Green Price Pressure*

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Abstract

We study the catering channel of sustainable investing: managers improve environmental performance to capture valuation premia from investor demand for sustainability. To quantify catering incentives, we use an asset demand system and introduce "green price pressure": the sensitivity of a firm's equilibrium stock price to improvements in its environmental performance. Unlike traditional measures of investor pressure, our measure accounts for differences in both investor price elasticities and preferences for sustainability. Instrumental variables analysis shows green price pressure leads to modest environmental improvements, but only among firms with strong pay-for-performance incentives and in easier-to-implement areas like waste management—raising greenwashing concerns. Applying our methodology to dividend policy yields comparable results, suggesting that our framework extends to catering behavior across other corporate policies.

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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 change. Much of the academic discussion has focused on whether these flows meaningfully raise the cost of capital for polluting firms (van der Beck 2021). Some see the effect as negligible or even counterproductive (Berk and van Binsbergen 2021, Hartzmark and Shue 2023), while others find tangible financing gains for green firms (Gormsen et al. 2023). In this paper, we step aside from this debate on the cost of capital channel and revisit developments in sustainable investing through a simple yet intuitive perspective: firms cater to shifting investor demand for sustainability, a view introduced by Baker and Wurgler (2004) in the context of dividends.

The catering view and the cost of capital view are not mutually exclusive; prices play a central role in both. Yet, highlighting their subtle differences affect how we interpret the data and what predictions we draw. For example, the catering view can explain corporate actions that do not depend on financing costs, such as operational changes or enhanced disclosures. It is also consistent with firms responding to episodic, shifting investor demand. These nuances therefore shape what we expect regarding the effect of sustainable investing on corporate behavior and the role of managerial incentives.

Sustainable investing features the three key ingredients of the catering theory (Baker and Wurgler 2004). First, many investors demand sustainability as a specific characteristic in their portfolios (Krueger et al. 2020). Second, these demand shifts are large, and limits to arbitrage—such as investment mandates and short-sale constraints—are significant enough to affect prices (Shleifer and Vishny 1997). Third, managers often weigh the immediate valuation gain from appearing greener against the long-run costs of backlash (Flammer et al. 2021). Together, these elements make the catering view a natural framework to examine sustainable investing.

We use a demand system framework to quantify firms' incentives to cater to investor demand for sustainability. This approach extends the traditional catering framework (Baker and Wurgler 2004), which relies on aggregate market-level measures of investor sentiment, by constructing firm-specific measures of catering incentives we term "green price pressure." Green price pressure is defined as the sensitivity of a firm's equilibrium stock price to improvements in its environmental performance, and its firm-specific variation stems from three sources of investor heterogeneity: sustainability preferences, price elasticities, and investment universes. Investment universe restrictions arising from fund mandates, regulatory requirements, and exclusionary screens create distinct investor clienteles across firms, and these clienteles differ in both their demand for greenness and their price sensitivity.

Consequently, green price pressure varies across firms even though each investor's preferences for firm characteristics remain constant across all stocks in their universe. Firms held by investors with strong sustainability preferences and low price elasticity experience the highest green price pressure, as green preferences set the direction and initial magnitude while lower price elasticity amplifies the effect: a price-inelastic investor requires larger price concessions in response to changes in greenness.

We document 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 and are limited to corporate environmental actions that are relatively easier to implement.

By quantifying the catering incentive through our demand system approach, our findings yield several takeaways regarding how market-based sustainability incentives operate in practice. On the investor side, less price-sensitive investors—such as passive funds—amplify the market impact of sustainability preferences. On the firm side, managerial incentives emerge as necessary conditions for translating market signals into environmental action. Yet the nature of firm responses raises potential concerns. Improvements concentrate in easier-to-implement areas like waste management, and our instrumental variables analysis finds effects on environmental scores but not on emissions intensity, a pattern consistent with firms pursuing rating improvements without substantive decarbonization.

We start by combining comprehensive data on institutional equity holdings, stock characteristics, and firm environmental performance metrics. 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 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 use the estimated demand system to construct firm-level green price pressure. Specifically, we derive a closed-form expression for the sensitivity of a firm's equilibrium stock price to changes in greenness by implicitly differentiating the market-clearing condition with respect to greenness. The resulting expression then takes the estimated investor-level coefficients as inputs. We first validate our measure by examining 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. As a placebo, sorting firms by environmental scores instead of green price pressure yields no systematic difference in stock price reactions, indicating that the effect is not mechanically driven by firms' environmental profiles.

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. This widening gap highlights an asymmetry in sustainable investing: price pressure intensifies mainly for firms that are already green, consistent with Hartzmark and Shue (2023) who find that sustainable capital flows toward firms with lower abatement potential.

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.

Having documented how green price pressure varies across firms and over time, we next test the core prediction of catering theory by studying how firms respond to green price pressure. Specifically, 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. To highlight the predictive power of our measure, we compare green price pressure to traditional proxies used in prior studies to capture investor pressure for environmental improvements, such as institutional ownership (Dyck et al. 2019) and the proportion of UN PRI signatories (Kim and Yoon 2023). In contrast to green price pressure, these traditional measures exhibit a smaller and statistically insignificant association with future environmental outcomes. This discrepancy highlights the advantages of our approach, which captures investor heterogeneity in sustainability preferences and incorporates differences in price elasticities that amplify the catering incentive.

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 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 (Core and Guay 2002, 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 and middle tercile exhibit statistically insignificant responses. 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.

We also benchmark the economic significance of green price pressure by comparing it to the original catering channel from Baker and Wurgler (2004): dividend policy. Using our methodology to construct an analogous measure of "dividend price pressure," we find that the effects of investor preferences on environmental performance are comparable in magnitude to their well-documented influence on dividend payments. This benchmarking exercise confirms that market-based sustainability incentives operate with economically meaningful magnitudes. Furthermore, it illustrates that our framework can be generalized to capture the firm's catering behavior across a range of corporate policies.

To support the causal interpretation of our findings, we conduct instrumental variable (IV) analyses that address two potential endogeneity concerns. First, green price pressure itself may be endogenous if unobserved factors simultaneously drive both investor composition and future environmental performance. We address this by constructing an instrument that isolates variation in green price pressure arising solely from differences in investor price elasticity, holding green preferences fixed at the economy-wide average. Second, greenness may be endogenous in our demand estimation if firms with higher valuations invest more in environmental initiatives. Following Koijen et al. (2023), we instrument for greenness using the residual component orthogonal to market valuations and firm characteristics. Both IV approaches support a causal effect of green price pressure on environmental scores, with positive and statistically significant coefficients. However, we find no statistically significant effect on emissions intensity in the IV specifications. Together with our finding that improvements concentrate in easier-to-implement dimensions like waste management rather than climate change themes, this pattern raises questions about firms pursuing rating improvements without substantive decarbonization.

Related literature Our paper relates to three main strands of literature. First, we contribute to the literature on sustainable investing. On the asset pricing side, the literature—reviewed in Giglio et al.

