Green Price Pressure*

Xicheng Li
HKUST

Don Noh
HKUST

Sangmin S. Oh
Columbia Business School

Sean Seunghun Shin
KAIST

Jihong Song
Cubist

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Abstract

We study how investor preferences for sustainability transmit to corporate environmental behavior through stock prices. Using an asset demand system, we develop a novel measure, "green price pressure," which quantifies the sensitivity of a firm's stock price to improvements in its environmental performance. Our measure accounts for heterogeneity in both investor price elasticity and preference for sustainability, distinguishing it from traditional measures based on institutional ownership. Firms facing stronger green price pressure subsequently exhibit larger improvements in environmental performance, provided that executive compensation is highly sensitive to stock performance. Overall, our findings suggest that sustainable investing can influence corporate behavior, but only when market forces align well with managerial incentives.

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Investors increasingly channel capital toward environmentally responsible firms, motivated by both financial and non-financial considerations (Krueger et al. 2020). This shift has led to a growing interest in whether and how sustainable investing brings about real environmental changes. At the center of this debate is the hypothesis that capital markets can incentivize environmental improvement through stock prices: the prospect of higher stock valuations, driven by investor preference for greener companies, incentivizes firms to improve their environmental performances.

But does this mechanism work in practice? While a growing body of research documents price effects from sustainability-oriented capital flows (van der Beck 2021), establishing a connection to real environmental outcomes has proven challenging. Price effects and environmental outcomes are often studied in isolation (Dyck et al. 2019; Barber et al. 2021), and existing models rely on high asset substitutability and abstract from investor heterogeneity (Berk and van Binsbergen 2021).

We introduce a firm-level measure, "green price pressure," which quantifies how investor demand translates changes in a firm's environmental performance into stock price movements in equilibrium. We formalize this concept using a stylized framework in which both stronger green preferences and lower price elasticities among investors are associated with greater green price pressure for a firm. Green preferences determine the direction and initial magnitude of price pressure, while lower elasticity amplifies this effect: a price inelastic owner will require larger price concessions in response to shocks to greenness. To estimate this measure empirically, we use an asset demand system that admits investor heterogeneity in both of green preferences and price sensitivity. We then examine how this measure varies across firms and over time, and test whether firms facing greater green price pressure subsequently improve their environmental performance.

Previous studies have used proxies such as institutional ownership (Dyck et al. 2019) and the proportion of UN PRI signatories (Kim and Yoon 2023) to measure the effects of green investors on stock prices. Our approach improves such existing measures in three ways. First, we capture investor heterogeneity in sustainability preferences at higher granularity with investor-level holdings data. Second, we disentangle preferences for sustainability from preferences for correlated characteristics. Finally, our framework incorporates differences in price elasticities across investors that interactively affect green price pressures.

We provide three main findings. First, green price pressure successfully captures the sensitivity of stock prices to environmental performance: firms with higher green price pressure experience larger negative stock price reactions to environmental scandals. Second, consistent with assortative matching between investors and firms, green price pressure has increased substantially more for green firms than for brown firms since 2016. Third, in the cross-section of firms, higher green price pressure today predicts subsequent improvements in corporate environmental performance, as evidenced by higher environmental scores and lower emissions. However, these improvements are concentrated among firms whose executive compensation is highly sensitive to stock prices; also, improvements are larger along corporate environmental actions that are relatively easier to implement.

These main results provide two takeaways. On the investor side, less price-sensitive investors amplify the market impact of sustainability preferences. This suggests that continued growth of passive investment may strengthen market-based incentives for environmental improvements. On the firm side, managerial incentives emerge as necessary conditions for translating market signals into environmental action.

We start by combining comprehensive data on institutional equity holdings, stock characteristics, and firm environmental performance metrics from MSCI. Our empirical model extends the characteristic-based demand function of Koijen and Yogo (2019) by incorporating firm-level greenness as an additional characteristic. We provide both theoretical and empirical justifications for this extension. Theoretically, greenness may enter an investor's demand function if (i) it is a factor that is informative about expected returns (Koijen and Yogo 2019) and/or (ii) investors face minimum greenness constraints. Empirically, we motivate the inclusion of greenness through a lasso variable selection procedure that identifies the characteristics that best predict portfolio weights. Our lasso results show that greenness consistently ranks within the top 10% among widely used firm characteristics (Jensen et al. 2023), confirming its importance in explaining institutional portfolio decisions.

We then estimate the demand curve of each investor in our sample. In identifying and estimating the parameters of the demand curve, we carefully address two key endogeneity concerns. First, stock prices are determined in equilibrium and are therefore correlated with unobserved demand shocks. We follow Koijen and Yogo (2019) and use the counterfactual log market capitalization instrument, which exploits variation in investor demand that is unrelated to firm-specific factors by leveraging institutional investors' specific investment mandates. Second, greenness may be endogenous if firms with higher valuations invest more in environmental initiatives, which raises concerns about reverse causality. We address this by controlling for social and governance scores to isolate the environmental component, and by showing robustness to instrumenting greenness with the residual component from a regression of environmental scores on market valuations and other firm characteristics, following Koijen et al. (2023).

We calculate our measure of green price pressure at the firm-quarter level from the estimated demand curves and first provide a validation of our measure. To do so, we examine how stock prices respond to environmental incidents. Using an event study design around environmental controversies reported in the RepRisk database, we find that firms with higher green price pressure experience significantly larger negative stock price reactions to environmental incidents. Firms in the top tercile of green price pressure experience a 0.37 p.p. larger stock price decline, as measured by CAPM alpha, over the four-day window around environmental controversies. On the other hand, firms in the bottom tercile show no significant price decline.

Next, we document that green price pressure has increased more for green firms than for brown firms since 2016, with the gap between them widening substantially over time. The timing of this divergence aligns with the post-Paris Agreement acceleration in sustainable investing and suggests that capital markets increasingly differentiate among firms based on environmental performance. The widening gap also highlights an important asymmetry: sustainable investing, as currently practiced, disproportionately benefits firms that are already green or are relatively easier to green.

To better understand the economic drivers of these trends, we decompose the cross-sectional variance of the change in green price pressure into components of the demand system. We find that changes in investor preferences for sustainability explain about half of the variation in green price pressure, while latent demand accounts for another third. Other factors such as changes in assets under management (AUM) and firm's environmental scores play relatively minor roles. For example, changes in AUM contributes only about 0.65% to the overall variation. These findings suggest that investor preferences have been the primary driver of the observed changes in green price pressure, particularly the substantial increase since 2016.

If capital markets reward environmental performance through price pressure, a natural follow-up question is whether firms respond to these incentives. To study how firms respond to green price pressure, we regress a firm's three-year ahead environmental score on its current green price pressure, controlling for standard firm characteristics such as size, profitability, and leverage. Importantly, we include the firm's current environmental score to account for persistence in environmental performance, ensuring that our results capture incremental improvements rather than level differences. We also include industry fixed effects to control for sector-specific environmental standards and year fixed effects to absorb aggregate time trends in environmental performance that might be driven by broader regulatory changes or shifts in social norms.

We find a positive and statistically significant relationship between current green price pressure and future environmental scores. This relationship is robust across different time horizons, including one-year and five-year forward periods. We also find similar environmental improvements when using future emissions intensity as the dependent variable. In contrast, institutional ownership exhibits a smaller and statistically insignificant association with future environmental outcomes. This discrepancy highlights the limitations of aggregate ownership measures, which conflate heterogeneous investor motives[1] and fail to account for differences in price elasticity.

Although the unconditional effect is positive, we document two important dimensions along which effects can vary. First, we show that the effect of green price pressure on firm behavior

[1]E.g., Dasgupta et al. (2021) provide a thorough overview on how institutional investors' roles in corporate governance can differ by their distinct aspects and heterogeneous characteristics.

is strongly mediated by managerial incentives. We proxy for these incentives using CEO delta which is the sensitivity of executive wealth to a 1% change in the firm's stock price. We follow the construction in Core and Guay (2002) and Coles et al. (2006). We find that the response to green price pressure is highly concentrated among firms in the top tercile of CEO delta, while firms in the bottom tercile exhibit statistically insignificant responses. Moreover, the relationship between green price pressure and subsequent environmental improvements increases monotonically across terciles of CEO delta. These results reveal the complementarity between external investor pressure and internal governance.

The second dimension is in the types of environmental improvements that firms undertake in response to green price pressure. We disaggregate the overall environmental score into its underlying theme components—climate change, natural resources, pollution and waste, and environmental opportunities—and examine each theme separately. We find that improvements are most pronounced in the areas of waste management and natural resource use, while themes related to climate change and environmental opportunities show weaker or no significant response. These results are consistent with the view that short-run improvements by firms often target low-hanging fruits, whereas deeper transformations require more time and capital.

Finally, we demonstrate the broader applicability of our methodology by applying it to another firm characteristic: dividend policy. Building on the catering theory of Baker and Wurgler (2004), we construct a measure of "dividend price pressure" that captures the sensitivity of a firm's stock price to changes in its dividend yield. We find that firms facing higher dividend price pressure are more likely to initiate or increase dividends in subsequent periods, consistent with the idea that managers respond to the premium investors place on specific firm attributes. Taken together, these findings highlight the general utility of our approach for studying how firms respond to investor demand.

On the surface, our results suggest that investor demand shapes corporate environmental behavior through green price pressure. However, we remain cautious in drawing strong conclusions. Greenness is ultimately a firm choice variable that firms may adjust in anticipation of investor preferences, not solely in response to them. In equilibrium, such forward-looking behavior could attenuate or obscure the predictive content of price pressure. However, if investor preferences shift more rapidly than firms can adjust their environmental practices, due to operational, regulatory, or strategic frictions, then green price pressure may still predict future improvements during the adjustment process. The relationship we document is consistent with such transitional dynamics, particularly given the speed and scale of the post-2016 rise in sustainable investing.

Related literature Our paper relates to three main strands of literature. First, we contribute to the literature on the asset pricing implications of sustainable investing. Giglio et al. (2021) and Pastor et al. (2024) provide comprehensive reviews. Most existing work has focused on the return gap between green and brown stocks, using both theoretical and empirical approaches.[2] Recent empirical work goes beyond realized returns to examine analyst forecasts (Pástor et al. 2022), corporate earnings calls (Gormsen et al. 2023), and portfolio holdings (Gibson et al. 2020; Pastor et al. 2023). Our approach complements this work by using an asset demand system to study investor preferences for sustainable assets. This allows us to measure how demand shocks related to environmental preferences affect prices and real firm outcomes. In this sense, our paper relates to van der Beck (2021) who estimates the price impact of ESG flows and Koijen et al. (2023) who examine climate-induced shifts in institutional demand. Relative to these papers, we extend the demand system framework to estimate a firm-level measure of green price pressure, which we then link to real firm outcomes.

Second, our paper contributes to the literature on the real impact of sustainable equity investing. Theoretical models suggest that sustainable investing is potentially limited in its efficacy given its modest effects on firms' cost of capital and managerial incentives (Berk and Green 2004; Davies and Van Wesep 2018). The empirical evidence is also generally mixed regarding the impact of sustainable investing on real firm decisions (Heath et al. 2023; Gantchev et al. 2022; Hartzmark and Shue 2023; Choi et al. 2023). We contribute to this literature by deriving a new measure of a firm's incentive to improve its environmental performance—capturing the price pressure it faces from its institutional owners—and by showing that firms subject to greater investor pressure subsequently exhibit larger improvements in their environmental performance. Importantly, we find that this effect is significantly stronger among firms with high managerial equity incentives, highlighting the role of managerial compensation in translating investor preferences into corporate environmental improvements.

Finally, our paper contributes to the burgeoning literature that studies questions in asset pricing based on estimation of asset demand in markets ranging from equity, fixed income, and country-level assets (Koijen and Yogo 2019, 2020; Bretscher et al. 2022; Koijen et al. 2023; Jiang et al. 2024). In particular, our paper relates to studies that uses the demand system framework to study specific asset pricing questions, including Gabaix et al. (2023) on the trading behavior of U.S. households, Jansen (2021) on long term bond demand, Huebner (2023) on the source of equity momentum, and van der Beck and Jaunin (2021) on retail investor demand. We contribute to this literature by studying one of the central channels through which sustainable investing can affect corporate behavior. We show that the demand system can be leveraged to yield a firm-level quantitative measure of green price pressure, and that this measure is predictive of future improvements in environmental performance.

[2]See, for example, theoretical models in Heinkel et al. (2001), Pástor et al. (2021), Pedersen et al. (2021), Zerbib (2022) and empirical analyses in Choi et al. (2020), Görgen et al. (2020), Bolton and Kacperczyk (2021), Glossner (2021), Ilhan et al. (2021), Derrien et al. (2022), Pástor et al. (2022), Bolton and Kacperczyk (2023), Hsu et al. (2023), Shi and Zhang (2024), and Zhang (2025).

