Chinese ESG funds act as impact investments and sacrifice financial returns for clean air. We take the asset-pricing approach to shed light on the ESG fund flows-performance relationship because fund returns are less susceptible to reverse causality and endogeneity problems than other financial performance measures. In particular, this study extends the literature on ESG investor behaviors in emerging markets. Although relations between ESG fund flows and performance are crucial, relevant research is just beginning, especially in emerging markets. We consider that taking a holistic approach to the overall assessment of flows and performance for each ESG fund is essential, particularly for those operating in emerging markets where the institutional infrastructure is less developed.

Second, this study directly relates air pollution to the behaviors of environmentally conscious fund investors. We provide new evidence that investors are willing to pay for environmental impact and ESG funds act as impact investment products during high air pollution periods. Barber et al. (2021) study venture capital (VC) funds and find that investors are willing to accept lower financial returns for impact. Our paper is different from Barber et al. (2021) in that we investigate investors' willingness to sacrifice return using a specific circumstance (i.e., high air pollution period). Similarly, Deschênes et al. (2017) argue that investors' WTP for air quality improvements depends on direct investments that help to determine factors that enter the utility function. However, the present study is distinct from the literature. We provide the direct impact of air pollution on ESG fund future performance and the empirical identification of the extent of WTP.

The remainder of this paper is organized as follows. Section II describes the literature and develops the hypotheses. Section III explains the data and defines the variables. Section IV provides the main empirical results regarding the association between air pollution and fund flows and performance. Section V presents robustness test results, and Section VI concludes this study.

II. Hypotheses development

Social norms are critical in forming economic behavior and market outcomes, overriding even the profit motive (Becker, 1957; Arrow, 1972; Hong and Kacperczyk, 2009). Becker (1957) initiates the model of discrimination. Subsequent theories of social norms (Akerlof, 1980; Romer, 1984; Glaeser and Sheinkman, 2003) provide sufficient conditions under which social customs that are disadvantageous to the individual nevertheless may persist if loss of reputation for disobedience of the social norm sanctions the individual. Researchers have examined various benefits of social norms. For example, Hong and Kacperczyk (2009) provide evidence of the significant effects of social norms on markets by studying the investing environment of "sin" stocks—publicly traded companies involved in producing alcohol, tobacco, and gambling, some subset of socially irresponsible stocks. In particular, they show a significant price effect on the order of 15–20% from large institutional investors shunning sin stocks.

We consider that combating air pollution has become a critical social norm in China. Because air pollution concerns are exogenous to the mutual fund industry, environmental and sustainability concerns may affect investor demand for ESG funds in a heterogeneous fashion. We also consider whether air pollution may affect fund managers' supply-side decisions in the later investigation. Past performance is one of the most critical determinants of conventional fund flows (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Del Guercio and Tkac, 2002). ESG (formerly SRI) investors seem less concerned about past returns. Instead, they are likely to derive utility from non-financial considerations (Bollen, 2007; Benson and Humphrey, 2008; Renneboog et al., 2011). Benson and Humphrey (2008) and Renneboog et al. (2011) show that SRI fund flows are less sensitive to past performance than conventional fund flows. In particular, Riedl and Smeets (2017) suggest that ESG investors are willing to forego financial performance to invest following their environmental preferences during high air pollution. Hartzmark and Sussman (2019) find that funds with the highest Morningstar sustainability ratings receive net inflows, while those with the lowest ratings experience net outflows. Pastor et al. (2021) claim that green assets have low expected returns because investors enjoy holding them and because green assets hedge climate risk.

These findings suggest that ESG investors emphasize non-financial attributes in their investment decisions and display loyalty to their funds. Therefore, we expect deteriorating air quality to affect ESG fund flows less responsive to past returns than corresponding effects on conventional funds. This argument leads to the first hypothesis:

H1: *Flow-performance relation of ESG funds becomes weaker during the high air pollution period.*

There are competing hypotheses regarding whether ESG funds can generate superior, inferior, or indifferent future performance, and the empirical study shows mixed evidence. On the one hand, ESG funds may underperform conventional funds because their screening process constrains the investment universe (Renneboog et al., 2008, 2011). On the other hand, ESG screens may eliminate poorly managed firms with underperforming stocks and thus generate superior fund performance (Edmans, 2011; In et al., 2019). Nevertheless, most literature shows that SRI funds perform similarly to conventional funds (Renneboog et al., 2008, 2011) or significantly underperform (El Ghoul and Karoui, 2017). To examine the relationship between ESG investor preference and fund performance, Renneboog et al. (2008, 2011) investigate whether ethical money flows can predict future fund performance. Renneboog et al. (2008), for instance, construct portfolios of SRI funds by tracking investors' decisions (inflows or outflows) and find that ethical investors cannot identify the funds that will outperform. Renneboog et al. (2011) further examine the effect of interactions between fund flows and specific SRI attributes on future fund performance. After considering the effects of various fund characteristics, they find that SRI funds that receive more inflows neither outperform nor underperform their benchmarks or conventional funds.

El Ghoul and Karoui (2017) show that high-scoring funds are associated with poor future performance. Riedl and Smeets (2017) similarly argue that socially responsible investors expect to earn lower returns on ESG funds than conventional funds and maintain that investors are willing to forgo financial performance to invest per their social preferences. Investors are willing to sacrifice financial performance or willing to pay a certain premium under their environmental and social preferences. Extant literature on impact investing by venture capital, Barber et al. (2021) shows that investors accept 2.5–3.7 ppts lower IRRs ex-ante for impact funds in random willingness-to-pay models. In behavioral economics, WTP is the maximum price at or below which a consumer will buy one product unit. This corresponds to the standard economic view of a consumer reservation price. Some researchers, however, conceptualize WTP as a range (Miller et al., 2011; Deschênes et al., 2017; Barber et al., 2021).

Pastor et al. (2021) suggest that "green" firms generate positive externalities for society while "brown" firms impose negative externalities. They argue that agents differ in their ESG preferences, which have multiple dimensions. First, agents derive utility from holdings of green firms and disutility from holdings of brown firms. Second, agents care about firms' aggregate social impact. They further maintain that agents are willing to pay more for greener firms, thereby lowering the firms' cost of capital.

Consequently, green assets have negative CAPM alphas, whereas brown assets have positive alphas. Henceforth, agents with stronger ESG preferences, whose portfolios tend toward green assets and away from brown ones, earn lower expected returns. Similarly, Pedersen et al. (2021) claim that expected excess returns of ESG-unaware investors are higher than those of ESG-motivated investors and show that the mean-variance frontier for all assets has higher returns and lower risk than the mean-variance frontier with ESG scores.

Based on prior literature, we postulate that ESG fund investing in China is inversely related to future fund performance, presumably due to its environmental protection and air pollution reduction motivations (Riedl and Smeets, 2017; Huang et al., 2020; Li et al., 2021). ESG and sustainability-conscious investors are more likely to act as impact investors during high air pollution periods because of their goals of providing social impact by reducing air pollution, even if they need to pay an additional WTP premium (Deschênes et al., 2017). This argument leads to the second hypothesis:

H2: *ESG funds underperform conventional funds following the high air pollution period.*

III. Sample and data

3.1. Base sample and fund variables

China's mutual fund data are obtained from the China Stock Market and Accounting Research (CSMAR) database provided by GTA Education Tech Ltd, a leading financial data provider in China. The CSMAR database contains information on fund codes, fund names, fund inception dates, expenses, total net assets (TNA) and NAV at the end of each quarter, and ex-rights and ex-dividend adjusted daily fund returns. We include actively managed ESG mutual funds that hold at least 70% of their assets in domestic stocks and exclude all index funds, passively managed funds (e.g., ETFs), and QDII funds. In this study, the base fund sample includes China's open-end equity and equity-oriented hybrid funds from 2014 to 2020.