(2021) and Pástor et al. (2024)—has largely focused on the cost of capital channel by examining the return gap between green and brown stocks, using both theoretical and empirical approaches.[1] We depart from this focus on expected return differences by using an asset demand system to measure how demand shocks related to environmental preferences affect valuations and real firm outcomes.[2] This approach yields a firm-level measure of green price pressure, capturing the marginal valuation benefit of improved environmental performance.

Our paper also speaks 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 (Davies and Van Wesep 2018, Berk and van Binsbergen 2021). 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 showing that firms subject to greater investor pressure subsequently exhibit larger improvements in their environmental performance. Importantly, our results highlight the role of managerial compensation in translating investor preferences into corporate environmental improvements.

Second, our paper contributes to the literature on the catering theory of corporate policy, which posits that managers adjust firm attributes to exploit valuation premia created by investor demand. Baker and Wurgler (2004) document this mechanism for dividends, with subsequent work extending it to stock splits (Baker et al. 2009), payouts (Hoberg and Prabhala 2008, Jackson et al. 2022), capital structure (Baker and Wurgler 2002, Greenwood et al. 2010, Ma 2019), investment (Polk and Sapienza 2008), restructuring (Sudarsanam and Qian 2007) and corporate policies in the product market (Aghion and Stein 2008, Lou 2014, Célérier and Vallée 2017). Sustainable investing offers a modern setting for this mechanism: a firm's environmental profile has become a key determinant of investor asset demand, and shocks to this demand can generate large price impacts. Our measure of green price pressure provides a direct, equilibrium-based estimate of these premia, allowing us to test whether managers cater to sustainability-driven demand in the same way they have historically catered to demand for other firm attributes.

[1] 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). 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, Pástor et al. 2023).

[2] 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.

Finally, our paper contributes to the burgeoning literature that estimates asset demand systems to study markets ranging from equity and fixed income to country-level assets (Koijen and Yogo 2019, 2020, Bretscher et al. 2022, Koijen et al. 2023, Jiang et al. 2024). To date, this literature has largely addressed asset pricing questions such as the trading behavior of U.S. households (Gabaix et al. 2023) and the effect of quantitative easing (Koijen et al. 2021). Instead, we provide one of the first applications of this framework to corporate finance by illustrating how it can be used to measure a firm's incentive to cater to investor demand. In this sense, our work relates to Mota and Siani (2023) on bond issuance catering to institutional investors and Choi et al. (2025) on sentiment-driven capital misallocation.

Recent studies raise important considerations for demand system estimation. Under the homogeneous substitution condition formalized by Haddad et al. (2025), the logit demand system satisfies the requirements for cross-sectional identification of relative demand elasticities, which are inputs into our measure of green price pressure. At the same time, the logit functional form does impose restrictions on substitution patterns, which may be strained in markets with tightly defined substitute groups and meaningful cross-asset spillovers (Chaudhary et al. 2022, Fuchs et al. 2023). However, this concern is most acute in corporate bond markets, where securities cluster by rating and maturity into close substitutes. Equity markets exhibit more diffuse substitution across firms and characteristics, reducing the severity of these concerns (Davis et al. 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. As in Pástor et al. (2021), each firm has a greenness characteristic and can adjust its greenness, facing quadratic adjustment costs. In our setting, investors differ not only in their preferences for greenness but also in their price elasticity. This heterogeneity drives the relationship between stock prices and firm greenness, and in turn, influences firms' incentives to adopt greener practices.

Consider a set of investors indexed by $i \in \mathcal{I}$ and assets (firms) indexed by $n \in \mathcal{N}$. Each investor i is restricted to an investment universe $\mathcal{N}_i \subseteq \mathcal{N}$. These restrictions arise from several sources. For example, benchmark constraints tie managers to specific indices, limiting their holdings to constituents of their designated benchmark (Cremers and Petajisto 2009). Fund mandates also restrict investments based on market-cap tiers, sector focus, or investment style (Barberis and Shleifer 2003, Gabaix and Koijen 2022), while fiduciary standards and governance constraints can further

narrow permissible holdings (Almazan et al. 2004). Exclusionary screens remove stocks based on sin stock criteria, faith-based restrictions, or ESG considerations (Hong and Kacperczyk 2009, Gantchev et al. 2022), which are particularly pertinent in the context of sustainable investing. This segmentation is also empirically substantial and persistent: Koijen and Yogo (2019) document that the median institutional investor holds only 67 stocks, and 95% of stocks held in a given quarter were also held in at least one of the previous eleven quarters. As a result, different firms have different investor bases, which can generate firm-specific variation in green price pressure as we show below.

Let $S_i \geq 0$ denote investor i's size (e.g., AUM), and let $q_i(n)$ denote investor i's demand for asset n per unit of size, so that investor i's total demand is $S_i q_i(n)$ for $n \in \mathcal{N}_i$ and zero otherwise. Suppose investor i's demand for assets in their investment universe can be written as

$$q_i(n) = -\zeta_i p(n) + \gamma_i g(n) + \varepsilon_i(n), \tag{1}$$

where $p(n)$ is asset n's price, $g(n)$ is its greenness (e.g., environmental score), ζ_i is the price elasticity, γ_i reflects preference for greenness, and $\varepsilon_i(n)$ is an investor–asset demand shifter (e.g., idiosyncratic taste).

We normalize the total supply of each asset to one share, so that the market clearing condition for each n is

$$\sum_{i:n\in\mathcal{N}_i} S_i q_i(n) = 1.$$

Because investment universes differ across investors, the set of investors who hold firm n varies by firm. To aggregate investor characteristics for firm n, define the firm-specific, size-weighted sums over investors for whom n is in their investment universe:

$$\zeta_S(n) \coloneqq \sum_{i:n\in\mathcal{N}_i} S_i\zeta_i, \quad \gamma_S(n) \coloneqq \sum_{i:n\in\mathcal{N}_i} S_i\gamma_i, \quad \varepsilon_S(n) \coloneqq \sum_{i:n\in\mathcal{N}_i} S_i\varepsilon_i(n).$$

Then the market clearing price as a function of greenness is

$$p\big(g(n)\big) = \frac{\gamma_S(n)g(n) + \varepsilon_S(n) - 1}{\zeta_S(n)}. \tag{2}$$

Equation (2) shows that a firm's environmental performance affects its stock price through the preferences of its investor clientele—those investors for whom the firm is part of their investment universe. 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:

$$\text{Green Price Pressure}(n) \coloneqq \frac{\partial p(n)}{\partial g(n)}. \tag{3}$$

This partial derivative effectively measures the "price boost" a firm can achieve for a one-unit improvement in its environmental performance.[4] 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 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 (Pástor 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, green price pressure for firm n simplifies to $\gamma_S(n)/\zeta_S(n)$, where $\gamma_S(n)$ is the size-weighted sum of environmental preferences among investors who can hold firm n, and $\zeta_S(n)$ is the corresponding aggregate of their price elasticities. The average green coefficient, $\gamma_S(n)$, determines the *direction* of the price pressure: a positive $\gamma_S(n)$ implies that firms can achieve higher valuations from greener investors. Together with the magnitude of $\gamma_S(n)$, the average price elasticity, $\zeta_S(n)$, 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). Importantly, green price pressure varies across firms even though each investor's parameters γ_i and ζ_i remain fixed across all stocks in their universe. In frictionless models where all investors hold all stocks—such as Pástor et al. (2021) and Pedersen et al. (2021)—green price pressure would be uniform across firms, reflecting economy-wide investor preferences. In contrast, our framework generates firm-specific green price pressure because investment universe

[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.