1 Motivating framework

We begin with a simplified framework that serves two purposes: (i) to define green price pressure and (ii) to outline the parameters that govern it in equilibrium. In our setting, investors vary in terms of both price elasticity and preferences for environmental performance, This heterogeneity drives the relationship between stock prices and firm greenness, ultimately shaping firms' incentives to adopt greener practices.

Consider a set of investors indexed by $i \in \mathcal{I}$ and assets indexed by n. Investor i's demand for asset n can be written as:

$$q_i(n) = -\zeta_i p(n) + \gamma_i g(n) + \varepsilon_i(n),$$

where $p(n)$ is the stock price of asset (n) and $g(n)$ is the firm's greenness (e.g., MSCI environmental rating). Here, ζ_i captures investor i's price elasticity and γ_i reflects the preference for greenness. By normalizing the total supply of shares to one ($\sum_{i \in \mathcal{I}} q_i = 1$), we aggregate investor demand using size-weighted averages denoted by subscript S, where weights correspond to investor size (e.g., assets under management). The market clearing condition implies that the equilibrium price is

$$p(g(n)) = \frac{\gamma_S g(n) + \varepsilon_S(n) - 1}{\zeta_S}. \tag{1}$$

The subscript S indicates size weighting, where the size of investor i, S_i, is its AUM. For example, $\gamma_S := \sum_i S_i \gamma_i$.

Equation (1) shows that a firm's environmental performance affects its stock price through the preferences of its investors. In practice, this link matters for two main reasons. First, managerial compensation, which is often tied to stock prices, provides a strong incentive for managers to improve their firm's environmental performance when investors reward greenness (Edmans et al. 2017). Second, higher valuations reduce the firm's cost of capital, outweighing green investments' high upfront costs and long-term payoff structure (Heinkel et al. 2001).[3]

To quantify the firm's benefit from becoming greener, we define green price pressure as the sensitivity of the equilibrium price with respect to changes in environmental performance:

$$\text{Green Price Pressure} \equiv \frac{\partial p}{\partial g}. \tag{2}$$

This partial derivative effectively measures the "price boost" a firm can achieve for a one-unit improvement in its environmental performance. This quantity can also be viewed as the marginal benefit of becoming greener from the firm's perspective. Many of the proxies conventionally used to measure green price pressure appear to be designed to capture this $\partial p / \partial g$. Examples

[3]For simplicity, we do not model the firm's decisions explicitly here, but we can imagine a firm that whose manager's objective is to maximize its stock price. See Pástor et al. (2021) or Choi et al. (2025) for models with firm decisions.

include institutional ownership (Dyck et al. 2019), the fraction of Principles for Responsible Investment (PRI) signatory ownership (Kim and Yoon 2023), and the green tilt (Pastor et al. 2023). These measures rely on the premise that "green owners" will punish (reward) any deterioration (improvement) in environmental performance through divestment (purchase) of the firm's shares. The higher the fraction of green owners, the greater the sensitivity per unit of change in greenness.

In this stylized framework, this derivative simplifies to γ_S/ζ_S, where γ_S is the size-weighted average of investors' preferences for environmental performance and ζ_S is the corresponding average price elasticity of demand. The average green coefficient, γ_S, determines the *direction* of the price pressure: a positive γ_S implies that firms can achieve higher valuations from greener investors. Together with the magnitude of γ_S, the average price elasticity, ζ_S, governs the *magnitude* of this green preference effect: lower price elasticity amplifies the price movements in response to changes in greenness. The intuition is that if the firm's representative owner values greenness and is inelastic, she will require a larger price concession in response to a shock to greenness (Koijen et al. 2021).

The expression for green price pressure highlights two important considerations in estimating green price pressure. The expression for green price pressure reveals that computing it for each firm requires estimating both environmental preference parameters (γ_i) and price elasticities (ζ_i) for all investors in that firm's shareholder base. Since green price pressure depends on the weighted average of these investor-specific parameters, accurate measurement demands a flexible empirical approach that can capture heterogeneous investor characteristics and their portfolio allocation decisions across the full spectrum of institutional investors. Section 2 develops this methodology using an asset demand system framework that estimates investor-level demand curves, allowing us to construct firm-specific measures of green price pressure that reflect the unique composition of each firm's investor base.

Second, green price pressure is not uniform across firms but depends on the composition of their investors. Firms held predominantly by investors with strong environmental preferences and low price elasticities, such as passive index funds with explicit sustainability mandates, experience a higher γ_S/ζ_S, and hence greater price pressure. In contrast, firms whose shares are mostly owned by active investors with high price sensitivity and weak environmental biases will face considerably lower pressure. This heterogeneity is further complicated by the fact that the size of each investor also affects how green price pressure evolves over time. In examining how green price pressure varies across firms and over time, Section 3 provides an analysis through a variance decomposition that identifies the relative importance of each component in explaining the variation in green price pressure.

To connect green price pressure to firm decision-making, we consider a scenario in which the firm experiences a shock to investor sustainability preferences and responds by adjusting its environmental performance subject to a quadratic adjustment cost, following Pástor et al. (2021). Suppose that γ_S shifts to a larger value γ_S' due to increased environmental awareness. The manager chooses the change in greenness, $\Delta g(n)$, to maximize firm value:

$$\max_{\Delta g(n)} \quad p(g(n) + \Delta g(n)) - \frac{1}{2}\chi(n)\Delta g(n)^2.$$

The first-order condition implies that the optimal change in greenness is given by:

$$\Delta g(n) = \frac{1}{\chi(n)} \frac{\gamma_S'}{\zeta_S}.$$

This expression shows that the firm's environmental adjustment is increasing in green price pressure. Firms facing stronger investor demand for sustainability have greater incentives to improve their environmental performance, as such improvements are rewarded with higher valuations. This relationship motivates our empirical analysis in Section 4 where we examine whether firms experiencing higher green price pressure subsequently exhibit greater improvements in their environmental profile.

2 Estimating the green price pressure

In this section, we outline the empirical methodology for estimating the green price pressure. We first describe the data and then lay out a model of characteristics-based investor demand. The model allows for heterogeneity in both demand for greenness and price elasticity. Next, we estimate investor-specific demand curves and use the estimated parameters to construct a firm-level measure of green price pressure, defined as the sensitivity of the equilibrium price to changes in environmental performance.

2.1 Data

Our empirical analysis is based on three primary data sources. First, we obtain data on quarterly institutional holdings from FactSet. Second, we obtain stock-level variables, such as prices and outstanding shares, from CRSP. We supplement these with accounting data from Compustat. Finally, we collect firm-level environmental performance metrics from MSCI ESG Research and S&P Trucost.

2.1.1 Institutional holdings

The data on institutional common stock holdings is obtained from the FactSet Ownership database, which has maintained a comprehensive record of 13F and international fund holdings since 1999. All institutional investment managers who exercise investment discretion over accounts holding Section 13F securities valued at more than $100 million are required to complete the Form 13F. FactSet enhances its 13F data by incorporating information from other regulatory filings. As in Koijen et al. (2023), institutions are grouped into investment advisors, hedge funds, long-term investors, private banking, and brokers. Given the substantial size of the investment advisor category, it is divided into four subgroups based on AUM and active share (Cremers and Petajisto 2009).

2.1.2 Stock characteristics

Our sample includes US firms with ordinary common shares listed on the NYSE, AMEX, or Nasdaq. Following Koijen et al. (2023), we first sort the firms in each quarter by their market equity. Then, we choose N largest stocks whose combined market equity covers at least 95% of total US stock market capitalization. These firms are classified as "inside assets," while the remaining firms are aggregated to be an "outside asset." This approach ensures that our estimates of the asset demand system focus on the largest and the most liquid stocks. We rely on the procedure in Koijen et al. (2023) to construct stock characteristics such as book equity, foreign sales share, the Lerner index, sales to book equity, dividend to book equity, and market beta. The environmental performance measure, or "greenness," is described in the next subsection.

2.1.3 Environmental performance

We obtain quarterly firm-level environmental performance from MSCI ESG Ratings database, which succeeds the MSCI KLD database used in previous studies related to ESG investing (Krüger 2015). We choose MSCI ESG ratings over other ESG rating datasets as MSCI covers more firms than do other raters, exhibits the least noise, and is based on a comprehensive set of corporate documents, government data, and news media (Pástor et al. 2022).[4] The MSCI scores capture both quantitative measures and qualitative assessments of the environmental policies of the firms.

Following Pástor et al. (2022), we define firm n's "greenness" at quarter t by

$$g_t(n) = \frac{-[10 - E_t(n)] \cdot w_t^E(n)}{100},$$

[4] Also, a potential alternative, Refinitiv ESG (ASSET4) score, has been retrospectively rewritten, raising concerns regarding data stability and the replicability of empirical findings (Berg et al. 2021).

where $E_t(n)$ and $w_t^E(n)$ are firm n's Environment Pillar Score and Environment Pillar Weight from MSCI in quarter t, respectively. This transformation reflects MSCI's design: the raw pillar score $E_t(n)$ is constructed to measure the distance from the ideal score of 10. We forward-fill both the score and weight for up to 11 quarters to avoid dropping firms with missing updates. This imputation is applied only in the estimation of investor demand; in Section 4, where we examine the real effects of green price pressure, we restrict the sample to firms with non-missing, contemporaneous environmental data. We also examine specific themes within the environmental pillar defined by MSCI: climate change, natural resource use, waste management, and environmental opportunities. For these theme scores, we utilize the raw scores provided by MSCI.

Finally, we obtain annual greenhouse gas emissions data from S&P Trucost. We use information on scope 1 carbon emissions, which are direct emissions from company-controlled sources, as our primary measure because it is one of the main objectives or reporting targets in various environmental initiatives (e.g., the UN PRI or Climate Action 100+) and is objectively quantifiable. We focus on scope 1 emissions intensity, defined as a company's annual scope 1 emissions divided by its annual revenue.

2.2 An empirical model of investor demand

We next introduce our empirical model of investor demand, which builds on the characteristic-based approach of Koijen and Yogo (2019). We expand the set of characteristics to incorporate heterogeneous green preferences and provide both a theoretical motivation and an empirical justification for this modification.

2.2.1 Characteristics-based demand

Koijen and Yogo (2019) develop a flexible model of investor demand that allows for heterogeneous beliefs about the expected returns of assets. Despite its flexibility, the model remains empirically tractable by leveraging two sets of assumptions. The first is a set of assumptions about investor preferences that make the mean-variance portfolio (Markowitz 1952) an approximate optimal portfolio. The second is that asset returns have a factor structure (Fama and French 1993) and that both expected returns and factor loadings depend only on the assets' own prices and characteristics. Given these assumptions, we can write an investor's desired portfolio weight for an asset as an exponential linear function of its price, vector of characteristics, and "latent demand" driven by unobservable characteristics. We omit some details of the derivation to avoid repetition.

There are N assets, indexed by $n = 1, \ldots, N$ and I investors, indexed by $i = 1, \ldots, I$, in the economy. We denote the "outside asset" as the 0th asset. Furthermore, let $P_t(n)$ and $S_t(n)$ denote the price and shares outstanding of asset n at time t, respectively. Market equity is then

$\mathrm{ME}_t(n) = P_t(n)S_t(n)$. We denote the logarithms of these variables in lowercase letters and the N-dimensional vectors in boldface. Each asset has K characteristics, indexed by $k = 1, \ldots, K$ so that the kth characteristic of asset n at time t is denoted $x_{k,t}(n)$ and the vector of characteristics for asset n is denoted by $\mathbf{x}_t(n)$.

Investor i optimally chooses at each time t her portfolio weight in asset n, $w_{i,t}(n)$, for each asset in her investment universe $\mathcal{N}_{i,t}$. The investment universe is assumed to be exogenous. Denoting the asset under management of investor i at time t by $A_{i,t}$, investor i maximizes expected terminal wealth $\mathbf{E}_{i,t}(\log(A_{i,T}))$ at time $t = T$, while satisfying the intertemporal budget constraint. Investors face short-sale constraints so that $\mathbf{w}_{i,t} \geq \mathbf{0}$ and $\mathbf{1}'\mathbf{w}_{i,t} < 1$, where $\mathbf{w}_{i,t}$ is the vector of portfolio weights. Investors have heterogeneous beliefs about the expected returns of assets, which they form by considering the observed characteristics. Investor i's unobserved latent demand for asset n is denoted by $\epsilon_{i,t}(n)$.