Fund flow is the first key variable in this study. Following the standard measure used in the literature (Sirri and Tufano, 1998), we define the net fund flow for fund i in quarter t as follows:

$$Flow_{i,t} = \left[TNA_{i,t} - TNA_{i,t-1}\left(1 + r_{i,t}\right)\right]/TNA_{i,t-1} \tag{1}$$

where $TNA_{i,t}$ is the total NAV of fund i at the end of quarter $t,$ and $r_{i,t}$ is the fund return in quarter t. We assume that inflows and outflows occur at the end of each quarter and that investors reinvest their dividend distributions in the same fund. $Flow$ is winsorized at the 1% and 99% levels.

To measure a fund's performance, we use $Perf$ defined as a fractional rank ranging from 0 to 1 for each fund based on the fund's quarterly return ($Return$). The higher the $Perf$ value, the better the fund performance. We also estimate a fund's risk-adjusted performance ($Alpha$) based on the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model. The alpha is the sum of daily alphas computed by summing up all daily abnormal returns within the quarter t. Following the literature (Bollen, 2007; Bialkowski and Starks, 2016; El Ghoul and Karoui, 2017; Hartzmark and Sussman, 2019), we include a series of fund-level control variables in the empirical analysis. Fund size ($LnSize$) is defined as the natural logarithm of fund TNA (in millions of yuan, RMB). Fund age ($LnAge$) is defined as the natural logarithm of the number of months from the date the fund was established. Fund expenses ($Expense$) are defined as total operating expenses divided by total TNA at the end of the quarter. Fund return volatility ($Volatility$) is the standard deviation of daily fund returns in the quarter.

3.2. ESG and non-ESG fund Sample construction

ESG funds refer to portfolios for which environmental, social and governance factors have been integrated into the investment process. However, due to the divergence across ESG data provider and uncertainty about the ESG profile which can affect the market premium and economic welfare (Abramov et al., 2021), it is difficult to find the true ESG funds. To construct the ESG fund sample, we use the fund list identified by Syntao Green Finance and China SIF. To the extent that Syntao Green Finance and China SIF correctly identify the ESG funds, this process enables us to mitigate potential self-classification issues or self-selection bias (Benson et al., 2006; Joliet and Titova, 2018) and ensure that the fund effectively implements ESG screens. SynTao Green Finance (2020) verifies 127 pan-ESG mutual funds[4] related to environmental, social, governance, and sustainability in the Chinese market (as of October 2020). Among those pan-ESG mutual funds, we identify ESG equity funds that can match CSMAR data and exclude index funds and ETFs. Among ESG equity funds, we further identify funds into four categories by fund labels: "environmental (E)," "social (S)," "governance (G)," and "others (Others)," which contains terms of "ESG," "Sustainability," "responsibility," or which are not categorized in specific E, S, or G criteria, similar to Pedersen et al. (2021).

[4] Pan-ESG mutual funds include 5 bond funds, 63 equity funds and 59 hybrid funds.

Table 1 Panel A summarizes the ESG funds sample. During the sample period (2014-2020), ESG equity funds proliferate. The number of ESG funds was 11 in 2014 and has increased to 42 in 2020. The average TNA of funds was 9.5 billion RMB in 2014 and has increased to 102.3 billion RMB in 2020, accounting for 6.6% of all equity funds. Also, note that environmental fund accounts for the highest majority of ESG funds in China to pursue environmental sustainability.

For each of the ESG funds in our sample, we construct a sample of matched conventional funds (non-ESG funds) based on the propensity score matching methodology (Rosenbaum and Rubin, 1983). Following previous literature, we estimate the propensity score as the similarity measure between funds with logistic regression on fund characteristics, including fund TNA, fund family TNA, fund return, fund family return, alpha, and expense ratio. Next, we conduct a 3:1 nearest neighbor matching, and the procedure results in 38 ESG funds and 109 non-ESG funds. Table 1 Panel B and C present the key characteristics of ESG and non-ESG funds before and after the matching procedure. Notably, before matching in Panel B, ESG funds show common characteristics such as larger size, lower age, higher volatility, and lower flows compared to conventional funds. After matching in Panel C, the average fund size, age, flows, and performance of the ESG funds are similar to those of the non-ESG funds, and we find no statistical difference between the variables.

[Table 1 about here]

3.3 High and low pollution periods

As a proxy for air pollution, we use China's air quality index (AQI) level obtained from the World Air Quality Index (WAQI), which is a non-profit project that provides worldwide air quality information with an open data framework (www.aqicn.org). Since 2014, it has provided city-based daily concentrations of air pollutants such as PM2.5, PM10 (particulate matter between 2.5 and 10 μm), nitrogen dioxide, ozone, sulfur dioxide, and carbon monoxide. Among these pollutants, PM2.5 has been directly associated with adverse effects on human health as it has smaller particles that can penetrate deeper into the lungs, enter the bloodstream, and move to other organs.

During the sample period of 2014-2020, we first construct AQI measure, which is defined as the quarterly mean value of the PM2.5 index for the ten-representative cities[5] in China: Beijing, Chengdu, Chongqing, Guangzhou, Hangzhou, Nanjing, Shanghai, Shenyang,

[5] The results remain valid when we compute AQI measures based on the largest five or three cities.

Tianjin, and Wuhan (in alphabetical order). These ten cities are selected as we: (i) sort the largest cities by population, (ii) include tier-one and tier-two cities to consider the extent of economic and financial development, and (iii) exclude adjacent cities within one province to consider geographical distribution. For example, Guangzhou and Shenzhen are ranked the top three and four largest cities by population, respectively; however, both cities are in Guangdong province and geographically close. We thus exclude Shenzhen from the list of the ten cities. The higher the value of AQI, the greater the level of air pollution and the greater the health concern nationwide. We then identify high (low) air pollution periods based on AQI as AQI is higher (lower) than the median value of the sample period.[6]

Table 2 reports the summary statistics of AQI levels of each city (Panel A) and the AQI measure (Panel B) during 2014–2020. According to the WAQI, AQI levels above 100 are generally considered to be unhealthy: 101-150 unhealthy for children, adults, and people with respiratory disease; and 151-200 unhealthy for everyone and can cause health problems. The average PM2.5 concentration of the ten cities (AQI) was 123 μg/m^3, implying that China, on average, was exposed to unhealthy air quality. In particular, high AQI periods recorded the average PM2.5 concentration of 141.7 μg/m^3 with a maximum value of 173.4 μg/m^3, mostly issuing "red alert." In contrast, low AQI periods have an average PM2.5 concentration of 105.5 μg/m^3 ranging from 81.9 μg/m^3 to 119.8 μg/m^3.

IV. Empirical results

4.1. Air pollution and the flow-performance relations

Unlike conventional fund investors, ESG investors are less likely to consider past financial returns (Riedl and Smeets, 2017; Baker et al., 2018; Hartzmark and Sussman, 2019). We thus hypothesize that non-financial attributes, air pollution, can change the flow-performance relationship. For each ESG and non-ESG funds sample, we first estimate the following regression model:

$$\begin{aligned} Flow_{i,t} = \alpha + \beta_1 Perf_{i,t-1} + \beta_2 Perf_{i,t-1} * AQI_{t-1}^{High} + \beta_3 AQI_{t-1}^{High} \\ + \beta_4 LnTNA_{i,t-1} + \beta_5 LnAge_{i,t-1} + \beta_6 Expense_{i,t-1} \\ + \beta_7 Volatiltiy_{i,t-1} + \beta_8 Flow_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

[6] For the robustness check in section 5.1, we use the alternative AQI measure defined as the quarterly mean value of the PM2.5 index of the city where the respective fund company headquarters is located. This measure associates the local air quality level with the location of fund investors to further explain investors' demand for ESG funds.

where $Flow_{i,t}$ is the flow of fund i in quarter t. $Perf_{i,t-1}$ indicates fund performance and is defined as a fractional rank ranging from 0 to 1 for each fund based on quarter t-1. AQI_{t-1}^{High} is a dummy variable equal to one if the quarter t-1 lies in the high air pollution periods and zero otherwise. The control variables include fund size, age, expenses, fund return volatility, and past fund flows. We adjust standard errors for clustering at the time level.