[4]This partial equilibrium expression defines the object of interest. In Section 2, we estimate green price pressure in a general equilibrium framework where the price derivative depends on all investors' demand coefficients, price elasticities, and cross-asset substitution patterns (see Equation (7)).

restrictions create heterogeneous investor clienteles across firms.

The expression for green price pressure highlights two important considerations for empirical implementation. First, computing green price pressure for each firm requires estimating environmental preference parameters (γ_i) and price elasticities (ζ_i) for all investors who hold or could plausibly hold that firm's shares. Since green price pressure aggregates these investor-specific parameters over each firm's unique shareholder base, accurate measurement demands a flexible approach that can capture heterogeneous investor characteristics 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.

Second, both components—environmental preferences $\gamma_S(n)$ and price elasticity $\zeta_S(n)$—jointly determine the level and dynamics of green price pressure. Environmental preferences set the direction and baseline magnitude, while price elasticity acts as a multiplier: low-elasticity investors amplify the price impact of a given preference for greenness. This interaction implies that green price pressure can evolve over time through multiple channels—shifts in investor preferences, changes in price elasticities, reallocation of assets under management, or migration of firms across investor clienteles. Section 3 examines how green price pressure varies across firms and over time through a variance decomposition that quantifies the relative importance of each channel.

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. Suppose that $\gamma_S(n)$ shifts to a larger value $\gamma'_S(n)$ due to increased environmental awareness among the firm's investor clientele. If the manager chooses the change in greenness, $\Delta g(n)$, she incurs an adjustment cost $\frac{1}{2}\chi(n)[\Delta g(n)]^2$ where $\chi(n)$ is a firm-specific adjustment-cost parameter. Then, the manager solves

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

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

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

This expression shows that the firm's environmental adjustment is increasing in green price pressure. Firms facing stronger investor demand for sustainability from their investor clientele 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 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.

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).[5] 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

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

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.

[5]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).

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.

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 $\text{ME}_t(n) = P_t(n)S_t(n)$. 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

$$\begin{aligned}\frac{w_{i,t}(n)}{w_{i,t}(0)} &= \delta_{i,t}(n) \\ &= \exp\left(b_{0,i,t} + \beta_{0,i,t} mb_t(n) + \beta'_{1,i,t}\mathbf{x}_t(n)\right)\epsilon_{i,t}(n),\end{aligned} \tag{4}$$

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

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)} \quad \text{and} \quad w_{i,t}(0) = \frac{1}{1 + \sum_{m \in \mathcal{N}_{i,t}} \delta_{i,t}(m)}. \tag{5}$$

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 (i) greenness is informative about expected returns, (ii) investors directly derive utility from holding greener stocks, or (iii) 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.

Second, 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.[6] More concretely, suppose that investor i faces an extra constraint,

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

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.[7] $\mathbf{b}_{i,t}$ 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) to test whether greenness belongs among the characteristics that best predict institutional portfolio weights. We start from 153 firm characteristics provided by Jensen et al. (2023) and add the MSCI environmental score, yielding 154 characteristics in total. For each investor i and quarter t, we estimate a cross-sectional lasso regression where the dependent variable is the log relative portfolio weight,

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

and the independent variables are the 154 firm characteristics. Specifically, we estimate:

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

where λ is the penalty parameter and $K+1 = 154$. The ℓ^1 penalty term forces the lasso to discard less relevant variables (set their coefficients to zero) as the penalty increases. We discard zero holdings for this exercise because the linear specification requires positive portfolio weights.

For each investor-quarter regression, we increase the penalty parameter λ until only 10 characteristics survive. We then count how many times each characteristic appears among these top

[6] A similar condition can be found in Pástor et al. (2023).

[7] 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.

10 survivors across all investor-quarter pairs in our sample. This counting procedure reveals which characteristics are consistently important for institutional portfolio decisions.

Figure 2 shows the survival frequencies for the 20 characteristics with the highest counts. The environmental score ranks 6th, appearing in the top 10 for a large fraction of the 128,572 investor-quarter regressions. This survival rate places the environmental score well within the top 10% of all characteristics and ahead of many traditional firm attributes. For context, other characteristics in our baseline demand specification—log market-to-book, log book equity, market beta, dividend-to-book, and foreign sales—also appear among the top 20 survivors, validating our variable selection. The main takeaway is that environmental performance is a first-order consideration for institutional investors' portfolio allocation decisions 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:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\left(b_{0,i,t} + \beta_{0,i,t} mb_t(n) + \beta'_{1,i,t}\mathbf{x}_t(n) + \beta_{g,i,t} g_t(n)\right)\epsilon_{i,t}(n), \tag{6}$$

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. A related concern is that greenness may be endogenous if firms with higher valuations invest more in environmental initiatives, biasing our demand estimates through reverse causality. To address this, we follow Koijen et al. (2023) and re-estimate the demand system using an instrument for greenness: the residual from a regression of environmental scores on market valuations and other firm characteristics. The resulting demand coefficients are highly correlated

with our baseline estimates (correlation = 0.974), and our subsequent results remain unchanged. We discuss this approach later in detail in Section 4.5.2.

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 (6) 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.[8] 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.

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*

[8] Ideally, a fully micro-founded model would incorporate firm-side decisions and adjustment costs. We leave this for future work and instead control for observed firm characteristics and industry classification, allowing us to compare firms with plausibly similar marginal costs of adjustment.

satisfies

$$\mathbf{P} := \frac{\partial \mathbf{p}}{\partial \mathbf{g}} = \left(\mathbf{I} - \sum_i \beta_{0,i} A_i \mathbf{H}^{-1} \mathbf{G}_i\right)^{-1} \left(\sum_i \beta_{g,i} A_i \mathbf{H}^{-1} \mathbf{G}_i\right), \tag{7}$$

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 nth 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 (7) 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.[9] The direction of an adverse change depends on the "AUM-weighted average coefficient" on greenness, as we can see from the nth diagonal entry of the

[9] 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.

second term:

$$\frac{\sum_i \beta_{g,i} A_i w_i(n)(1 - w_i(n))}{\sum_i A_i w_i(n)}. \tag{8}$$

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 (7). 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 (8), but is even simpler:

$$\text{Green Price Pressure}(n) \approx \frac{\sum_i s_i(n) \beta_{g,i}}{1 - \sum_i s_i(n) \beta_{0,i}}. \tag{9}$$

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 (7).