Combining the above assumptions on investor preferences with a factor structure in returns, one can derive characteristics-based demand functions. We omit these details to avoid repetition, and state investor i's exponential-linear demand which is represented by

$$\begin{aligned} \frac{w_{i,t}(n)}{w_{i,t}(0)} &= \delta_{i,t}(n) \\ &= \exp\left(b_{0,i,t} + \beta_{0,i,t} mb_t(n) + \beta_{1,i,t}' \mathbf{x}_t(n)\right) \epsilon_{i,t}(n), \end{aligned} \tag{3}$$

where $mb_t(n)$ is the log market-to-book of asset n and $\mathbf{x}_t(n)$ is the vector of characteristics. $b_{0,i,t}$ is the intercept, $\beta_{0,i,t}$ is the demand coefficient on valuation, $\beta_{1,i,t}$ is the vector of demand coefficients on other characteristics. Note that a passive index fund will have $\beta_{0,i,t} = 1$, and this will be the upper bound on this coefficient. It represents price *in*elasticity, so that smaller values indicate higher price elasticity. The latent demand $\epsilon_{i,t}(n)$ captures other unobservable aspects that affect portfolio weights. This implies that the weights can be written as

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)} \quad \text{and} \quad w_{i,t}(0) = \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}. \tag{4}$$

2.2.2 Rationale for greenness as a characteristic

Our starting set of firm characteristics includes log book equity, the foreign sales share, the Lerner index, sales-to-book, dividend-to-book, and market beta. We focus on these characteristics because they capture expected profitability and profitability risk (Koijen et al. 2023). Given concerns of collinearity and overfitting, justification for expanding this set is warranted (Koijen and Yogo 2019), which we subsequently describe below.

For a theoretical justification, we start from the observation regarding industry practices related to sustainable investing. Investors may value greenness for pecuniary reasons (e.g., if investors believe that environmental attributes predict higher returns) or for non-pecuniary reasons (e.g., if they face mandates or derive utility from sustainable holdings) (Barber et al. 2021; Giglio et al. 2021; Bansal et al. 2022). Based on these reasons, suppose that we add greenness as the $(K+1)$th characteristic of an asset:

$$x_{K+1,t}(n) = g_t(n),$$

where $g_t(n)$ is asset n's greenness at time t. Greenness $g_t(n)$ then enters the investor's characteristic-based demand if either (1) greenness is informative about expected returns, (2) investors directly derive utility from holding greener stocks, or (3) the investor faces a "minimum greenness constraint." First, if greenness is informative about expected returns, it immediately follows from the same line of argument as in Koijen and Yogo (2019) that it should enter the characteristics-based demand. Alternately, if investors derive utility from holding greener stocks, one can write a utility function similar to that in Pástor et al. (2021) and derive the desired results.

Finally, consider the case in which greenness is not informative about expected returns, but investors face a minimum greenness constraint instead.[5] More concretely, suppose that investor i faces an extra constraint,[6]

$$\mathbf{b}_{i,t}'\mathbf{w}_{i,t} = (d_i\mathbf{g}_t)'\mathbf{w}_{it} > c$$

where $\mathbf{g}_t$ is the $N \times 1$ vector of greenness whose nth entry is $g_t(n)$, $\mathbf{b}_{i,t}$ is the $N \times 1$ vector of non-pecuniary benefits, and $c > 0$ is some "cutoff" level of greenness. $\mathbf{b}_{i,t}$ is a product of d_i, investor i's green sensitivity, and $\mathbf{g}_t$, the vector of firms' greenness. In Appendix B, we show that greenness enters the characteristics-based demand even if greenness is not informative about expected returns. The intuition is that greener assets provide a shadow benefit, beyond their expected returns, because they relax the greenness constraint.

For an empirical justification, we use lasso variable selection (Tibshirani 1996). For each investor i and quarter t, we estimate the coefficients from a lasso regression:

$$\hat{\beta}^{\text{lasso}}(\lambda) = \arg\min_{\beta} \left\{ \frac{1}{2}\sum_{n=1}^{N}\left(y_{i,t}(n) - \beta_0 - \sum_{k=1}^{K+1}\beta_{i,t,k}x_{i,t,k}(n)\right)^2 + \lambda\sum_{k=1}^{K+1}|\beta_{i,t,k}|\right\},$$

where λ is the penalty parameter and

$$y_{i,t}(n) = \log\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right)$$

[5] A similar condition can be found in Pastor et al. (2023).

[6] The current formulation implicitly assumes that green stocks counteract the effects of brown ones. This simplifies the argument, and we motivate it by referring to Morningstar's ESG rating methodology which rates each fund using the weighted average of the fund's Sustainalytics scores. In order to incorporate negative screening against a group of stocks, the sensitivity d_i can be changed to a vector $\mathbf{d}_i$ with a very large $\mathbf{d}_i(n)$ value if stock n is screened.

is the logarithm of relative portfolio weights. Due to the ℓ^1 penalty term, lasso discards (i.e., sets the coefficient to zero) less relevant variables as the penalty increases. If environmental performance is of first-order importance to institutional investors' portfolio allocation problem, $\beta_{i,t,K+1}$ should be non-zero in many of the cross-sectional regressions. Because of the linear specification, we discard zero holdings for this exercise.

We start from 153 firm characteristics provided by Jensen et al. (2023) and add the MSCI environmental score to this set. For each estimation, we increase this penalty until 10 characteristics survive. Then, for each characteristic, we count the number of times it is included in the surviving characteristic. Figure 2 shows the survival frequencies of the 20 characteristics with the highest frequencies. The environment score is the 6th most frequent survivor. Note that log market-to-book, log book equity, market beta, dividend-to-book, and foreign sales are also among the top 20 most frequent surviving characteristics. The main takeaway is that the environment score is a significant consideration for institutional investors' portfolio choice based on their revealed preferences.

2.2.3 Model estimation

Having established the relevance of environmental performance in investors' demand, we now estimate investor-level demand curves. For each investor i and quarter t, we estimate the following equation using nonlinear generalized method of moments:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left(b_{0,i,t} + \beta_{0,i,t} mb_t(n) + \beta'_{1,i,t}\mathbf{x}_t(n) + \beta_{g,i,t} g_t(n)\right)\epsilon_{i,t}(n), \tag{5}$$

where $mb_t(n)$ is the log market-to-book ratio, $\mathbf{x}_t(n)$ is a vector of firm characteristics, including log book equity, the foreign sales share, the Lerner index, sales-to-book, dividend-to-book, market beta, as well as social and governance scores from MSCI, and $g_t(n)$ is the environmental score. To improve estimation stability, we add a ridge shrinkage as in Koijen et al. (2023).

The coefficient $\beta_{g,i,t}$ captures investor i's marginal demand for environmental performance, conditional on all other observable characteristics. A potential concern is that greenness may be endogenous to investor demand. For instance, firms with better unobserved fundamentals or reputational capital may simultaneously attract more capital and exhibit better environmental performance. By controlling directly for the S and G components of the ESG, our specification aims to isolate the variation in environmental scores that is orthogonal to the broader corporate quality or governance, allowing for a cleaner interpretation of $\beta_{g,i,t}$ as investor-specific demand for environmental performance.

Greenness may be endogenous if firms with higher valuations invest more in environmental initiatives, which raises concerns about reverse causality. Following Koijen et al. (2023), we instrument greenness with the residual component from a regression of environmental scores on market valuations and other firm characteristics. Figure A1 is a scatter plot of the estimated coefficient on greenness under the baseline assumption versus an alternative assumption that greenness is an endogenous characteristic. The two sets of estimated coefficients have a correlation of 0.974, which alleviates the above concern.

We assume that the latent demand shock $\epsilon_{i,t}(n)$ is exogenous to all stock characteristics except the log market-to-book ratio, each investors' assets under management $A_{i,t}$, and the set of stocks in the investor's investment universe $\mathcal{N}_{i,t}$. Under these assumptions, $mb_t(n)$ is the only endogenous regressor as it is correlated with latent demand $\epsilon_{i,t}(n)$ through market clearing. To address this endogeneity concern, we use a counterfactual log market capitalization instrument $\widetilde{me}_{i,t}$, where for each investor i, we construct counterfactual log market capitalization of stock n if all investors other than i or the household sector holds an equal-weighted portfolio of their investment universes. We estimate the demand equation (5) based on the instrument $\widetilde{me}_{i,t}(n)$ and all non-price characteristics using a two-step instrumental variables ridge estimation (Koijen et al. 2023). The procedure pools data at the annual level in the first stage and applies shrinkage to investor-quarter level coefficients in the second. The construction of the instrumental variable and details of the estimation methodology are discussed in more detail in Appendix C.

2.3 Green price pressure

We define the *price pressure* of firm n for characteristic k as the equilibrium price impact in response to a change in characteristic k:

$$\text{Pressure}_t(n) = \frac{\partial p_t(n)}{\partial x_{k,t}(n)}.$$

This quantity can be seen as the marginal benefit of a unit increase in characteristic k.[7] When the characteristic is greenness, we call this the *green price pressure*. We start from the market clearing condition:

$$\text{ME}_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n).$$

Then, by implicitly differentiating both sides of the market clearing condition, we can derive the equation for the green price pressure (see Appendix B). The quantity $\mathbf{P}_{n,n}$, which is the nth diagonal entry of $\mathbf{P}$ in Proposition 1, is the green price pressure for firm n. In the expression below, we omit the time subscripts for simplicity.

[7] We recognize that ideally, we need a fully micro-founded model with the supply side, or the firm side, of the demand system to relate this quantity back to the firms' objectives. Only in this way can we also account for the adjustment cost of making the marginal change, but this is outside the scope of this paper. Instead, we control for observed firm characteristics and industry classification in our empirical analysis and argue that doing so we can compare firms with similar adjustment or marginal cost of changing the characteristic in question.

Proposition 1. *The price impact of a change in the value of greenness* $\mathbf{g} = \mathbf{x}_{K+1}$ *is denoted by* $\mathbf{P}$ *and satisfies*

$$\mathbf{P} := \frac{\partial \mathbf{p}}{\partial \mathbf{g}} = \left(\mathbf{I} - \sum_i \beta_{0,i} A_i \mathbf{H}^{-1} \mathbf{G}_i\right)^{-1} \left(\sum_i \beta_{g,i} A_i \mathbf{H}^{-1} \mathbf{G}_i\right), \tag{6}$$

where $\beta_{g,i}$ *is investor i's demand coefficient for greenness. The matrices* $\mathbf{H}$ *and* $\mathbf{G}_i$ *are defined as follows:*

$$\mathbf{H} := diag\left(\sum_i A_i \mathbf{w}_i\right) = \sum_i A_i diag\left(\mathbf{w}_i\right)$$
$$\mathbf{G}_i := diag\left(\mathbf{w}_i\right) - \mathbf{w}_i \mathbf{w}_i'.$$

Green price pressure for firm n *is given by the* n*th diagonal entry of* $\mathbf{P}$*:*

$$Green\ Price\ Pressure(n) = \mathbf{P}_{n,n}.$$

Public firms, or their managers, have incentives to increase their stock valuations, as they are related both to the cost of capital and to the value of share-based compensations. Because we hold latent demand constant in the calculations above, this measure of price pressure only captures the pressure that arises from the intensive margin of investor demand. Given industry practices such as screening or divestment, this is likely to be a lower bound on the actual investor pressure that a firm experiences. If substantial variation in holdings operates through the extensive margin, then the current methodology understates how valuation would change with greenness as new investors start to newly hold the stock if greenness improves sufficiently. We believe that our measure still suffices given that the set of stocks that institutions invest in is usually small and highly persistent (Koijen and Yogo 2019).

The expression reveals that if a firm has a representative shareholder who is price-inelastic and exhibits a large and positive demand coefficient on greenness, this firm faces a large green price pressure. The matrix inside the inverse in Equation (6) can be interpreted as the aggregate demand elasticity. Therefore, the valuation of a stock reacts more to a change in greenness if the stock is held by less price-elastic investors: less price-elastic investors require a larger price concession in response to an "adverse" change in greenness.[8] The direction of an adverse change depends on the "AUM-weighted average coefficient" on greenness, as we can see from the nth

[8] In our setting, firms face different degrees of green price pressure depending on their investor base. This contrasts with models such as Pástor et al. (2021) in which investors have heterogeneous sustainability preferences but share the same investment universe, risk aversion, and beliefs. Under those assumptions, equilibrium prices reflect an average valuation of greenness, yielding uniform price pressure across firms with similar greenness.

diagonal entry of the second term:

$$\frac{\sum_i \beta_{g,i} A_i w_i(n)(1 - w_i(n))}{\sum_i A_i w_i(n)}. \tag{7}$$

If we assume that $w_i(n)$ are generally small, which will be true for well-diversified portfolios, we can drop the second-order terms for the portfolio weights in Equation (6). Also, denote $s_i(n) = A_i w_i(n) / \sum_i A_i w_i(n)$ to be investor i's ownership share in firm n. This yields an approximate expression for green price pressure that is related to Equation (7), but is even simpler:

$$\text{Pressure}(n) \approx \frac{\sum_i s_i(n)\beta_{g,i}}{1 - \sum_i s_i(n)\beta_{0,i}}. \tag{8}$$

The direction and initial baseline size of green price pressure is determined by the AUM-weighted average of coefficients on greenness of its institutional owners (numerator); then, the AUM-weighted average of price elasticities determines the "multiplier" effect (denominator). This is a channel through which passive investors can contribute to green price pressure. One advantage of this approximate expression is that it does not require the expensive computation of the full **P** matrix in Equation (6). The drawback is that this expression ignores the effects coming from cross-substitution of investors.