Table 3 Columns (1) and (2) compare the flow-performance sensitivity for ESG and non-ESG funds. In Column (1), the coefficient of $Perf$ is statistically insignificant, implying that ESG fund flows are not sensitive to past performance. However, the coefficient of the interaction term between $Perf$ and AQI^{High} is -5.797 (t-statistic = -2.08) and significant at the 5% level, while the coefficient of AQI^{High} is 3.761 and is marginally significant at the 10% level. These results suggest that high AQI negatively impacts the flow-return sensitivity, while high AQI positively impacts fund flows. Among control variables, lagged fund size (age) is significantly and negatively (positively) associated with fund flows for ESG funds. In contrast, Column (2) shows the positive flow-performance sensitivity for the non-ESG funds, consistent with the previous literature (Sirri and Tufano, 1998; Del Guercio and Tkac, 2002). However, high AQI has no significant impact on flow and flow-performance sensitivity in Column (2). Column (3) further investigates the AQI and Flow-performance relationship with triple interaction regression. The coefficient of $Perf * AQI^{High} * ESG$ is -5.413 (t-statistic = -2.16) and significant at the 5% level. Overall, these findings support H1 that high air pollution ESG funds' flows-performance association is lower than the corresponding effect on non-ESG funds.

[Table 3 about here]

4.2. Air pollution and Fund future performance

We run a panel regression to examine the future performance of ESG funds following the high air pollution period. We use the following regression model:

$$\begin{aligned} Alpha_{i,t} = {} & \alpha + \beta_1 ESG_i + \beta_2 ESG_i * AQI_{t-1}^{High} + \beta_3 AQI_{t-1}^{High} + \beta_4 LnTNA_{i,t-1} \\ & + \beta_5 LnAge_{i,t-1} + \beta_6 Expense_{i,t-1} + \beta_7 Volatiltiy_{i,t-1} \\ & + \beta_8 Flow_{i,t-1} + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

where $Alpha_{i,t}$ indicates the future risk-adjusted performance of fund i in quarter t based on the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model, respectively. ESG_i is a dummy variable equal to one if a fund i is the ESG fund. AQI_{t-1}^{High} is a dummy variable equal to one if the quarter t-1 lies in the high air pollution periods and zero otherwise. The control variables include fund size, age, expenses, fund return volatility, and past fund flows. We adjust standard errors for clustering at the time level.

Table 4 reports the estimation results. Column (1) shows the baseline regression with the excess return. The results show that ESG funds generate neither positive nor negative future performance. In Column (2), the coefficient of the interaction term between ESG and AQI^{High} is -0.023 (t-statistic = -2.12) and significant at the 5% level, and it shows similar results based on CAPM alpha and 3-factor alpha except for 4-factor alpha. A possible explanation for the underperformance of the ESG funds during the high air pollution period is that the performance of environmentally sensitive firms is temporarily forced to shut down their factory by the Chinese government. The coefficient of AQI^{High} is also negative and statistically significant, implying that air pollution adversely influences future trading performance (Huang et al., 2020). Among control variables, fund expense significantly and negatively impacts future fund performance. These results support H2 that ESG funds underperform conventional funds following the high air pollution period.

[Table 4 about here]

4.3. Ex-ante willingness-to-pay estimation

If ESG investors derive their utility primarily from non-financial considerations and care less about financial performance than conventional investors, we expect that they are willing to sacrifice returns. To estimate investors' WTP for ESG funds to combat air pollution, we develop a discrete choice model following Barber et al. (2021). We begin with a random utility model in which investors face a binary choice of whether to invest in fund i:

$$y_i^* = f(\mathbb{E}[r_i], X_i, AQI, e_i) \tag{4}$$

where $\mathbb{E}[r_i]$ represent the expected return, X_i is the observable vector of nonprice fund characteristics such as fund size, age, and expense, and AQI represents the air quality index that enters into the investment decision of the environmentally-conscious investors, and e_i is an error term representing unobserved attributes. We assume that the error term has a mean zero and variance $\pi^2/3$. The latent variable y_i^* can be interpreted as the utility difference between choosing y_i = 1 or 0. We do not observe the random utility y_i^*, hence the observed variable is as follows:

$$y_i = \begin{cases} 1 & if \quad y_i^* > 0, \\ 0 & if \quad y_i^* \leq 0 \end{cases} \tag{5}$$

We use logit estimation with the base sample of equity mutual funds. The dependent variable is assigned one of two outcomes: 1 = invest in ESG funds (ESG fund has positive fund inflows) and 0 = not invest in ESG funds. The probability that we observe $y_i = 1$ is given by:

$$\Pr[y_i = 1] = \alpha + \beta * \mathbb{E}[r_i] + \gamma' * X_i + \delta * AQI + \varepsilon_i \tag{6}$$

where $\mathbb{E}[r_i]$ is the quarterly expected returns. The expected return is calculated by the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model using i) daily returns in the last three months in a rolling base and ii) monthly returns in the previous 24 months. Calculation of the expected return is introduced in the Appendix. X_i is a vector of fund attributes, including fund size, age, and expenses at quarter-end immediately preceding the investment. AQI is the standardized value of AQI in the quarter immediately preceding the investment. The WTP for ESG funds is derived from the equation as follows:

$$WTP = = -\frac{\partial \mathbb{E}[r]}{\partial AQI} = -\frac{\left(\frac{\partial \Pr[y=1]}{\partial AQI}\right)}{\left(\frac{\partial \Pr[y=1]}{\partial \mathbb{E}[r]}\right)} = -\frac{\delta}{\beta} \tag{7}$$

Table 5 reports the results of logit regression and WTP estimates. Columns (1) to (3) show the results with the expected returns calculated by using daily returns in the last three months on a rolling base, and Columns (4) to (6) show the results with the expected returns calculated by using monthly return in the previous 24 months. In Column (1), the coefficient on $Expected\ returns$ is -1.585 but insignificant. The coefficient on AQI is 0.056 and significant at the 5% level, implying that investors are more likely to invest in ESG funds with a higher level of AQI. WTP estimate is the ratio of the coefficient of AQI divided by the coefficient of $Expected\ returns$ (presented in percentage). We find that investors are willing to pay 3.5% (= 0.056/1.585) for ESG funds to combat air pollution. Using different model specifications to estimate expected returns in Columns (2) to (6), we find that our WTP estimates are robust. Overall, the results show that investors are willing to give up 1.6%-4.9% of ESG funds for clean air.