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. This coefficient means 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.[10] This threshold captures meaningful changes in perceived ESG risk, independent of stated policies or commitments.[11]

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

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

at the 5% and 1% levels, respectively. Importantly, the effect varies systematically by terciles of 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 characteristics.

A natural concern is that this pattern could reflect greenness itself rather than investor-driven price sensitivity—greener firms may simply have more to lose from ESG incidents. To address this, Appendix Table A2 reports a placebo test in which we sort firms by environmental scores rather than green price pressure. We find no monotonic pattern across E-score terciles, suggesting that the differential market reaction is driven by investor composition, not by firms' environmental profiles.

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 (2.84% in 2013), 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. This pattern also echoes the concern raised by Hartzmark and Shue (2023) in the context of the cost of capital channel: market-based sustainability incentives may be "counterproductive" in the sense that price pressure concentrates on firms where the marginal environmental benefit of additional improvement is lowest.

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. This raises questions about whether such concentration maximizes real-world environmental impact, as the greatest potential for improvement may lie with browner firms. 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 testing the core prediction of catering theory: do firms actually respond to market-based incentives by adjusting their policies to capture valuation premia?

Consistent with the catering theory, we show that green price pressure predicts improvements in sustainability performance and the effect is stronger when managerial incentives are better aligned with shareholders (Sections 4.1 and 4.2). However, these improvements are concentrated in themes where operational changes may be more feasible and may not necessarily contribute to lower emissions, raising concerns about greenwashing (Section 4.3). These findings suggest that, while green price pressure can influence firm behavior, its impact varies with incentive structures and the feasibility of environmental improvements. To put these findings in perspective, we benchmark the effect sizes against the dividend catering channel (Section 4.4) and provide an instrumental variable analysis to strengthen the causal interpretation (Section 4.5).

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:

$$\text{Escore}_{n,t+h} = \delta \text{GPP}_{n,t} + \phi \text{Escore}_{n,t} + \boldsymbol{\gamma}' \mathbf{x}_{n,t} + \alpha_t + \alpha_{\text{ind}(n)} + \epsilon_{n,t} \tag{10}$$

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 a three-year horizon ($h = 3$) as our baseline results to allow time for firms

to adjust.[12] 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. Later, we show in Section 4.4 that this effect is also comparable in magnitude to the dividend catering channel, suggesting that the influence of sustainability preferences is economically meaningful.

In Column (2), we use the approximation in Equation (9) 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.

To assess the relative contribution of each channel, in Columns (3) and (4) we separately include the numerator and denominator of the approximation in Equation (9). Both coefficients are statistically significant at the 5% and 10% levels, respectively, and carry signs consistent with Equation (9): the numerator (green preference) is positive, while the denominator (aggregate elasticity) is negative. The weaker significance and smaller magnitude relative to the main specification is not surprising, as green price pressure is theoretically defined as the *ratio* of these two components. Nevertheless, the results confirm that green price pressure operates through both the green-preference and price-elasticity channels. This decomposition also motivates our instrumental variables strategy in Section 4.5: because price elasticity affects firm outcomes independently of green preferences, we can isolate variation in GPP arising solely from differences in elasticity to address endogeneity concerns.

In Column (5) we examine the relationship between green price pressure and a different measure of environmental performance: emissions intensity three years ahead, measured as tonnes of CO2 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

[12] We find similar results for a five-year horizon, as shown in Appendix Table A1.

tCO2/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 (10) 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 Managers' incentives to cater

We next test whether the relationship between green price pressure and environmental improvements operates through the catering channel. If managers improve environmental performance to capture valuation premia, we expect the response to green price pressure to be stronger when managerial

incentives are better aligned with stock prices. This 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 are in the top tercile of the wealth sensitivity to stock prices, while low delta firms are those in the bottom tercile of sensitivity.[13] 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. Columns (1) and (2) show that firms in the lowest and middle terciles of CEO delta exhibit no significant response to green price pressure; the coefficients are small and statistically indistinguishable from zero. In contrast, Column (3) reveals a strong response among firms in the highest tercile, with a coefficient of 0.154 (significant at the 1% level). This pattern is consistent with the catering view: managers are most likely to improve environmental performance to capture valuation premia when their own compensation is tightly linked to the stock price.

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[14], suggesting that similar incentive channels operate in the context of firms' environmental

[13] We define terciles based on the universe of Compustat firms for which CEO compensation data are available.

[14] 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.

policies.[15]

4.3 Which environmental dimensions respond?

The previous section establishes that managerial incentives mediate the response to green price pressure. We now examine which specific dimensions of environmental performance respond most strongly. This analysis matters for two reasons. First, it speaks to concerns about greenwashing: if firms respond to investor pressure by targeting superficial or easily achievable improvements rather than substantive changes, the real environmental impact of sustainable investing may be limited. Second, different environmental actions vary in their cost and implementation horizon: waste management practices can often be adjusted relatively quickly, while reducing carbon emissions may require capital-intensive overhauls. Examining which dimensions respond allows us to better understand the nature and scope of firm responses to market-based sustainability incentives.

To make progress on this question, we examine the specific themes that constitute the environmental score. MSCI ESG Ratings breaks down environmental performance into four themes. *Pollution and waste* evaluates management of toxic emissions, electronic waste, and packaging, which are operational issues where firms can often make relatively quick improvements. *Natural capital* assesses risks related to biodiversity, land use, water stress, and raw material sourcing. These two themes capture important environmental practices, but they are not primarily designed to measure carbon mitigation or transition exposure.

The remaining two themes are more directly tied to climate outcomes. *Climate change* captures a company's exposure to and management of carbon-related risks, including direct emissions, product carbon footprint, and vulnerability to climate regulation. Finally, *Environmental opportunities* measures a company's ability to generate revenue from clean technology, green buildings, and renewable energy. If green price pressure operates through decarbonization incentives, we would expect the strongest responses in these latter two themes.

Table 7 shows the results of estimating Equation (10) 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. Waste management shows the strongest effect (0.225), more than double the coefficient on the overall E-score, and natural resource use also responds meaningfully (0.145). In contrast, the climate change theme—which captures carbon

[15] 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).

emissions, and product carbon footprint—shows a notably smaller response (0.081), less than half the magnitude of waste management. Most notably, environmental opportunities, which includes clean tech adoption and renewable energy investments, shows no significant response at all (0.010, statistically insignificant).

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.

4.4 Benchmarking green price pressure: Comparison to dividend policy

The preceding analyses document a positive association between green price pressure and subsequent environmental improvements, though it is concentrated in easier-to-adjust dimensions like waste management. To provide a benchmark for interpreting these effect sizes, we compare green price pressure against the original catering channel through which investor preferences shape corporate decisions: the demand for dividends (Baker and Wurgler 2004).

Specifically, 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.