3 Dynamics of green price pressure

This section analyzes the dynamics of green price pressure. We begin by summarizing the estimated investor demand for environmental performance. We then validate green price pressure using market reactions to ESG incidents, quantify how green price pressure varies across firms and over time, and decompose its drivers into underlying components of the demand system.

3.1 Investor demand for sustainability

Table 1 provides summary statistics of our estimated demand coefficients. We compute the summary statistics across investors in every quarter, and then take an equal-weighted average across quarters. First, the demand for environmental score is positive on average, with an AUM-weighted average coefficient of 0.045. These coefficients mean that an average investor increases its demand by 4.5% per one standard deviation higher environmental score. The coefficients are larger than those for social and governance scores and are comparable in magnitudes with coefficients for the five non-green characteristics.

We also observe substantial heterogeneity across investors. The equal-weighted 25th/75th percentile of demand coefficients are $-0.080/0.121$ for environmental score. This result highlights the importance of allowing cross-investor heterogeneity for understanding demand for sustainability. Negative demand coefficients indicate that there are "brown" institutional investors who overweight brown stocks, even after controlling for other characteristics. Such patterns would be obscured by aggregate measures like institutional ownership shares. In addition, Figure 1 shows that investors with more price-elastic demand tend to place stronger weight on environmental performance. This challenges the popular narrative that active investors dilute sustainable demand by buying brown stocks.

3.2 Stock market response to green price pressure

Green price pressure is intended to capture the extent to which investors price sustainability into a firm's stock. If this pressure reflects how sensitive firm valuations are to sustainability considerations, then firms facing greater pressure should exhibit stronger market reactions to adverse ESG news. We test this hypothesis using RepRisk data, which tracks firm-level ESG controversies based on reports from public sources.

Specifically, we conduct an event study using each firm's RepRisk Index (RRI), which is a measure of a firm's ESG-related reputational risk, ranging from 0 to 100. It increases in response to new ESG incidents, with the magnitude of the change depending on the severity, dissemination, and uniqueness of the issue. For example, a firm's RRI may rise if a public source reports its mismanagement of wastewater leading to contamination. The increase is larger if the incident is severe or unprecedented. In the absence of new controversies, the index gradually declines. We define an ESG incident as any day when a firm's RRI rises by at least 10 points.[9] This threshold captures meaningful changes in perceived ESG risk, independent of stated policies or commitments.[10]

We implement an event study centered on these ESG incident dates. For each incident, we compute cumulative abnormal returns (CARs) using two methods for estimating daily abnormal returns: (i) raw abnormal returns, defined as the excess of the firm's return over the market return, and (ii) CAPM abnormal returns, computed using firm-specific betas estimated via the method in Welch (2021). We then construct CARs over two event windows: [–1, +3] and [–1, +10] trading days relative to the incident date.

Table 2 presents the results. In the full sample, ESG incidents are associated with negative abnormal returns. For example, using CAPM-based abnormal returns, the average CAR is –0.20% over the [–1, +3] window and –0.56% over the [–1, +10] window, both statistically significant at the 5% and 1% levels, respectively. Importantly, the effect varies systematically by terciles of

[9] This represents a large shift: the standard deviation of daily changes in RRI across our sample is approximately 0.7.
[10] For the full list of ESG issues classified by RepRisk, see here.

green price pressure: firms in the high-pressure group exhibit the strongest market reaction, with an 11-day CAPM-based CAR of –0.82% (t = –3.20). In contrast, abnormal returns are smaller and statistically insignificant among firms in the low-pressure group. This monotonic pattern supports the interpretation of green price pressure as a measure capturing how sensitive firm valuations are to its sustainability charateristics.

3.3 Green price pressure over time

We now study how green price pressure has evolved over time. Specifically, we compute the cross-sectional gap between green and brown firms each quarter, defined as the difference in average green price pressure between firms in the top and bottom terciles of the environmental score distribution, measured within each quarter.

Figure 3 plots the evolution of this gap over our sample period, along with the total assets under management (AUM) of sustainable investment funds. Several patterns emerge. First, the gap is consistently positive across all years, implying that greener firms have faced stronger green price pressure relative to their browner counterparts. This pattern is suggestive of assortative matching between green firms and sustainability-oriented investors (Green and Roth 2025): investors that care most about sustainability concentrate their demand in the greenest firms, while less-green firms are left to investors with weaker environmental preferences. Because the marginal buyer of an already-green firm therefore places a higher shadow value on an additional unit of greenness than the marginal buyer of a brown firm, the firm's stock price effectively becomes convex in the environmental score. In equilibrium, a small increase in a firm's greenness raises its price more when the firm is already green than when it is brown, producing the observed positive and widening green–brown gap.

Second, the gap widens sharply beginning in 2016, which coincides with the rapid rise of sustainable investing. This inflection point also aligns with several pivotal developments in the sustainable investing landscape such as the 2015 Paris Agreement and the improved sustainability disclosures of firms. It also coincides with several market-based indicators of growing influence of sustainable investing, including the widening of the equity greenium (Pástor et al. 2022), issuance of green bonds (Flammer 2021) and a lower perceived cost of capital for greener firms (Gormsen et al. 2023).

Taken together, the sharp widening of the green-versus-brown gap indicates that price pressure has become increasingly concentrated on firms that are already green. Recent evidence suggests that this allocation of pressure may not maximize real-world impact, as abatement potential is often greatest for browner firms (Hartzmark and Shue 2023). Later in Section 4 we test this explicitly by examining whether firms experiencing stronger green price pressure subsequently record larger improvements in their environmental metrics.

3.4 What drives green price pressure?

To better understand the economic drivers of green price pressure, we decompose the cross-sectional variance of its change into components of the demand system. Supply-side components are firms' current environmental (E) scores and other firm-level characteristics (such as size, profitability, and investment). On the demand side, we have assets under management (AUM), which captures the scale of institutional ownership, as well as several investor-specific factors estimated from the demand system: sensitivities to non-green firm characteristics; price elasticity of demand; green preferences; and latent demand.

The variance decomposition follows the approach in Koijen and Yogo (2019). Green price pressure GPP_t is expressed as a function of demand-system components at time t, as detailed in Proposition 1. The change from GPP_t to GPP_{t+1} is decomposed into a sum of marginal changes in GPP, where each component is updated from its value at t to $t+1$ sequentially. The variance of changes in GPP is equal to the covariance between the change in GPP and the sum of marginal changes. This can be eventually decomposed into the sum of covariances between the change in GPP and each individual marginal change. We detail this variance decomposition process in Appendix C.2.

Table 3 reveals that changes in green preferences explain about 52% of the variance in green price pressure changes, while latent demand accounts for 38%. In contrast, supply-side factors such as the E score and other stock characteristics contribute roughly 4% of the variation. Demand-side factors such as AUM and demand coefficients for characteristics other than the E score play relatively minor roles, contributing just 0.65% and 1.79% respectively. The price elasticity accounts for an additional 3.27% of the variance. These results suggest that investor preferences, rather than market structure or firm characteristics, are the primary driver of variation in green price pressure.

4 Firm response to green price pressure

Having documented how green price pressure varies across firms and over time – and shown that its evolution is primarily driven by changes in investor preferences – we now turn to the firm-side implications. We show that green price pressure predicts improvements in sustainability performance over a three-year horizon, which we use as the baseline time window to allow time for firms to adjust. The effect is stronger when managerial incentives are better aligned with shareholders and in specific themes where operational changes may be more feasible. These findings suggest that green price pressure can influence firm behavior, though its impact varies with incentive structures and the ease of environmental improvement.

4.1 Firm improvements in environmental performance

We first examine whether higher green price pressure predicts subsequent improvements in firms' environmental performance. Specifically, we regress a firm's future environmental score on its current green price pressure, controlling for standard firm characteristics. Importantly, we include the firm's current environment score to account for persistence in environmental performance. We also include year fixed effects to absorb aggregate time trends in environmental performance and industry fixed effects to account for industry-specific developments.

Formally, we estimate the following specification:

$$\text{Escore}_{n,t+h} = \delta\text{GPP}_{n,t} + \phi\text{Escore}_{n,t} + \boldsymbol{\gamma}'\mathbf{x}_{n,t} + \alpha_t + \alpha_{\text{ind}(n)} + \epsilon_{n,t} \tag{9}$$

where $\text{GPP}_{n,t}$ denotes the green price pressure faced by firm n at time t, $\mathbf{x}_{n,t}$ is a vector of control variables, and h indicates the forecast horizon in years. α_t and $\alpha_{\text{ind}(n)}$ are year and industry fixed effects, respectively. We use $h = 3$ in our baseline results. The coefficient δ captures whether firms facing higher green price pressure subsequently exhibit greater improvements in environmental performance. We standardize $\text{GPP}_{n,t}$ within each quarter to facilitate the interpretation of coefficient magnitudes.

Table 4 column (1) reports our baseline findings. The coefficient on lagged E-Score is large and highly significant, reflecting the strong persistence in firms' environmental profiles over time. The coefficient on green price pressure is positive and statistically significant: a one standard deviation increase in green price pressure is associated with a 0.101 increase in the firm's future environmental score. While modest in magnitude, this coefficient is larger than those on most traditional firm-level predictors included in the model and is estimated with greater precision.

In column (2), we use the approximation in Equation (8) discussed in Section 2.3 and estimate the same equation. Recall that the approximation effectively decomposes green price pressure into its numerator and denominator components. The numerator captures the strength of investor sustainability preferences—i.e., the degree to which investors tilt toward greener firms—while the denominator reflects the elasticity of firm valuation with respect to investor demand. We find a coefficient that is similar in magnitude and highly statistically significant as in column (1), which suggests that the approximation retains the predictive power of the green price pressure.

In column (3) we examine the relationship between green price pressure and a different measure of environmental performance: emissions intensity three years ahead, measured as tonnes of CO_2 emissions per million dollars of revenue. As before, we control for the current level of emissions intensity. We find that a one standard deviation increase in green price pressure predicts a reduction of 9.08 tCO_2/revenue. This pattern is consistent with our findings for the environmental score, suggesting that green price pressure leads to measurable but modest improvements in firms' environmental performance.

To further contextualize the role of green price pressure, we compare its predictive power for future environmental improvements to that of alternative measures of investor pressure commonly used in the literature. We consider three proxies. First is the institutional ownership (IO), defined as the fraction of shares held by institutions. IO is commonly used in the literature as a proxy for investor monitoring or governance, based on the idea that institutional investors have both the capacity and incentives to influence corporate behavior. We also consider the firm-level institutional ownership aggregated over investment managers that are signatories to the UN Principles for Responsible Investment (UNPRI). Finally, we consider the firm-level institutional ownership aggregated over block investors that hold 5% or more of total shares outstanding.

Columns (1)-(3) of Table 5 present the results from estimating Equation (9) using the three alternative measures of investor pressure. For all three measures, we do not find any statistically significant relationship with future environmental performance, and the point estimates are an order of magnitude smaller than the coefficient on green price pressure. To further assess the incremental explanatory power of green price pressure beyond these traditional IO-based measures, we next include both types of variables in the same regression specification. In columns (4)-(6), we re-estimate the regressions including both each IO-based measure and our green price pressure (GPP) variable. We find that GPP remains statistically significant, with magnitudes essentially unchanged, while the IO-based measures continue to show no significant effect.

These results suggest that GPP captures dimensions of investor pressure that IO-based measures cannot, and that IO alone is insufficient to explain future improvements in environmental performance. One possible reason is that IO reflects the presence of institutional investors but does not account for the underlying heterogeneity in sustainability preferences or the price sensitivity that green price pressure is designed to capture. Overall, these findings indicate that green price pressure provides a more nuanced and powerful measure of investor influence on firms' environmental outcomes than traditional ownership-based proxies.

4.2 Heterogeneity in firm response

4.2.1 By managerial incentives

Our earlier evidence suggests that firms facing higher green price pressure experience stronger market reactions to ESG incidents. This raises a natural question: do managers respond more strongly to green price pressure when their incentives are better aligned with stock prices? The hypothesis builds on a large literature showing that stock-based compensation helps align managerial and shareholder interests (Hall and Liebman 1998). In our setting, if managers' wealth is more sensitive to stock prices, they may be more likely to undertake environmental improvements when facing higher green price pressure, since such improvements appear to be valued by the market. Conversely, when managerial incentives are weakly tied to stock performance, the response to green price pressure may be muted even if investors value sustainability.

To test this effect, we bring in CEO-level data on compensation sensitivity to stock prices (delta), following the methodology of Core and Guay (2002) and using the extended dataset provided by Coles et al. (2006). The delta measure captures the dollar change in a CEO's wealth for a one-percent change in the firm's stock price, and provides a standardized way to compare stock-price sensitivity across executives and over time. We estimate the original equation for three samples of firms: low delta, medium, and high delta. High delta firms are those whose CEOs have above-median wealth sensitivity to stock prices, while low delta firms are those with below-median sensitivity. This split allows us to examine whether the relationship between green price pressure and environmental improvement varies with the strength of managerial incentives.