[Table 5 about here]

4.4. Ex-post performance estimation

Our findings suggest that ESG funds underperform conventional funds following the high air pollution period. In this section, we estimate the average ex-post performance of ESG funds relative to non-ESG funds based on the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model. Following the methodology in Nofsinger and

Varma (2014), we calculate a separate risk-adjusted abnormal return of the high AQI and low AQI periods. The model specification with Carhart's (1997) four-factor model is as follows:

$$r_t - r_{f,\mathrm{t}} = \alpha_{Low}LowAQI_t + \alpha_{High}HighAQI_t + \beta_{MKT}\left(r_{mkt,\mathrm{t}} - r_{f,\mathrm{t}}\right) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_t \quad (8)$$

where r_t is the monthly return on an equally weighted portfolio of funds in month t, $r_{f,t}$ is the risk-free rate, and $r_{mkt,t}$ is the value-weighted market index return. $HighAQI_t$ ($LowAQI_t$) is a dummy variable that is equal to one if the previous three-month rolling average of monthly AQI is above (below) the median value and zero otherwise.[7] SMB_t is the difference in returns between a small-cap portfolio and a large-cap portfolio, HML_t is the difference in returns between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks, and UMD_t is the difference in returns between a portfolio of past 12-month winners and a portfolio of past 12-month losers. The coefficient $\alpha_{High}(\alpha_{Low})$ is the monthly alpha during the high (low) air pollution period.

Table 6 Panel A presents alpha estimates of the portfolios of ESG and non-ESG during the entire sample period. The alphas are annualized for presentation. The results show that alphas for the ESG funds are not significantly different from the conventional fund alphas. Taking Carhart's (1997) four-factor alpha as an example, ESG funds have an average risk-adjusted return of 4.3%, and non-ESG funds have an average return of 4.7% with a 5% level significance. However, we find that the difference in alphas between ESG and non-ESG funds is statistically insignificant even at a 10% level significance, consistent with Renneboog et al. (2008, 2011).

Table 6 Panel B reports alpha estimates of the portfolios following the high and low AQI periods, respectively. Following the low AQI periods, both ESG and non-ESG funds generate significantly positive alphas ranging from 7.4% to 13.8% based on different models, but the ESG fund alpha is not significantly different from the non-ESG fund alpha. In contrast, the ESG funds significantly underperform the non-ESG funds following the high AQI periods. ESG funds are economically and statistically underperform 4.4 to 4.8% of the non-ESG funds following the high AQI periods. Panel C further shows factor loadings based on Carhart's (1997)

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[7] In this section, we estimate the monthly risk-adjusted abnormal returns using monthly returns and factors. However, we use longer time span for AQI (i.e., three-month rolling average), assuming that investors are not responsive to AQI a month immediately preceding investment, but responsive to at least previous three-month AQI.

four-factor model. We find that ESG funds are relatively more exposed to market risk and growth stock compared to conventional funds. Although not significant, ESG funds have more extensive exposure to large-cap and momentum stocks, which is different from the findings of Nofsinger and Varma (2014), which study US equity mutual funds.

[Table 6 about here]

V. Robustness tests

5.1. Air pollution and the flow-performance relations: alternative specification of AQI

We employ the alternative AQI measure (AQI_HQ), which enables us to link the location of fund investors to the local air pollution to explain investors' demand for ESG funds. We obtain a quarterly PM2.5 index of 380 cities in China from the CSMAR database, but the headquarters of the sample funds are mainly concentrated in five cities as Beijing, Shanghai, Guangzhou, Shenzhen, and Chongqing.[8] Table 7 reports the regression results of equation (2) using alternative definitions of AQI: $AQI\_hq_{i,t-1}^{High}$ is a dummy variable equal to one if the value of the PM2.5 index of the city where the respective fund i's headquarters is located is above the median cross-sectional value in quarter t-1. Consistent with the results in Table 3, the coefficient of the interaction term between $Perf$ and AQI_hq^{High} is -5.861 (t-statistic = -2.26) and significant at the 5% level for ESG funds in Column (1); however, it is not significant for non-ESG funds in Colum (2). Instead, the non-ESG funds show a positive flow-performance sensitivity. In Column (3), the coefficient of the triple interaction term is -5.509 (t-statistic = -2.26) and significant at the 5% level. These findings further support our first hypothesis that ESG fund flows are less sensitive to past performance during high air pollution.

[Table 7 about here]

5.2. Air pollution and ESG Fund inception decision

Although environmental and sustainability concerns mainly affect investor demand for ESG funds, they can also affect fund managers' supply-side decisions and motivate them to create new ESG funds. For example, suppose the compensation to fund managers increases if the fund managers design, create, and sell ESG funds that focus on securities that reduce air pollution. While the fund manager's compensation data is not readily available to the public in China, we run a logistic regression of the ESG fund inception by explanatory variables for fund family and ESG fund market characteristics. The dependent variable $ESGInception_{j,t}$ is a

[8] These cities (except Shenzhen) are also included in the calculation of AQI described in section 3.3.

dummy variable equal to one when a fund family j has inception of an ESG fund in a given quarter t and zero otherwise. $LnFamTNA_{j,t}$ is the natural logarithm of fund family TNA in quarter t. $NumFamInception_{j,t}$ is the number of any mutual fund inception by fund family j in quarter t. $NumESGInception_t$ is the number of ESG fund inception in the whole market in quarter t. $ESGReturn_t$ is the equal-weighted return of ESG funds in a 12-month period ending at the end of the quarter t.

Table 8 shows the regression results. Panel A shows descriptive statistics for each variable. Among the 871 fund family-quarter observations, there are 27 ESG fund inception decisions (3.1%). The average number of any mutual fund inception by fund family is 1.4 quarterly, with a maximum number of 8. The average number of ESG fund inception in the whole market is 1.4 quarterly, with a maximum number of 6. Panel B shows the logit regression result. The coefficient of AQI is 3.566 but statistically insignificant, implying that AQI does not affect the fund manager's inception decision, indirectly suggesting the relative weakness of the supply-side channel. However, family fund size and the equal-weighted return of ESG funds are positively associated with the new inception of ESG funds.

[Table 8 about here]

5.3. Diff-in-diff tests on Air pollution law

To mitigate a potential endogenous concern, we use the difference-in-difference analysis. On January 1, 2016, the Chinese New Air Prevention and Control Law came into effect to curb greenhouse gas emissions. To examine the impact of the air pollution law enactment on funds' future performance, we use the following specification:

$$Alpha_{i,t} = \alpha + \beta_1 ESG_i * Post_{t-1} + \beta_2 ESG_i + \beta_3 Post_{t-1} + \gamma' Contols_{i,t-1} + \varepsilon_{i,t} \qquad (9)$$

where $Alpha_{i,t}$ indicates the future risk-adjusted performance fund i in month t based on the Carhart's (1997) four-factor model. ESG_i is a dummy variable equal to one if the fund is the ESG fund. $Post_t$ indicates a dummy variable equal to one if month t is in the period after the law came into effect (2016-2017) and zero if month t is in the period before the law (2014-2015). $Controls_{i,t}$ includes fund size, age, expenses, fund return volatility, and past fund flows. The coefficient of diff-in-diff (β_1) captures the difference in fund alphas between the treatment and control groups included by the air pollution law.

Table 9 Panel A presents the univariate test results. During the pre-law period, ESG funds (treatment group) significantly underperform non-ESG funds (control group). However, during the post-law period, ESG funds are not significantly different from non-ESG funds. The

Diff-in-diff between ESG funds and non-ESG funds and between the pre- and post-law periods is 5.916% (t-statistic = 1.96) and significant. Panel B presents the multivariate regression results with and without control variables. In both specifications, the coefficient of the interaction term between ESG and $Post$ is negative and significant at the 5% level. These results suggest that governmental actions to implement the New Air Law may reduce air pollution and may cause a decrease in the underperformance of ESG funds.