4.5 Instrumental variables analyses

In this section, we address potential endogeneity concerns using instrumental variables to strengthen the causal interpretation of our results. There are two distinct concerns that could hamper such interpretation. First, green price pressure may be endogenous in the firm response regressions if unobserved factors simultaneously drive the green preferences of a firm's investor clientele and its future environmental performance. Second, greenness may be endogenous in the demand estimation if firms with higher valuations invest more in environmental initiatives; this could bias our measure of green price pressure. We address each concern with a separate instrument. Section 4.5.1 instruments for green price pressure directly using variation that arises solely from differences in investor price elasticity. Section 4.5.2 constructs green price pressure using residual greenness that is orthogonal to valuations and firm characteristics, following Koijen et al. (2023).

4.5.1 Instrumenting green price pressure

We first address the concern that green price pressure itself may be endogenous in the firm response regressions. Unobserved factors could drive both the composition of a firm's investor base and its future environmental performance. For instance, firms that anticipate making environmental improvements may attract green-oriented investors, generating a correlation between green price pressure and future environmental scores that does not reflect a causal effect of investor pressure on firm behavior.

To address this concern, we propose an instrument for green price pressure that isolates variation arising solely from differences in investor price elasticity. The core idea is as follows: green price pressure depends on both investor preferences for greenness and investor price elasticity (Equation (9)). The endogeneity concern operates primarily through the preference channel—firms may attract investors with green preferences precisely because they plan to improve environmental performance. In contrast, variation in price elasticity across investor bases is less likely to be driven by anticipated firm actions. We therefore construct an instrument that holds green preferences fixed at the economy-wide average while allowing price elasticity to vary across firms.

Specifically, let $\bar{\gamma}_t$ be the *economy-wide* average green preference across investors at time t, computed from the estimated demand coefficient $\beta_{g,i,t}$ in Equation (6). Let $\zeta_{n,t}$ be the firm-level price elasticity from the demand system, defined as the AUM-weighted average of investor i's elasticity $\zeta_{i,t}$ among investors who hold firm n. We construct the instrument as:

$$Z_{n,t}^{\text{GPP}} \equiv \frac{\bar{\gamma}_t}{\zeta_{n,t}}. \tag{11}$$

This instrument varies across firms only through differences in price elasticity, not through differences in the green preferences of their investors. The relevance condition is satisfied because price elasticity is a key determinant of green price pressure: holding green preferences fixed, firms held by less price-elastic investors experience larger price impacts from changes in environmental performance. The exclusion restriction requires that investor price elasticity affects future environmental performance only through its effect on green price pressure, conditional on controls.

We estimate the following two-stage least squares (2SLS) specification:

$$\text{(First stage)} \quad \text{GPP}_{n,t} = \pi Z_{n,t}^{\text{GPP}} + \rho\, \text{Escore}_{n,t} + \boldsymbol{\kappa}'\mathbf{x}_{n,t} + \alpha_t + \alpha_{\text{ind}(n)} + u_{n,t}, \tag{12}$$

$$\text{(Second stage)} \quad \text{Escore}_{n,t+h} = \delta\, \widehat{\text{GPP}}_{n,t} + \phi\, \text{Escore}_{n,t} + \boldsymbol{\gamma}'\mathbf{x}_{n,t} + \alpha_t + \alpha_{\text{ind}(n)} + \varepsilon_{n,t}. \tag{13}$$

Table 8 reports the results, which largely support a causal interpretation of our main results. Columns (1) and (2) replicate the OLS coefficients from Table 4 for comparison. Column (3) reports the first-stage regression, with an F-statistic of 467.63, well above the Staiger and Stock (1997) threshold of 10 for detecting weak instruments. Column (4) reports the second-stage estimates for future environmental scores. The coefficient on instrumented green price pressure is 0.149, which is positive and statistically significant at the 5% level. The IV estimate is somewhat larger than the OLS coefficient of 0.101, consistent with attenuation bias in the OLS specification. Such bias could arise if

green-oriented investors select into firms that have already made substantial environmental progress, leaving less headroom for future improvement and attenuating the OLS relationship.

Column (5) reports the second-stage estimates for emissions intensity. While the point estimate remains negative (-12.128), it is no longer statistically significant. This pattern echoes the findings in Section 4.3: the causal effect of green price pressure appears concentrated in environmental scores rather than in emissions reductions, which require more substantive operational changes. In other words, the market-based incentives captured by our instrument successfully induce firms to improve their measured environmental performance, but these improvements may not translate into the deeper decarbonization efforts that matter most for climate outcomes.

4.5.2 Instrumenting greenness

We next address the concern that greenness may be endogenous in the demand estimation. If firms with higher valuations invest more in environmental initiatives, our estimates of investor demand for sustainability could reflect reverse causality rather than genuine investor preferences. This would subsequently bias our measure of green price pressure.

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. Specifically, we model greenness as a function of log-market-to-book equity and the exogenous characteristics as

$$g_t(n) = \psi + \phi \mathrm{mb}_t(n) + \mathbf{x}_t(n)'\boldsymbol{\gamma} + \nu_t(n). \tag{14}$$

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

$$\begin{aligned} \mathbf{E}[\nu_t(n) \mid \mathrm{mb}_t(n), \mathbf{x}_t(n)] &= 0, \\ \mathbf{E}[\varepsilon_{i,t}(n) \mid \mathrm{mb}_t(n), \mathbf{x}_t(n)] &= 0. \end{aligned} \tag{15}$$

These moment conditions allow us to estimate asset demand consistently through a two-step estimator. In the first step, we estimate Equation (14) by ordinary least squares. We denote the vector of estimated residuals as $\widehat{\nu}_t(n)$. In the second step, we estimate asset demand (6) by generalized method of moments based on moment condition (15), using the estimated residuals $\widehat{\nu}_t(n)$ as the instruments.

Appendix Figure A1 plots the estimated demand coefficients on greenness from our baseline

specification against those obtained when instrumenting for greenness. The two sets of estimated coefficients have a correlation of 0.974. This result suggests that reverse causality—whereby high-valuation firms invest more in environmental performance—does not materially bias our demand estimates. Our baseline specification already controls for social and governance scores, which helps isolate the environmental component from broader corporate quality. The IV estimates confirm that this approach is largely sufficient.

We re-construct green price pressure using the instrumented greenness estimates and re-estimate our main firm response regressions. Appendix Table A3 reports the results. The coefficient for environmental scores remains positive and statistically significant, with a magnitude similar to our baseline estimates. However, as with our first instrument, the effect on emissions intensity is no longer statistically significant, reinforcing the finding that green price pressure shapes measured environmental performance more than actual emissions reductions.

5 Conclusion

This paper investigates the catering channel of sustainable investing: how managers improve environmental performance to capture valuation premia created by investor demand for sustainability. Using a demand system framework, we introduce a firm-level measure—green price pressure—that quantifies firms' incentives to cater to investor sustainability preferences. 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. Firms respond strongly when managerial incentives are better aligned with stock prices, consistent with the catering channel. However, 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 catering to investor demand. Green price pressure serves as a market signal that, when internalized by managers with sufficient incentives, can induce responses in sustainability performance. Yet the firm response is uneven, both across companies and across environmental dimensions. These results highlight that market-based incentives 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.