Table 6 reports the results of this analysis. Column (1) shows that firms in the lowest tercile of CEO delta exhibit no significant response to green price pressure, with a coefficient that is small in magnitude and statistically indistinguishable from zero. In contrast, columns (2) and (3) reveal that firms in the middle and highest terciles of CEO delta display increasingly stronger responses. The coefficient on green price pressure monotonically increases across the terciles, reaching 0.132 (significant at the 1% level) for firms with the highest CEO delta. This pattern suggests that managerial incentives play an integral role in translating market pressure into environmental improvements.

These results lend support to the notion that managerial incentives amplify the responsiveness of firms to sustainability signals embedded in stock prices. In firms where managers stand to benefit directly from higher valuations, the pressure to enhance environmental performance is more acute. This finding is in line with previous studies linking executive compensation structure to corporate environmental strategies (Kim and Yoon 2023) and underscores the importance of considering managerial incentives when assessing the impact of green price pressure. The results also complement the broader literature on how stock-based compensation influences managerial decision-making[11], suggesting that similar incentive channels operate in the context of firms' environmental policies.[12]

[11] See, for example, Heinkel et al. (2001), Admati and Pfleiderer (2009), Edmans (2009), Edmans and Manso (2011), McCahery et al. (2016), Broccardo et al. (2022), among others.

[12] Previous empirical studies linking environmental institutional investors to corporate decisions have primarily focused on the "voice" channel, such as voting and engagement (e.g., Kim et al. 2019; Naaraayanan et al. 2020; Ilhan et al. 2023; Hoepner et al. 2024).

4.2.2 By environmental themes

We next examine which specific aspects of environmental performance exhibit the strongest responses. This analysis is particularly important given concerns about greenwashing, where firms may focus on superficial or easily achievable environmental improvements rather than making substantive changes that meaningfully reduce their environmental impact.

To make progress on this question, we examine the specific themes that constitute the environmental score. MSCI breaks down environmental performance into four main themes: (1) pollution and waste, (2) natural capital, (3) climate change, and (4) environmental opportunities. Each theme reflects a specific area of environmental risk or opportunity and is built from a set of underlying key issues.[13] Each key issue is scored based on a company's exposure and management effectiveness, with scores aggregated—typically using industry-specific weights—to form theme scores. These theme scores are then combined to produce the overall environmental score.

Table 7 shows the results of estimating Equation (1) separately for each theme score to understand which aspects of environmental performance are most responsive to green price pressure. Column (1) reproduces our baseline result for the overall environmental score, while columns (2)-(5) report results for each thematic component. Our results reveal that firms subject to higher GPP are more likely to invest in relatively accessible initiatives—particularly waste management and natural resource conservation—while other sub-scores, such as emissions control or advanced climate-change mitigation, show less immediate response. These patterns are consistent with the view that short-run improvements often target low-hanging fruit (e.g., better resource usage), whereas deeper transformations (e.g., overhauling production processes to reduce emissions) require more time and capital.

Overall, our analysis indicates that, on average, higher green price pressure is associated with subsequent improvements in firms' environmental performance, as evidenced by both aggregate environmental scores and their subcomponents. While this relationship does not necessarily establish strict causality, it does suggest that investor preferences and price elasticities play a meaningful role in shaping firms' sustainability decisions. However, there are two important caveats: firm responses to green price pressure are strongly conditioned by managerial incentives, and environmental improvements are not uniform across dimensions. These findings underscore both the promise and limits of market-based sustainability incentives: investor preferences can shape firm behavior, but the impact depends on both firm-level incentive structures and the specific nature of the environmental outcomes being targeted.

[13] The four environmental themes are each composed of several key issues. Pollution and Waste includes Electronic Waste, Packaging Material and Waste, and Toxic Emissions and Waste. Natural Capital comprises Biodiversity and Land Use, Raw Material Sourcing, and Water Stress. Climate Change encompasses Carbon Emissions, Climate Change Vulnerability, Financing Environmental Impact, and Product Carbon Footprint. Environmental Opportunities includes Opportunities in Clean Tech, Opportunities in Green Building, and Opportunities in Renewable Energy.

4.3 Benchmarking green price pressure: A catering theory analogy

Our preceding analyses show that green price pressure meaningfully affects firm behavior, albeit modestly. To assess whether this influence is economically meaningful, this section benchmarks green price pressure against another well-documented channel through which investor preferences shape corporate decisions: the demand for dividends.

A rich literature, including the seminal work on catering theory by Baker and Wurgler (2004), demonstrates that investor demand for dividends significantly shapes corporate payout decisions. The catering theory posits that managers rationally respond to investor preferences by paying dividends when investors place higher valuations on dividend-paying firms. This creates a natural parallel to our setting, where managers may "cater" to investor preferences for environmental performance. Just as firms historically adjusted their dividend policies to meet investor demand and maximize valuations, they may now be responding to investor preferences for sustainability through the same market-based mechanism. This analogy motivates our comparison between green price pressure and dividend pressure as manifestations of how investor preferences translate into corporate actions through stock price incentives.

We adapt our methodology to construct an analogous measure of dividend price pressure. Specifically, we estimate how incremental changes in a firm's dividend policy would affect its valuation through shifts in investor demand. Following the same approach used for green price pressure, we first estimate investor-specific demand coefficients on dividend characteristics. We then compute how changes in dividend policy would affect each investor's demand and, through market clearing, the equilibrium stock price. This yields a firm-level measure of dividend price pressure that captures the valuation impact of marginal changes in dividend policy, allowing for direct comparison with our green price pressure measure.

Figure 4 compares the relative magnitudes of investor pressure effects on environmental performance and dividend policy. To facilitate direct comparison, we standardize both outcome variables and estimate their responses to investor pressure at one-, three-, and five-year horizons. The results reveal that both environmental and dividend pressures have persistent and growing effects over time, with the strongest impacts manifesting at the five-year horizon. Notably, the magnitudes are comparable across both dimensions—a one standard deviation increase in investor pressure leads to approximately 0.2-0.3 standard deviation increases in both environmental scores and dividend payouts at the five-year horizon. This similarity in effect sizes suggests that the influence of investor preferences on environmental performance is as economically meaningful as their well-documented influence on traditional financial policies like dividend payments.

More broadly, our approach of using price pressure to test catering theory could be applied to study how firms respond to other shifts in investor preferences. As investor bases evolve and new market trends emerge, firms may adjust their financial and operational decisions to cater to changing investor demands. Our methodology for measuring price pressure from different investor groups provides a systematic framework for examining these catering behaviors across various dimensions of investor preferences, extending beyond sustainability to other aspects of corporate decision-making.

5 Conclusion

This paper investigates whether and how institutional investor demand for sustainability is reflected in stock prices and firm behavior. We introduce a novel firm-level measure—green price pressure—that captures how investor preferences for environmental performance translate into stock price signals. Using a demand system framework and investor-level demand estimates, we show that institutional investors have increasingly tilted their portfolios toward firms with higher environmental scores, particularly since 2016. These preferences generate price pressure that predicts subsequent improvements in firms' environmental outcomes, including emissions intensity and ESG ratings. However, firms respond unevenly depending on managerial incentives, and the predictive power of green price pressure is not uniform across all environmental dimensions.

Our findings underscore the growing role of capital markets in shaping corporate environmental behavior through investor demand. Green price pressure serves as a market signal that, when internalized by managers with sufficient incentives, can induce meaningful improvements in sustainability performance. Yet the firm response is uneven, both across companies and across environmental dimensions. These results highlight that price signals alone are not sufficient to ensure broad environmental progress. Complementary mechanisms such as improved disclosure standards and incentive structures may be necessary to align market pressure with real and durable corporate change.

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Table 1
Summary statistics for the demand coefficients

This table presents summary statistics for the demand coefficients estimated from Equation (5). We compute the coefficients for each investor in each quarter and then average across quarters. We report both AUM-weighted and equal-weighted means, along with measures of dispersion.

	AUM-weighted		Equal-weighted				
	Mean	SD	Mean	SD	Q1	Q2	Q3
E-score	0.045	0.116	0.020	0.166	−0.080	0.021	0.121
S-score	0.015	0.102	−0.012	0.130	−0.092	−0.011	0.066
G-score	0.022	0.105	0.002	0.136	−0.080	0.004	0.086
Log market-to-book	0.845	0.255	0.498	0.295	0.300	0.478	0.701
Log book equity	1.238	0.388	0.732	0.374	0.471	0.672	0.951
Foreign sales	0.018	0.082	−0.004	0.115	−0.073	−0.003	0.064
Sales-to-book	0.015	0.109	0.001	0.126	−0.074	0.002	0.077
Dividend-to-book	−0.032	0.134	−0.001	0.153	−0.100	−0.003	0.094
Lerner index	0.026	0.100	0.044	0.131	−0.039	0.038	0.123
Beta	−0.012	0.105	−0.019	0.132	−0.098	−0.016	0.064

Table 2
Event returns of ESG incident news

The table presents cumulative abnormal returns (CARs) surrounding ESG incident events, defined as dates on which a firm's RepRisk Current RRI score increases by at least 10 points. We compute two types of daily abnormal returns: (i) *Market excess*, calculated as the excess of the firm's return over the daily market return, and (ii) *CAPM alpha*, calculated from firm-specific CAPM betas estimated using a pre-event window spanning 282 to 31 trading days before each event. Using these two measures of abnormal returns, we calculate CARs over two event windows: [-1, +3] and [-1, +10] trading days relative to the event date. We report results separately by terciles of green price pressure. Standard errors are shown in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

		GPP group		
	Full sample	Low	Medium	High
	(1)	(2)	(3)	(4)
Panel A: Window $[-1, +3]$				
Market excess	−0.078	−0.080	0.077	−0.250
	(0.094)	(0.166)	(0.150)	(0.171)
CAPM alpha	−0.202**	−0.153	−0.097	−0.373**
	(0.093)	(0.160)	(0.148)	(0.175)
Panel B: Window $[-1, +10]$				
Market excess	−0.319**	−0.120	−0.284	−0.573**
	(0.139)	(0.243)	(0.227)	(0.254)
CAPM alpha	−0.560***	−0.313	−0.563**	−0.823***
	(0.141)	(0.238)	(0.238)	(0.257)
Number of incidents	1,597	540	558	499

Table 3
Variance decomposition of green price pressure

This table shows the variance decomposition results. We decompose the cross-sectional variance of changes in green price pressure into supply- and demand-side components. The supply-side variables include firm-level non-green characteristics and the environmental (E) score. The demand-side components include asset under management, demand coefficients on non-green firm characteristics, elasticity of demand, demand coefficients on firm greenness (green preferences), and the latent demand. Heteroskedasticity-robust standard errors are shown in parentheses. The sample spans from 2013:Q1 to 2022:Q2.

	% of variance
Supply:	
Non-green stock characteristics	3.11
	(0.05)
E-score	0.66
	(0.12)
Demand:	
Asset under management	0.65
	(0.12)
Price elasticity	3.27
	(0.07)
Coefficients on non-green characteristics	1.79
	(0.08)
Green preference	52.06
	(0.02)
Latent demand	38.45
	(0.08)
Observations	33,843

Table 4
Green price pressure and future environmental improvement

This table examines the relationship between green price pressure (GPP) and future changes in firms' environmental performance. The dependent variable is the environmental (E) score in year $t+3$. All specifications control for firm characteristics, including current E/S/G scores, log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All explanatory variables are standardized within each year. We also include industry and year fixed effects. Standard errors are two-way clustered across firm and year. We report s.e. below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	E-score$_{t+3}$		Emission$_{t+3}$
	(1)	(2)	(3)
GPP	0.101**		−9.080*
	(0.028)		(3.884)
GPP approx		0.100**	
		(0.028)	
E-score$_t$	0.784***	0.784***	
	(0.039)	(0.039)	
Emission$_t$			0.797***
			(0.025)
Controls	✓	✓	✓
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
Within R^2	0.629	0.628	0.881
Observations	4,326	4,326	2,558

Table 5
Institutional ownership based alternatives of green price pressure

This table examines the relationship between alternative measures of green price pressure and future changes in firms' environmental performance. The dependent variable is the environmental (E) score in year $t+3$. We define alternative measures of investor pressure for each firm-quarter as follows: *IO* denotes institutional ownership; *IO UNPRI* denotes institutional ownership by investors that are signatories of the United Nations Principles for Responsible Investment (UNPRI); *IO Block* denotes institutional ownership by investors holding 5% or more of total shares outstanding. All specifications control for firm characteristics, including current E/S/G scores, log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All explanatory variables are standardized within each year. We also include industry and year fixed effects. Standard errors are two-way clustered across firm and year. We report s.e. below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	E-score$_{t+3}$					
	(1)	(2)	(3)	(4)	(5)	(6)
X	0.021	−0.005	−0.017	−0.011	−0.025	−0.044
	(0.030)	(0.032)	(0.030)	(0.029)	(0.033)	(0.028)
GPP				0.103**	0.105**	0.110**
				(0.030)	(0.030)	(0.031)
E-score	0.795***	0.796***	0.797***	0.784***	0.784***	0.783***
	(0.041)	(0.041)	(0.041)	(0.039)	(0.039)	(0.039)
X	IO	IO UNPRI	IO block	IO	IO UNPRI	IO block
Controls	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Within R^2	0.627	0.627	0.627	0.628	0.629	0.629
Observations	4,326	4,326	4,326	4,326	4,326	4,326