To differentiate the impact investing hypothesis from the regulation hypothesis, we compare the underperformance of ESG vs. non-ESG funds that took place before the regulatory shutdown (the pre-law period) to the underperformance of ESG vs. non-ESG funds that took place after the regulatory shutdown (the post-law period). The DID test results show that first, a larger difference in underperformance is found between the two sets of pre-law period (5.851% (t-statistic = 2.35)), and second, insignificant difference during the post-law period (0.065% (t-statistics = 0.045)). Thus, the DID results support the impact investing hypothesis more than the regulation hypothesis because, during the pre-law period, ESG funds significantly underperform the non-ESG funds.

[Table 9 about here]

5.4. ESG fund performance: Inclusion of ESG factor

If investors price the ESG beta risk, the previous four-factor alpha may not properly capture the risk-adjusted performance. To further investigate fund performance and exposure to an ESG factor, we use the following regression model:

$$\begin{aligned} r_t - r_{f,\mathrm{t}} = {} & \alpha_{Low} LowAQI_t + \alpha_{High} HighAQI_t + \beta_{MKT}\left(r_{mkt,\mathrm{t}} - r_{f,\mathrm{t}}\right) + \beta_{SMB} SMB_t \\ & + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_{ESG} ESG_t + \varepsilon_t \end{aligned} \tag{10}$$

where r_t is the monthly return on an equally weighted portfolio of funds in month t, $r_{f,t}$ is the risk-free rate, and $r_{mkt,t}$ is the value-weighted market index return. $HighAQI_t$ ($LowAQI_t$) is a dummy variable that is equal to one if the previous three-month rolling average of monthly AQI is above (below) the median value and zero otherwise.[9] SMB_t, HML_t, and UMD_t are the

[9] In this section, we estimate the monthly risk-adjusted abnormal returns using monthly returns and factors. However, we use longer time span for AQI (i.e., three-month rolling average), assuming that investors are not responsive to AQI a month immediately preceding investment, but responsive to at least previous three-month AQI.

same as Equation (8). The coefficient $\alpha_{High}(\alpha_{Low})$ is the monthly alpha during the high (low) air pollution period.

ESG_t indicates the excess return of the ESG benchmark index. We use the value-weighted return of the indices of CNI EP Index (index code: 399358), CNI CSR Index (index code: 399369), and CNI Corporate Governance Index (index code: 399322), which are related to environmental, social, and governance, respectively.[10] We use the environmental-related index (CNI EP Index) alone for the robustness check, and the results are not changed (not reported).

Table 10 reports alpha estimates and factor loadings of the monthly time-series returns of an equally weighted portfolio of funds based on Carhart's (1997) four-factor model. The alphas are annualized for presentation. As expected, ESG funds have significantly higher exposure to the ESG factor than non-ESG funds. During the low AQI periods, both ESG and non-ESG funds generate significantly positive alphas, but the difference is not statistically significant. Conversely, the ESG funds still significantly underperform the non-ESG funds during the high AQI periods. These results further confirm that ESG funds underperform their conventional matching funds following the high air pollution periods. These findings are consistent with the theoretical predictions provided by Pastor et al. (2021) and Pedersen et al. (2021).

[Table 10 about here]

VI. Conclusion

This study examines the effect of air pollution on fund flows and performance using Chinese ESG funds from 2014 to 2020. China provides an ideal setting because the country's high levels of air pollution have attracted national attention and caused investors to react. We find that while ESG fund flows are positively related to the PM2.5 AQI in the previous quarter, their flow-performance sensitivity is lower than that of conventional funds. This finding supports the proposition that ESG investors derive their utility mainly from non-financial considerations (Bollen, 2007; Benson and Humphrey, 2008; Renneboog et al., 2008, 2011; Riedl and Smeets, 2017; Baker et al., 2018; Hartzmark and Sussman, 2019; Pastor et al., 2021).

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[10] CNI index provided by Shenzhen Securities Information Company Limited (SSIC) which is the first independent index provider in mainland China. The CNI EP Index, launched on January 2, 2008, comprises 40 A-shares related to the environment-friendly industry; the CNI CSR Index, launched on November 4, comprises 100 A-shares related to a good performance in the performance of social responsibility; and CNI Corporate Governance Index, launched on December 12, 2005, comprises 50 A-shares based on shareholder protection, governance structure, external supervision, and business performance.

Although investors are likely to invest in ESG funds during high pollution periods, this trading behavior adversely influences future fund performance. We find that investors are willing to forgo 1.6%-4.9% for ESG funds for clean air. Based on the ex-post performance calculation, ESG funds are economically and statistically underperform 4.4 to 4.8% of the non-ESG funds following the high AQI periods.

To the best of our knowledge, this is one of the pioneering studies that relate air pollution to ESG mutual fund flows and performance in China, an emerging country. We show that ESG funds act as impact investments and sacrifice financial returns to combat nationwide air pollution. However, this study has a few limitations. We did not address how air pollution is likely to incite portfolio managers to rebalance their portfolios and what is the outcome of the rebalancing activity? It will be fruitful if future studies examine the economic channels of the effects of air pollution on fund future performance and the motives for the increase and decrease in fund flows. Furthermore, future studies could assess whether the various fee structures and compensation plans of ESG fund managers motivate them to advocate ESG portfolios.

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Table 1. ESG and Non-ESG sample construction

This table summarizes the construction of the ESG and Non-ESG sample used throughout this study. Panel A reports the numbers and TNAs of pan-ESG equity mutual funds verified by SynTao Green Finance (2020). TNA (in billion RMB) is the average total net assets. All equity mutual funds include funds in our base sample (before matching). Among ESG funds, funds are categorized into "environmental (E)," "social (S)," "governance (G)," and others (Others). Panel B and Panel C report the summary statistics for ESG and non-ESG funds before and after propensity score matching procedure, respectively. $LnTNA$ is defined as the natural logarithm of the fund TNA. $LnAge$ is defined as the natural logarithm of the number of months from the date the fund was established. $Expense$ is defined as total operating expenses divided by total TNA at the end of the previous quarter. $Volatility$ is the standard deviation of the daily fund returns in the previous quarter. $Flow$ is defined as the net growth in fund assets. $Perf$ is defined as a fractional rank ranging from 0 to 1 for each fund based on the fund's quarterly return ($Return$). $CAPM\ Alpha$, $3-factor\ Alpha$, and $4-factor\ Alpha$ are the sum of the daily alphas computed through the previous three-month rolling window based on the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model, respectively. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary of Pan-ESG equity mutual funds

Year	Number of funds					TNA (in billion RMB)					ESG funds (%) of all equity funds	
	ESG	E	S	G	Other	ESG	E	S	G	Other	By number of funds	By TNA
2014	11	6	2	1	2	9.51	1.50	0.77	0.12	7.13	2.24	1.37
2015	16	11	2	1	2	25.75	17.13	4.87	0.05	3.69	2.58	3.17
2016	26	21	2	1	2	29.13	25.85	3.01	0.16	0.11	2.67	2.76
2017	32	27	2	1	2	32.94	26.64	3.84	0.20	2.26	2.60	2.90
2018	38	33	2	1	2	24.29	20.06	2.51	0.05	1.67	2.70	3.06
2019	42	37	2	1	2	34.14	29.43	2.73	0.11	1.87	2.62	3.08
2020	42	37	2	1	2	107.71	102.30	1.96	0.26	3.19	2.59	6.55