Our methodology extends beyond environmental considerations to provide a general framework for studying how investor preferences shape corporate decisions. Our application to dividend policy demonstrates this versatility, yielding effects comparable in magnitude to those observed for environmental performance. This approach offers a systematic way to quantify market-based incentives and test catering theories across various firm characteristics, ranging from capital structure and investment policy to governance choices and strategic positioning.

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Table 1
Summary statistics for the demand coefficients

This table presents summary statistics for the demand coefficients estimated from Equation (6). 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 $t+3$. GPP approx is the approximation of green price pressure in Equation (9). GPP numerator and GPP denominator refer to the numerator and denominator of GPP Approx in Equation (9), respectively. 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 clustered by firm. We report standard errors 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)	(4)	(5)
GPP	0.101***				−9.080*
	(0.028)				(5.141)
GPP approx		0.100***			
		(0.028)			
GPP numerator			0.071**		
			(0.028)		
GPP denominator				−0.067**	
				(0.030)	
E-score	0.784***	0.784***	0.788***	0.792***	
	(0.017)	(0.017)	(0.017)	(0.016)	
Emission					0.797***
					(0.025)
Controls	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Within R^2	0.629	0.628	0.627	0.627	0.881
Observations	4,326	4,326	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. In Columns (4)–(6), we also include green price pressure (GPP). 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 clustered by firm. We report standard erros 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)
IO	0.021			−0.011		
	(0.031)			(0.032)		
IO UNPRI		−0.005			−0.025	
		(0.031)			(0.032)	
IO block			−0.017			−0.044
			(0.032)			(0.033)
GPP				0.103***	0.105***	0.110***
				(0.029)	(0.029)	(0.029)
E-score	0.795***	0.796***	0.797***	0.784***	0.784***	0.783***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
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 clustered by firm. We report the standard errors 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	0.033	0.014	0.154***
	(0.062)	(0.047)	(0.043)
E-score	0.657***	0.813***	0.787***
	(0.036)	(0.025)	(0.022)
Controls	✓	✓	✓
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
Within R^2	0.591	0.631	0.640
Observations	459	1,313	2,177

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 clustered by firm. We report standard errors below the parameters and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

		Theme score			
	E-score$_{t+3}$	Waste MGMT$_{t+3}$	Natural res$_{t+3}$	Climate change$_{t+3}$	E opp$_{t+3}$
	(1)	(2)	(3)	(4)	(5)
GPP	0.101***	0.225***	0.145***	0.081***	0.010
	(0.028)	(0.043)	(0.041)	(0.030)	(0.036)
E-score	0.784***				
	(0.017)				
Waste MGMT		0.629***			
		(0.024)			
Natural res			0.705***		
			(0.021)		
Climate change				0.750***	
				(0.016)	
E opp					0.626***
					(0.031)
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

Table 8
Green price pressure and future environmental improvement: Instrumenting green price pressure

This table reports instrumental variable estimates of the relationship between green price pressure (GPP) and future environmental performance. The instrument $Z^{\text{GPP}}_{n,t}$, as described in Section 4.5, isolates variation in green price pressure arising from differences in investor price elasticity, holding green preferences fixed at the economy-wide average. Columns (1) and (2) replicate OLS estimates from Table 4 for comparison. Column (3) reports the first-stage regression of GPP on the instrument. Columns (4) and (5) report second-stage estimates. 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 clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	OLS		First Stage	Second Stage (2SLS)	
	E-score$_{t+3}$	Emission$_{t+3}$	GPP	E-score$_{t+3}$	Emission$_{t+3}$
	(1)	(2)	(3)	(4)	(5)
GPP	0.101***	−9.080*		0.149***	−12.128
	(0.028)	(5.141)		(0.057)	(11.877)
Z^{GPP}			15.630***		
			(0.723)		
Controls	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
First-stage F-stat			467.63		
Within R^2	0.629	0.881	0.285	-	-
Observations	4,326	2,558	4,326	4,326	2,558

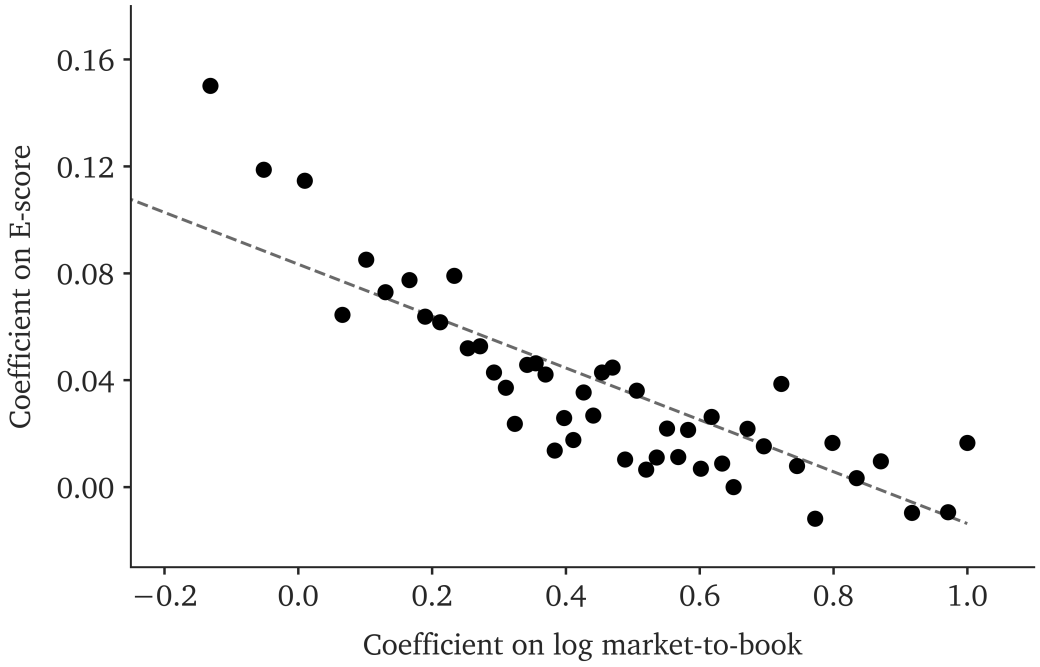


Figure 1. Binned scatterplot of demand coefficients. This figure shows the relationship between demand coefficients on environment score and price inelasticity in the binscatter plot.