Table 6
Environmental improvement and executive compensation

This table reports the results from regressions of three-year-ahead environmental (E) score on green price pressure (GPP), estimated separately across terciles of executive compensation sensitivity (Delta). Delta measures the dollar change in executive wealth associated with a 1% change in the firm's stock price (in thousands), obtained from Coles et al. (2006) based on the methodology in Core and Guay (2002). All specifications control for firm characteristics including current E/S/G scores, log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All explanatory variables are standardized within each year. We include industry and year fixed effects. Standard errors are two-way clustered across firm and year. We report s.e. below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	E-score$_{t+3}$		
	Low delta	Medium	High delta
	(1)	(2)	(3)
GPP	−0.002	0.115*	0.132**
	(0.048)	(0.057)	(0.043)
E-score$_t$	0.733***	0.798***	0.802***
	(0.043)	(0.043)	(0.037)
Controls	✓	✓	✓
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
Within R^2	0.592	0.622	0.659
Observations	1,154	1,354	1,441

Table 7
Firm responses in different environmental performance categories

This table reports the results from regressions of three-year-ahead environmental theme scores on green price pressure (GPP). The dependent variables are the environmental (E) score (Column 1) in year t+3 and its thematic subcomponents: Waste Management, Natural Resource Use, Climate Change, and Environmental Opportunities (Columns 2–5). Green price pressure (GPP) is the main independent variable of interest. All specifications control for firm characteristics including current theme score, log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All explanatory variables are standardized within each year. We include industry and year fixed effects. Standard errors are two-way clustered across firm and year. We report s.e. below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

		Theme score$_{t+3}$			
	E-score	Waste MGMT	Natural res	Climate change	E opp
	(1)	(2)	(3)	(4)	(5)
GPP	0.101**	0.225***	0.145**	0.081*	0.010
	(0.028)	(0.053)	(0.051)	(0.036)	(0.040)
Score$_t$	0.784***	0.629***	0.705***	0.750***	0.626***
	(0.039)	(0.041)	(0.055)	(0.033)	(0.061)
Controls	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Within R^2	0.629	0.472	0.598	0.642	0.513
Observations	4,326	2,367	3,230	4,238	1,712

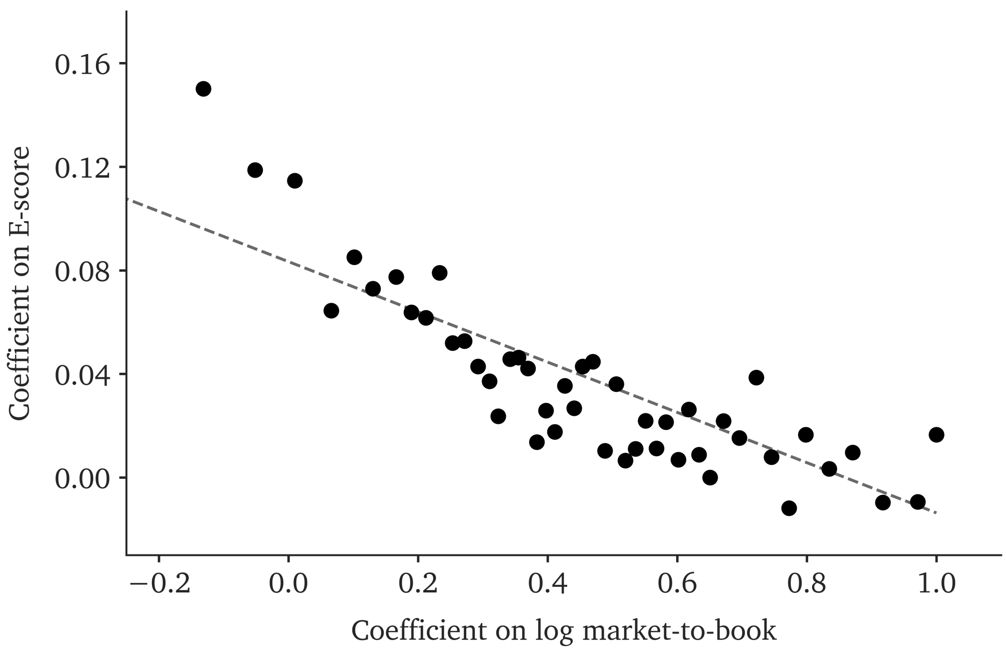

Figure 1. Binned scatterplot of demand coefficients. This figure shows the relationship between demand coefficients on environment score and price inelasticity in the binscatter plot.

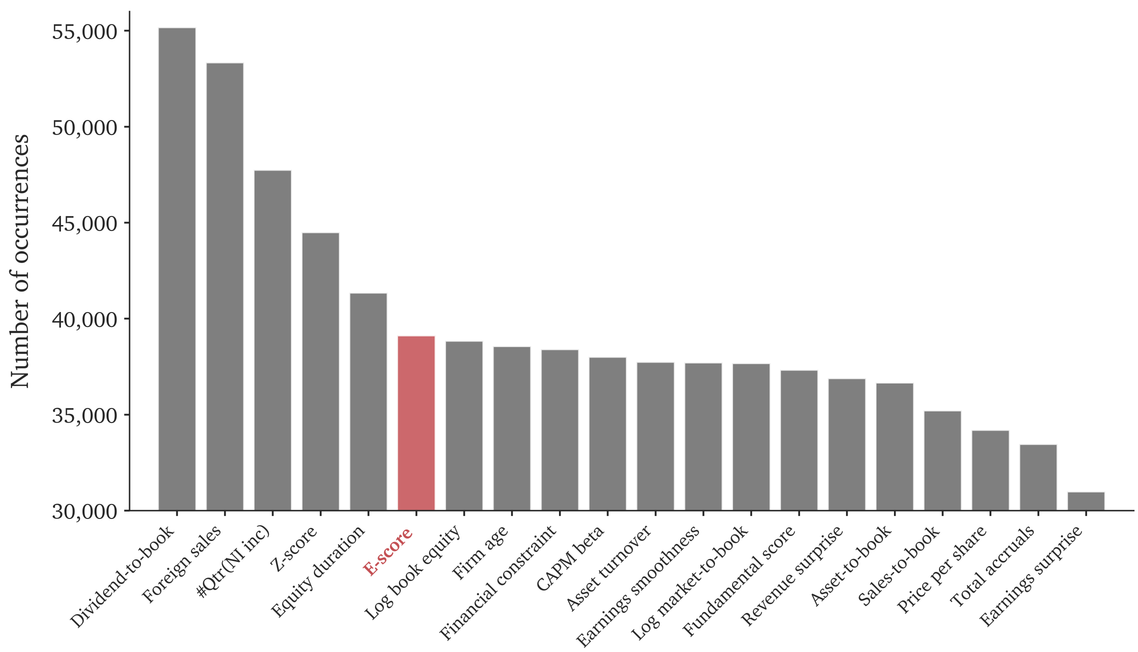

Figure 2. Importance of E-score relative to other characteristics. This figure shows the frequency with which each firm characteristic is selected by Lasso regressions predicting portfolio weights from 153 firm characteristics and MSCI environmental score. We start from 153 firm characteristics provided by Jensen et al. (2023) and add the MSCI environmental score. For each institution and quarter, we estimate a cross-sectional Lasso regression of log portfolio weights on a set of firm characteristics. We increase the Lasso regularization parameter until 10 characteristics survive. Then, for each characteristic, we count the number of times it is included in the surviving characteristics. The bar chart displays the total number of surviving occurrences out of 128,572 investor-quarter level Lasso regressions. E-Score is highlighted in red.

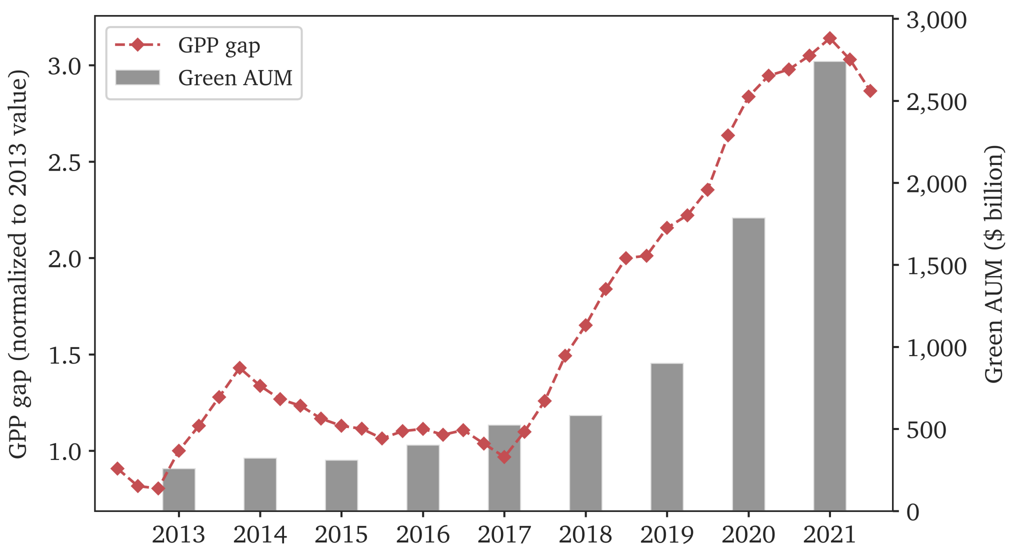

Figure 3. Green price pressure gap. This figure plots the green price pressure (GPP) gap over time (blue line) and the assets under management (AUM) of sustainable investment funds (green bars). The GPP gap is defined as the difference in average green price pressure between firms in the top and bottom E-Score terciles within each quarter, spanning from 2013:Q1 to 2022:Q2. The plotted line shows the four-quarter moving average of this gap normalized to 2013 value of 2.84%. We obtain the AUM data from UN Trade and Development (UNCTAD) and reported in billions of U.S. dollars, spanning from 2013 to 2021.

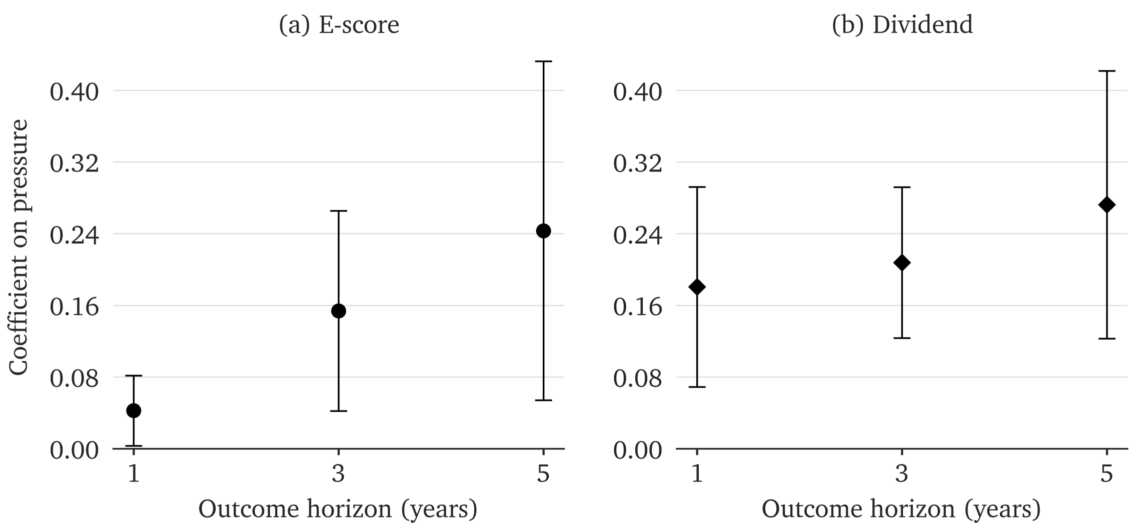

Figure 4. Benchmarking green price pressure to dividend price pressure. This figure shows the estimated coefficients from regressions of future firm outcomes on investor pressure, evaluated at horizons of 1, 3, and 5 years. We use two investor pressure measures: green price pressure and dividend price pressure. Dividend price pressure is defined similarly to green price pressure for firm's dividend payout instead of greenness. In the left panel, the green dots represent the effect of green price pressure on firms' environmental (E) scores at the future horizons. In the right panel, the red triangles show the effect of dividend price pressure on dividend payouts at the future horizons. All specifications control for firm characteristics, including current value of the outcome variables (E score or dividend payout), log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All dependent and independent variables are standardized within each year. We also include industry and year fixed effects in all specifications. Coefficients are standardized by the standard deviation of the change in outcome to make the two panels comparable. Error bands represent 95% confidence intervals based on standard errors clustered by firm and year.