Panel B. Fund sample before matching

	Mean	Std.Dev	Median	Mean	Std.Dev	Median	t-statistic
	ESG funds (n=786)			Conventional funds (n=29,439)			Difference
LnTNA	5.844	1.680	5.794	5.654	1.771	5.763	2.95***
lnAge	3.837	0.639	3.861	3.921	0.685	3.932	-3.39***
Expense	0.019	0.045	0.015	0.032	0.105	0.015	-3.42***
Volatility	0.014	0.007	0.013	0.013	0.007	0.012	7.30***
Flow	0.795	7.694	-0.041	1.634	11.115	-0.046	-2.05***
Return	0.056	0.144	0.035	0.048	0.124	0.030	1.78*
Perf	0.519	0.307	0.520	0.499	0.287	0.499	1.87*
CAPM Alpha	0.025	0.075	0.020	0.021	0.065	0.015	1.65*
3-factor Alpha	0.011	0.070	0.011	0.006	0.055	0.007	2.45**
4-factor Alpha	0.018	0.070	0.013	0.011	0.055	0.009	3.55***

Pane C. Fund sample after matching

	ESG funds (n=667)			Non-ESG funds (n=1,669)			Difference
LnTNA	5.762	1.689	5.550	5.766	1.735	5.854	-0.05
lnAge	3.893	0.598	3.892	3.911	0.629	3.892	-0.65
Expense	0.020	0.048	0.015	0.019	0.046	0.014	0.25
Volatility	0.014	0.007	0.013	0.013	0.006	0.012	4.40***
Flow	0.861	8.159	-0.042	1.025	9.032	-0.044	-0.40
Return	0.058	0.142	0.038	0.056	0.127	0.038	0.29
Perf	0.521	0.302	0.522	0.520	0.289	0.540	-0.06
CAPM Alpha	0.025	0.074	0.020	0.026	0.067	0.021	-0.35
3-factor Alpha	0.010	0.069	0.011	0.011	0.055	0.009	-0.09
4-factor Alpha	0.017	0.069	0.012	0.016	0.055	0.011	0.55

Table 2. Summary statistics of AQI

This table reports summary statistics of AQI measures during 2014-2020. Panel A reports the summary statistics of PM2.5 level (µg/m3) for the ten cities in China. Panel B reports the summary statistics of PM2.5 level (µg/m3) of AQI measure, which is the average PM2.5 quarterly level for the ten largest cities in China. High and Low periods are divided by the median value of AQI.

Panel A. PM2.5 level (µg/m3) by cities					
City	Mean	Std.Dev	Median	Min	Max
Beijing	123.599	26.291	116.237	87.098	187.289
Chengdu	132.028	25.878	129.967	76.835	182.100
Chongqing	125.409	26.786	128.383	71.989	177.767
Guangzhou	95.887	20.835	92.600	58.576	137.411
Hangzhou	127.963	23.912	127.811	87.120	169.644
Nanjing	123.573	25.766	121.315	76.511	176.811
Shanghai	107.000	17.552	105.319	79.580	135.167
Shenyang	127.166	29.665	119.102	82.380	188.101
Tianjin	130.758	25.144	127.200	93.696	189.011
Wuhan	142.430	30.373	136.209	90.275	209.900
Panel B. PM2.5 level (µg/m3) of AQI measure					
AQI	123.602	23.327	120.218	81.896	173.437
High AQI period	141.687	16.278	141.352	120.634	173.437
Low AQI period	105.516	12.675	107.594	81.896	119.803
Difference (t-statistics)	36.171***	(6.560)			

Table 3. AQI and Flow-performance relationship

This table reports the results from regressing fund flows in quarter t on lagged fund variables for ESG and non-ESG funds separately. AQI_{t-1}^{High} is a dummy variable equal to one if the quarter t-1 lies in the high air pollution periods and zero otherwise. ESG_i is a dummy variable equal to one if a fund i is the ESG fund. Control variables include fund size, age, expenses, volatility, and past fund flow. Columns (1) and (2) use ESG and non-ESG fund subsamples, respectively. Column (3) uses both ESG and non-ESG fund samples with triple interaction regression. We adjust standard errors for clustering at the time level. t-statistics are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	ESG funds	Non-ESG funds	All funds
	(1)	(2)	(3)
$Perf_{i,t-1} * AQI^{High}{}_{t-1} * ESG_i$			-5.413**
			(-2.16)
$Perf_{i,t-1}$	2.035	2.128***	2.097***
	(1.51)	(2.81)	(3.05)
$Perf_{i,t-1} * AQI^{High}{}_{t-1}$	-5.797**	-0.505	-0.500
	(-2.08)	(-0.46)	(-0.47)
$AQI^{High}{}_{t-1}$	3.761*	0.479	0.458
	(1.96)	(0.68)	(0.64)
$LnTNA_{i,t-1}$	-1.689***	-2.049***	-1.961***
	(-2.97)	(-3.76)	(-4.57)
$LnAge_{i,t-1}$	2.043***	1.274*	1.421**
	(3.02)	(1.96)	(2.76)
$Expense_{i,t-1}$	-14.335	-17.430**	-16.017**
	(-1.56)	(-2.72)	(-2.75)
$Volatility_{i,t-1}$	-16.421	-36.973	-30.930
	(-0.36)	(-0.88)	(-0.87)
$Flow_{i,t-1}$	-0.006	-0.020*	-0.013*
	(-0.96)	(-1.87)	(-1.77)
$AQI^{High}{}_{t-1} * ESG_i$			3.263*
			(1.88)
$Perf_{i,t-1} * ESG_i$			0.035
			(0.02)
ESG_i			-0.416
			(-0.54)
$Intercept$	1.804	7.588***	6.419***
	(1.10)	(3.01)	(2.90)
Observations	627	1548	2175
R-squared	0.152	0.130	0.134

Table 4. AQI and future performance of ESG funds

This table reports the panel regression results. The dependent variables are excess return and alphas based on the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model, respectively. AQI_{t-1}^{High} is a dummy variable equal to one if the quarter t-1 lies in the high air pollution periods and zero otherwise. ESG_i is a dummy variable equal to one if a fund i is the ESG fund. Control variables include fund size, age, expenses, volatility, and flow. Control variables include fund size, age, expenses, volatility, and past fund flow. We adjust standard errors for clustering at the time level. t-statistics are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Alpha =	Excess Return		CAPM Alpha		3-factor Alpha		4-factor Alpha	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AQI^{High}{}_{t-1} * ESG$		-0.023**		-0.019**		-0.018*		-0.012
		(-2.12)		(-2.24)		(-1.98)		(-1.32)
$AQI^{High}{}_{t-1}$		-0.081**		-0.024*		-0.020*		-0.022*
		(-2.15)		(-1.73)		(-1.84)		(-2.05)
ESG	-0.005	0.005	-0.004	0.004	0.001	0.008	0.003	0.008
	(-0.66)	(0.47)	(-0.69)	(0.53)	(0.22)	(1.14)	(0.60)	(1.04)
$LnTNA_{t-1}$	-0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.002*
	(-0.59)	(0.07)	(0.79)	(1.13)	(1.38)	(1.57)	(1.65)	(1.77)
$LnAge_{t-1}$	0.002	-0.000	-0.001	-0.002	-0.004**	-0.005**	-0.003	-0.004
	(0.51)	(-0.10)	(-0.55)	(-1.00)	(-2.14)	(-2.58)	(-1.24)	(-1.70)
$Expense_{t-1}$	-0.099*	-0.076	-0.086***	-0.077***	-0.090***	-0.082***	-0.084***	-0.076***
	(-1.91)	(-1.48)	(-3.01)	(-2.80)	(-3.63)	(-3.36)	(-4.02)	(-3.56)
$Volatility_{t-1}$	4.394	4.390	2.042**	2.044***	-0.648	-0.646	-0.674	-0.673
	(1.27)	(1.52)	(2.35)	(2.82)	(-0.60)	(-0.61)	(-0.82)	(-0.79)
$Flow_{t-1}$	0.000	-0.000	0.000***	0.000**	0.000*	0.000	0.000*	0.000
	(0.33)	(-0.49)	(2.94)	(2.26)	(2.02)	(1.38)	(1.72)	(1.10)
$Intercept$	-0.002	0.029	0.003	0.013	0.032**	0.041**	0.030*	0.039**
	(-0.04)	(0.58)	(0.17)	(0.77)	(2.13)	(2.76)	(1.90)	(2.52)
Observations	2175	2175	2175	2175	2175	2175	2175	2175
R-squared	0.049	0.150	0.041	0.086	0.014	0.061	0.014	0.060