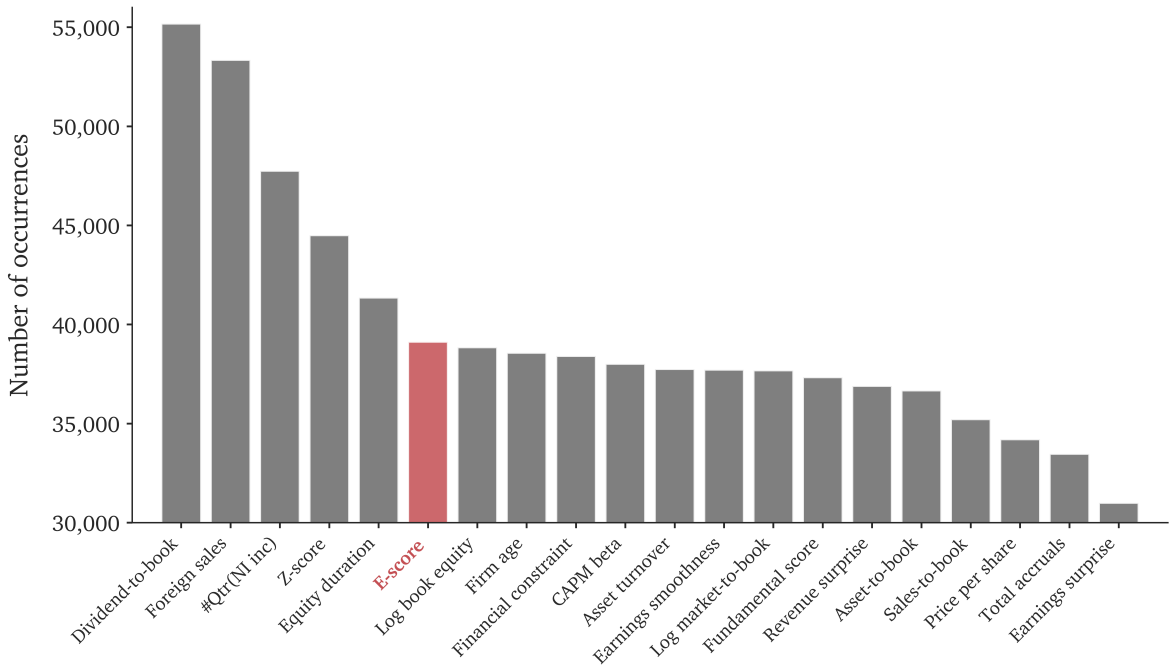


Figure 2. Importance of E-score relative to other characteristics. This figure shows the frequency with which each firm characteristic is selected by lasso regressions predicting institutional portfolio weights. We start with 153 firm characteristics from Jensen et al. (2023) plus the MSCI environmental score (154 total). For each investor and quarter, we estimate a cross-sectional lasso regression of log relative portfolio weights on all 154 characteristics. We increase the lasso penalty parameter until only 10 characteristics survive. We then count how many times each characteristic appears in the top 10 across all investor-quarter regressions. The bars display these survival counts for the 20 characteristics with the highest frequencies out of 128,572 investor-quarter regressions. The environmental score is highlighted in red.

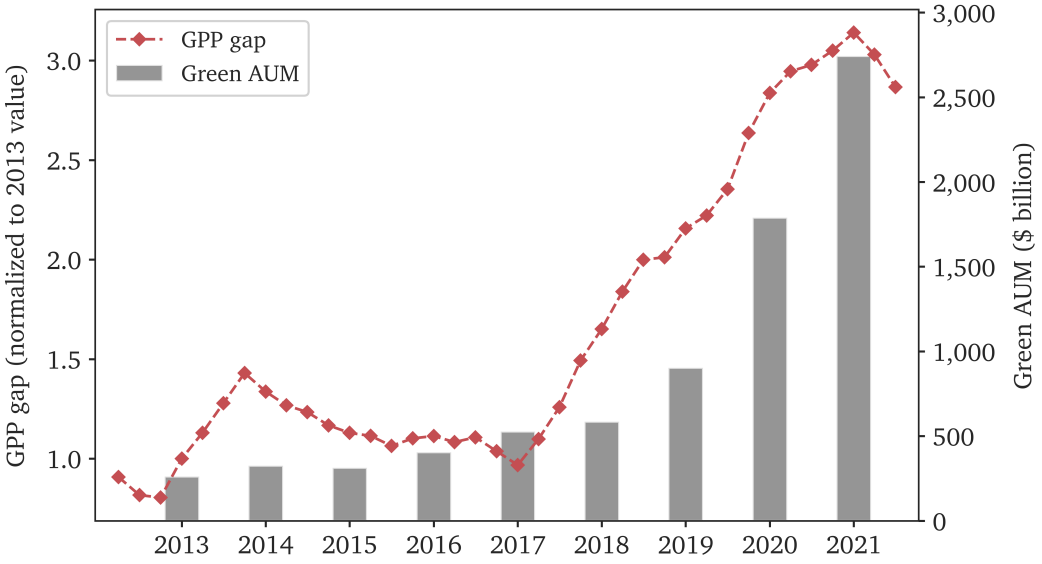


Figure 3. Green price pressure gap. This figure plots the green price pressure (GPP) gap over time (blue line) and the assets under management (AUM) of sustainable investment funds (green bars). The GPP gap is defined as the difference in average green price pressure between firms in the top and bottom 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.

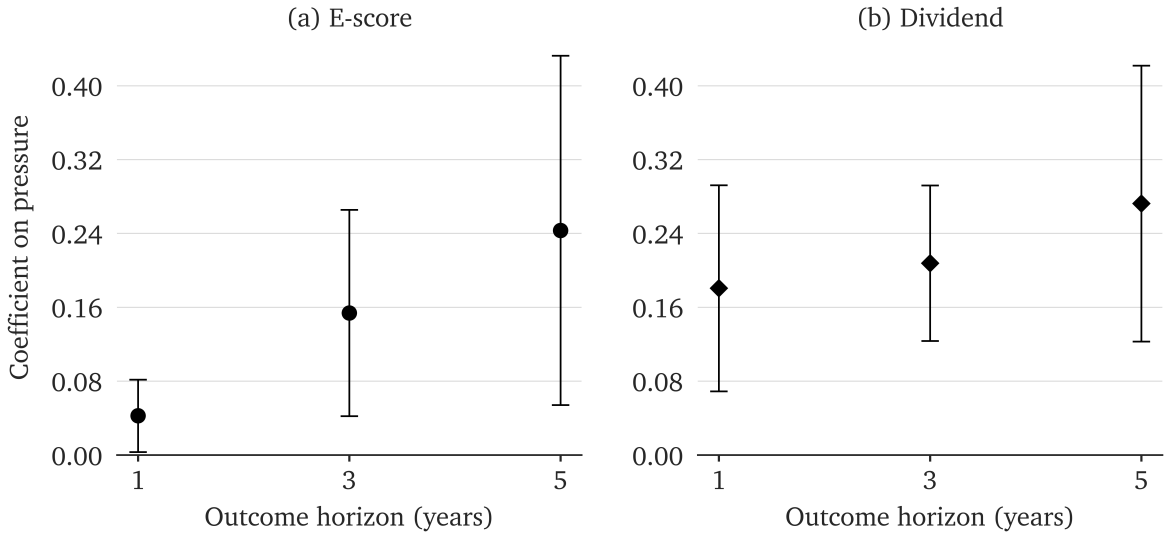


Figure 4. Benchmarking green price pressure to dividend price pressure. This figure shows the estimated coefficients from regressions of future firm outcomes on investor pressure, evaluated at horizons of 1, 3, and 5 years. We use two investor pressure measures: green price pressure and dividend price 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"

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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 $\upsilon_{it}(n)$ 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 $w^I_{it}(n) = \upsilon_{it}(n)/\sum_{n\in\mathcal{N}_{it}}\upsilon_{it}(n)$. 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[16]

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

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

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

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

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

[16] 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.