Internet Appendix for "Green Price Pressure"

Xicheng Li
HKUST

Don Noh
HKUST

Sangmin S. Oh
Columbia Business School

Sean Seunghun Shin
KAIST

Jihong Song
Cubist

July 2025

A Data construction

A.1 Institutional equity holdings

We focus on the largest 95% of U.S. firms by market equity, which capture the majority of economic activity among publicly traded firms. Following convention, we define inside assets as the set of firms that collectively make up the top 95% of total market value, while the remaining 5% are aggregated into an outside asset. This approach ensures that the demand system estimation is based on the largest and most liquid stocks.

We obtain data on quarterly U.S institutional equity holdings from 2000:Q1 to 2022:Q4 from FactSet. Following Koijen et al. (2023), we classify institutional investors into investment advisors, hedge funds, long-term investors, private banking, and brokers. Given the substantial size of the investment advisor category, we further divide it into four subgroups using a two-way conditional sort based sequentially on assets under management (AUM) and active share.

Let $v_{it}(n)$ be the dollar value of investor i's holdings of stock n at date t. Let $\mathcal{N}_{it}$ represent investor i's investment universe that includes inside assets only, then stock n's portfolio weight among inside assets is given by $w^I_{it}(n) = v_{it}(n)/\sum_{n\in\mathcal{N}_{it}} v_{it}(n)$. In contrast, $w^M_{it}(n) = \mathrm{ME}_t(n)/\sum_{n\in\mathcal{N}_{it}} \mathrm{ME}_t(n)$ is the corresponding portfolio weight if investor i were to hold the market portfolio within its investment universe. Thus, investor i's active share at date t is

$$\mathrm{AS}_{it} = \frac{1}{2}\sum_{n\in\mathcal{N}_{it}} \left|w^I_{it}(n) - w^M_{it}(n)\right|, \tag{A1}$$

which measures the extent to which an investor's portfolio deviates from the market weights. The division by two prevents double counting, ensuring that the active share ranges from zero to one.

A.2 Stock fundamentals

We gather monthly stock returns data from the Center for Research in Security Prices (CRSP) and quarterly firm fundamentals data from Compustat. We prioritize data on equity prices, shares outstanding, and market equity from FactSet. Motivated by the factor structure of future profitability in Koijen et al. (2023), we focus on eight characteristics in the specification of asset demand: cash flow duration, log book equity, the foreign sales share, the Lerner index, the ratio of sales to book equity, the ratio of dividends to book equity, and market beta, which are shown to be relevant for expected profitability and profitability risk in the cross section.

B Theory

B.1 Including sustainability as a characteristic

In this section, we show that sustainability enters the investor's characteristic-based demand if either it is informative about expected returns or investors face a minimum sustainability constraint.

If sustainability is informative about the expected returns, it immediately follows from the same line of argument as in Koijen and Yogo (2019) that it should enter the characteristics-based demand. Suppose on the other hand that sustainability is not informative about the expected returns, but investors face a minimum sustainability constraint instead, similar to Pástor et al. (2021). More concretely, suppose for some $c > 0$ investor i faces, on top of short-sale constraints, an extra constraint[14]

$$\mathbf{b}_{it}'\mathbf{w}_{it} = (d_i\mathbf{g}_t)'\mathbf{w}_{it} > c \tag{B1}$$

where $\mathbf{b}_{it}$ is an $N \times 1$ vector of non-pecuniary benefits which is a product of d_i, investor i's ESG sensitivity, and $\mathbf{g}_t$, the vector of firms' sustainability. Let $\nu_{it} \geq 0$ be the Lagrange multiplier associated with this new constraint. Also, let us denote the kth elementary vector by $\mathbf{e}_k$. Then we have the following result:

Proposition A1. *If an investor faces a sustainability constraint, the optimal portfolio weight on asset n for which the short-sale constraint is not binding is*

$$\mathbf{w}_{it}(n) = \mathbf{y}_{it}(n)'\Pi_{it} + \pi_{it},$$

where

$$\Pi_{it} = \frac{1}{\gamma_{it}}(\tilde{\Phi}_{it} - \Psi_{it}\tilde{\kappa}_{it}), \quad \pi_{it} = \frac{1}{\gamma_{it}}(\phi_{it} - \lambda_{it} - \psi_{it}\tilde{\kappa}_{it})$$

are constant across assets. The modified factor loading is given by

$$\tilde{\Phi}_{it} = \Phi_{it} + \nu_{it}d_i\mathbf{e}_k,$$

the modified constant is given by

$$\tilde{\kappa}_{it} = \frac{\Gamma_{it}^{(1)\prime}(\tilde{\mu}_{it}^{(1)} - \lambda_{it}\mathbf{1})}{\Gamma_{it}^{(1)\prime}\Gamma_{it}^{(1)} + \gamma_{it}},$$

[14] The current formulation implicitly assumes that green stocks counteract the effects of brown ones. This simplifies the argument, and we motivate it by referring to Morningstar's ESG rating methodology which rates each fund using the weighted average of the fund's Sustainalytics scores. In order to incorporate negative screening against a group of stocks, the sensitivity d_i can be changed to a vector $\mathbf{d}_i$ with a very large $\mathbf{d}_i(n)$ value if stock n is screened.

and $\tilde{\mu}_{it}$ is the expected returns adjusted for the shadow benefits of sustainability

$$\tilde{\mu}_{it} = \mu_{it} + \nu_{it}\mathbf{b}_{it}.$$

Proposition A1 is identical to Proposition 1 in Koijen and Yogo (2019) but with a slight modification to the constant terms to account for the shadow benefit of sustainability, $\nu_{it}\mathbf{b}_{it}$. This addition comes from the fact that green assets are valuable beyond their expected returns because they relax the sustainability constraint. Even with the new constraint, the key content remains: variation in characteristics $\mathbf{y}_{it}(n)$ is the only source of variation in the portfolio weights. Furthermore, the expression for $\tilde{\Phi}_{it}$ reveals that even if investors do not believe sustainability is informative about expected returns (the factor loading on sustainability is zero in Φ_{it}), the optimal portfolio weights will still be positively related to sustainability.

B.2 Derivation of investor pressure in proposition 1

To compute $\mathbf{M}$, recall the following identity that holds by market clearing:

$$\mathbf{p} = \log\left(\sum_i A_i \mathbf{w}_i\right) - \mathbf{s} \tag{B2}$$

Differentiating both sides by $\mathbf{p}$:

$$\begin{aligned}
\mathrm{I} &= \begin{pmatrix} \left(\frac{1}{\sum_i A_i w_i(1)}\right)\left(\frac{\partial}{\partial \mathbf{p}(1)} \sum_i A_i w_i\,(1)\right) & \cdots & \left(\frac{1}{\sum_i A_i w_i(1)}\right)\left(\frac{\partial}{\partial \mathbf{p}(n)} \sum_i A_i w_i\,(1)\right) \\ \\ \left(\frac{1}{\sum_i A_i w_i(n)}\right)\left(\frac{\partial}{\partial \mathbf{p}(1)} \sum_i A_i w_i\,(n)\right) & \cdots & \left(\frac{1}{\sum_i A_i w_i(n)}\right)\left(\frac{\partial}{\partial \mathbf{p}(n)} \sum_i A_i w_i\,(n)\right) \end{pmatrix} \\
&= \begin{pmatrix} \frac{1}{\sum_i A_i w_i(1)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{1}{\sum_i A_i w_i(n)} \end{pmatrix} \begin{pmatrix} \frac{\partial(\sum_i A_i w_i(1))}{\partial \mathbf{p}(1)} & \cdots & \frac{\partial(\sum_i A_i w_i(1))}{\partial \mathbf{p}(n)} \\ \vdots & & \vdots \\ \frac{\partial(\sum_i A_i w_i(n))}{\partial \mathbf{p}(1)} & \cdots & \frac{\partial(\sum_i A_i w_i(n))}{\partial \mathbf{p}(n)} \end{pmatrix} \\
&\equiv \mathbf{H}^{-1} \frac{\partial}{\partial \mathbf{p}}\left(\sum_i A_i \mathbf{w}_i\right)
\end{aligned} \tag{B3}$$

where

$$\mathbf{H} := \operatorname{diag}\left(\sum_i A_i \mathbf{w}_i\right) = \sum_i A_i \operatorname{diag}(\mathbf{w}_i) \tag{B4}$$

Furthermore, it can be shown that:

$$\frac{\partial w_i(n)}{\partial p(n)} = \beta_{0i} w_i(n)(1 - w_i(n)), \quad \frac{\partial w_i(n)}{\partial p(m)} = -\beta_{0i} w_i(n) w_i(m)$$

$$w_i(n) \equiv \frac{\delta_i(n)}{1 + \sum_\ell \delta_i(\ell)}$$

which can be rewritten as

$$\frac{\partial \mathbf{w}_i}{\partial \mathbf{p}} = \beta_{0i}\mathbf{G}_i, \quad \mathbf{G}_i = \mathrm{diag}(\mathbf{w}_i) - \mathbf{w}_i\mathbf{w}_i'$$

Through analogous steps, it can be shown that the derivative with respect to the kth characteristic is

$$\frac{\partial \mathbf{w}_i}{\partial \mathbf{x}_k} = \beta_i\mathbf{G}_i$$

Now going back to the market clearing condition (B2) and differentiating both sides by $\mathbf{x}_k$:

$$\mathbf{M} := \frac{\partial \mathbf{p}}{\partial \mathbf{x}_k} = \mathbf{H}^{-1}\left(\sum_i \beta_{0i}A_i\mathbf{G}_i\right)\mathbf{M} + \mathbf{H}^{-1}\left(\sum_i \beta_{ki}A_i\mathbf{G}_i\right)$$

Rearranging yields the desired expression:

$$\mathbf{M} = \left(\mathbf{I} - \sum_i \beta_{0i}A_i\mathbf{H}^{-1}\mathbf{G}_i\right)^{-1}\left(\sum_i \beta_{ki}A_i\mathbf{H}^{-1}\mathbf{G}_i\right)$$

$\square$

C Empirical methodology

C.1 Demand estimation

A logit demand system is empirically relevant because the portfolio holdings data is close to a lognormal distribution. We estimate the demand function for investor i in a given quarter t using the estimation equation below:

$$\frac{w_{it}(n)}{w_{it}(0)} = \delta_{it}(n) = \exp\left\{\alpha_{it} + \beta_{0it}\mathrm{mb}_t(n) + \beta_{1it}'\mathbf{x}_t(n)\right\}\varepsilon_{it}(n), \tag{C1}$$

where $\mathrm{mb}_t(n)$ is the log market-to-book ratio, a price measure following Koijen et al. (2023). The demand coefficients are identified from the cross-sectional relation between portfolio weights and stock characteristics. Institutions who tilt their portfolios towards firms with longer maturity cash flows exhibit a larger coefficient on the equity duration, controlling for other characteristics.

Instrumental variables We follow the same identifying assumption as in Koijen and Yogo (2019) that posits the observed characteristics $\mathbf{x}_t(n)$ are exogenous except for log market-to-book equity, akin to an endowment economy. Given this premise, $\mathrm{mb}_t(n)$ is the only endogenous variable that correlates with latent demand $\varepsilon_{it}(n)$ through market clearing. Furthermore, we follow Koijen and Yogo (2019) to estimate the investment universe each quarter as the set of stocks that an investor currently holds or has held in the past eleven quarters, which is shown to be highly stable over time.

To instrument for log-market-equity in the demand estimation for investor i, we construct a counterfactual market capitalization for stocks n at date t if all other investors, excluding the household sector, were to hold an equal-weighted portfolio within their investment universe. Let $\mathcal{N}_{it}$ denote the investment universe of investor i at date t, and let $|\mathcal{N}_{it}|$ represent the number of stocks in this investment universe. Define $\Bbbk_i(n)$ as an indicator function that equals one if stock n is in investor i's investment universe and zero otherwise. The instrument for the log market-to-book of stock n is given by:

$$z_{it}(n) = \log\left(\sum_{j\notin\{i,1\}} A_{jt}\frac{\Bbbk_j(n)}{1+|\mathcal{N}_{jt}|}\right), \tag{C2}$$

which utilizes the identifying assumption that the investment universe of other institutions affects the portfolio weights of investor i solely through stock prices.

Estimation methodology A significant challenge in demand estimation arises from the fact that most institutions maintain concertrated portfolios. Consequently, many investors lack sufficient observations in the cross-section of equity holdings for precise demand estimation. This issue is particularly pertinent given the definition of inside assets as the largest 90% of firms by market equity, which shrinks the cross-section relative to the entire universe of U.S. stocks. Moreover, Koijen et al. (2023) estimate the demand coefficients annually for each investor, while this paper allows for quarterly variations in the demand function. Consequently, the aforementioned identification challenge becomes even more pronounced for quarterly estimation.