Table 5. Ex-ante willingness-to-pay estimation

This table reports the logit estimation results and WTP estimates. The dependent variable is assigned one if ESG fund j have positive fund inflows and zero otherwise. The expected return is calculated based on the CAPM, Fama and French (1993) three-factor model, and Carhart's (1997) four-factor model using i) daily returns in the last three months in a rolling base and ii) monthly data in the previous 36 months. Calculation of the quarterly expected return is introduced in the Appendix. Expected returns are annualized for presentation. $LnTNA$ is defined as the natural logarithm of the fund TNA. $LnAge$ is defined as the natural logarithm of the number of months from the date the fund was established. $Expense$ is defined as total operating expenses divided by total TNA at the end of the previous quarter. AQI_{t-1} is the standardized value of AQI in quarter t-1. WTP estimate is the ratio of AQI coefficient divided by the coefficient of Expected returns and presented in percentage. t -statistics are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Expected return =	using daily returns in the last three months			using monthly data in the previous 36 months		
	CAPM model	3-factor model	4-factor model	CAPM model	3-factor model	4-factor model
	(1)	(2)	(3)	(4)	(5)	(6)
$Expected\ return_t$	-1.585	-1.295	-1.213	-1.192	-3.076	-1.951
	(-1.63)	(-1.60)	(-1.58)	(-0.42)	(-1.52)	(-1.30)
$LnTNA_{t-1}$	-0.040***	-0.040***	-0.041***	-0.039***	-0.039**	-0.039***
	(-2.66)	(-2.68)	(-2.70)	(-2.59)	(-2.57)	(-2.62)
$LnAge_{t-1}$	0.245***	0.247***	0.246***	0.242***	0.242***	0.244***
	(6.50)	(6.53)	(6.52)	(6.43)	(6.43)	(6.47)
$Expense_{t-1}$	2.331***	2.329***	2.327***	2.342***	2.341***	2.340***
	(4.29)	(4.28)	(4.28)	(4.30)	(4.30)	(4.30)
AQI_{t-1}	0.056**	0.059**	0.060***	0.056**	0.050**	0.053**
	(2.39)	(2.56)	(2.58)	(2.36)	(2.11)	(2.24)
$Intercept$	1.729***	1.726***	1.727***	1.726***	1.727***	1.726***
	(11.32)	(11.30)	(11.31)	(11.30)	(11.31)	(11.31)
WTP estimate (%)	3.533	4.556	4.946	4.698	1.625	2.717
Observations	26476	26476	26476	26476	26476	26476
Pseudo R-squared	0.0064	0.0063	0.0063	0.0064	0.0063	0.0063

Table 6. Ex-post fund performance and factor loadings

This table presents time-series returns of the equally weighted ESG and non-ESG funds portfolios based on the CAPM, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model. The difference is a portfolio constructed by subtracting non-ESG from ESG fund returns. Panel A reports alphas for the entire sample periods, and Panel B reports the separate alphas for high and low air pollution periods. Panel C reports the alphas and factor loadings on Carhart's (1997) four-factor model. $HighAQI_t$ ($LowAQI_t$) is a dummy variable that equals to one if the previous three-month rolling average of monthly AQI is above (below) the median value and zero otherwise. The estimates of alphas are annualized and presented in percentages. t-statistics are computed with the Newey-West standard errors and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Alpha during the entire period

	CAPM Alpha	3-factor Alpha	4-factor Alpha
ESG funds	4.784	4.465	4.261
	(1.04)	(1.42)	(1.41)
Non-ESG funds	5.079	4.813**	4.653**
	(1.43)	(2.49)	(2.62)
Difference	-0.295	-0.347	-0.391
	(-0.15)	(-0.17)	(-0.20)

Panel B. Alpha during the separate high and low AQI period

	Low AQI			High AQI		
	CAPM	3-factor	4-factor	CAPM	3-factor	4-factor
ESG funds	13.805**	12.158***	11.015***	-4.404	-3.358	-2.580
	(2.21)	(2.93)	(2.69)	(-0.69)	(-0.87)	(-0.71)
Non-ESG funds	9.689**	8.387***	7.461***	0.383	1.178	1.808
	(2.14)	(3.69)	(3.43)	(0.07)	(0.41)	(0.70)
Difference	4.115	3.771	3.554	-4.787**	-4.536*	-4.388*
	(1.32)	(1.27)	(1.18)	(-2.09)	(-1.98)	(-1.92)

Panel C. Alpha and factor loadings for the 4-factor model

	Alpha		MKT	SMB	HML	UMD	R-sq
	Low AQI	High AQI					
ESG funds	11.015***	-2.580	0.925***	-0.012	-0.609***	0.228***	0.927
	(2.69)	(-0.71)	(22.04)	(-0.14)	(-7.31)	(4.25)	
Non-ESG funds	7.461***	1.808	0.851***	0.037	-0.518***	0.185***	0.964
	(3.43)	(0.70)	(35.18)	(0.82)	(-8.54)	(5.60)	
Difference	3.554	-4.388*	0.074***	-0.049	-0.091*	0.043	0.212
	(1.18)	(-1.92)	(2.73)	(-0.88)	(-1.81)	(1.02)	

Table 7. AQI and Flow-performance relationship: alternative specifications of AQI

This table reports the results from regressing fund flows in quarter t on lagged fund variables for ESG and non-ESG funds separately. $AQI\_hq_{i,t-1}^{High}$ is a dummy variable equal to one if the value of the PM2.5 index of the city where the respective fund i's headquarters is located is above the median cross-sectional value in quarter t-1. ESG_i is a dummy variable equal to one if a fund i is the ESG fund. Control variables include fund size, age, expenses, volatility, and past fund flow. Columns (1) and (2) use ESG and non-ESG fund subsamples. Column (3) uses both ESG and non-ESG fund samples with triple interaction regression. We adjust standard errors for clustering at the time level. t-statistics are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	ESG funds	Non-ESG funds	All funds
	(1)	(2)	(3)
$Perf_{i,t-1} * AQI\_hq^{High}{}_{i,t-1} * ESG_i$			-5.509**
			(-2.26)
$Perf_{i,t-1}$	2.164	2.142***	2.108***
	(1.60)	(2.91)	(3.10)
$Perf_{i,t-1} * AQI\_hq^{High}{}_{i,t-1}$	-5.861**	-0.565	-0.544
	(-2.26)	(-0.47)	(-0.45)
$AQI\_hq^{High}{}_{i,t-1}$	3.813**	0.013	-0.018
	(2.10)	(0.02)	(-0.02)
$LnTNA_{i,t-1}$	-1.694***	-2.037***	-1.954***
	(-2.97)	(-3.73)	(-4.54)
$LnAge_{i,t-1}$	2.034***	1.268*	1.419**
	(3.01)	(1.96)	(2.74)
$Expense_{i,t-1}$	-14.417	-17.245**	-15.928**
	(-1.56)	(-2.70)	(-2.71)
$Volatility_{i,t-1}$	-24.681	-38.346	-34.470
	(-0.55)	(-0.91)	(-0.95)
$Flow_{i,t-1}$	-0.009	-0.022**	-0.015**
	(-1.39)	(-2.06)	(-2.07)
$AQI\_hq^{High}{}_{i,t-1} * ESG_i$			3.844**
			(2.51)
$Perf_{i,t-1} * ESG_i$			0.197
			(0.14)
ESG_i			-0.651
			(-0.82)
$Intercept$	1.948	7.727***	6.609***
	(1.22)	(3.08)	(2.99)
Observations	627	1548	2175
R-squared	0.152	0.130	0.134