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

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

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

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

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:

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

□

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:

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

where $\text{mb}_t(n)$ 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, $\text{mb}_t(n)$ 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 $\left|\mathcal{N}_{it}\right|$ represent the number of stocks in this investment universe. Define $\mathbf{1}_i(n)$ 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:

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

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 95% 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 $(\text{Type Bin}, \text{Year})$ group, we estimate the demand coefficients using the following moment conditions:

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

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 $(\text{Investor}, \text{Quarter})$ 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 $(\text{Type Bin}, \text{Year})$ group, corresponding to an infinite penalty on β_{0it}. The coefficients on the other characteristics are estimated through the following moment condition:

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

where $\hat{\delta}_{i,t}(n) = \delta_{i,t}(n)\exp(-\hat{\beta}_0 \text{mb}_t(n))$. This penalty is inversely related to $\left|\mathcal{N}_{it}\right|$, 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:

$$\begin{aligned}\mathrm{var}(\Delta\mathbf{GPP}) = {} & \mathrm{cov}(\Delta\mathbf{GPP}(\mathbf{x}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\mathbf{g}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\mathbf{A}), \Delta\mathbf{GPP}) \\ & + \mathrm{cov}(\Delta\mathbf{GPP}(\beta_\mathbf{0}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\beta_\mathbf{1}), \Delta\mathbf{GPP}) + \mathrm{cov}(\Delta\mathbf{GPP}(\beta_\mathbf{2}), \Delta\mathbf{GPP}) \\ & + \mathrm{cov}(\Delta\mathbf{GPP}(\epsilon), \Delta\mathbf{GPP})\end{aligned} \tag{C8}$$

where we omit the time subscripts for simplicity.

D Additional tables and figures

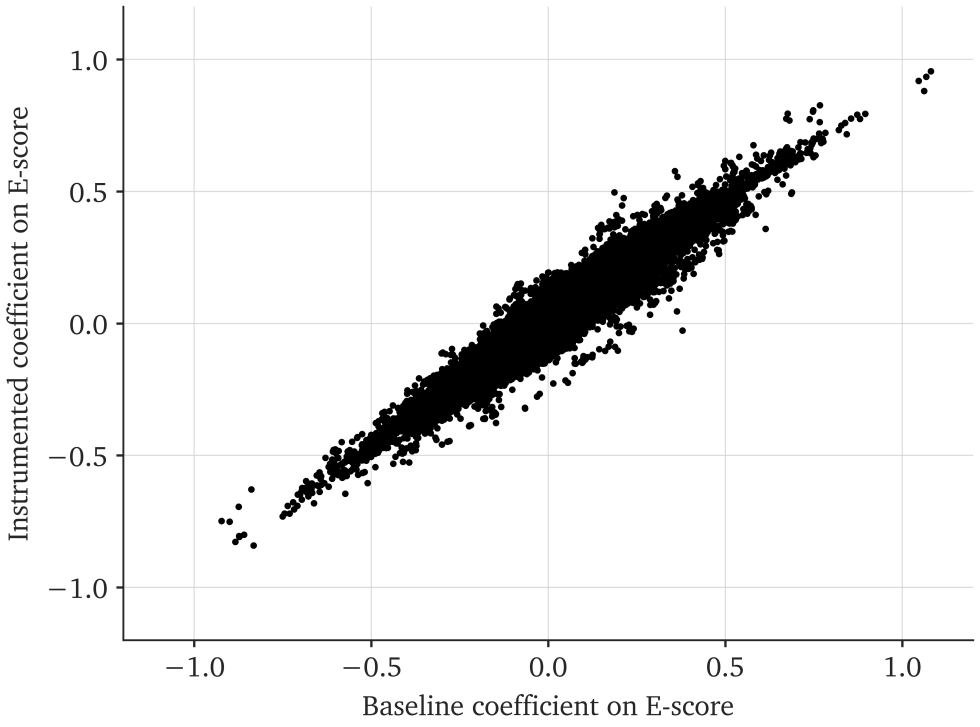


Figure A1. Scatterplot of demand coefficients with vs. without instrument for greenness. This figure compares demand coefficients on the environmental score estimated with and without instrumenting for firm greenness. Each point corresponds to an investor-firm-quarter observation. The construction of the instrument is detailed in Appendix 4.5.2.

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 clustered by firm. We report standard errors 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
	(0.044)	(10.899)	(0.050)	(0.052)	(0.046)	(0.054)
E-score	0.735***					
	(0.025)					
Emission		0.681***				
		(0.040)				
Waste MGMT			0.486***			
			(0.035)			
Natural res				0.626***		
				(0.028)		
Climate change					0.656***	
					(0.024)	
E opp						0.503***
						(0.042)
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
Event returns of ESG incident news: Placebo Test

This table reports a placebo test for the event study in Table 2. We sort firms into terciles by E-score rather than green price pressure. 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. CARs are calculated over two event windows: [–1, +3] and [–1, +10] trading days relative to the event date. Standard errors are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

		E-score group		
	Full sample	Low	Medium	High
	(1)	(2)	(3)	(4)
Panel A: Window $[-1, +3]$				
Market excess	−0.153	−0.113	−0.102	−0.132
	(0.108)	(0.150)	(0.155)	(0.187)
CAPM alpha	−0.229**	−0.215	−0.188	−0.178
	(0.104)	(0.144)	(0.152)	(0.181)
Panel B: Window $[-1, +10]$				
Market excess	−0.119	0.101	−0.161	−0.338
	(0.155)	(0.242)	(0.222)	(0.261)
CAPM alpha	−0.318**	−0.163	−0.366*	−0.397
	(0.146)	(0.228)	(0.219)	(0.250)
Number of incidents	3,115	1,339	947	617

Table A3
Green price pressure and future environmental improvement: Instrumenting 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 Section 4.5.2. The dependent variables are the environmental (E) score and emissions intensity 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 by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	E-score$_{t+3}$	Emission$_{t+3}$
	(1)	(2)
GPP	0.096***	–9.408
	(0.028)	(5.884)
Controls	✓	✓
Industry FE	✓	✓
Year FE	✓	✓
Within R^2	0.628	0.881
Observations	4,326	2,558