We estimate the demand coefficients for all investors, including the household sector, using a two-step instrumental variables ridge estimation following Koijen et al. (2023). In the first step, we conduct a pooled annual estimation to determine the group shrinkage target. Based on investor classification, we rank institutions by average market equity for each investor type annually, ensuring unique groupings. These institutions are then grouped into type bins, each containing at least 2,000 holdings across the four quarters. Consequently, investor i's holdings of stock n in different quarters are treated as distinct observations, with smaller institutions' holdings more likely to be pooled to minimize estimation error. Let $\mathbf{0}$ be a vector of zeros, with a dimension equal to the number of moment conditions. Let $\mathbf{e}_t$ be a four-dimensional vector representing quarter fixed effects, where the t-th element is one and the other elements are zero. For each (Type Bin, Year) group, we estimate the demand coefficients using the following moment conditions:

$$\mathbf{E}\left\{\big[\underbrace{\delta_{it}(n)\exp\left(-\beta_0 \mathrm{mb}_t(n) - \alpha_i' \mathbf{e}_t - \beta_1' \mathbf{x}_t(n)\right)}_{\varepsilon_{it}(n)} -1\big]\begin{pmatrix} z_{it}(n) \\ \mathbf{e}_t \\ \mathbf{x}_t(n) \end{pmatrix}\right\} = \mathbf{0}. \tag{C3}$$

Denote the first-stage pooled estimates for log market-to-book equity and other features as $\hat{\beta}_0$ and $\hat{\beta}_1$, respectively.

In the second step, we estimate the demand coefficients at (Investor, Quarter) level, using the first-stage pooled estimates as the shrinkage target. To mitigate weak identification, we use the group-level coefficient on log market-to-book equity for all investors within the (Type Bin, Year) group, corresponding to an infinite penalty on β_{0it}. The coefficients on the other characteristics are estimated through the following moment condition:

$$\mathbf{E}\left\{[\hat{\delta}_{it}(n)\exp\big(-\alpha_i'\mathbf{e}_t - \beta_1'\mathbf{x}_t(n)\big) - 1]\begin{pmatrix} \mathbf{e}_t \\ \mathbf{x}_t(n) \end{pmatrix}\right\} - \frac{\lambda}{|\mathcal{N}_{it}|^{\xi}}\begin{pmatrix} \mathbf{0} \\ \beta_{1it} - \hat{\beta}_1 \end{pmatrix} = \mathbf{0}, \tag{C4}$$

where $\hat{\delta}_{i,t}(n) = \delta_{i,t}(n)\exp(-\hat{\beta}_0 \mathrm{mb}_t(n))$. This penalty is inversely related to $|\mathcal{N}_{it}|$, the number of investor i's stock holdings in quarter t. The penalty shrinks the demand coefficients towards the group-level estimate $\hat{\beta}_1$. We select the penalty parameters by cross-validation, minimizing the mean squared error of predicted demand by randomly splitting the estimation sample in half within each quarter and using one subsample for estimation and the other for validation. This process yields $\lambda = 120$ and $\xi = 0.7$.

C.2 Variance decomposition of green price pressure changes

This section explains the variance decomposition method of Koijen and Yogo (2019) used in Section 3.4. As shown in Proposition 1, the estimated vector of green price pressure ($\mathbf{GPP}_t$) at quarter t is a function of greenness of stock ($\mathbf{E}_t$), other stock characteristics ($\mathbf{X}_t$), AUM ($\mathbf{A}_t$), price elasticity (β_{0t}), sensitivities to non-green firm characteristics (β_{1t}), preference for greenness (β_{2t}), and the latent demand (ϵ_t). We follow the variance decomposition by Koijen and Yogo (2019). We start by denoting $\mathbf{GPP}_t$ as an implicit function of its determinants:

$$\mathbf{GPP}_t = \mathbf{f}(\mathbf{x}_t, \mathbf{g}_t, \mathbf{A}_t, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t). \tag{C5}$$

Then, we can express changes in GPP between two periods $\Delta\mathbf{GPP}_{t+1} = \mathbf{GPP}_{t+1} - \mathbf{GPP}_t$ as follows:

$$\begin{aligned}\Delta\mathbf{GPP}_{t+1} = {} & \Delta\mathbf{GPP}_{t+1}(\mathbf{x}) + \Delta\mathbf{GPP}_{t+1}(\mathbf{g}) + \Delta\mathbf{GPP}_{t+1}(\mathbf{A}) + \Delta\mathbf{GPP}_{t+1}(\beta_{0t}) + \Delta\mathbf{GPP}_{t+1}(\beta_{1t}) \\ & + \Delta\mathbf{GPP}_{t+1}(\beta_{2t}) + \Delta\mathbf{GPP}_{t+1}(\epsilon)\end{aligned} \tag{C6}$$

where

$$\begin{aligned}\Delta\mathbf{GPP}_{t+1}(\mathbf{x}) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_t, \mathbf{A}_t, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) - \mathbf{f}(\mathbf{x}_t, \mathbf{g}_t, \mathbf{A}_t, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) \\ \Delta\mathbf{GPP}_{t+1}(\mathbf{g}) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_t, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) - \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_t, \mathbf{A}_t, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) \\ \Delta\mathbf{GPP}_{t+1}(\mathbf{A}) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) - \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_t, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) \\ \Delta\mathbf{GPP}_{t+1}(\beta_0) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t}, \beta_{2t}, \epsilon_t) - \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t}, \beta_{1t}, \beta_{2t}, \epsilon_t) \\ \Delta\mathbf{GPP}_{t+1}(\beta_1) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t+1}, \beta_{2t}, \epsilon_t) - \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t}, \beta_{2t}, \epsilon_t) \\ \Delta\mathbf{GPP}_{t+1}(\beta_2) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t+1}, \beta_{2t+1}, \epsilon_t) - \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t+1}, \beta_{2t}, \epsilon_t) \\ \Delta\mathbf{GPP}_{t+1}(\epsilon) &= \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t+1}, \beta_{2t+1}, \epsilon_{t+1}) - \mathbf{f}(\mathbf{x}_{t+1}, \mathbf{g}_{t+1}, \mathbf{A}_{t+1}, \beta_{0t+1}, \beta_{1t+1}, \beta_{2t+1}, \epsilon_t)\end{aligned} \tag{C7}$$

Finally, the cross-sectional variance of $\Delta\mathbf{GPP}$ can be decomposed as follows:

$$\begin{aligned}\mathrm{var}(\Delta\mathbf{GPP}) = {} & \mathrm{cov}(\Delta\mathbf{GPP}(\mathbf{x}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\mathbf{g}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\mathbf{A}), \Delta\mathbf{GPP}) \\ & + \mathrm{cov}(\Delta\mathbf{GPP}(\boldsymbol{\beta_0}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\boldsymbol{\beta_1}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\boldsymbol{\beta_2}), \Delta\mathbf{GPP}) \\ & + \mathrm{cov}(\Delta\mathbf{GPP}(\epsilon), \Delta\mathbf{GPP})\end{aligned} \tag{C8}$$

where we omit the time subscripts for simplicity.

C.3 Instrumenting greenness

Following Koijen et al. (2023), we model greenness as a function of log-market-to-book equity and the exogenous characteristics as

$$g_t(n) = \psi + \phi \mathrm{mb}_t(n) + \mathbf{x}_t(n)'\boldsymbol{\gamma} + \nu_t(n). \tag{C9}$$

The residual $\nu_t(n)$ represents an exogenous component of greenness that relates to technology or other factors that the firm does not control. Then our identifying assumptions are

$$\begin{aligned} \mathbf{E}[\nu_t(n)|\mathrm{mb}_t(n), \mathbf{x}_t(n)] &= 0, \\ \mathbf{E}[\varepsilon_{i,t}(n)|\mathrm{mb}_t(n), \mathbf{x}_t(n)] &= 0. \end{aligned} \tag{C10}$$

These moment conditions allow us to estimate asset demand consistently through a two-step estimator. In the first step, we estimate equation (C9) by ordinary least squares. We denote the vector of estimated residuals as $\widehat{\nu}_t(n)$. In the second step, we estimate asset demand (5) by generalized method of moments based on moment condition (C10), using the estimated residuals $\widehat{\nu}_t(n)$ as the instruments.

Figure A1 is a scatter plot of the estimated coefficient on greenness under the baseline assumption versus an alternative assumption that greenness is an endogenous characteristic. The two sets of estimated coefficients have a correlation of 0.974, which alleviates the endogeneity concern.

D Additional tables and figures

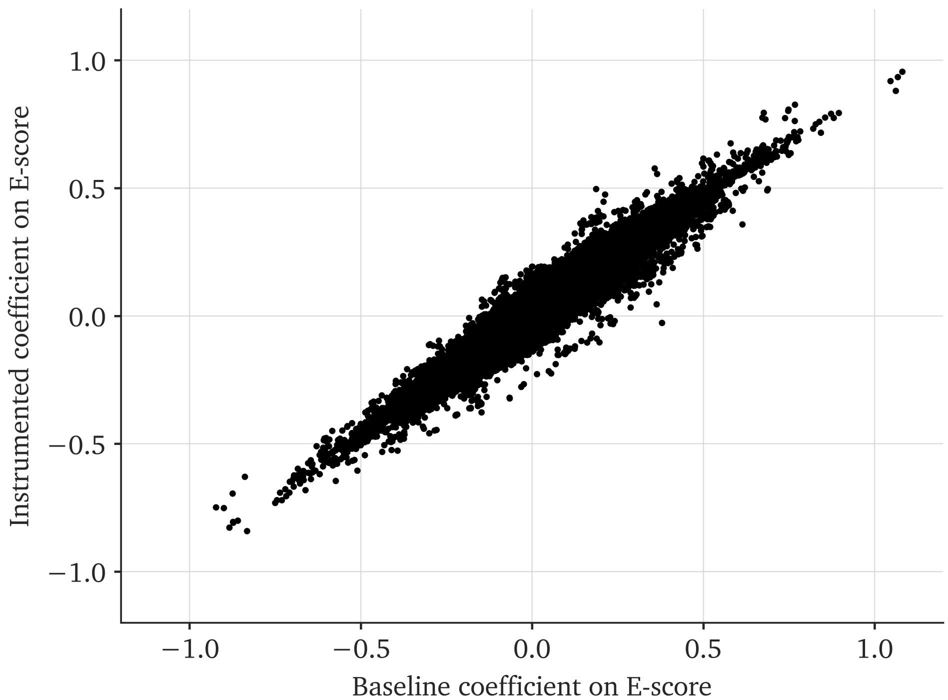

Figure A1. Scatterplot of demand coefficients with vs. without instrument for greenness. This figure compares demand coefficients on the environmental score estimated with and without instrumenting for firm greenness. Each point corresponds to an investor-firm-quarter observation. The construction of the instrument is detailed in Appendix C.3.

Table A1
Green price pressure and 5-year-ahead environmental improvement

This table examines the relationship between green price pressure (GPP) and 5-year changes in firms' environmental performance. For each corresponding variable, we control for the contemporaneous value and show the coefficient (Y_t). All specifications control for firm characteristics, including current E/S/G scores, log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All explanatory variables are standardized within each year. We also include industry and year fixed effects. Standard errors are two-way clustered across firm and year. We report s.e. below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

			Theme score$_{t+5}$			
	E-score	Emission	Waste MGMT	Natural res	Climate change	E opp
	(1)	(2)	(3)	(4)	(5)	(6)
GPP	0.120**	–33.189**	0.238**	0.179*	0.142	0.005
	(0.047)	(9.177)	(0.077)	(0.076)	(0.067)	(0.055)
Y$_t$	0.735***	0.681***	0.486***	0.626***	0.656***	0.503***
	(0.036)	(0.043)	(0.050)	(0.058)	(0.033)	(0.070)
Controls	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Within R^2	0.507	0.804	0.367	0.498	0.523	0.372
Observations	2,691	1,252	1,244	2,117	2,632	1,073

Table A2
Green price pressure and future environmental improvement:
Using instrument for greenness

This table examines the relationship between green price pressure (GPP) and 3-year changes in firms' environmental performance, where GPP is constructed with an instrument for greenness as described in Appendix C.3. For each corresponding variable, we control for the contemporaneous value and show the coefficient (Y_t). All specifications control for firm characteristics, including current E/S/G scores, log book equity, foreign sales, Lerner index, sales-to-book, dividend-to-book, and CAPM beta. All explanatory variables are standardized within each year. We also include industry and year fixed effects. Standard errors are two-way clustered across firm and year. We report s.e. below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

			Theme score$_{t+3}$			
	E-score	Emission	Waste MGMT	Natural res	Climate change	E opp
	(1)	(2)	(3)	(4)	(5)	(6)
GPP	0.096**	−9.408	0.175***	0.128*	0.031	0.052
	(0.035)	(5.503)	(0.029)	(0.061)	(0.032)	(0.039)
Y_t	0.785***	0.796***	0.638***	0.708***	0.756***	0.623***
	(0.039)	(0.025)	(0.038)	(0.056)	(0.033)	(0.059)
Controls	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Within R^2	0.628	0.881	0.468	0.597	0.641	0.514
Observations	4,326	2,558	2,367	3,230	4,238	1,712