Table 8. Determinants of ESG fund inception

This table reports the logistic regression result of the incidence of ESG fund inception by explanatory variables for fund family and ESG fund market characteristics. The dependent variable $ESGInception_{j,t}$ is a dummy variable equal to one when a fund family j has inception of ESG fund in a given quarter t and zero otherwise. $LnFamTNA_{j,t}$ is the natural logarithm of fund family TNA in quarter t. $NumFamInception_{j,t}$ is the number of any mutual fund inception by fund family j in quarter t. $NumESGInception_{t}$ is the number of ESG fund inception in the whole market in quarter t. $ESGReturn_{t}$ is the equal-weighted return of ESG funds in a 12-month period ending at the end of the quarter t. We adjust standard errors for clustering at the time level. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Descriptive statistics (n=871)

	Mean	Std.Dev	Median	Min	Max
$ESGInception_{j,t}$	0.031	0.173	0.000	0.000	1.000
$LnFamTNA_{j,t}$	8.645	1.923	9.195	-2.429	11.614
$NumFamInception_{j,t}$	1.447	0.876	1.000	1.000	8.000
$NumESGInception_{t}$	1.437	1.846	1.000	0.000	6.000
$ESGReturn_{t}$	0.157	0.305	0.084	-0.240	0.891

Panel B. Logit regression

	Coefficient	Walt test value (z)
AQI_{t-1}	3.566	1.51
$LnFamTNA_{j,t}$	0.546*	1.67
$NumFamInception_{j,t}$	0.112	0.32
$NumESGInception_{t}$	-0.208	-1.24
$ESGReturn_{t}$	1.691**	2.53
$Intercept$	-26.967**	-2.48
Observations	871	
Pseudo R-squared	0.151	

Table 9. Diff-in-diff tests on the air pollution law enactment

This table reports the diff-in-diff test results associated with China's air pollution law enactment in 2016. Panel A presents the average monthly four-factor alpha for ESG funds (treatment group) and non-ESG funds (control group) in the pre-law (2014–2015) and post-law (2016–2017) periods. The alphas are annualized and presented in percentages. Panel B presents the multivariate specification results. The dependent variable is the monthly four-factor alpha in quarter t. ESG_i is a dummy variable equal to one if the fund is the ESG fund. $Post_t$ indicates a dummy variable equal to one if month t is in the period after the law came into effect and zero if month t is in the period before the law. Control variables include fund size, age, expenses, fund return volatility, and past fund flows. t-statistics are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Univariate specification		
	Alpha	(t-statistic)
Pre-law period		
ESG (Treated)	-19.17	-
Non-ESG (Control)	-13.32	-
Diff	-5.851**	(-2.350)
Post-law period		
ESG (Treated)	0.887	-
Non-ESG (Control)	0.822	-
Diff	0.065	(0.045)
Diff-in-diff	5.916**	(1.961)
Observations	2787	
R-squared	0.0469	

Panel B. Multivariate specification		
	(1)	(2)
$ESG_i * Post_{i,t-1}$	0.0052**	0.0055**
	(2.06)	(2.07)
ESG_i	-0.0049**	-0.0045**
	(-2.34)	(-2.08)
$Post_{i,t-1}$	0.0118***	0.0111***
	(8.34)	(7.59)
$LnSize_{i,t-1}$		0.0009**
		(2.57)
$LnAge_{i,t-1}$		-0.0025***
		(-2.79)
$Expense_{i,t-1}$		-0.0132
		(-1.40)
$Volatiltiy_{i,t-1}$		-0.0481***
		(-3.10)
$Flow_{i,t-1}$		0.0000
		(0.28)
Intercept	-0.0111***	-0.0035
	(-9.66)	(-0.81)
Observations	2684	2452
R-squared	0.048	0.063

Table 10. Fund performance and factor loadings: including ESG style factor

This table presents time-series returns of the equally weighted portfolios of ESG and non-ESG funds based on Carhart's (1997) four-factor model and ESG factor. ESG_t indicates the excess return of the ESG benchmark index. We use the value-weighted return of the indices of CNI EP Index (index code: 399358), CNI CSR Index (index code: 399369), and CNI Corporate Governance Index (index code: 399322). The difference is a portfolio constructed by subtracting non-ESG from ESG fund returns. $HighAQI_t$ ($LowAQI_t$) is a dummy variable that equals to one if the previous three-month rolling average of monthly AQI is above (below) the median value and zero otherwise. The estimates of alphas are annualized and presented in percentages. t-statistics are computed with the Newey-West standard errors and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Alpha		MKT	SMB	HML	UMD	ESG	R-sq
	Low AQI	High AQI						
ESG funds	8.629***	-3.217	0.314*	0.213***	-0.533***	0.256***	0.647***	0.941
	(2.68)	(-0.97)	(1.84)	(2.70)	(-8.69)	(5.62)	(3.49)	
Non-ESG funds	6.639***	1.588	0.641***	0.115**	-0.492***	0.194***	0.223**	0.967
	(3.09)	(0.65)	(6.77)	(2.23)	(-9.18)	(6.52)	(2.13)	
Difference	1.990	-4.806**	-0.326**	0.098	-0.041	0.062	0.424***	0.346
	(0.85)	(-2.02)	(-2.46)	(1.64)	(-1.09)	(1.54)	(3.07)	

Appendix. Calculation of the expected return

As an example of Carhart's (1997) four-factor model, we calculate two types of expected returns on a quarterly basis. The first expected return is calculated by using daily returns in the last three months on a rolling base. For each fund i in month τ, we first fit the following factor model using daily data from τ-3 to τ -1:

$$r_{i,d} - r_{f,d} = a_{i,\tau} + b1_{i,\tau}(r_{m,d} - r_{f,d}) + b2_{i,\tau}SMB_d + b3_{i,\tau}HML_d + b4_{i,\tau}UMD_d + \varepsilon_{i,d}$$

For each fund i in month τ, we estimate the daily expected return using factor loadings estimated above.

$$Expected\ return_{i,d} = r_{f,d} + \widehat{b1}_{i,\tau}(r_{m,d} - r_{f,d}) + \widehat{b2}_{i,\tau}SMB_d + \widehat{b3}_{i,\tau}HML_d + \widehat{b4}_{i,\tau}UMD_d$$

We then compute quarterly expected returns by summing up all daily returns within quarter t.

The second expected return is calculated by using the monthly return in the previous 24 months. For each fund i in month τ, we first fit the following factor model from τ-24 to τ-1:

$$r_{i,\tau} - r_{f,\tau} = a_{i,\tau} + b1_{i,\tau}(r_{m,\tau} - r_{f,\tau}) + b2_{i,\tau}SMB_\tau + b3_{i,\tau}HML_\tau + b4_{i,\tau}UMD_\tau + \varepsilon_{i,\tau}$$

For each fund i in month τ, we estimate the monthly expected return using factor loadings estimated above.

$$Expected\ return_{j,t} = r_{f,t} + \widehat{b1}_{j,t}(r_{m,t} - r_{f,t}) + \widehat{b2}_{j,t}SMB_t + \widehat{b3}_{j,t}HML_t + \widehat{b4}_{j,t}UMD_t$$

We then compute quarterly expected return by summing up all monthly returns within quarter t.